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Economic valuation of innovative rainwater management solutions

Georges Farina

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THÈSE PRÉSENTÉE
POUR OBTENIR LE GRADE DE
DOCTEUR DE
L'UNIVERSITÉ DE BORDEAUX

École Doctorale Entreprise, Economie, Société
Spécialité : Sciences Economiques

Par Georges FARINA

Evaluation Economique de Solutions Innovantes De
Gestion Des Eaux Pluviales
Economic Valuation of Innovative Rainwater Management
Solutions

Sous la direction de :

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Titre : Evaluation économique de solutions innovantes de gestion des eaux pluviales

Résumé :

Les villes sont confrontées à la nécessité de s'adapter aux enjeux du changement climatique et de la croissance urbaine : risques d'inondations, problèmes de disponibilité de l'eau, effets d'îlot de chaleur, pollutions atmosphériques et aquatiques, etc. Les Solutions Fondées sur la Nature (SfN) ont émergé comme des solutions prometteuses dans les politiques publiques et permettant d'atténuer les enjeux climatiques tout en offrant de multiples bénéfices. Dans le domaine de la gestion des eaux pluviales urbaines, de nouvelles solutions ont émergé étroitement liées aux SfN, telles que les techniques « alternatives » de gestion des eaux pluviales. Malgré un intérêt croissant pour ces solutions et de nombreuses avancées dans l'évaluation de leurs multiples bénéfices, elles restent mises en œuvre à petite échelle dans les villes, et au cas par cas.

Cette thèse aborde deux lacunes dans les approches d'évaluation des SfN et d'aide à la décision. Tout d'abord, elle examine les dimensions spatiales des coûts et des bénéfices des SfN - les bénéfices et les coûts des SfN sont spatialement hétérogènes. Pourtant, peu de recherches ont approfondi cette question tout en prenant en compte la demande de la population. Deuxièmement, elle vise à adapter les méthodes d'aide à la décision aux enjeux de la planification urbaine. La planification des SfN à l'échelle d'une ville pour l'adaptation au changement climatique est un problème spatial complexe. Dans des contextes de ressources limitées, d'espace restreint, d'acteurs multiples et d'objectifs concurrents, comment optimiser l'emplacement et les types d'infrastructures, en tenant compte de leurs divers bénéfices et coûts spatialement hétérogènes ?

La thèse adopte une approche appliquée, basée sur une étude de cas à Bordeaux Métropole, en France : le développement d'infrastructures de recharge des eaux souterraines urbaines, dites « Solutions innovantes de gestion des eaux pluviales » (SIGEP), dédiées à la préservation des aquifères, ainsi qu'à la production de co-bénéfices. La thèse adopte une approche multidisciplinaire : elle utilise une approche d'expérience de choix discrets pour évaluer l'hétérogénéité spatiale des bénéfices multiples des SIGEP. Elle utilise également un cadre d'Optimisation Multi-Objectifs (OMO) pour fournir une approche de prise de décision.

Le chapitre 1 donne un aperçu du cas d'étude ainsi que du cadre général de l'OMO. Il met également en évidence les composants clés spécifiques des algorithmes évolutionnaires utilisés pour résoudre l'OMO.

Dans le chapitre 2, nous examinons la demande pour des scénarios contrastés de mise en place de SIGEP dans l'agglomération bordelaise, à travers une expérience de choix. Nous analysons et expliquons l'hétérogénéité spatiale des préférences individuelles à travers l'impact des inégalités environnementales : l'exposition des individus aux îlots de chaleur influence positivement leur demande pour des scénarios

visant à réduire les zones d'îlot de chaleur, et la dépendance des individus à l'utilisation de la voiture influence leur demande pour des stratégies qui mène à utiliser de l'espace de voirie.

Le chapitre 3 examine 1) le problème théorique de la planification des SIGEP en ville en présence de multiples objectifs définis par des gradients urbains-ruraux, et 2) la viabilité de l'OMO pour résoudre ce problème. Nous appliquons une OMO à un modèle de ville monocentrique simple dans un cadre expérimental. Nous identifions des stratégies polaires pour la planification des SIGEP, et mettons en évidence l'impact des effets de substitution des espaces verts existants sur la demande en SIGEP, et la possibilité de combiner les SfN et les infrastructures grises pour atteindre de hauts niveaux de bénéfices à de faibles coûts d'opportunité.

Le chapitre 4 présente l'application de l'OMO à l'agglomération bordelaise. Cette application inclut un volet participatif, l'intégration d'une évaluation spatiale de la capacité de recharge des eaux souterraines et d'une analyse spatiale de la demande de demande en rafraîchissement urbain. Il propose également de nouvelles méthodes pour explorer les fronts de Pareto. Nous mettons en évidence les principaux compromis en jeu et comment ils se traduisent par des stratégies distinctes.

Nous concluons la thèse en résumant les principales conclusions en termes de recommandations de politique publique pour la planification spatiale des SIGEP dans les villes. Nous fournissons également des idées et des perspectives pour de futures recherches concernant l'OMO et l'étude de l'hétérogénéité spatiale des préférences.

Mots-clefs: économie de l'environnement, services écosystémiques, solutions fondées sur la nature, optimisation multi-objectif, expérience de choix, gestion des eaux pluviales

Title: Economic Valuation of Innovative Rainwater Management solutions

Abstract

Cities are confronted with the need to adapt to the challenges of climate change and urban growth: flood risks, water availability issues, heat island effects, atmospheric and water pollutions, etc... Nature-Based Solutions (NBS) have emerged as promising solutions: they rely on ecosystems to mitigate climate challenges, while offering multiple co-benefits. In the field of urban rainwater management, new solutions have emerged closely related to NBS, such as Sustainable urban Drainage Systems (SuDS). Despite increasing interest in these solutions, and many advancements in the assessment of their multiple benefits, they have not been integrated widely in cities, and remain implemented on a small scale and on a case-by-case basis.

The thesis identifies and addresses two gaps in NBS assessment and decision-support approaches. First, it investigates the spatial dimensions of costs and benefits of NBS - the benefits and costs of NBS vary spatially, with the spatial scales of ecosystem services, and along urban-rural gradients. Yet little research has investigated thoroughly this question while taking into account the demand for urban NBS. Secondly, it aims at adapting decision-support methods to the challenges of urban planning. Planning NBS at a city scale for climate change adaptation is a complex spatial puzzle, with limited resources, scarce space, numerous stakeholders and competing objectives: how to optimize the location and types of infrastructures, considering their numerous spatially varying potential benefits and costs?

The thesis takes an applied approach, based on a case study in the Bordeaux metropolitan area, France: developing urban groundwater recharge infrastructures (GRI), including NBS, dedicated to preserving aquifers, as well as providing co-benefits. The thesis adopts a multidisciplinary approach: for evaluating the spatial heterogeneity of benefits of GRI, using a stated preference study and a hydrogeological study. It also uses a Multi-Objective Optimization (MOO) framework, for providing a decision-support approach.

Chapter 1 provides an overview of the case study, as well as the general MOO framework. It also highlights the specific key components of evolutionary algorithms used for solving MOO.

In Chapter 2, we investigate the demand for NBS co-benefits in the metropolitan area of Bordeaux, through a choice experiment. We analyze and explain the spatial heterogeneity of individual preferences through the impact of environmental inequalities: individual's exposure to heat islands affects positively their demand for urban cooling co-benefits, and individual's reliance on car use affects their preference for GRI strategies.

Chapter 3 investigates 1) the theoretical problem of planning GRI in city in the presence of multiple objectives defined by differentiated spatial gradients, and 2) the viability of MOO in addressing this problem. We apply a MOO on a simple monocentric model city in an experimental setting. We identify

polar strategies for planning recharge infrastructures, the impact of substitution effects in discarding centric locations, and the possibility to mix NBS and grey infrastructures for reaching high benefits for low opportunity costs.

Chapter 4 presents the MOO application to the Bordeaux Metropolitan Area, incorporating stakeholder participation, a spatial evaluation of groundwater recharge capacity, and a spatial analysis of demand for heat mitigation. It also provides novel methods for exploring Pareto fronts. We highlight the main trade-offs at play, and how they translate into distinct strategies.

We conclude the thesis by summing up the main findings in terms of public policy recommendations for the spatial planning of GRI and NBS in cities. We also provide insights and perspectives for future research regarding MOO and the investigation of spatial preference heterogeneity.

Keywords: Environmental economics, ecosystem services, Nature-based solutions, multi-objective optimization, choice experiment, urban hydrology

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Scientific contributions

These are the main scientific contributions of this thesis, featured within its various chapters.

Publications

Farina, G., Le Coënt, P., Hérivaux, C. (2023). Do urban Environmental inequalities influence demand for nature-based solutions ? (Under review at Ecological Economics as of October 2023)

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Acronyms

| | |
|-------|---|
| AT | Alternative Techniques |
| BM | <i>Bordeaux Métropole</i> |
| BMP | Best Management Practices |
| CBA | Cost-Benefit Analysis |
| CGRI | Conventional Groundwater Recharge Infrastructure |
| ES | Ecosystem Services |
| GRI | Groundwater Recharge Infrastructure |
| IRIS | <i>Ilots Regroupés pour l'Information Statistique</i> |
| MCDA | Multi-Criteria Decision Analysis |
| MEA | Millennium Ecosystem Assessment |
| MOO | Multi-Objective Optimization |
| MXL | Mixed Logit Model |
| NBGRI | Nature-Based Groundwater Recharge Infrastructure |
| NBS | Nature-Based Solutions |
| SuDS | Sustainable Urban Drainage Systems |
| WTP | Willingness To Pay |

Foreword

This thesis is the result of a Ph.D. conducted between July 2020 and October 2023. The specific doctoral framework underpinning this research is known as "*Conventions industrielles de formation par la recherche*" (CIFRE) in French law. The term "CIFRE" denotes an industrial doctoral thesis carried out as a collaboration between a company or organization, and a research center, with a focus on applied research and practical implications. In this instance, the doctoral thesis framework was tailored to a Research and Development (R&D) initiative undertaken in the Metropolitan Area of Bordeaux, France. The doctoral project was a collaborative effort involving the Metropolitan Area of Bordeaux's water treatment company (SABOM), where I was primarily employed during the project, alongside my affiliation with the Bordeaux School of Economics (BSE) at the University of Bordeaux, and the BRGM (French Geological Survey).

General introduction

Introduction

In the aftermath of a severe storm event in 2011, which led to widespread flooding, Copenhagen launched the Cloudburst Management Plan¹, a comprehensive 20-year initiative aimed at preparing the city for extreme rain events. This plan stands out significantly in the realm of urban climate change adaptation policies, as it represents one of the few large-scale efforts to proactively address the city's vulnerability to future climate change impacts. What sets this plan apart is its comprehensive approach, supported by a multidisciplinary investigation that encompasses the design, modeling, and evaluation of various adaptation scenarios. The urban adaptation strategy backed by the plan involves a phased approach, prioritizing specific areas for adaptation as a first step. In addition, its scope goes beyond flood protection; it also encompasses measures aimed at mitigating the various adverse consequences of climate change on urban environments.

Copenhagen serves as an example of the dual role played by cities: they find themselves at the forefront of climate change, and have both a role of vulnerability and one of potential resilience. Housing a substantial - and growing proportion - of the global population, approximately 4.2 billion inhabitants, as well as the majority of assets and economic activities, cities are particularly exposed to the impacts of climate change, such as floods, droughts, pollutions, heat stress, etc. (Revi et al., 2014). The 2022 IPCC report unequivocally underscores this reality: cities are climate change hotspots, where risks have not only surged but are projected to escalate in the next decades (Dodman et al., 2022).

But cities are also the main potential actors in climate change mitigation and adaptation. They command considerable financial resources and capacities for innovation, the ability to formulate and implement transformative actions (Dodman et al., 2022; European Commission Directorate-General for Research and Innovation, 2015). As urban centers grapple with the escalating consequences of climate change, they concurrently wield significant potential to spearhead efforts aimed at climate resilience and mitigation.

Amidst the strategies that have emerged over the past decades for enhancing urban resilience, Nature-Based Solutions (NBS) have gathered significant attention, particularly in Europe (Davies et al., 2021). NBS are solutions that harness natural processes and ecosystems as a means for providing solutions to climate mitigation and adaptation challenges. These solutions have gained traction across

¹ <https://climate-adapt.eea.europa.eu/en/metadata/case-studies/the-economics-of-managing-heavy-rains-and-stormwater-in-copenhagen-2013-the-cloudburst-management-plan>

cities, infusing urban planning with innovative approaches aimed at providing multiple co-benefits to humans - notably mitigating the risks related to climate change - while simultaneously providing benefits to biodiversity and to ecosystems.

While interest in NBS is steadily growing, significant challenges persist in integrating them into cities. Some cities have formulated climate adaptation plans, but the translation of these plans into actions remains limited (Hudson et al., 2023; Oijstaeijen et al., 2020). Indeed, NBS have yet to become a priority in the majority of cities (Oijstaeijen et al., 2020), or are often being implemented on a case-by-case basis and at small scales (Almenar et al., 2016; Elmqvist et al., 2013). Consequently, many cities are missing opportunities to scale-up the co-benefits of NBS (Hudson et al., 2023).

A particular challenge in implementing such a comprehensive urban planning approach to climate change adaptation lies in the spatial variability of costs and benefits. The success of Copenhagen's Cloudburst Management Plan in prioritizing neighborhoods for climate change adaptation can be attributed to its prior in-depth spatial analysis of the potential costs and benefits associated with adaptation policies. In essence, the impact of developing NBS varies significantly depending on their specific geographical placement.

NBS research has largely focused on studying the potential impacts of these solutions, demonstrating their efficacy to address specific (climate change) challenges, analyzing their co-benefits, and developing assessment methodologies adapted for these solutions (Nesshöver et al., 2017). Environmental economics has been an integral part of this research, providing valuation of the co-benefits of NBS, and contributing to the formulation of decision support frameworks (Jacobs et al., 2016; Pascual et al., 2017). However, despite numerous advancements in these fields, a knowledge gap remains to facilitate the scaling-up of NBS development which is, 1) the spatial distribution of costs and benefits associated with NBS within urban settings, and 2) on the decision-support methods required to aid the large-scale planning of NBS in cities.

The overall objective of this thesis is to delve into the challenges of planning the development of Groundwater Recharge Infrastructures (GRI), which include Nature-Based Solutions, in urban areas. This investigation serves a dual purpose: it acts as an applied study for addressing a specific public policy initiative in a French city, while simultaneously aiming at addressing the research gaps concerning the spatial challenges associated with NBS. Two research questions are investigated in this work:

1. What is the spatial distribution of benefits of urban Groundwater Recharge Infrastructures?

2. How to optimize the location and types of urban Groundwater Recharge Infrastructures for maximizing their benefits, and minimizing their costs?

Addressing these questions can provide valuable insights into the climate change adaptation strategies of cities. Furthermore, this work can illuminate new research prospects for environmental economics, including the study of spatial heterogeneity in the value of NBS, and the development of novel decision support tools tailored for NBS planning.

In this introductory chapter of the thesis, we first establish the overall context of urban climate change adaptation as well as the potential solutions ([Section 1](#)). Subsequently, we delve into the two primary research gaps addressed in this thesis, encompassing the spatial challenges associated with NBS planning ([Section 2](#)) and the methods for decision support in NBS planning ([Section 3](#)). Finally, we present the core research questions and the methodologies devised for their exploration ([Section 4](#)).

1 An overview of urban climate change adaptation

1.1 Cities and climate change

Cities worldwide are confronting a multitude of challenges arising from the combined drivers of urban growth and climate change (de Sherbinin et al., 2007). Urban growth is a fast phenomenon: with the current trend, more than half of the global population already resides in urban areas, and this number is projected to exceed 60% by 2030 (UN, 2018). The expansion of urban areas is a source of land use change, with an anticipated increase in urban land by 1.5 million km² by 2030 (Seto et al., 2011). The effects of climate change on the other hand are numerous and diverse (IPCC, 2021), and this combination of urban growth and climate change have far-reaching and deep consequences on the sustainability of cities (Elmqvist et al., 2013).

One the main challenges among these are water-related challenges. For instance, water-related hazards, such as floods and droughts account for about 90% of all natural hazards impacting cities (Koop & van Leeuwen, 2017). 1.2 billion people are exposed to flood risks today, in majority urban citizens, and this figure is expected to rise to 1.6 billion by 2050 (WWAP, 2018). As such, most cities around the world are exposed to water-related risks such as pluvial floods, which are themselves a consequence of land use change, increased water runoff, and a transformation in extreme weather patterns (Bulkeley, 2013; UN, 2018).

These water-related hazards are also linked with freshwater management. Freshwater availability in and around large urban areas is already severely impacted, with around 150 million people currently living in cities with perennial water shortage, a figure which is expected to increase by 100 million by 2050 (McDonald et al., 2011). These challenges are a consequence of urban growth on the one hand, and the impact of climate change on water consumption (WWAP, 2018), as well as its effects on the reduction in groundwater recharge (Jacobson, 2011) on the other hand. Altogether, the number of large cities in the world exposed to water scarcity could double by 2050, from 193 to 284 (He et al., 2021). This challenge also combines with the degradation of water quality across the globe, resulting mainly from nutrient loading and poor wastewater treatments (Livesley et al., 2016; WWAP, 2018). Addressing those water-related hazards is of priority for many cities, and a driver for many of their climate change adaptation strategies.

One approach to mitigating water shortages in cities and settlements involves securing local water resources and searching for alternative – and further - water sources. However, this strategy has the potential to produce conflicts (Gleick & Heberger, 2014). The failures in the management of this common good have been well investigated, and can notoriously lead to conflicts between users, cities, between urban areas and rural areas, and even between nations (Cosgrove & Loucks, 2015; Green, 2003). Concerning cities, one potential strategy identified by policy makers is to secure their local water resources, by restoring the hydrological cycles and improving urban water groundwater levels (Gao et al., 2014; WWAP, 2018). These strategies encompass various innovative solutions that fall within the broader category of climate change adaptation solutions. This thesis is focused primarily on such water management challenges.

In addition to these challenges, climate change and urban growth also have direct impacts on the quality of the environment. Urban growth, as well as population and human activity concentrations lead to an increase in solid waste emissions, significant air and water pollution issues (Kahn, 2007), as well as soil pollution (Rodríguez-Martín et al., 2015). It also impacts deeply biodiversity, mainly by reducing and degrading habitat (Revi et al., 2014), with an estimated 290 000km² of natural habitat forecasted to be transformed into urban land between 2000 and 2030 (McDonald et al., 2019). These pressures have profound implications for both ecosystem functionality and human well-being in urban environments (Koop & van Leeuwen, 2017; Sturm & Cohen, 2014; Wolch et al., 2014). It also has indirect effects which affects even greater areas, for instance through the transformation of natural areas into agricultural lands for the purpose of food production (McDonald et al., 2019). An example for such a consequence in Europe is for instance the loss of wetlands, approximately 60% to 70%, attributed to factors like intense agricultural practices, urban expansion, and various contaminations (Verhoeven, 2014).

Urban growth and climate change also pose more direct challenges on human well-being, as they affect negatively the livability of urban areas (Mader et al., 2011). Among these effects, certain extreme climate events are becoming more intense as well as more frequent due to climate change, exacerbating urban issues (IPCC, 2021). An example of such a challenge is the increase in heat island effects - whereby some urban areas are hotter than their surrounding suburban and rural areas - (Heaviside et al., 2017; Rizwan et al., 2008), which is a consequence of multiple drivers: climate change, land cover change, the increase in urban atmospheric pollution (Ulpiani, 2021). According to recent estimates, the urban heat island effect is directly responsible of approximately 6,700 deaths annually in European cities (Iungman et al., 2023). Furthermore, in European Mediterranean cities, like Barcelona and Milan, the average morbidity due to urban heat is anticipated to surge by 8 to 10 times in the near future, under a relatively optimistic emission scenario (RCP4.5) (Iungman et al., 2023). Heat island areas have many negative effects on human health, such as increasing the risks of cardiovascular and mental pathologies, as well as having a negative overall impact on well-being, livability, and productivity in cities (Heaviside et al., 2017).

In addition to impacting negatively human health (Iungman et al., 2023), heat islands produce high costs for society, for instance in terms of energy consumption and CO₂ emission (Phelan et al., 2015), or by producing other negative externalities, such as increasing atmospheric pollution (Piracha & Chaudhary, 2022; Sarrat et al., 2006; Ulpiani, 2021). Atmospheric pollution is in fact another central challenge for cities, affecting directly their citizens: air pollution has been identified among the top 10 factors affecting health across the world (Cohen et al., 2005; Dhimal et al., 2021), is a significant risk for about 90% of the global population, and accounts for about 7 million premature deaths annually (WHO, 2015). The emergence of these numerous challenge have called for new solutions for climate change adaptation.

1.2 Solutions for urban climate change adaptation

1.2.1 Urban nature based solutions

Urban Nature-Based Solutions (NBS) have gained increasing attention as solutions to the aforementioned many challenges. The concept of NBS emerged in the 2000s but gained significant popularity with the release of influential reports such as the World Bank's "Biodiversity, Climate Change and Adaptation" (MacKinnon et al., 2008), and the International Union for Conservation of Nature (IUCN) reports (Cohen-Schacham et al., 2016). The IUCN's definition of NBS is the most widely accepted:

“Nature-based Solutions (NBS) are defined [...] as actions to protect, sustainably manage and restore natural or modified ecosystems, which address societal challenges (*e.g.* climate change, food and water security or natural disasters) effectively and adaptively, while simultaneously providing human well-being and biodiversity benefits.” (Cohen-Schacham et al., 2016, p.13)

NBS embody a diverse array of solutions inspired by natural ecosystems to tackle various environmental and socio-economic issues. These solutions are characterized by the management of natural processes to achieve specific objectives, and deliver multiple benefits in environmental, social, and economic domains in a cost-effective manner (WWAP, 2018). Some examples of NBS interventions include green infrastructure, ecological restoration, natural area conservation, reforestation, and urban greening (Cohen-Schacham et al., 2016).

NBS have emerged as a promising approach to address the challenges posed by climate change and urban growth, while having benefits for biodiversity (Cohen-Schacham et al., 2016). This concept is rooted in the idea that development and nature conservation can complement each other, rather than being conflicting objectives (Nesshöver et al., 2017). NBS, as an "umbrella" term, is characterized by its ability to simultaneously benefit biodiversity and human well-being (Cohen-Schacham et al., 2016). Therefore, the concept is related to other approaches like blue/green infrastructures, ecosystem-based adaptation/mitigation, natural capital, and ecological engineering (Nesshöver et al., 2017). NBS have gained traction in scientific literature, institutional reports, and strategic planning (Nesshöver et al., 2017). The interest in NBS has surged in the 2010s, with the Horizon 2020 EU research program positioning the EU as a leader in NBS research (Davies et al., 2021).

Given the far-reaching impacts of climate change and ecosystem degradation, NBS have been used across diverse sectors and areas. Notable examples include for instance forest restoration and conservation, which not only facilitate climate change adaptation and biodiversity conservation but also support tourism, local incomes, and energy security (Cohen-Schacham et al., 2016; Naidoo & Ricketts, 2006; Sarkar et al., 2006); and the restoration of degraded floodplains (Hoang et al., 2018) mangrove forests (Owuor et al., 2019), and oyster reefs (Sturm & Cohen, 2014) for safeguarding shorelines and coastal populations from flooding while restoring biodiversity.

In urban settings, NBS programs encompass many different actions and infrastructures dedicated to protecting or introducing nature in urban areas. They can be the conservation or creation of urban forests (Escobedo et al., 2011) the creation of other green spaces such as parks (Alves et al., 2020; European Commission Directorate-General for Research and Innovation, 2015; Jim, 2004; Votsis, 2017), as well as urban "blue" areas like rivers, lakes, wetlands, and ponds (Axelsson et al., 2021; Bockarjova et al.,

2020; Nghiem et al., 2021; Primo C. et al., 2018; WWAP, 2018). Urban NBS are typically smaller scale vegetated infrastructures that can be implemented within streets and public spaces, including green areas, small urban parks, urban microforests, bioswales, bioretention basins, and ponds. They can also be integrated into private spaces and around buildings, exemplified by rain gardens, green roofs, and green facades (Hartig & Kahn, 2016; Kabisch et al., 2016; Mader et al., 2011).

One of the central characteristic of NBS is that they are actions that provide multiple benefits. Usually, they provide a central “benefit”, which is the main challenge at hand being addressed, and the main driver of a NBS policy (Nesshöver et al., 2017), for instance, risk mitigation. In addition, NBS provide a series of additional benefits, often dubbed “co-benefits”, which can be for instance regulating various pollution sources, mitigating heat island effects, providing various aesthetic and recreational amenities, as well as supporting biodiversity, and sequestering carbon from the atmosphere. Because of co-benefits, NBS are considered as more efficient and cost-effective solutions to more traditional approaches (Estrada et al., 2017; European Commission Directorate-General for Research and Innovation, 2015), as they provide the main functions of traditional infrastructures, but simultaneously provide benefits to biodiversity and human well-being (Raymond et al., 2017).

Co-benefits are inherently linked with the concept of Ecosystem Services (ES). ES are defined by the Millenium Ecosystem Assessment (2005) as the “benefit that people obtain from ecosystems”. They encompass for instance vital essentials such as sustenance, clean water, and raw materials, in addition to crucial processes like climate regulation and flood control¹ (Overpeck et al., 2005). This concept is closely intertwined with NBS, as NBS initiatives aim at actively harnessing and enhancing the flows of ES to tackle environmental challenges. ES are a broader concept that encompasses the various functions ecosystems provide to humans, while NBS co-benefits are the specific, positive outcomes that result from the implementation of NBS.

¹ The concept of Ecosystem Services was popularized by the Millennium Ecosystem Assessment (Overpeck et al., 2005), and refined through successive conceptual definitions. The Millennium Ecosystem Assessment introduced a classic typology of four distinct categories of ecosystem services. The first one are supporting services, which lay the foundation for all other ecosystem services. They include functions necessary for the existence of life and ecosystems, such as nutrient cycling, soil formation, and primary production. The second category are provisioning services: These services are directly obtained from ecosystems and contribute to human material needs. They encompass products like food, freshwater, raw materials, and resources harvested from natural systems. The third is regulating services. They govern environmental processes, often providing vital benefits to the balance and stability of ecosystems. They include services such as climate regulation, natural hazard mitigation (*e.g.*, flood control), and disease regulation. Finally, there are cultural services. They are the non-material in nature and pertain to the cultural, spiritual, and psychological aspects of human interaction with the environment. Cultural services encompass aesthetic experiences, recreational opportunities, and cultural heritage that are deeply intertwined with the natural world.

1.2.2 Sustainable urban Drainage Systems and rainwater management

Rainwater management is a critical topic in many cities, as it is closely linked to various challenges such as pluvial flood risks, the degradation of hydrological cycles and of water-based ecosystems. Interestingly, within the realm of rainwater management, a trend has emerged in the last decades, almost paralleling in this way NBS. Indeed, this trend also advocates for a shift from traditional mono-functional infrastructures, towards rainwater management approaches that benefit both to human welfare and to the environment (UN WATER, 2018).

To comprehend this trend better, it is essential to provide a brief background on rainwater management in cities. The history of wastewater and rainwater drainage systems can be traced back to around 3000 BC, with their coexistence alongside urban streams (Chouli, 2006; de Feo et al., 2014). However, it was during the 18th-century industrial revolution and widespread urban expansion that modern urban water management practices emerged in Great Britain and France. The "hygienism" doctrine aimed to drain all water out of cities quickly to improve their sanitation (Butler et al., 2018). Consequently, stagnant water, including natural wetlands and marshes, was viewed as a source of unhealthiness and was systematically drained, diverted, or buried (Dupuy et al., 1982). As urban areas grew, natural environments' capacity to purify urban waters was outstripped, leading to the development of separate networks: wastewater is purified, while rainwater is discharged directly into natural water bodies – usually the ocean or urban streams and rivers (Barraqué, 2014). Chemical and physical wastewater treatment knowledge developed in parallel. Throughout the 20th century, urban water management efforts predominantly focused on wastewater treatment and the development of separate sewer systems, although combined sewer systems still exist extensively, particularly in historical city centers (Butler et al., 2018; Thebault et al., 2020).

Over the years, rainwater management has witnessed a notable evolution marked by the emergence of new approaches since the 1970s (Thebault et al., 2020). Among these approaches, are noteworthy those called Sustainable Drainage Systems (SuDS), Best Management Practices (BMPs), Sponge Cities, and Alternative Techniques (AT), which have gained traction in addressing a range of urban challenges (Fletcher et al., 2015). The common motivation behind these approaches is twofold: prioritizing the mitigation of pollution in natural areas, and seeking more cost-efficient flood protection measures as costs escalate (Thebault et al., 2020; World Bank, 2018). Over time, rainwater management has expanded its scope from solely focusing on flood mitigation to encompassing first water quality enhancement, the restoration of flow regimes, up to the provision of aesthetic and recreational amenities, urban cooling, and more - in other words, co-benefits (Fletcher et al., 2015).

Sustainable Urban Drainage Systems (SuDS) have emerged as a transformative approach to stormwater management in the UK in the late 1980s and gained momentum in the 1990s (Fletcher et al., 2015). SuDS practices involve a range of technologies and techniques designed to drain stormwater in a more sustainable manner, aiming to replicate the pre-development natural drainage as closely as possible (Kellagher et al., 2007), and has been mandatory in most new developments since 2003 in large parts of the UK. Typically, SuDS are configured as a sequence of stormwater practices and technologies such as filter strips, swales, infiltration basins, pervious surfaces and green roofs, designed to be implemented as a management “train” in urban areas, to effectively reduce water runoff (Kellagher et al., 2007). The term SuDS has gained much momentum, especially in scientific literature, and is often the term used for all new sustainable rainwater management practices (Fletcher et al., 2015). In fact, from here forward, the term SuDS will be used in this thesis to relate to these type of initiatives.

Best Management Practices (BMPs) originated in North America and were initially aimed at reducing pollution in natural environments, notably established in the Clean Water Act (1972). Today, BMPs encompass a wide array of practices, operations, and works that prevent pollution in various domains, including urban stormwater management. The US Environmental Protection Agency (USEPA) has played a crucial role in defining BMPs and compiling a national database to concentrate and disseminate knowledge on their performance and effectiveness (Clar et al., 2004).

China's innovative initiative, Sponge Cities, was launched in 2013 with the ambitious goal of transforming all its major cities to enhance urban sustainability and climate resilience, representing the largest-ever effort by a government to achieve urban sustainability and adapt cities to climate change (Jia et al., 2017). These cities adopt the concept of becoming "sponges" capable of absorbing, storing, and filtering rainwater while reducing flood risks and improving water quality (Li et al., 2016). Sponge Cities embody an integrated approach, combining both grey infrastructure and Nature-Based Solutions (NBS) to achieve their objectives. Unlike other concepts mentioned here, the Sponge Cities concept places a greater emphasis on water resource management.

In France, the term "Alternative Techniques" (AT) was coined in the 1990s as a paradigm shift in stormwater management compared to the traditional “in pipe” rapid drainage approach. These techniques gained momentum as they provided more cost-effective solutions for managing stormwater amid urban sprawl (Thebault et al., 2020). Emphasizing “management at source” AT encourages infiltration, retention, and natural treatment of stormwater before its discharge into water bodies (Barraud et al., 2022).

All these trends show a convergence towards solutions closely resembling Nature-Based Solutions, though applied primarily to water-related challenges. They are techniques that aim at mitigating urban

development, return to a predevelopment state, by restoring natural hydrological functions. Some of these solutions also make use of vegetation to provide climate change adaptation benefits. These approaches prioritize sustainability, co-benefits, and resilience while departing from conventional civil engineering practices that dominated urban development in the past. These rainwater management solutions encompass NBS, applied to urban hydrology.

The emergence of these new family of solutions, both NBS as well as their similar techniques developed in the branch of rainwater management, have also led to revising public policy making and assessment methods.

1.3 The current state of NBS policies

1.3.1 New assessment methods for NBS

The emergence of NBS as viable solutions for climate change adaptation has led to the necessity to revise and adapt policy assessment frameworks, primarily because of their multifaceted co-benefits (Raymond et al., 2017). For this reason, NBS have become a significant area of research in the past decades, especially in the European Union (Nesshöver et al., 2017). Indeed, researchers have expressed early on the need for an operational framework and research to support the widespread adoption of NBS at all institutional levels (Cohen-Schacham et al., 2016). This encompassed the necessity for assessing the various effects of NBS, establishing the drivers for their acceptance and the limits that hinder it, the challenges and opportunities for their development within various contexts, and providing decision-making support that enable their consideration in public policies (Nesshöver et al., 2017).

A range of conceptual frameworks have been developed for this purpose, dedicated to identifying and evaluating the co-benefits of NBS, assessing their effectiveness in addressing specific challenges, and often comparing them to conventional solutions like grey infrastructures (Frantzeskaki, 2019; Nesshöver et al., 2017). For this reason, most of the attention has been on refining the understanding of co-benefits, embodied by the production of a series of different analysis frameworks, with a focus on Ecosystem Services (Almenar et al., 2016; Dumitru et al., 2021; Haines-Young & Potschin, 2012; Mader et al., 2011; Overpeck et al., 2005). These approaches aim primarily at revealing and assessing the multiple co-benefits of NBS, often by providing classifications of co-benefits as well as guidelines and indicators for their evaluation, while relying on the underlying assumption that identifying and objectifying these co-benefits would lead to an increase in adoption of NBS in policies (Daily et al., 2009). These approaches have aided in pinpointing the specific co-benefits of individual projects and assigning value to them. These frameworks were largely influenced by economic and natural science perspectives, rooted in the concept of natural capital (Nesshöver et al., 2017), and have aimed at

furthering the comprehension of the diverse nature of these co-benefits, including how different types of NBS yield varying effects and advantages, as well as their negative impacts (Turkelboom et al., 2018).

The focus in the assessment of NBS has also been on integrating and understanding the perspectives of the various actors concerned with such policies, and to acknowledge the plural values held by ecosystems (Mader et al., 2011). These initiatives have led to the development of a profusion of scientific and grey literature for NBS assessment, dedicated to analyzing NBS initiatives (Alves et al., 2019; Calliari et al., 2019; Dumitru et al., 2021; Giordano et al., 2020; Jarvie et al., 2017; Kabisch et al., 2016; Majidi et al., 2019; Raymond et al., 2017; Ruangpan et al., 2020; Wild et al., 2017). This focus on NBS Assessment allows to improve the understanding of the outcomes of NBS policy, and aid the selection of NBS policies in specific contexts. These assessments help answer pivotal questions like which Ecosystem Services should be prioritized, which techniques are best suited to address particular challenges (Croeser et al., 2021), and how various stakeholders should be approached, engaged, and mobilized for successful NBS implementation (Nesshöver et al., 2017; O'Donnell et al., 2017).

1.3.2 A limited adoption of NBS

Despite the advancements in knowledge regarding these solutions, NBS are yet to be developed at a large scale. An overview of the current adoption of NBS reveals that their integration into policies remains relatively low, at least within the European Union (Davies et al., 2021). In other words, while having been advocated by academics, policy-makers and practitioners for years, these solutions are still not mainstreamed into urban development (Dorst et al., 2022). This statement also applies to the adoption of Sustainable Urban Drainage Systems (SuDS) practices – as well as all the other related techniques in the field of urban rainwater management. These solutions still lack systematic and generalized implementation, and remain only an alternative to more traditional “grey” techniques (Dhakal & Chevalier, 2017; O'Donnell et al., 2017).

This limited integration of NBS into urban policies relates to different phenomena.

First, there is a tendency in urban policies to adhere to path dependency, favoring traditional "grey infrastructure" solutions over NBS alternatives (Sarabi et al., 2019). This is especially the case in the field of urban rainwater management (Axelsson et al., 2021).

Secondly, the current adoption of NBS tends to be opportunistic rather than systematic, lacking a structured and consistent approach to their implementation and utilization (Hudson et al., 2023; Oijstaeijen et al., 2020). In other words a case-by-case approach is still applied in the development of

NBS (Sarabi et al., 2019). This limit is of importance, because missing on an integrated large-scale approach to NBS planning may lead to a suboptimal allocation of public resources (Tardieu, 2017).

Thirdly, and perhaps most importantly, most cities have yet to design and implement spatially explicit NBS development strategies (Almenar et al., 2016; Elmqvist et al., 2013). Many NBS initiatives are currently implemented on available land opportunities that are usually located outside densely populated centers where the need for adaptation services is the highest (Andrea Ramírez-Agudelo et al., 2020; Hudson et al., 2023; Kabisch et al., 2016). Such approaches may provide many benefits, address local challenges, and may maximize welfare in a given urban development project. However, many challenges may be concentrated in already built urban environment (Kabisch et al., 2017), with a high density of population and activities (González-García et al., 2020). Current applications of NBS do not necessarily target these areas, and therefore do not address the hotspots of climate change adaptation needs (Kato-Huerta & Geneletti, 2022; Seddon et al., 2020). Yet many cities already have the tools to guide urban planning in both new and existing urban areas: zoning laws for instance are the main tools for public decision makers to promote and enact land use change in urban contexts, often acting against market failures (Andersson et al., 2014; Goldstein et al., 2012). For example, the French *Plan Local d'Urbanisme intercommunal* (PLUi) and the *Schéma de Cohérence Territoriale* (SCoT) are legally binding zoning documents that define the general planning rules that apply to large urban areas. Such approaches, spatial planning approaches, applied to NBS - and ecosystem services in general - are currently missing (Goldstein et al., 2012; Kato-Huerta & Geneletti, 2022; Pan et al., 2021; Soga et al., 2014).

Overall, it appears that years after the development of the NBS concepts, the implementation and development of these solutions remains somewhat suboptimal. Researchers have identified many factors and barriers limiting the development of NBS. Among those causes, in a few words, the most commented upon are:

1. The necessity to still demonstrate and produce clear information regarding the effectiveness of NBS to address challenges (especially compared to grey infrastructures) in order to break path dependency (Axelsson et al., 2021; Sarabi et al., 2019).
2. The necessity of implementing bottom-up approaches in the policy making and urban planning, *i.e.* involving citizens in NBS elaboration (Giordano et al., 2020; Kati & Jari, 2016).
3. The need to create and diffuse non-expert assessment methodologies and practices outside of the academic world towards all layers of policy-makers (Daily et al., 2009; European Commission Directorate-General for Research and Innovation, 2015).

4. The necessity to transform public operations and institutions towards less sectoral fragmentation and more “transversal” actions, thus facilitating synergies between services, and shedding light into the importance of co-benefits (Kabisch et al., 2017; Sarabi et al., 2019).
5. The necessity to develop ES valuation practices, which are still fairly rare - especially at the smaller urban scales - thus hindering a comprehensive assessment of NBS benefits and impacts (Oijstaeijen et al., 2020). The concept of ES has not yet been widely embraced in EU policies, with its usage primarily confined to nature conservation and natural resources policies (Bouwma et al., 2018). In consequence, NBS, which benefits primarily stem from their ability to generate ES, are not necessarily given the spotlight (Langemeyer et al., 2016).
6. The relative lack of financing mechanisms and business models adapted for NBS (Kabisch et al., 2016; Nesshöver et al., 2017): NBS require long-term and integrated strategies, which can be hindered for instance by the scarcity of public funds (Davies et al., 2021; Hudson et al., 2023), and the short-term perspective that often dominates urban development strategies (Kabisch et al., 2016).

In addition to those general limits to NBS policy making, there are several barriers resulting from the valuation methods and tools themselves. This type of limits is the central focus of this thesis. In fact, we argue here that there remains significant gaps in the approaches to NBS evaluation. Many NBS assessment methodologies have been developed and are effective for assessing and carrying individual projects on a case-by-case basis. However, we argue that the utility of existing tools is limited when considering the problems of planning for urban climate change adaptation policies. Addressing these limits carries importance, especially considering that NBS have yet to be seamlessly integrated into public policies.

These limits arise specifically from two dimensions of NBS evaluation and decision-support methods, they are i) the spatial dimensions of costs and benefits of NBS; and ii) the limitations of traditional decision-support methods for the development of NBS in cities. These two points are further developed in the two following sections.

2 The spatial nature of the NBS planning problem

Incorporating NBS into urban planning presents a multifaceted challenge, characterized by a complex interplay of spatial considerations. These spatial dimensions not only affect the formulation of NBS policies, but also concern NBS assessment and environmental valuation. In essence, the problem can be stated simply: the potential costs and benefits associated with the development of NBS exhibit complex spatial variations, demanding that urban planners incorporate these dimensions. However, the

toolbox of environmental valuation and NBS assessment has often overlooked these crucial spatial dimensions.

Within this section, we aim to shed light on these spatial considerations: first, we explore the spatial scales of ES, and then delve into the spatial variability of demand for NBS. Finally, we broaden our perspective, framing the challenge of NBS location selection, within the theoretical concepts of urban-rural gradients.

2.1 The spatial variability of Ecosystem Services

NBS offers a spectrum of co-benefits, benefiting both biodiversity and society. Among these co-benefits are the provisioning of ES (Raymond et al., 2017). Researchers investigating ES have recognized a major complexity in their management - their spatial variability.

A first level to consider this spatial variability is that ES are produced across diverse spatial scales and to varying extents (Hein et al., 2006). This implies two key points. Firstly, certain ES have an impact solely at a local level, while others can extend their impact to a broader scale (Rodríguez et al., 2006). For instance, the climate-regulating effects of vegetated areas and trees are limited to just a few meters (Aram et al., 2019), whereas carbon sequestration services have a global reach (Aram et al., 2019). Secondly, this variability in scale signifies that some services operate at multiple scales (Hein et al., 2006): the cooling and climate regulation services offered by green spaces, for example, can yield micro-level benefits through tree shading, and they may also aggregate into larger impacts at the urban or regional scale (Gallay et al., 2023; Livesley et al., 2016).

Another consideration is the high level of location-dependency in the production of ES. Simply put, depending on the location of NBS, they yield distinct co-benefits, each with varying degrees of intensity (Rodríguez et al., 2006; Tardieu, 2017). For example, the co-benefits related to air depollution from trees and green areas depend on their proximity to roads, where traffic emits air pollutants (Livesley et al., 2016). Consequently, the overall advantage of implementing NBS for air depollution can fluctuate significantly based on their proximity to pollution sources (Kremer et al., 2016; Livesley et al., 2016). A similar example plays out with biodiversity and ecological corridors. For instance, the improvements made to biodiversity - such as providing habitat for species - depends on the connection made to existing habitats (Ayram Correa et al., 2016; Hilty et al., 2012). In consequence the locations of urban NBS projects is a key factor on their ultimate effects on biodiversity (Beaugeard et al., 2020; Lapoint et al., 2015). This location-dependent variability inevitably results in trade-offs between different ES, emphasizing the intersection with urban planning (Langemeyer et al., 2016): specific locations may enhance one ES while diminishing others.

The issue is overall the same for SuDS and their multiple benefits related to water management, as these benefits can depend significantly on the location of SuDS : they depend a lot on the location of SuDS (Uribe-Aguado et al., 2022). For example, the reduction of surface runoff is contingent on the positioning of SuDS within a hydrographic basin and their integration into water flows (Paquette & Lowry, 2013; Uribe-Aguado et al., 2022). Similarly, water infiltration and the potential benefits of urban groundwater recharge – one of the central focus of this thesis - rely on multiple factors, such as soil infiltration capacity and the characteristics of hydrographic basins (Beganskas & Fisher, 2017), and these factors are themselves distributed spatially unevenly (Maréchal et al., 2020).

Recognizing this spatial variability, researchers have taken steps to develop tools explicitly designed for mapping ES (Tardieu, 2017). These tools are oriented towards non-experts and aim to provide a quick overview of ES distribution in a given area, to understand the biophysical functions of ecosystems, and to model quickly the increase in ES supply provided by NBS (Bagstad et al., 2013). Notable examples include the Invest model (González-García et al., 2020), the i-Tree suite (Bodnaruk et al., 2017), and the Aries (Villa et al., 2009) tools, among others.

However, other considerations must be taken into account to consider the spatial complexities of NBS planning: the value of NBS does not solely stem from their impact on the potential increase in ES supply (Raymond et al., 2017). A comprehensive understanding of the value of NBS requires considering the value of these enhanced ES to human welfare.

2.2 The spatial heterogeneity of the value of ES

The value of ES provided by NBS comes from the interaction of the supply and demand of ES (Calliari et al., 2019). Many studies have investigated the preferences of citizen's and their demand for NBS. Survey-based methods, such as stated preference methods, serve as valuable tools for evaluating citizens' preferences for contrasting NBS strategies, and estimating individual demand in the form of Willingness to Pay or Willingness to Receive for their multiple benefits. Authors have particularly explored the heterogeneity in preference for ES, with many studying how this variation can be attributed to socio-demographic characteristics of citizens and environmental attitudes (Aguilar et al., 2018; W. Chen et al., 2018; Collins et al., 2017; Escobedo et al., 2011; Faccioli et al., 2020; Macháč et al., 2022; Meyerhoff, 2013). However, demand can also be influenced by more intricate spatial factors beyond socio-demographics or environmental attitudes. Two main aspects have been investigated in this regard: the spatial heterogeneity of preferences and the concept of distance decay.

In environmental valuation studies, some approaches have started utilizing spatial econometric tools to analyze the spatial heterogeneity of demand for different types of environmental goods (Bateman et al., 2006; Broch et al., 2013; Brouwer et al., 2010; Budziński et al., 2018; Czajkowski et al., 2017; Hampson et al., 2017; Kim et al., 2022; Meyerhoff, 2013; Pinto et al., 2016; Traoré, 2019). These studies have revealed that Willingness to Pay for environmental programs derived from discrete choice experiments is often not randomly distributed spatially but displays spatial clustering phenomena: they can present national or regional spatial distributions (Campbell et al., 2008; Czajkowski et al., 2017; Toledo-Gallegos et al., 2021), or present local clustering of low or high Willingness to Pay for similar programs (Johnston et al., 2015; Johnston & Ramachandran, 2014; Kim et al., 2022; Toledo-Gallegos et al., 2021).

These spatial processes can be identified by resulting from the effect of observable spatial variables, for instance by including spatial variables into choice experiments (Budziński et al., 2018; Łaszkiwicz et al., 2022). They can also be entirely idiosyncratic, and result from unobservable components, such as peer effects (De Valck & Rolfe, 2018; Glenk et al., 2020). Overall, these investigations offer diverse approaches to identify the spatial processes at hand affecting the distribution of demand for environmental goods, to potentially map clusters of demand for NBS, and to inform decision-makers on areas of potential highly rewarding actions. However, few of these studies have approached explicitly the spatial heterogeneity of preferences with respects to small urban scale infrastructures such as NBS and SuDS. This dimension of spatial heterogeneity remains to be investigated.

Another spatial dimension of NBS that can affect demand is distance decay. This notion describes the fact that an increased distance to environmental goods diminishes the demand for them (Glenk et al., 2020). This interest in distance decay particularly comes from environmental valuation and accounting, especially in the context of applying spatial discounting of co-benefits when evaluating policies (Yamaguchi & Shah, 2020). In other words, when assessing the benefits from a program, what population should be taken into account for monetizing benefits?

Several studies have showed the significant effects of distance decay by incorporating a distance attribute into discrete choice experiments (Badura et al., 2020; Johnston & Ramachandran, 2014; Jørgensen et al., 2013; Pate & Loomis, 1997; Schaafsma et al., 2012), or by specifying the distance between the location of the residence and the environmental goods (Lizin et al., 2016; G. Tu et al., 2016). This concept of distance decay indicates that demand for NBS can vary greatly depending on their accessibility (Glenk et al., 2020). In the context of NBS planning, such a spatial process can impact greatly the value of NBS depending on their location (Yamaguchi & Shah, 2020). Yet similarly to the spatial heterogeneity of preferences, few studies have investigated distance-decay associated with small urban NBS and SuDS.

2.3 The spatial planning problem

Researchers have acknowledged the importance of identifying the issue of the spatial variability stemming both from the supply and the demand for ES. Some studies have focused on mapping the spatial mismatch between regulating ES supply and demand (Baró et al., 2015, 2017; González-García et al., 2020; Herreros-Cantis & McPhearson, 2021). Identifying these areas of mismatch allows pinpointing more precisely the areas of potential improvement in welfare, *i.e.* where ES supply is low and demand high.

However, the spatial challenges of planning NBS extend beyond the idiosyncratic distribution of spatial supply and demand. It is also about understanding the overarching spatial processes in cities that define the potential values of NBS. In essence, this entails defining conceptually the NBS spatial planning problem. To paint a more complete picture of the spatial challenges facing NBS, we must consider one final factor in the equation – spatial variability in costs. Implementing NBS is not as straightforward everywhere in urban areas; several factors like space constraints, land costs, and competition for land use can be more intense in some areas than others (Dorst et al., 2022; Madureira & Andresen, 2013). Dense areas in particular, which are often the historical urban centers in Europe, pose particular challenges for developing NBS: changing land use is harder and available space is scarcer (Mader et al., 2011).

Overall, this interaction between the variability of costs and benefits adds complexity to the problem. Theoretically, this complexity has been explored through the lens of urban-rural gradients. The value of implementing NBS increases as we move closer to urban centers, as ES flows can potentially benefit a larger population. However, as we get closer to urban centers, the implementation of NBS becomes more challenging due to heightened land competition and increased opportunity costs (Brander & Koetse, 2011). NBS are land-intensive solutions, competing with other mutually exclusive land uses such as housing or commercial development (Elmqvist et al., 2013). Implementing NBS farther from the city might be easier, but it would result in fewer co-benefits for urban dwellers. This situation leads to an urban-rural environmental paradox: ES are often scarcest precisely where they are in the highest demand, creating a complex dynamic in NBS planning (McDonald, 2015).

This urban-rural dynamic presents a critical challenge that extends beyond the scope of NBS knowledge alone. The central problem revolves around the question of how and where climate change adaptation projects should be located in cities, given the diverse spatial gradients of costs and benefits. This poses an opportunity for economists to offer theoretical insights to steer further research and establish guidelines for policymakers.

However, it is worth noting that the fields of economics have not yet explicitly addressed this question. Environmental economics have mostly delved into environmental valuation of NBS and applied economics, aiming to reveal preferences and establish the value of NBS co-benefits, among many other facets (Nesshöver et al., 2017; Tietenberg & Lewis, 2016), and addressing a demand for valuation knowledge stemming from policy makers (Primmer et al., 2018).

Urban and geographical economics have explored a wide array of questions surrounding urban development, employing tools to model spatial processes and decisions of urban actors (Duranton et al., 2015), and therefore adopting a theoretical standpoint which we deem would be needed to address the aforementioned NBS location challenges. However, to our knowledge, little investigation has been led to this point on this particular matter: providing decision support to urban public policy makes to select and prioritize the location of climate change adaptation infrastructures. Other research questions have gained the attention in the fields of urban economics, such as identifying optimal location choices for companies and citizens (Storper & Scott, 2016), examining the dynamics and growth of urban development (Brakman et al., 2009; Duranton & Puga, 2014) and spatial agglomeration phenomena (Storper & Scott, 2016), researching dynamics in land prices and housing markets (Choumert & Salanié, 2008; Gyourko & Krimmel, 2021; Vejchodská et al., 2022). Fewer research has investigated the questions of urban public policies dedicated to the location of climate change adaptation solutions, and the spatial processes at play in the planning of such policies.

In conclusion, we believe that there is a gap in the existing knowledge concerning NBS planning that deserves attention and research efforts. There has been little investigation into the spatial heterogeneity of NBS values in urban contexts. There are still avenues for investigation regarding aspects such as the spatial heterogeneity of preferences for urban NBS, the various spatial scales of ES, and the effects of distance decay. There are also theoretical concepts to elaborate, notably those involving spatial gradients of costs and benefits of NBS.

Investigating the spatial heterogeneity of NBS' costs and benefits, its causes and its impacts, could provide valuable insights into the complexity of urban NBS planning. This pursuit could help answer key questions, such as how to analyze the spatial gradients of costs and benefits associated with NBS, how to integrate NBS into urban planning, how to prioritize the development of urban climate change adaptation policies at the scale of large cities.

In this thesis, we advocate for an investigation into the spatial preference heterogeneity associated to urban NBS. We aim to investigate the links between the spatial preferences for NBS and the urban-rural gradients, and to ultimately integrate the spatial analysis of preferences into a decision support

framework. This latter question is the second central aspect tackled in this thesis. In the next section, we delve into the challenges of the current decision-support toolbox for planning NBS.

3 Decision-support to NBS planning

The past decade has witnessed rapid advancements in the understanding of Ecosystem Services, as well as the design, implementation and governance of NBS policies. This evolving knowledge has been paralleled by shifts in the valuation practices. As a result, NBS assessment methodologies have made significant strides, advocating for a multi-disciplinary, bottom-up approach, in line with the principles of the "new valuation school" (Jacobs et al., 2016).

The various existing ES assessment methodologies are suited both for *ex-post* and *ex-ante* assessment of NBS projects. However, it is arguable that their applicability to policy decision-making has been less addressed (Veerkamp et al., 2020). This is particularly relevant when addressing the complex challenges of urban climate change adaptation, where policymakers must navigate policy options, and select a single one based on a single or on multiple criteria. Examples of such decision-making challenges are the recurring debate on the choice between NBS or more traditional grey infrastructures (Frantzeskaki, 2019), or the decision on the location of NBS (Polasky et al., 2008). Consequently, conventional approaches to evaluating and deciding upon public policies continue to be relied upon (Frantzeskaki et al., 2019), including methodologies like Cost-Benefit analysis and Cost-Effectiveness Analysis.

In this thesis, we argue that there is a need to renew the decision-support framework for the planning of NBS in cities. To effectively address the aforementioned limitations of current NBS development in cities, this decision-making approach must incorporate several pivotal elements.

Firstly, it should be designed to account for the spatially heterogeneous and intricate distribution of costs and benefits associated with NBS implementation on a large scale. This entails a comprehensive assessment that considers both the demand for and supply of ES. This also entails the capacity to evaluate costs and benefits from diverse perspectives, accounting for the diverse values of Nature (Jacobs et al., 2016). Such a method should therefore accommodate for multi-disciplinary perspectives on decision-making problems.

Secondly, it should encompass the integration of diverse and often conflicting objectives inherent in urban planning. For instance, it should be capable of reconciling objectives such as NBS development and housing development, while also acknowledging the spatial gradients associated with these goals.

This becomes particularly critical as there is a need to consider the potential integration of NBS within existing built environments, not solely within new urban projects.

Thirdly, the method should possess the capability to elaborate upon, compare, and ultimately select spatial scenarios - or "plans" - from a potentially infinite array of alternatives. Indeed, considering the high number of locations where to develop NBS at a scale of a large city, there may be a vast number of possible combinations. The decision-support methods should help the elicitation of such options.

Lastly, it should have the capacity to uncover and elucidate trade-offs between various objectives, such as benefits and costs. This involves identifying how particular locations, infrastructure types, or policy choices may augment certain services, benefits or costs, while decreasing other services, benefits or costs. Such an approach empowers decision-makers with a comprehensive understanding of the available alternatives, missed opportunities, and inherent trade-offs to the available alternatives.

In this section, we scrutinize existing decision-support methodologies and assess their alignment with these requisites.

3.1 Cost-Benefit Analysis and Cost-Effectiveness analysis for NBS

Cost-Benefit Analysis is frequently used to assess potential future NBS policies and to determine the most favorable course of action. Given the multiple benefits of NBS, this approach relies on the ecosystem valuation framework which aims to assign monetary value to ecosystem services (Atkinson & Mourato, 2008). The foundational principle of this approach is to assign a monetary value to ecosystem services and subsequently compute the total economic value of a project by encompassing all co-benefits and associated costs (Atkinson & Mourato, 2008). This computation occurs within a predefined temporal scope to appropriately account for future costs and benefits (Pearce et al., 2006).

This approach employs both stated and revealed preference methods of environmental valuation to capture the various co-benefits of NBS. Concerning revealed preference methods, studies have mostly opted for hedonic pricing approaches to evaluate the monetary value of recreational and esthetic amenities of urban green areas to support the planning of future NBS (Łaszkiewicz et al., 2022; Poor et al., 2006; Votsis, 2017). On the other hand, within stated preference studies, discrete choice experiments have been widely used to capture the values of NBS's various co-benefits (Balderas Torres et al., 2015; Campbell et al., 2009; Chau et al., 2010; Collins et al., 2017; Gundlach et al., 2018; Hérivaux & Le Coënt, 2021; Johnston & Ramachandran, 2014; Kunwar et al., 2020; Londoño Cadavid & Ando, 2013; Mariel et al., 2021; Shoyama et al., 2013; G. Tu et al., 2016; Yao et al., 2014). Additionally, though, to

a lesser extent, contingent valuation has also been used (Brander & Koetse, 2011; Czajkowski & Hanley, 2009; Mell et al., 2013; Pinto et al., 2016; Reynaud et al., 2017).

As a side note, this area of research does not only serve the purpose of providing monetary values to cost benefit analyses, but is an area of investigation in itself. Numerous specific questions and debates have animated environmental valuation. Some examples of those include the investigation into non-use values of ecosystems such as existence value in the case of biodiversity protection (Shoyama et al., 2013; Yao et al., 2014), the investigation into ecosystem “disservices” or “negative effects” (Soto et al., 2018; Teixeira et al., 2019; Von Döhren & Haase, 2015), or the studying of preference heterogeneity of the population for NBS policies (Badura et al., 2020; Budziński et al., 2018; Hérivaux & Le Coënt, 2021; Kunwar et al., 2020; Tienhaara et al., 2021).

Concerning the estimation of costs, Lifecycle cost approaches have been favored for establishing the various costs elements of NBS (Houle et al., 2013; Jaffe, 2010; Neumann & Hack, 2022; Oladunjoye et al., 2021). In this regard, research has extended beyond the academic realm to encompass contributions from various non-academic sources. A significant body of "grey literature" has emerged from practitioners and professionals aimed at estimating costs, their distribution among different stakeholders, and other pertinent aspects. This is especially the case in the fields of rainwater management in the case of SuDS, BMP's, alternative techniques, etc. (Bixler et al., 2020; CEBEDEAU, 2018; GRAIE, 2018; Le Gat et al., 2023; Oladunjoye et al., 2021; Seters et al., 2013; Thebault et al., 2020).

The assessment of the monetary value of both co-benefits and costs of NBS using these approaches has been an integral component of Cost-Benefit Analysis across numerous fields involving NBS implementation. This includes contexts such as environmental conservation measures (S. Cao et al., 2018; Naidoo & Ricketts, 2006; Simelton et al., 2021) and flood risk protection measures, encompassing the approaches of SuDS, BMP's, alternative techniques, etc. (Biasin et al., 2023; Fraga et al., 2021; Ghafourian et al., 2021; Johnson & Geisendorf, 2019; Le Coent et al., 2021; Neumann & Hack, 2022; Oladunjoye et al., 2021), alongside Cost-Effectiveness Analysis (Joksimovic & Alam, 2014; Kumar et al., 2021).

Cost-Benefit Analysis and Cost-Effectiveness Analysis are deeply embedded in the making of public policies, especially because their cost-benefit and cost-effectiveness ratios on which they rely provides clear insights on whether policies may be beneficial for the society, thus enhancing the legitimacy of public choices. However these methods present strong limits in the case of NBS, as stated by Saarikoski et al. (2016). First, they do not necessarily allow for the integration of the multiple co-benefits of NBS. In the case of Cost-Effectiveness, the method relies upon one single function (*e.g.* flood risk mitigation),

and ignores co-benefits, which makes such approaches more adapted to single-function infrastructures (e.g. grey infrastructure). In the narrower area of rainwater management, the transition towards SuDS, BMP's, Sponge cities etc. has been started, though a slow pace (Fletcher et al., 2015). The scientific literature regarding these solutions has mostly been focused on establishing their effectiveness regarding flood risk reduction (Graveline et al., 2018; McClymont et al., 2020; O'Donnell et al., 2017; Ruangpan et al., 2020), and, to a lesser extent their impacts on groundwater recharge (Bhaskar et al., 2018; Kidmose et al., 2015; Tubau et al., 2017) and water quality enhancement (Alves et al., 2019; Charlesworth, 2010), therefore relying on the Cost-Effectiveness analysis framework.

Cost-Benefit Analysis has been both mainstreamed as a very common approach to environmental decision-making, and has been simultaneously criticized for a variety of reasons, ranging from technical to ethical concerns (Hwang, 2016). In particular, there exist several critical constraints which limit their use for NBS valuation in our context (Jacobs et al., 2016). These constraints are especially linked to monetarization.

First, monetarization limits strongly the integration of non-direct use ecological values and the social and cultural value of ES (Hwang, 2016). The reliance on a singular measurement unit (money) masks the intricate nature of ES and the diverse range of values attributed to ecosystems: some values are not reducible to a monetary value. This limitation has caused many debates surrounding the use of Cost-Benefit Analysis, focused on the challenges of incommensurability and on foregoing non-monetary considerations in public policy analysis (Adler, 2002; Jacobs et al., 2016; Lliso et al., 2020; Wild et al., 2017).

In addition, Cost-Benefit Analysis does not allow the expression of trade-offs, which is a fundamental component of NBS and Ecosystem Services (Hwang, 2016; Raymond et al., 2017; Rodríguez et al., 2006). Identifying clearly these trade-offs is an important requirement for the valuation framework of NBS policies (Nesshöver et al., 2017). Some locations may enhance certain co-benefits while diminishing others, and there may be an overall urban-rural gradient of trade-offs (Hérivaux & Le Coënt, 2021). In broad terms, this gradient involves deciding whether to implement NBS in densely populated areas with higher difficulty and costs or to opt for solutions outside the city where demand for co-benefits may be lower. To effectively plan and compare various spatial strategies, decision-support methods must incorporate an analysis of such trade-offs (Raymond et al., 2017).

Finally, NBS co-benefits span multiple fields and disciplines, each with their own unique assessment methodologies (Wild et al., 2017). Some of the co-benefits of NBS can even be assessed and analyzed by multiple disciplines (Seddon et al., 2020; Wegner & Pascual, 2011). In consequence, researchers

have advocated for adapting evaluation frameworks to be able to incorporate the values and outputs of various disciplines (Jacobs et al., 2016; Raum, 2018; Wegner & Pascual, 2011).

Multi Criteria Decision Analysis (MCDA) has been recognized as a suitable method to partially address these limits.

3.2 Multi-Criteria Decision Analysis

Several researchers have advocated for departing from monetary aggregation and Cost-Benefit Analysis, for using Multi-Criteria Decision Analysis (MCDA), particularly within the context of IPBES reports (Brondízio et al., 2019). Emerging initially from operational sciences, MCDA has evolved into a distinct scientific discipline aimed at addressing the multidimensional nature of decision-making processes (Cegan et al., 2017). Within the expansive spectrum of MCDA methods, this field encompasses a multitude of techniques, essentially forming an "umbrella term" for diverse approaches (Huang et al., 2011).

An exhaustive examination of all these methods extends beyond the scope of this thesis. It is sufficient to acknowledge that MCDA involves structuring and solving a complex decision problem by a series of different steps, and by involving at various stages the direct participation of key stakeholders (Thokala & Madhavan, 2018). The main steps are the definition of a set of alternatives and decision criteria, which can include factors such as benefits and costs (Ishizaka & Nemery, 2013). Subsequently, the assignment of weights to these criteria is conducted through various schemes. The subsequent step entails employing one of the numerous existing decision analysis method to translate the performance of these criteria, along with their relative weights, into the identification of preferred alternatives (Fishburn & Lavalley, 1999). This often involves calculating a multicriteria score, with some methods relying on aggregation (albeit non-monetary), while others diverge from aggregation techniques (Montibeller & Franco, 2010).

Overall, MCDA present three main advantages that effectively address some of the previously mentioned challenges within NBS decision-making.

Firstly, MCDA accommodates the integration of diverse nature values, aligning with the “new valuation school” claimed by several researchers (Jacobs et al., 2016). These methods offer versatility by enabling the utilization of a diversity of criteria and valuation metrics from different academic fields, such as social impacts, verbal assessments, monetary costs and benefits, non-monetary benefits, and environmental quality (Huang et al., 2011; Montis et al., 2008; Pascoe et al., 2019).

Secondly, MCDA is somehow more compatible with the notion of a bottom-up approach, particularly in contrast to Cost-Benefit Analysis (Saarikoski et al., 2016). On the one hand, it functions both as an analytical tool and a participatory or collective process, and therefore allows for the direct expressions of opinions of stakeholders with conflicting views (Paneque Salgado et al., 2009). In fact, certain MCDA implementations have even extended to large-scale public consultations (Estévez & Gelcich, 2015). On the other hand, by having the possibility to include different criteria, values and metrics, it can represent different perspectives on a given problem (Mendoza & Martins, 2006). This makes it a valuable method for navigating complex decisions in the presence of diverse perspectives.

Lastly, MCDA can acknowledge the possibility of various optimal solutions for a given problem (Brondízio et al., 2019). For instance some methods allow for the identification of different weighting scheme depending on stakeholders (Estévez & Gelcich, 2015). It then allows for the identification of various alternatives (Langemeyer et al., 2016). With this asset, scientists can not only take into account the existence of distinct viewpoints on a given issue but also provide insights into how these disparities translate into varied desirable outcomes (Liquete et al., 2016).

MCDA has been applied in diverse fields related to environmental protection and climate change adaptation (Cegan et al., 2017). Some instances include its use in natural resource management (Mendoza & Martins, 2006), fishery management (Estévez & Gelcich, 2015), groundwater management (Karjalainen et al., 2013), land use planning (Beier et al., 2008; Gregory et al., 2005; Langemeyer et al., 2016; Morio et al., 2013), Ecosystem Services valuation (Saarikoski et al., 2016), and urban NBS planning (Croeser et al., 2021; Kourtis & Papadopoulou, 2022; Kremer et al., 2016; Liquete et al., 2016; Uribe-Aguado et al., 2022).

Overall MCDA provides in these instances a simple and transparent method to decision-making, and one that can accommodate for a vast diversity of decision criteria. However it has two main limitations that may hinder the usability of this method for urban NBS planning.

First, the value of decision-making resulting from a MCDA is entirely context-specific: the weights attributed to the criteria are inherently linked with the stakeholders that gave them; and the criteria assessment often relies on expert methods which also depend on a particular context of implementation (Kangas et al., 2010). As a result, the MCDA does not hold meaning outside of the context of its implementation - unlike Cost-Benefit Analysis, which relies on an universal source of utility (money) (Saarikoski et al., 2016).

Secondly, the method's efficacy is bound by the pre-defined policy alternatives (Langemeyer et al., 2016). If all potential future policy alternatives are not explicitly identified and their main criteria

diligently evaluated, the approach may not necessarily lead to results that maximize total welfare. The issue is overall the same in the case of Cost-Benefit Analysis and Cost-Effectiveness Analysis. An important challenge of these approaches is therefore the following one: how can policymakers ascertain that the policies they devise and compare in Cost-Benefit Analysis, Cost-Effectiveness Analysis or MCDA are the most optimal solutions amidst these multifaceted challenges? To tackle these aspects, it is necessary to explore the full spectrum of NBS projects that could be implemented, and investigate trade-offs between alternatives. In addition, the complexity of such a task arises when dealing with large-scale urban planning problems that involves a diversity of objectives beyond just ES and climate change adaptation.

One approach that can address the shortcomings of Cost-Benefit Analysis and MCDA is Multi-Objective Optimization (MOO). In the next section, we provide a basic overview of this method, and its implementation in the field of NBS and SuDS decision-making.

3.3 Multi-Objective Optimization

3.3.1 Definitions and principles of Multi-Objective Optimization

MOO are initially a category of mathematical optimization problems that involve the simultaneous optimization of more than one objective function (Ngatchou et al., 2005). In these problems deterministic solving can at times be ineffective (Deb, 2014). They belong to a more general class of problems called “hard optimization” that cannot be solved with deterministic method, within a reasonable time limit (Boussaïd et al., 2013).

The meaning of “solving” a multi-objective optimization is not as straightforward as for single objective optimization (Emmerich & Deutz, 2018). In multi-objective optimization, there may not be a single optimal solution to the problem, but rather an entire set of solutions, that represents the optimal trade-offs between objectives (Konak et al., 2006). This set of solutions is often named the set of non-dominated solutions, or Pareto-optimal solutions, following the formalization of this concept by Vilfredo Pareto (1906). The concept of Pareto-optimality can be understood in this context as the ensemble of solutions for which, no improvement can be made on one objective function, without, at the same time, degrading one or more other objectives. Pareto-optimality in this context does not refer explicitly to micro-economics and market behavior, it is rather used as a formal framework for identifying best solutions within a solution space. The set of Pareto optimal solutions is often called a Pareto optimal front or Pareto front, as a reference to its graphical representation

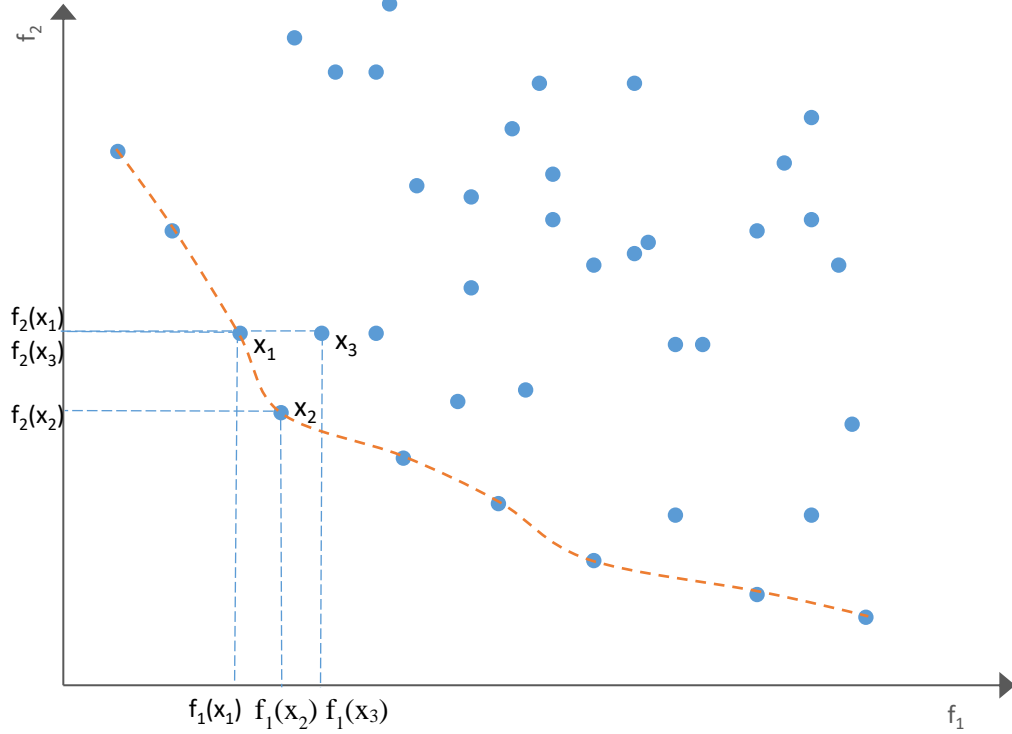


Figure 1: Pareto-optimal front for a minimization problem

The Pareto optimal front is made of the subset of solutions that are not dominated by any other solutions. More formally, Pareto dominance can be defined in the following manner as explained by Emmerich and Deutz (2018):

Given two vectors of solution within the solution space $x^{(0)} \in X$ and $x^{(1)} \in X$, then $x^{(0)}$ dominates $x^{(1)}$ (expressed as $x^{(0)} < x^{(1)}$) if and only if, for m objective functions:

$$\forall i \in \{1, \dots, m\}: x_i^{(0)} \leq x_i^{(1)} \text{ and } \exists j \in \{1, \dots, m\}: x_j^{(0)} < x_j^{(1)}$$

In the minimization example of Figure 1, the solutions on the orange line are non-dominated in the sense that, from these points, no other points can be found that betters one objective without at the same time degrading another one. Here $x_1 < x_3$ as $f_2(x_1) = f_2(x_3)$ and $f_1(x_1) < f_1(x_3)$. Also, $x_1 < x_3$ as well, as $f_2(x_2) < f_2(x_3)$ and $f_1(x_2) < f_1(x_3)$.

Solving the multi-objective problem therefore requires, within the set of possible or “feasible” solutions, to isolate the set of non-dominated solutions from dominated solutions (Deb, 2001). Thereafter, the goal is to obtain the most diverse non-dominated set of solution, as to illustrate as best as possible the trade-off among the solutions, as no single solution can a priori be identified as best

within the non-dominated set (Deb, 2001). In a given problem, finding the Pareto front then allows the decision makers to perform a choice based on the explicit trade-offs represented by the Pareto front (Jahan et al., 2016) Multi-objective problems differ from single objective problem in that sense that two spaces are of importance: both the decision variable search space, that is, the candidate solutions, and the objective space are of importance, that is, how candidates solutions fare between each other (Consoli & Darby-Dowman, 2006).

In theory, MOO offers several advantages for the spatial NBS planning problem. It can optimize to find the best solutions in a given problem, therefore trimming down the potential policy alternatives in a given problem to a handful of best options. It can identify and demonstrate trade-offs in the form of the Pareto front. It can also consider multiple objectives simultaneously, and these objectives do not have to be aggregated and can be expressed in various units and metrics coming from different scientific disciplines. In essence, this method complies with the important requisites to advance the integration of NBS in urban planning.

In the next sections, we delve into the application of MOO applied to supporting decisions regarding NBS planning, particularly focusing on its branch within rainwater management, and SuDS optimization.

3.3.2 MOO applied to urban climate change adaptation

Within the applications of MOO, three related domains of applications stand out: MOO applied to SuDS spatial optimization, to land use planning, and to green infrastructure location optimization.

3.3.2.1. SuDS Spatial Multi Objective Optimization

MOO has been applied for the selection and positioning of SuDS within a catchment area in several settings. These studies are the most closely linked to this thesis. The aim here is mainly to optimize both flood quantity and water quality (Bekele & Nicklow, 2005; Di Matteo et al., 2019; Dwivedula et al., 2021; Liu et al., 2023; Oraei Zare et al., 2012). Some studies delve further into enhancing the cost-effectiveness ratio of flood retention SuDS (Haghighatafshar et al., 2019). These works succeed in reaching and detailing spatial solutions for the optimal placement of SuDS at various spatial scales, from the small urban development project (Uribe-Aguado et al., 2022; Wan et al., 2022) to an entire watershed (Di Matteo et al., 2019; Perez-Pedini et al., 2005). They frequently identify the precise locations for SuDS installations, sometimes even specifying the types of SuDS (Uribe-Aguado et al., 2022). To achieve these outcomes, these investigations often rely on some form of hydrological modeling. This modeling plays a pivotal role in simulating and understanding the behavior of water within urban catchment areas, enabling the identification of strategic sites for SuDS implementation.

Furthermore, recent endeavors have also explored broader benefits of SuDS, employing MOO to maximize water quantity control while incorporating as an objective additional green amenities like aesthetics (Wan et al., 2022). Research has attempted to include all co-benefits of SuDS in addition to flood control, by adding as an objective the maximization of the whole package of co-benefits, encompassing heat mitigation, biodiversity improvements, and more (Alves et al., 2020; Uribe-Aguado et al., 2022). However, these considerations of co-benefits often rely on fundamental biophysical modeling approaches and do not take into account demand for co-benefits. These works are also not applied at the scale of large cities, and do not encompass the spatial dilemma associated to urban NBS.

3.3.2.2. Multi Objective Land Use Planning

MOO is also applied to design land use planning strategies. These applications focus on generating land use planning scenarios, either at the city or watershed scale, to optimize various, often conflicting, objectives, and give support to regional and urban planners for the long-term management of land.

Researchers have also used MOO to optimize land use patterns within cities, aiming to enhance multiple ecosystem services while considering other urban planning objectives, such as spatial continuity and urban densification (Bodnaruk et al., 2017; Elliot et al., 2019; Wicki et al., 2021; Y. Yu et al., 2020; W. Zhang & Huang, 2015). In these instances, the objective is to allocate and relocate actual land use types to improve a set of objectives. These works achieve to illustrate the trade-offs inherent to diverse future land use scenarios.

Furthermore, MOO has been applied to large-scale watershed land use planning, where the objective is to reconcile biodiversity conservation with various human activities (Neema et al., 2013; Polasky et al., 2008; Verhagen et al., 2018; Wu et al., 2018). These studies address the complex challenge of managing land use across extensive watersheds to ensure both the seemingly competing objectives of ecological preservation and various types of economic development.

These studies effectively demonstrate the trade-offs inherent in reconciling conflicting objectives, particularly when it comes to balancing conservation and development goals. Nevertheless, their direct applicability to urban NBS urban planning can be somewhat limited. They often do not address the pressing issue of limited urban space, nor do they focus on identifying suitable areas for NBS projects within urban environments. In fact, the problem of optimizing land use at an urban scale is not the same as optimizing the location for NBS projects within a constrained space.

3.3.2.3. NBS Multi Objective Location Optimization

Finally, MOO has also found a handful of applications in the optimization of the location for NBS such as urban parks and green infrastructures. In these cases, the goal is not to optimize the entire spectrum of land use in a specific region or city. Instead, the focus is on identifying the most suitable locations for implementing a predefined set of infrastructures, as a means to optimize a set of objectives and under specific constraints. While the term NBS does not appear in this literature, it is however very close to the problem at hand.

Neema et al. (2013) applied a MOO for optimizing the localization of green urban areas in large city according to three objectives: the maximization of air quality, the minimization of population distance to green areas and of noise levels. Zhanget al. (2017) performed a multi-objective optimization of location for new urban green space dedicated to the mitigation of the distinct day and night heat island effects, identified through the use of satellite heat maps. Yu et al. (2020) proposed an optimization framework for urban green areas, with the multiple objectives of minimizing their distance to inhabitants, the maximization of urban cooling and maximizing the rise in house property prices. Yoon et al. (2019) designed a MOO program for identifying optimal green area conversion plans for virtual neighborhoods, including maximization of urban cooling, ecological connectivity, and minimization of total development costs. There are also works dedicated to optimize the location of a finite amount of street trees within a city to maximize simultaneously two different co-benefits : urban cooling and air pollution mitigation (Bodnaruk et al., 2017).

These studies highlight the significant advantages of employing MOO in the context of locating NBS within urban environments. They recognize the multitude of urban planning objectives and certain associated constraints, such as cost, space availability, and accessibility. Additionally, MOO can effectively address the intricate issue of trade-offs between different ES and between ES and other objectives (Kati & Jari, 2016).

However, these instances of MOO implementations, while valuable, do not provide a complete solution to the problem. First, ES are approached only through their supply in these studies, mostly through basic biophysical modelling. Thus they do not encompass the demand for ES, which stems from spatial and socio-economic factors, such as population density and individual preferences (González-García et al., 2020). This omission results in an incomplete representation of ES value, as ES value arises from the interaction between their supply and demand (Herreros-Cantis & McPhearson, 2021). Overall this may lead to location recommendations that do not maximize welfare from NBS policies.

Additionally, these approaches have limitations in terms of offering comprehensive decision support. First, these studies tend to overlook a critical aspect: the analysis of actual land availability for SUDs or NBS projects. This oversight has resulted in optimization and spatial recommendations that may not align with practical opportunities on the ground. A few studies have attempted to address this issue by first analyzing land availability, but typically at a smaller, neighborhood-scale (Uribe-Aguado et al., 2022; Wan et al., 2022). However, this approach has not yet been widely applied to city-wide scales, where large urban planning challenges need to be resolved. Additionally, there has not been any European applications yet.

Secondly, the applicability of these studies to decision-making may be limited by the sheer scope of these studies. These studies focus on revealing the Pareto front and identifying trade-offs within the solution space for a particular complex problem, in other words, they focus on the optimization part of the MOO. Yet there is limited exploration of how this front can be effectively translated into actionable decision-making processes, how to go from the identification of a large amount of solutions, to the selection of one. This problem is particularly notable by the absence of stakeholder involvement in these applications. This gap indicates a need for further research in this area to bridge the divide between optimization outcomes and practical policy implementation.

Overall it appears that MOO is relatively underutilized in the field of NBS assessment and urban planning. Although it has experienced consistent technical evolution over the last decade, thanks to advancements in computer science and algorithmic development (Gunantara, 2018), we argue that its potential and relevance in environmental economics literature remains largely unexplored. The applicability and utility of MOO in addressing the multifaceted challenges inherent in environmental policy-making, in general, are yet to be comprehensively identified and scrutinized.

In this thesis, we aim at investigating the usefulness and applicability of MOO for applying it to the planning of NBS policies. We aim also at addressing the aforementioned limitations to current MOO applications. Our main objectives are described in the following section.

4 Research Questions and Methods

The planning of urban NBS at the scale of large cities is a complex spatial puzzle. This complexity comes from the limited resources that constrain urban policies, the involvement of multiple stakeholders, the multitude of policy objectives, all requiring and competing for finite urban space. The challenge is greater when considering the necessity of conceiving these strategies at the metropolitan scale, rather than on a case-by-case basis.

In this thesis, we aim at implementing an approach to address such challenges. In fact, this thesis' main theme and investigations are deeply embedded within the particulars of a case study: the metropolitan area of Bordeaux, France. This thesis represents in fact a specific segment of a larger R&D project aiming at developing groundwater recharge in urban surface aquifers. This approach aims at 1) alleviating the pressure on deep aquifers currently used for drinking water by substituting some water use with water from shallow aquifers recharged with rainwater recharge infrastructures (including both NBS and grey infrastructures, and 2) provide co-benefits, mainly for climate change adaptation. The R&D project includes a hydrogeological model on rainwater infiltration, storage and re-use, performed in parallel to this thesis by a team of hydrogeologists of the French Geological Survey (BRGM), which aims at creating a map of the capacity of urban soils and sub-soils to infiltrate and store rainwater - in essence, to recharge shallow aquifers. The second aspect of this R&D project is to provide decision-support for the mid-to-long term planning of the development of solutions for the aquifer recharge.

The objective of the PhD thesis is therefore to evaluate the benefits of the development of groundwater recharge, and assess the spatial heterogeneity of its costs and benefits. The objective is also to provide local urban planners and decision makers with a decision support approach to aid in the spatial planning of Groundwater Recharge Infrastructures (GRI). These infrastructures include two types of infrastructures. First, we consider mono-functional grey infrastructures, referred to as Conventional Groundwater Recharge Infrastructures (CGRI), which are essentially infiltration trenches and basins, and can be above ground and underground civil-engineered structures. We also consider Nature-Based Groundwater Recharge Infrastructures (NBGRI), such as infiltration vegetated basins, bioswales, wetlands, etc.. These are Nature-Based Solutions, with the sole distinction that their primary function is groundwater recharge. As a type of NBS, they also deliver climate adaptation co-benefits (urban cooling, air quality improvements, aesthetic amenities, etc.). From this point forward, the terms GRI, CGRI and NBGRI are used to describe these solutions.

The challenge lies in identifying and maximizing the potential values of these infrastructures in the city, and providing a decision framework to the Bordeaux case study. How are distributed the potential costs and benefits of GRI, where should they be implemented, and of what type of technology (NBGRI, CGRI) should they be?

Overall, the main research questions of our work are the following ones:

1. What is the spatial distribution of benefits of urban Groundwater Recharge Infrastructures?
2. How to optimize the location and types of urban Groundwater Recharge Infrastructures for maximizing their benefits, and minimizing their costs?

Both of our research questions have implications at two different levels: on the one hand, they are general research questions that aim to address the aforementioned gaps in the scientific literature; on another level, they are also practical and operational questions with respects to the particular problem at hand in the Metropolitan area of Bordeaux.

To address these research questions we developed two distinct methods: an evaluation of benefits of GRI, and a MOO.

The assessment of GRI benefits employs a spatial stated preference approach. This work innovates by analyzing the spatial heterogeneity of preferences with respect to two key benefits arising from groundwater recharge infrastructures: groundwater preservation and urban cooling. It should be noted that, while numerous co-benefits are associated with NBS, our analysis focuses exclusively on these two benefits. This choice stems from their paramount importance within the scope of our study. Groundwater preservation serves as the primary motivation behind the policy initiative under examination, thus holding a central position. Urban cooling represents a significant co-benefit at the center of the policies of the metropolitan government of Bordeaux.

This restriction in our scope enables us to concentrate on the challenges of the spatial dimensions of GRI benefits. Indeed, the benefits of groundwater recharge are contingent on location, because of the distribution of the key hydrogeological variables. Likewise, urban cooling underscores the spatial aspect of Ecosystem Services, with its reliance on infrastructure location, type (CGRI vs NBGRI), and the spatial heterogeneity of the demand of the population. The stated preference study allows to evaluate and map out this demand for urban cooling. The spatial distribution of the efficiency of groundwater recharge, on the other hand, is researched through the hydrogeological study.

The second methodology introduced in this thesis introduces an innovative framework for supporting the elaboration of urban adaptation strategies. The implementation of this MOO methodology unfolds in two distinct phases.

The first phase is a conceptual approach, implemented within the framework of a model city. This preliminary step serves as a foundational exploration of the capacity of MOO to address the research questions at hand. Additionally, it frames the urban NBS planning problem conceptually. In this approach, we suppose the co-existence of numerous spatial gradients of costs and benefits, and examine how considering all these spatial gradients at the same time with a MOO influences the optimal selection of GRI locations and types. This study brings to the literature a novel way to conceptualize urban climate

change adaptation policies. It also delineates generic urban strategies, which are then tested in the second phase.

In the second phase, the MOO methodology is implemented within the context of the Bordeaux case study. This application merges the spatial assessment of benefits and the hydrological study, thereby constituting the final step of the thesis. In this final step, we implement our overall decision-support framework. This approach aims at providing to the metropolitan government of Bordeaux optimal scenarios of implementation of GRI, in order to maximize groundwater recharge, urban cooling and minimize opportunity costs. This approach adds to the MOO literature by applying this method to a large city, by considering both hydrological benefits as well as urban cooling, and by considering small scale infrastructures. It also proposes a participatory approach, and a novel way to analyze the results of the MOO.

In both the conceptual model and the case study application, the MOO methodology is underpinned by a set of pivotal hypotheses.

Firstly, the MOO is implementing at the metropolitan scale, encompassing the entirety of the urban area, rather than delineating smaller, neighborhood-level or infra-municipal divisions. This choice is rooted in our overarching objective of furnishing support for metropolitan strategic planning endeavors. While previous literature has explored the application of MOO at various scales, including the neighborhood and large hydrographic basin levels, the absence of analyses conducted at the scale of a substantial administrative entity, such as a major city, highlights the significance of implementing MOO within this context. It is at this administrative scale that adaptation strategies are formulated, rendering the adoption of MOO at this level an important step towards addressing this research gap.

Secondly, our thesis adopts a simplified representation of the diverse array of GRI. We establish a straightforward dichotomy between two categories: CGRI and NBGRI. While acknowledging the existence of a multitude of techniques, our focus is set on these two broad categories of solutions. These categories are modeled with a degree of simplicity: CGRI occupy less spatial footprint than extensive NBGRI but come with fewer co-benefits. This hypothesis allows us to provide basic insights into the debate concerning the advantages of Nature Based Solutions versus grey infrastructures. Specifically, it allows drawing general conclusions regarding the optimal spatial patterns for developing these infrastructures: where should NBS and grey infrastructures be implemented? However, we abstain from delving into the intricacies of specific infrastructure types, as their diversity necessitates in-depth investigations into their distinctions and associated costs, which falls beyond the scope of our study.

Thirdly, within this thesis, our perspective on costs is very specific, focusing primarily on opportunity costs, *i.e.*, the costs incurred by utilizing scarce urban lands for groundwater recharge, thereby foregoing alternative land uses. Our central research emphasis in this thesis is on the spatial distribution of benefits rather than costs, while our consideration of costs is confined to opportunity costs. This limitation in the scope enables us to account for the spatial dimension of costs, recognizing that land scarcity varies across different areas of the city. Consequently, a key assumption of this work is the exclusion of other conventional implementation costs, such as investment, operation and maintenance.

The thesis is organized as 4 distinct chapters that describe this overall approach. Chapter 2, 3 and 4 are themselves presented as independent articles, which were either published, submitted or are to be submitted to peer-reviewed scientific journals, at the time of the redaction of this thesis. These chapters develop their own research questions, but also serve our overall research questions, and they feed into each other in order to serve the implementation of the MOO.

This thesis is organized as follows:

[Chapter 1](#) presents the general methodological framework of the thesis. This chapter provides a thorough description of the case study, as well as an overview of methods used for implementing the MOO, particularly in its application to the Bordeaux metropolitan area case study. This chapter focuses on presenting the MOO approaches developed in the thesis, excluding the discrete choice experiment approach from Chapter 2 and the model city MOO approach from Chapter 3, which have their own dedicated method sections. This chapter provides a general description of the implementation of the MOO, from its conception, to its design and implementation, along with its connection to the broader R&D initiative. The second part of this chapter also provides readers with fundamental insights into evolutionary algorithms, covering key concepts, algorithmic processes, and decision-making components, and specifying the methodological choices made in our MOO.

[Chapter 2](#) is entitled “Do Urban environmental inequalities influence demand for NBS”, and it presents a discrete choice experiment led in the Bordeaux Metropolitan area. This approach serves two purposes: investigate its own research questions regarding NBGRI co-benefits, and produce spatial inputs to use in the MOO. This work investigates the preference of the population for contrasted scenarios of groundwater recharge. It aims at analyzing the spatial heterogeneity of preferences. It also investigates one questions: how do various types of environmental inequalities (exposure to environmental hazards, inequality in access to green areas, and inequality regarding the negative outcomes of environmental policies) impact individual’s demand for GRI? The purpose of this work is

also to feed chapter 3, by providing estimates of the demand for the benefits of NBGRI, and to identify the spatial distribution of demand for urban cooling, in order to serve the MOO.

Chapter 3 is entitled “Multi objective optimization along an urban-rural gradient”. In this section, we investigate two main points. On the one hand, we investigate the viability of the MOO to solve a GRI location problem. On the other hand, this paper aims at addressing a generic problem that extends beyond individual case studies: in the case of urban-to-rural gradient of costs and benefits of GRI policies: where should decision makers implement their GRI, and of what type should they be, in order to maximize the recharge output, maximize urban cooling and minimize the opportunity costs of used land ? The paper develops a MOO on an ad hoc model city, tailored to address these questions. This work also feeds into chapter 3, by 1) providing a test for the MOO method in a controlled setting before its implementation on the real case study 2) providing spatial guidelines to test against in the final implementation.

Chapter 4 is entitled “A Multi Objective Optimization approach to urban multi-benefit groundwater recharge”. In this chapter, we apply the MOO to the case of Bordeaux Metropolitan Area. This work aims at developing a thorough approach, from inception to the end to provide a decision support tool for the metropolitan government of Bordeaux. It is a study that links the various facets of the R&D initiative, taking into account the insights of the hydrogeological study performed in the metropolitan area as well the spatialized results from chapter 2 into the MOO framework. This work is based on various rounds of stakeholder consultation, and aims at providing methods for exploration of Pareto fronts and their exploitation to provide real and usable insights to decision maker

Chapter 1: Case study and methods

In this method section, we present an overview of the main method developed for the implementation of the multi-objective optimization (MOO), especially the one applied to the case study of the Bordeaux metropolitan area. Therefore, we aim here to provide more details into the overall MOO approaches developed throughout the thesis, which is presented in [Chapter 4](#). Because the thesis is organized as a series of 3 independent articles, each with its method section, this method chapter does not aim to cover the entirety of the thesis: the discrete choice experiment approach of [Chapter 2](#), and the model city MOO approach of [Chapter 3](#) are not developed here. We refer the reader to the specific method sections of these chapters for a presentation of these aspects.

With this chapter, we aim at 1) providing a clear overview of the entire process, from conception to implementation of our MOO approach, in all the diverse approaches, methods and data that were mobilized in the process; and 2) provide the reader with a basic understanding of the fundamental functioning of evolutionary algorithms, covering essential concepts, the primary algorithmic process, and the critical decision-making components within the algorithm.

Therefore, the [first part](#) of this chapter will detail the main challenges at hand when developing our MOO approach, starting with the specifics of the case study, and detailing the necessary steps in developing this decision support approach, as well as the link between this work and the global R&D initiative. The [second part](#) will delve deeply into the technicality of the optimization: the Evolutionary Algorithm. Both parts of this chapter can be read independently by the reader.

1 Developing a Multi-Objective Optimization approach

1.1 The Bordeaux Metropolitan Area

The Bordeaux Metropolitan area is as a large urban area situated within the Aquitaine region, in southwestern France. Encompassing an ensemble of 28 municipalities distributed around the city of Bordeaux, this metropolitan expanse accommodates a population of approximately 813,000 individuals. The local government, called “*Bordeaux metropole*”, is an administrative entity – a *metropole*³ - constituted of the 28 communes that span this territory.

An emergent challenge in the Bordeaux Metropolitan area revolves around ensuring the sustainable management of the water supply. This challenge emerges at the scale of the whole hydrographic “Basin Adour-Garonne”, a substantial geographical area encompassing the periphery of the Bordeaux metropolitan area. The main water resources used for producing drinking water in the basin comes majorly from various deep aquifers (mainly located in the Eocene, Oligocene and Miocene geological stratas). The Bordeaux Metropolitan area requires the extraction of about 70 million cubic meters yearly from these aquifers.

These resources are at risk, with an annual deficit between the water needs and the available resources estimated to range between 200 to 250 million cubic meters (AEAG, 2017), at the scale of the hydrographic basin. This challenge may increase in gravity in the future, for at least two main reasons. On the one hand, the population inhabiting the basin currently stands at an approximate 7 million individuals, yet projections indicate significant growth, with an influx of an additional 1.5 million residents by the year 2050, increasing the stress on resources (AEAG, 2017). In addition, the effects of climate change may also increase the stress on the resources, though with uncertainty. On the one hand, climate change may affect water needs, by increasing water consumption per capita (De Grissac, 2018). It may also lead to affect precipitation pattern which would lead to reduced recharge rates in some aquifers (Lanini et al., 2019), though the impact of these precipitation changes on deep aquifers are uncertain.

The metropolitan area of Bordeaux is also exposed to other challenges regarding climate change adaptation. First, pluvial flood risk has been a historically important aspect in this area. It is exposed to an oceanic climatic regime, with strong precipitation and frequent storms. Climate change may impact

³ Metropoles in France are an administrative entity composed of various cooperating communes, and which has the right to levy local tax, allowing them, in principles, to address regional and urban challenges more effectively and in a more coordinated manner. There are 21 metropoles in France, centered around the cities of Bordeaux, Brest, Clermont-Ferrand, Dijon, Grenoble, Lille, Lyon, Marseille, Metz, Montpellier, Nancy, Nantes, Nice, Orléans, Paris, Rennes, Rouen, Saint-Étienne, Strasbourg, Toulon, Toulouse and Tours.

precipitation patterns by increasing extreme events (Artelia, 2015; IPCC, 2021), heightening even more flood risks in the area in the future. The Bordeaux Metropolitan government has been historically proactive in this regard. On the one hand, it has developed in the past an extensive centralized water drainage network dedicated to both flood risk protection and the depollution of drained rainwater in order to protect water ecosystems.

This urban drainage and water treatment system is particularly remarkable for an important innovation, initially introduced in 1992 and then improved upon: the majority of urban drainage systems and retention basins are remotely controlled by a centralized system (called “RAMSES”), which is designed to predict rainwater events and maximize the treatment of rainwater in sewage treatment plants. The consequence of this system is a significant improvement on the quality of the water effluents rejected to the ecosystems (principally the river “Garonne” in this case).

In addition to this, the metropolitan government has also shifted in the past decades towards the newer paradigms in rainwater management, advocating out of pipe solutions, and the infiltration, retention, and natural treatment of rainwater, before their discharge into water bodies. These solutions are mainly approached as compensation measures (dubbed “*solutions compensatoires de gestion des eaux pluviales*”). In 1982, the local inter-municipal government introduced new rainwater management rules: new urban developments leading to soil proofing - thus potentially increasing surface runoff and inundation risks – must be accompanied by the implementation of compensation measures on the developed plots (Bourgogne, 2010). These measures are aimed at limiting the volumes of surface runoff, by storing temporarily rainwater in place during rain episodes instead of immediately evacuating it towards the rainwater network. Concretely, these solutions are rainwater retention measures (stormwater basins, buried basins), infiltration infrastructures (infiltration trenches, bioswales), as well as oversize rainwater pipes designed to avoid overflows in rainwater pipe networks. This policy, though innovative at the times, shows some limits. First, grey infrastructures have been used massively, more frequently than NBS, so it has had few impacts on Ecosystem Services flows. Secondly, this policy concerns new urban development, hence few improvements are made on already built areas – which represent the majority of the Metropolitan territory. Finally, though water infiltration in the soils is explicitly described as the priority solution to implement for these compensation measures, most of them rely rather on retention measures, thus limiting the potential benefits of groundwater recharge.

In addition to the challenges of rainwater management, climate change has other more diverse effects impacting human well-being. Among those, a central one in the Bordeaux area is the rise in mean annual temperatures and the augmentation of the number of days of heat waves. Local climate modelling indicates that a scenario based on the IPCC RCP4.5 scenario would lead to an increase of mean yearly heat days from 8.4 to 20.7 by 2050 (Artelia, 2015). This combines with the presence of urban heat island

effects, urban areas that are significantly warmer than the rest of the city and its surroundings, which have important negative effects on human health (Heaviside et al., 2017). One of the central agenda of the Bordeaux Metropolitan government is to address those heat island effects. It is considering urban greening as a means of improving urban cooling (Livesley et al., 2016) as well as providing other co-benefits. An example of this initiative is embodied by a policy objective set since 2020, which aims at planting one million additional trees within the Bordeaux metropolitan area on a 10-year span⁴, either through public action, or on private gardens through various incitation mechanisms. Another example of initiative related to urban greening is an agenda of preserving and renaturing areas along ecological corridors (“*trames vertes et bleues*”).

These new adaptation initiatives have concerned both newly built urban developments and the adaptation of existing urban areas. Many of these challenges concern existing urban areas: flood risk and urban heat island notably. However, working within existing urbanized areas to adapt to climate change presents inherent complexities, often surpassing those encountered in new urban development projects. For instance available space is scarce and in high demand for a multitude of purposes: urban greening, housing development, the creation of bicycle lanes, etc.

The convergence of these several urban challenges, including drinkable water management, rainwater management, and climate change adaptation, coupled with the intricacies of retrofitting existing urban areas, prompted the city to engage in a comprehensive examination of these issues. Consequently, the local water services, a division of the Bordeaux Metropolitan government, launched a Research and Development (R&D) initiative in collaboration with its water treatment company under a public service concession (SABOM), the French geological survey (BRGM), and the University of Bordeaux.

1.2 A Research & Development initiative on urban groundwater recharge

An experimentation and a dedicated Research and Development (R&D) project has been initiated in 2020. It is a collaboration between the water department of the local government, the water treatment company (SABOM), as well as two research institutions, the French Geological Survey (BRGM), and the University of Bordeaux (BSE), and financed partly by the Adour-Garonne Water Agency (AEAG). The present thesis develops its own investigation, but it is partly a segment of this R&D initiative, consequently shaping the research inquiries and guiding the development of methodologies.

⁴ <https://www.bordeaux-metropole.fr/metropole/projets-en-cours/nature/plantons-1-million-darbre>

The strategy that is being experimented in the R&D project stems from the context exposed previously. Its objective is to develop groundwater recharge in urban shallow aquifers (Figure 1). This approach aims at investigating the possibility to alleviate the pressure on deep aquifers by developing Groundwater Recharge Infrastructures (GRI) in urban areas, at a large scale. This would lead to recharge shallow aquifers with rainwater, thus constituting water stocks that may be used for non-drinkable uses (irrigation, street cleaning, etc.). The objective of this strategy is also to substitute water uses that currently rely on clean water, even though they do not explicitly require such high-quality water (urban parks and gardens irrigation/watering, street cleaning, etc.) with water sourced from recharged shallow aquifers. The water quality of these shallow aquifers in urban areas is almost always not suitable for human consumption and drinkable uses, because they are highly impacted by human activities. However, these resources can be used for non-drinkable activities, and their use is currently not developed at a large scale.

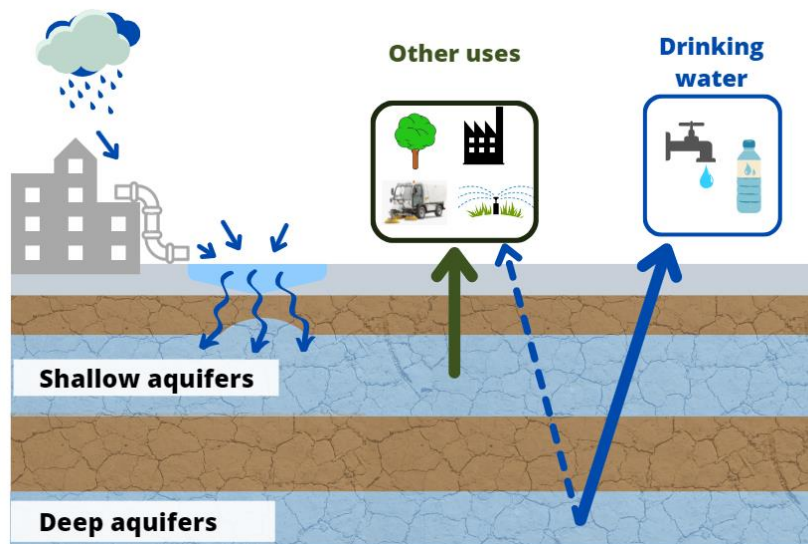


Figure 1: Basic water substitution principle

This approach aims to safeguard deep aquifers. It is intended to be a complement to a broader strategy of water resource management, involving water use optimization and savings, the elimination of leaks in public clean water networks, and using alternative water sources and aquifers. This approach also comes as an incentive to pursue the shift in rainwater management solutions initiated with the rainwater compensation measures discussed previously. Developing the infiltration of rainwater in place, “where it falls”, would also contribute to current rainwater management objectives (flood risk protection, water quality protection, and alleviating the pressure on the centralized drainage network). The secondary objective of this policy is to develop Nature Based Groundwater Recharge Infrastructures (NBGRI) at a large scale in the urban area, in order to provide co-benefits, especially to address heat island effects. A particular synergy is seen in this regard with the urban greening and tree planting plan

of the local government, as these NBGRI would in theory make readily available water resources for the vegetation needs.

This policy experimentation is accompanied by a specific R&D project, involving two distinct studies.

First, a central approach to this project is a hydrogeological study on rainwater infiltration, storage and re-use, which was performed in parallel to this thesis by a team of hydrogeologists of the French Geological Survey (BRGM). This study aims at creating a cartography of the capacity of urban sub-soils to infiltrate and store rainwater. It relied on first collecting and mapping the key geological and topographical data regarding groundwater recharge. The importance of these criteria was then estimated by experts and integrated using a multicriteria approach to elaborate a map, at the metropolitan scale, defining the favorability of urban soils to implementing groundwater recharge projects. This cartography aims at accompanying and aiding the development of rainwater management policies in the Bordeaux Metropolitan area. It is dedicated to the explicit use of urban developers, planners and water treatment operational, as a guide for deciding on the type of rainwater management infrastructures to be implemented for urban development projects, and whether they should rely on water infiltration and storage, or not.

The second aspect of this R&D project aims at supporting mid to long term urban planning and climate change adaptation, and it is the subject of this thesis. Implementing GRI is a complex spatial puzzle, in essence very similar to the NBS spatial planning problem: how to optimally allocate the limited available space and public funds to achieve the most favorable outcomes? Addressing this question necessitates considering the numerous trade-offs associated with NBS development, including the trade-offs between the advantages of groundwater recharge and urban cooling, all within the constraints of restricted land availability and budgetary limitations.

In this context, Multi-Objective Optimization (MOO) is used to tackle these inquiries. Nevertheless, the intricacies of employing such a method go beyond technical considerations. The development of such a method entails numerous complexities, spanning from its inception to practical implementation, and embodies a comprehensive, globally integrated research approach. This section is dedicated to offering a broad perspective on the general approach utilized for deploying MOO and its interconnectedness with other facets of the R&D initiative.

This section also intends to shed light on three pivotal aspects of the thesis. The first is stakeholder engagement. Given the orientation of this work towards providing practical decision support, it appears important to first provide an account of how stakeholders are integrated into the process. We also

develop the interdisciplinary nature of this approach, and the links between the MOO methodology and the various components of the broader R&D project. Lastly, we outline the key design aspects of the MOO framework, outlining how the various building blocks of the thesis come together within the MOO framework.

1.3 The overall approach to Multi-Objective Optimization

In this section, we outline the general approach undertaken for developing the MOO. This MOO is an integrated approach, necessitating active engagement and cooperation with various stakeholders throughout its inception, application, and subsequent analysis.

To sum up in simple terms, the implementation of this method is geared towards addressing the following key questions:

1. Location optimization: Where should GRI be strategically situated to maximize their diverse benefits, including those offered by multi-benefit NBGRI?
2. Infrastructure type: What types of infrastructures (NBGRI, CGRI) are most suitable for achieving the objectives of groundwater recharge optimization?

The MOO is essentially constituted of four essential building blocks:

1. Participatory elaboration of the framework (Section [1.3.1](#)): these steps involve conducting a series of workshops and interviews with stakeholders. This collaborative process is designed to ensure the practical utility of the MOO approach, and integrating the perspectives, inquiries, and insights of stakeholders. In our case, this phase allowed to establish three aspects of the framework: the objectives and constraints to include in the MOO, the potential plots and sites for developing groundwater recharge, the pertinent spatial scale for the MOO approach.
2. The analysis of the spatial distribution of groundwater recharge effectiveness (Section [1.3.2](#)): this map developed by the BRGM study is instrumental in delineating the favorability of urban soil conditions for developing groundwater recharge, and is used in the MOO.

3. The analysis of the spatial distribution of co-benefits (Section [1.3.3](#)): another facet of our methodology involves the development of a discrete choice experiment study, for examining the distribution of potential co-benefits associated with groundwater recharge. [Chapter 2](#) of this thesis is dedicated to this choice experiment, so a brief account is given here on the link between this study and the MOO.

1.3.1 Participatory elaboration of the MOO framework

The development of the MOO includes the engagement of stakeholders from its inception to the interpretation of results. This entails a collaboration with the local government bodies implicated in the R&D project. The primary objectives of this engagement include ensuring the usefulness of this approach in real-world decision-support, mainly by including the stakeholder's perspectives, insights and needs. Importantly, this participatory approach unfolded in parallel with the development of the hydrogeological project. This parallel progression facilitated a close alignment of objectives and methodologies between the MOO and the broader research project.

In practice, this approach required the initiation of successive multi-actor workshops. The goal of these workshops was to establish a dialogue among diverse public entities and services. Importantly, this dialogue sought to foster a transdisciplinary approach that bridges various services. Between 2020 and 2023, a series of workshops were organized to coincide with each stage of the MOO process. These workshops brought together stakeholders representing a range of entities, including water management authorities, urban development agencies, greening services, and urban planning services. These collaborative sessions served as a platform for sharing perspectives on climate change adaptation and exploring the interconnectedness of different concerns and objectives⁵. This phase allowed specifically to determine 3 central points regarding to the MOO:

⁵ As a side note, the importance of this participatory process is embodied in a specific anecdote. Organizing these workshops led to having various public entities meet and express the main urban challenges at hand and their difficulties regarding their objectives. Among those, the urban greening services expressed the important challenges regarding the ambitious urban greening and tree planting policy initiated by the local government: how to ensure sufficient water irrigation for urban greening (thus ensuring the survivability of planted trees) in the face of climate change and increased water pressure? This example illustrated the central benefit to the infiltration and groundwater recharge policy. It therefore appeared clearly that it was important that these stakeholders work hand in hand and participate in this R&D initiative.

1. The objectives and constraints to include in the MOO ([Section 1.3.1.1](#))
2. The potential plot locations for developing GRI ([Section 1.3.1.2](#))
3. The pertinent spatial scale of the optimization ([Section 1.3.1.3](#))

1.3.1.1. The objectives and constraints of the MOO

Through these engagements with stakeholders, we discerned the primary objectives to include in the MOO framework. The number of objectives to include in a MOO is limited for computational and visualization reasons (Deb & Jain, 2013). In consequence, we restricted the objectives to the priority objectives held by stakeholders. We reached this conclusion primarily after an initial open discussion with key stakeholders at the beginning of the R&D project (15/10/2020). They are:

- The maximization of groundwater recharge. This objective includes all the benefits resulting from the adaptation of urban rainwater management to enhance resilience against climate change challenges, to address the issues related to drinkable water resources, and in general, all the benefits of the restoration of natural hydrological cycles.
- The maximization of the benefits of urban cooling. Urban cooling is a central objective in the city's policies. It is therefore the central potential co-benefit of NBS in this case.
- The minimization of opportunity costs. The issue of limited urban space emerged as a pivotal element in public policies, due to the competition among various urban planning objectives, such as the allocation of resources for bicycle lane development and other urban amenities.

In addition to these objectives, we also identified one key constraint to include in the framework. The constraints to such an urban planning problem usually include for instance the various investment and operation & maintenance costs. However adopting a cost-centric approach would necessitate discounting mechanisms, and may not align with the needs and perspectives of stakeholders in this case. In this context, we adopted for the MOO a long-term planning perspective that prioritizes comprehensibility and easy communication with stakeholders. Therefore, after stakeholder consultation, we reached the conclusion that the main constraint should revolve around the space dedicated to implementing these solutions, instead of direct costs. It is therefore a spatial constraint, and represents a simple measure of the “effort” made by the public authorities to develop GRI.

In practical terms, this constraint is set at a maximum of 369 hectares (which represent 10% of the available sites identified in Figure 2). This constraint restricts the search space for potential solutions to

those that align with the municipality's implementation capacity. It also establishes an ambitious upper limit that is comparable with similar urban development initiatives in French cities⁶.

1.3.1.2. Identification of potential sites for GRI development

A second central input to the MOO resulting from the rounds of stakeholder consultation is the identification and mapping of real land plots that may be used in the future for the development of recharge infrastructures. This work that was performed both for the sake of designing the MOO framework, and for elaborating the discrete choice experiment (presented in [Chapter 2](#)). In a first workshop (11/01/2022) we gathered representatives of the local government services of urban greening, water management, urban planning, as well as public urban development agencies. We led an open brainstorming session dedicated to identifying the types of urban areas that could be transformed with GRI. Key land use categories were identified: parking lots of commercial and industrial areas, school yards, open public and private spaces available for urban greening projects (public squares, sidewalks, small parking lots, abandoned lots, etc.).

These plots consist of both public spaces and private spaces. In accordance with stakeholder discussions, it was decided to adopt a long-term approach in this work, envisioning the possibility of repurposing and transforming both private and public plots for climate change adaptation purposes, through various mechanisms involving public incentives. Notably, the specific mechanisms and policy instruments for this transformation fall beyond the scope of this thesis.

These diverse types of sites were collected and organized within a Geographic Information System (GIS) database, presented in Figure 2. This database is pivotal in determining the territory's capacity to generate Ecosystem Services, serving as the foundational basis for land use transformation. In addition, based on our review of the state of the art in MOO, this phase of identifying "opportunities" - even though it is a broad and simple approach - represents a significant contribution to the existing literature towards a realistic use of MOO outputs.

⁶ The Metropolitan area of Lyon ('Grand Lyon') for instance has initiated a project that aims at deproofing up to 400 hectares of artificial soils by 2026

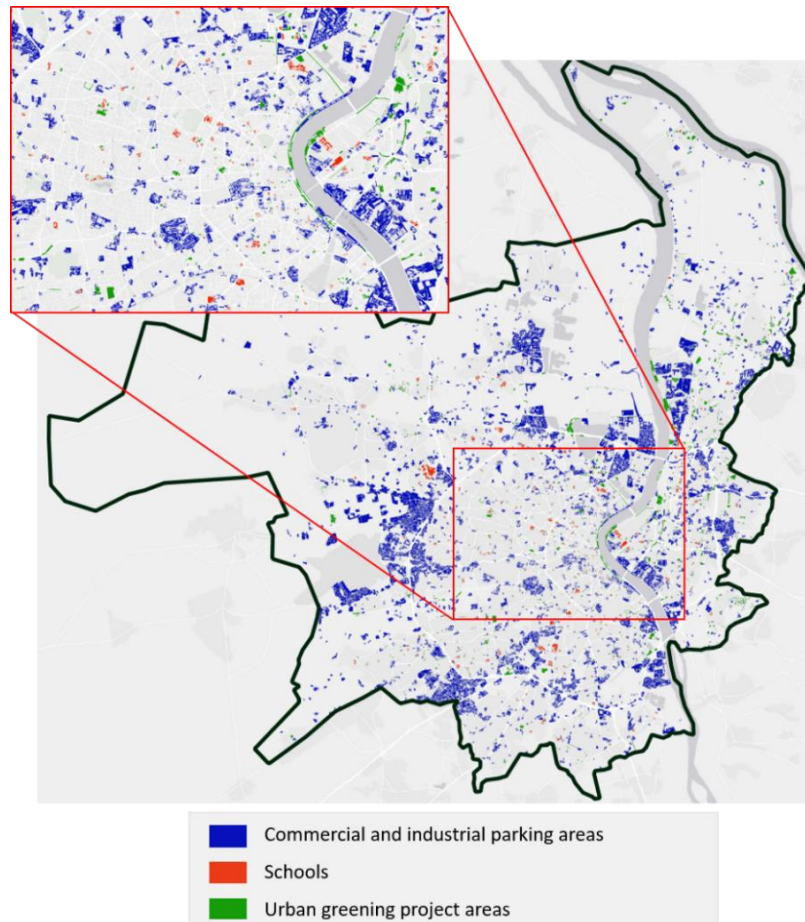


Figure 2: Available plots for developing Groundwater Recharge Infrastructures in the Bordeaux Metropolitan Area.

1.3.1.3. The spatial scale of the optimization

A central question to address in the early conception of the MOO is identifying the pertinent spatial scale for decision-support. Should the MOO be applied at the scale of the individual plots or at a larger scale? In other words, what is the relevant decision unit for urban planners: individual plots (illustrated by the database presented in Figure 2) or a larger scale, such as neighborhoods?

We opted for an intermediary neighborhood spatial scale for two reasons. First this decision unit was deemed more pertinent for long-term planning than individual plots. It appeared more interesting and cost-efficient for stakeholders to be able to prioritize and plan public actions in entire neighborhoods, than having to deal with solutions composed of combinations of a myriad of big and small individual plots located throughout the entire Metropolitan area. Secondly, the available plots are numerous (above 7000), leading to a great computational complexity of the MOO (Bandaru & Deb, 2016). Indeed, using this decision unit, each solution would be a combination of any number of sites

selected out of the 7000 sites, within the spatial constraint (section 1.3.1.1), thus leading to a combinatorial explosion problem (Consoli & Darby-Dowman, 2006).

Therefore, we decided to use the spatial scale of IRIS (“*Ilots Regroupés pour l’Information Statistique*”) units. IRIS units represent small geographical areas at the infra-municipal scale and are used for statistical purposes in France. Essentially, these units correspond to neighborhoods that possess distinct local identities within large cities, or small peri-urban and rural municipalities. These geographical units also have the advantage of featuring a great level of statistical information. In the Bordeaux Metropolitan Area, there are a total of 271 IRIS units, which is a practical number for the MOO (Figure 3).

However, we deemed crucial to rely on the prior identification of the individual available plots, since they are the defining factor of the capacity of the territory to be transformed and to generate benefits and co-benefits. Therefore, the main input for defining the capacity of each IRIS to receive GRI the database of available plots (Figure 2).

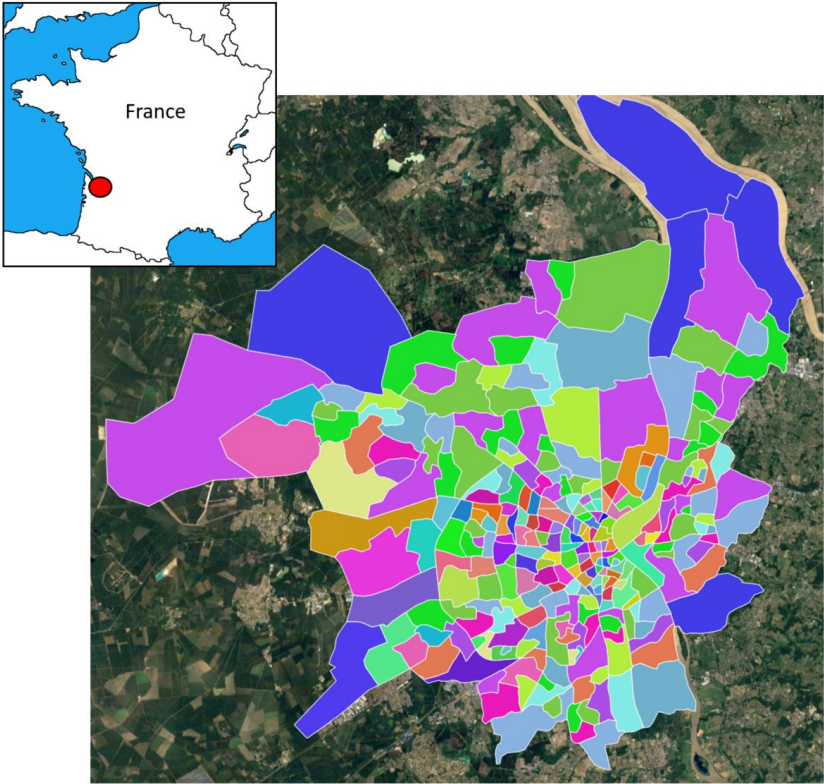


Figure 3: IRIS units in the Bordeaux Metropolitan Area (N=271).

The MOO is implemented at the scale of the IRIS units: “what combination of IRIS should be chosen for maximizing recharge, maximizing urban cooling and minimizing opportunity costs?”.

1.3.2 The spatial distribution of groundwater recharge effectiveness

The second central approach to the MOO framework is the hydrogeological study on rainwater infiltration, storage and re-use. Giving an entire account of this study falls outside of the scope of this thesis – it was led by BRGM partners in the R&D project. Still, we provide here its main components.

This study was motivated by the requisites of local decision makers - especially water services - for precise knowledge on the nature of urban soils and aquifers to further the advancement of the aforementioned Bordeaux rainwater management compensation measures ([section 1.1](#)), as well as to decide whether recharge infrastructures can be implemented. This study aimed at collecting geological and topographical data regarding the capacity of urban soils and aquifers for infiltrating, storing and extracting rainwater for re-use, and then elaborate a composite cartography of recharge favorability. In fact, the first phase of the R&D project (2020-2022) was dedicated to collecting all the available data regarding urban soils and aquifers possessed by public and private entities.

The most important parameters in determining the efficiency of GRI were identified after a stakeholder workshop (30/30/2023), and subsequent expert consultation. Six key parameters were identified, and mapped out across the BM area to determine this groundwater recharge efficiency. These parameters are soil permeability, the thickness of the non-saturated zones (the vadose zone) above the aquifer, aquifer depth, terrain slope, the capacity of terrain to extract water (aquifer width), the storing capacity of terrains (porosity), and the Network Development and Persistence Index index (IDPR), which is a metric that determines the spatial distribution of infiltration and runoff in a hydrographic network (Mardhel et al., 2021).

In a second stakeholder workshop (27/04/2023), the most and least favorable range of values for these parameters for GRI were identified, as well as the range of values defining complete impossibility for recharge (for instance, recharging very shallow aquifers may lead to increase aquifer flood risks). At the end of this step, all potential values for all parameters were assigned a normalized score between 0 and 10.

In parallel, all six parameters were attributed relative weights by the group of local stakeholders and by a group of national groundwater recharge experts, with a simple multi criteria ranking weighing scheme based on the Analytic Hierarchy Process method (Saaty, 1990). These two weight sets were then synthesized into one set of weights, as a means to incorporate both local perspectives and expert knowledge. The parameters were aggregated in a final step through a spatial multi-criteria analysis, using the weighting scheme in order to create a final single favorability map for recharge infrastructure projects. The final result is a map, presented in Figure 4, which defines the overall favorability of urban

areas for recharge projects, on a scale of 0 to 10. These results are used in the MOO as an input for evaluating the potential benefits of groundwater recharge.

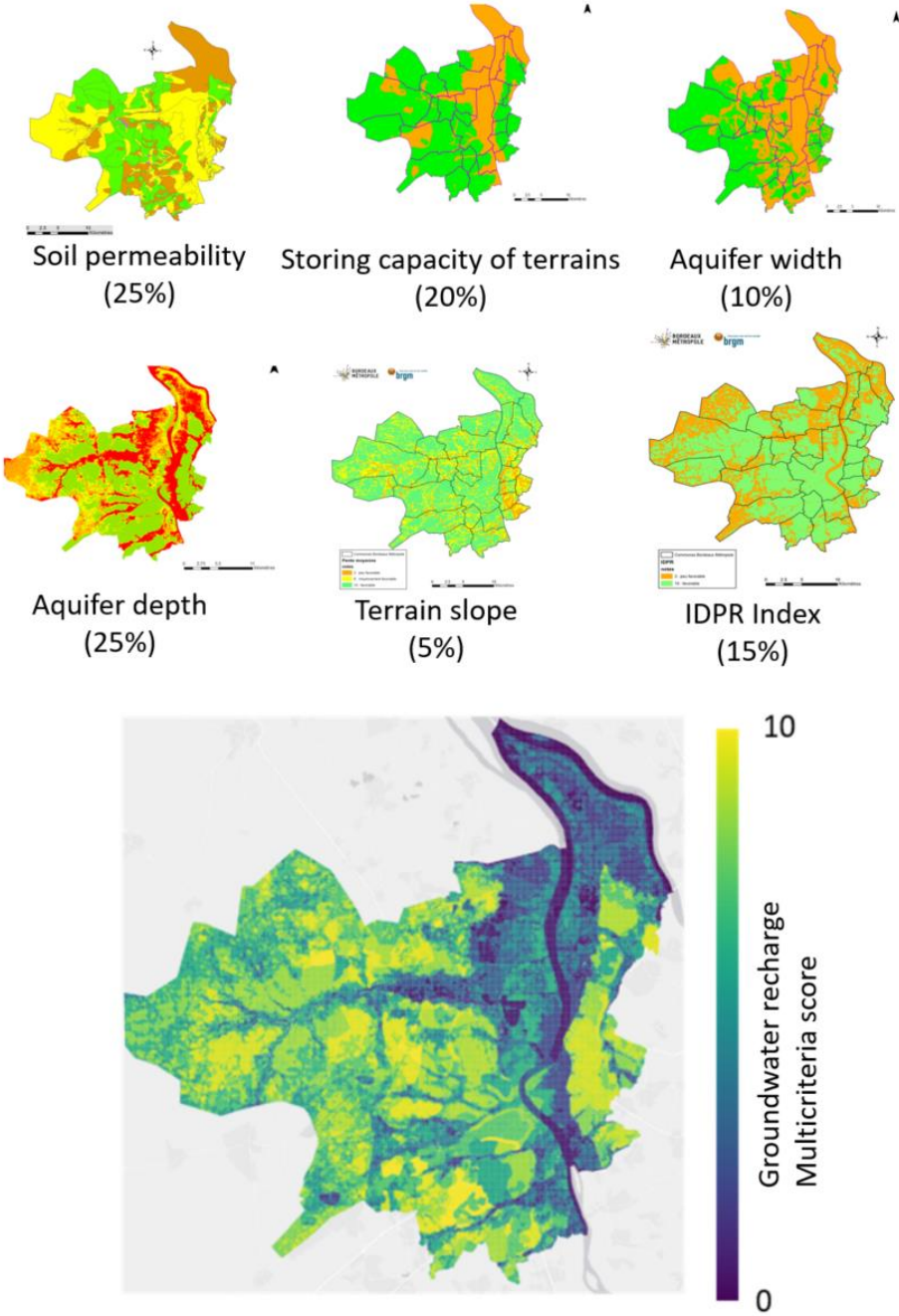


Figure 4: Multi criteria analysis performed for defining groundwater recharge effectiveness.

The 6 types of key parameters (in the upper side of the figure) were each associated a weight (in%), according to the AHP multicriteria weighting scheme. The final weighted aggregated map (on the lower side) defines the overall effectiveness of groundwater recharge, indicated by a unitless score on a 0 to 10 scale.

1.3.3 The spatial distribution of co-benefits

Resulting from the round of stakeholder consultation, we identified urban cooling as the central co-benefit in this case study.

The central innovation of this thesis regarding this co-benefit is that it relies on an approach centered on demand rather than supply. The review of the state of the art of MOO optimization applied to NBS ([Section 3.3.2](#) of the General introduction) indicated that most current applications overlook demand for Ecosystem Services (ES), and rather focus on supply, mainly through ES modelling approaches. Yet foregoing demand for co-benefits and focusing entirely on supply may not capture the entire spatial heterogeneity of the possible benefits of NBS (González-García et al., 2020). It may even lead to location choices that do not maximize welfare. In other words, some areas may see great improvements in ES flows once NBS are implemented, but with few residents to benefit from them (S. Wolff et al., 2015). For instance, developing NBS in proximity to heavy traffic areas may improve locally air quality, leading to an optimal spatial choice that consists in developing NBS close to these areas (Neema et al., 2013). However, it may be the case that some of these heavy traffic areas – which can often be suburban areas dominated by economic activities in France - are not densely populated, meaning a relatively low aggregate demand for air quality improvements. In consequence, there may be spatial mismatches between ES demand and ES potential supply improvements (Baró et al., 2017). In this thesis, we argue that a strategic planning approach to climate change adaptation would require a spatial analysis of ES demand in order to optimize the overall welfare of such policies.

The characterization of urban cooling is therefore based on the survey conducted through the choice experiment, which enabled the estimation of individuals' willingness to pay (WTP) for various benefits and negative effects of NBGRI, and was specifically tailored to align with the requirements of the MOO. This study explored the preferences expressed by the population for various policy alternatives defined by their benefits, negative effects and characteristics: these attributes were the preservation of deep aquifers allowed by groundwater recharge policies, urban cooling, the impact on car space of the policies, and the distance of NBGRI to individual's residence. The entire study and its results are presented in details in [Chapter 2](#).

Simply put, in this study, a preference model (mixed logit model) was used to evaluate the respondents' individual willingness to pay for the various attribute levels based on their choices. In a second level of analysis we identified hot spots of high demand for urban cooling in the city using spatial autocorrelation indicators. We also established relations between environmental inequalities and preferences for NBGRI in a post-estimation analysis, linking the estimated willingness to pay of individuals with a series of explicative variables, including socio-demographic variables, as well as

environmental indicators. From the post-estimation phase, we concluded that exposure to heat has a significant positive effect on individual's willingness to pay for urban cooling. This relation was used to map out the population's mean willingness to pay for urban cooling, at the neighborhood scale. This map is used in the MOO for estimating the urban cooling benefits of groundwater recharge.

All the elements presented up to this point come together in the MOO applied in [Chapter 3](#) and [Chapter 4](#). In [Chapter 3](#), the basic framework – the overall logic of the MOO, the objectives and constraint, the optimization process – is used as such. It is however applied in a theoretical context, defined by theoretical gradients of costs and benefits in a model city. Therefore the aforementioned analysis of the distribution of the benefits of groundwater recharge and urban cooling in the case of the Bordeaux Metropolitan area does not come into play in this chapter yet. The method section of [Chapter 3](#) details precisely the methodology. In [Chapter 4](#), the overall framework is used as described here. Similarly, the method section of this chapter delves precisely into the methodology.

This first section of this chapter has given on account of the general process of elaboration of the MOO, and the main building elements and hypotheses – alongside their justification - defining the optimization framework - the decision variables, objectives, evaluation functions and constraint. However we have not described at this stage the actual optimization process, but only the basic framework for the optimization. The second section of this chapter delves deeply into the optimization process: the evolutionary algorithm.

2 The Evolutionary Algorithm

MOO is not a traditional approach in economic sciences. For this reason, we deemed necessary to provide a reader who is not accustomed with these methods with a basic overview, though without delving too deep into the technicalities of algorithms, which is in fact beyond the scope of this thesis. The goal of this section is also to provide more details to complete the method sections of chapter [3](#) and [4](#), which do not describe entirely the optimization process. Complete understanding of the inner workings of the evolutionary algorithm is not entirely necessary to follow through the rest of this thesis, so the reader may refer back to this section at a later stage, if necessary.

Throughout this section, we detail our specific approaches and methodologies used for handling the various aspects of the algorithm. We start by providing some insights regarding the metaheuristics family of methods. Then we provide an overview of the main building blocks of the optimization and the evolutionary algorithm, detailing the methodological options at hand, and the choice we realized at each step when implementing the final optimization applied to the Bordeaux case study. When relevant, we also provide the Python program used specifically in this MOO, for any reader interested in replicating a study or interested in using the same tools (the entire program is also available in [supplementary material](#)).

2.1 Metaheuristics: an introduction

Metaheuristics is the umbrella term that defines methods and procedures designed to solve optimization problems without using traditional deterministic solving (Glover & Kochenberger, 2006). Instead, these methods use a way of trial and error to reach within practical time optimal or near-optimal solutions, by exploring the search space. This group of methods, unlike heuristics, do not need to be specially designed for each individual problems, and can be used with slight adjustments to categories of problems (El-Ghazali, 2009). They are particularly applied in problems that feature incomplete information, a very large number of solutions, as well as multiple objective functions (Glover & Kochenberger, 2006).

Metaheuristics have been developed alongside the steady increase of computation capacities (Sörensen et al., 2018). Therefore they have become a dedicated field of research in computer science and mathematics, with a high number of publications (Sörensen et al., 2018). Their high generality of use has also pushed metaheuristics to be used in an increasing number of practical contexts, such as medical decision-making, financial portfolio optimization, agricultural land-use optimization, transport network planning, or environmental conservation (Sörensen et al., 2018). These rapid developments are

due to the efficacy of metaheuristics for approximating optimal solutions in a very diverse set of problems (Glover & Kochenberger, 2006).

The key factor in the efficacy of metaheuristics is the balance between the so-called concepts of exploration and exploitation (Boussaïd et al., 2013). Metaheuristics are often implemented for problems with a large number of possible solutions, and for non-linear and non-convex problems. For this reason, avoiding local optima is a crucial challenge for these problems (Sörensen et al., 2018). It is solved by most metaheuristics by allowing a type of exploration of solutions in a large search space (Deb, 2001). For instance, exploration consists in allowing some degree of freedom to an algorithm to diversify its search direction and to move further from an identified best solution (Kirkpatrick et al., 1983). Exploration is also a mechanism through which the metaheuristic can increase the diversity of solutions in the objective space, in order to obtain a well-diversified set of non-dominated solutions. Exploitation on the other hand consists in the intensification of search within a solution region of interest.

Hundreds of different metaheuristics approaches have been developed over the past decades (Boussaïd et al., 2013). However, they can be classified according to various factors that is, whether they are population-based or single point searching methods, whether they are nature-inspired or not, whether they use memory or not during the search, whether the objective function are dynamic or static throughout the search (Consoli & Darby-Dowman, 2006). One of the main categories of methods deal with a subset of solutions at a time, called “population”, in order to find the best solutions within a search space (Sörensen et al., 2018). This category includes various subgroup of metaheuristics; and among those are evolutionary algorithms. Evolutionary algorithms are especially useful for multi-objective combinatorial problems, as by exploring sets of solutions at the same time, they can offer ways of finding sets of non-dominated solutions (Emmerich & Deutz, 2018).

Many traditional methods of solving multi-objective problems have been focused on scalarization, that is, the conversion of multi-objective problems into single objective problems, through the process of creating a single composite objective function, by assigning weights to the various goals (Gunantara, 2018). This method requires to assign weights to the various objective function, thus requiring prior knowledge on the solution space in order for the decision maker to assign these weights, or participation from stakeholder and/or expert opinion to assign these weights (Miettinen, 2012). This type of method then falls within the category of multi-criteria decision analysis (Fishburn & Lavalley, 1999). While it can provide sound optimization results, scalarization with stakeholder participation can lead to bias the results towards one part of the Pareto front – usually the convex portions of it (Zitzler, 1999), and can lead to a low extrapolation of results, as they remain highly dependent on a specific set of weights associated with a group of stakeholders (Miettinen, 2012). In addition, these methods do not allow the representation of trade-offs between objectives (Miettinen, 2012). Metaheuristics, and in particular

evolutionary algorithms offer ways of avoiding this method, by considering simultaneously all objective functions (Bandaru & Deb, 2016).

Metaheuristics have seen an increase in use in numerous domains of engineering, logistics, and industrial processes (Sörensen et al., 2018). But despite the borrowing of economic concepts such as the Pareto frontier, implementation of metaheuristics in economic sciences remain scarce. Research have tackled portfolio optimization and risk management with evolutionary algorithms (Doering et al., 2019), but very few research has been led in environmental economics (Katoch et al., 2021). In fact, metaheuristics have the main disadvantage that they do not guarantee to obtain global optimal solutions in any given problems, and as such are not considered as exact methods (Bandaru & Deb, 2016). Rather, they allow for reaching satisfying or near-optimal solutions within practical time (Glover & Kochenberger, 2006).

2.2 Main elements of the evolutionary algorithm

The search process of evolutionary algorithms is based on the selecting and combining of groups of solutions by simulating the natural processes of evolution (X. Yu & Gen, 2010). For this reason, they are often named “population-based” metaheuristics: solution candidates are called “individuals” and sets of solutions “populations”. The terms individual and solutions are often used interchangeably, yet “individuals” refers more to the search space and evolutionary mechanisms of the algorithm, while “solution” refers to the solution space and the global problem (Emmerich & Deutz, 2018). The term “individual” will be used in this section when speaking about the details of the evolutionary algorithm in order to keep consistent with the literature terminology.

Evolutionary algorithms are indeed a sub-group of population-based metaheuristics that mimics the mechanism of natural evolution. The basic functioning is therefore intuitive: the algorithm evaluates population of individuals, keeps the fittest, discards the other, and creates new individuals from the fittest in order to obtain an optimal population after a series of iterations (Deb, 2014). Evolutionary algorithms present various advantages that make them very suitable to address multi-objective problems (Gunantara, 2018). Mainly, it is adequate for finding multiple solutions to the problem at the same time (Emmerich & Deutz, 2018). As evolutionary algorithms operate on multiple solutions simultaneously, they are particularly appropriate for multi-objective optimization where one looks for a subset of Pareto-optimal solutions. Single-point search methods, on the other hand, have to go through multiple runs to do so and characterize the Pareto front.

The way evolutionary algorithms treat problems is also an advantage from a decision making point of view. Indeed, not only do they yield results in terms of exploring the search space for a given problem

and retrieving best-suited solutions, but they also provide rules for studying multi-objective trade-offs, isolating interesting and diverse solutions, applying specific decision rules for the diversification of solutions, etc (X. Yu & Gen, 2010). Evolutionary algorithms are also fairly simple and intuitive in their design and can be adapted to most problem configurations, which can be of great help when dealing with real-life problem involving stakeholders, so as to avoid black box effects. Yet the foremost advantages of evolutionary algorithm is that they can work with discontinuous or concave Pareto fronts, while this is a severe limitation in exact methods (Bhargava, 2013).

These methods operate on a set of individual and allow for the selection of the “best fitted” solutions from the population through the use of exploration mechanisms. These exploration mechanisms, often called “genetic operators”, are twofold: recombination and mutation operators. Recombination operators, or “crossover operators” in genetic terms, are used to combine individual sets into new individuals: the creation of new “children” individual from “parent” individuals – thus mimicking natural reproduction. Mutation operators are also used to make random changes in parent genes to create children solutions, thus allowing for exploration of new search space. Most operators in standard evolutionary algorithms rely heavily on the use of randomness. The algorithms thus performs a series of iteration of creating populations, selecting its best elements, and recombining them with these two special operators into new populations. With these two mechanisms, repeated over a series of loops, the best overall individuals can be identified within the search space, and a good diversity of search can be maintained. The basic algorithm loop is presented in Figure 5.

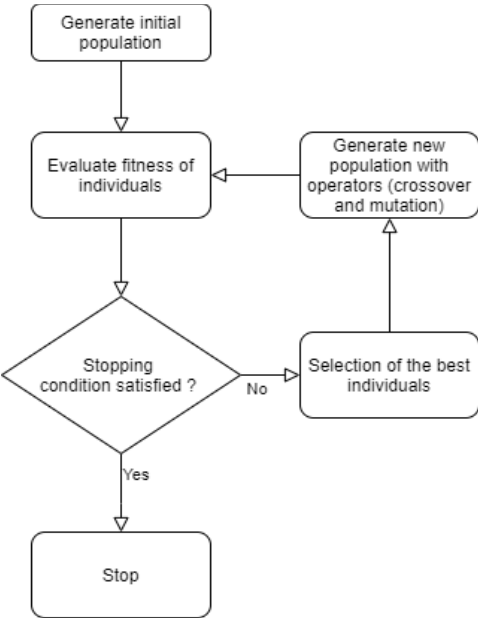


Figure 5: Basic evolutionary algorithm loop

This design is the core design of evolutionary algorithms. However, due to the rich diversity of algorithms within this category, this standard design can be altered in many ways (Fortin et al., 2012). Evolutionary algorithms allow for a large degree of freedom in the designing of the various part of the algorithm, to adapt it as much as possible to the problem at hand. For instance, the selection operator will be selected according to the number of objectives. The order of the loop of population generation, selection and evaluation can also slightly change in evolutionary strategies, yet the fundamental design is always based on population generation and survival of the fittest individuals.

Overall, the design of the evolutionary algorithm is composed of several key components: the representation of the decision variables, the genetic operators, the selection operator, the termination condition. Moreover, the interactions between these various components, often called the evolutionary “strategy” is also one central element of the algorithm. The other central part of an evolutionary algorithm is the evaluation functions designed for assessing the fitness of individuals according to the selected objectives. These elements are detailed in the following sections, with most of the information presented here based on the handbooks by Deb et al., (2016) and Glover & Kochenberger (2006).

2.2.1 Representation

The representation of variables is often considered the first element to decide in the algorithm, as it defines what operators can be used, and how (Hassanat et al., 2019). In population-based techniques such as evolutionary algorithms, potential solutions within the search space are often called “individuals”. These individuals are represented or “encoded” through a specific encoding scheme. This encoding scheme allows transcribing a real solution to the problem into a solution that can be operated by the evolutionary algorithm, transformed and mutated, by the various operators. In our case for instance, a real solution to the MOO would be a series of distinct locations selected for developing GRI, as well as the types of infrastructures. In order for the algorithm to operate on such a solution, we need to represent it in such a way that we can apply evolutionary operators on it. In other words, there is a need to translate this solution into algorithmic language. The most common representations are binary encoding and integer or real strings (Emmerich & Deutz, 2018).

As a side note, “genetic algorithms” is a frequently used denomination for evolutionary algorithms. Genetic algorithms are in fact a subclass of evolutionary algorithms (Bandaru & Deb, 2016). The difference between the two approaches is that genetic algorithms employ a thorough “genetic” representation of the problem based on binary encoding (Man et al., 1999). In other words, all genetic algorithms are evolutionary algorithms, but not all evolutionary algorithms are genetic algorithms (Bandaru & Deb, 2016). Evolutionary algorithms provide a broader framework for optimization, and genetic algorithms are a specialized implementation of this framework but algorithms fundamentally

follow the same principles as evolutionary algorithms. Other types of evolutionary algorithms may use different representations for solutions, employ different genetic operators, or have unique characteristics tailored to specific optimization problems.

Binary representation consists in representing solutions into bitstrings of 0 and 1 - often called “chromosomes” - and 0 and 1 bits - called “genes”. In continuous optimization problems, the values of “x” are thus encoded into binary code, usually of base 2. However this binary encoding is also applied for other types of problems, such as combinatorial problems. For instance, different strings of 0 and 1 can represent different combinations of items in a combinatorial portfolio optimization, where 0 is the absence of any given asset and 1 its presence (Doering et al., 2019). Binary encoding is the most common form of encoding. Integer or real encoding is also common, in which each chromosome is represented as a string of values that represent a decision element of the problem at hand. This type of representation can also be used for combinatorial problems: each integer value can represent a distinct item for instance.

Permutation encoding can be applied for ordering combinatorial problems, for which the order of decision variable also matters. A string of integers represents the sequence of decision variables. For instance, in the classic traveling salesman problem - whereby we aim to minimize the overall distance travelled by a salesman forced to visit every city of a given region and then return to his origin city - the position of each visited cities in the traveling sequence is of equal importance to what cities are visited (El-Ghazali, 2009). Permutation encoding would therefore encode each solutions to the traveling salesman problem as strings of numbers or letters, each one representing a city. The position of a number or letter within this string would determine its place within the sequence.

In our implementation, we used a form of integer representation, with some specific elements added because of the complexity of the problem at hand. The decision variables in our problem are the N neighborhoods (the IRIS geographical units), as well as the type of Groundwater Recharge Infrastructures to implement on each of these locations, and the implementation level for each of these locations, *i.e.*, what proportion of the potential plots and sites for developing GRI in each neighborhoods should be used. In a way therefore, the problem is threefold: where to implement GRI, of what types should they be, and how intense should the development be?

These 3 elements of the decision is represented in the algorithm through the representation of our individuals. They are encoded as a string of integers of a size twice the number of selectable neighborhoods ($N = 271$). Figure 6 proposes a simplified representation of an individual. Each of the neighborhoods is identified by a position within the string (between position 0 and N), and is therefore repeated (between N and 2N), as illustrated by the repeated map examples in Figure 2. The first half of

the string determines the infrastructure types developed in each neighborhood: a 0 is no development of infrastructures, 1 is NBGRI, and 2 stands for CGRI.

In the second half of the string, we represent the level of implementation of the neighborhood. We opted for a discrete representation of the levels, with 5 different options: 20%, 40%, 60%, 80% or 100% of all the potential plots for developing GRI within a neighborhood can be “activated”. This choice is noteworthy as it bounds dramatically the problem. It is also noteworthy to add that for all levels, the same plots are in essence developed for GRI, there is no selection of some plots over others within a neighborhood. In fact, the implementation levels impacts the surface area of each potential plots that is developed, which is reflected in the evaluation functions (see section).

We opted for this approach for two main reasons. First, given the already high level of complexity of the problem, we observed that this discrete approach gave more satisfactory results in terms of optimization effectiveness. Secondly, we decided that although using these 5 dramatic implementation categories led to some loss in details and finesse in the optimization, it did not affect this much the scope of the model, which is after all to provide gross and macro spatial recommendations to the local government and strategic planning.

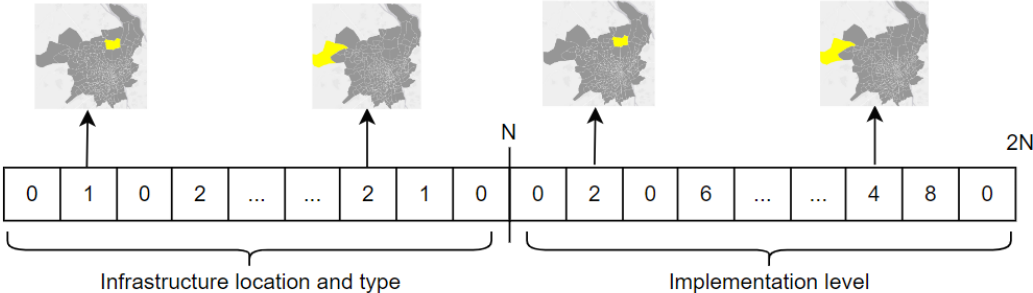


Figure 6: Individual representation example used in the MOO developed for the case study (see Chapter 4)

2.2.2 Genetic operators

Genetic operators are the main search elements of evolutionary algorithms. Recombination, mutation and selection are the three categories of operators that work in various different sequences for the algorithm to optimize properly. Operators allow to explore the search space by moving within it both randomly, through mutation and recombination, as well as exploiting local search spaces with selection operators. The choice of these operators depend on the type of problem at hand, the number of objectives, the importance of local optimas, the degree of a priori knowledge on the search space. We

will examine here these three key elements of the MOO, give some basic insights into the main options at hand when elaborating an evolutionary algorithm, and explain the choice made for our MOO.

2.2.2.1. Recombination

Recombination consists broadly in operating an exchange of information between two or more existing solutions. For this reason, these operators work on two or more solutions at the same time. To keep with the canonical genetic metaphor, this operator mimics genetic crossover between chromosomes during meiosis. The types of recombination operations vary depending on the type of variable representation. In traditional genetic algorithms, where solutions to the problem are for instance discrete integer variables, they are encoded into binary strings. Recombination happens therefore between two or more vectors of 0 and 1, which, after the operation and after decoding, provide completely different integers. For combinatorial problems, where individuals (*i.e.* solutions) are not just a numeric value but an ensemble (*e.g.* a portfolio), the recombination happens on the vectors of combinations that are used as solutions.

Recombination can be applied in a vast diversity of manners. The most common ways of performing it is by single-point and multiple point crossover (Figure 7). In single-point crossover, a single point within both parent strings is designated, and bits between the two parents are snapped between each other. In two-point crossover the same operation is applied to bits of parent strings located within two location points.

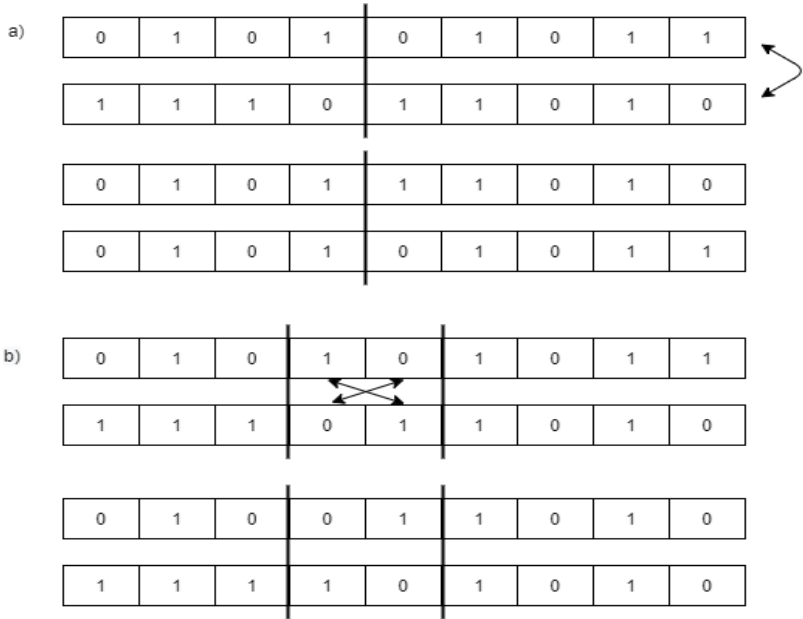


Figure 7: Types of genetic crossover for individual recombination: a) single point crossover; b) two-point crossover (Katoch et al., 2021)

Single-point crossover is the simplest approach and does not require high computation time, though it does not ensure that the offspring individual carries desirable parts or qualities of the parent individuals (Kora & Yadlapalli, 2017). Two-points and multiple point crossover, in turn, can offer a more complex approach to exploration. With these types of crossover, only a segment of parent individuals are interchanged, which can be located anywhere on the individual, allowing for a more precise exploration (Kora & Yadlapalli, 2017).

In addition to the type of crossover used for recombination, the rate at which it is applied to individuals is a crucial parameter. This parameter determines the probability that an offspring of the new population (a “child” individual created from two “parents”) is created by a crossover operation. According to common practices in evolutionary algorithms, this probability is usually set between 0.6 and 0.95, making recombination the primary searching operator in evolutionary algorithms (Hassanat et al., 2019).

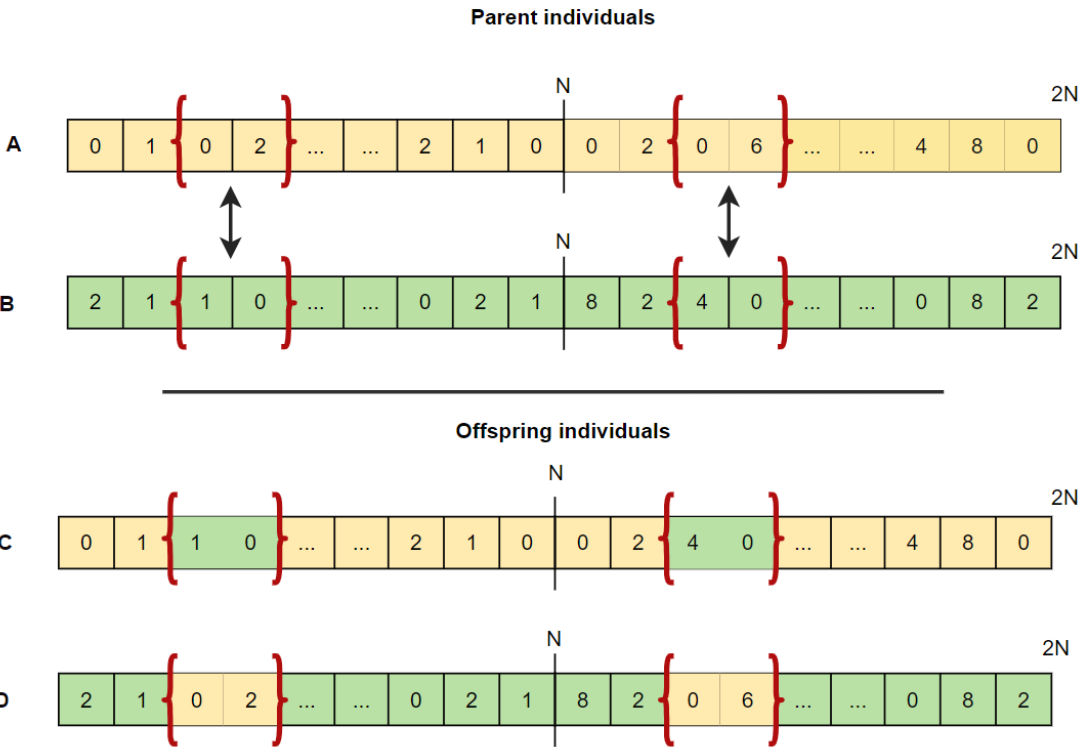


Figure 8: Recombination designed for our MOO.

A two-point crossover is applied at two random points of the parent individuals. The crossover is applied symmetrically on both halves of the strings (in the infrastructure selection part, and in the implementation level part).

A two-point crossover approach was used in our implementation of MOO. We opted for this considering the necessity to ensure that desirable elements were kept from parent to offspring during the

recombination phases. For instance, it can be in our case that one particular neighborhood in the problem, identified by a position somewhere along the encoded integer string, is of particular importance and desirability for an objective at hand, in other words, that it “needs” to be selected within the individual for reaching an optimal solution. In this case, two-point crossover allow such an approach: there is a probability that only this interesting part of the string be transmitted from a parent to an offspring. In contrast, single-point crossover may lead to transmit a whole half of the string to an individual, in essence, “drowning” the important information.

In addition, our recombination operation is applied to both halves of the individual symmetrically (see Figure 8). In other words, both the types of GRI and the levels at which they are implemented can be transmitted, as an entire “package” of data, from parent to offspring. This ensures, that if the algorithms has discovered a specific region of the city of particular interest, under the conditions of a type of infrastructure (CGRI or NBGRI) and with a specific level of development, then all of this information can be transmitted to an entirely new individual. This allows a thorough level of exploration in our algorithm. This approach was selected - as with all the methodological options presented here - after a series of trials and errors with other methods.

Because, this function was designed particularly for this implementation, while relying on the DEAP library (Fortin et al., 2012), we provide here the code snippet for this function:

```
from deap import tools
def cxCustom(ind1, ind2):
    size = len(ind1) // 2
    cx_point1, cx_point2 = random.sample(range(size), 2)
    ind1[:size], ind2[:size] = tools.cxTwoPoint(ind1[:size], ind2[:size], cx_point1,
cx_point2)
    ind1[size:], ind2[size:] = tools.cxTwoPoint(ind1[size:], ind2[size:], cx_point1,
cx_point2)
    return ind1, ind2
```

2.2.2.2. *Mutation*

Just as in natural evolution, genetic mutation is the other key mechanism to provide genetic diversity from one generation to the next. The mutation operators modifies one or more random values in the encoding of decision variables. In bitstrings of genetic algorithms, mutation usually consists in flipping one or more random binary bits within the chromosome sequence that compose individuals. The number of changed elements is not fixed, and depends entirely on randomness. It can consequently lead to the creation of a completely different individual, as one small change in binary encoding produces, once decoded, an entirely new value.

In combinatorial problems where the strings represent components of the solution, mutation can have less dramatic effect, as the adding or deleting of a given random item does not change the entire sequence. At any rate, mutation is a tool for avoiding local optima entrapment by avoiding parent and

child populations to be too similar. Indeed, only mutation can in fact introduce brand new information into individuals, recombination merely recombines them. It is therefore a key exploration mechanism.

In practical terms, mutation is an operator that, under a given probability, takes one individual parent and transforms it into a child by applying a randomized change on its representation. The most common mutation operator in binary encoding allows each bits to switch (0 to 1 and 1 to 0) under a small probability (Figure 9). In integer or real encoding, this mutation allows similarly to modify each integer or element in the chain of values so as to transform into a completely different integer or real value taken within the search space.

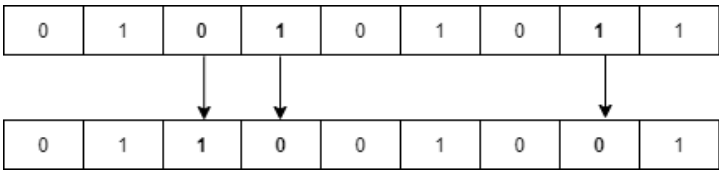


Figure 9: Simple mutation operator on a binary string

The choice of mutation rate is among the most important choices in the design of evolutionary algorithms, and a great field of investigation is dedicated to parameter setting (Eiben et al., 1999). Mutation strength is known to be the most prominent parameter in the success or failure of evolutionary algorithm (Beyer & Schwefel, 2002). The most common approach to setting these parameters is by “tuning”, that is fixing parameter values before algorithm runs, and adjusting it with each run so as to improve overall performance (which is usually evaluated by the time required by the algorithm to attain the Pareto front). Parameter control, on the other hand, regroups a group of techniques of endogenization of these parameters: the mutation and crossover rates can be set as functions within the algorithm and evolve with it, in order to evolve in a similar manner as individuals in standard genetic algorithms. For instance, mutation rate can be set to be high at the beginning of the algorithm so as to allow in-depth exploration of the search space, and then decrease once a satisfying fitness is obtained, so as to intensify the search within a given region of interest. In most implementations of real-life problems, parameter tuning is generally considered as a sufficient method (Lobo et al., 2007), and is the approach we used.

In our implementation, we developed a mutation operator that allows to retrieve or add more selected neighborhoods to the individual. This way, the algorithm can explore individuals made of a small amount of highly rewarding areas, as well as evaluate individuals made of a large amount of less performing solutions for instance.

In simple terms, the operator first randomly determines how many changes to make to the individual, between 1 and 3 changes. For each changes, it randomly selects one of two possible options:

- It can select a random index in the first half of the individual (in the infrastructure type section), and change the value at that index to a new random value (0, 1 or 2), ensuring that the new value differs from the previous one. As a consequence, a neighborhood previously not selected can be thus selected with either types of infrastructures; or a selected neighborhood can be removed from the individual, or have its type of infrastructures be flipped (from NBGRI to CGRI or vice-versa)
- The operator can select a random index in the second half of the individual (which represents the implementation levels of each neighborhood) and change the value at that index to a new random value (from 1 to 5), again ensuring that the new value is different from the previous one. A condition to this change is set so that the change in implementation level is only applied for neighborhood that are indeed selected in the individual. In consequence, the percentage of implementation of one neighborhood is flipped to another percentage.

This mutation operator ensures that a certain number of changes are applied randomly on all three elements of our decision variables: adding or retrieving neighborhood, changing their favored types of infrastructures, flipping the implementation of a neighborhood. All these changes can happen independently on different parts of the individual, and between and 3 changes can happen at a time on an individual. Though this operator is quite intricate, it was necessary to design a function that can have an effect on all the key elements of our individuals. Because, this mutation operator was also designed particularly for this implementation, we provide here the snippet of the program:

```
def mutation(individual, indpb1):
    num_changes = random.randint(1, 3) # Generate a random number of changes between 1 and 3

    # Create a list of valid indexes where changes can be made (only if the first half value
    is not 0)
    valid_indexes = [i for i in range(len(individual) // 2, len(individual)) if individual[i
    - len(individual) // 2] != 0]

    for _ in range(num_changes):
        if random.random() < indpb1: # First type of change (first half)
            index1 = random.randint(0, len(individual) // 2 - 1)
            new_value1 = individual[index1]
            while new_value1 == individual[index1]:
                new_value1 = random.randint(0, 5)
            individual[index1] = new_value1
        else:
            if valid_indexes:
                index2 = random.choice(valid_indexes) # Second type of change (second half)
                new_value2 = individual[index2]
                while new_value2 == individual[index2]:
                    new_value2 = random.randint(1, 2)
                individual[index2] = new_value2
    return individual,
```


2.2.2.3. Selection operators

Selection operators are the final operator applied in evolutionary algorithms. Their function is to select the optimal solutions within an entire population, allowing them to be transmitted from generation to generation. This selection operation is key since it defines in a way the meaning of optimality in a multi-objective optimization problem, *i.e.* the meaning of what is a “better” solution. In MOO, many selection operators based on the identification of non-dominated solutions have been created. In fact, the selection operators are often the main distinctions between evolutionary algorithms, such that evolutionary algorithms are often named according to the type of selection operator applied to them. Among the main selection operators applied in literature (X. Yu & Gen, 2010) are the Strength Pareto Evolutionary Algorithm (SPEA2), and the Non Sorting Genetic Algorithm (NSGA2).

NSGA2

Deb et al. (2002) introduced in a seminal paper a novel selection operator for multi-objective problems. NSGA-II relies on an approach called non-dominated sorting to assign fitness ranks to individuals. This sorting technique categorizes individuals of a given population into different levels, or “fronts”, based on their dominance relationships and assigns fitness values based on these ranks. It also incorporates a crowding distance element into this fitness value. In essence, the algorithm works as follow:

1. **Dominance Relation:** Each individual in the population is characterized by its set of objective values, resulting from their separate evaluations on all objectives (in our case, the 3 objectives of recharge, urban cooling and opportunity costs). An individual A is said to dominate another individual B if:
 - A is no worse than B in all objectives, and
 - A is strictly better than B in at least one objective.

In other words, A dominates B if it is a Pareto improvement over B. If no individual dominates another, they are considered non-dominated.

2. **Rank Assignment:** The goal of non-dominated sorting is to assign a rank to each individual in the population based on their dominance relationships. The individuals in the first rank (Front 1) are non-dominated; they are not dominated by any other individual in the population. These individuals represent the Pareto front of the generation.
3. **Crowding Distance Calculation:** An additional measure called "crowding distance" is calculated for individuals within each rank. The crowding distance measures how close an individual is to its neighbours in the objective space. Large average crowding distance thus implies a better diversity in the population of individuals, which is one crucial characteristic to obtain a set of

Pareto-optimal individuals. It is used to encourage diversity in the Pareto front, and individuals that are as distinct as possible.

4. Next Front: After assigning ranks to individuals in Front 1, the algorithm proceeds to identify individuals in the next front (Front 2). These individuals are dominated only by those in Front 1 but not by any other individuals in Front 2 or later ranks.
5. Repeat: The process continues, with the algorithm identifying individuals in each subsequent front until all individuals are assigned ranks.
6. Selection: The best individuals from the current population are directly selected for the next generation. The criteria for choosing these individuals is to choose those with the smallest domination rank are selected in priority (starting with Front 1), and within this category, solutions with the highest crowding distance get first priority.

SPEA2

The Strength Pareto Evolutionary Algorithm 2 (SPEA2) is an evolutionary algorithm proposed by Zitzler et al. (2001), which introduced a novel selection operator.

SPEA2 functions almost similarly to NSGA2, with 2 distinct features. The first difference is that SPEA2 introduces the concept of "strength" for individuals in the population, instead of assigning ranks (step 2 of NSGA2). An individual's strength is the number of other individuals it dominates in the objective space. Dominance relies on the same definition as in NSGA2 (step1). A crowding distance is also attributed to each individuals, the same way as in NSGA2: it is a measure on how close a given individual is to other individuals. In SPEA2, we assign a fitness value to each individual based on its strength and on its crowding value. Individuals with higher strengths and lower crowding values are more likely to be selected for the next generation. The second difference is that SPEA2 relies on maintaining an archive of non-dominated individuals found during the entire optimization process. The archive starts out empty, and non-dominated individuals are added throughout the process. At each step, newly created individuals are compared with all individuals of the archive, and they either replace individuals of the archive, or are removed.

Overall, the NSGA2 algorithm has become the most popular approach for multi-objective Pareto selection, due to its simplicity, speed, and great adaptability to different problem situations, up to the point that it is included in most evolutionary algorithm programming libraries (Katoch et al., 2021). Both SPEA2 and NSGA-2 have seen great interest in the literature, as they behave quite similarly, especially in combinatorial problems. The main difference between both algorithms is their attribution of fitness values and their selection mechanisms. A consequence of these differences is that SPEA2 performs better with a high number of objective functions, while NSGA2 performs better at providing

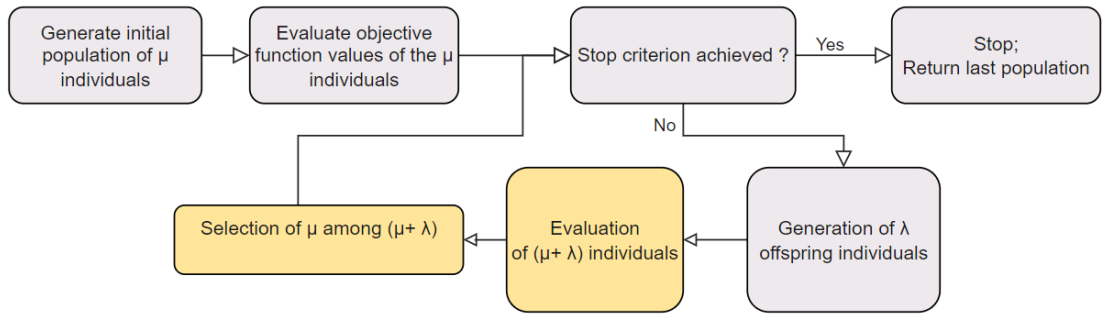
a broad and diverse set of non-dominated solutions (Zizler et al., 2001) and runs in less time (Khare & Deb, 2003). It is to be noted however, that, above a certain amount of objective functions, all methods face a wall and cannot solve the problem (Ishibuchi et al., 2008).

In our case, the emphasis of the optimization is given on the exploration of the solution space, in order to cover as much as possible the trade-offs between the 3 objectives, and how these trade-offs produce different options in terms of locations within the city and in terms of groundwater recharge infrastructures. Therefore we opted for the NSGA2 algorithm for maximizing the exploration of diverse solutions. We restricted our implementation of MOO to 3 objectives for a variety of reasons, though we did identify that more objectives could have been considered in our case (for instance other types of co-benefits of NBS). If more objectives were to be considered into future research using MOO, we would probably consider relying rather on the SPEA2 algorithm.

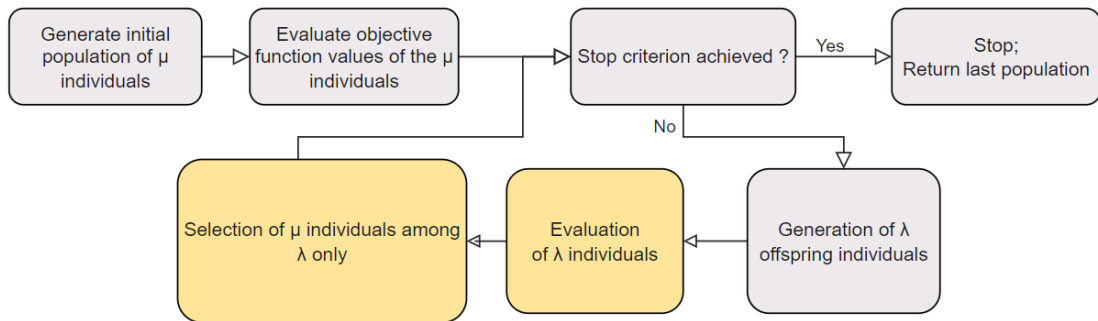
2.2.3 The evolution strategy

The evolution strategy is the fourth main element defining the evolutionary algorithm approach. It defines how the previously exposed elements are intertwined. It defines how the various operators are applied, to which group of solutions, in which order. The most widespread strategies are the $(\mu + \lambda)$ and (μ, λ) strategies (Fortin et al., 2012).

- The $(\mu + \lambda)$ (“Mu plus Lambda”) strategy (Figure 10a) is a method in which μ parent solutions generate λ children solutions ; and only then, after mating, the entire group $\mu + \lambda$ is evaluated. Then the λ worst solutions are discarded, so as to keep a constant population of μ , which then become the next parent solutions.
- The (μ, λ) (“Mu comma Lambda”) strategy (Figure 10b): the population of μ parents generates λ children solutions at each iteration. Then, the selection takes place within the λ children solutions only, thus discarding the parents, no matter their fitness values.



a) The $(\mu + \lambda)$ evolutionary strategy



b) The (μ, λ) evolutionary strategy

Figure 10: Simplified representation of the $(\mu + \lambda)$ and (μ, λ) Evolutionary Strategy (Fortin et al., 2012)

The adjustment of the parameters μ and λ is particularly crucial and does not have a systematic approach for finding optimal parameter values. Both parameters are usually defined as the following relation:

$$1 \leq \mu \leq \lambda < \infty$$

In (μ, λ) strategy, the reason for this relation between parameters is quite straightforward. λ is preferably larger than μ , since λ is selected only from μ . If $\mu = \lambda$, no changes would be made from generation to generation. In $(\mu + \lambda)$, this condition is not as high, as the pool of selection is the sum of $(\mu + \lambda)$. This strategy relies on a “birth surplus”, that is, that $\lambda > \mu$, therefore allowing to statistically improve the chance that good solutions emerge in lambda (Beyer & Schwefel, 2002). However, for $(\mu + \lambda)$, this relation is not justified by a necessity of the strategy, but rather solely because of the birth surplus. The course of action is then to select a λ parameter as high as possible, without being a penalty in computation time (Rowe & Sudholt, 2014).

These two strategies ultimately differ in their application of “elitism”, namely how best fitted individuals are kept throughout the algorithm (Bäck et al., 2000). In $(\mu + \lambda)$, the best μ can be systematically kept in the process, since they are always part of the selection step. This is particularly useful when keeping the best found solutions is more important than exploring the search space, that is,

when the “optimization” is the main focus of the algorithm. In (μ, λ) on the other hand, no specific scheme prevents the best components of μ to be replaced, there is no “elitism”, yet this can be useful when the problem requires an emphasis on exploration mechanisms. Overall, the choice between both approaches therefore depends on the importance and difficulty of the exploration of the solution space, but, as with many aspects of evolutionary algorithm, the choice has to be done after a run of trial and errors (Fortin et al., 2012).

In our case, we opted for the $(\mu + \lambda)$ strategy, after various trials with both attempts, as it provided better consistency in the results across multiple runs. In our implementation in Chapter 4, $\mu=500$, and $\lambda=2000$. These parameters were set also after multiple runs. In particular the population size $\mu=500$ gave a good balance between covering the entire Pareto front, and practical computation time.

2.2.4 Constraint handling

The final main point of the algorithm is constraint handling. There are three main ways of handling constraints in evolutionary algorithm, and no systematic methodology, as presented by Coello (2022):

One way is to handle the constraints as hard conditions for the search space (Coello, 2022). This way, the infeasible solutions cannot even be created in the first place, and therefore no invalid solutions will be created in the search process. This method by limitation of the searching domain is however only applicable in problems where the search domain can be easily known prior to evaluation. This way infeasible solutions can be eliminated prior to the search process. In combinatorial problems, this scheme would require a high degree of *a priori* knowledge on feasible and infeasible combinations, which cannot be obtained in practical problems, or requires a great deal of prior computation.

Another widespread solution to constraint handling consists in penalty scheme (Coello, 2022). Solutions that violate constraints get assigned the worst possible values regarding objective functions, thus ensuring that they perform badly. In this scheme, solutions are therefore first created, then evaluated, and then discarded or kept according to their feasibility within constraints, and then according to their domination status, their desirability. In this design, constraints are therefore applied only after the creation and valuation of the solutions. The efficiency of the algorithm can be altered if the search space features a high number of infeasible solutions, as computing resources are wasted in evaluating invalid solutions.

A way to go over this limitation is by using the final approach: “repair mechanisms”. This mechanism is inspired by genetic repair systems at cellular levels (Salcedo-Sanz, 2009). When a solution is found to be violating a constraint, it can be modified to become acceptable. Various mechanisms can

be applied for this purpose. One way is that the invalid solution can be randomly modified: in combinatorial problem, some component items of the individual are randomly modified; in continuous problems with binary encoding, the chromosomes that encodes the solution can be randomly modified to create a different solution altogether. Besides random modification, repair techniques can also use genetic backtracking to create a feasible solutions (Salcedo-Sanz, 2009): a feasible solution can be recreated based on the characteristics of the parent solutions which led to the creation of the currently invalid one. This method is nevertheless particularly resource consuming, and its benefits can be outweighed by penalty functions schemes if the number of infeasibilities is too high.

In our case, after a series of trial and errors, we opted for a simple repair method based on mutation. Our MOO implemented in chapter 4 features only one constraint: a spatial limit. Whenever a newly created individual under evaluation features a total amount of surface areas dedicated to GRI that passes the limit that we fixed, it is readapted through mutation. In essence, random elements of this individual (*i.e.* neighborhoods) are removed entirely, one by one, until the individual fits into the constraint scheme.

This way, the main characteristics of the individual is kept in the evolutionary procedure, though with a random removal of one of its constituents. The logic behind this choice is that we do not remove what may have been otherwise a potential good candidate to our problem. Overall, the choice of this constraint handling method was reached also after a run of trial and error of other approaches, and this one gave the most satisfactory solutions in terms of run time.

```
def readapt(individual): #Strong constraint for the evaluation function

    (when space constraint > max) : removes some random elements
    stop = 0
    while stop < 1:
        if len(decode(individual)) == 0: # do not readapt an empty individual
            break
        non_null = []
        for i in range(len(individual)//2):
            if individual[i] > 0: #list the non-empty individuals
                non_null.append(i)
        j = random.choice(non_null) #pick a random one and remove it
        individual[j] = 0
        stop +=1
        break
    return individual
```

Overall, this chapter provided 1) an overview of the overall framework of the R&D project and the Multi-Objective Optimization (MOO) method; and 2) a detailed description of the evolutionary algorithm used for solving the MOO. These methodological elements are a complement to the method sections of Chapter 3 and Chapter 4. In the upcoming chapter, we present the discrete choice experiment approach developed for analyzing the spatial distribution of the benefits of GRI.

Chapter 2: Do urban environmental inequalities influence demand for Nature-Based Solutions?

This chapter is an expanded version of the following paper:

Farina, G., Le Coënt, P., Hérivaux, C. (2023). Do urban Environmental inequalities influence demand for nature-based solutions? (Under review at Ecological Economics as of October 2023)

Abstract

Nature-based solutions (NBS) are currently being promoted for urban climate change adaptation. We argue that urban planners should account for the demand for NBS, which may be spatially heterogeneous and influenced by environmental inequalities. We develop a discrete choice experiment to evaluate preferences for two co-benefits (aquifer preservation and local climate regulation), as well as one potential negative effect of NBS policies (their impact on the reduction of space available for cars in cities). The survey in a large French city reveals a strong heterogeneity of preferences for local climate regulation and for the reduction of car space. We analyze the spatial heterogeneity of preferences, and find significant spatial autocorrelation and local clusters of high/low demand for local climate regulation and for the reduction of car space. In a subsequent post-estimation model, we identify that individual's exposure to heat islands affects positively their demand for NBS policies, which allows us to effectively create a city-wide demand map for local climate regulation. In addition, individual's reliance on car use influence their demand for NBS policies. Overall, our analysis highlight that analyzing environmental inequalities is important for planning sound NBS policies.

1 Introduction

In the coming decades, cities will need to adapt to a variety of challenges posed by climate change, demographic growth, increased urbanization and densification resulting in air, soil, and water pollution, heat island effects, and increased flood risks. Urban nature-based solutions (NBS) - *e.g.*, urban greening, urban deproofing, sustainable urban drainage systems (SuDS), preservation of natural areas, are being increasingly considered by cities to tackle these issues. As the challenges are spatially unequally distributed in cities and their surroundings, their solutions need to be implemented in those areas where they are needed the most. Most cities have yet to design and implement spatially explicit NBS development strategies (Almenar et al., 2016; Elmqvist et al., 2013), rather most NBS are currently implemented based on available land opportunities that are usually located outside densely populated centers where the need for adaptation services is the highest (Kabisch et al., 2016). To avoid such outcomes, decision makers need the right tools to better target and plan the spatial development for NBS (Bulkeley, 2013). In particular, these assessment tools need to account for the spatial patterns of supply and demand for the ecosystem services (ES) provided by NBS (Cortinovis & Geneletti, 2018; González-García et al., 2020), in order to maximize the benefits of public investments for society (Mader et al., 2011).

Most approaches to planning the development of urban NBS are based on the study and modeling of biophysical indicators of ES supply (Elliot et al., 2019; Hu et al., 2015; Oraei Zare et al., 2012; Polasky et al., 2008). These approaches tend to use the distribution of ES supply as the main criterion to select the most pertinent areas for NBS projects (Bulkeley, 2013; Cohen-Schacham et al., 2016). These approaches are intuitive and easy to implement thanks to non-expert ES supply modeling tools (Tardieu, 2017). Moreover, they rely on a strong rationale for action: by mapping explicitly ES supply, they allow for the identification of spatial environmental inequalities (EI). These approaches thus base their spatial recommendations for NBS projects on the incentive to prioritize areas of scarce ES supply, to ultimately mitigate these EI (Liotta et al., 2020). Environmental justice (EJ) has developed the thorough analysis of EI in urban contexts as a means to inform policy makers. Indeed, identifying the spatial distribution of EI prior to the planning phase of NBS policies may improve their outcome.

However, supply-based approaches can encounter many shortcomings by not explicitly accounting for actual urban dwellers' demand (Langemeyer et al., 2016; Nesshöver et al., 2017; Oijstaeijen et al., 2020). First, while in some cases, these ES supply biophysical approaches may effectively target areas with low supply and high demand for ES at the same time, there are certainly cases where this is not true. In some cases, focusing exclusively on supply does not capture the full extent of the spatial heterogeneity of the possible benefits of NBS policies, and can potentially lead to suboptimal choices of location (González-García et al., 2020). For instance, using a supply focus when planning an NBS

policy aimed at mitigating urban heat islands could prioritize commercial or industrial areas endowed with large parking lots and few green and natural areas, but with few residents, rather than selecting densely populated areas of the city where the demand for heat mitigation is higher. In addition, failure to analyze demand may leave unnoticed the potential existence of populations or areas strongly opposed to the implementation of NBS policies. This opposition can result from the perceived negative effects of greening policies, such as their potential consequence for gentrification (Gould & Lewis, 2016; Laurent, 2011); or because of ecosystem disservices generated by NBS (Blanco et al., 2019; Lyytimäki & Sipilä, 2009).

Survey-based methods, *e.g.*, stated preference methods, can be used to evaluate citizens' preferences for contrasted NBS strategies and to estimate individual demand. By surveying representative samples of the population, researchers and policymakers can acquire a better understanding of the preferences of the population concerned. Such approaches have started using spatial econometric tools to analyze the spatial heterogeneity of demand for different types of environmental goods (Bateman et al., 2006; Broch et al., 2013; Brouwer et al., 2010; Budziński et al., 2018; Czajkowski et al., 2017; Hampson et al., 2017; Kim et al., 2022; Meyerhoff, 2013; Pinto et al., 2016). Studies have shown how willingness to pay (WTP) for environmental programs derived from discrete choice experiments are not distributed randomly but show national or regional spatial disparities (Campbell et al., 2008; Czajkowski et al., 2017; Toledo-Gallegos et al., 2021). Other authors have pointed to local clustering of low or high WTP for similar programs (Johnston et al., 2015; Johnston & Ramachandran, 2014; Kim et al., 2022; Toledo-Gallegos et al., 2021). These studies offer different approaches to map the spatial distribution of demand for environmental goods specific to their case studies, as well as to identify the sociodemographic or attitudinal characteristics that explain this demand.

However, few studies have established a clear link between the spatial heterogeneity of demand for NBS and the distribution of EI. Clarifying this link will provide insights into the spatial heterogeneity of the rationale for demand beyond individual case studies. In fact, this link has been shown implicitly in analyses of how preferences for urban green areas are ordered along an urban-rural gradient (Hérivaux & Le Coënt, 2021; T. Zhou et al., 2018), since the urban-rural gradient can encompass the distribution of EI. However, the degree to which EI are themselves determinants of the spatial heterogeneity of demand has yet to be explicitly investigated.

In this paper, we evaluate the influence of distributional EI on the demand for NBS. We implemented a choice experiment to evaluate the preferences for contrasted alternatives of development of Groundwater Recharge Infrastructures (GRI), including Nature-Based Groundwater Recharge Infrastructures (NBGRI), aimed at protecting groundwater resources as well as at providing other urban

ES. This choice experiment was led in the Bordeaux Metropolitan (BM) area, France, where the local government is currently designing a plan to develop GRI.

Our analysis addresses two research questions:

- Are preferences for GRI spatially heterogeneous?
- Are preferences for GRI influenced by Environmental Inequalities?

The novelty of this paper lies in three points:

Firstly, while the spatial distribution of EI and the spatial heterogeneity of demand for urban ES have been both explored, to our knowledge very few studies have actually bridged the gap between these questions (Jacobs et al., 2016), and analyzed how EI may impact preference for GRI at city scale. The goal of this paper is to address this point in order to 1) characterize the spatial distribution of preferences, 2) identify rationales for these distributions, and 3) predict maps of demand for GRI benefits and negative effects.

Secondly, although preferences for the multiple benefits provided by NBS, urban green areas, and sustainable urban drainage systems (SuDS) have been thoroughly studied, this work focuses on a different type of NBS that provides a particular benefit that has not been extensively evaluated in this literature: the preservation of groundwater resources.

Thirdly, this paper evaluates potential tradeoffs between GRI development and availability of space for cars in cities, which is at the core of many urban planning debates (Cortinovis & Geneletti, 2018; European Commission Directorate-General for Research and Innovation, 2015). In particular, the paper explores another aspect not thoroughly explored to date: the impact of this trade-off on demand for GRI.

2 State of the art

Distributional justice is one dimension of EJ that classically focuses on the distribution and allocation of environmental costs, burdens and benefits between individuals and groups (Walker, 2012). These inequalities have been analyzed through the lens of vertical inequalities (the distribution of a variable between individuals); as well as horizontal inequalities (the analysis of the distribution of variables between sub-populations, *e.g.* communities) (Boyce et al., 2016). The latter assumes that EI may interact with other types of socio-economic inequalities (Walker, 2012). This paper applies a vertical perspective to analyze the three dimensions of distributional environmental inequalities that are particularly salient in the context of NBS policies (Kato-Huerta & Geneletti, 2022), and that may impact

demand for urban ES: inequality in exposure to environmental hazards, inequality in access to urban green areas, and inequality caused by the adverse effects of greening policies. In this section, we look at how these dimensions of inequalities can affect demand for NBS.

Inequality in exposure to environmental hazards is the most widely studied aspect in classical EJ considerations (Calderón-Argelich et al., 2021). Traditionally, EI was analyzed through the lens of the exposure of social and racial minorities to environmental hazards (Diekmann et al., 2022; Laurent, 2011; Yi et al., 2019). Many authors have explored the exposure of different populations to different types of pollution (Boyce et al., 2016; Diekmann et al., 2022; Samoli et al., 2019), the risk of flooding (Fielding & Burningham, 2005), or the effect of heat islands in urban contexts (Darrel et al., 2011; Hsu et al., 2021; Wong et al., 2016).

Some studies have approached the relation between exposure to environmental hazards and demand for NBS by mapping the spatial mismatch between regulating ES supply and demand (Baró et al., 2015, 2017; González-García et al., 2020; Herreros-Cantis & McPhearson, 2021). Indeed, identifying areas of low regulation of ES supply (air purification, temperature regulation, etc.) is equivalent to analyzing exposure to environmental hazards. However, these works do not explicitly analyze demand heterogeneity: Herreros-Cantis & McPhearson (2021) and Baró et al., (2017) consider population density as a proxy for demand without considering preference heterogeneity. Although it is commonly assumed that exposure to environmental hazards increases demand for the regulation of ES, this relation remains to be studied.

The second type of inequality that may affect demand for ES is inequality in access to green areas, which has been demonstrated and stratified as a function of sociodemographic characteristics (income, etc.) (Y. Chen et al., 2022; Nghiem et al., 2021; Nyelele & Kroll, 2020; Wolch et al., 2014), and along an urban-rural gradient (Liotta et al., 2020). To date, studies have investigated the link between access to environmental goods –such as green areas - and demand, mainly through a single entry: by analyzing how increased distance to environmental goods reduces WTP for environmental programs, *i.e.* “distance decay” (Glenk et al., 2020). Indeed understanding distance decay is particularly important in environmental valuation to apply spatial discounting of ES when evaluating policies (Yamaguchi & Shah, 2020). Significant distance decay effects have been identified by including a distance attribute in discrete choice experiments, either as a travel distance to environmental goods (Badura et al., 2020; Jørgensen et al., 2013; Pate & Loomis, 1997; Schaafsma et al., 2012), or by specifying the distance between the location of the residence and the environmental goods (G. Tu et al., 2016). Johnston & Ramachandran (2014) showed a significant effect of distance decay on access to environmental goods, by analyzing estimated individual WTP from a choice experiment using a spatial econometrics model. The above works focus exclusively on large-scale environmental goods (parks, lakes, rivers, etc.), not

on small urban NBS while the impact of EI in access to green areas on demand for NBS remains to be investigated.

Finally, NBS policies may have negative impacts due to their own adverse effects, for instance, the policy designs themselves can amplify inequalities (Calderón-Argelich et al., 2021). Up to now, these negative effects have been overlooked in environmental valuation (Langemeyer & Connolly, 2020). Indeed, stated preference literature has mostly investigated ecosystem disservices as one of the main negative policy implications of NBS and urban greening policies (Blanco et al., 2019; Gómez-Baggethun & Barton, 2013; Soto et al., 2018). Ecosystem disservices can impact preferences as urban green infrastructure can be associated with a variety of negative outcomes, such as causing allergies or introducing harmful species (Von Döhren & Haase, 2015).

However, urban greening policies may involve trade-offs beyond ecosystem services and disservices only. The main implication and most widely studied aspect being green gentrification (Wolch et al., 2014): urban greening policies that may initially seem inclusive may subsequently lead to the displacement of entire populations through land price mechanisms (Gould & Lewis, 2016). In the context of planning for the development of urban green infrastructures in compact cities, a more direct and short-term possible negative impact for some populations may be the reduction in space for car-related infrastructure, roads and car parks that can limit car use (Gundlach et al., 2018; Lyytimäki & Sipilä, 2009). Certain populations, especially those who live in the periphery of cities may depend to a great extent on individual car use, and feel a loss of well-being due to policies that constrain car transport, especially in the absence of suitable alternatives (Gundlach et al., 2018). Hérivaux & Le Coënt (2023) showed that these populations may have a low acceptance for such policies. The influence on demand for NBS of the impact of NBS policies on car space has not yet been estimated directly.

Based on these findings, we hypothesize that these three types of EI influence individual demand for ES.

3 Method

3.1 The survey

3.1.1 The survey design: water infiltration NBS in Bordeaux metropolitan area, France

The Bordeaux metropolitan area (814 000 inhabitants) is located in the southwest of France, and covers 28 municipalities. For its public water supply, the area depends largely on deep aquifers that are currently overexploited due to rapid demographic growth. The city is also experiencing increasingly

strong heat waves that are predicted to increase from a mean of 8.4 days/year to 20.7 days/year by 2050 (Artelia, 2015). To mitigate these two adverse effects, the local government aims to develop GRI and urban greening as a way of combining two objectives, the preservation of deep aquifers, and adaptation to urban climate change, mainly through heat island mitigation. To this end, both Nature Based Groundwater Recharge Infrastructures (NBGRI) and Conventional Groundwater Recharge Infrastructures (CGRI) are being considered. Their main purpose will be to enable infiltration and storage of rainwater in shallow aquifers so it can later be reused for uses that are currently covered by drinking water even though lower quality water would suffice (irrigation of green spaces, street cleaning, industrial uses, etc.). The goal of this water use substitution is therefore to help preserve deep aquifers. The other main objective of this policy is to address heat island effects.

We conducted a choice experiment survey to assess both the resident population's preferences for various alternative implementations of GRI, and demand for their benefits. The choice experiment attributes and their levels were constructed in a participatory process with stakeholders. We held two workshops with members of the local administration involved in the management of the different issues at stake: water basin authorities, water service and urban greening personnel, and public developers. The first workshop (January 2022) aimed at (i) identifying available urban spaces that could be used for the development of GRI; (ii) discuss their main benefits, and negative effects, (iii) select which of these benefits and negative effects should be included in the choice experiment. The aim of the second workshop (March 2022) was to validate the range of levels for these effects.

The choice experiment was designed to both (i) respond to the policy questions identified during the participatory process on the preference for the benefits and negative effects generated by GRI, and (ii) test the impact of the three types of EI discussed in the state of the art section on preferences. The selection of attributes in particular was the result of these two objectives.

3.1.2 Attributes and levels

The attributes included in the choice sets were the following:

- The first attribute is the preservation of deep aquifers enabled by replacing the water currently used by infiltrated rainwater. This attribute is the main benefit attributed to GRI by workshop actors for which they expect to estimate preferences. It is formulated as the percentage of achievement of the official local deep aquifer water saving goals.
- The second attribute is linked to the regulation of local climate by reducing heat-island effects resulting from NBGRI. It is the second objective attributed to GRI by local actors. It is expressed as the total city-wide proportion of reduction in heat islands area due to NBGRI. This attribute

is also well suited to test the impact of the inequality to exposure to environmental hazards on preferences.

- The third attribute is the impact of developing GRI on urban space dedicated to cars. This attribute may be perceived as either a negative effect, for instance by car-dependent citizens; but it can also involve other services and benefits, such as noise reduction or improved air quality due to reduced use of cars. It is considered by local actors as the potential main source of opposition to the development of infrastructures. As the authors, we also expect that inequality regarding the adverse effects of greening policies may strongly affect preferences for this attribute.
- The fourth attribute is the distance of inhabitants to the closest NBGRI. It is expressed as a simple distance between the respondent's home and a NBGRI. We included this attribute to estimate the distance decay associated with GRI. We also expect that it may be affected by the inequality in access to green areas.
- The payment vehicle is an annual increase in water bills for a duration of 10 years. Respondents were given the explanation that implementing infiltration policies may require using this source of financing, as part of the water bills is dedicated to financing rainwater policies in the Bordeaux metropolitan area.

To identify plausible levels for the deep aquifer preservation and local climate regulation attributes, we estimated potential future benefits of GRI using a simple GIS modeling approach. We identified and mapped urban spaces that are really available for NBGRI projects in collaboration with workshop actors, and quantified the maximum possible levels for both of these benefits. The method is described in supplementary materials. The final attributes and their levels are listed in Table 1.

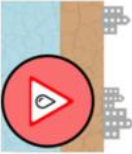


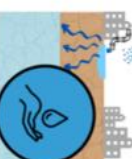







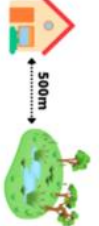
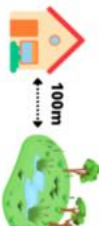
| Attributes | Levels | | | | | | | | |
|-----------------------------------|---|---|---|--|---|---|---|---|---|
| Preservation of the deep aquifers | No groundwater savings due to infiltration (status quo level) |  | 25% of groundwater savings goal thanks to infiltration |  | 50% of groundwater savings goal thanks to infiltration |  | 100% of groundwater savings goal thanks to infiltration |  | |
| | Local climate regulation | No reduction of heat island areas (status quo level) |  | 20% decrease of heat island areas |  | 40% decrease of heat island areas |  | 60% decrease of heat island areas |  |
| | Impact on urban space dedicated to car use | No reduction of space dedicated to cars (status quo level) |  | Reduction of space dedicated to cars |  | | | | |
| | | Distance to the nearest green infrastructure | No new green infrastructure in the vicinity of your home (status quo level) |  | Nearest green infrastructure is located 500m from your home |  | Nearest green infrastructure is located 100m from your home |  | Nearest green infrastructure is located right next to your home |
| Increase in annual water bill | 0€ (status quo level) | 30€ | 60€ | 90€ | 120€ | 150€ | 180€ | | |

Table 1: Attributes and levels

3.1.3 Hypotheses

We aim to assess the impact of inequality in exposure to environmental hazards, inequality in access to green areas, and inequality regarding the adverse effects of greening policies on preferences for GRI. We transformed these questions into testable hypotheses in our case study:

- High exposure to heat island risks increases demand for local climate regulation (inequality in exposure to environmental hazard) (H1);
- Poor access to green spaces leads to a higher demand for NBGRI close to the individual's residence (inequality in access to green areas) (H2);
- Dependence on car use lowers demand for GRI policies that reduce car space (inequality regarding the adverse effects of greening policies) (H3).

Based on these hypotheses and on our set of attributes and levels, we created a questionnaire and the experimental design for the choice experiment.

3.1.4 Survey administration

The questionnaire comprised three parts. The first part explained the urban challenges faced by the Bordeaux metropolitan area regarding the preservation of water resources, as well as adaptation to climate change (heat island effects) and the benefits of infiltration. The second part contained the choice sets (for an example of a choice set, see Figure), in which respondents chose between GRI alternatives defined by the attributes listed in Table 1. The third and final part was a series of questions regarding the individual's lifestyle and environment (*e.g.* type of residence, car use, distance to existing green areas, etc.), and sociodemographic variables (*e.g.*, gender, age, employment, education, income).

A first round of face-to-face pre-tests of the survey (n=34) was implemented in June 2022 to be sure the questionnaire was clear, and to establish priors. The final levels of payment were raised after these pre-tests, as it appeared that we did not capture the full range of WTP.

The survey was then administered online by a polling company and sent to residents of all the municipalities that make up the Bordeaux metropolitan area in September 2022.

Please select your favorite alternative:

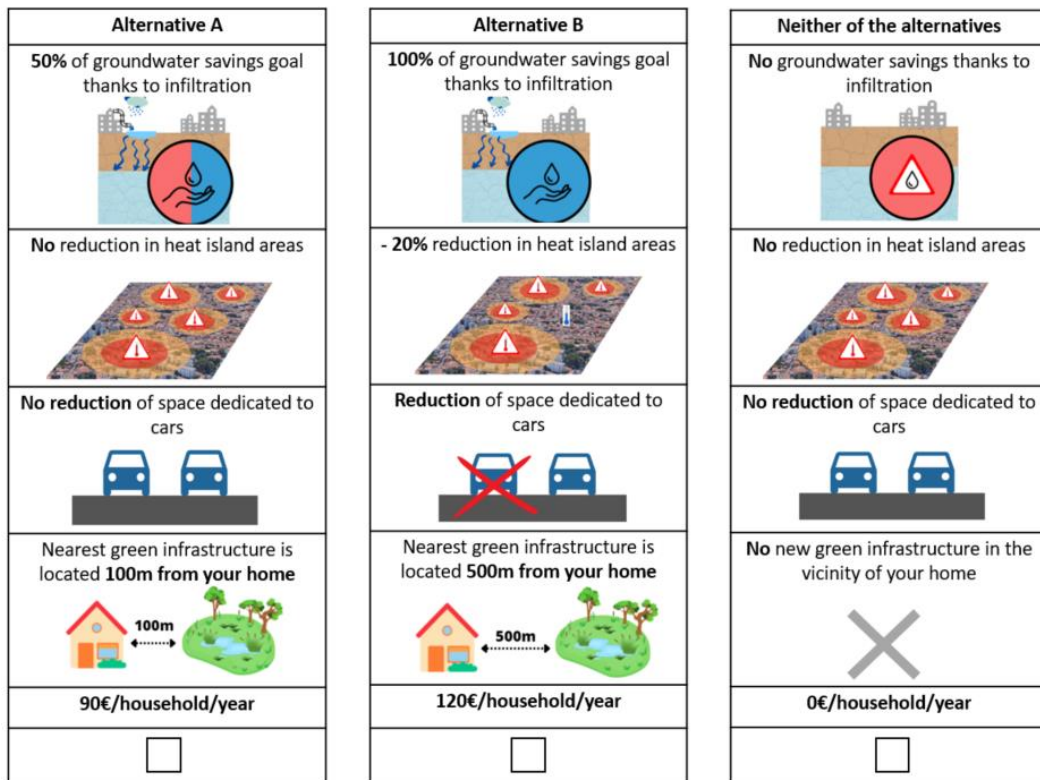


Figure 1: Example of a choice set

3.1.5 Survey design

We used a fractional D-efficient design for the experiment. Each choice set featured 2 alternatives resulting from different levels of implementation of GRI, and a ‘status quo’ option representing the absence of development of GRI - whether NBGRI or CGRI - and was characterized in terms of all attributes. With this design, 10 parameters had to be estimated (2 for deep aquifer preservation, 3 for local climate regulation, 1 for car space reduction, 3 for the distance attribute, and 1 for payment). Based on general guidelines (Hensher et al., 2005), we decided on 12 choice sets to be on the safe side for model estimation and guarantee a balanced attribute level. We chose a hybrid blocking design, where 6 random sets out of the 12 would be presented to each respondent.

This design has a specificity: the attribute for deep aquifer preservation has a level that only appears in the status quo option (“no groundwater savings”), while all other non-payment attributes have a status-quo level that can also appear in the choice cards. It would have been illogical to present alternatives in which GRI are implemented, but do not improve groundwater preservation. Consequently, preference for the first level of aquifer groundwater preservation is combined with the preference for the status quo. In contrast, the heat reduction attribute featured a status quo level within the choice sets, as only grey

infrastructure can be constructed for these infiltration policies, which would not result in delivering urban cooling ecosystem services. The levels and their coding are detailed in supplementary material.

3.2 Overall econometric approach

Our overall econometric approach aimed first to analyze preference heterogeneity, and then to test how EI impacts demand for NBS. The analysis is done in four stages:

- First, we used a mixed logit (MXL) model in preference and WTP space in order to estimate average and individual-specific coefficients and WTP.
- For variables that present heterogeneity in the MXL model, we tested for spatial dependence of estimated individual WTP; and mapped hot/cold spots of individual WTP.
- In order to analyze EI, and to identify potential predictors of spatial preference heterogeneity, we created indicators of EI and tested their spatial dependence.
- Finally, we performed a post-estimation regression model, in which the individual WTP_n estimates from the MXL model are explained using environmental indicators and individual socio-demographic variables.

This two-step approach to analyzing the influence of EI on WTP does not avoid the potential loss of efficiency caused by the dependent variable (WTP_n) being conditional on the estimated parameters from the MXL model. Moreover, the WTP_n are not the actual unique set of estimates of each individual, but rather an estimation of the mean individual-specific WTP_n , derived from the individual's conditional distribution. However, it enables the inclusion of a large number of variables (Glenk et al., 2020) and has been used in a number of studies thanks to its tractability (Broch et al., 2013; Campbell, 2007; De Valck & Rolfe, 2018; Garrod & Willis, 1999; Johnston & Ramachandran, 2014; Newell & Swallow, 2013; G. Tu et al., 2016; Yao et al., 2014).

The alternative, *i.e.* to focus the analysis more on the spatial heterogeneity of preferences would have meant using another choice modeling framework, namely a geographically weighted multinomial logit model (GWMNL), as in Budziński et al. (2018). However, this approach assumes that all heterogeneity is location-specific, *i.e.*, that individuals in the same location have homogeneous preferences. With these specifications, heterogeneity is not individual-specific, in other words, it does not allow testing of specific hypothesis on the influence of other sociodemographic characteristics (for instance income, or individual car use in our case). Considering all these factors, we decided that our two-step approach was the best available option to test our hypotheses.

3.2.1 Model specification

The econometric models are based on the random utility model. Respondent n faces T choice sets, where each choice situation t is made of J alternative. The respondent would choose alternative j based on its utility U_{njt} . The observable component of U_{njt} comprises the set of attributes X_{njt} , the corresponding coefficient for the vector of attributes β_n , and the unobserved error term ε_{njt} :

$$U_{njt} = \beta_n X_{njt} + \varepsilon_{njt} \quad (1)$$

The standard conditional logit model assumes homogeneous distribution of preferences among individuals, they share the same utility functions, so it does not allow the study of preference heterogeneity. In contrast, the mixed logit model accounts for the heterogeneity of preferences by allowing the β_n coefficients to vary randomly across individuals, according to a continuous distribution $f(\beta_n|\theta)$, of which we can specify the parameters θ to be a normal, log-normal or triangular distribution. We used this model directly to analyze preference heterogeneity. The mixed logit model estimates the probability that the individual n makes the sequence of T choices, selecting alternative i_{nt} among J alternatives in choice situation t . The probability of this sequence of choices, conditional on knowing the individual taste coefficient β_n is given by:

$$P_n(j_{n1}, \dots, j_{nT}|\beta_n) = \prod_{t=1}^T P_n(j_{nt}|\beta_n) = \prod_{t=1}^T \frac{\exp(\beta_n X_{int})}{\sum_{j \in J} \exp(\beta_n X_{jnt})} \quad (2)$$

From Eq. (2), we can express the unconditional probability P_{nT} that individual n makes the observed sequence of choice j , by integrating over the known distribution of β_n :

$$P_{nT} = \int \prod_{t=1}^T \frac{\exp(\beta_n X_{int})}{\sum_{j \in J} \exp(\beta_n X_{jnt})} f(\beta_n|\theta) d\beta \quad (3)$$

With this model, we can estimate the individual β_n preference parameters of each individual. It is therefore called a preference space model. We used also a mixed logit model in ‘WTP space’, by reformulating the model. In this way, the WTP of attribute coefficients are the direct results of the econometric model. Indeed, this method is better than the traditional method used to estimate WTP, *i.e.*, calculating the ratio between attribute and payment coefficients, which leads to a skewed distribution of WTP as two randomly distributed parameters are associated (Train & Weeks, 2005). In Eq. (1), we separate the payment attribute p_{njt} from the other attributes X'_{nji} , hence the utility of the respondent n in choosing alternative i in choice situation t is :

$$U_{njt} = \alpha_n p_{njt} + \beta'_n X'_{njt} + \varepsilon_{njt} \quad (4)$$

with α_n a random parameter for payment, and β'_n individual random parameters for the other attributes. ε_{njt} is a random term that follows a Gumble distribution with a variance of $k_n^2(\pi^2/6)$, k_n is a scale parameter associated with individual n. By dividing Eq.(4) by k_n , we obtain the equation of utility in WTP space:

$$U_{njt} = \lambda_n [p_{njt} + \gamma_{njt} X'_{njt}] + \varepsilon_{njt} \quad (5)$$

with $\lambda_n = \alpha_n/k_n$ and $\gamma_{njt} = \beta'_n/\alpha_n$.

Both these models were estimated using maximum simulated likelihood methods (500 Halton draws) using the STATA 12' "gml" package.

3.2.2 Test for spatial dependence of estimated WTP_n

We first tested for spatial dependence of the estimated WTP_n from the MXL model. The goal of this step is to identify which attributes may present spatial clustering, thus indicating which attribute or attribute levels can be explained by spatially varying variables including environmental indicators.

Moran's I statistic is a common and practical measure to identify spatial dependence, and has been used in non-parametric approaches to identify significant WTP clustering phenomena (Campbell et al., 2008; Toledo-Gallegos et al., 2021). It tests if variables are distributed significantly differently from random, thus suggesting an underlying phenomenon of spatial association.

In the second step, we also identified hot/cold spots of individual WTP_n using Getis-Ord Gi. Getis-Ord Gi indicates local spatial autocorrelation clustering of variables. It can detect the subsets of values that contribute significantly to global autocorrelation, and identify clusters that do not appear in the global Moran I's analysis (Glenk et al., 2020). The purpose of this analysis was to create informative maps of hot/cold spots of WTP (Johnston & Ramachandran, 2014; Toledo-Gallegos et al., 2021), and to help identify the most suitable explanatory variables for the following step in the parametric approach.

3.2.3 Analysis of environmental inequalities

We used three indicators to describe EI in the Bordeaux metropolitan area and test our hypotheses. These indicators were used to describe EI in the area, and then to further analyze individual preferences

in the post-estimation phase and test our hypotheses. The first two indicators were estimated at the “IRIS” unit scale (IRIS is an infra-municipal “neighborhood” geographical unit used by the French National Institute of Statistics) to represent the environment in which respondents live. The third was estimated at the individual respondent level because no data existed at the IRIS scale.

The first indicator describes exposure to heat island effects: it is the mean surface temperature of the IRIS of the respondent during a heat wave. We used it to test H1. We calculated the mean surface temperature for each IRIS unit during a heatwave using thermal satellite imagery (*Landsat 7 Band 6, 07/08/2018*). The second indicator describes access to green areas and was used to test H2. It is the sum of the surface area of “managed” green areas - parks and urban green areas – and tree cover, divided by the number of inhabitants per IRIS unit. Finally, the questionnaire included a series of questions about respondents’ use of a car, including how frequently they use their individual car every week, as a way to measure individual dependency on car use, and to test H3.

We then tested the spatial dependence all three of these indicators using the same Moran statistic. This analysis tests the extent to which the environmental indicators represent real spatial inequalities. A significant autocorrelation shows that some areas are more exposed to a heat island effect than others, have less access to green areas, and that some respondents are more dependent on car use, denoting a potential general phenomenon of EI. These indicators were then used as explanatory variables in the post-estimation stage.

3.2.4 Post-estimation of WTP

In the final stage, the individual WTP_n estimated with the MXL model in WTP space were analyzed using each respondent’s socio-demographic variables, exposure to heat island, access to green areas, and car use. An OLS regression was performed for each attribute level for which significant spatial autocorrelation was detected. In this specification, each WTP_n is of the following form:

$$WTP_n = c_n + \sum_{k=1}^K z_{kn} L_{kn} + \varepsilon_n \quad (6)$$

where c_n is the constant term, ε_n the error term, z_{kn} is the k^{th} coefficient associated to the L_{kn} explanatory variable. For each WTP estimate, the independent variables included one of the indicators of environmental inequality, as well as 3 socio-demographic variables (age, income and education level). These 3 variables were selected as they can influence WTP. All three variables showed no significant collinearity, so their simultaneous inclusion in the models was not problematic.

Upon performing these post-estimations, we systematically tested for spatial dependence in the linear regression models. We tested for the spatial dependence of the errors (ε_n) using Moran's index, which would indicate that the independent variables do not account for all existing? possible? spatial autocorrelation, hence that some spatial phenomenon were missing in the explanation of WTP_n . Based on the diagnostic tests developed by Anselin et al. (1996), we also used the Lagrange multiplier (LM) test for dependence of the error terms, and to test for a missing spatially lagged dependent variable; and two variants of those tests robust to the presence of the other (*i.e.* a test for error dependence in the possible presence of a missing lagged dependent variable, and inversely). The tests were systematically performed using different spatial weighting schemes: a neighboring matrix based on Delaunay's triangulation, Gabriel's Graph, nearest neighbors and distance-based neighbors, as well as an inverse square distance weight matrix. In all cases, the tests indicated no significant spatial dependence in the errors of the model. In other words, all spatial heterogeneity was captured by the independent variables. For this reason, we did not deem it necessary to expand the modeling approach to include spatial models as there was no reason to assume an impact of WTP feedback effects (spatial lag models), or of a missing lagged spatial variable (spatial error models).

4 Results

4.1 Heterogeneity of preferences

4.1.1 MXL preference heterogeneity

We obtained 302 answers from people living in the Bordeaux metropolitan area. From this sample, we excluded 9 protest respondents using guidelines from Johnston et al. (2017). The representativeness of the sample for the population of the Bordeaux metropolitan area was generally good in terms of gender, age and employment rate despite under-representation of unemployed individuals and individuals of primary education levels. Details concerning the sample data are given in [supplementary materials](#).

The results of the MXL model (Table 2) in both preference and WTP space showed the coefficients of all levels to be significant. Overall, mean coefficients and WTP were higher for the highest levels of both benefits, aquifer preservation and local climate regulation. Mean yearly WTP for the highest level of aquifer preservation ("Inf_100") was about 94€ per household and about 179€ for the highest level of local climate regulation ("Heat_60"). The SD were significant for both of these levels in WTP space, suggesting that our sample includes heterogeneity of preferences in the population that requires further investigation.

| | MXL (preference space) | | MXL (WTP space) | |
|---------------------------------|---------------------------|----------|-----------------------------------|------------|
| | Coef (mean) | SD | WTP (mean €/year/household) | SD |
| Inf_50 | 0.546*** | 0.047 | 79.584*** | 1.656 |
| Inf_100 | 0.761*** | 0.535*** | 94.668*** | -90.906*** |
| Heat_20 | 0.765*** | -0.028 | 101.483*** | 2.606 |
| Heat_40 | 1.122*** | 0.344 | 156.1*** | 52.326 |
| Heat_60 | 1.327*** | 0.403 | 179.758*** | -68.899* |
| Red_car | -0.208** | 1.148*** | -26.940* | 161.808*** |
| Dist_0 | 0.708*** | 0.042 | 103.287*** | 6.828 |
| Dist_100 | 0.632*** | -0.059 | 83.039*** | -1.191 |
| Dist_500 | 0.705*** | 0.188 | 95.546*** | 9.640 |
| SQ | -3.530*** | 2.959*** | -411.677*** | 412.741*** |
| Payment | -5.399*** | 1.537*** | - | - |
| Log-likelihood | -1407.77 | | -1454.1457 | |
| LR chi²(11) | 386.55 | - | - | - |
| Wald chi²(11) | - | - | 3155.13 | - |
| AIC | 2859.544 | | 2959.291 | - |
| BIC | 3003.946 | | 3096.693 | - |

Table 2: Results of MXL models.

“Inf_50” and “Inf_100” are the variables for the two levels of groundwater preservation, “Heat_20,” “Heat_40” and “Heat_60” the three levels of climate regulation, “Red_Car” is the level of car space reduction, “Dist_0”, “Dist_100” and “Dist_500” the three distance levels, “SQ” the status-quo attribute, and “Payment” is the payment attribute. Significance of the coefficients are marked by asterisks: *** p value < 1%, ** p value in [1, 5%), * p value in [5, 10%): n (observations) = 5,238

On average, car space reduction was perceived as a negative effect, with a mean WTP at -26€ per household. However, the SD was significant and was the highest for this attribute in both preference and WTP space. In fact, the magnitude of the SD indicates that there are both individuals with highly positive and highly negative WTP for this attribute. Car space reduction is a strong source of heterogeneity, a polarizing factor in the sample.

Regarding the distance attributes, respondents preferred overall proximity to new NBGRI over no NBGRI close to their residence. However the difference between immediate proximity, 100m and 500m from their home was not significant, suggesting no distance decay effects under 500m. Furthermore these attributes had no significant SD, suggesting no heterogeneity among respondents.

The status quo option (SQ) had negative coefficients, revealing that respondents had a strong preference for the implementation of GRI scenarios. However, this preference was confounded with the base level of aquifer preservation (“Inf_25”), leading to an upward bias: the real coefficient for status quo should be even lower. As expected, the payment coefficient had a negative sign.

4.1.2 Spatial preference autocorrelation

Based on the MXL model estimates, we tested for the spatial autocorrelation of preferences. We identified spatial autocorrelations only for the individual WTP_n of the highest level of the local climate regulation level “Heat_60”, with a Moran’s I of 0.0878 (p-value 0.0311). We also identified significant hot/cold spots for “Heat_60” and “Red_Car” (see Figure 2). Based on this finding, we decided to test the impact of our indicators of EI for these attribute levels.

The hot spot for “Heat_60” is located in the city center, in an area where mean temperature during heat waves is potentially particularly high, as is the case in many large cities, suggesting a link between preferences for heat reduction and the mean temperature per IRIS unit. Because spatial autocorrelation was previously identified for this level, this hot spot is interpreted as playing a significant role in the phenomenon of spatial autocorrelation. In contrast, the hot and cold spots for the car space reduction attribute are to be interpreted only as being significant local clusters of similar WTP, which do not reflect on the more general spatial distribution of this variable. In the post-estimation step, we thus tested the relationship between these levels and the EI indicators. Considering the lack of spatial dependence of the aquifer preservation and distance attributes, we disregarded them in the following stage.



Figure 2: Hot/cold spot analysis.

The analysis done for the individual WTP_n associated with the highest level of heat island reduction “Heat_60” (1) and the reduction of car space “Red_car” (2).

4.2 Analysis of environmental inequalities

We identified significant spatial autocorrelation for all three EI indicators (see Figure 3). It appears that centric populations are significantly more exposed to heat island effects, and have less access to green areas. In fact, the map shows that there is a clear distinction between rural and peri-urban IRIS on the one hand, and inner city centric IRIS on the other, indicating an urban-rural gradient for these EI. The frequency of car use indicator indicates that overall, in our sample, centric respondents and residents of the city of Bordeaux use their cars less than respondents who live in other parts of the Bordeaux metropolitan area. A policy that impacts car use would therefore affect peri-urban and rural areas more, suggesting potential inequality with respect to an adverse effect on the outcome of the GRI policy.

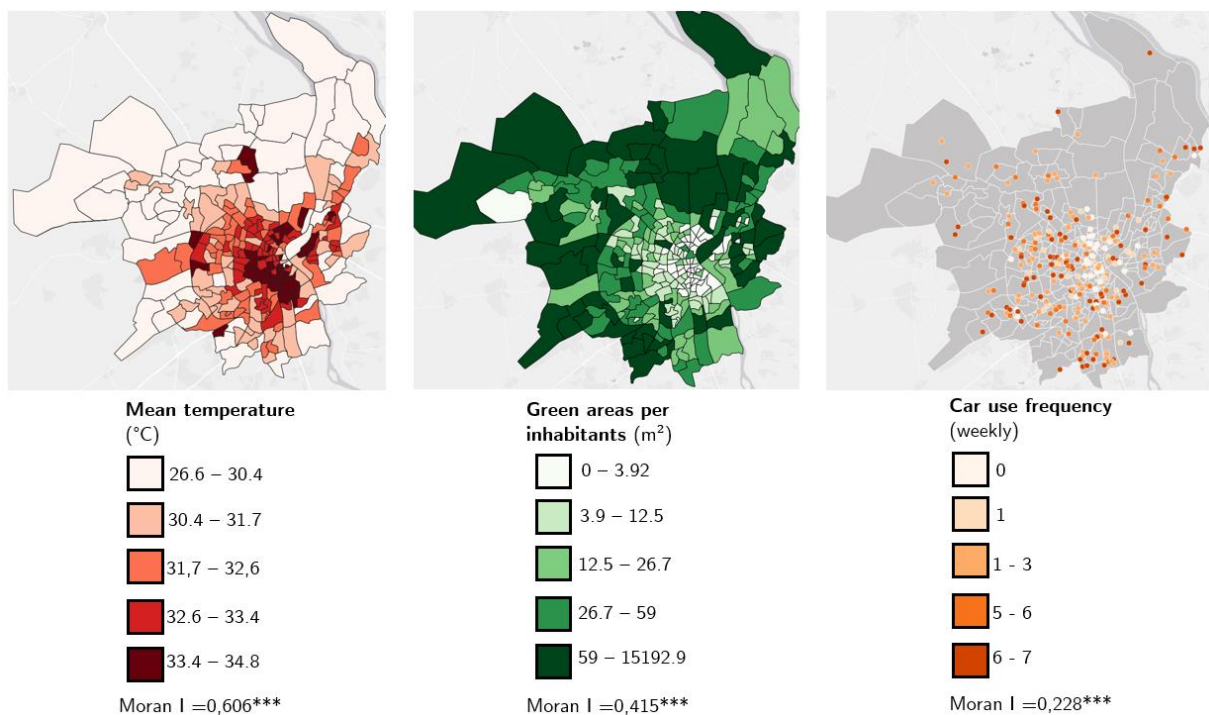


Figure 3: Environmental indicators and Moran test.

Significance of the Moran I marked by asterisks: *** p value <1%, ** p value in [1, 5%), * p value in [5, 10%)

The following regression model is only presented for the attribute levels for which significant heterogeneity (in MXL model) and some spatial autocorrelation phenomenon - either global autocorrelation or local clustering - were detected, *i.e.* the attribute levels “Heat_60” and “Red_car”. Regarding the distance attributes, the tests for spatial autocorrelation were inconclusive, nor did we identify any significant link between the indicator access to green areas and the preference for alternatives that include neighboring new NBGRI. Not only did we not observe an impact of access to green areas on the distance attribute, but in our study, no distance decay was observed under 500m.

Regarding the post-estimation model, as expected, the WTP for the level “Heat_60” depended to a great extent on the mean temperature in the respondent’s neighborhood (Table 3), and, to a lesser extent, on the respondent’s age. The other sociodemographic variables were not significant. The individual WTP_n estimated for the level “Red_car” depended solely and negatively on the respondent’s frequency of car use. Individuals who rely on using their car are indeed more likely to consider the reduction of car space as a negative effect and have a negative WTP for this level. Most socio-demographic variables, including income, were not significant in either case.

In the following section, we discuss these results in relation to our hypotheses.

| | Heat_60 (WTP) | Red_car (WTP) |
|-------------------------|---------------|---------------|
| Constant | 93.332 | 23.418 |
| Mean temperature | 2.823*** | - |
| Car use frequency | - | -12.086*** |
| Age | -2.607* | 2.149 |
| Income | 0.350 | -6.289 |
| Education | 0.580 | 6.596 |
| F-statistic | 5.07*** | 2.835** |
| Adjusted R ² | 0.0779 | 0.0246 |

Table 3: Post-estimation regressions.

Significance of the coefficients marked by asterisks: ***p value < 1%, **p value in [1, 5%), *p value in [5, 10%); n (observations) = 291. Only the appropriate indicator was used each time to test each hypothesis: car use frequency is not included as an explanatory variable in the regression for Heat_60, and mean temperature is not in the regression for “Red_car”.

5 Discussion

The analysis of the spatial patterns of demand for NBS and the influence of environmental inequalities on WTP allowed us to answer our three questions. We were thus able to draw conclusions concerning the contrasted influence of the three types of environmental inequalities considered in this work.

Our first hypothesis (H1) was confirmed: exposure to high temperatures leads to a preference for the most ambitious alternatives of local climate regulation. Individual WTP_n estimates for the highest level (“Heat_60”) were spatially autocorrelated, and a cluster of high WTP for local climate regulation was identified in the city center, where the mean temperature is particularly high (see Figure 3). Post

estimation indicated that WTPn estimates for heat reduction depend on mean temperature of the resident’s neighborhood. The result of the post-estimation can thus be used to estimate WTP for each neighborhood of the city, and to create a demand map (Figure 4). Furthermore, mean temperatures were themselves auto-correlated and revealed an urban-rural gradient.

This result suggests that the urban-to-rural gradient of exposure to environmental hazards, illustrated here by the ‘mean temperatures in heat wave episodes’ indicator is matched by a similar gradient of demand for NBS. Inner city dwellers may have higher WTP for the implementation of urban climate change adaptation strategies than peri-urban and rural inhabitants who are less exposed to environmental hazards. This demand gradient for ecosystem services is in line with the results of other studies (Baró et al., 2017; Hérivaux & Le Coënt, 2021). Overall, this analysis suggests that inequality in exposure to environmental hazards may be a strong driver in the spatial heterogeneity of demand for NBGRI.

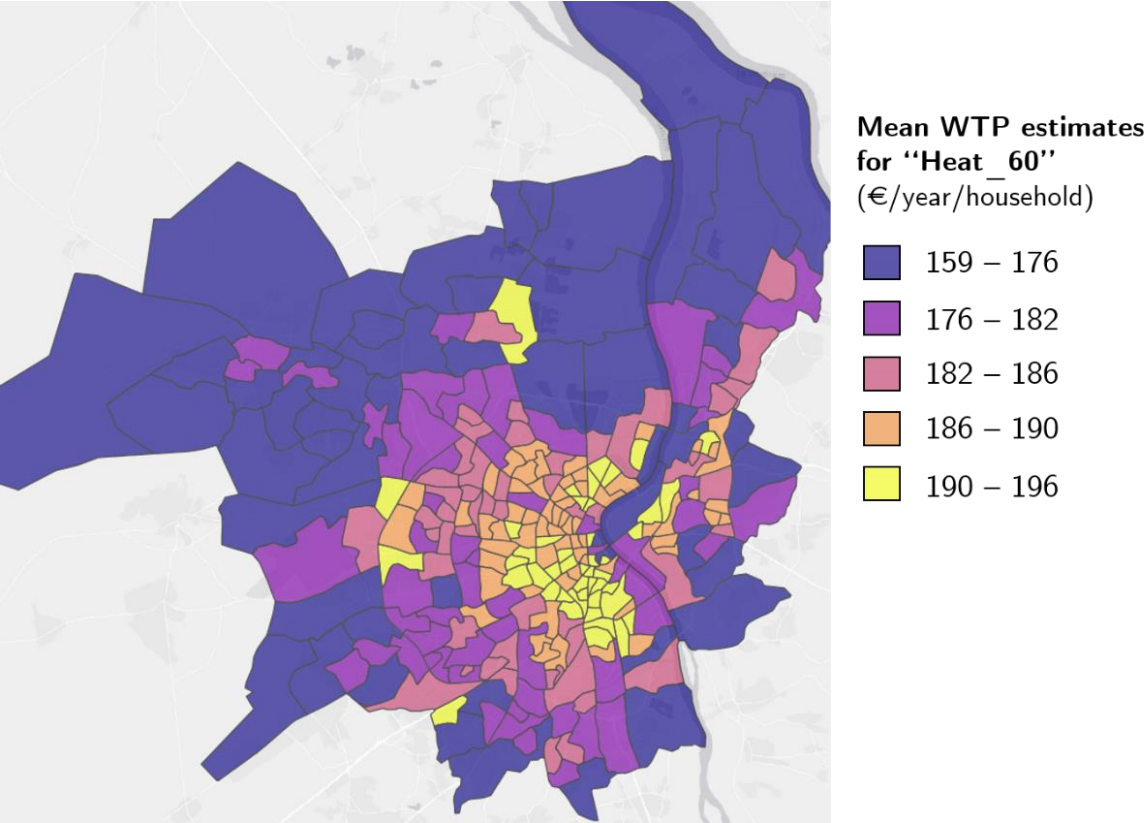


Figure 4: WTP post-estimation for heat island reduction at 60%.

The map was made using the relation between mean temperature and WTP estimated in the post-estimation.

The second hypothesis (H2) was invalidated. Thus our general assumption of distance decay must also be rejected, like in Johnston & Ramachandran (2014) and Lizin et al. (2016). A possible explanation is that there is no distance decay at such a small scale and for such small-scale infrastructure. Stated preference studies that do identify distance decay appear to be carried out at much larger scales,

i.e., country wide (Badura et al., 2020; Czajkowski et al., 2017), or at least region wide (Schaafsma et al., 2012). Another reason may be that we lack statistical power to analyze this effect ($n = 293$). . Consequently, we cannot draw any firm conclusions concerning the impact of the inequality in access to green areas on demand for NBGRI.

Our third hypothesis (H3) was confirmed: strong dependence on car transport led respondents to favor alternatives that do not require reducing the space dedicated to cars, and vice versa. In fact, the attribute “Red_car” seemed to be the main source of preference heterogeneity, and was a polarizing attribute in our sample. We argue that this reflects the impact of environmental inequalities caused by NBGRI and urban greening policies on individual preferences: reducing car space can have either a strong negative or a strong positive impact on individual well-being, depending on how much their individual well-being relies on car use.

Based on this finding, it appears critical to include this kind of spatial tradeoff in valuation studies. To our knowledge, no other study has focused on evaluating the possible negative effect of consumption of space by urban green infrastructure. Yet our result is in line with that of another stated preference study showing that preference for changes towards car-free city centers may depend on individual’s transport practices (Gundlach et al., 2018). In our case, the reduction of car space was perceived as a negative effect by respondents, but this variable may also have been considered as a benefit by a large proportion of respondents. Reducing car space, and hence the presence of cars in cities can be perceived as a benefit alone or as part of a package of co-benefits (air quality improvements, noise reduction, increased city walkability, increased safety for cyclists, etc.).

We did not identify any other proof of spatial heterogeneity for this attribute, and the results of the global spatial autocorrelation tests were not significant. Consequently we did not further explore its spatial heterogeneity other than by identifying significant local hot/cold spots. The analysis of hot/cold spots would help identify areas of strong resistance to - or acceptance of - such policies, but only in this particular case study. In addition, further investigations on the subject would be advised to use IRIS or neighborhood car use data rather than individual data (as we did), in order to draw more generic conclusions, since car use was the main variable explaining individual WTP for this attribute (Table 3). For the same reason, we did not map the demand for reduced car space as we did in Figure 4. But while our indicator only describes our sample, we can nonetheless assume that the total Bordeaux metropolitan area would show a similar distribution, because the dense city center is more walkable, cyclable and connected to public transport than the peri-urban and rural areas. We suggest that collecting such data through mode of transport surveys is important for any cities that aim to implement similar policies that may affect urban car space.

Our analysis proves that (i) NBS policies may lead to the emergence of environmental inequalities as they have adverse effects that essentially target specific vulnerable populations, and (ii) that these environmental inequalities have a dramatic influence on the demand for these policies. This phenomenon has been largely overlooked by NBS planning and assessment tools to date (Oijstaeijen et al., 2020). While this type of analysis of preference heterogeneity allows policy makers to more efficiently target areas and populations in a way that reduces the impact on inequalities as much as possible, there may be cases where affecting the well-being of a proportion of citizens is unavoidable. For instance, in our case, many individuals with a high reliance on car use may reside in areas with an overall high demand for car space reduction. Targeting these areas would penalize these very individuals. This indicates that for such policies to be accepted, (monetary) transfers may be necessary to plan and include in these policies, *e.g.* paying compensation for the use of other modes of transport. This result also underlines the need to combine urban NBS development policies with ambitious mobility policies aimed at reducing dependence on cars.

This work contributes to the urban ES valuation literature by revealing the importance of analyzing the spatial heterogeneity of demand for NBS combined with the analysis of the underlying factors that systematically explain this heterogeneity, *e.g.* environmental inequalities. Exploring this line of research will advance our understanding of the spatial heterogeneity of demand for NBS, thereby making it possible to draw conclusions that are more generic than those that can be drawn from individual case studies. However, it is possible that the EI were not entirely covered by our simple distributive indicators of exposure to hazards, access to green areas and car use. In fact, these EI may rather be the results of a more complex set of interactions between inequalities and income levels, as well as sociodemographic characteristics (Gould & Lewis, 2016; Walker, 2012). In addition, the effect of inequalities on demand levels has been shown to depend on whether the environmental goods at play are substitutes for manufactured consumer goods (Meya, 2020). In our case, we did not explore these dimensions: the income variable was not significant in the post-estimation models, and the socio-demographic variables (income, education, age) did not present any significant spatial autocorrelation, *i.e.*, they did not represent significant spatial inequalities.

Analyzing the interactions between income levels and EI could advance our understanding of the effect of environmental inequalities on demand. Another possible perspective for further research is a “horizontal” EI, by dividing the sample into groups - *e.g.* by income categories – in order to measure between-group differences (Boyce et al., 2016), and then to analyze variations in demand across these groups. This would allow - for instance - the explicit identification of populations or communities with low or high demand for NBS.

This work also contributes to NBS planning by incorporating the current debate surrounding environmental justice. Environmental inequalities have mostly been studied from the point of view of “distributional justice”, *i.e.* the exposure of individuals and communities to environmental risks and the equitable allocation of wealth and ES (Calderón-Argelich et al., 2021). Based on this observation, several authors have argued that urban NBS decision making approaches need to push further toward a recognitional and procedural conception of justice (Langemeyer & Connolly, 2020). The former term means acknowledging and accounting for the different needs, preferences and values of citizens; the latter allows the involvement and participation of citizens in decision-making procedures. Indeed, individuals may have contrasted needs, preferences and aspirations (Jacobs et al., 2016; Langemeyer et al., 2016), which may strongly affect the well-being to be obtained from NBS policies (Turkelboom et al., 2018), and distributional analyses overlook these complexities (Langemeyer & Connolly, 2020).

Our study contributes to the adoption of a recognitional justice perspective in NBS policy-making: it illustrates the importance of broadening the vision of environmental justice in urban ES studies to include citizen’s heterogeneous demand for nature, their preferences and constraints, which can be strongly influenced by their living environment and individual practices (Jacobs et al., 2016).

Conclusion

This paper investigates the preferences expressed by the population of the metropolitan area of Bordeaux, for the positive and negative effects of the implementation of GRI. To our knowledge, this is the first time a stated preference study has analyzed the link between environmental inequalities and preferences for the benefits of GRI. It is also the first study to investigate the impact of the space taken by cars by urban NBS on preferences. Our analysis demonstrates that respondents exhibit a strong willingness to pay for the preservation of deep aquifers and the regulation of local climate. Moreover, an increased exposure to heat waves heightens the willingness to pay for scenarios offering greater urban cooling benefits. The influence of scenarios on reducing car space emerges as the primary source of preference heterogeneity in this case study.

The study highlights that GRI policies may lead to the emergence of environmental inequalities as they have adverse effects that essentially target specific vulnerable populations, and that these environmental inequalities have a dramatic influence on the demand for these policies. These findings offer valuable insights to urban NBS planning, as it highlights the need to account for preference heterogeneity and analyze environmental inequalities to maximize the welfare of NBS policies.

In this chapter, we presented the results of the discrete choice experiment study performed in the metropolitan area of Bordeaux. It is presented in this chapter as an independent study that investigates the links between NBS and environmental inequalities. Additionally, this study was designed to serve the decision-support approach to our overall case study. It provides valuable insights on the acceptance of the population of the Bordeaux Metropolitan area for ambitious groundwater recharge strategies, and it successfully analyses the spatial distribution of the demand for the main co-benefit (urban cooling) of GRI. The resulting cartography of demand for urban cooling is used in [Chapter 4](#), in the final application of the MOO to the case study.

In the upcoming chapter 3, we present a first application of our MOO, applied in a conceptual framework. It investigates the viability of the MOO to solve our groundwater recharge location problem in a controlled setting before its implementation on the Bordeaux case study. It also adopts a generic perspective on this spatial planning problem as a means to extend it beyond individual case studies. In the case of various spatial gradient of costs and benefits of GRI strategies: where should decision makers implement their recharge projects, and of what type should they be, in order to maximize the recharge output, maximize urban cooling and minimize the opportunity costs of used land?

Chapter 3: Multi-objective optimization of Groundwater Recharge Infrastructures along an urban-rural gradient

This chapter is an expanded version of the following paper :

Farina, G., Le Coënt, P., & Neverre, N. (2024). Multi-objective optimization of rainwater infiltration infrastructures along an urban–Rural gradient. *Landscape and Urban Planning*, 242, 104949.

Abstract

Many cities are developing Groundwater Recharge Infrastructures (GRI) aimed at restoring natural hydrological processes. Among those, Nature-Based Groundwater Recharge Infrastructures (NBGRI) can generate co-benefits, which contribute to cities' adaptation to climate change. However, choosing optimal locations for GRI within limited available urban space is a complex spatial problem. It requires taking into account spatial patterns of infiltration potential as well as urban-rural gradients of costs and benefits. To address this, we apply a multi-objective optimization on a simple monocentric model city designed to give generic insights into location choices. We test a series of hypotheses: in comparison with a reference situation, we test the impact of the impossibility to infiltrate rainwater in city centers, the impact of substitution effects due to the presence of urban parks, and the possibility to mix NBGRI with grey infrastructures. The solutions reveal two polar strategies: locating infrastructures in the city center with higher co-benefits despite higher opportunity costs, or selecting suburban locations with the highest infiltration potential and lower opportunity costs - and a diversity of hybrid solutions. Substitution effects lead to discarding locations near urban parks, especially in centric locations. Finally, mixing NBS and grey infrastructures leads to a specialization of solutions by area and the potential to reach higher benefits at less opportunity costs.

1 Introduction

Cities around the globe increasingly face rainwater management challenges as a result of two factors: climate change, which will lead to an increase in the frequency and intensity of extreme rainfall events (IPCC, 2021); and urban growth, which affects natural hydrological cycles, resulting in an increase in flood frequency and magnitude, water contamination, and a reduction in groundwater recharge (Jacobson, 2011). To address these challenges, large cities have started to shift towards sustainable water management, for instance with Sustainable Urban Drainage Systems (SuDS) (Fletcher et al., 2015). These practices aim to transform traditional in-pipe systems towards on-site management and the restoration of natural hydrological processes, most notably water infiltration (Bhaskar et al., 2018). A distinction is usually drawn between traditional “grey” infrastructures: these are human-engineered processes such as artificial basins, trenches and underground structures; and “green” infrastructures: vegetated basins, infiltration bioswales, wetland creation and restoration, etc. (Dong et al., 2020).

In addition to urban rainwater management, these solutions, more recently referred to as Nature-Based Solutions (NBS) (IUCN, 2016), provide multiple co-benefits (Raymond et al., 2017). These co-benefits are ecosystem services that can address many adverse urban phenomena, such as flood risks, heat island effects, air and water contamination, etc. (Mader et al., 2011). NBS for rainwater management are considered cost-effective alternatives to traditional “grey” civil engineering infrastructures (Cohen-Schacham et al., 2016), and have been shown to be equally effective for the infiltration of rainwater (Page et al., 2018). However the adoption of NBS into urban planning is still limited (Bush & Doyon, 2019), for at least three reasons:

First, current choices of infrastructures for addressing rainwater management challenges are mostly based on a single objective approaches, and with single-benefit infrastructures (*e.g.* “grey” infrastructures) (Dhakal & Chevalier, 2017). The reason guiding these policies and the choice of infrastructure type has been almost exclusively flood risk reduction (Axelsson et al., 2021).

Secondly, the implementation of NBS can compete with other urban planning objectives (Baró et al., 2015), leading to a spatial trade-off between addressing demand for ES or preserving valuable lands for other uses (McDonald, 2009). Indeed, the value of implementing NBS increases with the proximity to urban centers as the ES flows can potentially benefit more people. However, moving towards urban centers increases the difficulty of implementing NBS, because of land competition and increased opportunity costs (Brander & Koetse, 2011): rainwater management infrastructures, and especially NBS, are land intensive solutions, and as such compete with other mutually exclusive land uses, *e.g.* housing or commercial development (Elmqvist et al., 2013). Implementing NBS farther from the city would be easier, however it would mean less co-benefits for urban dwellers.

A third difficulty impeding NBS implementation relates to co-benefits trade-offs. Co-benefits may not be generated as effectively in all locations (Raudsepp-Hearne et al., 2010). Different locations for NBS may enhance one co-benefit while decreasing another (Bush & Doyon, 2019). Infiltration-based NBS are confronted with such trade-offs (Alves et al., 2020). Optimal locations for infiltration may or may not be the ones that favour other co-benefits, for instance NBS close to dense residential areas may favour the co-benefits of air quality improvement, but not necessarily be optimum in terms of infiltration (Madureira & Andresen, 2013).

Authors have put forward the need for new decision-support methods that may address these issues (Elmqvist et al., 2013). Such methods should 1) be spatially-explicit, to help locate infrastructures (Nesshöver et al., 2017), 2) account for trade-offs between providing co-benefits and other planning objectives (Turkelboom et al., 2018), and 3) include multifunctional infrastructures such as NBS, and therefore account for their multiple benefits (Bush & Doyon, 2019).

This study aims at proposing such a method. We develop a Multi-Objective Optimization (MOO) framework for locating the implementation of urban Groundwater Recharge Infrastructures (GRI), taking into account three objectives: maximization of rainwater infiltration, maximization of co-benefits, and minimization of opportunity costs. The central novelty of this work is that this optimization framework is developed and implemented on a simple model city. Working on a model city instead of a specific case study is meant as an exploratory approach by simplifying the benefits and costs variables to their most generic spatial patterns, *i.e.*, urban-rural gradients, as highlighted by the literature. As such, this approach makes it easier to illustrate the spatial trade-offs between benefits, and explicitly visualize the impacts of these trade-offs on maps. It also makes it possible to test various hypothesis on the nature of this decision-making challenge within a controlled experiment and draw generic conclusions applicable to many cities around the world, instead of addressing a specific case study.

This paper first presents the state of the art in multi-objective spatial optimization dedicated to urban NBS. Then it describes the MOO method and the series of experiments we developed. Finally, we present the results, discuss them and provide concluding remarks.

2 Optimization of urban infrastructures location: a state of the art

The main methods for supporting urban rainwater and environmental policies have historically been Cost-Benefit Analysis (CBA) and Multi Criteria Decision Analysis (MCDA) (Jacobs et al., 2016; Oijstaeijen et al., 2020). CBA and MCDA provide a clear framework for comparing and selecting policy alternatives (Saarikoski et al., 2016). However the application of these methods is limited in complex

spatial problems, because they may not consider the entire solution space (Seppelt et al., 2013). In location problems, the solution space - all the possible combinations of asset location - can potentially be too large for stakeholders to identify and represent in a set of comparable alternatives (Bush & Doyon, 2019). In addition, CBA and most MCDA methods use a form of aggregation of benefits and costs (Pascual et al., 2017), leading to performing single-objective optimization. This approach assumes that there is a single best alternative (Langemeyer et al., 2016), or the possibility to rank alternatives (Saarikoski et al., 2016), therefore not taking into account trade-offs between large numbers of solutions (Turlkelboom et al., 2018).

Multi-objective optimization (MOO) can address some of these issues. The result of a MOO is not a single optimal solution, but a set of non-dominated solutions, the Pareto front, which represents the diversity of trade-offs between objectives. Solving multi-objective problems means obtaining the most diverse non-dominated set of solution, to illustrate as best as possible the trade-offs (Emmerich & Deutz, 2018).

Several studies have used MOO to identify optimal locations for Sustainable Urban Drainage Systems (SuDS) with regard to their hydrological benefits and co-benefits (Alves et al., 2020; Dwivedula et al., 2021; Shen et al., 2013; K. Zhang & Chui, 2018). Nevertheless, they haven't considered the objectives of maximizing co-benefits such as heat reduction and amenities, as well as the challenges associated with space scarcity or other urban planning constraints (K. Zhang & Chui, 2018). Therefore, to our knowledge, the problem of infiltration-based NBS implementation has not yet been addressed in an integrative framework, taking into account at the same time their multiple co-benefits and the possible competing objectives in urban planning that may limit their implementation.

MOO has also been performed for optimizing the location of urban greening and NBS projects, considering their multiple potential co-benefits (Alves et al., 2020; Majidi et al., 2019; S. Yang et al., 2023; Yoon et al., 2019; W. Zhang & Huang, 2015; Y. Zhang et al., 2017, 2022). In these instances, the optimization is performed based on both biophysical and economic objectives, balancing biophysical benefits such as heat mitigation, noise reduction or air depollution, with economic costs. These works successfully achieve the identification of trade-offs between various co-benefits, as well as between co-benefits and costs. They also identify how some of these trade-offs translate into different choice of infrastructures. For example, focusing solely on hydrological benefits may lead to prioritize the use of grey infrastructures (Alves et al., 2020), and NBS dedicated to urban cooling should be implemented in densely populated areas (Majidi et al., 2019).

However, some elements limit the generalization of the results of these works. Primarily, the recommendations provided by these works for the implementation of NBS strategies are only dedicated

somehow to their individual related case studies. In other words, these studies do not establish generic conceptual guidelines. In addition to this, co-benefits are modelled in these works on the supply side of ES, and thus do not necessarily provide thorough insights into the repartition of the potential benefits of these ES, which result from the interactions between ES supply and demand (Pascual et al., 2010). This approach might lead to prioritize locations that do not maximize co-benefits (Seppelt et al., 2013). Thirdly, while costs are expressed as direct investment monetary costs, either to be minimized as an objective (W. Zhang & Huang, 2015), sometimes including spatial elements (Yoon et al., 2019), or as a constraint (Bekele & Nicklow, 2005; Y. Zhang et al., 2017), they do not consider opportunity costs resulting from the issue of using scarce urban space.

In this study, we aim at establishing basic general guidelines to the planning of NBS in cities, when confronted with the presence of multiple benefits and costs, which are distributed along various spatial gradients. We consider simultaneously the environmental co-benefits of NBS, the benefits of rainwater infiltration and the issue of space scarcity by considering opportunity costs. We also experiment with these spatial gradients of costs and benefits in order to identify optimal solutions of locations of GRI. We build on existing multi-objective optimization literature by taking into account the demand side for co-benefits, in the form of urban-rural gradients. We investigate how substitute goods such as urban parks can influence the spatial choices for GRI. We finally question whether Nature-Based Groundwater Recharge Infrastructures (NBGRI), or “grey” Conventional Groundwater Recharge Infrastructures (CGRI) should be used as GRI, and how this choice is reflected spatially.

3 Method

3.1 A multi-objective problem of Groundwater Recharge Infrastructure implementation

This work originates from a case study in the Bordeaux metropolitan area located in southwest France. The local government is aiming to develop GRI as a means to address two broad objectives, developing rainwater infiltration on the one hand, and providing other ecosystem services to residents (mainly, urban cooling), while operating on limited available land. Both CGRI and NBGRI are considered. This city therefore faces an asset location problem. In this paper, we do not address specifically this case study, but use it as the basis for modelling and responding to a generic urban problem.

We implement a MOO of GRI location within a simple model city, whose characteristics were created as archetypal as possible in order to provide a framework that is representative of most European cities. The model city is represented as a monocentric city, with a grid of 500*500 cells. It consists of

three concentric areas: a city center, an inner-suburban area, and an outer-suburban area. The potential benefits and costs of GRI are represented as urban-rural gradients in this model city. The gradients have been chosen in order to be representative of the generic gradients existing in many cities (including the illustrative case of Bordeaux). The 3 gradients are simplified and unit-less representations of the potential outputs of a real infiltration model and an analysis of co-benefits and costs.

3.1.1 The infiltration potential distribution

We assume in this work that infiltration efficacy is one of the main parameter that influences the benefits of GRI: the reduction of flood risk, the increase of groundwater recharge and the subsequent impact on water quality due to limited discharge of polluted rainwater in surface water during storm events. More generally, this variable does not depict one particular benefit, but it may be any physical variable which distribution is unrelated to the demand for co-benefits and the opportunity cost gradient.

The efficacy of infiltration depends mostly on hydrogeological parameters (K. Zhang & Chui, 2019) which are considered independent from the urban-rural gradients of ES. The evaluation of these parameters (Vallin et al., 2016) reveals a complex pattern of infiltration capacity. We therefore choose to represent the distribution of the infiltration efficacy as four distinct areas (Figure 2a). This checker distribution is voluntarily designed as orthogonal to the circular urban form. As a consequence, each concentric area (*i.e.* the outer-suburban, the inner-suburban and the centric area) present a low, a medium-low, a medium-high and a high infiltration potential area, thereby creating 12 distinct areas. We choose the numerical values associated to this infiltration gradient according to the value range of soil permeability, which is one of the main drivers of water infiltration (J. L. Yang & Zhang, 2011). This specific parameter varies with an order from 1 to 10^3 . These values are to be interpreted in this model city as a very simple index of infiltration efficacy.

3.1.2 The co-benefit gradient

The value of co-benefits provided by NBGRI can vary within the city. Population density, and therefore aggregate demand for co-benefits, increases with the proximity to the city center, since adverse climate change and urbanization effects tend to be stronger towards denser areas (Aram et al., 2019). We model the distribution of co-benefits accordingly, as following an urban-rural gradient (Figure b). The proxy used to represent the co-benefit gradient is the density of population: it is strongly correlated with the demand for the main co-benefits at stake, such as the mitigation of heat island effect, air quality improvement, and recreational and aesthetic amenities. These have mostly local impacts (Hein et al., 2006), which means that their distribution can be linked directly with proximity to local demand. We assume that individual have a constant individual demand for these co-benefits across the city (S. Wolff

et al., 2015). The specific values given to each cell are based on the mean population densities in the Bordeaux metropolitan area.

3.1.3 The opportunity cost gradient

Finally, the space scarcity problem is represented here through the lens of opportunity costs of land. It is represented in the model as an urban-rural gradient (Figure c), as space availability becomes scarcer as we get close to the center. Average real estate prices from the Bordeaux metropolitan area, using the French notarial database (DVF), are used as value inputs for the opportunity cost, though values from other cities could have been used: the important factor here being that it features an urban-to-rural gradient of decreasing estate prices. The assumption here is that the real estate market represents the most profitable value of land that would be lost by implementing GRI, *i.e.*, an opportunity cost.

The gradients are discrete for the benefit, co-benefit and opportunity costs, *i.e.* they are organized in three homogeneous categories (center, suburban and rural areas). These gradients are meant to be a simpler version to the real distribution of co-benefits and opportunity costs. The real form of the urban-rural gradient may be a complex function of distance to city centers (Kroll et al., 2012) and vary greatly between cities (Hou et al., 2015). Our choice is therefore a first approximation that we consider to reflect adequately the GRI location problem.

3.2 MOO design

3.2.1 Decision variables

The decision variables consist of 200 cells selected randomly within all the cells of the city grid, distributed evenly in all 12 combinations of city area (center, inner and outer-suburbs) and infiltration areas (four infiltration index areas) (Figure f). These candidate cells are considered potential “sites” for the implementation of a GRI. They are characterized by the infiltration capacity, potential co-benefit, and opportunity cost of the city area on which they are located. The goal of the MOO is to select among these 200 candidate sites the optimal combinations of sites (1 combination = 1 solution) where to implement GRI, and the type of infrastructure, NBGRI or CGRI.

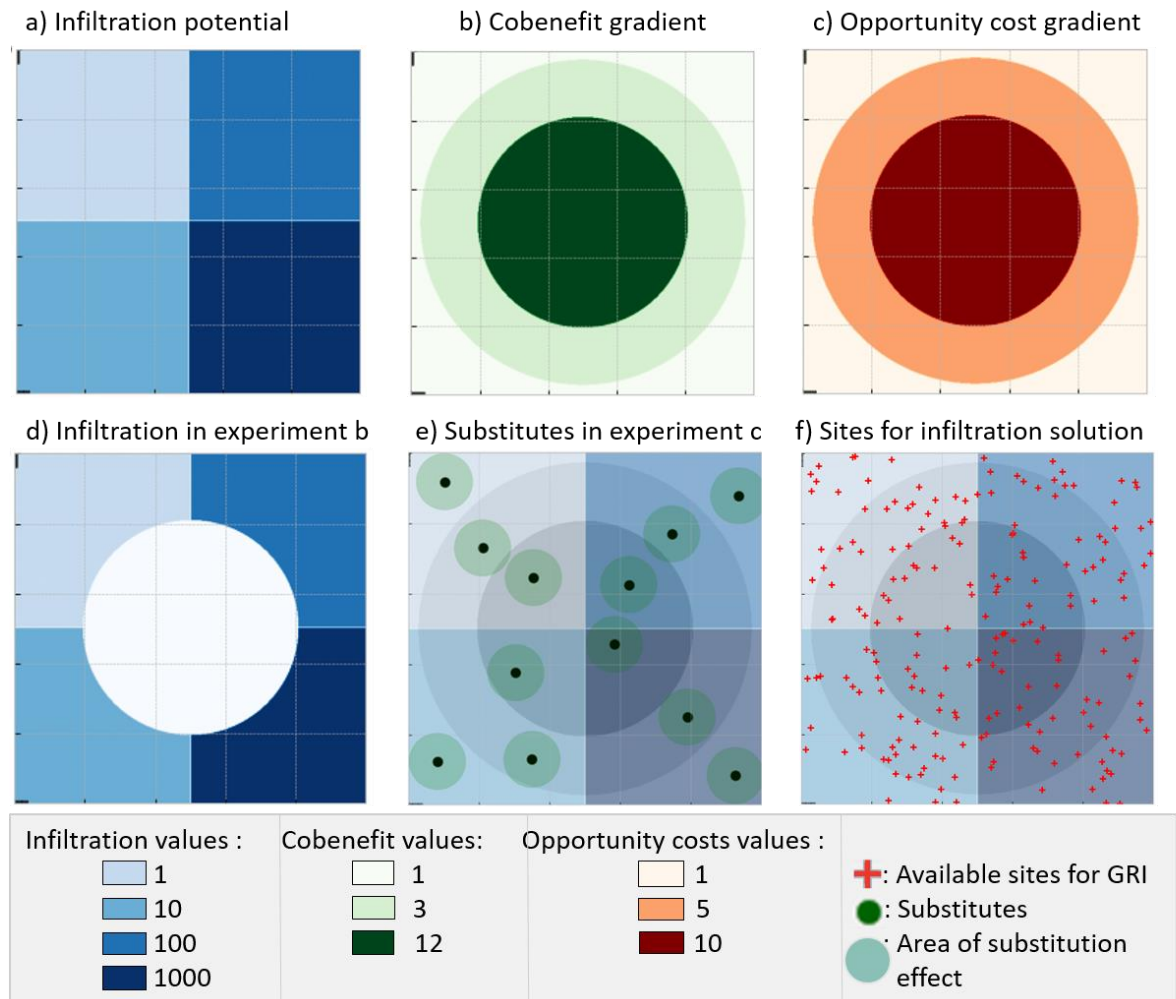


Figure 1: Model city characteristics

3.2.2 Objectives

This MOO features three objectives: maximization of infiltration, maximization of co-benefits and minimization of opportunity costs.

The infiltration objective (Inf_i) is the sum of infiltration values (inf_j) of the selected j sites of solution i [Eq. (1)]. It represents how deciders may want to maximize the overall effectiveness of the overall rainwater infiltration and groundwater recharge plan. We assume here that GRI, being grey or NBGRI, would perform similarly in a same context (K. Zhang & Chui, 2019). Differences in infiltration efficacy that may arise from reduced infiltration due to evapotranspiration in NBGRI for instance are not considered in this paper.

$$Inf_i = \sum_{j \in i} inf_j \quad (1)$$

The co-benefit objective function is also a linear sum of the co-benefits provided by each selected site [Eq. (2)]. It depicts how urban planners may want to maximize the amount of population that benefit from the co-benefits provided by NBGRI. The co-benefits for each site (cob_j) is calculated as the sum of the population located at the specific selected cells, as well as the population located in the cells within a three cell radius around the NBS [Eq. (3)]. Indeed, NBGRI may benefit not only to the population living in its direct vicinity but also to those living a bit further. The 3-cell radius amounts to approximately 600m, which is the order of magnitude of the effect radius of the main co-benefits of interest (Lin et al., 2015). In contrast, CGRI are mono-functional, their only benefit is infiltration, they do not provide co-benefits [Eq. (3)].

$$Cob_i = \sum_{j \text{ in } i} cob_j \quad (2)$$

$$cob_j = \begin{cases} pop_j + \sum_{k=1}^K adjacent_pop_k & \text{if infrastructure } j \text{ is NBGRI} \\ 0 & \text{if infrastructure } j \text{ is CGRI} \end{cases} \quad (3)$$

The opportunity cost of a site i (Cos_i) is calculated as the sum of all land prices associated to the individual cells selected in the solution [Eq. (4)]. The opportunity cost depends on the type of infrastructure [Eq. (5)]. For a NBGRI, we assume that all the surface of the cell has to be dedicated to it, therefore, the opportunity cost (Cos_j) is equal to the cell's land price (p_j). For CGRI, which are generally less land-intensive, this cost is assumed to be 50% of the cell's land price. This value of 50% is arbitrary. It illustrates the known disadvantage of NBS, which is to potentially have a larger spatial footprint for an equal effectiveness (European Commission Directorate-General for Research and Innovation, 2015). For instance, a bioswale occupies much less space than infiltration trenches. A sensitivity analysis was performed on this parameter, and is available as [supplementary materials](#).

This objective reflects how urban planners may aim to minimize the impact of these infiltration policies on land use.

$$Cos_i = \sum_{j \text{ in } i} cos_j \quad (4)$$

$$Cos_j = \begin{cases} p_j & \text{if } j \text{ is NBGRI} \\ \frac{1}{2}p_j & \text{if } j \text{ is CGRI} \end{cases} \quad (5)$$

Finally, investment of GRI are considered in the MOO through a simple budget constraint. It is calculated simply as the number of selected sites in the solution, thus assuming a standard unitary investment cost for all sites and both technologies. It is therefore a limit to the maximum number of projects implemented. We consider that the location within the urban rural gradient does not influence the investment and management costs of GRI.

3.2.3 MOO algorithm

This location problem amounts to a form of combinatorial optimization. A powerful family of methods for solving such problems are evolutionary algorithms, which use a way of trial and error to reach near-optimal solutions, using population-based approaches (Sörensen et al., 2018). The whole approach was programmed in Python, and we solve the optimization using the evolutionary algorithm ($\mu + \lambda$) from the DEAP library (Fortin et al. 2012) and incorporating the NSGA-2 selection algorithm, which is particularly efficient to produce a diverse Pareto-optimal set of solutions (Deb et al., 2002). We use a population size of 200 solutions, and crossover and mutation probabilities of 0.7 and 0.3. We run the algorithm for 500 generations until it reaches satisfactory solutions (Figure 2).

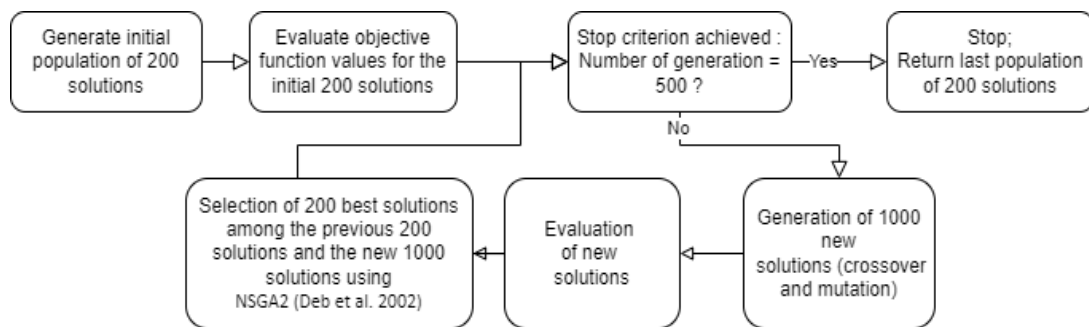


Figure 2: Main process of the evolutionary algorithm

3.3 Experimental design

We use the optimization model to test the impact of different experimental settings, reflecting real world city planning issues, on the optimal location of GRI.

3.3.1 Experiment a: Reference situation

This first experiment is the standard situation used as a basis for comparison with the other experiments. The setting uses the distribution of variables and urban-rural gradients described in section 3.1 (Figure 1 ,a,b,c). In the first three experiments, only one type of infrastructure, NBGRI, can be used.

This experiment features a number of sites that present a simultaneous gain situation. These are a subgroup of sites located in the city center, which have high co-benefit and a high infiltration potential. The main hypothesis (H1) for this first experiment is that when a situation of simultaneous gain is possible, the planner should aim at prioritizing these locations.

3.3.2 **Experiment b: no infiltration in the city center**

This scenario aims at accounting for limitations to rainwater infiltration. We introduce an impossibility to infiltrate rainwater in the city center due to urban constraints (sub-surface infrastructure, ...), which is a frequent situation in real contexts (Pitt et al., 2008). The co-benefit and opportunity costs gradients remain unchanged, but the distribution of infiltration potential features a 0 infiltration potential in the center (Figure d). In consequence of this setting, the NBS located in the city center would not be exactly GRI, but rather multifunctional green areas.

In this situation, decision makers have to make a choice between choosing sites with high infiltration and low opportunity costs or with high co-benefits and high opportunity costs. Our hypothesis (H2) is that the trade-offs at hand here would be more drastic than the reference situation, as decision-makers would have to choose between providing co-benefits or infiltration, but with fewer options of synergies.

3.3.3 **Experiment c: substitution effect of pre-existing urban parks**

Experiment c introduces the notion of substitute environmental goods. The value of ES can vary depending on the presence of substitutes, their spatial distribution and their distance to populations (De Valck & Rolfe, 2018). To our knowledge, no study has specifically assessed the issue of NBS as a substitute good for urban parks. However, the co-benefits provided by NBGRI may be the same as those of urban green spaces: air quality, heat island effects mitigation..., especially if they are designed as multifunctional infrastructures (Pascual et al., 2017). The main assumption in this experiment is therefore that additional NBGRI in urban space may be considered as substitute goods for parks and green spaces.

This is modelled as a reduction of co-benefits whenever a NBGRI is implemented within a 2km range from a pre-existing substitute. This distance radius is based on evidence of the impacts of travel distance on urban parks visits, which, for neighborhood parks has been show to amount roughly to 2km (X. Tu et al., 2020). The substitution effect itself is modelled as a 50% reduction of NBGRI co-benefits. This is based on upper estimates observed in a stated preference study (Schaafsma et al., 2013).

Because of this impact on co-benefits, the substitution effect gives a disadvantage to the sites located near substitutes. We make the subsequent hypothesis (H3) that the presence of substitution effect leads to discarding GRI located near the substitutes and that this effect is accentuated in centric sites.

3.3.4 Experiment d: Infrastructure type choice

In this experiment, we use the reference setting, and introduce a second decision variable in addition to the site choice; the type of infiltration technique can be either a CGRI or NBGRI. In this experiment, we posit that CGRI do not provide any co-benefits, and present a reduction of 50% in opportunity costs compared to NBGRI. These differences may translate into different optimal spatial patterns for these two types of GRI. We posit that a complementarity is observed between these solutions, and is reflected in distinct optimal locations for these two types of infrastructures (H4).

4 Results

For each of the four experiments, we applied the evolutionary algorithm to optimize the selection of sites where to implement GRI and obtained 200 Pareto-optimal solutions over the three objectives.

We first present the number of sites selected within each of the optimal solutions (Figure 3), in the infiltration and co-benefits dimensions. Benefits are positively correlated to the number of GRI implemented in each solution. The budget constraint limit is clearly visible at the top-right of the plots (darkest dots). Interestingly, these solutions, which saturate the budget constraint, display trade-offs along the infiltration and co-benefit dimensions. These solutions in particular are of interest in the following analysis of the results.

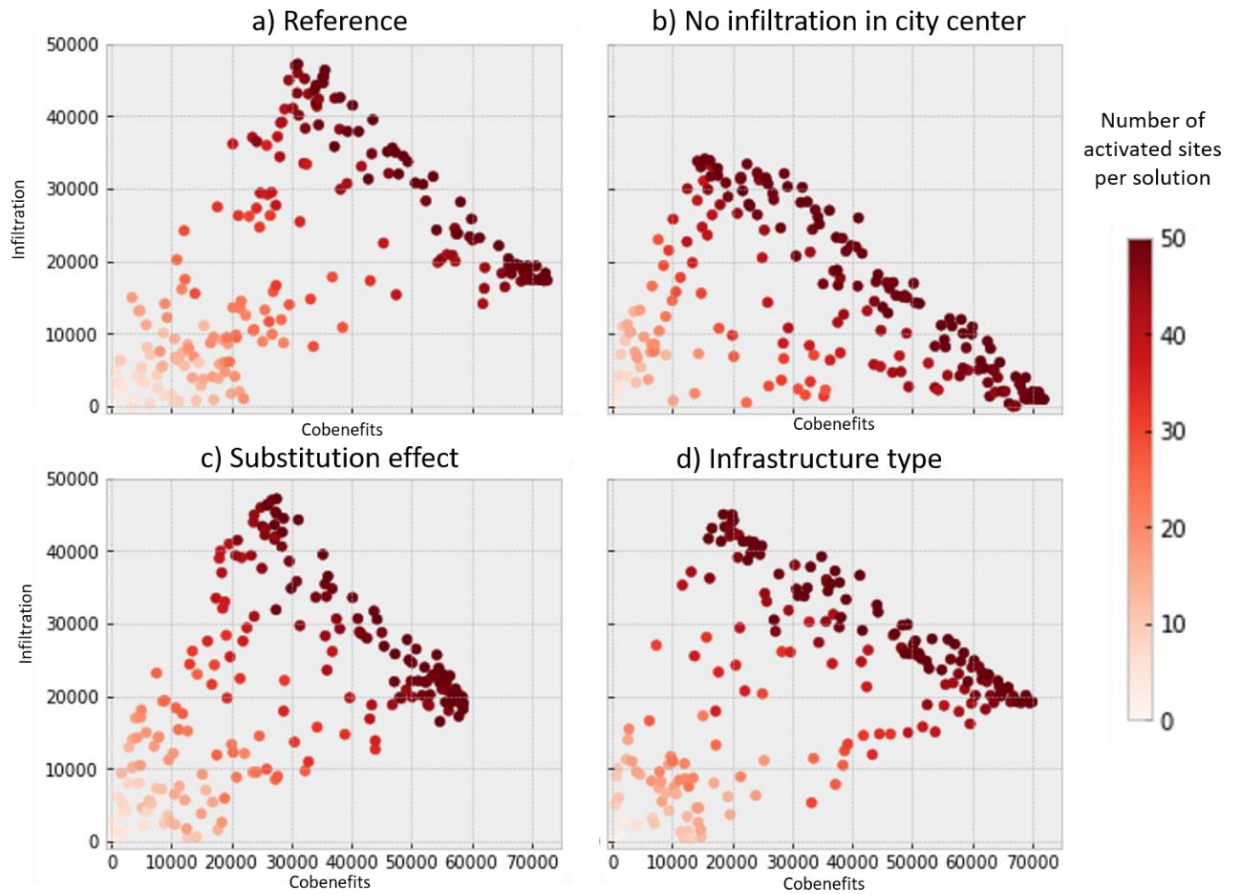


Figure 3: Pareto fronts for all four experiments, featuring the number of GRI implemented per solutions.

Opportunity costs are omitted to improve readability

The analysis of the results of the MOO algorithm is a challenge since it generates a large number of solutions in a three dimensional space. Following Yoon *et al.* (2019), we use interactive decision mapping (IDM) as an exploratory graphical method for transforming 3D information into more easily readable 2D representations. We present solutions in the co-benefit and infiltration dimensions, while opportunity cost is transformed into a categorical variable represented by a scale of five colours (Figure 4). This representation is completed with the spatial representation of some individual typical solutions. In addition to this representation, we look at the frequency of selection of the available sites within the city, across all solutions of the Pareto front (Figure 5), in order to identify general location recommendations.

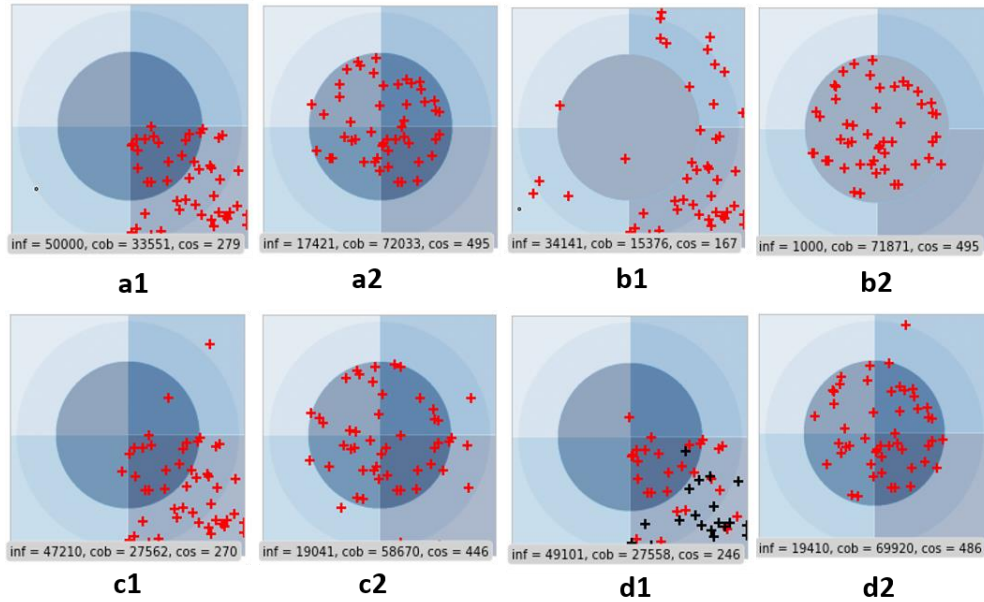
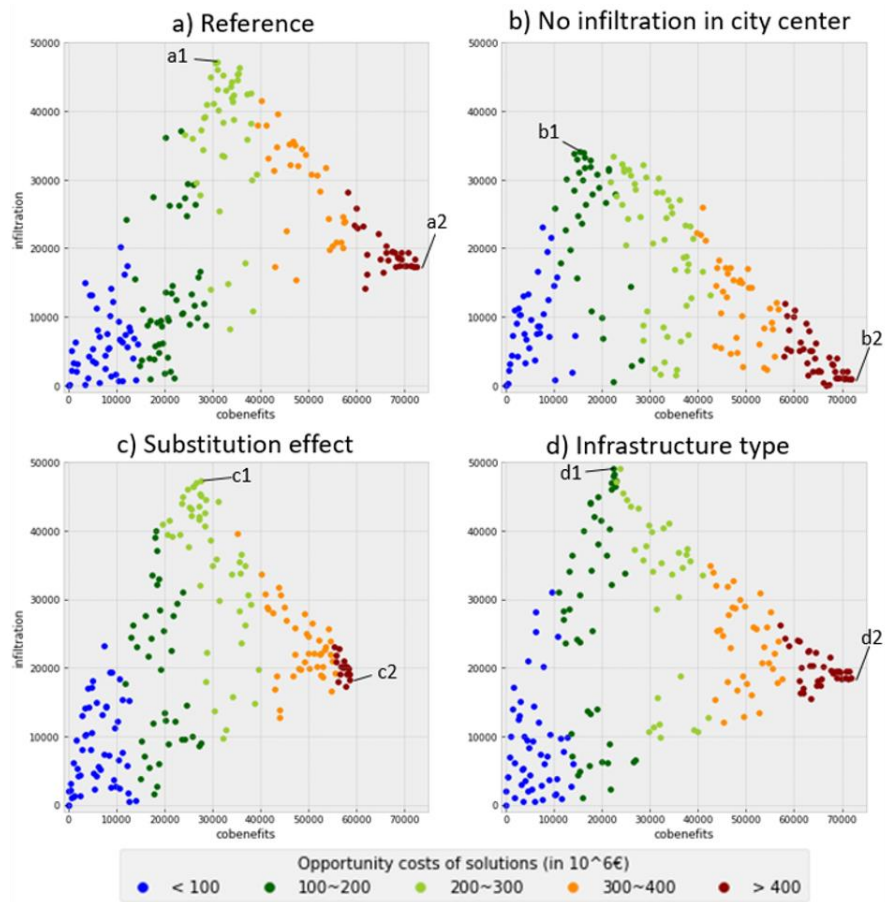


Figure 4: Interactive decision maps for the four experiments.

Extreme solutions (a1, a2, b1, b2, c1, c2, d1, d2) are pointed out in the 2-dimensional maps, and then represented spatially in the individual maps in the lower part. The red crosses are the location for NBGRI, and the black crosses in (d1) are CGRI.

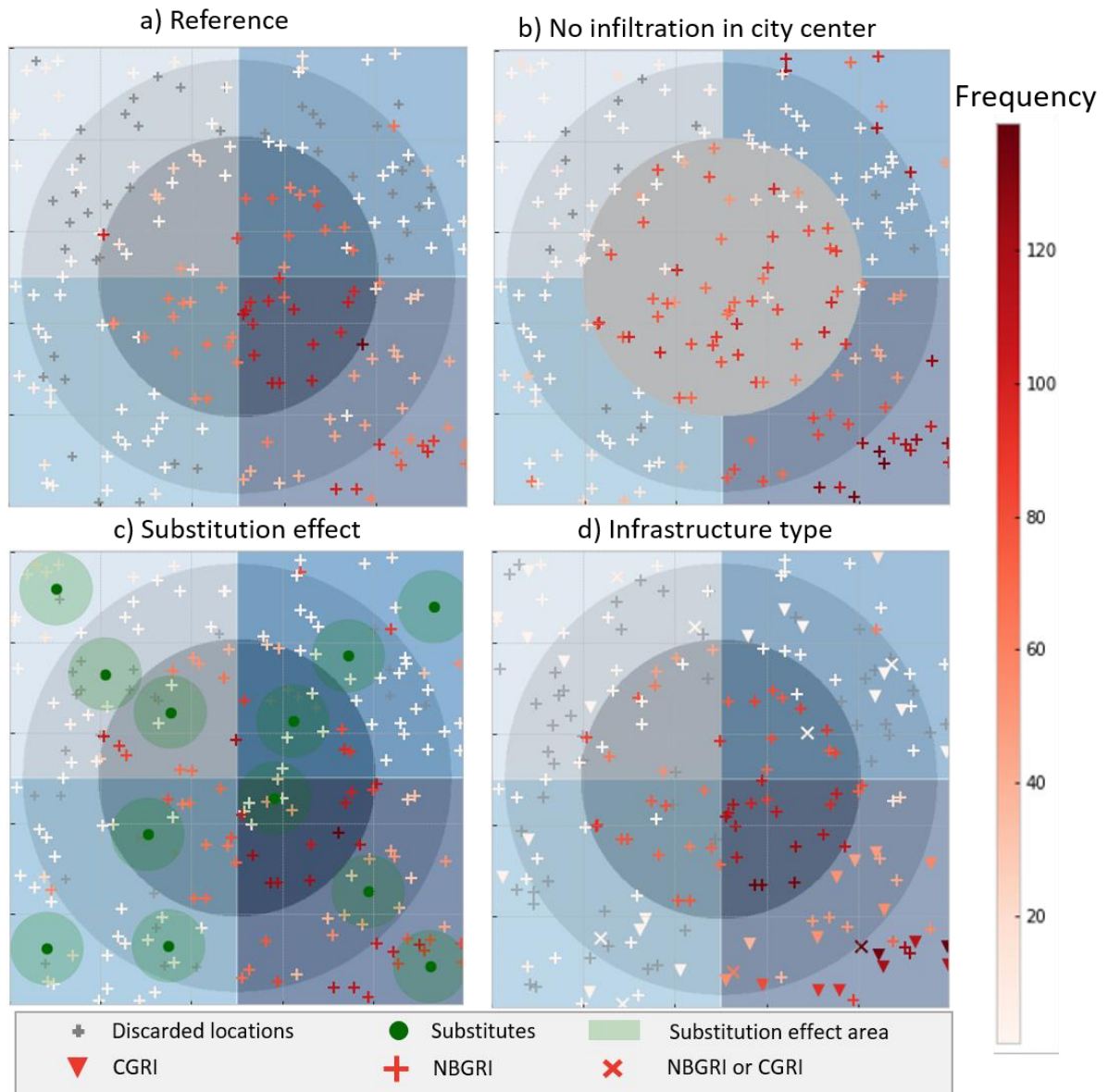


Figure 5: Site selection frequency in the four experiments.

The frequency of selection of each site is calculated over the optimal solutions and represented by the red color gradient. In maps a), b) and c), the cross markers represent the location of available sites for GRI. In map d), the cross and triangle markers represent whether each site is chosen mostly as a NBGRI (>60% of the time), as a CGRI (>60% of the time), or equivalently as NBGRI or CGRI (40- 60% of the time as NBGRI)

Some results are common to all experiments. First, in agreement with the construction of the optimization objectives, the opportunity cost minimization objective strongly competes with the co-benefit objective. There is a clear trade-off between locating GRI next to population area or further away in less valuable lands. Second, the results display a trade-off between selecting solutions that focus either on co-benefits or infiltration, or stand at a middle point between these two objectives. This trade-off appears throughout the range of solutions, from those of low overall investment cost, up to solutions of

higher investment costs (Figure 4). In other words, trade-offs between co-benefits and infiltration have to be made whatever the ambition level for the implementation of GRI.

In each experiment, we are able to highlight a diversity of optimal strategies of GRI implementation.

In the reference experiment (a), two broad group of strategies can be identified, as illustrated by the extreme points in Figure 4. In solution a1, which yields the highest level of infiltration, all selected sites are located in the southeast quarter of the city (Figure 4a1), where infiltration levels are high. Of particular interest are solutions located on the front between a1 and a2 that saturate the budget constraint and therefore represent the highest effort that could be implemented by decision makers: the high effort front.

When moving from a1 towards a2, infiltration levels decrease while co-benefit levels and opportunity costs increase. Indeed, there are no sites left available with high co-benefits and high infiltration, allowing for a concomitant increase in both objectives. Since the budget constraint is saturated (Figure 3), increasing co-benefits implies substituting a high infiltration site with a more centric site with lower infiltration. In the extreme solution a2, only centric sites with high co-benefits are selected, whatever their level of infiltration. In a1 as in a2, the simultaneous gain sites - located in the centric sites south-east quadrant - are selected, which is confirmed when looking at overall cross-solutions site selection frequency (Figure 5a). We therefore confirm H1.

In the three next experiments, the Pareto fronts have similar overall shapes (Figure 4). It features a group of solutions focused on infiltration located on the top left side of the plot, and a group of solutions focused on co-benefits on the lower right side, as well as the high effort front.

In experiment b (Figure 4b), where infiltration is impossible in the city center, the same extreme strategies appear but the high effort front has shifted down and left. The infiltration-focused extreme solution (b1) features lower infiltration levels and lower co-benefits than the reference experiment (a1). It also belongs to a lower opportunity cost category. This solution tends to select all sites located in both suburban areas with the highest levels of infiltration. It also uses sites located in the slightly lower infiltration areas (north-east and south west quarters), in order to ‘fill’ the budget constraint with the next best infiltration-performing sites, when all the best sites of the south-east quadrant are already selected. Finally, the co-benefit maximizing solution (b2) is similar to the reference test case (a3), but it yields almost no infiltration benefit. This confirms hypothesis H2: this situation provides possibilities for specialized solutions in both benefits, but less opportunities of win-win solutions. This result appears clearly in Figure 5b. The situation translated in this experiment therefore provides possibilities for specialized solutions in both benefits, but less opportunities of simultaneous gains between the two.

In experiment c, the shape of the Pareto front is shifted to the left. The levels of co-benefits throughout the Pareto front are lower, as the substitution effect reduces the overall potential for co-benefits. Spatially, this means that the extreme solutions (c1) and (c2) follow the same patterns as the reference experiment (a1, a2) but differ on the levels of co-benefits. The substitution effect has a particularly strong impact in the center area (Figure 5c), as it leads to disregarding almost completely some centric sites that were the most selected in the reference case, thus confirming H3. Its effect is less strong in outer suburban areas, where co-benefits were not as high to begin with.

In experiment d, featuring the distinction between NBGRI and CGRI, there are two main differences to the reference experiment. First, the solutions that focus on infiltration (on the left and upper side of the Pareto front) feature lower overall opportunity costs. The extreme infiltration-maximizing solution (d1) for instance belongs to a lower opportunity cost category than the (a2) solution (dark green instead of light green), because solution d1 features a certain amount CGRI combined with NBGRI, which lowers its opportunity costs (Figure 4d1). Second, because of this integration of CGRI in the solutions focused on infiltration (around d1), their levels of co-benefits are slightly lower compared to the reference experiment. In summary, integrating CGRI leads to adding more options for infiltration-oriented solutions at lower opportunity costs, but does not impact solutions focused on co-benefits (around d2).

Furthermore, Figure 5d shows, in addition to the frequency of selection of each site, whether they were mostly selected as NBGRI or as CGRI. It appears that centric sites are mostly selected as NBGRI, while the selected sites of the bottom right quarter are mostly selected as CGRI. Implementing CGRI in the center would indeed mean depriving the solution from a large amount of co-benefits and it therefore does not occur in the majority of optimal solutions. On the contrary, as outer suburban sites do not have high co-benefits, they may as well be selected as CGRI, thus enabling infiltration at a lower cost. This result does confirm H4; that the complementarity between CGRI and NBGRI is characterised by different location choices: NBGRI in the city centers, and CGRI in both inner and outer suburban areas.

One has to remind at this point that exact numeric values attached to these solutions do not bear importance. The solutions' objectives values depend on the numerical values that define the gradients and the various spatial effects. However, the main results of the optimization (*i.e.* the spatial patterns of selected sites) are sensitive to a limited extent to the parameters values. This aspect is explored in the sensitivity analysis available as supplementary material. Our main conclusions should therefore be generalizable to other contexts with monocentric cities presenting similar infrastructure location problem.

5 Discussion

We draw two types of lessons from our results: we first draw general lessons based on the implementation of our optimization method on a model city, then we identify how it could be used as a decision-support tool for the selection of GRI in a real setting.

First, based on the assumption that the distribution of our gradients are roughly representative of actual conditions in large European cities, generic conclusions can be drawn on spatial decision-making. A first decision rule would be to select, in priority, sites that present both high infiltration and co-benefits potential, *i.e.* centric sites with good infiltration potential, despite their high opportunity costs, as well as sites that present high infiltration potential and low opportunity costs in outer suburban areas. However, depending on the emphasis that decision makers place on either infiltration or co-benefits, different combination of centric and suburban sites may be selected: a mixture of centric locations of various infiltration performance and inner and outer suburban locations of better infiltration performance.

These optimal spatial patterns for GRI can be observed at various levels of implementation ambition, *i.e.*, budgets. The optimal locations are roughly identical for all levels of ambition, they just include a larger or lower number of infrastructures. This result goes in line with a policy recommendation identified in a similar work by Perez-Pedini *et al.* (2005) : deciders can adopt an “incremental approach”, instead of directly deciding on a long-term optimal plan made of a rigidly fixed number of infrastructures. This means implementing first a few GRI, within the limit of available public budgets, in the identified optimal locations, and then adding more later by navigating in the Pareto front.

This spatial rule is slightly modified when specific hydrological conditions or economic effects come into play. When the city center is not fit for infiltration, it should be absolutely avoided if infiltration is of sole priority. Compromise solutions should rather aim at planning for NBGRI locations that mix any centric locations with out-of-town locations for which infiltration is more efficient. This situation is observed in real world case studies when simultaneous gain situations may not be available (McClymont *et al.*, 2020); in these cases, the optimal spatial plans in terms of rainwater management may not guarantee improvements in terms of co-benefits. The introduction of substitution effects can also lead to discarding some centric locations where demand for public urban green areas is already met.

This conclusion is consistent with the recommendations made for developing NBS as way to reduce environmental inequalities: deciders should prioritize populated areas with low ES endowment (Kato-Huerta & Geneletti, 2022). The introduction of two different infrastructure types reflects a double choice for the decision maker: a spatial choice and a technical one. Our final experiment shows that when the

choice is available, one should use a mix of city-centric NBGRI and inner and outer suburban CGRI, as the combination can greatly reduce the use of scarce urban land and the overall opportunity costs.

The implementation of this work delivers a second lesson: it serves as a proof of concept. On such a simple model, we are able to replicate optimal location choices that make sense. Consequently, a MOO framework is therefore validated as a sound method for real case studies of decision-making. The method holds the potential to be used as a decision-support tool for urban planners to solve the complex spatial, technical and economic problem of selecting sites for infiltration solution in a real-case setting. The IDM method allows the simplification of the complex 3-dimensions Pareto front into a clearer visualization of trade-offs. This illustration of trade-offs is by itself the advantage of MOO over aggregation methods (CBA). It provides decision-makers with an informed framework to navigate and select optimal policies based on their own set of criteria and priorities.

The main challenge that remains is that MOO provide a multitude of solutions which may be difficult to use for practical decisions. A remaining question is therefore to determine how to operationalize this method. Figure 6 is a suggestion of solutions that could be directly used by decision makers, if run on a real case. The decision makers could quickly visualize their range of options, identify trade-offs, and visualize the actual corresponding maps. A smaller decision problem appears, of assigning priorities between objectives. This prioritization could be undertaken in future research by coupling a MCDA to the evolutionary algorithm, as a means to incorporate the decision maker's priorities.

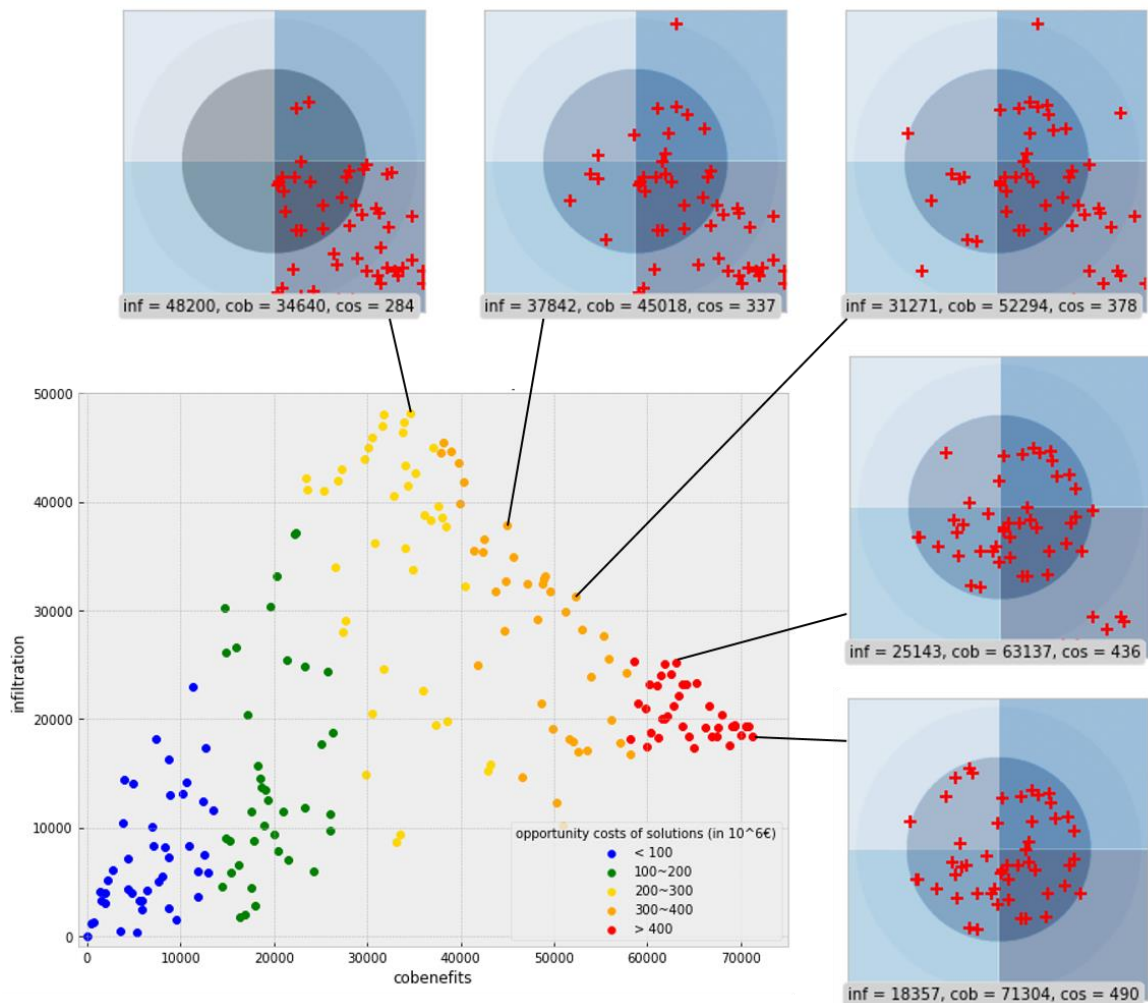


Figure 6: Visualization of a sample from the set of solutions of an equal investment cost

To summarize, this method can offer a way to solve a vast array of spatial problems associated to urban planning for which there is a multiplicity of objectives. It provides a framework to work out the issue of competing objectives in urban policies, in a context of limited available budget and limited available space for making changes in the city. This framework can help close the gap between the progress in spatial optimization methods for urban ES and for rainwater management infrastructures.

This work could be further refined on several points. First, other types of urban-rural contexts could be modelled to draw generic conclusions: the inverse co-benefit - opportunity costs gradient we selected may not translate to all cases. Experimenting with other distributions may change significantly the optimums. Furthermore, the parameters defining the range of co-benefits and the intensity of the substitution effect could be based on more evidence, for instance drawing from distance decay estimations from stated preference studies. Another element that could be improved to further generalize these conclusions is the assumption of equal investment costs of NBGRI and CGRI, which may have given an advantage to CGRI.

As a final note, this work based the urban space preservation objective on the minimization of opportunity costs of public space, and defined those with land prices. This choice is based on works that used the same method (De Valck et al., 2019; Primo C. et al., 2018; Yoon et al., 2019). However, to our knowledge, there are no clear guidelines yet for integrating the opportunity costs of using public space, especially for small and linear NBGRI such as bioswales and trenches. This may penalize NBGRI in comparison to CGRI

Conclusion

This work was motivated by i) the need to establish cross-case guidelines to the planning of multi-benefit GRI in cities, when confronted with the presence of multiple objectives characterized by various spatial gradients, and ii) to close the gap between the literature on spatial optimization of rainwater infrastructure and spatial optimization of NBS in urban areas. Using multi-objective optimization and a simple archetypal monocentric model city, we were able to provide generic guidelines for implementing such strategies. These guidelines were elaborated with different experimental settings characterized by various hydrogeological constraints, substitution effects with existing urban green space, and the availability of alternative infiltration technologies. Considering that many dense and large cities have started developing climate change adaptation plans that include the development of multifunctional NBS, this type of integrated planning tool may become of particular interest in the future.

In this chapter, we presented the results of a first implementation of our MOO methodology. It was presented in this chapter as an independent study that investigates the spatial planning problem in a generic framework. Within the framework of theoretical spatial gradients of costs and benefits of urban GRI, we established conceptual guidelines for spatial planning, *i.e.* the areas and types of infrastructures to use in different decision contexts, and when giving priority to one of the three objectives. This study has the additional role of being a first step, from which we move to the final application of the MOO. Indeed, it ascertains the viability of the MOO method to solve our groundwater recharge location problem in a controlled setting, before its implementation on the Bordeaux case study. Additionally, it provides a set of initial results and guidelines, which we can then test and compare in the case study, using real data. The final implementation of the MOO on the Bordeaux case study is presented in the following chapter.

Chapter 4: A Multi Objective Optimization approach to urban multi-benefit groundwater recharge

This chapter is an expanded version of the following paper :

Farina, G., Neverre, N., Hérivaux, C., Barriere, J, Pinson, S., Habarou, H., Pereau, JC., Le Coënt, P., (2023). A Multi-Objective Optimization Approach for the Planning of Urban Groundwater Recharge Solutions. (Not submitted to a review yet as of October 2023)

Abstract

Urban Nature-based Solutions have emerged as potential strategies for urban climate change adaptation. However, urban decision makers require effective decision-support tools to plan and implement these solutions, considering multiple objectives and constraints, and addressing the complexities of spatial problems and do not depict trade-offs. This paper advocates for the use of multi-objective optimization (MOO), and the consideration of actual space availability, simultaneous objectives of climate change adaptation and water management, the integration of demand for co-benefits, and exploration and visualization of results for decision makers. To address these shortcomings, this paper presents an integrated approach to MOO that focuses on stakeholder needs. This method is applied to a real case study in Bordeaux, France, to identify the optimal location of Groundwater Recharge Infrastructures (GRI) that include Nature Based Solutions. This paper provides decision-makers with comprehensive and actionable strategies for developing GRI, with the objectives of maximizing groundwater recharge, maximizing urban cooling, while minimizing opportunity costs, in the context of urban climate change adaptation. The main resulting strategies show the strong competition between opportunity costs and the other objectives, the existence of extreme points where solutions focus mostly on recharge or on urban cooling. The trade-off analysis and pathway analysis proposed in this paper are novel ways for exploring the Pareto front and inform decision makers about the available choices, spatial strategies, and optimal planning steps, facilitating the implementation of urban groundwater recharge policies.

1 Introduction

In the face of climate change and rapid urban population growth, cities encounter substantial challenges, *e.g.*, a rise in the frequency and intensity of extreme weather events, the emergence of heat island effects and the contamination of air and water resources (de Sherbinin et al., 2007). Nature-based Solutions (NBS) are increasingly considered as cost-effective methods to address these urban challenges (Nesshöver et al., 2017). NBS are defined as actions to protect, sustainably manage, and restore natural or modified ecosystems, that address societal challenges, such as mitigating flood risk, improving water quality, regulating water flows or creating resilient and sustainable communities, simultaneously providing human well-being and biodiversity benefits (Cohen-Schacham et al., 2016). These solutions additionally provide a variety of ecosystem services (ES), ultimately improving the overall well-being of communities (European Commission Directorate-General for Research and Innovation, 2015).

Urban decision makers require spatially explicit decision-support tools for planning the development of NBS (Frantzeskaki, 2019). Firstly, decision-makers need to account for a wide range of objectives and constraints. Implementing such projects requires managing limited resources and scarce available space for developing public NBS (Bush & Doyon, 2019). Secondly, selecting the best available locations for climate change adaptation projects is a complex spatial problem that requires *ex-ante* evaluation of costs and benefits of different locations, and selecting those that maximize the welfare outcomes (Tardieu, 2017).

Traditionally, decision-support methods such as cost-benefit analysis (CBA) (Bockarjova et al., 2020; Estrada et al., 2017; Fraga et al., 2021; Johnson & Geisendorf, 2019; Naidoo & Ricketts, 2006; Oladunjoye et al., 2021) and Multicriteria Decision Analysis (MCDA) (Di Matteo et al., 2019; Langemeyer et al., 2018; Liqueste et al., 2016; Martínez-Sastre et al., 2017) have been used to evaluate and select urban planning strategies. However, these methods often fall short when confronted with the complexities of spatial problems: they often do not handle the presence of multiple simultaneous and potentially conflicting objectives, and as such do not represent the possible trade-offs associated with various scenarios (Langemeyer *et al.*, 2016). They may present difficulties associated with spatial considerations : in a complex spatial problem where there is a high number of potential policy options, not all can be soundly represented, analyzed and compared with these methods (Seppelt *et al.*, 2013; Turkelboom *et al.*, 2018). Indeed, CBA requires monetizing the cost and benefits for each alternatives, and MCDA would require performing a high number of comparisons and evaluations (Saarikoski et al., 2016). Consequently, other approaches are needed to address these limitations and provide decision support.

Multi objective optimization (MOO) can address these limitations. MOO is a decision-making approach that aims to find solutions that optimize simultaneously more than one objective function (Deb, 2014). Unlike traditional aggregation-based methods, MOO allows decision-makers to explore trade-offs and then make informed choices (Emmerich & Deutz, 2018). It involves evaluating and comparing various solutions based on their performance across multiple criteria. MOO seeks to identify a range of optimal solutions known as the Pareto front, which represents the trade-offs between objectives. By considering multiple objectives, MOO enables a more comprehensive analysis of decision problems, providing valuable insights for urban planning and other complex decision-making processes (Jankowski et al., 2014).

MOO has been applied in a series of decision cases, leading to the identification of optimal location scenarios for NBS (Alves et al., 2020; Bekele & Nicklow, 2005; Dwivedula et al., 2021; Neema et al., 2013; Yoon et al., 2019; W. Zhang & Huang, 2015; Y. Zhang et al., 2017). However these approaches remain in the domain of academic research, and MOO has not yet been incorporated systematically in decision-making processes. We argue that current applications of MOO may fall short of providing reliable decision support for three reasons: they do not analyze the availability of land for implementing NBS, do not consider demand for ES, and provide few tools to analyze Pareto fronts.

First, most MOO studies dealing with land use planning and NBS decision-support have neglected the analysis of actual land availability for NBS projects, resulting in optimization and spatial recommendations that are not grounded in practical opportunities. Some works have approached the location optimization of green areas and NBS by first analyzing land availability, though at a small (neighborhood) scale (Uribe-Aguado et al., 2022; Wan et al., 2022). This approach has not been used at a city-wide scale, for resolving large urban planning challenges. Another approach in the literature has consisted in introducing within the optimization the objective of minimizing changes in land use to take into account space availability (Elliot et al., 2019; W. Zhang & Huang, 2015), or by specifying a constraint in the maximum quantity of land use change (Y. Zhang et al., 2017). In this paper, the MOO relies on an inventory of actual available sites at the scale of a large city.

Second, existing MOO applications rely only on modeling the impact of their solutions on the supply of ecosystem services (ES), through biophysical indicators, without taking into account the demand for ES. This omission limits the accuracy and relevance of the evaluations (Laurans et al., 2013). Solely considering supply disregards the spatial heterogeneity of potential NBS benefits, which can lead to suboptimal location choices (González-García et al., 2020). Furthermore, overlooking the analysis of demand may result in ignoring individuals strongly opposing NBS policy implementation (Gould & Lewis, 2016; Laurent, 2011; Lyytimäki & Sipilä, 2009). In this paper, the demand for one of the objectives is accounted for.

Third, current MOO applications do not reach the identification of actionable solutions for decision makers out of the exploration of the Pareto front. Few of these studies explore the practical applicability of MOO results for stakeholders, in other words, translate the optimal solutions into actionable and operational decisions. These studies often stop at revealing the Pareto front (K. Cao et al., 2011; Dwivedula et al., 2021; Elliot et al., 2019; Yoon et al., 2019; W. Zhang & Huang, 2015), assuming that stakeholders can independently choose their preferred individual solution within that set. With this assumption, MOO remains a fairly top-down approach (Girard et al., 2015), and does not necessarily provide tangible help in the decision-making process. Literature on analyzing Pareto fronts suggests approaches that can enhance the exploration and usability of MOO results. Some studies suggest performing a form of multicriteria aggregation on the Pareto front (Blasco et al., 2008). This approach amounts to selecting the solutions of a front that are the closest to an ideal point (Blasco et al., 2008; Sacchelli & Bernetti, 2019), and therefore provides a clear unique solution to decision makers. The understanding of the various trade-offs at hand may however be lost in the process. Another approach introduces stakeholder preferences in the aggregation, by applying a weighting scheme to the various objectives (Kaim et al., 2020). In this paper, we provide an original and participative approach for the exploration of the results of the MOO.

Overall, this paper advocates for the utilization of MOO techniques to overcome the limitations of traditional decision-support methods and provide more comprehensive and actionable solutions for climate change adaptation in complex spatial problems. We implement a MOO approach to address the aforementioned shortcomings in a real decision problem case study. In this problem situation, the urban planners of a large metropolitan area face the decision problem of planning the development of land use intensive solutions aiming at addressing several urban adaptation challenges.

[Section 2](#) exposes the case study and its decision problem. In [section 3](#), we present the MOO approach. Then we present the main results in [section 4](#), and discuss them in [section 5](#), before providing concluding remarks.

2 Case study

This study is applied to the Bordeaux metropolitan area (57,000 ha, 814,000 inhabitants), located in southwest France. The municipality faces the main issue of managing sustainably its water supply in the face of climate change and demographic growth. These drivers may increase the pressure on water resources, which are mainly deep aquifers. A proposed approach to alleviate this pressure is to develop Groundwater Recharge Infrastructures (GRI) - including both Nature-Based Groundwater Recharge Infrastructures (NBGRI) and grey Conventional Groundwater Recharge Infrastructures (CGRI) - at a

large scale to recharge shallow aquifers with rainwater, thus constituting water stocks that may be used for non-drinkable uses (urban parks and gardens irrigation, street cleaning, industrial uses, etc.).

The objective of this strategy is to substitute water uses that currently rely on drinking water supply, even though they do not explicitly require such high-quality water (urban parks and gardens watering, street cleaning, etc.) with water sourced from recharged shallow aquifers. This approach aims to safeguard the deep aquifers by utilizing alternative water sources for appropriate purposes. This is intended to be a complement to a broader strategy of water resource management, involving water use optimization and savings, the elimination of leaks in public drinking water networks, and using other water sources and aquifers. This policy represents a significant shift in the way stormwater is managed, as the city is transitioning from the conventional approach of managing rainwater centrally, which involves collecting and redirecting it away from the city, to embracing decentralized rainwater management solutions. These solutions, such as NBS, rely on the restoration of hydrological cycles and the infiltration of rainwater where it falls.

Additionally, the local government is facing the issue of adapting the city to climate change, mainly by tackling heat island effects. For instance, the average number of days of heat waves in the region may rise from 8.4 per year up to 20.7 by 2050, based on the RCP 4.5 emission scenario (Artelia, 2015). The local government is considering urban greening as a means of improving urban cooling (Livesley et al., 2016) as well as providing other co-benefits. For example, as part of a local policy objective, there is a goal to plant one million trees within the Bordeaux metropolitan area. For this reason, NBGRI, which may include several vegetation layers (tree, shrub and herb layer), are considered along conventional grey recharge infrastructures, as a means to achieve simultaneous objectives of groundwater recharge and urban cooling.

The space for implementing GRI is scarce. This is especially true in the denser centric areas, where there are needs for climate change adaptation services, but with few empty space. In consequence, climate change adaptation competes with many other potential urban planning objectives, such as housing and commercial development, the creation of alternative transportation modes, such as bike lanes, etc.

The urban planning decision problem is therefore more complex than just implementing GRI where the conditions are the best: urban planners need to take into account the scarcity of available space for such projects and how different locations will have different benefits both in terms of groundwater recharge and urban cooling. The decision problem therefore amounts to a complex spatial problem: how to allocate optimally the available areas and public budgets in order to provide the best possible outcomes? What types of infrastructures should be developed in each areas?

3 Method

In this work, we search for the best combination of sites to implement GRI. The goal of this approach is to provide decision makers with the optimal planning solutions that take into account simultaneously their various policy objectives, and reduce the potentially infinite number of planning scenarios to the subset of best available options.

The main steps of this approach are the following. First, we present the overall design of the MOO, the decision variables, the objectives, and the optimization algorithm (Section 3.1). The second stage is the identification of potential plots for developing GRI (Section 3.2). Then, we detail the evaluation functions (Section 3.3). Finally, we highlight the approaches used to analyze and visualize the outcomes derived from the Pareto front (Section 3.4).

The development of this MOO involved a participatory approach that included multiple sessions with key stakeholders at different stages of the process. A first workshop of open discussion (15/10/2020) was conducted to identify the primary optimization objectives and constraints associated with water infiltration and groundwater recharge. An additional brainstorming session (11/01/2022) was organized with stakeholders to determine suitable locations for the development of GRI. A final presentation session (14/09/2023) allowed to visualize and discuss the implications of the MOO results.

3.1 The multi objective optimization design

In this section, we detail the main elements of the MOO. This design builds on the design developed in [Chapter 3](#).

3.1.1 Decision variables

The first question addressed by this MOO is a spatial one: where to develop groundwater recharge. All potential plots available within the metropolitan area for developing groundwater recharge have been identified and mapped. But considering this spatial scale (above 7000 plots) would be too computationally intensive. The decision variables therefore consists of a list of 271 IRIS units⁷. In the rest of the paper, this spatial unit is referred to as “neighborhoods”. In this case, the optimization problem is approached at this spatial scale, rather than focusing on the individual plots. This decision was made in consultation with stakeholders, as prioritizing neighborhoods aligns with the context of long-term

⁷ IRIS units are small geographical areas at the infra-municipal scale used for statistical purposes in France. In essence, IRIS units correspond to discrete neighborhoods that possess a local identity within large cities, or they can also be small periurban or rural municipalities.

planning and proves more relevant than considering individual plot-level spatial scale. On each of these 271 neighborhoods, there are two more levels of decision.

Firstly, two distinct types of technology can be used: NBGRI or CGRI. In order to reduce computational time, the choice of technology type is made at the neighborhood level, wherein the plots within a particular neighborhood are developed using either one technique or the other. Each neighborhood is itself characterized by the available plots that are located within it (section 3.2), which are themselves characterized in terms of estate price costs and groundwater recharge efficacy.

Secondly, different implementation levels can be considered: the potential plots within the neighborhood do not have to be used entirely. GRI may be implemented only on 40% of the available surface, for example. To limit the complexity of the decision problem, we decided to make it a discrete choice between six implementation levels: 0%, 20%, 40%, 60%, 80% or 100% of the potential of plots of a given neighborhood can be selected.

Following this design, each solution n to the MOO features I selected neighborhood, with each individual neighborhood i developed with an implementation level r_i and an infrastructure type τ_i . The I neighborhood is composed of two subsets: a subset of J neighborhood implemented with NBS, and K neighborhood implemented with grey infrastructures.

3.1.2 Objective functions

The three objectives of the MOO are to maximize groundwater recharge (R_n), maximize urban cooling (C_n), and minimize opportunity costs (O_n).

The first objective aims at maximizing the effectiveness of groundwater recharge at the scale of the metropolitan area. This objective represents the aim of decisions makers to maximize overall groundwater recharge benefits (R_n). We draw the assumption that maximizing the amount of surface areas dedicated to recharge projects in areas where recharge effectiveness is the highest is a good approximation of this.

The urban cooling objective is approached in this study through the mitigation of heat islands. We make two assumptions: urban green areas reduce surface temperatures during heat waves, and the larger these green areas are, the larger the areas of heat mitigation. We also assume that this urban cooling benefit (C_n) is composed of two distinct effects: a global and a local benefit. The global part C_n^G of the cooling function assumes that implementing NBGRI in the city benefits to the entirety of the city

population, by mitigating the areas of intense heat. The function also features a local benefit C_n^L because local urban cooling benefits also directly to the population surrounding a NBGRI.

The third objective of the optimization is the minimization of opportunity costs (O_n). Opportunity costs are taken into account through mean real estate prices. The underlying assumption is that prices in the real estate market represents the most profitable value of land that would be lost by implementing GRI (Thurston, 2011). This objective acknowledges the challenge faced by decision makers when implementing policies within the constraints of limited land and resources. Additionally, decision makers often have multiple policy priorities that compete for land use, such as developing transportation options like bike lanes and public transit systems, as well as creating residential and commercial areas to accommodate population and economic growth. Consequently, policy makers may be motivated to minimize the effects of this policy on land use.

The evaluation functions of each objectives are detailed in section 3.3.

3.1.3 Effort constraint

The MOO features a single constraint, expressed as a simple effort constraint in terms of amount of land converted to GRI. It states that the maximum surface area dedicated to recharge infrastructures is 10% of all the available identified plots, or 369ha. This serves the purpose to limit the searchable solution space to solutions that are within the implementation capacity of the municipality, while still representing an ambitious maximum level, comparable to other similar plans in French cities⁸. Using a space constraint is a simple approach compared to a more traditional cost constraint. It is also an easier indicator to discuss and set for decision makers rather than costs.

3.1.4 Optimization algorithm

The optimization problem is a combinatorial optimization (Stewart et al., 2004): we are looking for the best combinations of neighborhoods, infrastructure types and implementation levels. It is solved using the evolutionary algorithm ($\mu + \lambda$) from the DEAP library (Fortin et al. 2012) and the NSGA-2 selection algorithm, for producing a diverse Pareto-optimal set of solutions (Deb *et al.*, 2002). The population size is 500 solutions, crossover and mutation probabilities set at 0.7 and 0.3. We run the algorithm until satisfactory solutions are obtained, in this case, after 1000 generations (Figure 1). This amount of generations is decided after trial and error, by incrementing the number of generations across runs, until the Pareto front remains stable. The details of the algorithm are further explained in the

⁸ The Metropolitan area of Lyon ('Grand Lyon') for instance has initiated a project that aims at deproofing up to 400 hectares of artificial soils by 2026

appendix section. The optimization program is written in Python, and uses geographical shapefiles as inputs.

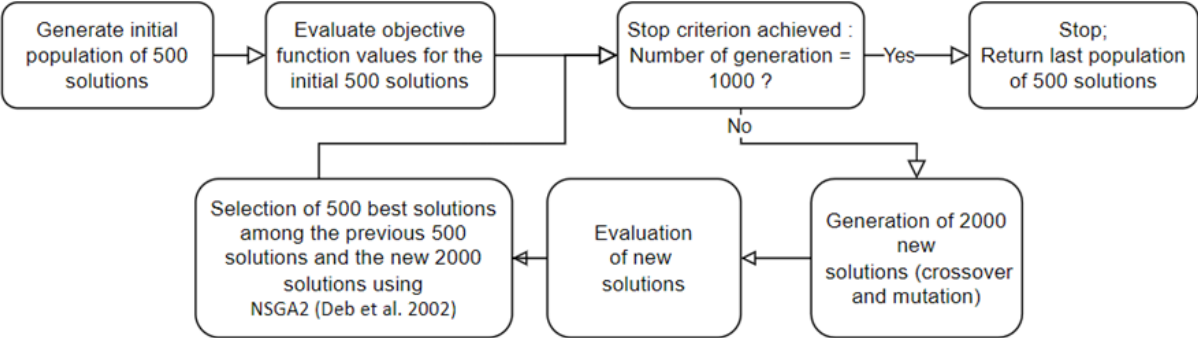


Figure 1: Main process of the evolutionary algorithm

3.2 Identification of the potential plots

A central input to the MOO is the identification and mapping of real land plots that may be used in the future for the development of GRI. The identification of these sites is based on a series of workshops with key stakeholders of the Bordeaux Metropolitan area, *i.e.*, urban planners, water distribution and management representatives, urban parks managers, ... Key land use types were identified for this purpose: parking lots of commercial and industrial areas, schoolyards, open public and private spaces available for urban greening projects (public squares, sidewalks, small parking lots, abandoned lots, etc.).

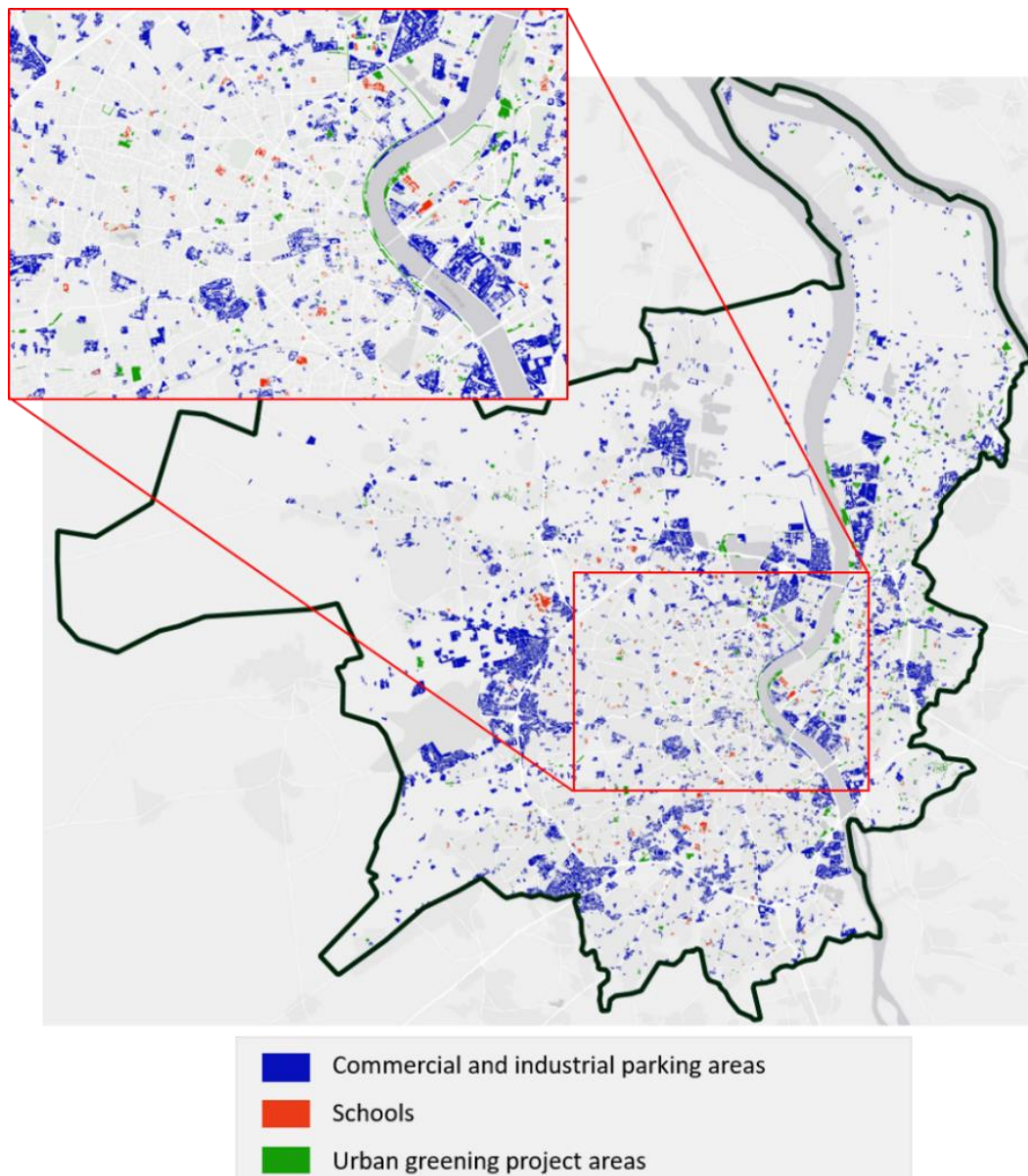


Figure 2: Available plots for developing infiltration projects in the Bordeaux Metropolitan Area

3.3 Evaluation of the three objectives

3.3.1 Maximization of groundwater recharge

The characterization of groundwater recharge relies on a hydrogeological study conducted in the Bordeaux Metropolitan area, to identify and map the potential benefits of the development of groundwater recharge. This study aimed at collecting geological and topographical data regarding the capacity of urban soils and aquifers for infiltrating, storing and extracting rainwater for re-use. The most important parameters in determining the efficiency of infiltration and GRI were identified after rounds of stakeholder interviews and expert consultation. They are the soil permeability, the thickness of the vadose zone, the aquifer depth, the terrain slope, the capacity of terrain to extract water (aquifer width),

the storing capacity of terrains (porosity), and the Network Development and Persistence Index (IDPR), which is a metric that determines the spatial distribution of infiltration and runoff in a hydrographic network (Mardhel et al., 2021).

In a second round of stakeholder concertation, the most and least favorable range of values for these parameters for groundwater recharge projects were identified. The range of values defining complete impossibility for recharge projects were identified this way. At the end of this step, all potential values for all parameters were assigned a normalized score between 0 and 10. In parallel, all six parameters were attributed relative weights by a group of local stakeholders and by a group of national groundwater recharge experts, with a simple multi criteria ranking weighing scheme based on the Analytic Hierarchy Process method (Saaty, 1990). These two weight sets were then synthesized into one set of weights, as a means to incorporate both local perspectives and expert knowledge. The parameters were aggregated in a final step through a spatial multi-criteria analysis, using the weighting scheme in order to create a final single recharge favorability map. The final result is a map, presented in Figure 3a, which defines the overall favorability of urban areas for recharge projects. Each individual site s was attributed a value g_s of this score, on a scale of 0 to 10, according to its location. This unique value for groundwater recharge effectiveness does not represent one tangible benefit. It integrates the most important spatially heterogeneous parameters - and their relative weights - defining the effectiveness of GRI for infiltration, storing and reusing rainwater.

The groundwater recharge yield R_n of solution n is calculated as the sum of the groundwater recharge score of the I neighborhood that make the solution. The groundwater recharge of each neighborhood i is itself the sum of the recharge score g_s of each recharge site s within the neighborhood, multiplied by the implemented surface of GRI on these sites, which is the product of the plots surface area a_s multiplied by the implementation level r_i of the associated neighborhood i (Eq. 1).

$$R_n = \sum_{i=1}^I \sum_{s \text{ in } i} g_s * a_s * r_i \quad (1)$$

A central assumption is that no distinction is being made in groundwater recharge efficiency between NBGRI and CGRI. The central factors influencing the groundwater recharge yield are considered to be the soil and subsurface parameters, which are independent from the technology used (Bhaskar et al., 2018).

3.3.2 Maximization of urban cooling

The characterization of urban cooling is based on a choice experiment survey (Chapter 2), which enabled the estimation of individuals' willingness to pay (WTP) for various benefits and negative effects

of future groundwater recharge projects. This study explored the preferences expressed by the population for various policy alternatives defined by their benefits, negative effects and characteristics: i) the preservation of deep aquifers allowed by groundwater recharge policies, ii) the impact on urban cooling, iii) the impact on the reduction of space for car transportation (roads, parking lots...), and the distance of NBGRI to individual's residence. A preference model (mixed logit model) was used to evaluate the respondents' individual willingness to pay for the various attribute levels based on their choices. One of the conclusion of this study is that the exposure to heat has a significant positive effect on individual's willingness to pay for strategies that incorporate the highest possible levels of urban cooling. This relation was used to map out the population's mean willingness to pay for urban cooling, at the neighborhood scale (Figure 3b). This map is used in the MOO for estimating the urban cooling benefits of NBGRI.

To estimate this benefit, we first model the physical climate cooling effect provided by each plot converted to NBGRI, which is a consequence of increased shading and evapotranspiration due to the vegetation, and the reflection of short-wave radiation (Z. Yu et al., 2020). We make two assumptions. First, that heat islands will basically cover the same areas by 2050, *i.e.*, areas of artificial land cover (parking lots, etc.). We are therefore making the assumption of no dramatic land use changes in the future. Secondly, we do not model the cooling impact of NBGRI in terms of temperature reduction, but instead assume that if a heat island area is within the cooling range of a NBGRI, it will provide sufficient cooling to the extent that the area will no longer be classified as a heat island. Heat island are defined here as areas where the surface temperature during heat wave episodes are significantly higher than the rest of the metropolitan area (mean temperature + standard deviation) (Rizwan et al., 2008).

The cooling effect occurs on a variable buffer extent surrounding NBGRI (Aram et al., 2019). We model this cooling effect by creating buffer polygons on and around implemented NBGRI, in the subset of J neighborhood selected for NBGRI projects, within the I neighborhoods selected for recharge projects in solution n . The buffer extent γ_s of each NBGRI is itself a function of the implemented area. This implemented area is the product of the neighborhood implementation level r_j in the associated neighborhood j and the surface area of the plot a_s , multiplied by a scaling factor σ , set to 10^{-2} (Eq. 2). The buffer extent γ_s then serves as the radius parameter for creating buffer areas around the NBGRI.

$$\gamma_s = r_j * a_s * \sigma \quad (2)$$

The scaling factor σ is added to have the cooling radius based on state of the art on cooling extent of green areas and NBS (Aram et al., 2019). For instance, NBGRI covering total implemented surfaces in our MOO of 0.5 or 2 ha would have cooling extents of 50 and 200m respectively. For comparison,

estimates by Aram et al. (2019) indicate that a 0.8 ha park would have an impact up to 44 meters, and a 2.5ha solution, an impact up to 218m.

We then calculate the global C_n^G and local C_n^L cooling benefits generated by this effect for each solutions.

The global function evaluates the total area of mitigated heat island areas, which is the difference in area of heat islands between the solution and the baseline (*i.e.* the current state of heat islands in the Bordeaux Metropolitan area). The resulting percentage P_n of mitigated heat island areas is then multiplied by the mean city-wide WTP of households for the incremental mitigation of heat island surface areas (in € per percentage point of eliminated heat island area), equal to 2.946, and the total number of households in the BM area (399 989 in 2020) (Eq. 3).

$$C_n^G = P_n * 2.946 * 399\,989 \quad (3)$$

The local benefit simply assumes that the households h_s situated within the cooling buffers of the s NBGRI benefit from it. We estimate this number of households for each NBGRI by multiplying the buffer surface area by the mean household density of the neighborhood, after having merged the buffers for avoiding double counting. We then multiply this number of households by the variation α_j in mean neighborhood-specific household's WTP for heat island reduction, estimated in the choice experiment (Figure 2b), thus obtaining the total WTP for urban cooling at the neighborhood scale. The local cooling benefit C_n^L is then the sum of the benefits of each selected NBGRI neighborhood g (Eq. 4).

$$C_n^L = \sum_j^J \sum_{s \in j} h_s * \alpha_j \quad (4)$$

The final resulting cooling function C_n is the linear sum of the global C_n^G and local term C_n^L (Eq.5).

$$C_n = C_n^L + C_n^G \quad (5)$$

3.3.3 Minimization of opportunity costs

Opportunity costs O_n of solution n is the sum of the land estate prices of the plots p_s used for implementing recharge infrastructures. These real estate prices from the Bordeaux metropolitan area originate from the French notarial database (Figure 3c).

An important difference is set between NBGRI and CGRI: the latter tend to occupy less ground space, and are often partially or entirely built underground. As such, they are modelled as having a fraction of the opportunity costs of NBGRI (Haaland & van den Bosch, 2015; Maliva, 2014). This is represented through the τ coefficient, set as 0.5, which is an approximation of the difference in size between NBGRI and CGRI. A distinction is thereby made between the two subsets of neighborhood within the j neighborhood of solution n , with J neighborhoods selected for NBGRI and K neighborhoods selected for CGRI infrastructures (Eq. 6).

$$O_n = \sum_{j=1}^J \sum_{s \in n_j} a_s * r_j * p_s + \sum_{k=1}^K \sum_{s \in n_k} a_s * r_j * p_s * \tau \quad (6)$$

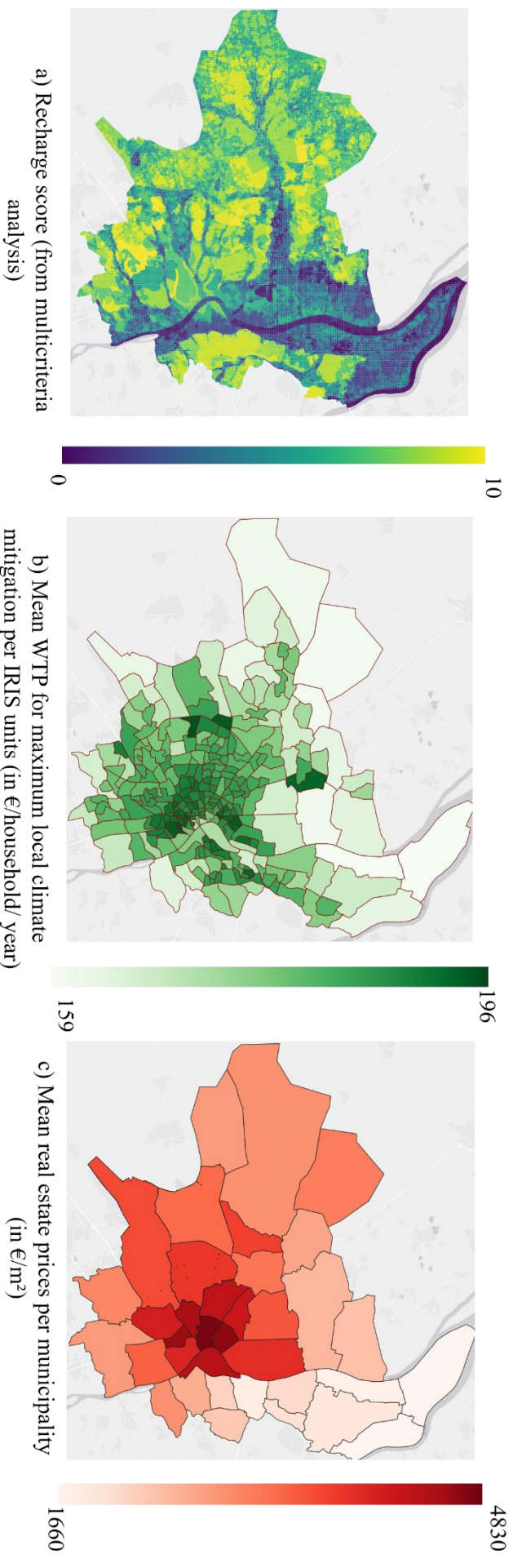


Figure 3. Indicators used for representing infiltration efficiency, urban cooling and opportunity costs. Participatory analysis of solutions a) Multi-criteria score defining groundwater recharge favorability b) The map was made using the relation between mean temperature and WTP estimated in the post-estimation from the choice experiment (Farina et al., in Press). c) Mean real estate prices are collected from the French notarial database (2018)

The Pareto front resulting from the MOO contains an infinity of solutions, which are difficult to analyze and turn into actionable scenarios for decision makers. We develop two approaches to investigate the main trade-offs at play in the Pareto front, and interact with stakeholders for the selection of future scenarios of implementation of GRI.

3.4 Pareto front analysis

Finally, we included three approaches dedicated to the exploration and analysis of the Pareto front. It consists in two novel visualization approaches, dedicated to the visualization of trade-offs (Section 3.4.1) and to identifying planning pathways (Section 3.4.2), as well as a participatory analysis session with key stakeholders (Section 3.4.3).

3.4.1 Trade-off analysis

A central advantage of the MOO is its capacity to explore and identify trade-offs between objectives. Identifying these trade-offs require analyzing the Pareto front. We suggest here a novel analysis designed for this purpose. We restrict our focus on the section of the front with the highest levels of opportunity costs, as they represent the level of ambition of deciders in the Bordeaux metropolitan area. They also represent the largest span of trade-offs between groundwater recharge and urban cooling. We identify and represent the different groups of solutions that constitute this part of the front.

To achieve this, we separate these solutions into 5 quantiles, along the recharge-cooling trade-off dimension. We then present the frequency of selection of each neighborhoods within each of those quantiles. For both NBGRI and CGRI, we display the average implementation level for each neighborhood within the solutions of the quantile. We thereby obtain two series of 5 city maps, which represent the average intensity of implementation in each neighborhood, for NBGRI and for CGRI. While aggregating non-dominated solutions defeats the purpose of multi-objective optimization, this type of representation does take into account the various trade-offs of the most ambitious solutions, while still allowing for manageable visualization. These representations reveal spatial trends among the solutions, and the spatial trade-offs at play.

3.4.2 Pathway analysis

Decision makers may be looking for suitable transition pathways of climate change adaptation, instead of just a collection of final long term ideal solutions (Carter et al., 2015). Urban planners may implement such projects by going through incremental steps, for instance planning the construction of some areas before others. This is a necessary step since not all areas can be developed at the same time:

public authorities need to manage constrained budgets, materials and workforce, and implement such projects one area at a time.

To verify that the multi-optimization approach is compatible with such a practical concern, we suggest a second level of analysis of the Pareto front. A possible approach is that the decision-makers first identify a target, an ideal solution to be reached within a given timeframe. In this example, we assume that the decision maker establishes an ideal solution by assigning varying degrees of importance to each of the benefits. We create a scenario based on this assumption, where greater importance is placed on recharge. Two more scenarios are presented in [supplementary material](#).

We implement a simple aggregation of the objective values of the solutions of the Pareto front, based on fuzzy weights inspired by fuzzy Multi Criteria Decision Analysis (Malczewski, 2006). We apply a linear normalization on the objective values for cooling and recharge, and then calculate a ratio between those: the normalized recharge value divided by the normalized urban cooling value. We then select all solutions that have a ratio that falls within a given range, according to our scenario (a ratio superior to 3). We obtain a subset of solutions for each of these three scenarios, located across the whole Pareto front, but which give more or less importance to both recharge and cooling. Finally, we implement a similar approach to the trade-off analysis, and separate the subset of solutions into 5 quantiles, but this time along the opportunity costs dimension. The resulting 5 quantiles represent general trends of this subset, from lowest to highest ambition levels.

3.4.3 Participatory analysis

In the final phase to this study, the results of the optimization were presented to the key stakeholders of the Bordeaux Metropolitan area (14/09/2023). In this workshop, we proceeded with a two-step method to analyze and explore the results of the MOO, and extract operational recommendations from it. This participatory session followed a two-step method.

First, we presented the entire methodology to the participants, up to the resulting Pareto front and its trade-offs. In this first discussion, we asked the participants to select areas of interest within the Pareto front, alongside the justification for their interest on the areas, *i.e.*, what groups of solutions they would like to explore more deeply, especially through their spatial representation.

Then, in a second step, we presented the selected group of solutions - *i.e.* those that created consensus during the first session – using webmaps. These maps presented the main spatial patterns of these solutions, the selected neighborhoods and sites for developing GRI. The ensuing discussion was oriented

towards the analysis of these spatial strategies, their operational implications, and the overall pertinence of the tool.

4 Results

4.1 Final population of solutions

The main output is the final population of the 500 optimal solutions, each defined by the neighborhoods selected for implementing GRI, their implementation levels and technology choices, as well as their objective values in the recharge, opportunity costs and cooling dimensions. This final population, referred from this point forward as the Pareto front⁹, is represented in a two dimensional space in Figure 4, with the opportunity cost presented in color categories, using the approach proposed in [Chapter 3](#).

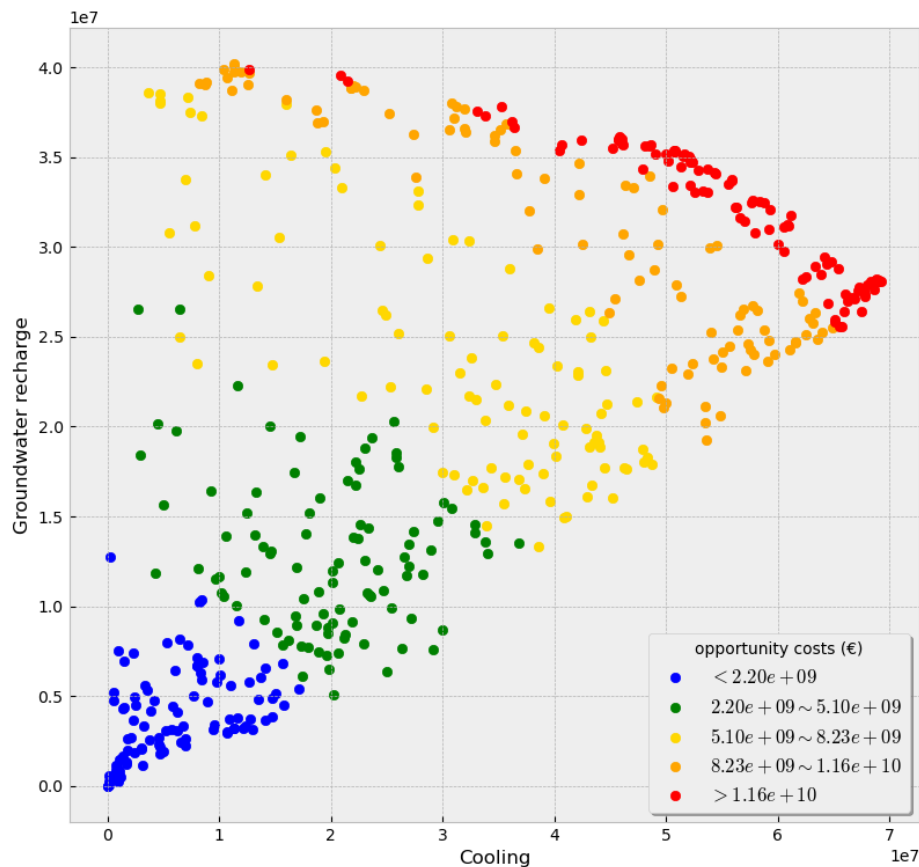


Figure 4: Optimal solutions of the MOO problem, represented along the infiltration and urban cooling dimensions

⁹ These 500 solutions are not exactly all the possible solutions of the Pareto front, which in essence can be an almost infinite subset. This number of 500 is in fact defined by the population parameter (μ) of the evolutionary algorithm. However these solutions do cover all the areas of the actual Pareto front within the space constraint, and therefore present all the main trade-offs at play, and are in essence, a thorough overview of the Pareto front.

The front presents several characteristics. First, opportunity costs competes strongly with both other objectives: increasing either infiltration or urban cooling requires increasing opportunity costs, and this effect is even stronger for urban cooling. Secondly, solutions can go to extreme points - they can focus almost entirely on infiltration or urban cooling, or stand at intermediate points between both benefits. This trade-off appears in all ranges of opportunity costs. Thirdly, there is an area of “high effort” on the front, which saturates the effort constraint. This high-effort front is particularly interesting as it represents the tradeoffs for the highest attainable impact. Fourthly, a main aspect of this high-effort area is that the solutions that maximize groundwater recharge (on the top left side of the front) provide relatively low urban cooling, while the solutions that maximize urban cooling (on the top right of the front) also generate a relatively high potential in groundwater recharge, and belong to a higher opportunity costs. Therefore this maximal urban cooling solution and its surrounding ones – the area on the top right side – suggests there is a more synergic solution space here, in terms of benefits. In other words, the trade-off between both benefits is less strong in this area of solutions, we can reap both benefits at the same time.

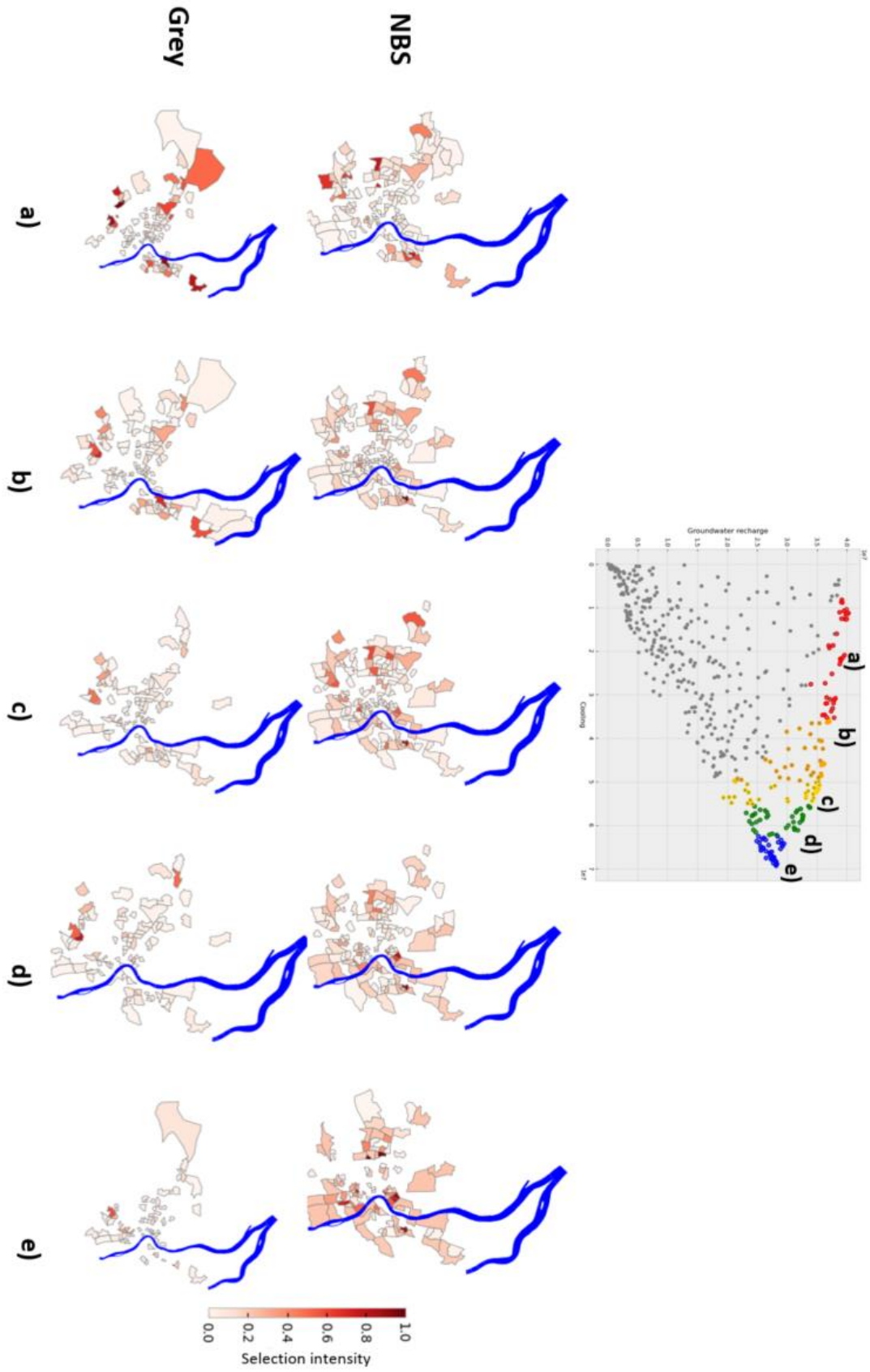


Figure 5: Trade-off analysis along the high effort front.

The red color grading indicates the implementation intensity of each individual neighborhood: it is the average implementation levels in each neighborhoods, across the corresponding subset of solutions

4.2 Trade-off analysis along the high effort front

Figure 5 presents the maps resulting from the trade-off analysis approach (Section 0). This approach allows for the exploration of the spatial trade-offs in the high-effort front commented above. The maps located on the left correspond to the area of the high-effort front where recharge is at its highest and urban cooling the lowest (Figure 5a). At the other extremity, on the right side, the maps display the area of the front where solutions feature the highest scores in urban cooling (Figure 5e). The maps between those points (Figure 5b,c,d) show trade-off solutions that balance more both of these objectives.

First, in solutions on the left side (a), we observe that the main neighborhoods – *i.e.* the most frequently and intensely selected neighborhoods either to implement NBGRI or CGRI - are located outside of the city center, in specific areas along the periphery. These neighborhoods are almost selected in all solutions of this subset of solutions, with high implementation levels (in deep red). In contrast the other neighborhoods are only occasionally selected.

As we move towards the maps on the right side – those that favor more urban cooling - we observe a few changes. In maps (b), (c), (d) and (e), solutions give an increasing importance to NBGRI and use less CGRI, as urban cooling is increasingly favored. Furthermore, the pattern of selected areas shifts gradually. More centric neighborhoods are selected, and the implementation of centric areas is gradually rising while peri-urban areas decrease. In group of solutions (e), solutions are mostly constituted of NBGRI, and are located either in peri-urban areas with low implementation level, or in centric areas, with a high intensity. CGRI are not totally dismissed, and there are still a few neighborhoods that are selected for the implementation of them, but with a low intensity.

The spatial patterns identified in the extreme groups of solutions ((a) and (e)) can also be identified in the extreme solutions of the Pareto front. In Figure 6, we present the individual solution that maximizes recharge out of the whole front, as well as the solution that maximizes urban cooling. These solutions are similar to the groups presented in Figure 5a and Figure 5e. Figure 6 reveals that the spatial distribution of recharge potential and heat islands is a determining factor of these results. The best recharge solution consists in developing both types of GRI in the areas of the city where recharge potential is the highest, and where there are available plots for developing recharge projects. The solution that maximizes the benefits of urban cooling in contrast tends to only require NBGRI, and their location tend to concur with the location of heat island areas.

We can also identify a reason why the best urban cooling solution also has a rather high level of recharge, thus leading to an overall synergic solution. Some neighborhoods selected for NBGRI in

Figure 6b (for instance those located in the west side of the city, where there are noticeable heat island areas), are also selected in the best recharge solution (Figure 6a). Indeed, heat islands can be located where recharge potential is high. In this context, maximizing urban cooling using NBGRI leads to spatial choices that are also optimal for recharge.

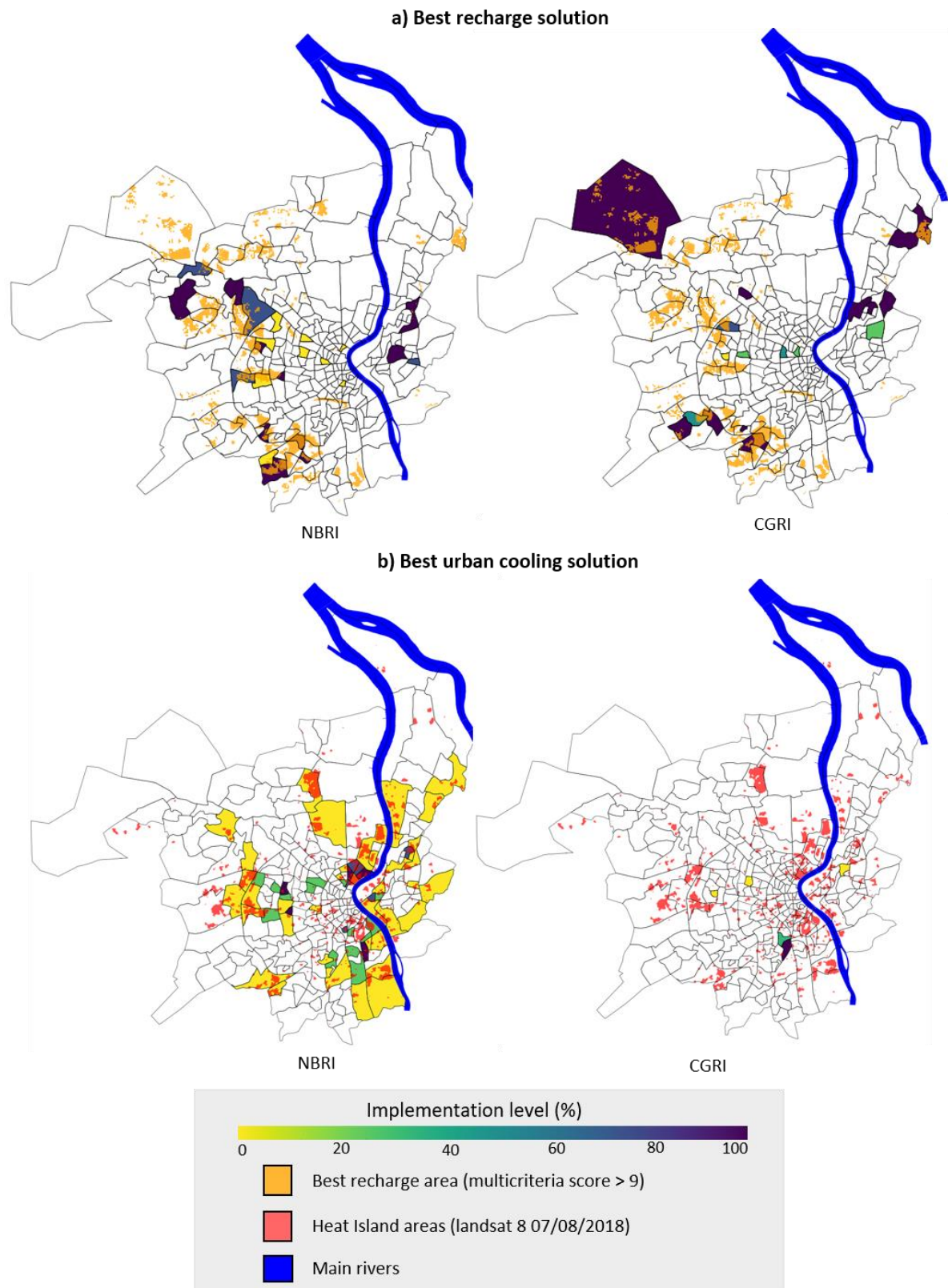


Figure 6: Best solutions in the recharge and cooling dimensions resulting from the MOO.
 The colour gradient in the maps represent the implementation level in each selected neighborhoods, *i.e.*, what percentage of the available sites are used. The maps on the top present the best recharge solution, with the best areas for recharge, as per the multicriteria analysis (Figure 2a). The maps on the bottom present the best recharge solution, with the location of heat island areas during a heat wave episode.

4.3 Pathway analysis

Figure 7 presents the results of the pathway analysis in a situation where the emphasis is entirely given on recharge. Sub-figures a, b, c, d and e correspond to groups of solutions of increasing opportunity cost along the targeted pathway (from blue to red).

Most solutions in these categories are constituted in majority of CGRI, although NBGRI are also used, especially at higher levels of opportunity costs. We observe that there is a continuity in the spatial choices. In the 4 subsets of increasing opportunity costs (b), (c), (d), and (e), the almost same neighborhoods are selected for CGRI.

The analysis also provides some insights regarding the prioritization of these particular neighborhoods: it seems that at lower level of opportunity costs, neighborhoods located on the eastern side of the river and the large one in the north-western area of the city are selected. In solutions of higher cost categories, the solutions build up on this first pattern, and add more neighborhoods. In the subset of solutions of the higher opportunity costs (e), there is a larger span of solutions on the recharge-cooling axis. Therefore, these spatial choices appear less clearly. There are also more NBGRI, providing urban cooling benefits.

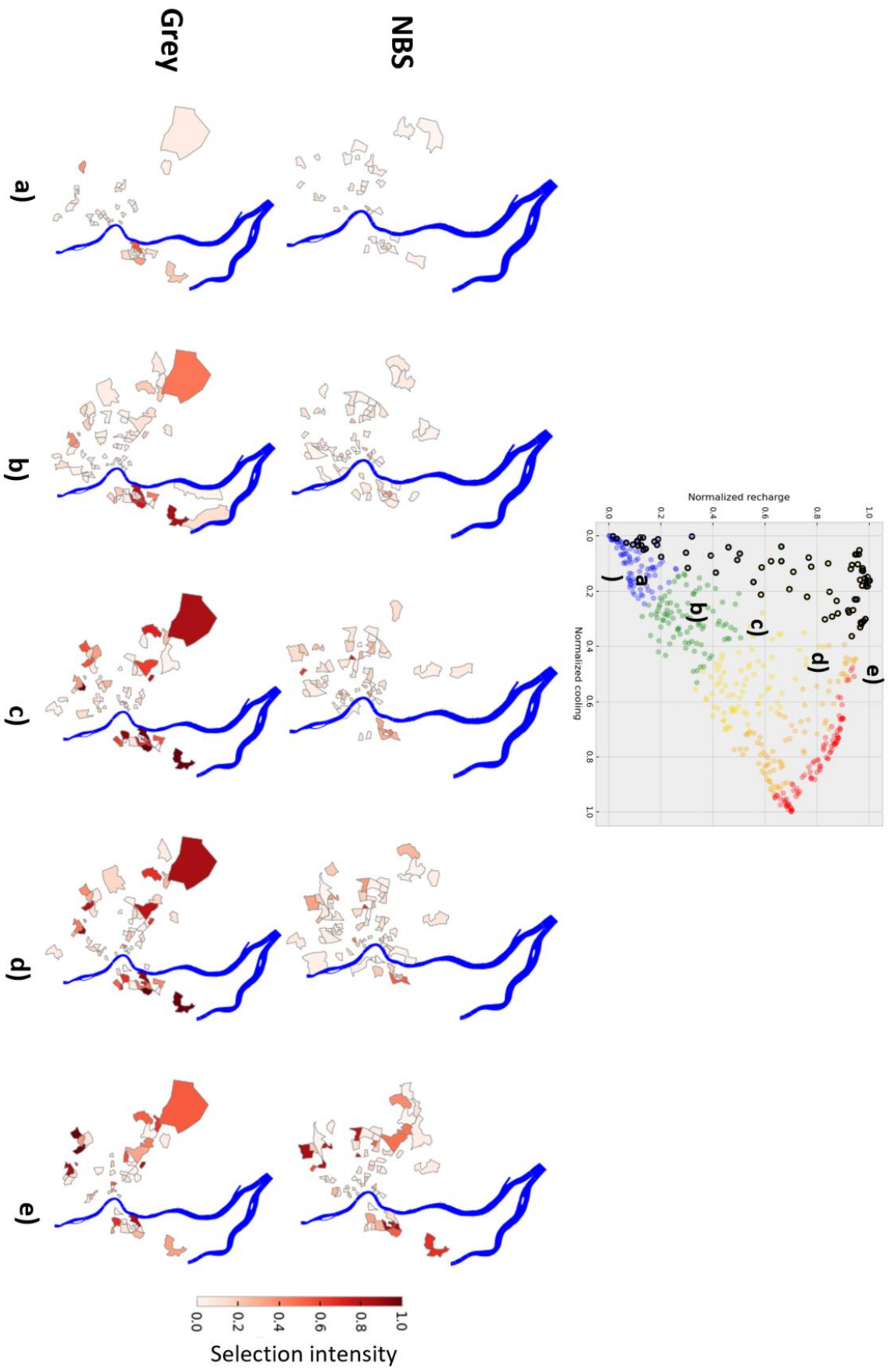


Figure 7: Pathway analysis example. In this scenario, more weight is attributed to the recharge objective.

5 Discussion

The main results of the MOO inform on the spatial choices for the implementation of GRI within a large city, their type of technology, and their implementation intensities, to be selected for reaching the desired outcomes. Giving priority to the aquifer recharge or the urban cooling objectives translates into different spatial and technical choices. This approach provides stakeholders of the Bordeaux metropolitan area with a clear perspective on these choices. In essence, solutions with an emphasis on recharge appear rather as “specialized” solutions, with a relatively few number of NBGRI, and with mostly CGRI implemented in the few areas that feature the best possible physical parameters for infiltrating and storing rainwater, with at the same time low opportunity costs. These solutions therefore tend to concentrate GRI in peri-urban areas, with a high implementation level.

On the other side of the spectrum, solutions with a higher emphasis on the urban cooling objective have distinct designs. They feature mostly NBGRI, located in areas of heat island, not necessarily in the most central area of the city. This contrasts with the theoretical findings obtained in Chapter 3, which suggested implementing NBGRI mostly in the city center, in densely populated areas. However, this previous study did not specifically address the location of heat island areas; instead, it solely relied on population as a proxy for demand, leading to the observed disparity. This application to Bordeaux metropole demonstrates the importance of a finer representation of the spatial demand for urban cooling. CGRI are also implemented in most of these cooling-focused solutions, mostly in the periphery of the center and in peri-urban areas, providing some high recharge yield at a low opportunity cost.

Both of these polar strategies - focusing either on recharge and cooling solutions - feature some amount of common choices. Some neighborhoods located on the eastern bank of the city for instance are systematically selected as CGRI or as NBGRI throughout the front. These sites are to be considered as sure choices for the planner. Furthermore, compromise solutions, located at intermediate points between both strategies, take from both these spatial choices. Moving from recharge-oriented solutions towards more urban cooling oriented solutions requires trading suburban grey infrastructure implementation for centric NBS implementation, and vice-versa.

Finally, a central result of this MOO is the presence of an area of simultaneous high gains in the front: high-ambition urban cooling-focused solutions tend to perform very well in terms of both benefits, recharge and cooling. This result can be of particular interest for local stakeholders as it indicates that they may not have to make a choice between focusing on one benefit or the other. These solutions provide clear synergies, though they have the highest opportunity costs. Therefore a critical consideration in this case study, for acting upon these results is what importance is placed on minimizing

opportunity costs: if this objective is of upmost priority for stakeholders, then other solutions should be considered, while if it is not, then this particular group of solutions would be the preferred choice.

We must acknowledge certain limitations of this MOO application. Firstly, it did not consider the demand for water resources, despite water use substitution being a primary objective of the metropolitan policy. As such, the benefits from this policy would be realized through the creation of alternative water stocks in close proximity to potential users, for watering green areas, street cleaning, industrial purposes, etc. Therefore, while the urban cooling objective took spatial demand into consideration, we did not extend this approach to the recharge objective, since identifying and mapping potential demand for urban recharge across the entire city was beyond the scope of this study. Another potential limitation is the absence of representation of certain constraints in our design. For example, we did not account for the “Protected Areas for Drinking Water Sources”, which prohibit entirely rainwater infiltration near crucial drinking water resources, as a means to avoid pollution. As a result, some areas and sites within the city might actually be entirely disqualified from consideration.

This work shows that MOO is a valuable approach to explore the possibilities in complex urban planning projects. It is useful in situations where policymakers do not have a clear overview of all potential policy options. For instance, in complex problems such as infrastructure location problems, the number of potential actions can be almost infinite. MOO enables the exploration and narrowing down of potential alternatives, effectively reducing the vast number of actions. In this way, MOO differs significantly from MCDA or CBA methods because of this capacity to identify policy alternatives. Traditional decision-support methods such as CBA and MCDA do not offer approaches to address this type of challenges. Some MCDA incorporate a preliminar phase of identification and constitution of alternatives (Estévez & Gelcich, 2015; Gregory et al., 2005). However, this approach is limited by the practical constraints imposed by the number of feasible comparisons. Moreover, in complex problems like the combinatorial challenge addressed in this study, it becomes exceedingly challenging to pre-determine potential optimal policy alternatives.

Nevertheless, the exploration the Pareto front is a central challenge of MOO – especially in spatial problems, and one that has been neglected in the literature. MOO can produce a very large Pareto front, whose solutions may not be immediately compared, and interpreted – in our case, spatially – to provide decision support. Effectively identifying and categorizing the various types of solutions from the optimized front requires substantial effort. In this study, we introduced two novel approaches incorporating trade-off analysis to address this issue. Furthermore, MOO, on its own, does not provide explicit guidance for policy making comparable to MCDA or CBA methods. It lacks a clear signal, such as a cost-benefit ratio or stakeholder-based policy ranking, to indicate which solution should be preferred. As a result, analyzing the Pareto front requires constructing a decision narrative: identifying

the main trade-offs at hand in the Pareto front, and how they may represent contrasted – and even opposing – view of the problem at hand. It can require also establishing an interpretation framework, to explain how different regions of the Pareto front correspond to distinct policy ambitions or different stages within a temporal context. In this study, we developed the pathway analysis to accomplish this interpretive task.

The analysis of the Pareto front developed in this work can inform on the best available choices and spatial strategies available to the decision makers. It can also be used as a more practical and operational support for the planning of recharge policies. It is in fact compatible with an actual project planning approach. With the pathway exploratory approach we can ascertain the possibility to implement such policies through incremental steps, and identify what these steps are. We observe that solutions of lower ambition levels feature mostly the same core choices than solution of highest opportunity costs, which allows to identify “no-regret” solutions. In this case, there is no dramatic path dependency incompatibility. This analysis can therefore inform potential decision maker on the optimal planning steps in order to reach a target solution. If the decision maker aims at reaching an optimal solution located on the high effort front, they could implement each of these intermediary steps identified with this approach. These intermediary steps would have two benefits: they are themselves optimal solutions, and their implementation would not inhibit the possibility to move towards the solutions of higher ambition levels.

The final phase of this work is the participatory analysis. The first step of it revealed that stakeholders gave particular interest to the solutions located on the high effort front, at the highest level of opportunity costs, at a middle point between urban cooling and recharge. The rationale behind this selection was to pinpoint the most ambitious solutions, considering these solutions as long-term goals, and opt for those that struck a balance between both benefits. In the second step, these solutions were presented spatially with a webmap¹. The presented map is an aggregation of a small subset comprising 10 solutions located in the selected area of the front, which typify the prevailing trend within these solutions. Given the stakeholders expertise and familiarity with the Bordeaux Metropolitan Area and its ongoing adaptation projects, we engaged in a discussion to compare the spatial patterns from the webmap with their local knowledge. This facilitated the identification of areas where the MOO recommendations either conflicted with existing projects or exhibited potential synergies. Furthermore,

¹ An example of webmap shown during the workshop is available at https://georgesfarina.github.io/Opti_group_c/. This map shows the main data inputs used in the MOO (the database of available plots, the heat island areas and the best recharge areas). It also shows the main neighbourhoods (IRIS units) most frequently selected within the group of solutions identified by the deciders, as well as the type of infrastructure to develop (grey vs NBS), and the implementation level of each neighbourhood (revealed when clicking on a neighbourhood)

the workshop served as an avenue for identifying prospective strategies to incorporate these findings into urban planning tools, specifically zoning laws.

This workshop discussion also allowed to identify limits to this work. Among these, a central limitation pertains to the inventory of available plots, a noteworthy innovation within this study. The identification, mapping and inclusion of the available plots in the MOO (see Figure 2) was deemed a strength of our work, thus confirming the pertinence of including this task in the scope of the study, in contrast to prevailing practices in the literature. However, the decision-makers highlighted the need for a more comprehensive understanding of the nature of these plots. This includes for instance identifying whether these plots are publicly or privately owned, as this information carries significant weight for urban developers when executing public initiatives and implementing land-use changes. Future research endeavors employing MOO methodologies should consider this aspect in order to keep progressing towards an approach that enhances urban planning decision support.

Conclusion

This study proposes an integrated approach to MOO oriented towards decision-support. We provide insights into the spatial choices and optimal strategies for developing GRI, with the objectives of maximizing groundwater recharge, maximizing urban cooling, while minimizing opportunity costs, in the context of urban climate change adaptation. The analysis of the Pareto front offers a comprehensive overview of the trade-offs at play: the strong competition between opportunity costs and the other objectives, the existence of extreme points where solutions focus mostly on recharge or on urban cooling. The trade-off analysis and pathway analysis proposed in this paper are novel ways for exploring the Pareto front, moving from aggregated results to spatially explicit results, which can effectively inform decision makers about the available choices, spatial strategies, and optimal planning steps, facilitating the implementation of urban groundwater recharge policies

General Conclusion

This thesis investigates the challenges of planning the adaptation of cities to climate change and water scarcity. This thesis is driven by a specific research and development project, initiated by the water services of the Metropolitan Area of Bordeaux, France. Local decision makers are aiming at developing GRI in the city, as a means to preserve groundwater, as well as providing urban cooling and other co-benefits, while operating on limited space.

The two main objectives of this thesis are to analyze the spatial distribution of the co-benefits provided by GRI; and to provide a novel decision-support approach adapted to the planning of GRI in cities, and adapted to a multidisciplinary approach. Within this context, this research tackles specific research questions inherent to NBS, the economics of ecosystem services, urban planning, urban rainwater management, and climate change adaptation. The parallel objective of this thesis is also to provide decision-support tools tailored to our specific case study, driven by the research and development project.

In this final concluding section, we first highlight the main findings of our research. Then, we draw general conclusions regarding the planning of NBS in cities. Finally, in the third section, we outline the limits of this work, as well as perspectives for further research.

1 Main findings

The main findings of this thesis are presented in Chapter 2, 3 and 4.

In [Chapter 2](#), we develop the first methodological phase of the thesis: a discrete choice experiment that investigates the population's preferences for the benefits and negative effects generated by the implementation of GRI. Notably, this study innovates in the stated preference literature by analyzing impact of three types of environmental inequalities on preferences for the various benefits and effects of groundwater recharge metropolitan-scale strategies. It is also one of the first studies to investigate the impact on preferences of the car space trade-off inherent to the development of these infrastructures in a city.

The analysis indicates high willingness to pay of residents for both the preservation of deep aquifers and for urban cooling. The analyses also focuses on studying the spatial heterogeneity of preferences.

We identify a phenomenon of global spatial dependence of the demand for local climate regulation, and we identify hot/cold spots for the willingness to pay associated to the outcome on car space reduction.

The spatial heterogeneity of demand for urban cooling is then analyzed as resulting from the impact of environmental inequalities: high exposure to heat increases the demand for urban cooling. This finding indicates that inequalities in exposure to environmental hazards may be a strong driver in the spatial heterogeneity of demand for ecosystem services generated by NBGRI, especially those closely tied to climate change adaptation. This demand gradient for ecosystem services is in line with the results of other studies (Baró et al., 2017; Hérivaux & Le Coënt, 2021). We also find that dependence on car use of individuals impacts negatively their demand for policies that may reduce car space availability: it is considered as a negative impact by a part of the population, especially those who rely on car use, and as a benefit for another part of the population. We argue that this reflects the impact of environmental inequalities caused by NBGRI and urban greening policies on individual preferences: reducing car space can have either a strong negative or a strong positive impact on individual well-being, depending on how much their individual well-being relies on car use.

Finally, the significant relation established in the post-estimation analysis between exposure to heat island and demand for urban cooling allows to create a demand map for urban cooling in the metropolitan area of Bordeaux. The resulting demand map for urban cooling is also a result in itself and interests local decision makers, and urban greening services. This demand map is also integrated as a key input in the final multi objective optimization for planning groundwater recharge for the Bordeaux case study.

[Chapter 3](#) investigates the applicability of multi-objective optimization in a generic decision problem. Within this work, the central focus is on urban planners aiming at determining optimal locations for the development of GRI, in the presence of urban-to-rural gradients of costs and benefits. This chapter also aspires to bridge the gap between existing literature on spatial optimization of rainwater management infrastructures and the spatial optimization of NBS. Using a MOO design and a fairly simple monocentric model city, we highlight contrasting strategies of GRI location in different experimental settings. These settings introduce variations in hydrogeological constraints, substitution effects with existing urban green space, and the availability of alternative recharge techniques.

This work yields two primary sets of findings. First, it establishes a proof of concept, positioning MOO as a relevant decision support tool for navigating urban climate change adaptation strategies, and for revealing trade-offs. Secondly, the simplicity of our model city setting allows to deliver generic findings on spatial recommendations to urban decision makers that extend beyond individual case studies. On the one hand, there is a clear trade-off between introducing NBGRI into city centers or

implementing CGRI in peripheral regions. Moreover, the study highlights the potential influence of substitution effects, demonstrating their diminishing impact on the desirability of city center sites. Finally, the spatial rules are modified when the city centers are not fit for groundwater recharge: in that case, compromise solutions should rather aim at planning for NBGRI locations that mix any centric locations with out-of-town locations for which recharge is more efficient.

In [Chapter 4](#), we propose an integrated approach to GRI planning. This chapter is the conclusion of the two previous approaches proposed in the thesis, as well as the hydrogeological study performed during the research project in parallel to this thesis. We propose a novel way of using MOO for linking urban climate change adaptation, rainwater management and groundwater recharge. This work aims at addressing our second research question, in an applied and interdisciplinary context: where to localize GRI in the context of a complex distribution of costs and benefits? What type of infrastructure should be implemented?

In this chapter, we use the MOO framework to identify the optimal neighborhoods for the location of GRI in the metropolitan area of Bordeaux, as well as the extent of the development of groundwater recharge in each neighborhood and the type of technique to use. This chapter notably innovates by considering actual space availability for land use change, the integration of demand for urban cooling, and a participatory exploration and visualization of results for decision makers.

The first key findings from the MOO are the spatial patterns resulting from the analysis of optimal solutions. A first pattern emerging from this study is that prioritizing aquifer recharge over urban cooling leads to favoring specialized grey techniques, located primarily in areas with ideal conditions for rainwater infiltration and low opportunity costs. These areas are mainly located on the city's periphery. In contrast, solutions emphasizing urban cooling exhibit distinct characteristics, favoring NBGRI over CGRI, and concentrating these infrastructures in proximity to important heat island areas and to populated areas. This outcome diverges from theoretical findings of [Chapter 3](#), which did not account for heat island localization, focusing solely on demand. Moreover, CHRI are incorporated into both strategies, often on the outskirts of the city and in suburban areas, offering recharge yield at a lower opportunity cost. Some sites consistently emerge as preferred choices, regardless of the chosen strategy: they are non-regret choices.

Hybrid solutions combining aspects of both polar strategies are possible, involving trade-offs between suburban CGRI and central NBGRI sites. Additionally, the examination of the Pareto front reveals an area with high gains, where ambitious urban cooling-focused solutions perform well in terms of both benefits (recharge and cooling). This finding suggests that decision-makers may not necessarily need to prioritize one benefit over the other: this solution allows to perform well in both dimensions,

though these solutions come with higher opportunity costs. In conclusion for this case study, stakeholders must consider their priority on minimizing opportunity costs when enacting strategies upon these results. If opportunity cost reduction is paramount, alternative solutions may be more suitable, while those valuing comprehensive benefits may favor the high-ambition urban cooling-focused solutions.

2 The spatial planning of urban NBS

Urban transformation is slow, and so has been the adoption of innovative practices like NBS and new urban drainage systems, *e.g.* SuDS. These options remain alternatives to conventional urban planning, centered on car-centric urban planning, and relying on traditional grey and centralized water management techniques. In fact, NBS and SuDS applications are primarily observed in new urban developments, rather than in already built urban areas. While some larger European cities, particularly capitals, are embracing the concept of Ecosystem Services and developing ambitious climate change adaptation strategies, these practices remain on the fringes (Maes & Jacobs, 2017). In contrast, the adverse impacts of climate change are growing rapidly (Dodman et al., 2022). In other words, most cities risk falling behind the adaptation curve.

In this thesis, we contributed to providing insights into viable pathways to close this adaptation gap, by identifying general spatial strategies for planning groundwater recharge techniques closely related to NBS and SuDS. Our conclusions extend further than the domain of groundwater recharge infrastructures to all types of urban NBS. Given limited resources and space, optimizing the impact of these NBS policies becomes an imperative objective in order to face of the adaptation gap. This thesis also delved into the spatial aspects of the benefits associated with NBS and their implications for urban planning.

The first main contributions concerns the spatial distribution of the benefits considered in this thesis. We gathered insights both on the spatial distribution of the potential effectiveness of NBS to deliver urban cooling benefits, as well as on the demand for it. In broad terms, demand for their co-benefits is predominantly located in areas at high environmental risk, especially when they are located in densely populated areas. These areas are potentially highly rewarding in terms of co-benefits, as they have high aggregate demand, but critically, space constraints often limit the implementation of NBS, especially when these areas are located in densely built neighborhoods. In practical terms, there may be few available “empty” spaces, parking areas or wide streets that can be transformed into NBS. When there exist such possibilities, it often comes at a very high opportunity cost.

This result emerges particularly in the difference in the results from the approach of Chapter 3 and Chapter 4. In the basic setting in Chapter 3, we considered all centric locations as highly rewarding

locations for co-benefits. Yet, in Chapter 4, high co-benefits emerges mostly in the neighborhood where there is both many available plots, and a high demand, particularly when combining individual and population density-based demand. These neighborhoods are rather located outside of the immediate city center, in the near peri-urban areas. In other words, the urban-rural gradient of NBS potential benefits is non-linear in this case, and presents its peak at a middle point between urban and rural areas.

Regarding groundwater recharge, the hydrogeological study led in parallel to this thesis revealed that the efficacy of groundwater recharge does not follow an urban-rural gradient: it is an entirely different spatial gradient than the distribution of co-benefits. In addition, there is no particular spatial phenomenon associated with demand for groundwater preservation, suggesting no particular spatial pattern either. Although we relied principally on theoretical groundwater recharge (not actual modelling), it appears that our hypothesis of theoretical checkered distribution of Chapter 3 is coherent with the actual distribution from Chapter 4. In other words, there may be highly efficient areas for developing groundwater recharge both in the city center and outside of it.

The second type of contributions of this thesis stems from the previous analysis of the spatial distribution of the benefits of groundwater recharge, and concerns the spatial patterns for optimizing the location for GRI. The first pattern suggests implementing NBGRI near the areas that present the following conditions: densely populated areas with severely degraded ecosystem services, high individual demand for co-benefits, and with a lot of available space for developing NBGRI. These areas may be potential hotspots of environmental inequalities, so this approach can deliver substantial welfare improvement to cities, and they are not necessarily located in the city centers. In our case, they are mostly located in peri-urban neighborhoods.

This pattern comes at a contrast with current greening policies, which are mostly aimed at either relatively wealthy centric neighborhoods or at newly built or under construction urban developments (Kato-Huerta & Geneletti, 2022). In other words, the current distribution of greening projects tend to often perpetuate socio-economic inequities (Calderón-Argelich et al., 2021). Consequently, maximizing NBS locations for delivering co-benefits is inherently linked with distributional environmental justice considerations: the spatial insights resulting from our MOO would potentially lead to mitigate environmental inequalities.

This result may also come as a counter-intuitive insight: city centers, which in Europe are often densely populated, with few green areas, and with few supply of Ecosystem Services (Liotta et al., 2020), do not necessarily appear here as the most optimal areas to target by NBS strategies. Our case study revealed that adaptation strategies should rather be implemented in peri-urban neighborhoods that

immediately surround the city center in order to maximize the benefits of climate change adaptation. Potentially, these areas are the result of 20th century car-centric urban growth, and feature a high amount of car-centric land use (parking lots, large car-centric roads, etc.), leading to more needs for adaptation needs, such as regulating Ecosystem Services (heat mitigation, air depollution, etc.). This result – giving priority to populated car-centric peri-urban areas - comes as a difference to one of our base hypothesis: we supposed in the choice experiment that peri-urban citizens may have more access to private gardens and natural and public green areas, leading to less individual demand for co-benefits. This particular effect remains to be studied though, as we did not identify successfully a substitution effects between NBS and private gardens or existing parks.

In any case, public policies aiming at developing NBS in these areas may need to use a combination of various policy instruments. First, they may require direct public actions for developing NBS, especially along public roads and on public areas. They may also require the implementation of incitation mechanisms, because in peri-urban and centric areas, public policies may need to consider alternative NBS types with less footprint, such as green roofs and facades, or permeable pavements, which have to be implemented on privately owned buildings or gardens. These mechanisms can be for instance subvention mechanisms (Shuster et al., 2013), installation financing (Dhakal & Chevalier, 2017), tax credits (Marshall, 2020; Spiegel-Feld & Sherman, 2017) or even insurance discounts (Mol et al., 2018). These private economic incentive mechanisms would however require to be able to target the specific optimal areas designated by the MOO, so not all may be suitable.

Concerning specialized infrastructures, such as CGRI, our results indicate that they are rather to be developed in the few peri-urban areas that meet the following conditions: having the best hydrogeological conditions for recharge and presenting ample and cheap space for developing recharge infrastructures. Implementing such strategies potentially offers high economies of scale, and a high cost-effectiveness ratio regarding recharge.

This spatial pattern does not come as a stark contrast to existing practices - creating large mono-functional infrastructures outside of urban areas. However, the comparison of this pattern with the optimal patterns for developing NBGRI is of high importance. Potentially, the same peri-urban areas may appear either as optimal for developing multifunctional NBGRI, as mentioned previously, or for specialized CGRI. We can interpret this result as the fact that urban plots which may appear at first to be of interest for developing highly specialized grey infrastructures, may, under the right condition, also be optimal for developing NBS. In this situation, opting for NBS rather than grey infrastructures could lead to reduce environmental inequalities, providing great improvements to public welfare. The goal of the planner is therefore to prioritize the development of NBS at the locations that can simultaneously be very efficient for recharge while yielding high co-benefits. Then, the planners can either develop grey

recharge infrastructures at the locations with only high recharge efficiency (and no particular co-benefit potential), or develop NBS at the locations with only high co-benefit potential. In conclusion, deciders should absolutely adopt a spatial approach to planning adaptation and rainwater management strategies: it can lead to reveal these synergetic solutions that would not necessarily appear otherwise, and an overall guideline to spatial planning.

The second research question of this thesis also concerns the tools for optimizing the location and type of GRI, it is the second meaning of the research question “how to optimize the locations for GRI?”. In conclusion of this thesis, we can assert that MOO is a valuable approach for urban spatial planning. This method fits in a specific niche in decision-support: it provides a framework for creating and comparing spatial strategies, when engaging in the difficult task of designing large-scale strategies with conflicting objectives. As such, this approach has a slightly different scope to Cost-Benefit Analysis and MCDA, which do not provide tools for designing spatial plans.

Nevertheless, MOO poses visualization challenges due to the substantial data and outputs generated. Engaging stakeholders from the outset and devising effective methods to visualize and explore Pareto front results are imperative aspects of using MOO effectively. In fact, this approach is not yet a fully operational and practical method regarding supporting GRI urban planning. Setting aside the fact that implementing a MOO requires a fairly high technical knowledge and risks incurring a black box effect, we argue that this method still lacks proper guidelines for diffusing its implementation for urban decision makers. In particular, there is still much work to do by researchers to incorporate this tool in urban adaptation decision-making frameworks. For instance the analysis of Pareto fronts, and the analysis of the spatial insights resulting from Pareto fronts is still lacking in clear guidelines. The development of these tools may remain still within the domain of expert knowledge and academic research.

However, we argue that there is an opportunity for researchers and particularly environmental economists to seize this method and develop it. MOO is undeniably a valuable tool that can help bridging the gaps between ecosystem services economics and decision-support sciences, and a tool that provides a multidisciplinary interface for all disciplinary fields related to climate change adaptation and land use planning. As a multi-disciplinary interface, it fits well into the requisites of plural valuation culture outlined by environmental valuation researchers and NBS practitioners (Jacobs et al., 2016; Wild et al., 2017). As a spatial planning tool, it fits into the need for integrated spatial assessment and decision-support expressed by researchers (De Groot et al., 2010; Tardieu, 2017). Finally, as a tool that can integrate a variety of perspectives and objectives in spatial planning problems, it can foster transversal actions in public organizations and reduce the fragmentation of services. In fact, there is ample

investigation opportunities for increasing its diffusion towards local decision makers: through stakeholder feedback loops collaborative elaboration, participative analysis processes, its limitations can be overcome (Wicki et al., 2021).

3 Limits and perspectives for further research

This thesis presents various limits. In this section, we highlight first two limitations inherent to the scope of the research, as well as suggestions to improve on these limitations. Then we present two interesting perspectives for further research that emerged from the insights of this thesis.

Starting with the limitations of this work, the first and perhaps most notable element is the almost entire absence of financial costs considerations. Notably, the MOO focused solely on opportunity costs and overarching spatial constraints, excluding other dimensions of costs such as traditional operational and investment costs. We adopted in fact an approach of long term urban planning, consciously omitting notions of costs of GRI and focusing solely on the incentives of managing urban land - with the objective of minimizing opportunity cost. The goal of this approach was to limit our perspective on costs on the most spatially distributed type of costs, those that may be best represented as urban-rural gradients – relying on a hypothesis of spatially constant investment costs. In this case, when dealing with the challenge of urban planning and the spatial prioritization of public policies in a city, it appeared that the inherent cost of using scarce and competed-for space was the best representation of the urban-rural gradient dimension under investigation. In other words, deciding to account solely for spatial opportunity costs was a modelling choice that we made in order to model as best as possible the core of the spatial challenge at hand: the spatially varying complexity of implementing climate adaptation infrastructures, along urban-rural gradients.

As a consequence of this choice, our approach omits a significant portion of the problems of the NBS urban planning problem: how to operate and implement the planning of NBS in cities, under the constraints of limited public budgets and resources? Therefore, further research could reconnect with works being made on the analysis of costs elements of NBS and SuDS. Such approaches could include a lifecycle costing modelling within the MOO approach, while including as well financial budget constraints, established with stakeholders, to represent as best as possible the reality of the problem. This approach would aim at working with public stakeholders at estimating budget levels based on their operational reality. This would also point towards adopting a more dynamic approach in the optimization, by actualizing costs and benefits over a given period of time for instance. In such an approach, the MOO would have an even more operational approach, and would be both a decision-support approach for the planning of NBS strategies, but also for the management of these assets in the long run.

Another avenue for research regarding costs would be to link these costs elements to their potentially different bearers, and therefore bridge this research with recent investigations into the dissemination of NBS costs among various actors in the context of urban planning (Le Gat et al., 2023; Thebault et al., 2020). For instance, plot owners, urban developers, urban greening public services, water treatment services may bear various differentiated parts of the costs of the scenarios ensuing from the MOO. One can imagine that urban green area services would bear the costs of maintenance of NBS, while water and sewage treatment companies and public administration could bear more of the maintenance of underground grey infiltration infrastructures. Such an approach would provide even more operational detail for the organizational planning part of these urban planning scenarios. Including such considerations would illustrate yet another type of trade-offs into the MOO: the trade-offs between the various management entities and departments of a large city. A practical way to implement this addition to our design would be to first investigate and classify the cost sharing elements, according to the types of urban spaces, areas, and types of implemented infrastructures, and add these details to the description of the solutions. This would not add require to add an objective or change the constraints of the problem, yet add interesting layers of information for the interpretation of the solutions.

Extending this logic further, one can imagine that such considerations would allow to consider how public and private entities would be mobilized with different relative intensity for implementing NBS strategies. In an urban spatial planning problem like the one investigated in this thesis, this involves delving more deeply into the land ownership of the selected plots. With such an addition, the MOO would also be a way to investigate further the policy instruments required to develop NBS strategies, for instance, the required monetary transfer approaches that could incentivize actors to develop NBS.

A second crucial point that fell outside of the scope of this thesis is the consideration of the most common reason behind the incentive to develop NBS and SudS in cities: flood risk mitigation. This work really focused on the policy innovation of the specific R&D project initiated in the Bordeaux Metropolitan area: groundwater recharge dedicated to the preservation of deep water stocks, through the mechanism of water use substitution, by using GRI. However, despite this novelty, the objective of mitigating flood risks in the metropolitan area is still present and a central one – it is in fact the main objective of rainwater management. Flood risk mitigation is also one of the objectives of the interest of the metropolitan government of Bordeaux into groundwater recharge, although a secondary one in this particular case. Indeed, infiltrating rainwater can reduce surface water runoff, and thus participate to mitigate flood risks. In the case of the Metropolitan area of Bordeaux, including such extensions on risk mitigation is in fact an interesting perspective, identified by the rainwater management services.

Flood risk mitigation is the main policy driver in most cities, linking our decision support approach to flood risk mitigation could extend the applicability and value of this work. Such an approach could also extend how the benefits of rainwater infiltration are represented in this thesis. Taking into account both the benefits on groundwater preservation and flood risk mitigation could lead to obtain a more thorough appreciation of the nature of the multiple benefits related to groundwater preservation (Hérivaux & Rinaudo, 2016).

One possibility to extend this work to include such considerations can be to link the MOO with an approach of risk modelling. It would consist in interfacing a hydrological model of surface runoff, and simulating the risk reduction added by the various planning solutions, as in scenario-based approach. This would lead to increase even more the focus on the spatial heterogeneity of the potential benefits of GRI: the distribution of potential benefits would not only depend on hydrogeological characteristics of urban soils – illustrated in our approach through the multicriteria score of the recharge favorability map – but also on other spatially varying factors such as water runoff characteristics or the particular placement of GRI within the hydrological basin. Recent advancements in MOO have successfully achieved such objectives in incorporating flood risk modelling, though it requires deeper expertise on water runoff models (Alves et al., 2020; Behroozi et al., 2018; Majidi et al., 2019).

Such extensions would however have to deal with the computational limitations of MOO. Increasing the number of objectives to include in a MOO - without relying on scalarization approaches - is notoriously complex for reasons of computational burden and output visualization difficulty, and most applications in economics typically stand at a maximum of four objectives (Allmendinger et al., 2022; Deb & Jain, 2013). There is therefore a trade-off between increasing the scope of a MOO approach by adding objectives, and maintaining a solvable and practical framework. In consequence, a crucial approach to developing a MOO is the prior identification and ranking of potential objectives. This first step is especially important in the case of environmental planning problems, as a great diversity of Ecosystem Services have been neatly classified (De Groot et al., 2002; Mader et al., 2011). This method is suitable in other environmental planning decision problems, on the condition that either not all Ecosystem Services have to simultaneously be optimized, or that a handful of them can be picked out as most important and deserving to be considered as an optimization objective.

Finally, this thesis also presents interesting perspectives for future research.

The first area of potential exploration arises from the choice experiment approach used in Chapter 2. The goal of this study was to shed light onto the spatial determinants of the demand for co-benefits, and, encouragingly, our research identified significant relationships between inequalities and the

demand for co-benefits, which is a relatively novel research area in stated preference studies, offering numerous avenues for further investigation.

Firstly, future research could delve deeper into the three types of environmental inequalities addressed in this study. Concerning inequalities related to environmental hazards, research could focus particularly on flood risks, and how perceived or actual exposure to flood risks impacts the demand for policies aimed at reducing such risks. This exploration may uncover disparities between areas with high demand for flood mitigation and those where implementing mitigation measures, such as SuDS would be most effective.

Additionally, regarding the second type of inequality investigated in [Chapter 2](#) (access to green areas), further research could expand upon this theme. Existing literature has identified significant socio-demographic disparities in access to green spaces (M. Wolff, 2021), yet our study did not find a noticeable impact on the demand for NBS. Subsequent research in stated preference could delve into the practices of individuals regarding urban green spaces (Bülow et al., 2022), to better determine the nature of this type of environmental inequality and its relationship with demand for urban NBS. This investigation could uncover the relationship between these practices and the demand for NBS. There is also avenue with this approach to refine the substitution effect hypothesis elaborated in [Chapter 3](#).

Finally, an innovative avenue of research lies in a more in-depth exploration of the third type of inequality. Our study offered a preliminary analysis of car use frequency and its influence on the demand for NBS policies affecting car space, positing that this reflects inequalities concerning the adverse effects of policies. Contemporary public greening policies often involve the restriction of car access to city centers, sparking debates and controversies. In very broad terms, these policies have been criticized for potentially excluding low-income and suburban populations from inner-city areas. Analyzing car dependency at the broader urban scale and its impact on the acceptance of urban NBS and greening policies could provide valuable insights for urban planners. To further investigate this line of inquiry, a more detailed analysis of transportation practices and individual car dependency within a discrete choice experiment could shed light on the nature of this inequality. An essential aspect of this investigation would involve examining the relationship with socio-demographic characteristics, particularly income.

The second potential extension to the research developed in this thesis concerns the innovations in decision-support methods. A promising area of investigation can be the interfacing of MOO and Multi-Criteria Decision Analysis, for linking the implementation of a MOO with the subsequent exploration of its outputs alongside stakeholders. Both methods indeed have advantages that may be combined. In essence one strength of MOO in such a context is to reduce a potentially quasi-infinite set of solutions to just a handful of solutions. However it does not necessarily provides easy signals for the elicitation

of a best course of actions among these solutions. The MOO exposes the stakeholders to a large Pareto front, often constituted of a myriad of complex solutions. The exploration and visualization of these solutions is in itself a challenge and a limit to the broader diffusion of this method, and one we started to address by integrating novel participative exploration methods in chapter 3. In addition, once these solutions are visualized and understood by stakeholders, and once the main trade-offs are identified, deciding on a single best solution is a complex task, and one that has been relatively less studied.

Multi Criteria Decision Analysis, in contrast, provides a clear, participative, and tractable way of making decisions collectively, when faced with a handful of well-defined options. In this regard, this decision-making method provides potentially a good solution to the limits of MOO. Such an approach would result in mixing a top-down “expert” approach - here the MOO - and a bottom-up approach - the MCDA - into the decision-making process (Girard et al., 2015). It could lead to select which parts of the Pareto front and which solution are favored by stakeholders, and even to provide insights into the different values and opinions between stakeholders, and how these differences materialize in terms of favored solutions. This approach could even be developed up to the point of analyzing multi-criteria analysis with weighting schemes that comes from the public (Estévez & Gelcich, 2015).

In conclusion, our investigations showed that there are valuable synergies to be found in urban groundwater recharge development. These synergies hinge on the spatial distribution of potential environmental benefits. Addressing our first research question, we have unveiled that the distribution of these benefits can deviate from prevailing practices in NBS and groundwater recharge implementation. Notably, urban greening initiatives may not always yield optimal results in city centers, and large suburban sites may not be the most efficient areas for groundwater recharge, especially in the context of small scale water use substitution, as in the case of the Bordeaux Metropolitan area.

Urban strategies aiming for effective climate change adaptation must account for these spatial dimensions; because proactive environmental action requires a comprehensive exploration of spatial trade-offs, the consideration of citizen demands, the anticipation of policy acceptance, and the optimization of spatial resources, among other factors. Emerging methodologies, such as Multi-Objective Optimization, may assume greater significance in future environmental economics toolkits to address these intricate spatial challenges.

The effects of climate change on cities and on their water supplies are too numerous and too severe for academics and policy makers to pass on the exploration of all existing decision-support approaches. This line of investigation holds the potential to uncover new policy-making methodologies that may

help achieve the widespread adoption of integrated, precise and effective climate adaptation strategies, before the window of opportunity for adaptation closes.

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Supplementary materials

1 Supplementary material to Chapter 2

1.1 Maximum benefits estimation for the selection of levels in the Choice Experiment

This supplementary material explains the methods used for the estimation of the maximum levels of benefits (groundwater preservation and heat island mitigation) of the choice experiment. Rather than estimating the real impacts of future recharge policies, the objective of this work was to estimate plausible maximum levels for the choice experiment, and subsequently adjust the other levels.

The first workshop dedicated to the choice experiment led to identifying spaces that may be dedicated to GRI (Figure 1). In the second workshop, we quantified the maximum proportion of these spaces that may be used for NBGRI and CGRI. We then estimated the level of benefits resulting from this highest level of ambition.

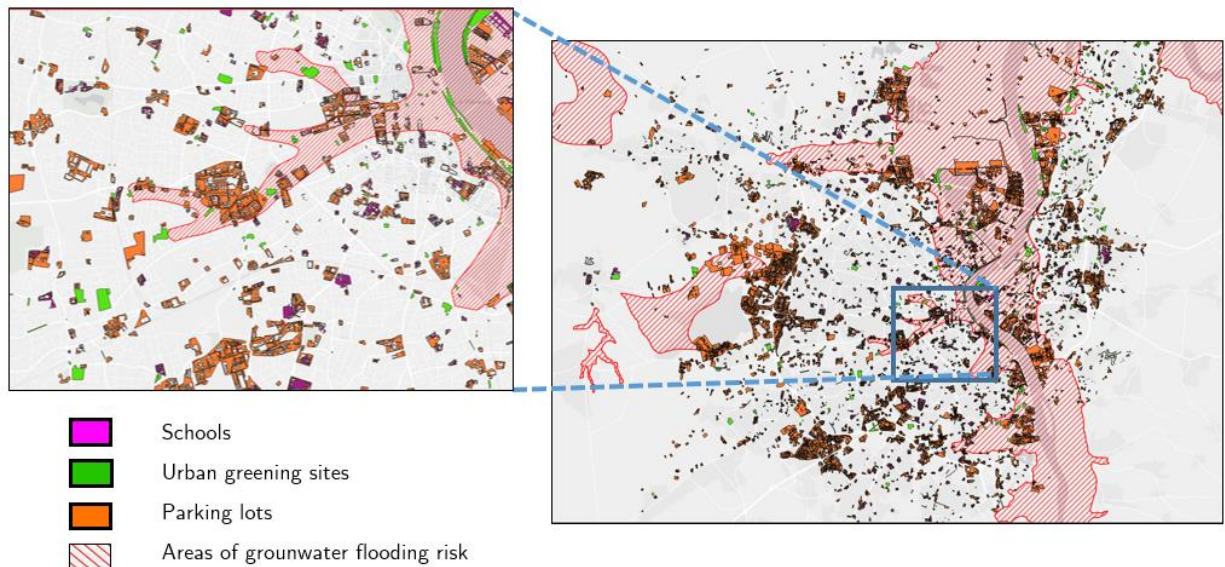


Figure 1: Available sites for GRI

For the groundwater savings benefit, we estimated how substituting water uses that are currently covered by drinkable water with infiltrated rainwater could allow reaching the consumption objectives of deep aquifer stocks. These extraction goals are fixed at the water basin level (“SAGE nappes profondes”), and define the maximum annual volumes of water that can be extracted in order to reach a sustainable long term states of aquifers, at the scale of regional sub-units, and for each exploited aquifers. The current extraction rate for some of these aquifers sub-units (“Eocène Centre”) is deemed

unsustainable, as the extracted levels are superior at about 3 million m³ to the maximum extractable objective volumes. This regional sub-unit do represent a larger area than the Bordeaux Metropolitan Area though, therefore the deficit volume of 3 million m³ may be an overestimation.

We proceeded to identify and quantify the possible substitutable uses for infiltrated water in surface aquifers. We restricted this estimation to water uses that are currently covered by drinkable water but that could use water of a lesser quality. This work was done by collecting public water consumption data and by performing a series of interviews with employees of the local government. We listed and quantified the volumes used for watering urban green areas, parks and sports facilities, and for street cleaning. We included the annual volumes consumed by private or public consumers with specific water meters dedicated to garden watering (“compteur vert”). Finally, we added a broad estimation of the annual water volumes required for the watering of the trees that may be planted in the future within the territory of the Bordeaux Metropolitan Area as part of its urban greening policy (“1 million d’arbres”). This sum reached 2.8 million m³, that is to say a comparable order of magnitude to the annual deficit in the aquifer sub-units.

The last phase of this work consisted in estimating the volumes of water that could be infiltrated and “stored” in surface aquifers, with the purpose of using it for covering the uses listed above. This work was also done in a very simplistic way, we only quantified the potential volumes of infiltrated water, without considering water movements in aquifer. We considered a very simple “bathtub” model linking soil permeability, infiltration surfaces and rain volumes.

We used the local rules for stormwater management in new construction projects to estimate how much active infiltration areas would be associated to the infiltration project areas that would be developed at the maximum ambition level (as decided during the choice experiment workshop). This allowed to define the sum of active infiltration areas, and link these areas with the mean annual days of rain in the area. Using this surface areas estimate, we calculated the maximum volume (V_{max}) that can be infiltrated daily in all the GRI sites, that is to say, at the Metropolitan Area Scale, using the following formula:

$$V_{max} = S_a * T * K$$

Where S_a is the sum of active infiltration areas (in m²), K is the mean soil permeability (in m/s), T is the duration of infiltration (in s). K was set to be equal to 1.10^{-5} , which is an approximate mean of soil permeability in the area. T was set as 86400s (24 hours), which is the maximum legal duration of time that a stormwater management infrastructure can store water before it has to be evacuated, according to local rules.

We proceeded to compare V_{\max} to the potential volumes of rainwater that would be available daily, during the whole 1990-2020 period. We considered that above V_{\max} , the “excess” water would be evacuated in the traditional in-pipe management system. All the volumes of rainwater under V_{\max} would therefore be infiltrated. These simulations indicated that annual infiltrated water volumes could range between 10^6 and 10^7 m³.

Overall this simulation indicated that infiltrating rainwater may produce a resource at an order of magnitude similar to the needs for water use substitution, and sufficient for reaching almost entirely the deep aquifer extraction goals. Although extremely simplistic, these comparisons and simulations were presented to the stakeholders during workshop and validated. Consequently, the maximum level of the attribute “Deep aquifer preservation” was set as “100% of groundwater savings thanks to infiltration”.

1.1.1 Local climate regulation

The method for estimating the maximum level of reduction of heat island areas was calculated in a very simple manner. We mapped the areas of heat island using thermal imagery captured by the Landsat satellite during a heat wave episode (08-07-2018). We selected all areas with surface temperature superior to the mean plus standard deviation (34.1°C) of all areas (*Figure 2*). Then we calculated a buffer zone of 100m around all sites (see *Figure 1*). This distance area is a mean of estimations of the cooling effect of small urban green infrastructures found in literature (Aram et al., 2019; Lin et al., 2015; Z. Yu et al., 2020). We then clipped the heat areas with the buffer zones, therefore making the strong assumption that these areas “covered” by the cooling effect of SuDS would be entirely cooled, up to the point that they would not be heat islands anymore. This simple estimation indicated that 60% of the identified heat island areas would be eliminated. This approach was later refined with in Chapter 4, where we modelled buffers of varying size.



Figure 2: Heat island areas in the Bordeaux Metropolitan Area (Landsat 8 B10, 08-07-2012)

1.1.2 Distance attribute

The maximum value for the distance attribute was based on literature: 500m has been identified as a reasonable maximum walking distance for small urban green areas (Jarvie et al., 2017; Q. Zhou et al., 2013).

1.2 Level coding in the choice experiment

The following table explains how levels and attributes are coded in the choice experiment.

| Attribute | Levels | Coding |
|---|--|---------------|
| Deep aquifers preservation | Inf_25 | [0, 0] |
| | Inf_50 | [0, 1] |
| | Inf_100 | [1, 0] |
| | Status Quo | [0, 0] |
| Reduction of heat island areas during heat waves | Heat_20 | [1, 0, 0] |
| | Heat_40 | [0, 1, 0] |
| | Heat_60 | [0, 0, 1] |
| | Status Quo (No reduction) | [0, 0, 0] |
| Impact on urban space dedicated to car use | Red_car | 1 |
| | Status Quo (No reduction) | 0 |
| Distance to the nearest green infrastructure | Dist_0 | [1, 0, 0] |
| | Dist_100 | [0, 1, 0] |
| | Dist_500 | [0, 0, 1] |
| | Status Quo (No new green infrastructure) | [0, 0, 0] |
| Increase in annual water bill | 30 | 30 |
| | 60 | 60 |
| | 90 | 90 |
| | 120 | 120 |
| | 150 | 150 |
| | 180 | 180 |
| | Status Quo (0) | 0 |

Table 1: Attribute and level coding. In the analysis phase, the two levels of groundwater preservation are coded ‘Inf_50’ and ‘Inf_100’; the three levels of heat island reduction are ‘Heat_20’, ‘Heat_40’ and ‘Heat_60’; the reduction of car space is ‘Red_car’, the distance attribute levels are ‘Dist_0’, ‘Dist_100’ and ‘Dist_500’, the Status Quo is ‘SQ’, and the payment attribute is ‘Payment’.

1.3 Sociodemographic data

The following table details the socio-demographic representativeness of our sample.

| | Sample Average | Bordeaux Area | Metropolitan |
|--|----------------|------------------|--------------|
| Sample size | 293 | 814,049 | |
| Socio-demographic data | | | |
| Age | | | |
| 18-29 (%) | 16.9 | 27.4 | |
| 30-44 (%) | 24.2 | 20.2 | |
| 45-59 (%) | 31.5 | 18.1 | |
| 60-75 (%) | 24.8 | 13.5 | |
| 75-99 (%) | | 8 | |
| Gender (% of female) | 55.2 | 52 | |
| Unemployed (%) | 8.9 | 20 | |
| Retired (%) | 22.2 | 21.3 | |
| Education | | | |
| Primary (%) | 1.7 | 15 | |
| Lower Secondary (%) | 14.2 | 5.1 | |
| Upper secondary (%) | 25.8 | 37.1 | |
| Tertiary (%) | 58.3 | 42.6 | |
| Income (%) | | | |
| < 500€ | 1.7 | - | |
| 500 - 1000 € | 6.3 | - | |
| 1000 - 1500 € | 7.0 | - | |
| 1500 - 2000 € | 21.2 | - | |
| 2000 - 3000€ | 24.8 | - | |
| 3000€ - 4000€ | 21.9 | - | |
| 4000€ - 5000€ | 8.6 | - | |
| 5000€ - 6000€ | 6.0 | - | |
| > 6000€ | 2.6 | - | |
| Household characteristics | | | |
| Household size (mean) | 2.2 | 1.9 | |
| Household with dependent children (%) | | | |
| Lives in a house (%) | 46 | 39.1 | |
| Home owner | 52.6 | 42.5 | |
| Private car ownership (%) | 85.4 | 77.1 | |
| Spatial characteristics | | | |
| Approximate distance to closest green urban area (%) | | | |
| ≤ 100m | 34.8 | - | |
| 200m | 18.2 | - | |
| 500m | 25.8 | - | |
| 1km | 10.9 | - | |
| Lives in proximity to a heat island | 46.7 | - | |
| Perception of the level of information provided by the questionnaire (%) | | | |
| Totally insufficient | 1.0 | - | |
| Insufficient | 7.6 | - | |
| Sufficient | 25.2 | - | |
| Totally sufficient | 66.2 | - | |

Table 4: sociodemographic representativeness of the sample

1.4 Latent class (LC) model

We also explored the heterogeneity of preferences suggested by the MIXL model, with al Latent class (LC) model.

The latent class (LC) model addresses preference heterogeneity across respondents by grouping them in a number of classes with homogeneous preferences. Each respondent is assigned to one of the S classes: the probability for respondent n to belong to class c is denoted $M_{n,s}$ (with $\sum_{s=1}^S M_{n,s} = 1$) and is equal to :

$$M_{n,s}(\theta) = \frac{\exp(\theta_c Z_n)}{\sum_{s=1}^S \exp(\theta_{nc} Z_n)} \quad (5)$$

With θ a vector of class membership parameters. The probability of respondent n of class c choosing i in situation t :

$$P_{nit}(i|\beta^s) = \frac{\exp(\beta_n X_{it})}{\sum_{j=1}^J \exp(\beta_n X_{it})} \quad (6)$$

Because the class of each individual is *a priori* unknown, that same probability is given by :

$$P_{nit} = \sum_{s=1}^S M_{n,s} \prod_{t=1}^T P_{nit}(i_{nt}|\beta_c) \quad (7)$$

In this study, the estimation of the LC model is done using the STATA “lcllogit” package.

A 3 class model is selected. A 2 class and a 4 class model led to having at least one class with no significant attributes, making interpretation impossible. Above 4 classes, the LC model did not converge.

| LC | | | |
|--------------------------|----------|---------|-----------|
| coefficients | Class1 | Class2 | Class3 |
| Inf_50 | 0.393 | 0.168 | 0.413** |
| Inf_100 | 0.437 | 0.379 | 0.551*** |
| Heat_20 | 0.389 | 0.116 | 0.706*** |
| Heat_40 | 0.461 | 0.546 | 0.903*** |
| Heat_60 | 0.758* | 0.553 | 1.106*** |
| Red_car | -0.379** | - | 0.335*** |
| | | 1.977** | |
| Dist_0 | 0.553 | 0.236 | 0.615*** |
| Dist_100 | -0.228 | 0.704 | 0.507** |
| Dist_500 | 0.021 | 1.414** | 0.484*** |
| SQ | -0.970* | - | -2.648*** |
| | | 1.672** | |
| Payment | - | -0.001 | -0.004*** |
| | 0.022*** | | |
| Constant | 2.503 | -5.035 | - |
| Mean | -0.122 | 0.074 | - |
| Temperature | | | |
| Car use | 0.027 | 0.437** | - |
| frequency | | | |
| Age | 0.264 | -0.137 | - |
| Education | -0.033 | -0.311 | - |
| Income | -0.082 | 0.350** | - |
| Class Share | 0.189 | 0.292 | 0.519 |
| Log-likelihood | - | | |
| | 1428.899 | | |
| LR chi ² (11) | 386.55 | | |
| | - | | |
| AIC | 2927.798 | | |
| BIC | 3157.528 | | |

Table 5: LC model results.

Significance of the coefficients marked by asterisks: *** p value < 1%, ** p value in [1, 5%), * p value in [5, 10%) ; n(observations) = 5238

The LC model confirms the existence of heterogeneity within our population sample. Only for class 3 are all coefficients significant, while the other two have only significant coefficients for very few attributes. Only class 3 has significant and positive coefficients for Inf_50 and Inf_100. Class 1 and 2 do not consider this benefit.

Class 1 has a significant coefficient only for the highest level of heat reduction, while both classes have significant and increasing coefficient for the 3 levels of this attribute.

Class 1 and 2 have negative coefficients for Red_car, suggesting that they consider it as a disservice, as suggested by mean estimates from the MIXL model. Class 3 on the other hand has positive coefficient, suggesting car reduction is rather perceived as a benefit.

The distance levels coefficients are all significant for class 3, with the highest one for dist_0, indicating a preference for close-by infrastructures. Class 2 seems to indicate some preference for further infrastructures, with a positive coefficient for dist_500, although with little significance.

All 3 classes have a significant and negative coefficient for the SQ attribute, with the highest in absolute value for class 3, indicating a preference for the implementation of GRI alternatives rather than nothing at all. The payment coefficient is significant (and negative) for class 1 and 3, but it is not for class 2. It is higher in absolute value for the first class. This suggests that the attributes of heat reduction and car reduction were the only one influencing the choice of the individual of this class.

The LC model indicates 3 contrasted profiles in our sample:

- Class 3 is made of individuals who are sensitive to both groundwater preservation and heat island reduction, with a high demand for NBGRI in their immediate surroundings. They also represent more than half respondents.
- Class 1 are individuals with the lowest demand for GRI alternatives. The reduction of car space and increase in annual water bills affect strongly and negatively their choices.
- Class 2 has a more ambiguous profile. It indicates individuals with a strong aversion to car space reduction, and that favour solutions further away from their home, showing a potential “Not In My Backyard” effect. These are individual that depend on car use, and of higher income, which would explain that their payment coefficient is not significant (our payment levels may not have captured their range of WTP).

1.5 Choice experiment questionnaire

In the following appendix, we present the questionnaire used for the discrete choice experiment survey of 2022. All 12 choice sets are presented here, but respondents were only presented with 6 of them (chosen randomly out of the pool of 12 choice sets). The French language version of the questionnaire is presented here. An English translation may be made available upon request.

Des solutions d'infiltration des eaux pluviales pour préserver les ressources en eau potable

Bonjour,

Ce questionnaire a été développé par l'Université de Bordeaux* et le BRGM* dans le cadre d'un projet de recherche de Bordeaux Métropole. **Il porte sur la mise en place de solutions d'infiltration des eaux pluviales sur le territoire**, et leur contribution à **la préservation des ressources en eau potable et l'adaptation de la ville au changement climatique**.

Ce questionnaire vise à recueillir votre opinion sur la mise en oeuvre de ces solutions. Les résultats de ces travaux seront pris en compte par Bordeaux Métropole dans la conception de programmes d'action. Vous aurez besoin d'environ 10 minutes pour répondre à l'ensemble des questions.

*Le laboratoire *Bordeaux Sciences Économiques* (BSE) est une unité de recherche de l'Université de Bordeaux, spécialisée dans la recherche en sciences économiques <https://www.bse.u-bordeaux.fr/>

*Le *Bureau de Recherches Géologiques et Minières* (BRGM) est un établissement public de recherche dans le domaine de l'eau, de l'environnement et des risques naturels <https://www.brgm.fr>

Toutes les données seront traitées de manière confidentielle et vos données personnelles ne seront pas publiées. Les données personnelles recueillies sur ce formulaire sont enregistrées dans un fichier informatisé par le BRGM et l'Université de Bordeaux uniquement pour réaliser cette étude. Elles ne seront en aucun cas utilisées à des fins commerciales. La base légale du traitement de vos données personnelles relève de la satisfaction de l'intérêt public. Les données personnelles sont conservées pendant cinq (5) ans. Vous pouvez accéder aux données personnelles vous concernant, les rectifier, demander leur effacement ou exercer votre droit à la limitation de leur traitement. Vous pouvez retirer à tout moment votre consentement au traitement de vos données personnelles. Vous pouvez également vous opposer à leur traitement de vos données. Vous pouvez enfin exercer votre droit à la portabilité de vos données personnelles. Pour exercer ces droits ou pour toute question sur le traitement de vos données personnelles dans ce dispositif, vous pouvez contacter le Délégué à la Protection des Données du BRGM (dpo@brgm) Si vous estimez, après nous avoir contactés, que vos droits « Informatique et Libertés » ne sont pas respectés, vous pouvez adresser une réclamation à la CNIL.

Avant de commencer, pouvez-vous répondre à ces questions préliminaires ?

Avez-vous déjà répondu à ce questionnaire ?

Oui

Non

Vous êtes:

un homme

une femme

Quel âge avez-vous ?

- Moins de 18 ans
- 18 - 29 ans
- 30 - 44 ans
- 45 - 59 ans
- 60 - 74 ans
- 75 - 99 ans



Résidez-vous dans une des communes de Bordeaux Métropole ?

Oui

Non

Résidez-vous à Bordeaux ?

Oui

Non

Dans quelle autre commune de la Métropole résidez-vous ?

Quelle est votre catégorie socio-professionnelle ?

- Agriculteurs exploitants
- Artisans, commerçants et chefs d'entreprise
- Cadres et professions intellectuelles supérieures
- Professions intermédiaires
- Employés
- Ouvriers
- Retraités
- Inactifs

Bordeaux Métropole et l'eau potable

La métropole de Bordeaux compte 28 communes et **800 000 habitants**.

L'alimentation en **eau potable** de la métropole est assurée par des prélèvements dans les **nappes d'eaux profondes**, à hauteur de **55 millions de m³** par an (soit 22 000 piscines olympiques). Ces nappes profondes sont des ressources d'**excellente qualité**, dont le renouvellement est très lent (plusieurs milliers d'années).

D'ici **2050**, les **prélèvements** nécessaires pour **assurer l'alimentation en eau potable** de la population vont augmenter. Ceci pose un risque sérieux de **surexploitation des nappes profondes** du territoire, pouvant entraîner d'importants surcoûts pour les collectivités, qui devront alors acheminer de l'eau à partir d'autres ressources plus distantes.

Les collectivités engagent un ensemble d'actions pour économiser l'eau et assurer l'équilibre des nappes.

Saviez-vous que l'eau potable que vous utilisez provient des nappes profondes ?

Oui

Non

Les solutions d'infiltration des eaux pluviales

La métropole connaît des précipitations importantes. La gestion actuelle des eaux pluviales consiste à les collecter, les épurer, et les rejeter dans les cours d'eau. **Les eaux de pluie sont très peu réutilisées sur le territoire.**

Dans ce contexte, la métropole envisage de **développer l'infiltration des eaux pluviales dans les nappes superficielles**. Cela vise à favoriser le **stockage** de ces eaux dans les **nappes superficielles**, qui peuvent alors être **réutilisées** localement pour **certains usages ne nécessitant pas une qualité d'eau potable** (arrosage des espaces verts, nettoyage des voiries, etc.).

Ceci contribue à **préserver** les nappes profondes.

Connaissez-vous la gestion actuelle des eaux pluviales ?

Oui

Non

Les solutions d'infiltration des eaux pluviales

Plusieurs types de solutions existent pour infiltrer des eaux pluviales:

- Des **solutions classiques** : puits d'infiltration, revêtements perméables, etc.
- Des **solutions végétalisées**, similaires à des espaces verts, qui infiltrent les eaux pluviales et **gènèrent d'autres bénéfices** (rafraîchissement des températures en période de canicule, amélioration de la qualité de l'air, soutien à la biodiversité, etc.).

Ces solutions peuvent être développées sur divers **espaces**: sur des places, le long d'axes de circulation, dans des cours privées, cours d'écoles, etc.

Exemples de solutions classiques :



Puits d'infiltration



Exemples de solutions d'infiltration végétalisées :



Fossé végétalisé (Bordeaux)



Bassin végétalisé (Bordeaux)



Bassin végétalisé (Montpellier)

Quelles solutions connaissiez-vous ?

Les solutions d'infiltration
végétalisées

Les solutions d'infiltration
classiques

Aucune des deux

Résidez-vous déjà à proximité d'une solution végétalisée ?

Oui

Non

Je ne sais pas

A quelle distance de chez vous se situe-t-elle environ ?

Bénéfices des solutions d'infiltration

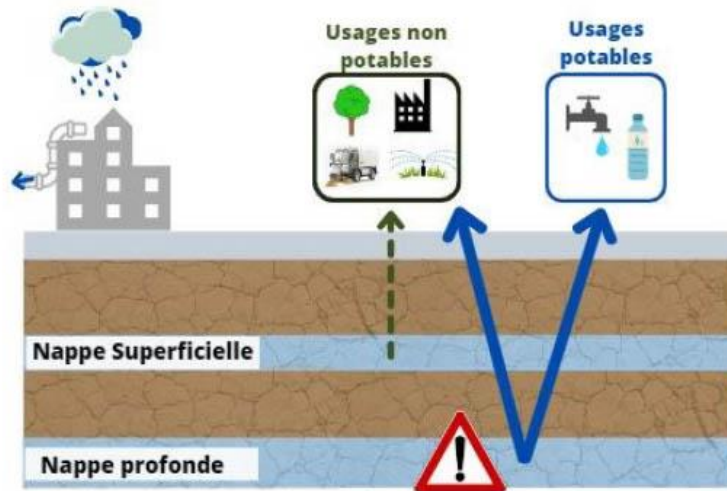
1. L'économie d'eau des nappes profondes

Afin de gérer durablement ces nappes profondes, la Métropole s'est fixée comme objectif de réduire les prélèvements de **2,5 millions de m³** d'eau par an.

Pour atteindre cet objectif d'**économie d'eau**, il est possible de **reporter des usages d'eau** vers les **nappes superficielles**. Toutefois aujourd'hui, l'**imperperméabilisation** des sols empêche le remplissage de ces nappes superficielles. Développer l'**infiltration des eaux pluviales** est donc nécessaire pour assurer le remplissage de ces nappes.

Sans développement de l'infiltration :

Les eaux pluviales ne s'infiltrent pas.
Les **nappes superficielles** sont peu utilisées.
Les **nappes profondes** sont surexploitées.

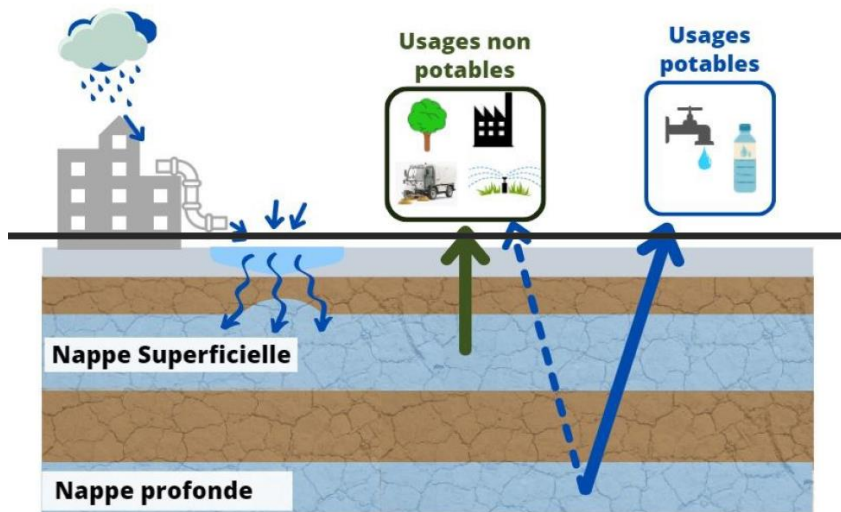


Développement de l'infiltration:

Des solutions d'infiltration sont mises en place.

Les **nappes superficielles** sont utilisées pour les usages non potables.

Les **nappes profondes** sont privilégiées pour les usages potables.



Atteindre l'objectif d'économie d'eau des nappes profondes grâce au développement de l'infiltration vous semble-t-il plausible ?

Tout à fait

Plutôt oui

Plutôt non

Pas du tout

Pouvez-vous préciser pourquoi ?

2. La réduction des surfaces de forte chaleur

En période caniculaire, certains espaces urbains deviennent des **zones de forte chaleur** qui ont un **impact fort sur la santé** (inconforts thermiques, perturbation du sommeil, surmortalité des personnes vulnérables...).

Elles couvrent environ **10%** (3100 hectares, soit 4200 terrains de football) des zones bâties de la métropole, et il est estimé que les épisodes de canicule vont passer de **8 à 20 jours par an** en moyenne d'ici 2050 du fait du changement climatique.

Les **solutions classiques** d'infiltration permettent **seulement d'infiltrer** les eaux pluviales, tandis que les **solutions d'infiltration végétalisées** pourraient permettre de **réduire jusqu'à 60% les zones de forte chaleur en ville**, comme l'illustre cette vidéo :



La vidéo s'est-elle correctement affichée ?

Oui

Non

Avez-vous déjà vécu un épisode caniculaire sur le territoire de Bordeaux Métropole ?

Oui

Non

Habitez-vous à proximité d'une zone de forte chaleur ?

Oui

Non

Je ne sais pas

Est-ce qu'atteindre cet objectif de réduction (-60%) des surfaces de forte chaleur avec les solutions végétalisées vous semble plausible?

Tout à fait

Plutôt oui

Plutôt non

Pas du tout

Pouvez-vous préciser pourquoi ?

Des scénarios de développement de l'infiltration



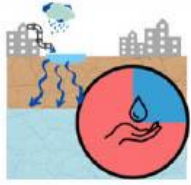
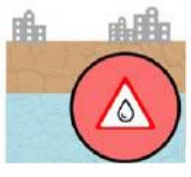
Développer l'infiltration nécessite pour Bordeaux Métropole de choisir parmi différents **scénarios** d'action. Ces scénarios peuvent combiner **des solutions de différents types** (végétalisées ou non), et être mises en œuvre à **différentes échelles**, et ainsi avoir des **impacts différents**.

Ces scénarios présentent 5 caractéristiques différentes :

- L'économie d'eau des nappes profondes
- La réduction des zones de forte chaleur en période caniculaire
- La réduction de l'espace dédié à la voiture
- La distance entre votre lieu de résidence et la solution végétalisée la plus proche
- La contribution monétaire

Caractéristique 1 : L'économie d'eau des nappes profondes

Les scénarios proposés permettent d'atteindre différents niveaux d'économie d'eau des nappes profondes grâce à l'utilisation d'eau pluviale réinfiltrée dans les nappes superficielles :

| | |
|--|---|
| 100% de l'objectif d'économie d'eau des nappes profondes grâce à l'infiltration |  |
| 50% de l'objectif d'économie d'eau des nappes profondes grâce à l'infiltration |  |
| 25% de l'objectif d'économie d'eau des nappes profondes grâce à l'infiltration |  |
| Pas d'économie d'eau des nappes profondes grâce à l'infiltration |  |

Quel niveau d'atteinte de l'objectif d'économie d'eau des nappes profondes grâce à l'infiltration préférez-vous ?

100% de l'objectif d'eau des nappes profondes grâce à l'infiltration

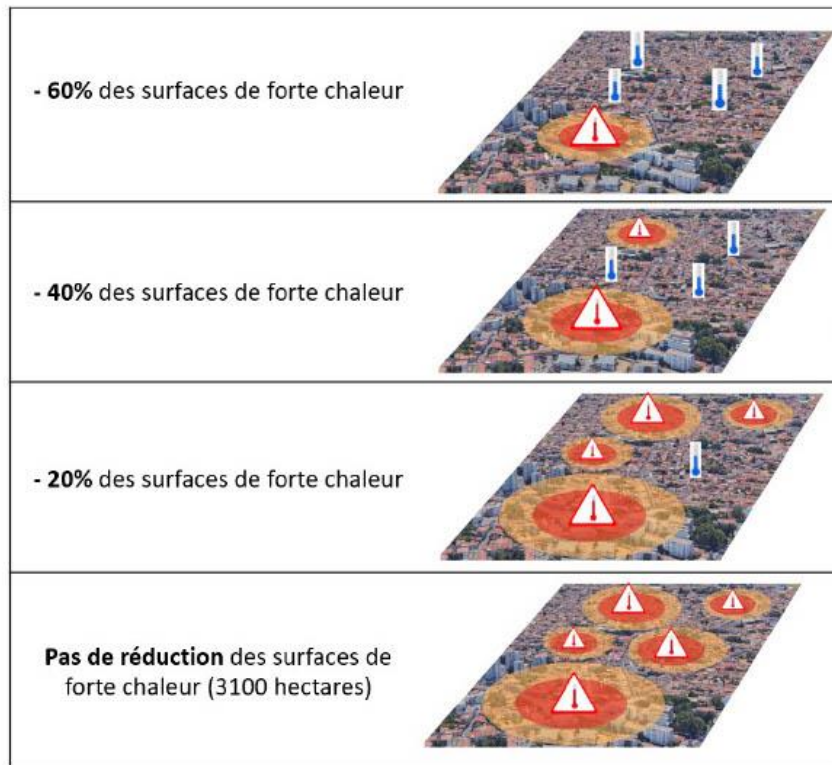
50% de l'objectif d'eau des nappes profondes grâce à l'infiltration

25% de l'objectif d'eau des nappes profondes grâce à l'infiltration

Pas d'économie d'eau des nappes profondes grâce à l'infiltration

Caractéristique 2 : La réduction des zones de forte chaleur en période caniculaire

Les scénarios de développement de l'infiltration permettent de réduire plus ou moins les surfaces de fortes chaleurs :



Quel niveau de réduction des surfaces de forte chaleur préférez-vous ?

- 60% des surfaces de forte chaleur

- 40% des surfaces de forte chaleur

- 20% des surfaces de forte chaleur

Pas de réduction des surfaces de forte chaleur

Caractéristique 3 : Implantation des solutions et espace dédié à la voiture

La mise en place de solutions d'infiltration des eaux pluviales peut nécessiter **d'utiliser plus ou moins d'espace dédié à la voiture** (axes de circulation, parkings). Les scénarios présentent deux possibilités:



Laquelle de ces deux possibilités préférez-vous ?


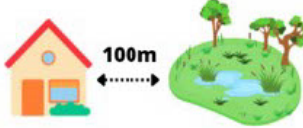
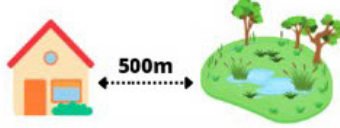

Réduction de l'espace dédié à la voiture

Pas de réduction de l'espace dédié à la voiture

Je suis indifférent

Caractéristique 4 : Distance aux solutions végétalisées

Des solutions d'infiltration pourraient être développées à proximité de votre domicile. Selon les scénarios, la **solution d'infiltration végétalisée la plus proche** peut se situer plus ou moins loin:

| | |
|---|---|
| Solution végétalisée en face de chez vous |  |
| Solution végétalisée à 100m de chez vous |  |
| Solution végétalisée à 500m de chez vous |  |
| Pas de nouvelle solution végétalisée proche de chez vous |  |

Parmis ces différentes distances entre votre lieu de domicile et la solution végétalisée la plus proche, que préférez-vous ?

Solution végétalisée en face de chez vous

Solution végétalisée à 100m de chez vous

Solution végétalisée à 500m de chez vous

Pas de nouvelle solution végétalisée proche de chez vous

Je suis indifférent

Caractéristique 5 : votre contribution

La mise en place de ces scénarios nécessite pour Bordeaux Métropole de réaliser d'importants **investissements**. Nous souhaitons donc déterminer la contribution que vous seriez prêts à réaliser sous la forme d'une **augmentation de vos factures d'eau annuelles** pendant 10 ans.

Les montants perçus seraient dédiés exclusivement au financement de ces scénarios.

Connaissez-vous le montant de vos factures d'eau annuelles ?

Oui

Non

Quel est le montant annuel approximatif de vos factures d'eau (en €) ?

Pour information : la facture annuelle moyenne d'une famille de 4 personnes est d'environ 440€.




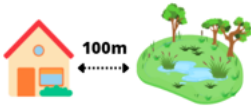
Choix de scénarios futurs de développement de l'infiltration




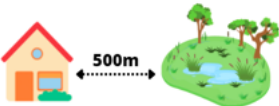
A présent, vous allez devoir faire une série de **6 choix** de scénarios.





Dans chaque choix, **vous devrez choisir entre deux scénarios** (scénario A ou scénario B) et **une option « aucun des deux scénarios »**. Les scénarios A et B présentent des combinaisons de caractéristiques et de contribution différentes. Dans l'option **« aucun des deux scénarios »**, aucun effort additionnel n'est mis en place pour l'infiltration des eaux pluviales et la contribution est de 0€.





Pour chaque choix, nous vous demandons de choisir le scénario que vous préférez (« A » « B » ou Aucun des deux scénarios »), **même si ce n'est pas votre scénario idéal**. Il est important de tenir compte des caractéristiques du scénario et du montant dans votre choix, et de considérer chaque choix **isolément** sans tenir compte des autres choix qui vous sont proposés.

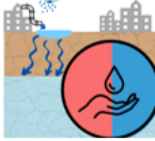


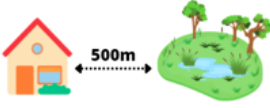
NB. Si vous êtes sur un smartphone, nous vous recommandons d'utiliser l'orientation "paysage".





| |
|---|
| Scénario A |
| 50% d'économie d'eau des nappes profondes grâce à l'infiltration |
|  |
| Pas de réduction des surfaces de forte chaleur |
|  |
| Pas de réduction de l'espace dédié à la voiture |
|  |
| Solution végétalisée à 100m de chez vous |
|  |
| 90€/ménage/an |
| <input type="checkbox"/> |





| |
|---|
| Scénario B |
| 100% d'économie d'eau des nappes profondes grâce à l'infiltration |
|  |
| - 20% de surfaces de forte chaleur |
|  |
| Réduction de l'espace dédié à la voiture |
|  |
| Solution végétalisée à 500m de chez vous |
|  |
| 120€/ménage/an |
| <input type="checkbox"/> |

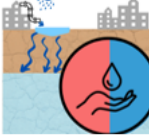



| |
|---|
| Aucun des deux |
| Pas d'économie d'eau des nappes profondes grâce à l'infiltration |
|  |
| Pas de réduction des surfaces de forte chaleur |
|  |
| Pas de réduction de l'espace dédié à la voiture |
|  |
| Pas de nouvelle solution végétalisée |
|  |
| 0€/ménage/an |
| <input type="checkbox"/> |





| Scénario A |
|---|
| <p>100% d'économie d'eau des nappes profondes grâce à l'infiltration</p>  |
| <p>- 40% de surfaces de forte chaleur</p>  |
| <p>Réduction de l'espace dédié à la voiture</p>  |
| <p>Pas de nouvelle solution proche de chez vous</p>  |
| <p>30€/ménage/an</p> |

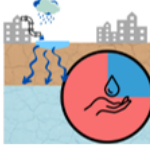



| Scénario B |
|--|
| <p>50% d'économie d'eau des nappes profondes grâce à l'infiltration</p>  |
| <p>- 60% de surfaces de forte chaleur</p>  |
| <p>Pas de réduction de l'espace dédié à la voiture</p>  |
| <p>Solution végétalisée à 500m de chez vous</p>  |
| <p>180€/ménage/an</p> |

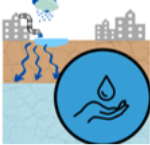



| Aucun des deux scénarios |
|--|
| <p>Pas d'économie d'eau des nappes profondes grâce à l'infiltration</p>  |
| <p>Pas de réduction des surfaces de forte chaleur</p>  |
| <p>Pas de réduction de l'espace dédié à la voiture</p>  |
| <p>Pas de nouvelle solution végétalisée</p>  |
| <p>0€/ménage/an</p> |





| |
|---|
| Scénario A |
| 100% d'économie d'eau des nappes profondes grâce à l'infiltration |
|  |
| - 60% de surfaces de forte chaleur |
|  |
| Pas de réduction de l'espace dédié à la voiture |
|  |
| Solution végétalisée à 100m de chez vous |
|  |
| 150€/ménage/an |

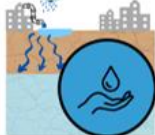



| |
|---|
| Scénario B |
| 50% d'économie d'eau des nappes profondes grâce à l'infiltration |
|  |
| - 40% de surfaces de forte chaleur |
|  |
| Réduction de l'espace dédié à la voiture |
|  |
| Solution végétalisée en face de chez vous |
|  |
| 60€/ménage/an |





| |
|---|
| Aucun des deux scénarios |
| Pas d'économie d'eau des nappes profondes grâce à l'infiltration |
|  |
| Pas de réduction des surfaces de forte chaleur |
|  |
| Pas de réduction de l'espace dédié à la voiture |
|  |
| Pas de nouvelle solution végétalisée |
|  |
| 0€/ménage/an |

| |
|---|
| Scénario A |
| 25% d'économie d'eau des nappes profondes grâce à l'infiltration |
|  |
| - 20% de surfaces de forte chaleur |
|  |
| Réduction de l'espace dédié à la voiture |
|  |
| Solution végétalisée à 100m de chez vous |
|  |
| 60€/ménage/an |

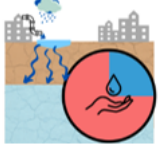


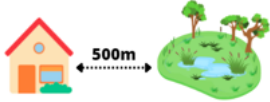
| |
|---|
| Scénario B |
| 100% d'économie d'eau des nappes profondes grâce à l'infiltration |
|  |
| - 60% de surfaces de forte chaleur |
|  |
| Pas de réduction de l'espace dédié à la voiture |
|  |
| Pas de nouvelle solution proche de chez vous |
|  |
| 120€/ménage/an |

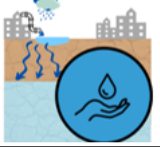



| |
|---|
| Aucun des deux scénarios |
| Pas d'économie d'eau des nappes profondes grâce à l'infiltration |
|  |
| Pas de réduction des surfaces de forte chaleur |
|  |
| Pas de réduction de l'espace dédié à la voiture |
|  |
| Pas de nouvelle solution végétalisée |
|  |
| 0€/ménage/an |





| |
|---|
| Scénario A |
| 100% d'économie d'eau des nappes profondes grâce à l'infiltration |
|  |
| Pas de réduction des surfaces de forte chaleur |
|  |
| Réduction de l'espace dédié à la voiture |
|  |
| Solution végétalisée en face de chez vous |
|  |
| 180€/ménage/an |

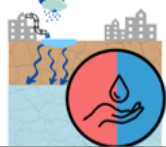



| |
|---|
| Scénario B |
| 50% d'économie d'eau des nappes profondes grâce à l'infiltration |
|  |
| - 20 % de surfaces de forte chaleur |
|  |
| Pas de réduction de l'espace dédié à la voiture |
|  |
| Solution végétalisée à 100m de chez vous |
|  |
| 30€/ménage/an |

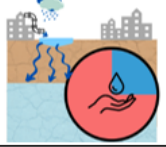



| |
|---|
| Aucun des deux scénarios |
| Pas d'économie d'eau des nappes profondes grâce à l'infiltration |
|  |
| Pas de réduction des surfaces de forte chaleur |
|  |
| Pas de réduction de l'espace dédié à la voiture |
|  |
| Pas de nouvelle solution végétalisée |
|  |
| 0€/ménage/an |





| |
|--|
| Scénario A |
| <p>25% d'économie d'eau des nappes profondes grâce à l'infiltration</p>  |
| <p>- 60% de surfaces de forte chaleur</p>  |
| <p>Pas de réduction de l'espace dédié à la voiture</p>  |
| <p>Solution végétalisée à 500m de chez vous</p>  |
| 60€/ménage/an |




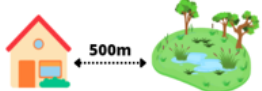
| |
|---|
| Scénario B |
| <p>100% d'économie d'eau des nappes profondes grâce à l'infiltration</p>  |
| <p>- 20% de surfaces de forte chaleur</p>  |
| <p>Réduction de l'espace dédié à la voiture</p>  |
| <p>Solution végétalisée à 100m de chez vous</p>  |
| 150€/ménage/an |

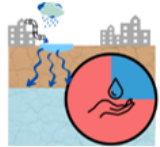



| |
|--|
| Aucun des deux scénarios |
| <p>Pas d'économie d'eau des nappes profondes grâce à l'infiltration</p>  |
| <p>Pas de réduction des surfaces de forte chaleur</p>  |
| <p>Pas de réduction de l'espace dédié à la voiture</p>  |
| <p>Pas de nouvelle solution végétalisée</p>  |
| 0€/ménage/an |





| |
|---|
| Scénario A |
| 50% d'économie d'eau des nappes profondes grâce à l'infiltration |
|  |
| - 20% de surfaces de forte chaleur |
|  |
| Pas de réduction de l'espace dédié à la voiture |
|  |
| Solution végétalisée en face de chez vous |
|  |
| 90€/ménage/an |


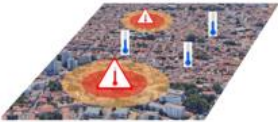


| |
|---|
| Scénario B |
| 25% d'économie d'eau des nappes profondes grâce à l'infiltration |
|  |
| - 40% de surfaces de forte chaleur |
|  |
| Réduction de l'espace dédié à la voiture |
|  |
| Solution végétalisée à 100m de chez vous |
|  |
| 90€/ménage/an |





| |
|---|
| Aucun des deux scénarios |
| Pas d'économie d'eau des nappes profondes grâce à l'infiltration |
|  |
| Pas de réduction des surfaces de forte chaleur |
|  |
| Pas de réduction de l'espace dédié à la voiture |
|  |
| Pas de nouvelle solution végétalisée |
|  |
| 0€/ménage/an |





| |
|---|
| Scénario A |
| 50% d'économie d'eau des nappes profondes grâce à l'infiltration  |
| Pas de réduction des surfaces de forte chaleur  |
| Réduction de l'espace dédié à la voiture  |
| Solution végétalisée à 500m de chez vous  |
| 30€/ménage/an |





| |
|---|
| Scénario B |
| 25% d'économie d'eau des nappes profondes grâce à l'infiltration  |
| - 40% de surfaces de forte chaleur  |
| Pas de réduction de l'espace dédié à la voiture  |
| Solution végétalisée en face de chez vous  |
| 150€/ménage/an |


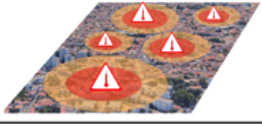


| |
|--|
| Aucun des deux scénarios |
| Pas d'économie d'eau des nappes profondes grâce à l'infiltration  |
| Pas de réduction des surfaces de forte chaleur  |
| Pas de réduction de l'espace dédié à la voiture  |
| Pas de nouvelle solution végétalisée  |
| 0€/ménage/an |





| |
|---|
| Scénario A |
| 100% d'économie d'eau des nappes profondes grâce à l'infiltration |
|  |
| - 40 % de surfaces de forte chaleur |
|  |
| Pas de réduction de l'espace dédié à la voiture |
|  |
| Solution végétalisée à 500m de chez vous |
|  |
| 120€/ménage/an |

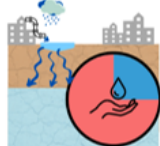



| |
|---|
| Scénario B |
| 50% d'économie d'eau des nappes profondes grâce à l'infiltration |
|  |
| - 60% de surfaces de forte chaleur |
|  |
| Réduction de l'espace dédié à la voiture |
|  |
| Pas de nouvelle solution proche de chez vous |
|  |
| 60€/ménage/an |





| |
|---|
| Aucun des deux scénarios |
| Pas d'économie d'eau des nappes profondes grâce à l'infiltration |
|  |
| Pas de réduction des surfaces de forte chaleur |
|  |
| Pas de réduction de l'espace dédié à la voiture |
|  |
| Pas de nouvelle solution végétalisée |
|  |
| 0€/ménage/an |

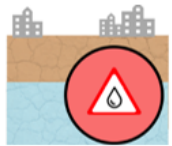



| |
|--|
| Scénario A |
| <p>50% d'économie d'eau des nappes profondes grâce à l'infiltration</p>  |
| <p>- 40% de surfaces de forte chaleur</p>  |
| <p>Réduction de l'espace dédié à la voiture</p>  |
| <p>Pas de nouvelle solution proche de chez vous</p>  |
| 180€/ménage/an |

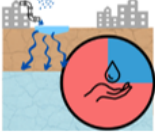
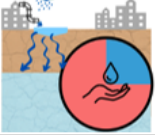








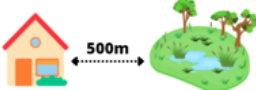

| |
|--|
| Scénario B |
| <p>25% d'économie d'eau des nappes profondes grâce à l'infiltration</p>  |
| <p>Pas de réduction des surfaces de forte chaleur</p>  |
| <p>Pas de réduction de l'espace dédié à la voiture</p>  |
| <p>Solution végétalisée en face de chez vous</p>  |
| 30€/ménage/an |

| |
|--|
| Aucun des deux scénarios |
| <p>Pas d'économie d'eau des nappes profondes grâce à l'infiltration</p>  |
| <p>Pas de réduction des surfaces de forte chaleur</p>  |
| <p>Pas de réduction de l'espace dédié à la voiture</p>  |
| <p>Pas de nouvelle solution végétalisée</p>  |
| 0€/ménage/an |

| |
|--|
| Scénario A |
| <p>25% d'économie d'eau des nappes profondes grâce à l'infiltration</p>  |
| <p>- 60 % de surfaces de forte chaleur</p>  |
| <p>Réduction de l'espace dédié à la voiture</p>  |
| <p>Solution végétalisée en face de chez vous</p>  |
| 120€/ménage/an |

| |
|---|
| Scénario B |
| <p>100% d'économie d'eau des nappes profondes grâce à l'infiltration</p>  |
| <p>Pas de réduction des surfaces de forte chaleur</p>  |
| <p>Pas de réduction de l'espace dédié à la voiture</p>  |
| <p>Pas de nouvelle solution proche de chez vous</p>  |
| 90€/ménage/an |

| |
|--|
| Aucun des deux scénarios |
| <p>Pas d'économie d'eau des nappes profondes grâce à l'infiltration</p>  |
| <p>Pas de réduction des surfaces de forte chaleur</p>  |
| <p>Pas de réduction de l'espace dédié à la voiture</p>  |
| <p>Pas de nouvelle solution végétalisée</p>  |
| 0€/ménage/an |

| Scénario A | Scénario B | Aucun des deux scénarios |
|--|---|---|
| <p>25 % d'économie d'eau des nappes profondes grâce à l'infiltration</p>  | <p>25% d'économie d'eau des nappes profondes grâce à l'infiltration</p>  | <p>Pas d'économie d'eau des nappes profondes grâce à l'infiltration</p>  |
| <p>- 20% de surfaces de forte chaleur</p>  | <p>Pas de réduction des surfaces de forte chaleur</p>  | <p>Pas de réduction des surfaces de forte chaleur</p>  |
| <p>Pas de réduction de l'espace dédié à la voiture</p>  | <p>Réduction de l'espace dédié à la voiture</p>  | <p>Pas de réduction de l'espace dédié à la voiture</p>  |
| <p>Pas de nouvelle solution proche de chez vous</p>  | <p>Solution végétalisée à 500m de chez vous</p>  | <p>Pas de nouvelle solution végétalisée</p>  |
| <p>150€/ménage/an</p> | <p>180€/ménage/an</p> | <p>0€/ménage/an</p> |



Vous avez choisi « aucun des 2 scénarios » à chaque fois. Pouvez-vous nous indiquer pourquoi?

- Ces scénarios sont intéressants mais je n'ai pas les moyens de payer.
- Ces scénarios sont intéressants mais les montants proposés sont trop élevés.
- Je ne suis pas d'accord avec les scénarios qui sont proposés.
- Les scénarios proposés n'apportent selon moi aucun bénéfice significatif.
- Il n'est pas juste que ce soit moi qui paye pour ces évolutions, ma facture d'eau est assez élevée.
- Ces scénarios devraient être payés par d'autres sources de financement que la facture d'eau.
- Autre (précisez)

Autre (précisez) :

Quelques questions vous concernant

Les questions suivantes vous concernent ainsi que votre foyer. Elles seront traitées de façon strictement **anonymes** et **confidentielles**.

Nous vous demanderons par exemple votre adresse mais pas votre nom.

Il est très important que vous y répondiez de façon juste pour que nous puissions évaluer la représentativité des réponses obtenues dans cette enquête.

Pourriez-vous préciser votre rue ?

Si votre rue n'apparaît pas, merci de sélectionner la plus proche de chez vous.

Pourriez-vous préciser votre rue ?

Si votre rue n'apparaît pas, merci de sélectionner la plus proche de chez vous.

Pourriez-vous préciser votre rue ?

Si votre rue n'apparaît pas, merci de sélectionner la plus proche de chez vous.

Pourriez-vous préciser votre rue ?

Si votre rue n'apparaît pas, merci de sélectionner la plus proche de chez vous.

Pourriez-vous préciser votre rue ?

Si votre rue n'apparaît pas, merci de sélectionner la plus proche

Pourriez-vous préciser votre rue ?

Si votre rue n'apparaît pas, merci de sélectionner la plus proche

Pourriez-vous préciser votre rue ?

Si votre rue n'apparaît pas, merci de sélectionner la plus proche

Pourriez-vous préciser votre rue ?

Si votre rue n'apparaît pas, merci de sélectionner la plus proche

Pourriez-vous préciser votre numéro dans la rue ?

Depuis combien d'années habitez-vous sur le territoire de Bordeaux Métropole ?

Vous habitez dans:

une maison

un appartement

autre (précisez)

autre (précisez) :

Vous êtes:

propriétaire

locataire

Combien de personnes composent votre foyer (y compris vous-même)?

1

2

3

4

5 et plus

Combien de personnes de moins de 18 ans vivent dans votre foyer?

0

1

2

3

4 et plus

Possédez-vous un jardin individuel ?

Oui

Non

Utilisez-vous un puits ou un forage pour votre alimentation en eau ?

Oui

Non

A quel distance environ se situe l'espace vert public ou l'espace de nature le plus proche de chez vous ?

De quel type d'espace vert ou d'espace de nature s'agit-il ?

Autre (précisez) :

Pouvez-vous en préciser le nom ?

exemple : forêt de Bourghail, Parc Bordelais, etc.

Possédez-vous une voiture individuelle ?

 Oui Non

A quelle fréquence vous en servez-vous ?

Moins d' un jour / semaine

1 à 3 jours / semaine

4 à 5 jours / semaine

6 à 7 jours / semaine

Quel est votre niveau d'études?

- Primaire (certificat d'études)
- Secondaire court (CAP, BEP, BEPC)
- Secondaire long (Bac, brevet professionnel)
- Supérieur court (Bac +2 à Bac +4)
- Supérieur long (Bac +5 et plus)

Veillez cocher la case correspondant le mieux aux revenus nets mensuels de votre foyer (sommes de tous les salaires du foyer, allocations familiales, pensions).

- | | | |
|-------------------------------------|-------------------------------------|-------------------------------------|
| <input type="radio"/> < 500 € | <input type="radio"/> 500 – 1000 € | <input type="radio"/> 1000 – 1500 € |
| <input type="radio"/> 1500 – 2000 € | <input type="radio"/> 2000 – 3000 € | <input type="radio"/> 3000 – 4000 € |
| <input type="radio"/> 4000 – 5000 € | <input type="radio"/> 5000 – 6000 € | <input type="radio"/> > 6000 € |

Estimez-vous que l'information qui vous a été fournie dans ce questionnaire était suffisante pour faire vos choix de scénarios de développement de l'infiltration ?

- Largement suffisante
- Suffisante
- Insuffisante
- Absolument insuffisante



université
de BORDEAUX



Géosciences pour une Terre durable

brgm

Merci pour votre participation à cette enquête!

[Cliquez-ici](#) pour terminer l'enquête

2 Supplementary material to Chapter 3

2.1 Optimization algorithm specification

We use an evolutionary algorithm from the DEAP library (Fortin *et al.* 2012), incorporating the NSGA-2 selection algorithm, which is particularly efficient to produce a diverse Pareto-optimal set of solutions (Deb et al., 2002). Each solution is represented as a string of 200 integers, for the 200 available sites. Each site is represented by its position within the string, and can take three values: “0” means no GRI is implemented in this specific site, “1” means a NBGRI is implemented, and “2” a CGRI.

The algorithm works by creating first an initial random population of 200 solutions (Figure 2). Then the algorithm evaluates each individual solution with regard to the three objective functions. Then 1000 new solutions are generated by combining the previous solutions, using two-point crossover and mutation (Glover & Kochenberger, 2006), with a 0.7 and 0.3 probability. The mutation simply performs a random transformation between a 0, 1 or 2, at one random location within the integer string. It can either lead to introducing a new NBGRI or a CGRI or deleting one from a previous solution. The 1000 new solutions are also evaluated, and the best 200 solutions among the 1200 resulting solutions are selected. This design introduces an “elitist” approach: both the 200 “parent” solutions and the 1000 “child” solutions can be selected, meaning that best “elite” solutions can be conserved throughout the generations.

This method classifies and ranks all the 1200 candidate solutions on the three objectives dimensions (infiltration, co-benefits and opportunity costs), and selects all the non-dominated solutions that are as much distinct and spread out from each other as possible (selection function from NSGA-2). These 200 best solutions are then used to generate new solutions, and this cycle of generation-evaluation-selection is repeated 500 times. This number of generations is set by trial and error through multiple runs, increasing the amount of generations up to the point when the algorithm does not “find” better and new solutions. The final population of 200 solutions are non-dominated solutions that constitute the Pareto front.

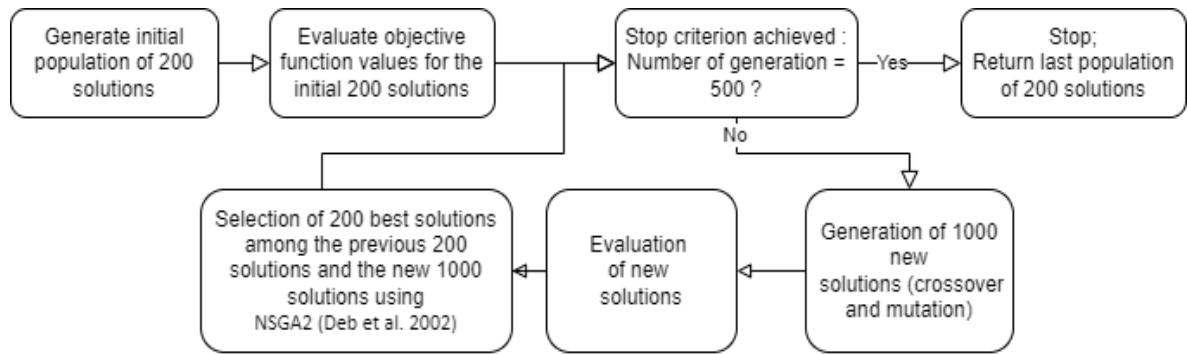


Figure 2: Main process of the evolutionary algorithm used for the multi-objective optimization

2.2 Sensitivity Analysis for the experiments

A sensitivity analysis is performed on two main parameters of the model: the intensity of the substitution effect in experiment c) and the difference between NBGRI and CGRI opportunity costs in experiment d). This sensitivity analysis is performed by modifying the values of the parameters and running again the optimization experiments.

2.2.1 Sensitivity to the substitution effect intensity

In experiment c , we introduced the substitution effect of existing urban parks on NBGRI potential co-benefits. We modelled this effect as a 50% reduction in NBGRI co-benefits whenever it is introduced within range of an urban park. Considering how little is known on the impact of substitution effects of urban parks on the demand for ES provided by NBGRI, we tested two other distinct values for this parameter. We tested the same experiment setting with 0.25 and 0.75 values for this co-benefit reduction parameter.

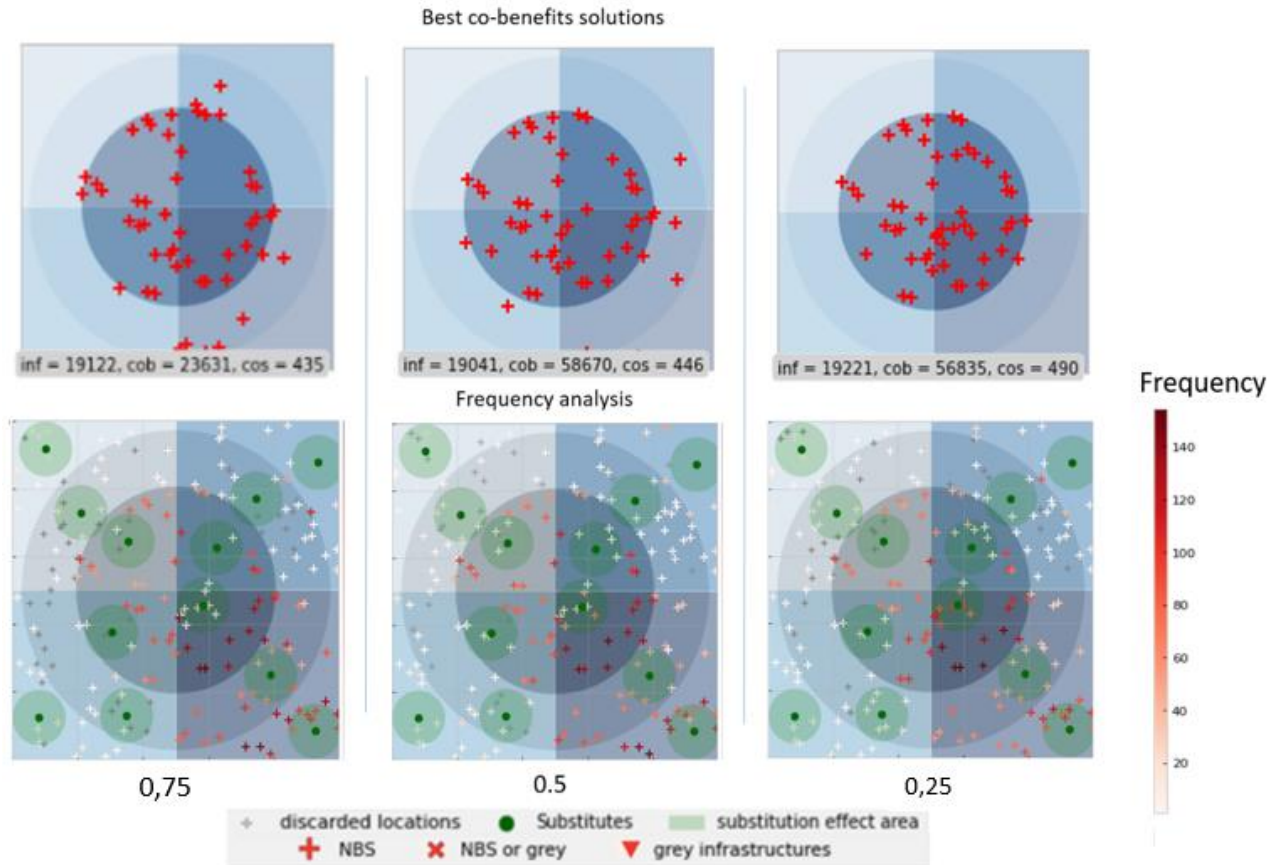


Figure 3: Sensitivity to the substitution effect parameter

For each column a different parameter value is used (0.25, 0.5, 0.75 reduction in co-benefits), and we presented the best co-benefits map (at the top), and the site selection frequency map (bottom)

The results for these three settings (Figure 3) indicate a strong sensitivity to the intensity of this effect. In the 0.25 setting, the substitution effect is the strongest, and leads to entirely discarding the centric locations within range. Consequently, inner suburban locations are selected in the best co-benefits solution instead of the centric locations within range of substitutes. On the contrary, in the 0.75 setting the substitution effect is considerably less strong, and does not lead to discarding centric locations. The substitution effect is still visible in the frequency analysis, but not in the optimal co-benefit solution (compared to the reference situation in experiment a).

2.2.2 Sensitivity to the grey infrastructure opportunity cost parameter

NBGR and CGRI were defined in the method (3.3.4) as having different opportunity costs, as follow:

$$cos_j = \begin{cases} p_j & \text{if } j \text{ is NBGRI} \\ \frac{1}{2}p_j & \text{if } j \text{ is CGRI} \end{cases} \quad (5)$$

A 50% value was used in experiment d to define how CGRI have less opportunity costs than NBGRI. Considering the variety of existing GRI (swales, trenches, basins, subsurface infiltration galleries, permeable pavements, etc.), this reduction in opportunity costs may vary a lot. Therefore, we tested the same experiment with two other values for this parameter: 0.25 and 0.75. They respectively describe how CGRI can require 75% and 25% less space than NBGRI. These values are to be understood here as a plausible range of values, and were tested to assess the conclusions on experiment d.

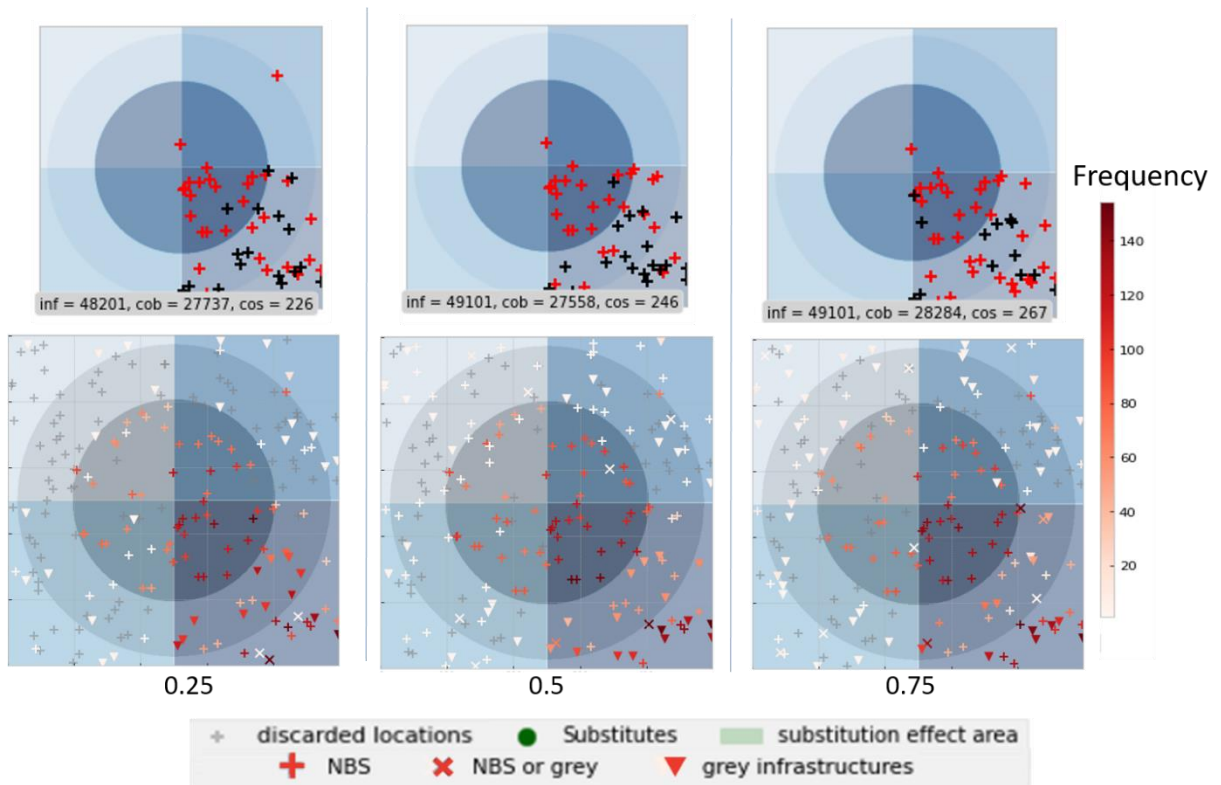


Figure 4: Sensitivity to the opportunity cost reduction parameter.

For each columns a different parameter value is used (0.25, 0.5, 0.75 opportunity cost ratio), and we presented the best infiltration maps (at the top), and the site selection frequency map (bottom).

The results from these runs (Figure 4) indicate the impact of the opportunity cost difference between NBGRI and CGRI on site selection. We only represented here the best infiltration solution map, since we observed in the result section that CGRI were not represented in solutions dedicated to co-benefits. This parameter does not have a clear impact on site selection: it appears that across the three runs, the sites selected for grey infrastructures do not show overall different patterns. The inner southeast suburban area seems to be more frequently selected in the 0.25 run frequency analysis. This can be an indication of a threshold effect. As the opportunity costs of CGRI is considered as a smaller fraction of the opportunity costs of NBGRI, “costly” areas are more selected.

3 Supplementary material to chapter 4

3.1 Sensitivity analysis on opportunity costs

We performed a basic sensitivity analysis on the central parameter under our MOO specification: the parameter defining the opportunity costs discount of CGRI, relative to NBGRI. The base opportunity cost discount parameter τ was set as 0.5, based on the assumption that CGRI occupy overall half the surface area of NBGRI. This assumption being a gross generalization of the difference in size between these two types of infrastructures, we identified this parameter as a main source of uncertainty and a potential strong driver in the results. For this reason, we proceeded to test the MOO with two dramatically different specification for this parameter, *ceteris paribus*, as a means to identify visually how this parameter drives the results. In one instance, we assumed that the discount would be far higher, with CGRI representing only 20% ($\tau=0.2$) of the opportunity costs of NBGRI. In another one, τ was set as 80%.

3.1.1 Opportunity costs at 0.2

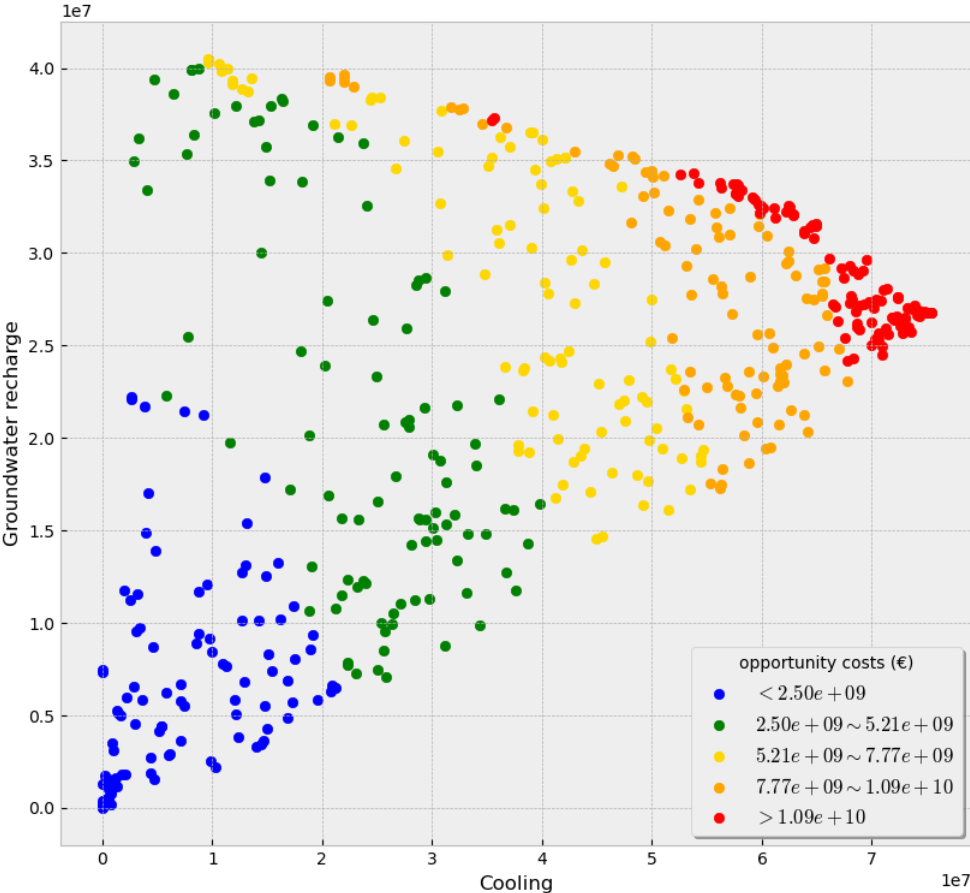


Figure 5: Optimal solutions of the MOO problem for sensitivity analysis, represented along the recharge and urban cooling dimensions. Opportunity costs of CGRI are set as 20% of NBGRI.

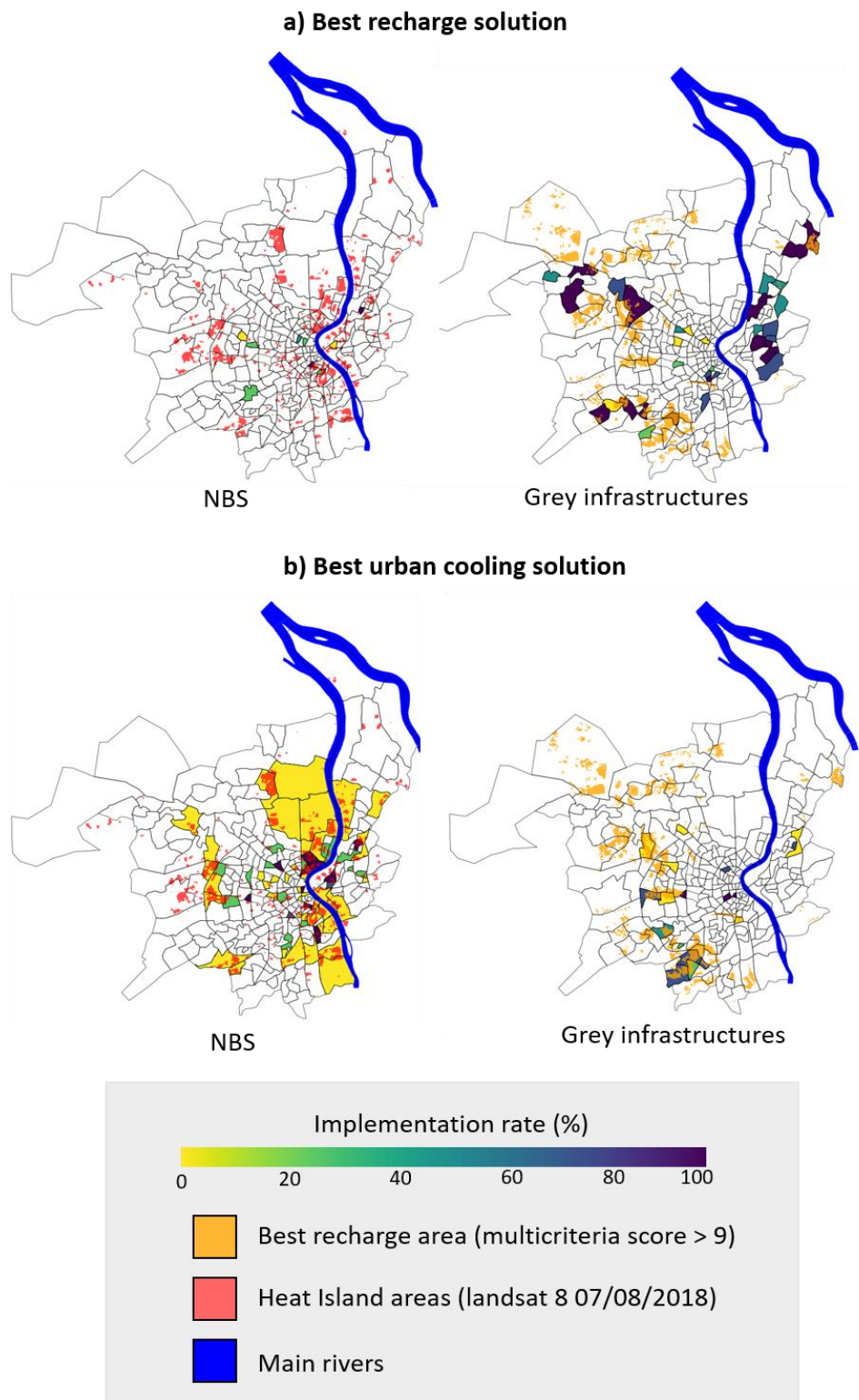


Figure 6: Best solutions in the recharge and cooling dimensions resulting from the MOO.

The colour gradient in the maps represent the associated implementation levels to each selected IRIS, *i.e.*, what percentage of the available sites are used for GRI. The maps on the top present the best recharge solution, and present also in grey the best areas for recharge, as per the multicriteria analysis (Figure 2a). The maps on the

bottom present the best recharge solution, and present also in red the location of heat island areas in the Bordeaux Metropolitan area during a heat wave episode. Opportunity costs of CGRI are set as 20% of NBGRI.

3.1.2 Opportunity costs at 0.8

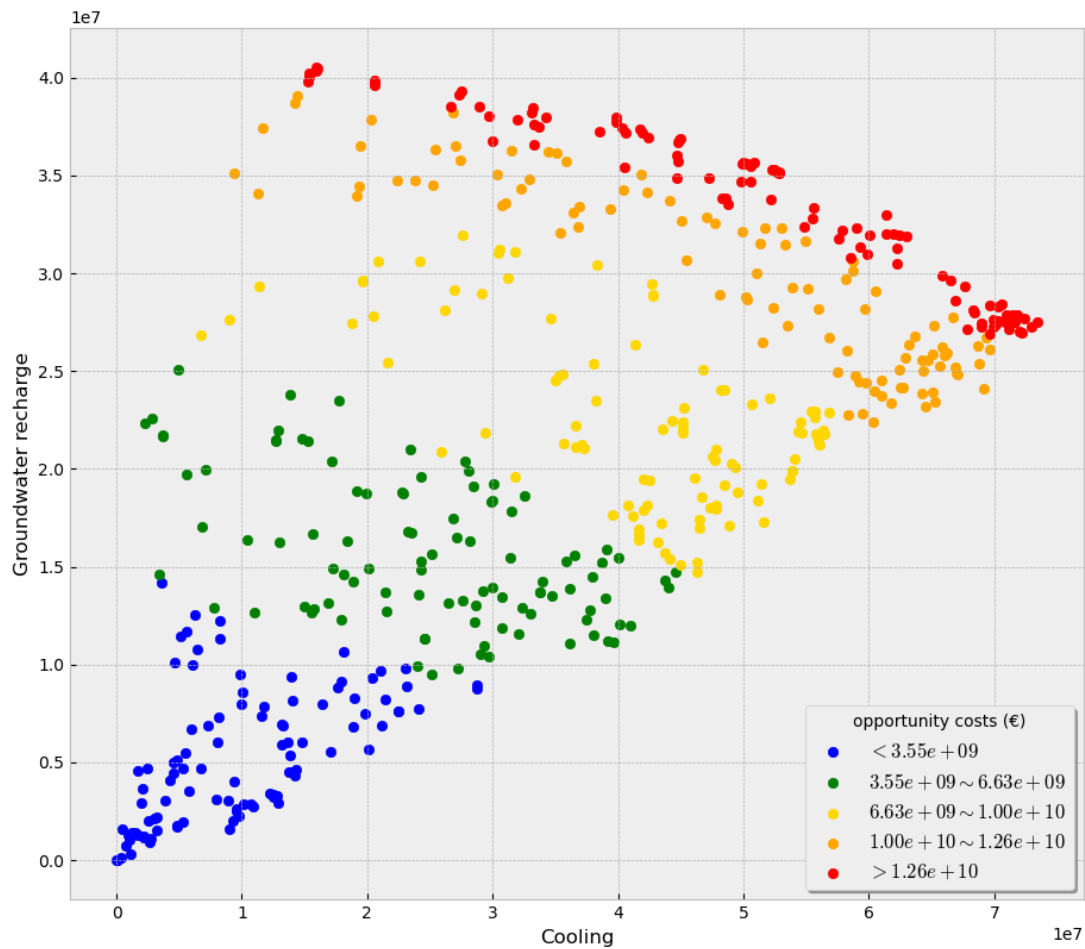


Figure 7: Optimal solutions of the MOO problem for sensitivity analysis, represented along the recharge and urban cooling dimensions.

Opportunity costs of CGRI are set as 80% of NBGRI.

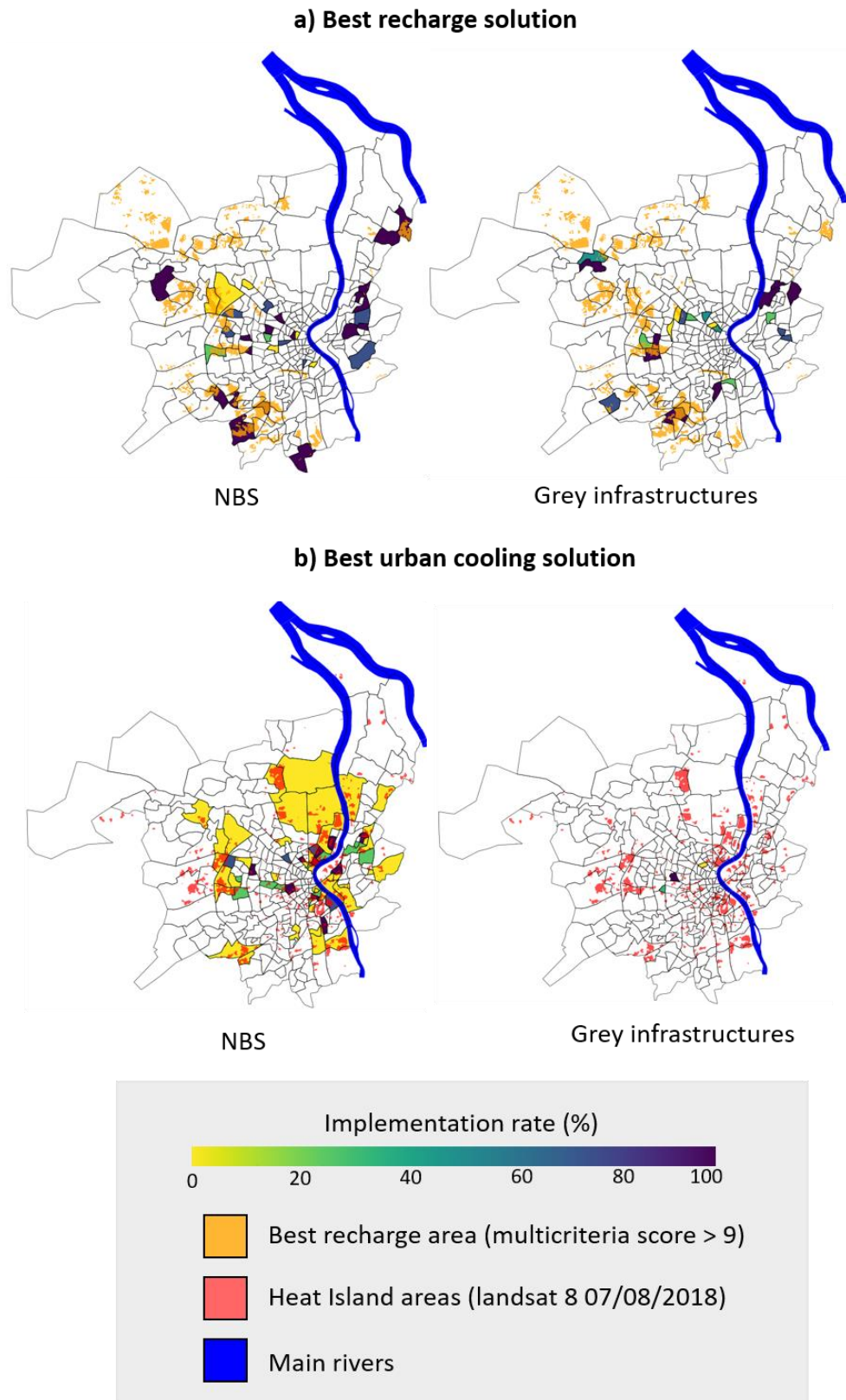


Figure 8: Best solutions in the recharge and cooling dimensions resulting from the MOO.

The colour gradient in the maps represent the associated implementation levels to each selected IRIS, *i.e.*, what percentage of the available sites are used for groundwater recharge projects. The maps on the top present the best recharge solution, and present also in grey the best areas for recharge, as per the multicriteria analysis

(Figure 2a). The maps on the bottom present the best recharge solution, and present also in red the location of heat island areas in the Bordeaux Metropolitan area during a heat wave episode. Opportunity costs of CGRI are set as 80% of NBGRI.

This sensitivity analysis indicates a central difference in the nature of trade-offs at hand. We observe that the fronts (Figure 5 and Figure 7) do not have overall very different shape, but they do have a different distribution of opportunity costs across the solutions. The extreme points are in fact more or less at the same locations, and the Pareto fronts cover overall the same area within the solution space. It is notable however that the distribution of opportunity costs changes dramatically: Figure 5 features an almost “vertical” distinction between opportunity costs categories, while Figure 7 bears a more “horizontal” differentiation. In addition, the extreme solutions for urban cooling belong to the highest opportunity cost categories (in dark red) in both cases, but the extreme solutions focused on recharge do belong to a much higher category of opportunity costs in Figure 5 than in Figure 7.

Overall, the first situation presents a trade-off that mostly happens between urban cooling and opportunity costs; while the second situation has a general trade-off between incrementing any of the benefits and opportunity costs. In the first case, with the parameter $\tau=0.2$, more relative advantage is given to grey infrastructures. This difference is shown also when depicting the extreme points (Figure 6 and Figure 8). While the best urban cooling solutions are basically the same in both cases, making use almost exclusively of NBGRI, as expected, the best recharge solution do vary a lot. The best recharge solution in the first case (Figure 6 a) features in fact less NBGRI than in the second case (Figure 8b), though in both cases the selected locations are the same. In conclusion this simple sensitivity analysis indicates that the opportunity cost parameter does not influence dramatically the optimal spatial patterns, but do have an impact on the mix of recharge infrastructure techniques, especially on the side of recharge-focused solutions.

3.2 Pathway analysis scenarios

Figure 8 and Figure 9 show the pathway analysis approach, repeated on two other situations: one where equal emphasis is given to both benefits, and one where more emphasis is given to urban cooling.

Figure 8 indicates that there is a gradient in the level of implementation of GRI: as we move towards solutions of higher opportunity costs, more neighborhoods are selected, with higher intensity, as expected. There is also a distinct pathway in terms of implementing NBGRI and CGRI. Solutions of the lower cost categories (Figure 7a) feature NBGRI and CGRI in seemingly random locations. However as we move towards solutions of higher opportunity costs, NBGRI and CGRI tend to be located in distinct locations, and “specialize” in some areas. Finally, on this particular example, because we chose solutions that give an equal weight to both benefits, the final solutions located on the high effort front resemble the middle point in the trade-off analysis. Therefore, these solutions show a mixture of both NBGRI located close to heat island, as well as CGRI in specific locations of high recharge efficiency.

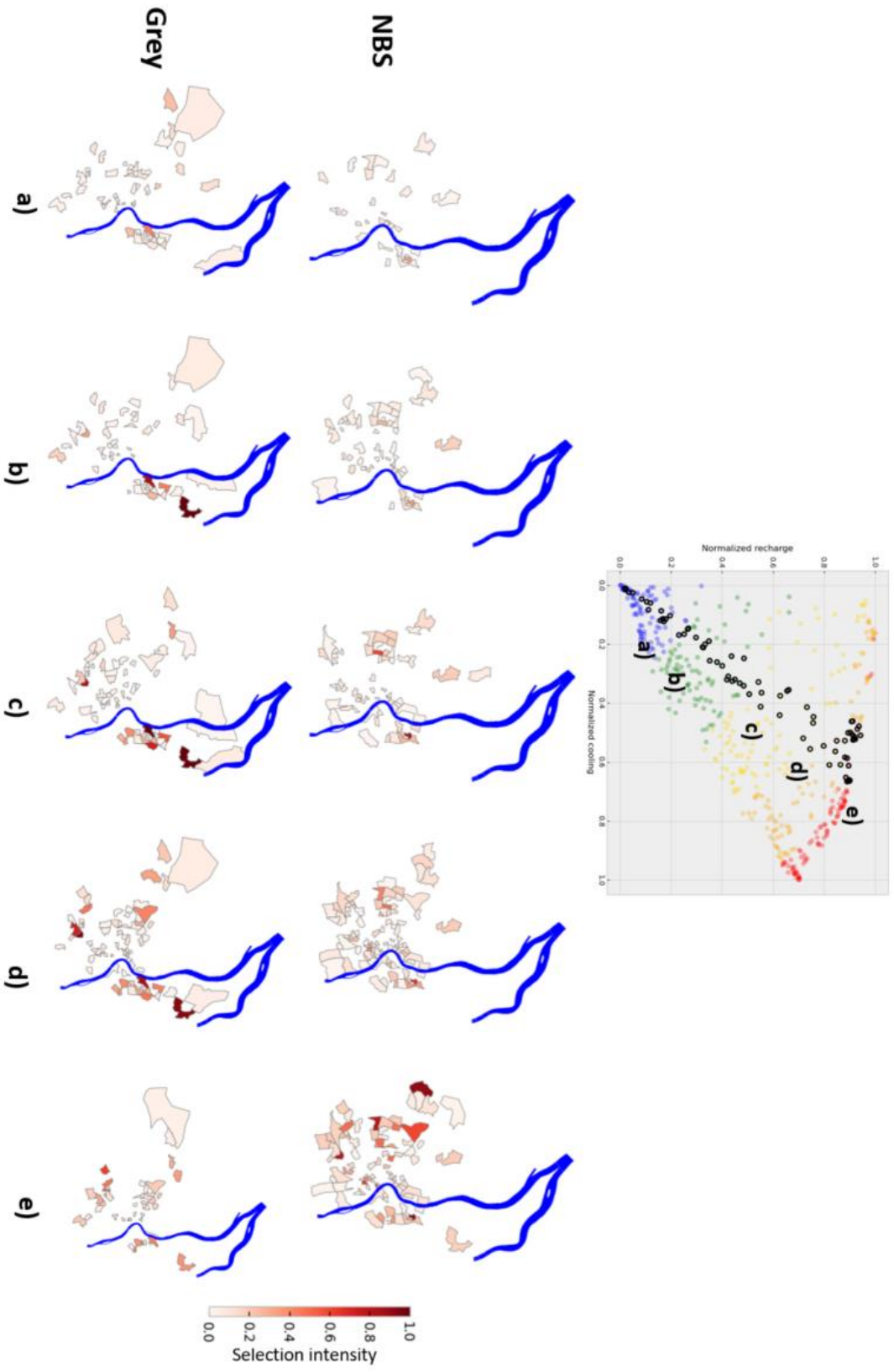


Figure 8: Pathway analysis example. In this scenario, the same weights are attributed to both benefits.

In figure 9, the pathway analysis is realized by focusing on urban cooling. We observe that these solutions are mainly constituted of NBGRI. This analysis informs on what the optimal locations are for each level of opportunity costs when aiming towards a scenario that addresses urban cooling as a priority over other objectives. These solutions tend to start at low levels of opportunity costs with few neighborhoods located in peri-urban areas. Then the solutions tend to aim at selecting many neighborhoods for NBGRI, almost all over the metropolitan area, first with low implementation levels, and then increasing these levels (b, c, d). Then, at the highest levels (e), solutions are the same as those in the trade-off analysis (Figure 5e). Finally, grey infrastructures are comparatively of low interest in these solutions, although two neighborhoods of high interest for recharge appear in the middle groups. This analysis informs us that an optimal strategy when aiming at solutions that emphasize urban cooling consists in targeting almost as “soon as possible” all locations that may provide urban cooling benefits, and then increasing the intensity of the NBGRI projects in these locations.

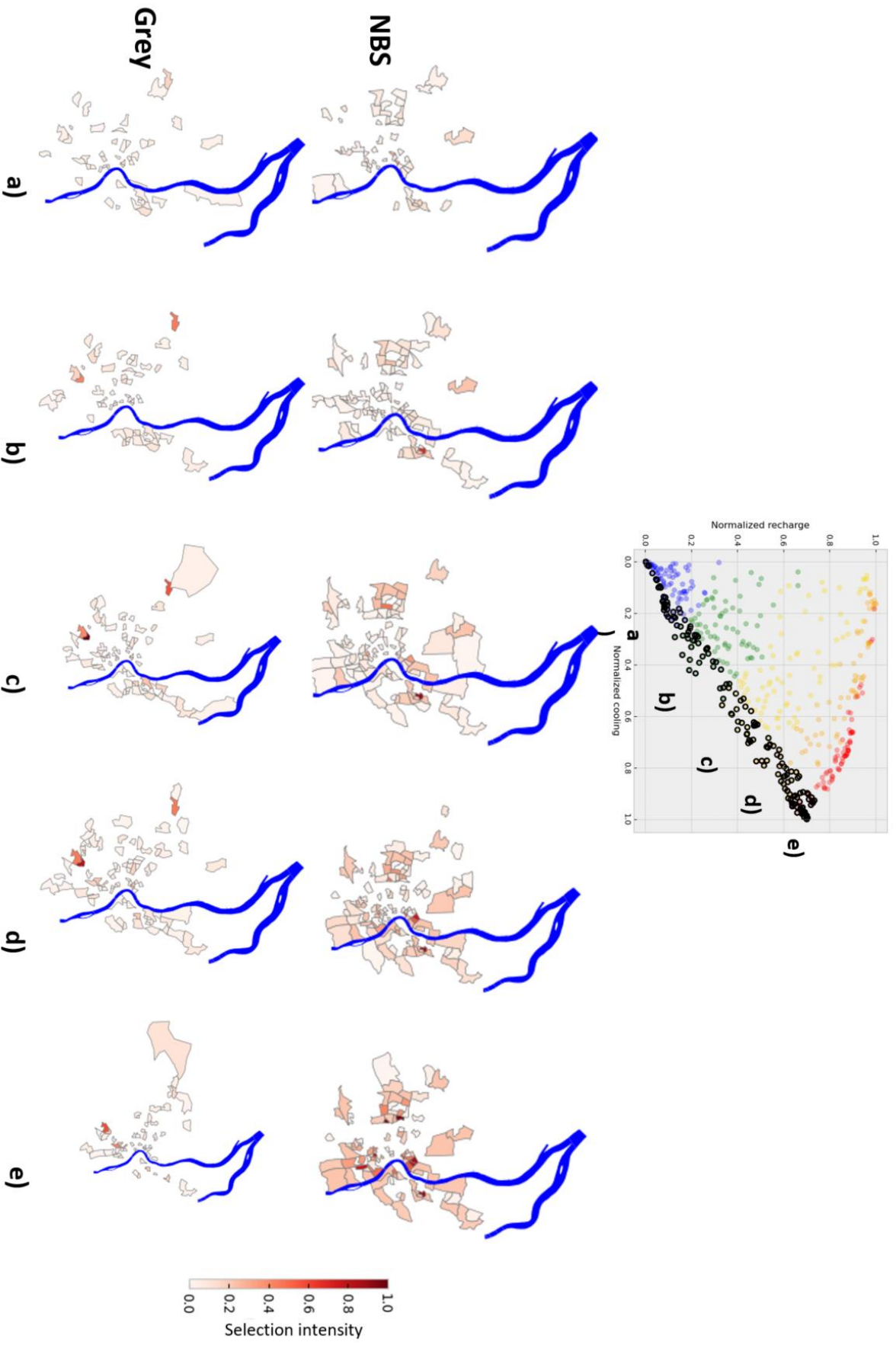


Figure 9: Pathway analysis example. In this scenario, more weight is attributed to the urban cooling objective.

3.3 Multi-Objective Optimization Python program

In this section, the reader may find the entire code snippet of the main lines of the multi-objective optimization program used for the main implementation (as presented in Chapter 4). These sections of codes just contain the bear essential data preparation, evaluation functions and the evolutionary algorithm itself, and does not feature all the visualization codes used for plotting results.

```
"""
Created on Wed Aug 23 14:34:28 2023

@author: Georges Farina
"""

import ast
import matplotlib.pyplot as plt
import matplotlib as mpl
import matplotlib.cm as cm
#from matplotlib.colors import DivergingNorm
import pandas as pd
import random
import numpy as np
from deap import algorithms
from deap import base
from deap import creator
from deap import tools
import geopandas as gpd
import os
random.seed(64)
plt.style.use('bmh')

#####
#####
#1. SET UP
#####
#####

#####
#1.1 Files import
#####

# set the path to the source directory
source_dir = 'C:/Users/gefarina/Documents/thèse CIFRE/opti_main'

sites = gpd.read_file(os.path.join(source_dir, 'inputs/sites.shp'))
sites['CODE_IRIS'] = sites['CODE_IRIS'].astype(np.int64)

ICU = gpd.read_file(os.path.join(source_dir, 'inputs/ICU_dissolved.shp'))
ICU_area = ICU.area.sum() #Surface initiale d'ICU dans BM

IRIS_shp = gpd.read_file(os.path.join(source_dir, 'inputs/IRIS.shp'))
IRIS_shp['CODE_IRIS'] = IRIS_shp['CODE_IRIS'].astype(np.int64)
IRIS_shp = IRIS_shp.reset_index()
IRIS_shp = IRIS_shp.rename(columns={'index': 'ID'})
IRIS_shp = IRIS_shp.drop(IRIS_shp[IRIS_shp['CODE_IRIS'] == 332811201].index)
IRIS_shp = IRIS_shp.drop(IRIS_shp[IRIS_shp['CODE_IRIS'] == 330631107].index)
IRIS_shp = IRIS_shp.drop(IRIS_shp[IRIS_shp['CODE_IRIS'] == 330630803].index)
IRIS_shp = IRIS_shp.drop(IRIS_shp[IRIS_shp['CODE_IRIS'] == 334490111].index)
IRIS_shp = IRIS_shp.reset_index(drop=True)
fleuve = gpd.read_file(os.path.join(source_dir, 'inputs/to_hydro_s.shp'))

#####
#####
#1.2 PARAMETERS
#####

MAX_COST = sites.area.sum()*0.1 #Max surface area (369 ha)
NGEN = 1000 #Max generations
```



```

MU = 500 #Number of individuals for next generation
LAMBDA = 2000 #Children created at each generation
CXPB = 0.6 #Probability of crossover birth
MUTPB = 0.4 #Probability of mutation birth
max_cooling_distance = 200 #Maximum cooling distance effect (Aram, 2019)
min_cooling_distance = 0.5 #Min cooling distance effect (Aram, 2019)
buffer_factor = 0.01 #Buffer factor for calculating cooling buffers

grey_oppcost = 0.5 #Main parameter of opportunity costs of grey solutions
total_menages = 399989 #Households in Bordeaux metropolitan area
WTP = 2.946744 #Mean WTP for heat ICU mitigation (in annual €, per %
of heat reduction, per household)

#####
#1.3 Data preparation
#####

#Calcul des bénéfices en amont pour plus de rapidité
# Merge the two shapefiles
merged_df = IRIS_shp.merge(sites, on='CODE_IRIS')

# Calculate the inf, oppcost and area column
merged_df['inf'] = merged_df['inf_score'] * merged_df.area
merged_df['oppcost'] = merged_df['cost_med'] * merged_df.area
merged_df['total_site_area'] = merged_df.area

# Group by 'CODE_IRIS' and sum the columns
inf_total = merged_df.groupby('CODE_IRIS')['inf'].sum().reset_index()
oppcosts = merged_df.groupby('CODE_IRIS')['oppcost'].sum().reset_index()
total_site_area = merged_df.groupby('CODE_IRIS')['total_site_area'].sum().reset_index()

# Merge the columns with the initial IRIS_shp shapefile
# IRIS_shp = IRIS_shp.merge(K_totals, on='CODE_IRIS')
IRIS_shp = IRIS_shp.merge(inf_total, on='CODE_IRIS')
IRIS_shp = IRIS_shp.merge(oppcosts, on='CODE_IRIS')
IRIS_shp = IRIS_shp.merge(total_site_area, on='CODE_IRIS')

#IRIS_shp = IRIS_shp.rename(columns={'K': 'K_total'})
IRIS_shp = IRIS_shp.rename(columns={'inf_score': 'inf_total'})

# Pre-calculation of benefits for each potential implementation levels (0,20, 40, 60, 80, 100)
#RUN JUST ONCE these lines

from shapely import affinity

#Function creation of smaller polygons
def create_smaller_polygon(polygon, percentage):
    old_area = polygon.area
    new_area = old_area * percentage
    scaling_factor = (new_area / old_area) ** 0.5 # Calculate the scaling factor based on area
ratio
    centroid = polygon.centroid
    scaled_polygon = affinity.scale(polygon, xfact=scaling_factor, yfact=scaling_factor,
origin=centroid)
    return scaled_polygon

NBS_buffer_20 = sites.copy()
NBS_buffer_40 = sites.copy()
NBS_buffer_60 = sites.copy()
NBS_buffer_80 = sites.copy()
NBS_buffer_100 = sites.copy()

#Apply the buffer on the implemented sites
NBS_buffer_20["buffer_size"] = NBS_buffer_20.geometry.apply(create_smaller_polygon,
percentage=0.2).area * buffer_factor
NBS_buffer_40["buffer_size"] = NBS_buffer_40.geometry.apply(create_smaller_polygon,
percentage=0.4).area * buffer_factor
NBS_buffer_60["buffer_size"] = NBS_buffer_60.geometry.apply(create_smaller_polygon,
percentage=0.6).area * buffer_factor

```

```

NBS_buffer_80["buffer_size"] = NBS_buffer_80.geometry.apply(create_smaller_polygon,
percentage=0.8).area * buffer_factor
NBS_buffer_100["buffer_size"] = NBS_buffer_100.geometry.area * buffer_factor

# Apply limits to buffer sizes
NBS_buffer_20["buffer_size"] = NBS_buffer_20["buffer_size"].clip(lower=min_cooling_distance,
upper=max_cooling_distance)
NBS_buffer_40["buffer_size"] = NBS_buffer_40["buffer_size"].clip(lower=min_cooling_distance,
upper=max_cooling_distance)
NBS_buffer_60["buffer_size"] = NBS_buffer_60["buffer_size"].clip(lower=min_cooling_distance,
upper=max_cooling_distance)
NBS_buffer_80["buffer_size"] = NBS_buffer_80["buffer_size"].clip(lower=min_cooling_distance,
upper=max_cooling_distance)
NBS_buffer_100["buffer_size"] = NBS_buffer_100["buffer_size"].clip(lower=min_cooling_distance,
upper=max_cooling_distance)

#Create the buffer shapefiles
NBS_buffer_20["geometry"] = NBS_buffer_20.geometry.buffer(distance = NBS_buffer_20["buffer_size"])
NBS_buffer_40["geometry"] = NBS_buffer_40.geometry.buffer(distance = NBS_buffer_40["buffer_size"])
NBS_buffer_60["geometry"] = NBS_buffer_60.geometry.buffer(distance = NBS_buffer_60["buffer_size"])
NBS_buffer_80["geometry"] = NBS_buffer_80.geometry.buffer(distance = NBS_buffer_80["buffer_size"])
NBS_buffer_100["geometry"] = NBS_buffer_100.geometry.buffer(distance =
NBS_buffer_100["buffer_size"])

#Plot the buffers to check their sizes and shapes
# NBS_buffer_20.plot()
# NBS_buffer_40.plot()
# NBS_buffer_60.plot()
# NBS_buffer_80.plot()
# NBS_buffer_100.plot()

# Merge overlapping buffers by CODE_IRIS
NBS_buffer_merged_20 = NBS_buffer_20.dissolve(by="CODE_IRIS")
NBS_buffer_merged_40 = NBS_buffer_40.dissolve(by="CODE_IRIS")
NBS_buffer_merged_60 = NBS_buffer_60.dissolve(by="CODE_IRIS")
NBS_buffer_merged_80 = NBS_buffer_80.dissolve(by="CODE_IRIS")
NBS_buffer_merged_100 = NBS_buffer_100.dissolve(by="CODE_IRIS")

#####
#Local cooling effect
# Calculate the number of households within each buffer
NBS_buffer_merged_20['nb_men_20'] = NBS_buffer_merged_20['men_densit'] * NBS_buffer_merged_20.area
NBS_buffer_merged_40['nb_men_40'] = NBS_buffer_merged_40['men_densit'] * NBS_buffer_merged_40.area
NBS_buffer_merged_60['nb_men_60'] = NBS_buffer_merged_60['men_densit'] * NBS_buffer_merged_60.area
NBS_buffer_merged_80['nb_men_80'] = NBS_buffer_merged_80['men_densit'] * NBS_buffer_merged_80.area
NBS_buffer_merged_100['nb_men_100'] = NBS_buffer_merged_100['men_densit'] *
NBS_buffer_merged_100.area

# Calculate the total number of households per CODE_IRIS polygon
nb_men_20 = NBS_buffer_merged_20.groupby('CODE_IRIS')['nb_men_20'].sum().reset_index()
nb_men_40 = NBS_buffer_merged_40.groupby('CODE_IRIS')['nb_men_40'].sum().reset_index()
nb_men_60 = NBS_buffer_merged_60.groupby('CODE_IRIS')['nb_men_60'].sum().reset_index()
nb_men_80 = NBS_buffer_merged_80.groupby('CODE_IRIS')['nb_men_80'].sum().reset_index()
nb_men_100 = NBS_buffer_merged_100.groupby('CODE_IRIS')['nb_men_100'].sum().reset_index()

# Merge nb_menages_sum with IRIS_shp based on CODE_IRIS
IRIS_shp = IRIS_shp.merge(nb_men_20, on='CODE_IRIS', how='left')
IRIS_shp = IRIS_shp.merge(nb_men_40, on='CODE_IRIS', how='left')
IRIS_shp = IRIS_shp.merge(nb_men_60, on='CODE_IRIS', how='left')
IRIS_shp = IRIS_shp.merge(nb_men_80, on='CODE_IRIS', how='left')
IRIS_shp = IRIS_shp.merge(nb_men_100, on='CODE_IRIS', how='left')

IRIS_shp['local_wtp_20'] = IRIS_shp['wtp_delta']*IRIS_shp['nb_men_20']
IRIS_shp['local_wtp_40'] = IRIS_shp['wtp_delta']*IRIS_shp['nb_men_40']
IRIS_shp['local_wtp_60'] = IRIS_shp['wtp_delta']*IRIS_shp['nb_men_60']
IRIS_shp['local_wtp_80'] = IRIS_shp['wtp_delta']*IRIS_shp['nb_men_80']
IRIS_shp['local_wtp_100'] = IRIS_shp['wtp_delta']*IRIS_shp['nb_men_100']

#####
#Global cooling effect
# Calculate the area of intersection between buffer and ICU geometries for global benefit
#Do the operation for each %

NBS_buffer_merged_20 = NBS_buffer_merged_20.reset_index()

```

```

NBS_buffer_merged_40 = NBS_buffer_merged_40.reset_index()
NBS_buffer_merged_60 = NBS_buffer_merged_60.reset_index()
NBS_buffer_merged_80 = NBS_buffer_merged_80.reset_index()
NBS_buffer_merged_100 = NBS_buffer_merged_100.reset_index()

NBS_buffer_intersection_20 = gpd.overlay(NBS_buffer_merged_20, ICU, how='intersection')
NBS_buffer_intersection_40 = gpd.overlay(NBS_buffer_merged_40, ICU, how='intersection')
NBS_buffer_intersection_60 = gpd.overlay(NBS_buffer_merged_60, ICU, how='intersection')
NBS_buffer_intersection_80 = gpd.overlay(NBS_buffer_merged_80, ICU, how='intersection')
NBS_buffer_intersection_100 = gpd.overlay(NBS_buffer_merged_100, ICU, how='intersection')

#NBS_buffer["eliminated_ICU"] = NBS_buffer.geometry.area
NBS_buffer_intersection_20["eliminated_ICU_by_IRIS_20"] = NBS_buffer_intersection_20.geometry.area
NBS_buffer_intersection_40["eliminated_ICU_by_IRIS_40"] = NBS_buffer_intersection_40.geometry.area
NBS_buffer_intersection_60["eliminated_ICU_by_IRIS_60"] = NBS_buffer_intersection_60.geometry.area
NBS_buffer_intersection_80["eliminated_ICU_by_IRIS_80"] = NBS_buffer_intersection_80.geometry.area
NBS_buffer_intersection_100["eliminated_ICU_by_IRIS_100"] =
NBS_buffer_intersection_100.geometry.area

# Calculate the total number of households per CODE_IRIS polygon
icu_20 =
NBS_buffer_intersection_20.groupby('CODE_IRIS')['eliminated_ICU_by_IRIS_20'].sum().reset_index()
icu_40 =
NBS_buffer_intersection_40.groupby('CODE_IRIS')['eliminated_ICU_by_IRIS_40'].sum().reset_index()
icu_60 =
NBS_buffer_intersection_60.groupby('CODE_IRIS')['eliminated_ICU_by_IRIS_60'].sum().reset_index()
icu_80 =
NBS_buffer_intersection_80.groupby('CODE_IRIS')['eliminated_ICU_by_IRIS_80'].sum().reset_index()
icu_100 =
NBS_buffer_intersection_100.groupby('CODE_IRIS')['eliminated_ICU_by_IRIS_100'].sum().reset_index()

IRIS_shp = IRIS_shp.merge(icu_20, on='CODE_IRIS', how='left')
IRIS_shp = IRIS_shp.merge(icu_40, on='CODE_IRIS', how='left')
IRIS_shp = IRIS_shp.merge(icu_60, on='CODE_IRIS', how='left')
IRIS_shp = IRIS_shp.merge(icu_80, on='CODE_IRIS', how='left')
IRIS_shp = IRIS_shp.merge(icu_100, on='CODE_IRIS', how='left')

IRIS_shp["eliminated_ICU_by_IRIS_20"] = IRIS_shp["eliminated_ICU_by_IRIS_20"].fillna(0)
IRIS_shp["eliminated_ICU_by_IRIS_40"] = IRIS_shp["eliminated_ICU_by_IRIS_40"].fillna(0)
IRIS_shp["eliminated_ICU_by_IRIS_60"] = IRIS_shp["eliminated_ICU_by_IRIS_60"].fillna(0)
IRIS_shp["eliminated_ICU_by_IRIS_80"] = IRIS_shp["eliminated_ICU_by_IRIS_80"].fillna(0)
IRIS_shp["eliminated_ICU_by_IRIS_100"] = IRIS_shp["eliminated_ICU_by_IRIS_100"].fillna(0)

#####
#1.4 Class and functions for the algorithm
#####

N = len(IRIS_shp)

creator.create("Fitness", base.Fitness, weights=(1.0, 1.0, -1.0)) #DEAP syntax : maximize,
maximize, minimize
creator.create("Individual", list, fitness=creator.Fitness) #Create the Individual class (is a
list + has fitness)

#For initial pop
def random_num(): #Just a random number function
(0 to 5) for generating base implementation rate #creates a list of 6 zeros and
choices = [0] * 50 + list(range(1, 6)) #1-10 numbers
return np.random.choice(choices) # the zeros represent the higher
probability of generating 0

toolbox = base.Toolbox() #Toolbox object from DEAP
toolbox.register("attr_percentage", random_num) #1st part of the chromosome =
implemenation rate
toolbox.register("attr_color", np.random.choice, [1,2]) #2e part = grey (2) or green
(1): IRIS all grey or all NBS

def individual_init(icls, content): #Functions for initializing the
individuals
return icls(content)
def create_individual():

```

```

    return creator.Individual([toolbox.attr_percentage() for i in range(N)] + [toolbox.attr_color()
for i in range(N)])

toolbox.register("individual", create_individual)
toolbox.register("population", tools.initRepeat, list, toolbox.individual)

def mutation(individual, indpb1):      #Mutation function used in the algorithm
    num_changes = random.randint(1, 3) # Generate a random number of changes between 1 and 3

    for _ in range(num_changes):
        if random.random() < indpb1:
            index1 = random.randint(0, len(individual) // 2 - 1)
            new_value1 = individual[index1]
            while new_value1 == individual[index1]:
                new_value1 = random.randint(0, 5)
            individual[index1] = new_value1
        else:
            index2 = random.randint(len(individual) // 2, len(individual) - 1)
            new_value2 = individual[index2]
            while new_value2 == individual[index2]:
                new_value2 = random.randint(1, 2)
            individual[index2] = new_value2

    return individual,

def readapt(individual): #Strong constraint for the evaluation function (when budget > max) :
removes some random elements
    stop = 0
    while stop < 1:
        if len(decode(individual)) == 0: # do not readapt an empty individual
            break
        non_null = []
        for i in range(len(individual)//2):
            if individual[i] > 0: #list the non-empty individuals
                non_null.append(i)
        j = random.choice(non_null) #pick a random one and shoot it
        individual[j] = 0
        stop +=1
        break
    return individual

def cxCustom(ind1, ind2):              #Crossover function (adapted for individuals expressed as
(2 *N)
    size = len(ind1) // 2
    cx_point1, cx_point2 = random.sample(range(size), 2)
    ind1[:size], ind2[:size] = tools.cxTwoPoint(ind1[:size], ind2[:size], cx_point1, cx_point2)
    ind1[size:], ind2[size:] = tools.cxTwoPoint(ind1[size:], ind2[size:], cx_point1, cx_point2)
    return ind1, ind2

def decode(individu):                 #important decoding function (input 'individual' objects, output
dictionary of items)
    individu_item = {}
    for position in range(0, len(individu)//2) :
        if individu[position] > 0:
            individu_item[position] = [(individu[position]), individu[position+len(individu)//2]]
    return individu_item

#Register functions in the toolbox
toolbox.register("mate", cxCustom)
toolbox.register("mutate", mutation, indpb1 = 0.5)
toolbox.register("readapt", readapt)
toolbox.register("select", tools.selNSGA2)      #NSGA2 genetic algorithm for the selection step (Deb
et al. 2002)

#####
#1.5 Objective functions
#####

def describe(individual):             #Function that separates each small elements within the solution and
creates sub-dataframes

```

```

IRIS_NBS = []
IRIS_NBS_percent = []
IRIS_grey = []
IRIS_grey_percent = []
for i in decode(individual):
    if decode(individual)[i][1]==2:      #IRIS with grey infrastructures
        IRIS_grey.append([IRIS_shp['CODE_IRIS'][i], decode(individual)[i][0]])
        IRIS_grey_percent.append(decode(individual)[i][0]*0.2)

    if decode(individual)[i][1]==1: #IRIS with NBS
        IRIS_NBS.append([IRIS_shp['CODE_IRIS'][i], decode(individual)[i][0]])
        IRIS_NBS_percent.append(decode(individual)[i][0]*0.2)

#Adding to the dataframes (subset_NBS & subset_grey) the specific implementation level (%) of each
IRIS
IRIS_NBS_shp = IRIS_shp[IRIS_shp['CODE_IRIS'].isin([item[0] for item in IRIS_NBS])].copy()
IRIS_grey_shp = IRIS_shp[IRIS_shp['CODE_IRIS'].isin([item[0] for item in IRIS_grey])].copy()
IRIS_NBS_shp['percent'] = IRIS_NBS_percent
IRIS_grey_shp['percent'] = IRIS_grey_percent

subset_NBS = sites[sites['CODE_IRIS'].isin([item[0] for item in IRIS_NBS])].copy()
subset_NBS['percent'] = subset_NBS.apply(lambda x: next((y[1] for y in IRIS_NBS if y[0] ==
x['CODE_IRIS']), None), axis=1)*0.2

subset_grey = sites[sites['CODE_IRIS'].isin([item[0] for item in IRIS_grey])].copy()
subset_grey['percent'] = subset_grey.apply(lambda x: next((y[1] for y in IRIS_grey if y[0] ==
x['CODE_IRIS']), None), axis=1)*0.2

return IRIS_NBS_shp, IRIS_grey_shp, subset_NBS, subset_grey

#Main evaluation function
def mainEval(individual):
    inf = 0.0 #creating empty variables to assign to the individual
    cob_global = 0.0
    cob_local = 0.0
    cob = 0.0
    cos = 0.0
    IRIS_grey = []
    cob_percent = 0.0
    total_eliminated = 0

#First strict constraint : no empty individuals
    if len(decode(individual)) == 0:
        toolbox.mutate(individual)

#Describing the individual
    IRIS_NBS, IRIS_grey, subset_NBS, subset_grey = describe(individual)

#Second strict constraint : if bidget is above the constraint, then use the "readapt" function
    inv_cost = (subset_NBS.area * subset_NBS['percent']).sum() + (subset_grey.area *
subset_grey['percent']).sum()
    while inv_cost > MAX_COST :      #while loop to check if the condition is satisfied
        toolbox.readapt(individual)
        IRIS_NBS, IRIS_grey, subset_NBS, subset_grey = describe(individual)
        inv_cost = (subset_NBS.area * subset_NBS['percent']).sum() + (subset_grey.area *
subset_grey['percent']).sum()

    while len(decode(individual)) == 0:
        toolbox.mutate(individual)

#####
#1) Infiltration benefit function (simple sum)
    inf+= (IRIS_NBS['inf']*IRIS_NBS['percent']).sum() +
(IRIS_grey['inf']*IRIS_grey['percent']).sum()

#####
#2) cooling function (in two parts: local and global)

#Local benefit (adds the pre-calculated local total Willingness to Pay depending on the
implementation level of the given site)
    cob_local += IRIS_NBS.loc[IRIS_NBS['percent'] == 0.2, 'local_wtp_20'].sum()
    cob_local += IRIS_NBS.loc[IRIS_NBS['percent'] == 0.4, 'local_wtp_40'].sum()
    cob_local += IRIS_NBS.loc[IRIS_NBS['percent'] == 0.6, 'local_wtp_60'].sum()

```

```

cob_local += IRIS_NBS.loc[IRIS_NBS['percent'] == 0.8, 'local_wtp_80'].sum()
cob_local += IRIS_NBS.loc[IRIS_NBS['percent'] == 1, 'local_wtp_100'].sum()

#Global benefit (adds the pre-calculated amounts of eliminated heat island areas, depending on the
implementation level)

total_eliminated += IRIS_NBS.loc[IRIS_NBS['percent'] == 0.2, 'eliminated_ICU_by_IRIS_20'].sum()
total_eliminated += IRIS_NBS.loc[IRIS_NBS['percent'] == 0.4, 'eliminated_ICU_by_IRIS_40'].sum()
total_eliminated += IRIS_NBS.loc[IRIS_NBS['percent'] == 0.6, 'eliminated_ICU_by_IRIS_60'].sum()
total_eliminated += IRIS_NBS.loc[IRIS_NBS['percent'] == 0.8, 'eliminated_ICU_by_IRIS_80'].sum()
total_eliminated += IRIS_NBS.loc[IRIS_NBS['percent'] == 1, 'eliminated_ICU_by_IRIS_100'].sum()

percent_reduction = 100 * ((ICU_area - (ICU_area - total_eliminated)) / ICU_area) #Total
reduction in heat island effect in %
cob_global = total_menages * percent_reduction * WTP #Total benefit of heat island reduction
(relation from the choice experiment)

cob += cob_local+cob_global #Total cooling benefit = local + global

#####
#3) opportunity cost function (additive)
cos += (IRIS_NBS['oppcost']*IRIS_NBS['percent']).sum() + (grey_oppcost * IRIS_grey['oppcost'] *
IRIS_grey['percent']).sum()

return inf, cob, cos

toolbox.register("evaluate", mainEval) #register the function

# # #####
# # #1.6. Main algorithm function
# # #####

random.seed(64) #Random seed
pop = toolbox.population(n=MU) #Use initial population from 1.2

hof = tools.ParetoFront()
stats = tools.Statistics(lambda ind: ind.fitness.values)
stats.register("avg", np.mean, axis=0)
stats.register("std", np.std, axis=0)
stats.register("min", np.min, axis=0)
stats.register("max", np.max, axis=0)

#Main algorithm function from DEAM ("mu + lambda" is the best performing one in our case)
def eaMuPlusLambda(population, toolbox, mu, lambda_, cxpb, mutpb, ngen,
stats=None, halloffame=hof, verbose=__debug__):

logbook = tools.Logbook()
logbook.header = ['gen', 'nevals'] + (stats.fields if stats else [])

# Evaluate the individuals with an invalid fitness
invalid_ind = [ind for ind in population if not ind.fitness.valid]
fitnesses = toolbox.map(toolbox.evaluate, invalid_ind)
for ind, fit in zip(invalid_ind, fitnesses):
ind.fitness.values = fit

if halloffame is not None:
halloffame.update(population)

record = stats.compile(population) if stats is not None else {}
logbook.record(gen=0, nevals=len(invalid_ind), **record)
if verbose:
print(logbook.stream)

dominated_fitnesses = []
fronts = []
fronts_objectives = []

# Begin the generational process
for gen in range(1, ngen + 1):
# Vary the population
offspring = algorithms.varOr(population, toolbox, lambda_, cxpb, mutpb)

```

```

# Evaluate the individuals with an invalid fitness
invalid_ind = [ind for ind in offspring if not ind.fitness.valid]
fitnesses = toolbox.map(toolbox.evaluate, invalid_ind)
for ind, fit in zip(invalid_ind, fitnesses):
    ind.fitness.values = fit

# Update the hall of fame with the generated individuals
if halloffame is not None:
    halloffame.update(offspring)

# Select the next generation population
population[:] = toolbox.select(population + offspring, mu)

fronts.append([list(decode(ind)) for ind in pop])
fronts_objectives.append([ind.fitness.values for ind in pop])

# Update the statistics with the new population
record = stats.compile(population) if stats is not None else {}
logbook.record(gen=gen, nevals=len(population), **record)
if verbose:
    print(logbook.stream)
for ind in population:
    dominated_fitnesses.append(ind.fitness.values)

return population, logbook, dominated_fitnesses, fronts, fronts_objectives

#####
#2.1 Run the algorithm
#####
pop, log, dominated_fitnesses, fronts, fronts_objectives = eaMuPlusLambda(pop, toolbox, MU, LAMBDA,
CXPB, MUTPB, NGEN, stats, halloffame=hof)

#####
#2.2 Export the results (Important!)
#####

front = np.array([ind.fitness.values for ind in pop])

# # Form each column for the DataFrame
pop_dict = {
    "individual": [decode(ind) for ind in pop],
    "ind_size" : [len(decode(ind)) for ind in pop],
    "inf" : [ind.fitness.values[0] for ind in pop],
    "cob" : [ind.fitness.values[1] for ind in pop],
    "cos" : [ind.fitness.values[2] for ind in pop],
}

# Create a DataFrame from the data dict where keys are the columns
bestpop = pd.DataFrame(data=pop_dict)
bestpop.to_csv(r'C:/LOCATION/bestpop.csv')

```

4 Traductions en français

Résumé de la thèse

Questions de recherche

À la suite d'un évènement pluvieux survenu en 2011 qui a entraîné de fortes inondations, la ville de Copenhague a lancé le *Cloudburst Management Plan* (« plan de gestion des risques d'orage »), une initiative de vaste ampleur, étalée sur 20 ans, visant à préparer la ville aux fortes précipitations et au risque d'inondation. Ce plan se distingue significativement dans le domaine des politiques d'adaptation au changement climatique urbain, car il représente l'un des rares efforts à grande échelle pour aborder de manière proactive la vulnérabilité de la ville aux impacts futurs du changement climatique. Ce plan se distingue d'une part par son approche de recherche multidisciplinaire englobant la conception, la modélisation et l'évaluation de divers scénarios d'adaptation. D'autre part, la stratégie d'adaptation urbaine soutenue par ce plan implique une approche en phases, avec une priorisation de zones spécifiques de la ville pour l'adaptation en plusieurs étapes. De plus, son champ d'application va au-delà de la protection contre les inondations ; il englobe également des mesures visant à atténuer les diverses conséquences néfastes du changement climatique sur les environnements urbains (pollution atmosphérique, effets de chaleur, etc.).

Copenhague sert d'exemple du double rôle joué par les villes : elles se trouvent en première ligne du changement climatique et ont à la fois un rôle de vulnérabilité et un rôle de résilience potentielle. Abritant une part substantielle - et croissante - de la population mondiale, soit environ 4,2 milliards d'habitants, ainsi que la majorité des actifs et des activités économiques, les villes sont particulièrement exposées aux impacts du changement climatique, tels que les inondations, les sécheresses, la pollution, le stress thermique, etc. (Revi et al., 2014). Le rapport du GIEC de 2022 souligne de manière indiscutable cette réalité : les villes sont des points chauds du changement climatique, où les risques ont non seulement augmenté, mais vont aussi s'aggraver au cours des prochaines décennies (Dodman et al., 2022).

Pourtant, les villes sont également les principaux acteurs potentiels de l'atténuation et de l'adaptation au changement climatique. Elles disposent de ressources financières considérables, de fortes capacités d'innovation, et de la capacité à formuler et mettre en œuvre des actions transformatrices (Dodman et al., 2022 ; Commission européenne, Direction générale de la recherche et de l'innovation, 2015). Alors que les villes font face aux conséquences croissantes du changement climatique, elles ont en même temps le potentiel significatif de diriger des efforts visant à accroître leur résilience.

Parmi les stratégies qui ont émergé au cours des dernières décennies pour renforcer la résilience urbaine, les Solutions Fondées sur la Nature (SFN) ont suscité beaucoup d'attention, notamment en Europe (Davies et al., 2021). Les SFN sont des solutions qui utilisent les processus naturels et les écosystèmes comme moyen de fournir des solutions aux défis de l'atténuation et de l'adaptation au changement climatique. Ces solutions ont gagné en popularité car il s'agit d'approches qui ont la particularité d'offrir de multiples bénéfices à la société - notamment atténuer les risques liés au changement climatique - tout en bénéficiant aussi à la biodiversité et aux écosystèmes. On parle ainsi de « co-bénéfices ». Ce sont aussi des solutions qui sont considérées comme ayant un ratio coût-efficacité égal sinon supérieur aux solutions « grises » classiques (Frantzeskaki et al., 2019).

Alors que l'intérêt pour les SFN ne cesse de croître, d'importants défis persistent pour les intégrer dans l'environnement urbain. Certaines villes ont formulé des plans d'adaptation au changement climatique, mais la traduction de ces plans en actions reste limitée (Hudson et al., 2023 ; Oijstaeijen et al., 2020) : développer des SFN n'est pas une priorité dans la majorité des villes (Oijstaeijen et al., 2020), et ces solutions sont souvent mises en œuvre au cas par cas, et à petite échelle (Almenar et al., 2016 ; Elmqvist et al., 2013). Par conséquent, de nombreuses villes passent à côté des opportunités offertes par les bénéfices multiples des SFN (Hudson et al., 2023).

La recherche sur les SFN s'est largement concentrée sur l'étude des impacts de ces solutions, en cherchant à démontrer leur efficacité pour répondre à des enjeux spécifiques (liés au changement climatique), et analysant leurs bénéfices multiples et développant des méthodologies d'évaluation adaptées à ces solutions (Nesshöver et al., 2017). L'économie environnementale a été une partie intégrante de cette recherche, fournissant et raffinant des méthodes d'évaluation des co-bénéfices des SFN, et contribuant à la formulation de nombreux cadres d'aide à la décision (Jacobs et al., 2016 ; Pascual et al., 2017). Cependant, malgré de nombreuses avancées dans ces domaines, il existe toujours une zone grise dans la connaissance de ces solutions, concernant 1) l'hétérogénéité spatiale des coûts et des bénéfices associés aux SFN, et 2) les méthodes de soutien à la décision nécessaires pour aider à la planification à grande échelle des SFN dans les villes.

L'objectif global de cette thèse est d'explorer les enjeux spécifiques de la planification spatiale pour les SFN dans les zones urbaines. Cet objectif se décline à deux niveaux : d'une part, il s'agit d'investiguer les enjeux spatiaux associés à la planification des SFN, et donc de contribuer à ce champ de recherche ; d'autre part, il s'agit de répondre aux enjeux d'un cas d'étude spécifique d'une initiative de politique publique lancée dans une métropole française. Deux questions de recherche sont examinées dans ce travail :

1. Quelle est l'hétérogénéité spatiale des coûts et bénéfices des SFN en ville ?
2. Comment prioriser le développement spatial des SFN, en tenant compte de leurs nombreux bénéfices potentiels et coûts ?

Apporter des éléments de réponse à ces problématiques peut permettre de fournir des recommandations aux décideurs publics, portant sur les stratégies d'adaptation au changement climatique des villes. De plus, ce travail peut délivrer de nouvelles perspectives de recherche pour l'économie environnementale, notamment l'étude de l'hétérogénéité spatiale de la valeur des SFN et le développement de nouveaux outils de soutien à la décision adaptés à la planification des SFN.

Cas d'étude

Les travaux de cette thèse CIFRE portent sur un cas d'étude particulier. Il s'agit d'une expérimentation en matière de gestion des eaux pluviales et d'un projet de R&D, menés à Bordeaux Métropole, en France. Cette expérimentation a été initiée par le service en charge de l'assainissement de la Métropole, mais présente néanmoins un intérêt général pour tous les services métropolitains, ainsi que pour les acteurs de l'aménagement. Cette thèse représente un segment spécifique de cette initiative de R&D.

L'objectif de cette politique publique est de développer la recharge maîtrisée des aquifères de surface urbains à Bordeaux Métropole. Cette approche vise à soulager la pression sur les nappes profondes en développant la valorisation des eaux pluviales en ville (y compris à la fois des SFN et des infrastructures grises), à grande échelle. La logique de cette approche est la suivante : les ressources en eau potable sont en majorité issue des aquifères profonds de la région, dont la disponibilité future est menacée, du fait du changement climatique et de la croissance démographique. Des solutions innovantes de gestion des eaux pluviales (SIGEP) sont donc mises à l'étude. Ces SIGEP sont des ouvrages dont la fonction principale est de permettre l'infiltration des eaux pluviales dans les nappes libres en utilisant celle-ci comme des infrastructures naturelles de stockage, dans le but de rendre disponibles ces ressources lors des périodes de besoins, et ce afin de se substituer à la consommation d'eau potable pour certains usages ne nécessitant pas une qualité d'eau potable (arrosage des espaces verts, nettoyage de l'espace public, usages industriels...). La finalité recherchée de cette approche est de créer une ressource alternative en eau, permettant de préserver les aquifères profonds.

Parmi ces SIGEP, nous considérons à la fois des infrastructures classiques, dites « grises » (tranchées infiltrantes, puits d'infiltration et d'injection...), dont la seule fonction est de favoriser la recharge maîtrisée des aquifères ; et d'autre part des SfN (noues végétalisées, bassins d'infiltration multi-usages, etc.) qui permettent à la fois la recharge, et fournissent des co-bénéfices. Les SIGEP correspondent

donc à une gestion des eaux pluviales hors réseaux, et sont assimilables ainsi aux termes de « techniques alternatives », « infrastructures vertes » et « solutions compensatoires de gestion des eaux pluviales », avec la nuance de chercher à mettre l'emphase sur l'infiltration, le stockage et la valorisation des eaux pluviales. Cette approche est donc aussi quelque part liée au nouveau paradigme dans la gestion des eaux pluviales urbaines, à l'œuvre dans de nombreuses grandes villes européennes et mondiales, visant à la gestion à la source des eaux pluviales.

La mise en place de SIGEP pose une problématique complexe de décision publique. Dans un cadre de ressources budgétaires contraintes et d'espace rare en milieu urbain, le décideur public doit déterminer la localisation, l'étendue et le type de solutions permettant de maximiser le bien-être social (Bush & Doyon, 2019). Or, les coûts et les bénéfices associés aux SIGEP présentent tous une fonction de répartition spatiale (Hein et al., 2006; Naidoo & Ricketts, 2006; Tardieu, 2017). Les espaces de centre-ville et d'urbain dense concentrent des effets néfastes du changement climatique et des populations importantes (Bulkeley & Betsill, 2003), ce qui accentue les bénéfices potentiels des SfN (Bush & Doyon, 2019; Luederitz et al., 2015). En revanche, les coûts d'opportunités y sont plus élevés car la compétition entre usages des sols plus forte. Les bénéfices liés à la recharge varient également en fonction des caractéristiques pédologiques et hydrogéologiques et de la localisation de la demande pour l'eau réinfiltrée (Maréchal et al., 2020).

L'initiative de R&D comprend une étude hydrogéologique sur l'infiltration, le stockage et la réutilisation des eaux pluviales, menée en parallèle de cette thèse par une équipe d'hydrogéologues du Bureau de Recherches Géologiques et Minières (BRGM) français. Cette étude vise à créer une cartographie de la favorabilité des sols de Bordeaux Métropole à infiltrer et à stocker les eaux pluviales, et visant à guider le développement opérationnel de SIGEP. Le deuxième aspect de ce projet de R&D est de fournir un soutien à la prise de décision à moyen et long terme en matière de planification urbaine et d'adaptation au changement climatique, et ceci est le cœur du sujet de cette thèse. Ce travail de thèse s'attache d'une part à caractériser et évaluer les bénéfices et coûts associés aux SIGEP. Il s'agit d'en évaluer les différents bénéfices, ainsi que d'en analyser leur hétérogénéité spatiale. D'autres parts, ce travail vise à proposer un support d'aide à la planification urbaine permettant de déterminer le type et la localisation de projets de recharge maîtrisée dans un contexte d'espace et de ressources contraintes, de manière à en optimiser les différents bénéfices. Il apporte des éléments de réponses aux questions relatives à la répartition des coûts et bénéfices potentiels de ces infrastructures, à la localisation optimale de ces solutions et aux choix techniques à privilégier (SFN, infrastructures grises)?

Méthodes

Pour répondre à ces questions, deux approches méthodologiques sont mises en place dans le cadre de cette thèse. D'une part, il s'agit d'une expérience de choix discret (1), d'autre part d'une optimisation multi-objectif (2).

1. L'expérience de choix a pour objectif d'évaluer les multiples bénéfices produits par les SIGEP et d'analyser leur hétérogénéité spatiale dans le but de cartographier la valeur des co-bénéfices associés aux SIGEP en fonction de leur emplacement. Cet objectif de cartographie de la demande en co-bénéfices des SIGEP vise à fournir une couche d'information spatiale, qui est mobilisée dans l'application de l'optimisation multi-objectif. Cette enquête examine également une problématique spécifique: comment divers types d'inégalités environnementales (exposition aux risques environnementaux, inégalité d'accès aux espaces verts et inégalité relative aux impacts négatifs des politiques environnementales) impactent la demande des individus pour les SIGEP ? L'expérience de choix que nous avons menée innove dans la littérature sur les préférences déclarées en analysant l'impact des inégalités environnementales. Il s'agit également de l'une des premières études à examiner l'impact sur les préférences de l'utilisation d'espaces de voiries pour le développement des SFN dans une ville.

Dans cette enquête, les répondants (n=302) doivent réaliser une série de choix successifs entre 2 alternatives contrastées de développement des SIGEP, caractérisés par leurs divers bénéfices et impacts, et un scénario « status quo ». Ces alternatives sont définies par 5 attributs: le niveau de protection des ressources en eau potable ; la réduction des surfaces de forte chaleur de la métropole induit par le scénario ; l'impact de mise en place de solutions d'infiltration et stockage sur l'espace dédié à la voiture ; la distance d'une solution végétalisée au lieu de résidence des répondants ; la contribution monétaire que devraient réaliser les citoyens sous la forme d'une augmentation de leur facture d'eau. Cette expérience de choix est présentée dans le chapitre 2 de la thèse.

2. L'optimisation multi-objectifs. La méthode d'optimisation ne consiste pas en une recherche de site unique, mais en une méthode pour la sélection de combinaisons de sites où ces SIGEP peuvent être mises en place de manière simultanée. En cela, il s'agit d'une approche stratégique : cette optimisation vise à composer des plans d'aménagements à l'échelle de la métropole entière, où des sous-ensembles de sites de SIGEP sont choisis parmi l'ensemble des sites possibles. Etant donné qu'une combinaison de site est recherchée, il y a un phénomène d'explosion combinatoire du nombre de combinaisons possibles. Un algorithme évolutionnaire (Deb, 2014) est utilisé pour effectuer cette optimisation.

Les solutions comparées et évaluées par cette méthode consistent en des plans d'aménagement de SIGEP diversifiés, constitués de combinaisons d'emplacements de la métropole où des SIGEP peuvent être mises en place (Yoon et al., 2019). L'algorithme crée ainsi ces solutions en constituant dans un premier temps des sous-ensembles aléatoires de sites. Puis, il conserve les meilleures solutions, les

recombinent entre elles, de manière à créer de nouvelles populations de solutions. Ce processus est répété un grand nombre de fois, jusqu'à aboutir à un ensemble de solutions optimales ou quasi-optimales. L'avantage de cette méthode est de pouvoir délivrer des solutions diversifiées le long d'une frontière Pareto-optimale. Un problème multi-objectifs n'ayant pas de solutions uniques non ambiguës, cette méthode permet d'illustrer les arbitrages inhérents aux problèmes multi-objectifs, et de visualiser les choix concrets de localisation qui en découlent. Le chapitre 1 est dédié à l'explication de cette méthode.

Cette méthode d'optimisation est appliquée en premier lieu dans le cadre d'une réflexion théorique (chapitre 3). Ce travail porte sur les problématiques de choix de localisation d'infrastructures d'infiltration en ville, lorsque plusieurs objectifs stratégiques sont considérés simultanément par le planificateur : la maximisation des services écosystémiques, de l'infiltration des eaux pluviales, et la minimisation des coûts d'opportunité. En particulier, nous recherchons quelles sont les stratégies spatiales optimales lorsque ces objectifs présentent des motifs spatiaux hétérogènes et en présence de gradients urbain-rural de coûts et bénéfiques. Une ville-modèle, éclairée par le cas de Bordeaux Métropole, est élaborée pour y appliquer l'optimisation. Une série d'expériences sont menées sur cette ville-modèle, visant à faire varier les conditions de l'optimisation, 1) en restreignant les possibilités d'infiltration dans la zone centrique de la ville-modèle, 2) en introduisant des effets de substitutions des services écosystémiques par l'introduction d'espaces verts existants, et 3) en introduisant la distinction entre infrastructures grises et SfN. Ces travaux permettent l'exploration de front d'optimalité (de Pareto) pour chacune des expériences, et de comparer les différences de stratégies entre chaque front.

Pour finir, dans le chapitre 4, nous appliquons l'optimisation multi-objectif à l'étude de cas de Bordeaux Métropole. Ce travail vise à développer une approche approfondie, depuis la conception, jusqu'à la mise en œuvre et l'exploitation des résultats de l'optimisation multi-objectif. Il s'agit d'une étude qui lie les différentes facettes de l'initiative de R&D, en tenant compte des enseignements de l'étude hydrogéologique réalisée dans la région métropolitaine ainsi que des résultats spatialisés du chapitre 2 dans le cadre de l'optimisation multi-objectif. Ce travail est basé sur plusieurs volets de consultation des principaux acteurs et décideurs, et vise à fournir des méthodes pour l'exploration des fronts de Pareto et leur exploitation pour fournir des informations réelles et exploitables aux décideurs.

Résultats principaux

L'analyse de l'expérience de choix indique une importante demande de la part des résidents, à la fois pour la préservation des aquifères profonds et pour la lutte contre les îlots de chaleur urbain. L'impact sur les espaces de voirie dédiés à la voiture est la principale source d'hétérogénéité au sein de la population : il est considéré comme un impact négatif par une partie de la population, en particulier ceux

qui dépendent de l'utilisation de la voiture, et comme un avantage pour une autre partie de la population. L'analyse se concentre également sur l'étude de l'hétérogénéité spatiale des préférences. Nous identifions un phénomène de dépendance spatiale globale de la demande en matière de régulation climatique locale, et nous identifions des points chauds et froids pour le consentement à payer associé à la réduction de l'espace dédié à la voiture.

L'hétérogénéité spatiale de la demande en rafraîchissement urbain est ensuite analysée comme résultant de l'impact des inégalités environnementales : une forte exposition à la chaleur augmente la demande individuelle en rafraîchissement urbain. Cette constatation indique que les inégalités en matière d'exposition aux risques environnementaux peuvent être un important moteur de l'hétérogénéité spatiale de la demande en SFN. Ce gradient de demande pour les services écosystémiques est en ligne avec les résultats d'autres études (Baró et al., 2017 ; Hérivaux & Le Coënt, 2021). Nous constatons également que la dépendance à l'égard de l'utilisation de la voiture impacte négativement la demande des individus pour des politiques susceptibles de réduire la disponibilité des espaces de voirie. Nous soutenons que cela reflète l'impact des inégalités environnementales causées par les SFN et les politiques d'embellissement urbain sur les préférences individuelles : la réduction de l'espace de voiture peut avoir un impact soit fortement négatif, soit fortement positif sur le bien-être individuel, en fonction de la mesure dans laquelle celui-ci dépend de l'utilisation de la voiture.

Enfin, la relation significative établie dans l'analyse de post-estimation entre l'exposition aux îlots de chaleur urbain et la demande en rafraîchissement permet de créer une carte de demande pour ce co-bénéfice à l'échelle de Bordeaux Métropole. La carte de demande résultante est également un résultat en soi et peut intéresser les décideurs locaux et les services de gestion des espaces verts. Cette carte de demande est également intégrée en tant qu'élément clé dans l'optimisation multi-objectifs finale pour la planification de la recharge des aquifères dans l'étude de cas de Bordeaux.

Le chapitre 3 examine l'applicabilité de l'optimisation multi-objectifs dans un problème de décision générique. Dans le cadre de ce travail, l'accent central est mis sur les décideurs cherchant à déterminer les emplacements optimaux pour le développement d'infrastructures d'infiltration, en présence de gradients urbains-ruraux de coûts et d'bénéfices. Ce chapitre vise également à relier la littérature existante sur l'optimisation spatiale des infrastructures de gestion des eaux pluviales à celle portant sur les gradients urbains-ruraux. En utilisant une optimisation multi-objectifs et une ville-modèle théorique mono-centrique simple, nous mettons en évidence des stratégies contrastées de localisation des infrastructures d'infiltration dans différents contextes caractérisés par diverses contraintes hydrogéologiques, des effets de substitution avec les espaces verts urbains existants et la disponibilité de technologies d'infiltration alternatives.

Ce travail génère deux ensembles principaux de résultats. Tout d'abord, il établit notre positionnement méthodologique, mettant en lumière l'optimisation multi-objectifs comme un outil pertinent d'aide à la décision, permettant la compréhension des multiples approches possibles et leurs arbitrages, pour l'adaptation au changement climatique. Deuxièmement, la simplicité de notre modèle de ville permet de fournir des conclusions générales sur les recommandations spatiales aux décideurs urbains qui vont au-delà des études de cas individuelles. D'une part, il existe un arbitrage fort entre l'introduction des SFN dans les centres-villes ou la mise en œuvre d'infrastructures grises dans les zones périurbaines et rurales, aux alentours de la ville. De plus, l'étude met en évidence l'influence potentielle des effets de substitution, démontrant leur impact décroissant sur l'attrait des sites du centre-ville. Enfin, les règles spatiales sont modifiées lorsque les centres-villes ne sont pas adaptés aux projets de recharge des aquifères : dans ce cas, les solutions de compromis devraient plutôt viser la planification des emplacements des SFN qui mélangent les emplacements centraux avec des emplacements hors de la ville où l'infiltration est plus efficace.

Dans le chapitre 4, nous proposons une approche intégrée de la planification d'infrastructures de recharge. Ce travail est en quelque sorte la conclusion des deux approches précédentes proposées dans la thèse, ainsi que de la carte multicritère de favorabilité des sols à l'infiltration, réalisée en parallèle de cette thèse. Nous avons proposé une nouvelle manière d'utiliser l'optimisation multi-objectifs pour relier l'adaptation urbaine au changement climatique, la gestion des eaux pluviales et la recharge des aquifères. Ce travail visait à répondre à notre deuxième question de recherche dans un contexte appliqué et interdisciplinaire : où localiser les infrastructures de recharge dans le contexte d'une distribution complexe des coûts et des bénéfices, et quel type d'infrastructure devrait être mise en place.

Les principales conclusions de l'optimisation multi-objectifs informent les décisions concernant les zones et les quartiers à privilégier pour le développement de la recharge, ainsi que les types d'infrastructures à utiliser et les intensités de mise en œuvre à développer. Une première stratégie qui émerge de ce travail est que la priorisation de la recharge des aquifères favorise les solutions grises spécialisées, situées principalement dans des zones présentant des conditions idéales pour l'infiltration des eaux pluviales et des coûts d'opportunité faibles, principalement en périphérie de la ville. En revanche, les solutions mettant l'accent sur le rafraîchissement urbain présentent des caractéristiques distinctes, avec des SFN concentrées dans les zones d'îlots de chaleur. Ce résultat diverge des conclusions théoriques du chapitre 3, qui n'ont pas tenu compte de la localisation des îlots de chaleur, se concentrant uniquement sur la densité de la demande. De plus, les solutions grises sont intégrées dans les deux stratégies, souvent en périphérie de la ville et dans les zones suburbaines, offrant un rendement de recharge à un coût d'opportunité moins élevé. Certains sites IRIS émergent de manière constante comme des choix préférés, quelle que soit la stratégie choisie : ce sont des choix sans regrets.

Des solutions hybrides combinant des aspects des deux stratégies polaires sont possibles, impliquant des compromis entre les sites gris suburbains et les sites SFN centraux. De plus, l'examen du front de Pareto révèle une zone de gains élevés, où des solutions axées sur de hauts niveaux de rafraîchissement urbain offrent de hauts niveaux dans les deux bénéfiques (recharge et rafraîchissement). Ce constat suggère que les décideurs n'ont pas nécessairement besoin de privilégier un bénéfice par rapport à l'autre : cette solution permet de bien performer dans les deux dimensions, bien que ces solutions s'accompagnent de coûts d'opportunité plus élevés. En conclusion pour cette étude de cas, les parties prenantes doivent tenir compte de leur priorité dans la minimisation des coûts d'opportunité lorsqu'elles agissent sur ces résultats. Si la réduction des coûts d'opportunité est primordiale, d'autres solutions alternatives peuvent être plus appropriées, tandis que ceux qui valorisent les bénéfiques globaux peuvent privilégier les solutions ambitieuses axées sur le rafraîchissement urbain.

Conclusions de la thèse

La transformation des villes est lente, tout comme l'adoption de pratiques innovantes telles que les SFN et les nouvelles techniques, dites « alternatives », de gestion des eaux pluviales. Ces options restent des alternatives à l'aménagement urbain conventionnel, centré sur la voiture, et s'appuient sur des techniques traditionnelles de gestion de l'eau grise et centralisée. En fait, les applications des SFN et des techniques alternatives sont principalement observées dans les nouveaux développements urbains, et non dans les anciennes zones urbaines marquées par les conceptions centrées sur la voiture du XXe siècle, qui ont largement négligé les services écosystémiques. Bien que certaines grandes villes européennes, en particulier les capitales, commencent à s'approprier le concept de services écosystémiques et des stratégies ambitieuses d'adaptation au changement climatique, ces pratiques restent marginales. En revanche, les impacts négatifs du changement climatique augmentent rapidement, et avec d'importantes incertitudes. Les villes risquent de prendre du retard dans la course contre la montre pour développer l'adaptation au changement climatique.

Dans cette thèse, nous avons participé à identifier des pistes en matière d'adaptation en identifiant des stratégies spatiales générales pour la planification des SFN de recharge des aquifères: compte tenu des ressources et de l'espace limités, optimiser l'impact des SFN devient un objectif impératif pour faire face à l'écart d'adaptation. Cette thèse s'est également penchée sur les aspects spatiaux des coûts et des bénéfiques associés aux SFN et de leurs implications pour l'aménagement urbain.

La première contribution majeure concerne la distribution spatiale des bénéfiques. En ce qui concerne les co-bénéfices, nous avons rassemblé des informations à la fois sur la distribution spatiale de l'efficacité potentielle des SFN pour fournir des co-bénéfices, ainsi que sur la demande pour ces co-bénéfices. En termes généraux, la demande de SFN est principalement concentrée dans les zones à haut

risque climatique, qui peuvent souvent être situées dans des zones densément peuplées. Ces zones centrales sont potentiellement très rémunératrices en termes de co-bénéfices, car elles ont une demande agrégée élevée, mais les contraintes d'espace limitent souvent la mise en œuvre des SFN. En termes pratiques, il existe peu d'espaces « vides » disponibles, de zones de stationnement ou de larges rues, pouvant être transformés en SFN. Lorsqu'il existe de telles possibilités, cela se fait souvent à un coût d'opportunité très élevé. Dans de telles zones centrales, les politiques publiques peuvent envisager des types de SFN alternatifs avec une empreinte plus faible, tels que les toits et façades végétalisés, ou d'autres techniques alternatives, tels que les revêtements perméables.

Le deuxième type de contributions de cette thèse découle de cette analyse de la distribution spatiale des bénéfices de la recharge des aquifères, et concerne les modèles spatiaux pour optimiser l'emplacement des infrastructures de recharge des aquifères. Le premier modèle suggère de mettre en œuvre des SFN près des zones qui présentent les conditions suivantes : des zones densément peuplées avec des services écosystémiques gravement dégradés, une forte demande individuelle pour les SFN, et beaucoup d'espace disponible pour développer les SFN. Ces zones peuvent être des points chauds potentiels des inégalités environnementales, de sorte que cette approche peut apporter une amélioration substantielle du bien-être des villes, et elles ne se trouvent pas nécessairement dans les centres-villes. Dans notre cas, elles se trouvent principalement dans les quartiers périurbains.

Ce modèle contraste avec la dynamique des politiques actuelles de végétalisation à l'œuvre dans de nombreuses villes – pas nécessairement dans le cas de la Métropole de Bordeaux - qui visent principalement soit les quartiers relativement aisés du centre, soit les développements urbains récemment construits ou en construction (Kato-Huerta & Geneletti, 2022). En d'autres termes, la répartition actuelle des projets de végétalisation tend souvent à perpétuer les inégalités socio-économiques (Calderón-Argelich et al., 2021). Par conséquent, maximiser les emplacements des SFN pour fournir des co-bénéfices est intrinsèquement lié aux considérations de justice environnementale en matière de distribution : les perspectives spatiales résultant de notre OMO pourraient potentiellement contribuer à atténuer les inégalités environnementales.

En ce qui concerne les infrastructures spécialisées, telles que les infrastructures d'infiltration grises, nos résultats indiquent qu'elles devraient plutôt être développées dans les rares zones péri-urbaines qui remplissent les conditions suivantes : avoir les meilleures conditions hydrogéologiques pour la recharge et présenter un espace abondant et bon marché pour développer les infrastructures de recharge. La mise en œuvre de telles stratégies offre potentiellement des économies d'échelle élevées et un ratio coût-efficacité élevé en ce qui concerne la recharge. De plus, dans de nombreuses villes, il s'agit souvent de zones moins peuplées, ce qui se traduit par moins de co-bénéfices potentiels, de sorte que ces stratégies se concentrent davantage sur la recharge que sur la fourniture de multiples bénéfices. Il est aussi possible

que ces résidents d'espaces péri-urbains soient mieux pourvus en jardins privés ou en accès à des espaces verts naturels et publics, ce qui entraîne une demande moindre pour les co-bénéfices des SFN. Cet effet particulier reste à étudier, car nous n'avons pas réussi à identifier avec succès des effets de substitution entre les SFN et les jardins privés ou les parcs existants dans l'expérience de choix.

Ce modèle spatial ne constitue pas un contraste net par rapport aux pratiques existantes - la création de grandes infrastructures monofonctionnelles en dehors des zones urbaines. Cependant, la comparaison de ce modèle avec le premier - lié aux SFN - est d'une grande importance. Potentiellement, les mêmes zones péri-urbaines peuvent apparaître comme optimales soit pour développer des SFN multifonctionnels, comme mentionné précédemment, soit pour des infrastructures grises spécialisées. Une interprétation de ce résultat est que les parcelles péri-urbaines qui peuvent sembler initialement intéressantes pour développer des infrastructures grises hautement spécialisées peuvent, dans les bonnes conditions, être également optimales pour développer des SFN. Dans cette situation, opter pour des SFN plutôt que des infrastructures grises pourrait contribuer à réduire les inégalités environnementales, apportant de grandes améliorations au bien-être public. En conclusion, les décideurs doivent absolument adopter une approche spatiale pour planifier les stratégies d'adaptation et de gestion des eaux pluviales : cela peut permettre de révéler ces solutions synergiques qui ne se manifesteraient pas nécessairement autrement.

Notre deuxième question de recherche dans cette thèse concernait également les outils pour optimiser l'emplacement et le type d'infrastructures de recharge des aquifères. En conclusion de cette thèse, nous pouvons affirmer que l'OMO est une approche précieuse pour la planification spatiale urbaine. Cette méthode s'inscrit dans une niche spécifique en matière de prise de décision : elle fournit un cadre robuste pour la création et la comparaison de stratégies spatiales, lorsque la conception de telles stratégies à grande échelle avec des objectifs conflictuels est une tâche complexe. Ainsi cette approche a une portée légèrement différente de l'analyse coûts-bénéfices et de l'analyse multicritères : elle vise avant tout à élaborer des plans spatiaux optimaux.

Néanmoins, l'OMO pose des enjeux de visualisation en raison de la quantité de données et de résultats générés. Impliquer les parties prenantes dès le début et élaborer des méthodes efficaces pour visualiser et explorer les résultats du front de Pareto sont des aspects impératifs pour utiliser efficacement l'OMO. En fait, cette approche n'est pas encore une méthode entièrement opérationnelle et pratique pour soutenir la planification urbaine des SFN. Outre le fait que la mise en œuvre de l'OMO nécessite une connaissance technique assez élevée, nous soutenons que cette méthode manque encore de directives appropriées pour diffuser sa mise en œuvre auprès des décideurs urbains. En particulier, il reste encore beaucoup de travail aux chercheurs pour incorporer cet outil dans les cadres de prise de

décision des SFN. Par exemple, l'analyse des fronts de Pareto et l'analyse des perspectives spatiales résultant des fronts de Pareto manquent encore de directives claires.

Cependant, nous soutenons qu'il y a dans cette approche une opportunité pour les chercheurs, et en particulier les économistes de l'environnement : il s'agit indéniablement d'un outil précieux qui peut combler les lacunes entre l'économie des services écosystémiques et les sciences de la prise de décision, et un outil qui fournit une interface multidisciplinaire pour tous les multiples domaines liés à l'adaptation au changement climatique et à la planification de l'usage des sols.

En conclusion, nos investigations ont montré qu'il existe des synergies possibles dans le développement d'infrastructures de recharge des eaux souterraines. Ces synergies dépendent notamment de la distribution spatiale des potentiels bénéfiques des SfN. En répondant à notre première question de recherche, nous avons mis en lumière que la distribution de ces bénéfiques peut différer des pratiques actuelles en matière de SfN et de mise en œuvre de la recharge des eaux souterraines. Notamment, les initiatives de végétalisation ne produisent pas toujours des résultats optimaux dans les centres-villes, et de grands sites suburbains ne sont pas systématiquement les zones les plus efficaces pour développer des initiatives de recharge des eaux souterraines, en particulier dans le contexte de la substitution de l'utilisation de petits volumes d'eau, comme c'est le cas dans l'agglomération bordelaise.

Les stratégies urbaines visant une adaptation efficace au changement climatique doivent prendre en compte ces dimensions spatiales, car une action environnementale proactive nécessite entre autre une exploration globale des compromis spatiaux, la prise en compte des demandes des citoyens, l'anticipation de l'acceptation des politiques par les populations, et l'optimisation des ressources spatiales. De nouvelles méthodologies, telles que l'Optimisation Multi-Objectif, pourraient revêtir une plus grande importance dans les outils futurs d'économie environnementale pour relever ces défis spatiaux complexes.

Les effets du changement climatique sur les villes et sur leurs approvisionnements en eau sont trop nombreux et trop graves pour que les chercheurs et les décideurs politiques négligent l'exploration de toutes les approches de soutien à la décision existantes. Cette d'investigation offre le potentiel de découvrir de nouvelles méthodologies de formulation et d'évaluation des politiques. *In fine*, cela pourrait contribuer à favoriser l'adoption généralisée de stratégies d'adaptation urbaine intégrées, précises et efficaces, avant que la fenêtre d'opportunité pour s'adapter aux changements climatiques ne se referme.

Introduction générale

Introduction

À la suite d'un évènement pluvieux survenu en 2011 qui a entraîné de fortes inondations, la ville de Copenhague a lancé le *Cloudburst Management Plan* (« plan de gestion des risques d'orage »), une initiative globale sur 20 ans visant à préparer la ville aux fortes précipitations. Ce plan se distingue significativement dans le domaine des politiques d'adaptation au changement climatique urbain, car il représente l'un des rares efforts à grande échelle pour aborder proactivement la vulnérabilité de la ville aux impacts futurs du changement climatique. Ce qui distingue ce plan, c'est son approche globale, soutenue par une enquête multidisciplinaire englobant la conception, la modélisation et l'évaluation de divers scénarios d'adaptation. La stratégie d'adaptation urbaine soutenue par le plan implique une approche en phases, avec une priorisation de zones spécifiques de la ville pour l'adaptation en plusieurs étapes. De plus, son champ d'application va au-delà de la protection contre les inondations ; il englobe également des mesures visant à atténuer les diverses conséquences néfastes du changement climatique sur les environnements urbains (pollution atmosphérique, effets de chaleur, etc.).

Copenhague sert d'exemple du double rôle joué par les villes : elles se trouvent en première ligne du changement climatique et ont à la fois un rôle de vulnérabilité et un rôle de résilience potentielle. Abritant une part substantielle - et croissante - de la population mondiale, soit environ 4,2 milliards d'habitants, ainsi que la majorité des actifs et des activités économiques, les villes sont particulièrement exposées aux impacts du changement climatique, tels que les inondations, les sécheresses, la pollution, le stress thermique, etc. (Revi et al., 2014). Le rapport du GIEC de 2022 souligne de manière indiscutable cette réalité : les villes sont des points chauds du changement climatique, où les risques ont non seulement augmenté, mais vont aussi s'aggraver au cours des prochaines décennies (Dodman et al., 2022).

Pourtant, les villes sont également les principaux acteurs potentiels de l'atténuation et de l'adaptation au changement climatique. Elles disposent de ressources financières considérables, de fortes capacités d'innovation, et de la capacité à formuler et mettre en œuvre des actions transformatrices (Dodman et al., 2022 ; Commission européenne, Direction générale de la recherche et de l'innovation, 2015). Alors que les villes font face aux conséquences croissantes du changement climatique, elles ont en même temps le potentiel significatif de diriger des efforts visant à accroître leur résilience.

Parmi les stratégies qui ont émergé au cours des dernières décennies pour renforcer la résilience urbaine, les Solutions Fondées sur la Nature (SFN) ont suscité beaucoup d'attention, notamment en

Europe (Davies et al., 2021). Les SFN sont des solutions qui utilisent les processus naturels et les écosystèmes comme moyen de fournir des solutions aux défis de l'atténuation et de l'adaptation au changement climatique. Ces solutions ont gagné en popularité car il s'agit d'approches qui ont la particularité d'offrir de multiples bénéfices à la société - notamment à atténuer les risques liés au changement climatique - tout en bénéficiant aussi à la biodiversité et aux écosystèmes. On parle ainsi de « co-bénéfices ». Ce sont aussi des solutions qui sont considérées comme ayant un ratio coût-efficacité égal sinon supérieur aux solutions « grises » classiques (Frantzeskaki et al., 2019).

Alors que l'intérêt pour les SFN ne cesse de croître, d'importants défis persistent pour les intégrer dans l'environnement urbain. Certaines villes ont formulé des plans d'adaptation au changement climatique, mais la traduction de ces plans en actions reste limitée (Hudson et al., 2023 ; Oijstaeijen et al., 2020) : développer des SFN n'est pas une priorité dans la majorité des villes (Oijstaeijen et al., 2020), et ces solutions sont souvent mises en œuvre au cas par cas, et à petite échelle (Almenar et al., 2016 ; Elmqvist et al., 2013). Par conséquent, de nombreuses villes passent à côté des opportunités offertes par les bénéfices multiples des SFN (Hudson et al., 2023).

La recherche sur les SFN s'est largement concentrée sur l'étude des impacts de ces solutions, en cherchant à démontrer leur efficacité pour répondre à des enjeux spécifiques (liés au changement climatique), et analysant leurs bénéfices multiples et développant des méthodologies d'évaluation adaptées à ces solutions (Nesshöver et al., 2017). L'économie environnementale a été une partie intégrante de cette recherche, fournissant et raffinant des méthodes d'évaluation des co-bénéfices des SFN, et contribuant à la formulation de nombreux cadres d'aide à la décision (Jacobs et al., 2016 ; Pascual et al., 2017). Cependant, malgré de nombreuses avancées dans ces domaines, il existe toujours une zone grise dans la connaissance de ces solutions, concernant 1) l'hétérogénéité spatiale des coûts et des bénéfices associés aux SFN, et 2) les méthodes de soutien à la décision nécessaires pour aider à la planification à grande échelle des SFN dans les villes.

L'objectif global de cette thèse est d'explorer les enjeux spécifiques de la planification spatiale pour les SFN dans les zones urbaines. Cet objectif se décline à deux niveaux : d'une part, il s'agit d'investiguer les enjeux spatiaux associés à la planification des SFN d'une part, contribuant à ce champ de recherche ; d'autre part, il s'agit de répondre aux enjeux d'un cas d'étude spécifique d'une initiative de politique publique lancée dans une grande ville française. Deux problématiques de recherche sont examinées dans ce travail :

1. Quelle est l'hétérogénéité spatiale des coûts et bénéfices des SFN en ville ?
2. Comment prioriser le développement spatial des SFN, en tenant compte de leurs nombreux bénéfices potentiels et coûts ?

La réponse à ces questions peut fournir des informations précieuses sur les stratégies d'adaptation au changement climatique des villes. De plus, ce travail peut ouvrir de nouvelles perspectives de recherche pour l'économie environnementale, notamment l'étude de l'hétérogénéité spatiale de la valeur des NBS et le développement de nouveaux outils de soutien à la décision adaptés à la planification des NBS.

Dans ce chapitre introductif de la thèse, nous établissons d'abord le contexte général de l'adaptation au changement climatique en milieu urbain ainsi que les solutions potentielles (Section 1). Ensuite, nous nous penchons sur les deux principales lacunes de recherche abordées dans cette thèse, englobant les défis spatiaux associés à la planification des NBS (Section 2) et les méthodes de soutien à la décision dans la planification des NBS (Section 3). Enfin, nous présentons les questions de recherche essentielles et les méthodologies élaborées pour leur exploration (Section 4).

1. Enjeux de l'adaptation des villes au changement climatique

1.1. Villes et changement climatique

Les grandes villes sont de plus en plus confrontées à de multiples enjeux découlant des facteurs combinés de la croissance urbaine et du changement climatique (de Sherbinin et al., 2007). La croissance urbaine est une source centrale de changement : avec la tendance actuelle, plus de la moitié de la population mondiale réside déjà dans des zones urbaines, et ce chiffre devrait dépasser 60 % d'ici 2030 (ONU, 2018). L'expansion des zones urbaines est source de changement dans les usages des sols, avec une augmentation prévue de la superficie urbaine de 1,5 million de km² d'ici 2030 (Seto et al., 2011). Les effets du changement climatique, quant à eux, sont nombreux et divers (GIEC, 2021), et cette combinaison de croissance urbaine et de changement climatique a des conséquences profondes et étendues sur la durabilité des villes (Elmqvist et al., 2013).

Tout d'abord, ils ont des impacts directs sur la qualité de l'environnement. La croissance urbaine, ainsi que la concentration de la population et des activités humaines, entraînent une augmentation des émissions de déchets solides, des problèmes importants de pollution de l'air et de l'eau (Kahn, 2007), de la pollution des sols (Rodríguez-Martín et al., 2015). Elle a aussi un impact significatif sur la biodiversité, principalement en réduisant et en dégradant les habitats (Revi et al., 2014), avec une estimation de 290 000 km² d'habitat naturel transformé en zones urbaines prévue entre 2000 et 2030 (McDonald et al., 2019). Ces pressions ont des implications profondes à la fois sur l'état et le fonctionnement des écosystèmes et sur le bien-être humain (Koop & van Leeuwen, 2017 ; Sturm & Cohen, 2014 ; Wolch et al., 2014).

La croissance urbaine et le changement climatique posent également des défis plus directs pour les sociétés, car ils ont un impact négatif sur la qualité de vie des zones urbaines (Mader et al., 2011). Parmi ces effets, il y a d'abord l'augmentation de la fréquence et de l'intensité des événements climatiques extrêmes, exacerbant notamment les problèmes urbains mentionnés plus haut (GIEC, 2021). Un exemple d'enjeu de ce type est l'augmentation des îlots de chaleur urbains (Heaviside et al., 2017 ; Rizwan et al., 2008), qui sont une conséquence de plusieurs facteurs : le changement climatique, l'artificialisation des sols, l'augmentation de la pollution atmosphérique (Ulpiani, 2021). En plus d'avoir un impact négatif sur la santé humaine (Iungman et al., 2023), les îlots de chaleur engendrent des coûts élevés pour la société, par exemple en termes de consommation d'énergie et d'émissions de CO₂ (Phelan et al., 2015), ou en produisant d'autres externalités négatives, telles que l'augmentation de la pollution atmosphérique (Piracha & Chaudhary, 2022 ; Sarrat et al., 2006 ; Ulpiani, 2021). De fait, la pollution atmosphérique est un autre enjeu majeur pour les villes, affectant directement leurs citoyens : la pollution de l'air a été identifiée comme l'un des 10 principaux facteurs affectant la santé dans le monde (Cohen et al., 2005 ; Dhimal et al., 2021), elle représente un risque significatif pour environ 90 % de la population mondiale, et est responsable d'environ 7 millions de décès prématurés chaque année (OMS, 2015).

L'un des principaux défis parmi ceux-ci concerne les problématiques liées à l'eau. Par exemple, les risques liés à l'eau, tels que les inondations et les sécheresses, représentent environ 90 % de tous les risques naturels qui touchent les villes (Koop & van Leeuwen, 2017), ce qui en fait une priorité absolue pour les villes. Aujourd'hui, 1,2 milliard de personnes sont exposées aux risques d'inondations, en majorité des citoyens, et ce chiffre devrait passer à 1,6 milliard d'ici 2050 (WWAP, 2018). La majorité des villes à travers le monde sont exposées à des risques liés à l'eau, tels que les inondations pluviales, qui sont elles-mêmes une conséquence de l'artificialisation et l'imperméabilisation des sols, de l'augmentation des ruissellements d'eau et d'une augmentation des événements météorologiques extrêmes (Bulkeley, 2013 ; ONU, 2018).

Ces risques liés à l'eau sont également liés à la gestion de l'eau douce. La disponibilité de l'eau douce dans et autour des grandes agglomérations urbaines est déjà sévèrement impactée : environ 150 millions de personnes vivent actuellement dans des villes souffrant de pénuries d'eau perpétuelles, un chiffre qui devrait augmenter de 100 millions de plus d'ici 2050 (McDonald et al., 2011). Ces enjeux sont la conséquence de la croissance urbaine d'une part, et de l'impact du changement climatique sur la consommation d'eau (WWAP, 2018), ainsi que de ses effets sur la réduction de la recharge des aquifères (Jacobson, 2011) d'autre part. Dans l'ensemble, le nombre de grandes villes exposées à des pénuries d'eau pourrait doubler d'ici 2050, passant de 193 à 284 (He et al., 2021). Cet enjeu s'accompagne également de la dégradation de la qualité de ressources en eau, principalement due aux charges en nutriments agricoles, et aux traitements insuffisants des eaux usées (Livesley et al., 2016 ; WWAP,

2018). La résolution de ces risques liés à l'eau est une priorité pour de nombreuses villes, et souvent le principal moteur derrière leurs stratégies d'adaptation au changement climatique.

Une approche visant à atténuer les pénuries d'eau dans les villes et les agglomérations consiste à sécuriser les ressources en eau locales et à rechercher des sources d'eau alternatives - et supplémentaires. Cependant, cette stratégie a le potentiel de provoquer des conflits (Gleick & Heberger, 2014). La mauvaise gestion de ce bien commun peut mener à de nombreux conflits: des conflits entre usagers, entre agglomérations et villes, entre zones urbaines et rurales, et même entre nations (Cosgrove & Loucks, 2015 ; Green, 2003). En ce qui concerne les villes, une stratégie potentielle identifiée par les décideurs politiques est de sécuriser leurs ressources en eau locales en restaurant les cycles hydrologiques et en améliorant les niveaux des aquifères urbaines (Gao et al., 2014 ; WWAP, 2018). Ces stratégies englobent diverses solutions innovantes qui s'inscrivent dans la catégorie plus large des solutions d'adaptation au changement climatique.

1.2 Les solutions d'adaptation des villes au changement climatique

1.2.1 Les Solutions fondées sur la Nature

Les Solutions fondées sur la Nature (SFN) ont suscité une attention croissante en tant que solutions aux nombreux enjeux mentionnés précédemment. Le concept de SFN est apparu dans les années 2000, et a gagné rapidement en popularité. La définition des SFN de l'UICN, telle qu'elle est présentée dans le rapport "Les Solutions fondées sur la Nature pour lutter contre les changements climatiques et réduire les risques naturels en France" (2016), est la plus largement acceptée :

« Les Solutions fondées sur la Nature sont définies comme les actions visant à protéger, gérer de manière durable et restaurer des écosystèmes naturels ou modifiés pour relever directement les défis de société de manière efficace et adaptative, tout en assurant le bien-être humain et en produisant des bénéfices pour la biodiversité »

Les SFN englobent une variété de solutions inspirées par les écosystèmes pour résoudre divers problèmes environnementaux (WWAP, 2018). Quelques exemples d'interventions de type SFN comprennent le développement d'infrastructure verte, la restauration écologique, la conservation d'espaces naturels, la reforestation (Cohen-Schacham et al., 2016).

Les SFN à l'échelle des villes englobent de nombreuses actions et infrastructures différentes. Il peut s'agir de la conservation ou de la création de forêts urbaines (Escobedo et al., 2011), de la création d'autres espaces verts tels que les parcs (Alves et al., 2020 ; Commission européenne, Direction générale

de la recherche et de l'innovation, 2015 ; Jim, 2004 ; Votsis, 2017), ainsi que de zones urbaines "bleues" comme les rivières, les lacs, les zones humides et les étangs (Axelsson et al., 2021 ; Bockarjova et al., 2020 ; Nghiem et al., 2021 ; Primo C. et al., 2018a ; WWAP, 2018). Les SFN urbaines sont généralement des infrastructures végétalisées à plus petite échelle qui peuvent être mises en œuvre dans les rues et les espaces publics : espaces verts, parcs, microforêts urbaines, noues, fossés, bassins de rétention et d'infiltration des eaux pluviales, zones humides, étangs, etc. Les SFN peuvent également être développées dans des espaces privés, comme en témoignent les jardins de pluie, les toits et façades végétalisées (Hartig & Kahn, 2016 ; Kabisch et al., 2016 ; Mader et al., 2011).

Les SFN se sont révélées être une approche prometteuse pour relever les enjeux posés par le changement climatique et la croissance urbaine, tout en bénéficiant à la biodiversité (Cohen-Schacham et al., 2016). Ce concept repose sur l'idée que le développement et la conservation de la nature peuvent se compléter mutuellement plutôt que de constituer des objectifs contradictoires (Nesshöver et al., 2017). Les SFN, en tant que terme "parapluie", se caractérisent par leur capacité à bénéficier simultanément à la biodiversité et au bien-être humain (Cohen-Schacham et al., 2016). Par conséquent, le concept est lié à d'autres approches telles que les infrastructures bleues/vertes, l'adaptation/mitigation basée sur les écosystèmes, le capital naturel et l'ingénierie écologique (Nesshöver et al., 2017). Les SFN ont gagné en importance dans la littérature scientifique, les rapports institutionnels et la planification stratégique (Nesshöver et al., 2017). L'intérêt pour les SFN a explosé dans les années 2010, avec le programme de recherche de l'UE Horizon 2020 positionnant l'UE en tant que leader dans la recherche sur les SFN (Davies et al., 2021).

L'une des caractéristiques centrales des SFN est qu'elles sont des actions qui fournissent de multiples bénéfices. En général, elles offrent un bénéfice central, qui est le principal défi à relever, et le principal moteur d'une politique de SFN (Nesshöver et al., 2017), par exemple, la réduction des risques. De plus, les SFN offrent une série de bénéfices supplémentaires, souvent appelés "co-bénéfices", qui peuvent être, par exemple, réguler diverses sources de pollution, atténuer les effets d'îlot de chaleur, prodiguer des aménités esthétiques et récréatives, soutenir la biodiversité, capturer du carbone atmosphérique... Grâce aux co-bénéfices, les SFN sont considérées comme des solutions plus efficaces et rentables que les approches plus traditionnelles (Estrada et al., 2017 ; Commission européenne, Direction générale de la recherche et de l'innovation, 2015), car elles fournissent les principales fonctions des infrastructures traditionnelles tout en offrant simultanément des bénéfices pour la biodiversité et le bien-être humain (Raymond et al., 2017).

Les co-bénéfices sont intrinsèquement liés au concept de Services Écosystémiques (SE). Les SE sont définis par le Millenium Ecosystem Assessment (2005) comme les "bénéfices que les personnes tirent des écosystèmes". Ils englobent, par exemple, des éléments essentiels tels que la production de

matériaux essentiels à la subsistance humaine, la filtration et la production d'eau potables, ainsi que de multiples autres processus, comme la régulation du climat et le contrôle des inondations (Overpeck et al., 2005). Ce concept est étroitement lié aux SFN, car les initiatives de SFN visent à générer et à améliorer les flux de SE pour relever les défis environnementaux. Les SE sont un concept plus large qui englobe les diverses fonctions que les écosystèmes fournissent aux humains, tandis que les co-bénéfices des SFN sont les résultats spécifiques et positifs qui découlent de la mise en œuvre des SFN.

1.2.2 Les nouvelles approches de gestion des eaux pluviales

Cette thèse est consacrée à un domaine spécifique des politiques urbaines confrontées aux enjeux du changement climatique : la gestion des eaux pluviales. La gestion des eaux pluviales est un sujet crucial dans de nombreuses villes, car elle est étroitement liée à une multitude d'enjeux, tels que les risques d'inondations, la dégradation des cycles hydrologiques naturels, et la dégradation des écosystèmes aquatiques. En matière de gestion des eaux pluviales, une nouvelle catégorie de solutions est apparue au cours des dernières décennies, de manière parallèle aux SFN. En effet, cette tendance plaide également en faveur d'un passage des infrastructures monofonctionnelles traditionnelles, dites « grises », vers des approches visant à gérer les eaux pluviales « à la source » (UN WATER, 2018).

Ces nouvelles approches sont apparues à partir des années 1970 (Thebault et al., 2020). Parmi ces approches, on peut citer les *Sustainable Urban Drainage Systems* (SuDS) au Royaume-Uni, les *Best Management Practices* (BMP) en Amérique du nord, les Villes-Éponges en Chine et les Techniques Alternatives (AT) en France. Il y a derrière l'émergence de chacun de ces concepts une double justification: prioriser la réduction de la pollution dans les zones naturelles, et rechercher des mesures de protection contre les inondations d'avantage optimisées en terme de coût-efficacité (Banque mondiale, 2018). Au fil du temps, la gestion des eaux pluviales a élargi son champ d'application, passant de la simple réduction des inondations à l'amélioration de la qualité de l'eau, à la restauration des régimes d'écoulement, à la fourniture d'aménités esthétiques et récréatives, au rafraîchissement urbain, et plus encore - en d'autres termes, aux co-bénéfices (Fletcher et al., 2015).

Toutes ces tendances illustrent une convergence vers des solutions ressemblant étroitement aux Solutions Basées sur la Nature, bien qu'appliquées en priorité aux enjeux liés à l'eau. Ce sont des techniques visant à atténuer les impacts négatifs du développement urbain, c'est-à-dire à revenir à un état des processus hydrologiques préalable à l'urbanisation, en restaurant les fonctions hydrologiques naturelles. Elles s'appuient également sur la végétalisation pour fournir des bénéfices en matière d'adaptation au changement climatique. Ces approches privilégient la durabilité, les co-bénéfices et la résilience tout en s'éloignant des pratiques traditionnelles de génie civil qui dominaient le développement urbain par le passé. En tant que telles, elles constituent une forme de SFN appliquée à

l'hydrologie urbaine. Concrètement, il s'agit d'infrastructures relativement petites développées en ville à grande échelle, comme des noues, des fossés, des bassins de rétention et d'infiltration des eaux pluviales, des revêtements perméables, pavés poreux, tranchées d'infiltration, etc.

L'émergence de cette nouvelle famille de solutions, à la fois les SFN et leurs techniques similaires développées dans le domaine de la gestion des eaux pluviales, a également conduit à une révision des politiques publiques et des méthodes d'évaluation.

1.3 Un état de l'art des SfN

1.3.1. De nouvelles méthodes d'évaluation

L'émergence des SFN en tant que solutions pour l'adaptation au changement climatique a conduit à la nécessité de réviser et d'adapter les cadres d'évaluation des politiques, principalement en raison de leurs multiples co-bénéfices (Raymond et al., 2017). Pour cette raison, les SFN sont devenues un domaine de recherche important au cours des dernières décennies, notamment dans l'Union européenne (Nesshöver et al., 2017). En effet, la communauté scientifique a exprimé dès le début le besoin de cadres opérationnels et de cadres d'évaluation pour soutenir la généralisation de l'utilisation des SFN à tous les niveaux institutionnels (Cohen-Schacham et al., 2016). Cela englobe la nécessité d'évaluer les différents effets et bénéfices des SFN, d'établir les clefs pour accroître leur acceptation, ainsi que les principaux freins, les défis et les opportunités pour leur développement dans différents contextes, et de fournir une aide à la prise de décision permettant de les prendre en compte dans les politiques publiques (Nesshöver et al., 2017).

Une gamme de cadres conceptuels a été développée à cette fin, dédiée à l'identification et à l'évaluation des co-bénéfices des SFN, à l'évaluation de leur efficacité pour relever des défis spécifiques, et souvent à leur comparaison avec des solutions conventionnelles comme les infrastructures grises (Frantzeskaki, 2019 ; Nesshöver et al., 2017). Pour cette raison, l'essentiel de l'attention s'est tourné vers la compréhension des co-bénéfices, incarnée par la production de différents cadres d'analyse (Almenar et al., 2016 ; Dumitru et al., 2021 ; Haines-Young & Potschin, 2012 ; Mader et al., 2011 ; Overpeck et al., 2005). Ces approches visent principalement à révéler et à évaluer les multiples co-bénéfices des SFN, souvent en fournissant des classifications des co-bénéfices ainsi que des lignes directrices et des indicateurs pour leur évaluation, en partant du postulat sous-jacent que l'identification et l'objectivation de ces co-bénéfices conduiraient à une augmentation de l'adoption des SFN dans les politiques (Daily et al., 2009). Ces approches visent notamment à identifier les co-bénéfices spécifiques de projets individuels et à leur attribuer une valeur. Ces cadres ont largement été influencés par les perspectives économiques et des sciences naturelles, ancrées dans le concept de capital naturel (Nesshöver et al.,

2017), et visent à approfondir la compréhension de la nature diversifiée de ces co-bénéfices, y compris comment différents types de SFN produisent des effets et des bénéfices variés (Turkelboom et al., 2018).

L'accent a également été mis sur l'intégration et la compréhension des perspectives des différents acteurs concernés par de telles politiques, et sur la reconnaissance des valeurs plurielles portées par les écosystèmes (Mader et al., 2011). Ces initiatives ont conduit au développement d'une multitude de littérature scientifique et spécialisée sur l'évaluation des SFN, dédiée à l'évaluation de projets de SFN (Alves et al., 2019 ; Calliari et al., 2019 ; Dumitru et al., 2021 ; Giordano et al., 2020 ; Jarvie et al., 2017 ; Kabisch et al., 2016 ; Majidi et al., 2019 ; Raymond et al., 2017 ; Ruangpan et al., 2020 ; Wild et al., 2017). Cette focalisation sur l'évaluation des SFN permet de mieux comprendre les résultats des politiques en matière de SFN, et offre un cadre pour aider à la décision dans des contextes spécifiques. Ces évaluations aident à répondre à des questions cruciales telles que quelles services écosystémiques doivent être priorités, quelles techniques sont les mieux adaptées pour résoudre des défis particuliers (Croeser et al., 2021), et comment diverses parties prenantes devraient être abordées, impliquées et mobilisées pour une mise en œuvre réussie de projets de SFN (Nesshöver et al., 2017 ; O'Donnell et al., 2017).

1.3.2 Un développement limité des SFN

Malgré les avancées dans la recherche sur ces nouvelles solutions, les SFN n'ont pas encore été développées et adoptées à grande échelle. Leur intégration dans les politiques publiques reste relativement faible, du moins au sein de l'Union européenne (Davies et al., 2021). En d'autres termes, bien qu'elles aient été préconisées par le monde académique, par les décideurs politiques et les praticiens depuis des années, ces solutions ne sont toujours pas intégrées dans le développement urbain (Dorst et al., 2022). C'est aussi le cas pour les techniques de gestion des eaux pluviales à la source. Ces solutions manquent encore d'une mise en œuvre systématique et restent seulement une alternative aux techniques plus traditionnelles "grises" (Dhakal & Chevalier, 2017 ; O'Donnell et al., 2017).

Cette intégration limitée des SFN dans les politiques urbaines se manifeste à travers plusieurs aspects. Tout d'abord, il existe une tendance à la dépendance au sentier, favorisant les solutions traditionnelles grises par rapport aux alternatives de SFN (Sarabi et al., 2019). C'est fortement le cas dans le domaine de la gestion urbaine des eaux pluviales (Axelsson et al., 2021). Deuxièmement, l'adoption actuelle des SFN tend à être opportuniste plutôt que systématique, en l'absence d'une approche structurée et cohérente de leur mise en œuvre et de leur utilisation (Hudson et al., 2023 ; Oijstaeijen et al., 2020). En d'autres termes, une approche au cas par cas est encore appliquée dans le développement des SFN (Sarabi et al., 2019). Troisièmement, la plupart des villes n'ont pas encore conçu et mis en œuvre de stratégies de développement des SFN explicites sur le plan spatial (Almenar et al., 2016 ;

Elmqvist et al., 2013). De fait, de nombreuses initiatives de SFN sont actuellement mises en œuvre sur la base des opportunités foncières disponibles, qui se trouvent généralement en dehors des centres densément peuplés où le besoin de services d'adaptation est le plus élevé (Andrea Ramírez-Agudelo et al., 2020 ; Hudson et al., 2023 ; Kabisch et al., 2016).

Dans l'ensemble, il semble qu'après des décennies de développement des concepts de SFN, la mise en œuvre et le développement de ces solutions restent quelque peu suboptimal. Les chercheurs ont identifié de nombreux facteurs et obstacles limitant le développement des SFN. Parmi ceux-ci, en quelques mots, les plus commentés sont :

1. La nécessité de démontrer l'efficacité des SFN pour relever les enjeux (surtout par rapport aux infrastructures grises), afin de briser la dépendance au sentier (Axelsson et al., 2021 ; Sarabi et al., 2019).
2. La nécessité de mettre en œuvre des approches ascendantes dans l'élaboration des politiques d'aménagement urbain, c'est-à-dire d'impliquer les citoyens dans l'élaboration des SFN (Giordano et al., 2020 ; Kati & Jari, 2016).
3. La nécessité de créer et de diffuser des méthodologies et des pratiques d'évaluation non expertes en dehors du monde académique, à l'attention de toutes les couches des décideurs politiques (Daily et al., 2009 ; European Commission Directorate-General for Research and Innovation, 2015).
4. La nécessité de transformer les opérations et les institutions publiques vers une fragmentation sectorielle moindre et des actions plus "transversales", facilitant ainsi les synergies entre les services, et mettant en lumière l'importance des co-bénéfices (Kabisch et al., 2017 ; Sarabi et al., 2019).
5. La nécessité de développer des pratiques d'évaluation des services écosystémiques (SE), qui sont encore assez rares - surtout à l'échelle urbaine - entravant ainsi une évaluation complète des bénéfices et des impacts des SFN (Oijstaeijen et al., 2020). Le concept de SE n'a pas encore été largement adopté dans les politiques de l'UE, son utilisation étant principalement limitée aux politiques de conservation de la nature et de gestion des ressources naturelles (Bouwma et al., 2018). Par conséquent, les SFN, dont les bénéfices découlent principalement de leur capacité à générer des SE, ne sont pas nécessairement mis en avant (Langemeyer et al., 2016).
6. Le manque relatif de mécanismes de financement et de modèles économiques adaptés aux SFN (Kabisch et al., 2016 ; Nesshöver et al., 2017) : les SFN nécessitent des stratégies à long terme et intégrées, qui peuvent être entravées par la rareté des fonds publics destinés à l'adaptation au changement climatique (Davies et al., 2021 ; Hudson et al., 2023), et par les stratégies de court terme dominant souvent le développement urbain (Kabisch et al., 2016).

En plus de ces limites générales à l'élaboration des politiques relatives aux SFN, il existe plusieurs obstacles résultant des méthodes et des outils d'évaluation. En fait, nous soutenons ici qu'il subsiste d'importantes lacunes dans les approches d'évaluation des SFN, qui ont peut-être été négligées. Malgré le développement de nombreuses méthodologies d'évaluation des SFN et de lignes directrices pour l'élaboration des politiques, nous soutenons que l'utilité des outils existants, bien qu'efficaces pour évaluer et mener des projets individuels au cas par cas, devient limitée lorsqu'il s'agit de plusieurs défis à plus grande échelle des politiques d'adaptation au changement climatique urbain. Confronter ces limites a une grande importance, en particulier compte tenu du fait que les SFN doivent encore être intégrées de manière transparente dans les politiques publiques. Ces limites découlent spécifiquement de deux dimensions des méthodes d'évaluation et de soutien à la décision pour les SFN qui ont été sous-scrutées par la littérature, à savoir i) les dimensions spatiales des coûts et des bénéfices des SFN ; et ii) les limites des méthodes de décision traditionnelles pour le développement des SFN dans les villes. Ces deux points sont développés plus en détail dans les sections suivantes.

2. Les dimensions spatiales des SFN

L'incorporation des SFN dans l'aménagement urbain représente un enjeu complexe, caractérisé par l'interaction de considérations spatiales. Ces dimensions spatiales ont un impact non seulement sur la formulation des politiques en matière de SFN, mais aussi sur l'évaluation des SFN et l'évaluation environnementale. En essence, les coûts et les bénéfices associés aux SFN présentent des variations spatiales, exigeant que les urbanistes intègrent ces dimensions. Cependant, l'ensemble des outils d'évaluation environnementale et d'évaluation des SFN ont souvent négligé ces dimensions spatiales cruciales.

Dans cette section, nous visons à éclairer ces considérations spatiales : tout d'abord, nous explorons les échelles spatiales des services écosystémiques (SE), puis nous plongeons dans la variabilité spatiale de la demande envers les SFN. Enfin, nous élargissons notre perspective en encadrant le défi de la sélection des emplacements des SFN, dans le contexte des concepts théoriques des gradients urbains-ruraux.

2.1. La variabilité spatiale des services écosystémiques

Les SFN offrent un éventail de co-bénéfices, profitant à la fois à la biodiversité et à la société. Parmi ces co-bénéfices se trouve la fourniture de services écosystémiques (SE) (Raymond et al., 2017). Les chercheurs qui étudient les SE ont reconnu une grande complexité dans leur gestion - leur variabilité spatiale.

Pour élaborer, un premier niveau pour considérer cette variabilité spatiale est que les SE sont produits à des échelles spatiales diverses et dans des proportions variables (Hein et al., 2006). Cela implique deux points clés. Premièrement, certains SE ont un impact uniquement au niveau local, tandis que d'autres peuvent étendre leur impact à une échelle plus large, voire mondiale (Rodríguez et al., 2006). Par exemple, les effets de régulation du climat des zones boisées et des arbres se limitent à quelques mètres seulement (Aram et al., 2019), tandis que les services de séquestration du carbone ont une portée mondiale (Aram et al., 2019). Deuxièmement, cette variabilité d'échelle signifie que certains services opèrent à plusieurs échelles (Hein et al., 2006) : les services de rafraîchissement et de régulation climatique offerts par les espaces verts, par exemple, peuvent apporter des bénéfices au niveau micro grâce à l'ombrage des arbres et se regrouper en impacts plus importants à l'échelle urbaine ou régionale (Gallay et al., 2023 ; Livesley et al., 2016).

Une autre considération est le haut niveau de dépendance à l'emplacement dans la production de SE. En d'autres termes, en fonction de l'emplacement des SFN, ils produisent des co-bénéfices distincts, chacun avec des degrés d'intensité variables (Rodríguez et al., 2006 ; Tardieu, 2017). Par exemple, les co-bénéfices liés à la dépollution de l'air par les arbres et les espaces verts dépendent de leur proximité avec les routes, où la circulation émet des polluants atmosphériques (Livesley et al., 2016). Par conséquent, le bénéfice global de la mise en œuvre des SFN pour la dépollution de l'air peut varier considérablement en fonction de leur proximité avec les sources de pollution (Kremer et al., 2016 ; Livesley et al., 2016). Un exemple similaire se produit avec la biodiversité et les corridors écologiques. Par exemple, l'amélioration de la biodiversité - comme fournir un habitat pour les espèces - dépend de la connexion établie avec les habitats existants (Ayram Correa et al., 2016 ; Hilty et al., 2012). Par conséquent, les emplacements des projets de SFN urbains sont un facteur clé de leurs effets ultimes sur la biodiversité (Beaugeard et al., 2020 ; Lapoint et al., 2015). Cette variabilité entraîne inévitablement des compromis entre différents SE, mettant en évidence la convergence avec la planification urbaine (Langemeyer et al., 2016) : prioriser certaines zones peut renforcer un SE tout en diminuant d'autres.

Le problème est globalement le même pour les SuDS et leurs multiples bénéfices liés à la gestion de l'eau, car ces bénéfices peuvent dépendre considérablement de l'emplacement des SuDS (Uribe-Aguado et al., 2022). Par exemple, la réduction des ruissellements de surface dépend de la position des SuDS dans un bassin hydrographique et de leur intégration dans les flux d'eau (Paquette & Lowry, 2013 ; Uribe-Aguado et al., 2022). De même, l'infiltration de l'eau et les bénéfices potentiels de la recharge des eaux souterraines dépendent de multiples facteurs, tels que la capacité d'infiltration du sol et les caractéristiques des bassins hydrographiques (Beganskas & Fisher, 2017), et ces facteurs sont eux-mêmes distribués de manière hétérogène dans l'espace (Maréchal et al., 2020).

Reconnaissant cette variabilité spatiale, les chercheurs ont entrepris de développer des outils spécifiquement conçus pour cartographier les SE (Tardieu, 2017). Ces outils sont orientés vers les non-experts et visent à fournir un aperçu rapide de la distribution des SE dans une zone donnée, à comprendre les fonctions biophysiques des écosystèmes et à modéliser rapidement l'augmentation de l'offre de SE fournie par les SFN (Bagstad et al., 2013). Parmi les exemples notables, citons le modèle Invest (González-García et al., 2020), la suite i-Tree (Bodnaruk et al., 2017) et les outils Aries (Villa et al., 2009), entre autres.

Cependant, d'autres considérations doivent être prises en compte pour tenir compte des complexités spatiales de la planification des SFN : la valeur des SFN ne découle pas uniquement de leur impact sur l'augmentation potentielle de l'offre de SE (Raymond et al., 2017).

2.2. L'hétérogénéité spatiale de la valeur des SE

La valeur des SE fournis par les SFN découle de l'interaction entre l'offre et la demande de SE (Calliari et al., 2019). De nombreuses études ont cherché à examiner les préférences des citoyens et leur demande envers les SFN. Les méthodes basées sur des enquêtes, telles que les méthodes des préférences déclarées, constituent des outils précieux pour évaluer les préférences des citoyens envers des stratégies contrastées de SFN et estimer la demande individuelle, sous la forme du Consentement à Payer (CAP) ou du Consentement à Recevoir pour leurs multiples bénéfices. Certains auteurs ont notamment exploré l'hétérogénéité des préférences pour les SE, en analysant comment cette variation peut être attribuée aux caractéristiques socio-démographiques des citoyens et aux attitudes environnementales (Aguilar et al., 2018 ; W. Chen et al., 2018 ; Collins et al., 2017 ; Escobedo et al., 2011 ; Faccioli et al., 2020 ; Macháč et al., 2022 ; Meyerhoff, 2013). Cependant, la demande peut également être influencée par des facteurs spatiaux plus complexes que les caractéristiques socio-démographiques ou les attitudes environnementales. Deux aspects principaux ont été étudiés à cet égard : l'hétérogénéité spatiale des préférences et le concept de dégradation spatiale.

Parmi les études d'évaluation environnementale, certaines approches ont commencé à utiliser des outils d'économétrie spatiale pour analyser l'hétérogénéité spatiale de la demande pour différents types de biens environnementaux (Bateman et al., 2006 ; Broch et al., 2013 ; Brouwer et al., 2010 ; Budziński et al., 2018 ; Czajkowski et al., 2017 ; Hampson et al., 2017 ; Kim et al., 2022 ; Meyerhoff, 2013 ; Pinto et al., 2016 ; Traoré, 2019). Ces études ont révélé que les CAP pour les programmes environnementaux estimés dans des expériences de choix discrets ne sont souvent pas répartis de manière aléatoire dans l'espace, mais présentent des phénomènes de regroupement spatial : elle peuvent présenter des distributions spatiales nationales ou régionales (Campbell et al., 2008 ; Czajkowski et al., 2017 ; Toledo-

Gallegos et al., 2021), ou présenter un regroupement local de CAP faibles ou élevés (Johnston et al., 2015 ; Johnston & Ramachandran, 2014 ; Kim et al., 2022 ; Toledo-Gallegos et al., 2021).

Ces processus spatiaux peuvent être analysés par l'influence de variables spatiales observables, par exemple en incluant des variables spatiales dans les expériences de choix (Budziński et al., 2018 ; Łaskiewicz et al., 2022). Ils peuvent également être entièrement idiosyncratiques et résulter de composantes non observables : c'est le cas pour les effets de pairs (De Valck & Rolfe, 2018 ; Glenk et al., 2020). Dans l'ensemble, ces recherches offrent diverses approches pour identifier les processus spatiaux affectant la distribution de la demande de biens environnementaux, cartographier éventuellement les regroupements de demande pour les SFN, et informer les décideurs sur les zones et quartiers où des actions seraient potentiellement très efficaces. Cependant, peu de ces études ont abordé explicitement l'hétérogénéité spatiale des préférences en ce qui concerne les petites infrastructures urbaines telles que les SFN et les SuDS.

Une autre dimension spatiale des SFN qui peut influencer la demande est la dégradation spatiale (*distance decay*). Cette notion décrit le fait qu'une distance accrue par rapport aux biens environnementaux diminue la demande pour ceux-ci (Glenk et al., 2020). Cet intérêt pour la dégradation spatiale provient notamment du domaine de l'évaluation environnementale, notamment dans le contexte de l'application d'une actualisation spatiale des co-bénéfices lors de l'évaluation des politiques (Yamaguchi & Shah, 2020). En d'autres termes, lors de l'évaluation des bénéfices d'un programme, quelle population doit être prise en compte pour monétiser les bénéfices ?

Plusieurs études ont montré les effets significatifs de la dégradation spatiale en incorporant un attribut de distance dans les expériences de choix discrets (Badura et al., 2020 ; Johnston & Ramachandran, 2014 ; Jørgensen et al., 2013 ; Pate & Loomis, 1997 ; Schaafsma et al., 2012), ou en spécifiant la distance entre l'emplacement de la résidence et les biens environnementaux (Lizin et al., 2016 ; G. Tu et al., 2016). Ce concept de déclin spatial indique que la demande pour les SFN peut varier considérablement en fonction de leur accessibilité (Glenk et al., 2020). Dans le contexte de la planification des SFN, un tel processus spatial peut avoir un impact considérable sur la valeur des SFN en fonction de leur emplacement (Yamaguchi & Shah, 2020). De même, peu d'études ont enquêté sur le déclin spatial associé aux petits SFN urbains et aux SuDS.

2.3. Le problème de la planification spatiale de SfN

Certains chercheurs ont commencé à reconnaître l'importance de l'identification de la variabilité spatiale découlant à la fois de l'offre et de la demande en SE. Certaines études visent à cartographier les différences spatiales entre l'offre et la demande de SE de régulation (Baró et al., 2015, 2017 ; González-

García et al., 2020 ; Herreros-Cantis & McPhearson, 2021). Identifier ces zones permet de cibler plus précisément les domaines où des améliorations potentielles du bien-être sont possibles, c'est-à-dire là où l'offre de SE est faible et la demande élevée.

Cependant, les défis spatiaux de la planification des SFN vont au-delà de la distribution idiosyncratique de l'offre et de la demande. Il s'agit également de comprendre les processus spatiaux globaux à l'œuvre dans les villes, qui définissent les valeurs potentielles des SFN. En essence, cela consiste à définir conceptuellement le problème de la planification des SFN. Pour dresser un tableau plus complet des défis spatiaux auxquels sont confrontés les SFN, nous devons également prendre en compte un dernier facteur dans l'équation : la variabilité spatiale des coûts. La mise en œuvre des SFN n'est pas aussi aisée partout en milieu urbain ; plusieurs facteurs tels que les contraintes d'espace, les coûts fonciers et la concurrence pour l'utilisation des sols peuvent être plus intenses dans certaines zones que dans d'autres (Dorst et al., 2022 ; Madureira & Andresen, 2013). Les zones denses en particulier, qui sont souvent les centres historiques en Europe, posent des défis particuliers pour le développement des SFN : le changement d'usage des sols est plus difficile et l'espace disponible est plus rare (Mader et al., 2011).

Cette interaction entre la variabilité des coûts et des bénéfices ajoute de la complexité au problème. Théoriquement, cette complexité a été explorée à travers le prisme des gradients urbains-ruraux des coûts et bénéfices. La valeur de la mise en œuvre des SFN augmente à mesure que l'on se rapproche des centres urbains, car les flux de SE peuvent potentiellement bénéficier à une population plus importante. Cependant, à mesure que l'on se rapproche des centres urbains, la mise en œuvre des SFN devient plus difficile en raison de la concurrence foncière accrue et des coûts d'opportunité plus élevés (Brander & Koetse, 2011). Les SFN sont des solutions intensives en espaces, et entre en concurrence avec d'autres utilisations foncières mutuellement exclusives telles que le logement ou le développement commercial (Elmqvist et al., 2013). La mise en œuvre des SFN plus loin de la ville pourrait être plus facile, mais elle entraînerait moins de co-bénéfices pour les habitants des zones urbaines. Cette situation conduit à un paradoxe environnemental urbain-rural: les SE sont souvent les plus rares précisément là où ils sont le plus demandés, créant une dynamique complexe dans la planification des SFN (McDonald, 2015).

Cette dynamique urbain-rural présente un enjeu majeur. Le problème central tourne autour de la question de comment et où devraient être situés les projets d'adaptation au changement climatique dans les villes, compte tenu des divers gradients spatiaux de coûts et de bénéfices des SFN ? Cela offre une opportunité aux économistes de proposer des aperçus théoriques pour orienter les recherches futures et établir des lignes directrices fondamentales pour les décideurs.

Cependant, il convient de noter que le domaine de l'économie de l'environnement n'a pas encore abordé explicitement cette question. Le sous-domaine traitant des SFN s'est principalement penché sur la valorisation de l'environnement et l'économie appliquée, visant à révéler les préférences et à établir la valeur des co-bénéfices des SFN, entre autre (Nesshöver et al., 2017 ; Tietenberg & Lewis, 2016), répondant à une demande de connaissances en matière de valorisation de la part des décideurs (Primmer et al., 2018).

L'économie urbaine et géographique a exploré un large éventail de questions liées au développement urbain, utilisant des outils pour modéliser les processus spatiaux et les décisions des acteurs urbains (Duranton et al., 2015), adoptant donc un point de vue théorique que nous estimons nécessaire pour aborder les défis de localisation des SFN mentionnés ci-dessus. Cependant, à notre connaissance, peu de recherche ont été menées jusqu'à présent sur cette question particulière. D'autres questions de recherche ont retenu l'attention dans les domaines de l'économie urbaine. Par exemple, les domaines centraux de recherche ont porté sur l'explication et l'anticipation des choix de localisation pour les entreprises et les choix résidentiels (Storper & Scott, 2016), l'examen de la dynamique et de la croissance du développement urbain (Brakman et al., 2009 ; Duranton & Puga, 2014) et des phénomènes d'agglomération spatiale (Storper & Scott, 2016), la recherche sur la dynamique des prix fonciers et des marchés immobiliers (Choumert & Salanié, 2008 ; Gyourko & Krimmel, 2021 ; Vejchodská et al., 2022). Moins d'investigations ont abordé les questions des politiques publiques urbaines dédiées à l'adaptation au changement climatique et des processus spatiaux en jeu dans la planification de telles politiques.

En conclusion, nous pensons qu'il existe un manque de connaissances sur la planification des SFN qui mérite de l'attention et des efforts de recherche. Tout d'abord, en matière d'évaluation environnementale, il existe un domaine qui a été relativement peu étudié. Bien que des travaux récents aient commencé à étudier l'hétérogénéité spatiale des valeurs des SFN et des biens environnementaux en général, en ce qui concerne des facteurs tels que l'hétérogénéité des préférences spatiales, les échelles spatiales des SE et la dégradation spatiale, des questions subsistent concernant l'objet de recherche spécifique que sont les petits SFN urbains. Deuxièmement, des aspects théoriques sont en jeu, notamment ceux liés aux gradients urbains-ruraux des coûts et des bénéfices des SFN. Pousser les investigations vers ces aspects pourrait fournir des éclairages précieux sur la complexité de la planification des SFN urbains. Cette démarche peut aider à répondre à des questions clés, telles que la manière d'analyser les gradients urbains-ruraux des coûts et des bénéfices associés aux SFN, et comment prioriser la planification urbaine en tenant compte de ces aspects spatiaux.

Dans cette thèse, nous plaidons en faveur d'une enquête sur l'hétérogénéité spatiale des préférences associées aux SFN urbains. Nous visons à étudier les liens entre les préférences spatiales pour les SFN

et les gradients urbains-ruraux, et à intégrer finalement l'analyse spatiale des préférences dans un nouveau cadre d'aide à la décision. Cette dernière question est le deuxième aspect central abordé dans cette thèse. Dans la section suivante, nous nous pencherons sur les méthodologies actuelles d'aide à la décision pour la planification des SFN.

3. L'aide à la décision pour la planification urbaine

La décennie passée a été témoin d'avancées rapides dans la compréhension des services écosystémiques, ainsi que dans la conception, la mise en œuvre et la gouvernance des politiques de SFN. Cette évolution des connaissances a été parallèle à des changements dans les pratiques de valorisation. Par conséquent, les méthodologies d'évaluation des SFN ont fait d'importants progrès, préconisant une approche multidisciplinaire ascendante conforme aux principes de la "nouvelle école de la valorisation" (Jacobs et al., 2016).

Les différentes méthodologies existantes d'évaluation des SE conviennent à la fois à l'évaluation *ex-post* et *ex-ante* des projets de SFN. Cependant, leur applicabilité à la prise de décision politique a été moins abordée (Veerkamp et al., 2020). Ceci est particulièrement pertinent lorsqu'il s'agit de relever les défis complexes de l'adaptation au changement climatique en milieu urbain, où les décideurs doivent naviguer dans la sélection de politiques avant leur mise en œuvre et les choisir en fonction de critères multiples. Des exemples de ces défis de prise de décision sont le débat récurrent sur le choix entre les SFN ou les infrastructures grises plus traditionnelles (Frantzeskaki, 2019), ou lorsque l'on est confronté à des problèmes spatiaux complexes concernant la recherche de zones où mettre en œuvre des SFN (Polasky et al., 2008). Par conséquent, les approches conventionnelles pour évaluer et décider des politiques publiques continuent d'être utilisées (Frantzeskaki et al., 2019), y compris des méthodologies telles que l'analyse coûts-bénéfices et l'analyse coût-efficacité.

3.1. Analyse coûts-bénéfices et analyse coût-efficacité

L'analyse coûts-bénéfices est fréquemment utilisée pour évaluer les politiques futures potentielles de SFN et déterminer la voie d'action la plus favorable. Étant donné les multiples bénéfices des SFN, cette approche repose sur le cadre de valorisation des écosystèmes qui vise à attribuer une valeur monétaire aux services écosystémiques (Atkinson & Mourato, 2008). Le principe fondamental de cette approche est d'attribuer une valeur monétaire aux services écosystémiques, puis de calculer la valeur économique totale d'un projet en incluant tous les co-bénéfices et les coûts associés (Atkinson & Mourato, 2008). Ce calcul se fait dans une période temporelle prédéfinie pour tenir compte également des coûts et des bénéfices futurs (Pearce et al., 2006).

Cette approche utilise à la fois des méthodes de préférence déclarée et des méthodes de préférence révélée en matière d'évaluation environnementale pour capturer les différents co-bénéfices des SFN. En ce qui concerne les méthodes de préférence révélée, les études ont principalement opté pour des approches de prix hédonique pour évaluer la valeur monétaire des équipements récréatifs et esthétiques des espaces verts urbains afin de soutenir la planification future des SFN (Łaszkiwicz et al., 2022 ; Poor et al., 2006 ; Votsis, 2017). D'autre part, dans le cadre des études de préférence déclarée, les expériences de choix discrets ont été largement utilisées pour capturer les valeurs des différents co-bénéfices des SFN (Balderas Torres et al., 2015 ; Campbell et al., 2009 ; Chau et al., 2010 ; Collins et al., 2017 ; Gundlach et al., 2018 ; Hérivaux & Le Coënt, 2021 ; Johnston & Ramachandran, 2014 ; Kunwar et al., 2020 ; Londoño Cadavid & Ando, 2013 ; Mariel et al., 2021 ; Shoyama et al., 2013 ; G. Tu et al., 2016 ; Yao et al., 2014). De plus, bien que dans une moindre mesure, les méthodes d'évaluation contingente ont également été employées (Brander & Koetse, 2011 ; Czajkowski & Hanley, 2009 ; Mell et al., 2013 ; Pinto et al., 2016 ; Reynaud et al., 2017).

Il convient de noter que ce domaine de recherche ne sert pas uniquement à fournir des valeurs monétaires pour les analyses coûts-bénéfices, mais constitue en lui-même un domaine d'investigation. De nombreuses questions spécifiques et débats ont animé le domaine de l'évaluation environnementale. Quelques exemples de ceux-ci comprennent l'étude des valeurs de non-usage des écosystèmes, comme la valeur d'existence dans le cas de la protection de la biodiversité (Shoyama et al., 2013 ; Yao et al., 2014), l'étude des "disservices" ou des "effets négatifs" des écosystèmes (Soto et al., 2018 ; Teixeira et al., 2019 ; Von Döhren & Haase, 2015), ou l'étude de l'hétérogénéité des préférences de la population pour les politiques de SFN (Badura et al., 2020 ; Budziński et al., 2018 ; Hérivaux & Le Coënt, 2021 ; Kunwar et al., 2020 ; Tienhaara et al., 2021).

En ce qui concerne l'estimation des coûts, les approches basées sur le coût du cycle de vie ont été privilégiées pour établir les différents éléments de coûts des SFN (Houle et al., 2013 ; Jaffe, 2010 ; Neumann & Hack, 2022 ; Oladunjoye et al., 2021). À cet égard, la recherche a dépassé le domaine académique pour englober les contributions de diverses sources non académiques. Un ensemble significatif de "littérature grise" a émergé de la part de praticiens et de professionnels visant à estimer les coûts, leur répartition entre différents acteurs et d'autres aspects pertinents. Cela est particulièrement le cas dans les domaines de la gestion des eaux pluviales en ce qui concerne nouvelles techniques de gestion des eaux pluviales (Bixler et al., 2020 ; CEBEDEAU, 2018 ; GRAIE, 2018 ; Le Gat et al., 2023 ; Oladunjoye et al., 2021 ; Seters et al., 2013).

Ces approches d'analyse coûts-bénéfices ont été mises en place dans de nombreux domaines d'application des SFN. Cela inclut des contextes tels que les mesures de conservation de l'environnement (S. Cao et al., 2018 ; Naidoo & Ricketts, 2006 ; Simelton et al., 2021), de protection contre les risques

d'inondation, englobant les approches des SuDS, des BMP, des techniques alternatives, etc. (Biasin et al., 2023 ; Fraga et al., 2021 ; Ghafourian et al., 2021 ; Johnson & Geisendorf, 2019 ; Le Coent et al., 2021 ; Neumann & Hack, 2022 ; Oladunjoye et al., 2021), aux côtés de l'analyse coût-efficacité (Joksimovic & Alam, 2014 ; Kumar et al., 2021).

L'analyse coûts-bénéfices et l'analyse coût-efficacité sont profondément ancrées dans l'élaboration des politiques publiques, notamment parce que les ratios coûts-bénéfices et coût-efficacité sur lesquels elles s'appuient offrent des signaux transparents pour les décisions politiques, renforçant la faisabilité et la légitimité des choix publics. Cependant, ces méthodes présentent des limites importantes dans le cas des SFN, comme l'ont souligné Saarikoski et al. (2016). Tout d'abord, ces méthodes ne permettent pas nécessairement l'intégration des multiples co-bénéfices des SFN. Dans le cas de l'analyse coût-efficacité, la méthode repose sur une seule fonction (par exemple, la réduction des risques d'inondation) et ignore les co-bénéfices, ce qui rend de telles approches plus adaptées aux infrastructures monofonctionnelles (par exemple, les infrastructures grises). Dans le domaine plus spécifique de la gestion des eaux pluviales, la transition vers les SuDS, les BMP, les villes éponges, etc. a été amorcée, bien que lentement (Fletcher et al., 2015). La littérature scientifique concernant ces solutions s'est principalement concentrée sur l'établissement de leur efficacité en ce qui concerne la réduction des risques d'inondation (Graveline et al., 2018 ; McClymont et al., 2020 ; O'Donnell et al., 2017 ; Ruangpan et al., 2020), et, dans une moindre mesure, leur impact sur la recharge des aquifères (Bhaskar et al., 2018 ; Kidmose et al., 2015 ; Tubau et al., 2017), et l'amélioration de la qualité de l'eau (Alves et al., 2019 ; Charlesworth, 2010), s'appuyant ainsi sur le cadre de l'analyse coût-efficacité.

L'analyse coûts-bénéfices a été à la fois généralisée comme une approche très courante pour la prise de décisions environnementales, et critiquée simultanément pour diverses raisons, allant des préoccupations techniques aux enjeux éthiques (Hwang, 2016). En particulier, il existe plusieurs critiques qui limitent leur utilisation pour la valorisation des SFN dans notre contexte (Jacobs et al., 2016). Ces limites sont particulièrement liées à la monétarisation.

Tout d'abord, la monétarisation limite fortement l'intégration des valeurs écologiques de non-usage et de la valeur sociale et culturelle des SE (Hwang, 2016). Le recours à une unité de mesure unique (l'argent) masque la nature complexe des SE et la diversité des valeurs attribuées aux écosystèmes : certaines valeurs ne sont pas réductibles à une valeur monétaire. Cette limitation a suscité de nombreux débats sur l'utilisation de l'analyse coûts-bénéfices, axés sur les défis de l'incommensurabilité et l'abandon des considérations non monétaires dans l'analyse des politiques publiques (Adler, 2002 ; Jacobs et al., 2016 ; Lliso et al., 2020 ; Wild et al., 2017).

De plus, l'analyse coûts-bénéfices ne permet pas d'exprimer les arbitrages, ce qui est un élément fondamental des SFN (Hwang, 2016 ; Raymond et al., 2017 ; Rodríguez et al., 2006). Identifier clairement ces compromis est une exigence importante pour le cadre d'évaluation des stratégies de SFN (Nesshöver et al., 2017). Comme mentionné précédemment, dans le contexte des SFN urbains, il existe d'importants arbitrages spatiaux qui doivent être pris en compte. Certains endroits peuvent renforcer certains co-bénéfices tout en diminuant d'autres, et il peut exister un gradient global d'arbitrages spatiaux le long d'un gradient urbain-rural. En termes généraux, ce gradient implique de décider s'il faut mettre en œuvre des SFN dans des zones densément peuplées avec des difficultés et des coûts plus élevés ou opter pour des solutions en dehors de la ville où la demande de co-bénéfices peut être moindre. Pour planifier et comparer efficacement diverses stratégies spatiales, les méthodes d'aide à la décision doivent intégrer une analyse de ces compromis.

Enfin, les co-bénéfices des SFN couvrent plusieurs domaines et disciplines, chacun ayant ses propres méthodologies d'évaluation uniques (Wild et al., 2017). Certains des co-bénéfices des SFN peuvent même être évalués et analysés par plusieurs disciplines (Seddon et al., 2020 ; Wegner & Pascual, 2011). L'analyse coût-bénéfice invisibilise ces différents apports des différentes disciplines, à travers le processus de monétarisation. Toutes les valeurs sont ramenées fondamentalement à une valeur économique. En conséquence, les chercheurs ont plaidé pour permettre aux cadres d'évaluation d'incorporer les valeurs et les résultats de diverses disciplines (Jacobs et al., 2016 ; Raum, 2018 ; Wegner & Pascual, 2011).

L'Analyse Multicritère d'Aide à la Décision (MCDA) a été identifiée notamment comme une méthode appropriée pour aborder ces limites.

3.2 L'Analyse Multicritères

Plusieurs chercheurs ont préconisé de s'éloigner de l'agrégation monétaire et de l'analyse coûts-bénéfices, et d'utiliser l'Analyse Multicritères (AMC), en particulier dans le contexte des rapports de l'IPBES (Brondízio et al., 2019). Issu initialement des sciences opérationnelles, l'AMC s'est développée en une discipline scientifique distincte visant à traiter la nature multidimensionnelle des processus de prise de décision (Fishburn & Lavalley, 1999). Dans le vaste spectre des méthodes d'AMC, ce domaine englobe une multitude de techniques, formant essentiellement un terme générique pour des approches diverses (Huang et al., 2011).

Un examen exhaustif de toutes ces méthodes dépasse le cadre de cette thèse. Une définition simple de l'AMC est que cette méthode consiste à structurer et à résoudre un problème de décision complexe par une série d'étapes, en impliquant à divers stades la participation directe des principales parties

prenantes (Thokala & Madhavan, 2018). Les principales étapes consistent à définir un ensemble d'alternatives et de critères de décision, qui peuvent inclure des facteurs tels que les bénéfices et les coûts. Ensuite, l'attribution de poids à ces critères est réalisée par le biais de divers schémas de pondération. L'étape suivante consiste à utiliser l'une des nombreuses méthodes d'analyse de la décision pour traduire la performance de ces critères, ainsi que leurs poids relatifs, en l'identification des alternatives préférées (Fishburn & Lavalley, 1999). Cela implique souvent le calcul d'un score multicritères, certaines méthodes reposant sur l'agrégation (bien que non monétaire), tandis que d'autres divergent des techniques d'agrégation.

L'AMC présente trois bénéfices principaux qui permettent de répondre efficacement à certains des défis précédemment mentionnés dans la prise de décision concernant les SFN. Tout d'abord, le l'AMC permet d'intégrer des valeurs diverses de la nature, s'alignant sur la culture de la valorisation plurielle mise en avant par le monde académique (Jacobs et al., 2016). Ces méthodes offrent de la flexibilité en permettant l'utilisation de critères hétérogènes et de mesures de valorisation issues de différents domaines académiques, tels que les impacts sociaux, les évaluations verbales, les coûts et bénéfices monétaires, les bénéfices non monétaires et la qualité de l'environnement (Montis et al., 2008 ; Pascoe et al., 2019).

Deuxièmement, l'AMC est d'une certaine manière plus compatible avec l'idée d'une approche ascendante (ou « *bottom-up* »), en particulier par rapport à l'analyse coûts-bénéfices (Saarikoski et al., 2016). D'une part, elle fonctionne à la fois comme un outil analytique et un processus participatif ou collectif, permettant ainsi l'expression directe des opinions des parties prenantes aux points de vue divergents (Paneque Salgado et al., 2009). En fait, certaines mises en œuvre d'AMC ont même été étendues à des consultations publiques à grande échelle (Estévez & Gelcich, 2015). D'autre part, en ayant la possibilité d'inclure différents critères, valeurs et métriques, cette méthode peut représenter différentes perspectives sur un problème donné (Mendoza & Martins, 2006). Cela en fait une méthode précieuse pour naviguer dans des décisions complexes en présence de perspectives diverses.

Enfin, l'AMC peut reconnaître la possibilité de diverses solutions optimales pour un problème donné (Brondízio et al., 2019). Par exemple, certaines méthodes permettent d'identifier différents schémas de pondération en fonction des parties prenantes (Estévez & Gelcich, 2015). Cette méthode permet ensuite d'identifier différentes alternatives (Langemeyer et al., 2016). Avec cet atout, les scientifiques peuvent non seulement prendre en compte l'existence de points de vue distincts sur une question donnée, mais également comprendre comment ces disparités se traduisent par diverses issues souhaitables (Liquete et al., 2016).

L'AMC a été appliqué dans divers domaines liés à la protection de l'environnement et à l'adaptation au changement climatique. Certains exemples incluent son utilisation dans la gestion des ressources naturelles (Mendoza & Martins, 2006), la gestion des pêcheries (Estévez & Gelcich, 2015), la gestion des eaux souterraines (Karjalainen et al., 2013), l'aménagement du territoire (Beier et al., 2008 ; Gregory et al., 2005 ; Langemeyer et al., 2016 ; Morio et al., 2013), la valorisation des services écosystémiques (Saarikoski et al., 2016), et la planification des SFN urbains (Croeser et al., 2021 ; Kourtis & Papadopoulou, 2022 ; Kremer et al., 2016 ; Liqueste et al., 2016 ; Uribe-Aguado et al., 2022).

Dans ces cas, l'AMC offre une méthode simple et transparente de prise de décision, et qui peut accueillir une grande diversité de critères de décision. Parmi ses diverses limitations, deux aspects principaux peuvent entraver l'utilité de cette méthode pour la planification des SFN urbains.

Tout d'abord, la valeur de la prise de décision résultant d'une AMC est entièrement spécifique au contexte : les poids attribués aux critères sont intrinsèquement liés aux parties prenantes qui les ont donnés, et l'évaluation des critères repose souvent sur des méthodes d'experts qui dépendent également d'un contexte particulier de mise en œuvre (Kangas et al., 2010). Par conséquent, l'AMC n'a pas de sens en dehors du contexte de sa mise en œuvre - contrairement à l'analyse coûts-bénéfices, qui repose sur un critère universel d'utilité (l'argent) (Saarikoski et al., 2016).

Deuxièmement, l'efficacité de la méthode est limitée par les alternatives politiques préalablement définies (Langemeyer et al., 2016). Si toutes les alternatives politiques futures potentielles ne sont pas explicitement identifiées et que leurs principaux critères ne sont pas soigneusement évalués, l'approche ne conduira pas nécessairement à des résultats qui maximisent le bien-être total. Un défi important de ces approches est donc le suivant : comment les décideurs peuvent-ils s'assurer que les politiques qu'ils conçoivent et comparent dans l'analyse coûts-bénéfices, l'analyse coûts-efficacité ou l'AMC sont les solutions les plus optimales face à ces défis multidimensionnels ? Pour résoudre cette problématique, il est nécessaire d'explorer l'ensemble du spectre des projets de SFN qui pourraient être mis en œuvre, et d'examiner les compromis entre les alternatives. De plus, la complexité d'une telle tâche se pose lorsqu'il s'agit de problèmes de planification urbaine à grande échelle qui impliquent une diversité d'objectifs au-delà des seuls services écosystémiques et de l'adaptation au changement climatique.

Une approche qui peut répondre aux limites de l'analyse coûts-bénéfices et de l'AMC est l'Optimisation Multi-Objectif (OMO). Dans la section suivante, nous fournissons un aperçu de base de cette méthode, et de sa mise en œuvre dans le domaine de la prise de décision concernant les SFN et les SuDS.

3.3. L'Optimisation Multi-Objectif

3.3.1. Définitions et principes de l'Optimisation Multi-Objectif

L'Optimisation Multi-Objectif (OMO) est une catégorie de problèmes d'optimisation mathématique qui implique l'optimisation simultanée de plus d'une fonction objectif (Ngatchou et al., 2005). Pour cette raison, il s'agit d'une catégorie de problèmes pour lesquels la résolution déterministe peut parfois être inefficace (Deb, 2014). Ils appartiennent à une classe de problèmes plus générale appelée "optimisation complexe", car ce sont des problèmes qui ne peuvent pas être résolus de manière optimale par une méthode déterministe dans un temps raisonnable (Boussaïd et al., 2013).

La signification de "résoudre" une optimisation multi-objectif n'est pas aussi simple que pour une optimisation à objectif unique (Emmerich & Deutz, 2018). En optimisation multi-objectif, il peut ne pas y avoir une seule solution optimale au problème, mais plutôt un ensemble complet de solutions qui représente les compromis optimaux entre les objectifs (Konak et al., 2006). Cet ensemble de solutions est souvent appelé l'ensemble de solutions non dominées, ou solutions Pareto-optimales, suivant la formalisation de ce concept par Vilfredo Pareto (1906).

Le concept d'optimalité de Pareto peut être compris dans ce contexte comme l'ensemble de solutions pour lesquelles aucune amélioration ne peut être apportée à une fonction objectif sans dégrader simultanément un ou plusieurs autres objectifs. Il convient de noter que cette notion d'efficacité de Pareto dans ce contexte ne fait pas explicitement référence à la microéconomie et au comportement du marché, mais elle est plutôt utilisée comme un cadre formel pour identifier les meilleures solutions dans un espace de solutions. L'ensemble des solutions Pareto-optimales est souvent appelé un front Pareto optimal ou front de Pareto, en référence à sa représentation graphique.

Résoudre un problème multi-objectif consiste donc, parmi l'ensemble des solutions possibles ou "faisables", à isoler l'ensemble des solutions non dominées parmi les solutions dominées (Deb, 2001). Ensuite, l'objectif est d'obtenir l'ensemble le plus diversifié possible de solutions non dominées, afin d'illustrer au mieux les compromis entre les solutions, car aucune solution unique ne peut *a priori* être identifiée comme la meilleure dans l'ensemble non dominé (Deb, 2001). Dans un problème donné, trouver le front de Pareto permet aux décideurs de prendre une décision basée sur les compromis explicites représentés par le front de Pareto (Jahan et al., 2016). Les problèmes multi-objectifs diffèrent des problèmes mono-objectifs en ce sens que deux espaces sont importants : à la fois l'espace de recherche des variables de décision, c'est-à-dire les solutions candidates, et l'espace objectif, c'est-à-dire la manière dont les solutions candidates se comparent les unes aux autres (Consoli & Darby-Dowman, 2006).

En théorie, L'OMO offre plusieurs bénéfices pour notre problème de soutien à la décision. Elle peut optimiser pour trouver les meilleures solutions dans un problème donné, montrer les compromis et prendre en compte simultanément plusieurs objectifs. L'OMO est particulièrement adaptée à la prise de décisions dans des scénarios complexes. Dans les sections suivantes, nous approfondirons l'application de l'OMO appliquée à la prise de décisions concernant la planification des SFN, en mettant particulièrement l'accent sur sa branche dans la gestion des eaux pluviales et l'optimisation des SuDS.

3.3.2. OMO appliquée à l'adaptation au changement climatique urbain

Dans les applications de l'OMO, trois domaines d'application connexes se distinguent : l'optimisation spatiale des ouvrages de gestion des eaux pluviales, la planification de l'utilisation des sols, et l'optimisation spatiale d'infrastructure vertes.

3.3.2.1. Optimisation Multi-Objectif spatiale appliquée à la gestion des eaux pluviales

Il s'agit du domaine étroitement lié à la thèse et qui présente l'utilisation la plus fréquente des techniques de l'OMO. Il vise principalement à optimiser la sélection et la position des SuDS dans une zone de captage. L'objectif ici est d'optimiser la gestion des eaux de ruissellement en intégrant des contrôles à la fois sur la quantité d'inondations et sur la qualité de l'eau (Bekele & Nicklow, 2005 ; Di Matteo et al., 2019 ; Dwivedula et al., 2021 ; Liu et al., 2023 ; Oraei Zare et al., 2012). Certaines études vont plus loin en cherchant à optimiser le rapport coût-efficacité des SuDS de rétention des eaux pluviales (Haghighatafshar et al., 2019). Ces travaux réussissent à identifier et à détailler des solutions spatiales pour le placement optimal des SuDS à différentes échelles spatiales, depuis des échelles locales d'aménagement de quartiers (Uribe-Aguado et al., 2022 ; Wan et al., 2022) jusqu'à un bassin versant entier (Di Matteo et al., 2019 ; Perez-Pedini et al., 2005). Ils identifient les emplacements précis pour les installations SuDS, parfois même en spécifiant les types de SuDS (Uribe-Aguado et al., 2022). Pour atteindre ces résultats, ces enquêtes reposent souvent sur une forme de modélisation hydrologique. Cette modélisation joue un rôle central dans la simulation et la compréhension du comportement de l'eau dans les zones de captage urbaines, permettant l'identification de sites stratégiques pour la mise en place de SuDS.

De plus, des recherches récentes ont également exploré les différents autres bénéfices des SuDS, en utilisant l'OMO pour maximiser le contrôle quantitatif des flux d'eaux pluviales, tout en intégrant comme objectif la maximisation d'autres aménités telles que les aménités esthétiques (Wan et al., 2022), l'atténuation de la chaleur, l'amélioration de la biodiversité, et plus encore (Alves et al., 2020 ; Uribe-Aguado et al., 2022). Cependant, il est à noter que ces considérations de bénéfices secondaires reposent

souvent sur des approches fondamentales de modélisation biophysique et ne tiennent pas compte de la demande en co-bénéfices.

3.3.2.2. Planification Multi-Objectif de l'usage des sols

L'OMO est également appliquée dans des domaines étroitement liés à la planification de l'usage des sols. Ces applications visent à générer des scénarios de planification de l'usage des sols, que ce soit à l'échelle de la ville ou du bassin versant, pour optimiser divers objectifs souvent contradictoires, et à soutenir les planificateurs régionaux et urbains pour la gestion à long terme des sols.

Dans le domaine de la planification spatiale, où divers objectifs tels que la continuité spatiale et la densité de population sont souvent en compétition, l'OMO a été utilisée pour optimiser les modèles d'utilisation des terres, bien que sans considérer les services écosystémiques (Ligmann-Zielinska et al., 2008 ; Mohammadi et al., 2015). Les chercheurs ont également utilisé l'OMO pour optimiser les modèles d'utilisation des terres à l'intérieur des villes, dans le but d'améliorer plusieurs services écosystémiques (Bodnaruk et al., 2017 ; Elliot et al., 2019 ; Y. Yu et al., 2020 ; W. Zhang & Huang, 2015). Dans ces cas, l'objectif est de rechercher les types d'usages des sols à implémenter pour améliorer un ensemble d'objectifs. Ces travaux parviennent à illustrer les compromis inhérents à divers scénarios futurs d'utilisation des terres.

De plus, l'OMO a été appliquée à la planification à grande échelle de l'usage des sols dans des bassins versants, où l'objectif est de concilier la conservation de la biodiversité avec diverses activités humaines (Neema et al., 2013 ; Polasky et al., 2008 ; Verhagen et al., 2018 ; Wu et al., 2018). Ces études abordent le défi complexe de la gestion de l'utilisation des terres sur de vastes bassins versants pour assurer à la fois la préservation écologique et divers types de développement économique.

Ces études illustrent efficacement les arbitrages inhérents à la conciliation d'objectifs contradictoires, en particulier lorsqu'il s'agit d'équilibrer les objectifs de conservation et de développement. Cependant, leur applicabilité directe à la planification des SFN urbains peut être quelque peu limitée. Elles n'abordent souvent pas le problème de l'espace urbain rare et contraint, et ne se concentrent pas sur l'identification des zones appropriées pour les projets de SFN dans les environnements urbains. En fait, le problème de l'optimisation de l'usage des sols à l'échelle urbaine n'est pas le même que l'optimisation de l'emplacement des projets de SFN dans un espace restreint.

3.3.2.3. L'optimisation spatiale appliquée aux infrastructures vertes

Enfin, l'OMO a également trouvé quelques applications dans l'optimisation de l'emplacement des infrastructures vertes. Dans ces cas, l'objectif n'est pas d'optimiser l'ensemble du spectre de l'usage des sols dans une région ou une ville spécifique. Au lieu de cela, l'accent est mis sur l'identification des emplacements les plus adaptés pour la mise en place d'un ensemble prédéfini d'infrastructures, dans le but d'optimiser un ensemble d'objectifs et dans des contraintes spécifiques. Bien que le terme SFN n'apparaisse pas dans cette littérature, ce problème en est cependant très proche.

Neema, Maniruzzaman, et Ohgai (2013) ont appliqué une OMO pour optimiser la localisation des espaces urbains verts dans une grande ville selon trois objectifs : la maximisation de la qualité de l'air, la minimisation de la distance de la population aux espaces verts et des niveaux sonores. Y. Zhang, Murray et Turner (2017) ont effectué une OMO de l'emplacement de nouveaux espaces verts urbains dédiés à l'atténuation des effets distincts d'îlot de chaleur diurne et nocturne, identifiés grâce à l'utilisation de cartes thermiques satellitaires. Yu et al. (2020) ont proposé un cadre d'optimisation pour les espaces verts urbains, avec les objectifs multiples de minimiser leur distance par rapport aux habitants, de maximiser le rafraîchissement urbain et d'augmenter les prix de l'immobilier. Yoon, Kim et Lee (2019) ont conçu un programme OMO pour identifier des plans de conversion d'espaces verts optimaux pour des quartiers virtuels, en maximisant le rafraîchissement urbain, la connectivité écologique et en minimisant les coûts de développement totaux. Il existe également des travaux visant à optimiser l'emplacement d'une quantité finie d'arbres de rue dans une ville pour maximiser simultanément deux co-bénéfices différents : le rafraîchissement urbain et l'atténuation de la pollution de l'air (Bodnaruk et al., 2017).

Ces études mettent en évidence les bénéfices significatifs de l'utilisation de l'OMO dans le contexte de la localisation des SFN dans les environnements urbains. Elles reconnaissent la multitude d'objectifs dans l'aménagement urbain, et certaines contraintes associées, telles que le coût, la disponibilité de l'espace et l'accessibilité. De plus, l'OMO peut efficacement aborder la question complexe des arbitrages entre différents services écosystémiques et entre les services écosystémiques et d'autres objectifs (Kati & Jari, 2016).

De plus, l'OMO offre un moyen de développer des politiques de SFN à grande échelle. Ces politiques, formulées grâce à l'OMO, se manifestent sous forme de scénarios spatiaux, que ce soit en termes d'usage des sols ou de placement d'infrastructures. Cependant, ces exemples de mises en œuvre d'OMO, bien qu'utiles, ne fournissent pas une solution complète au problème. Tout d'abord, les services écosystémiques sont abordés à travers leur offre dans ces études, principalement grâce à une modélisation biophysique de base. Ainsi, ils ne tiennent pas compte de la demande en services écosystémiques, qui découle de facteurs spatiaux et socio-économiques, tels que la densité de population et les préférences individuelles (González-García et al., 2020). Cette omission entraîne une

représentation incomplète de la valeur des services écosystémiques, car leur valeur découle de l'interaction entre leur offre et leur demande (Herreros-Cantis & McPhearson, 2021). Dans l'ensemble, cela peut conduire à des recommandations d'emplacement qui ne maximisent pas la valeur des politiques de SFN.

De plus, ces approches ont des limites sur leur capacité à proposer un soutien à la décision complet et pratique. Tout d'abord, il est important de noter que bon nombre des études précédemment citées ont tendance à négliger un aspect critique : l'analyse de la disponibilité réelle des terres pour les projets de SFN. Cet oubli peut conduire à des recommandations d'optimisation et d'emplacement spatial qui peuvent ne pas correspondre aux opportunités pratiques sur le terrain. Quelques études ont tenté de résoudre ce problème en analysant d'abord la disponibilité des terres, mais généralement à une échelle plus petite, celle du quartier (Uribe-Aguado et al., 2022 ; Wan et al., 2022). Cependant, cette approche n'a pas encore été largement appliquée à l'échelle de la ville, où de grands défis en matière de planification urbaine doivent être relevés.

Deuxièmement, l'applicabilité de ces études à la prise de décision peut être limitée par la portée même de ces études. Ces études se concentrent sur la révélation de la frontière de Pareto et l'identification des compromis dans l'espace des solutions pour un problème complexe particulier, en d'autres termes, elles se concentrent sur la partie optimisation de L'OMO. Cependant, il y a peu d'exploration de la manière dont cette frontière peut être efficacement traduite en processus de prise de décision opérationnels, par exemple, comment passer de l'identification d'un grand nombre de solutions à la sélection d'une seule. Cette lacune indique un besoin de recherches supplémentaires dans ce domaine pour combler le fossé entre les résultats de l'optimisation et la mise en œuvre d'actions concrètes.

Dans l'ensemble, il semble que l'OMO soit relativement sous-utilisée dans le domaine de l'évaluation des SFN et de la planification urbaine. Bien qu'elle ait connu une évolution technique constante au cours de la dernière décennie, grâce aux avancées en informatique et au développement algorithmique (Gunantara, 2018), nous soutenons que son potentiel et sa pertinence dans la littérature sur l'économie de l'environnement restent largement inexplorés. L'applicabilité et l'utilité de l'OMO pour relever les défis multiples inhérents à l'élaboration de politiques environnementales, en général, doivent encore être identifiées et examinées de manière exhaustive.

Dans cette thèse, nous visons à étudier l'utilité et l'applicabilité de l'OMO pour l'application à la planification de politiques de SFN. Nous visons également à aborder les limitations susmentionnées des applications actuelles de l'OMO. Nos principaux objectifs sont décrits dans la section suivante.

4. Problématique et méthodes

La planification des SFN urbains à l'échelle des grandes villes est un casse-tête spatial complexe. Cette complexité découle des ressources et des budgets limités qui contraignent les politiques urbaines, ainsi que de la participation de multiples parties prenantes, de nombreux décideurs et d'une multitude d'objectifs politiques, tous nécessitant et entrant en compétition pour un espace urbain fini et des ressources publiques. Cet enjeu est encore plus complexe lorsque l'on considère la nécessité de concevoir des stratégies d'adaptation au changement climatique urbain à l'échelle métropolitaine intégrée, plutôt qu'au cas par cas.

Pour relever ces défis, les méthodologies d'aide à la décision doivent inclure divers aspects. Cela inclut l'étude de la distribution spatiale des valeurs des services écosystémiques, non seulement l'offre mais aussi la demande en services écosystémiques, l'intégration des objectifs multiples et contradictoires de planification urbaine, la capacité à visualiser les compromis entre les objectifs et entre les services écosystémiques, en particulier dans des contextes spatiaux, l'intégration d'une approche interdisciplinaire pour analyser les bénéfices et les impacts des SFN, et créer un cadre opérationnel pour aider les décideurs urbains.

Dans cette thèse, nous visons à mettre en œuvre une telle approche, dans un contexte appliqué. De fait, le thème principal de cette thèse et de cette étude est profondément ancré dans les particularités d'une étude de cas. Il s'agit d'une expérimentation de politique innovante en matière de gestion des eaux pluviales accompagnée d'un projet de R&D spécifique, menée dans la région métropolitaine de Bordeaux, en France. Cette thèse représente en fait un segment spécifique de cette initiative de R&D. L'objectif de cette politique est de développer la recharge maîtrisée des aquifères de surface urbains. Cette approche vise à 1) soulager la pression sur les nappes profondes en développant des infrastructures d'infiltration des eaux pluviales dans la zone urbaine (y compris à la fois des SFN et des infrastructures grises), à grande échelle, et 2) fournir des co-bénéfices, principalement pour l'adaptation au changement climatique.

Aux enjeux urbains cités précédemment se rajoute dans le cas de cette ville un enjeu fort sur la gestion de la ressource en eau potable, qui est issue des aquifères profonds et dont la disponibilité future est menacée. En effet, bien qu'une baisse de la consommation d'eau potable par habitant ait été observée depuis les années 2000, la consommation en eau reste stable de par la croissance démographique de la métropole, supérieure à 1% par an. D'autre part, les changements climatiques menacent d'augmenter la consommation d'eau future, notamment en période caniculaire (De Grissac, 2018), en plus d'altérer la recharge des nappes. En réponse à ces multiples enjeux, des solutions innovantes de gestion des eaux pluviales (SIGEP) sont mises à l'étude.

Ces SIGEP sont des ouvrages dont la fonction principale est de permettre l'infiltration des eaux pluviales dans les nappes libres en utilisant celle-ci comme des infrastructures naturelles de stockage, dans le but de rendre disponibles ces ressources lors des périodes de besoins, et ce afin de se substituer à la consommation d'eau potable pour certains usages ne nécessitant pas une qualité d'eau potable (arrosage des espaces verts, nettoyage de l'espace public, usages industriels...). Il s'agit, en d'autres termes, d'ouvrages de recharge maîtrisée des aquifères urbains. Parmi ces SIGEP, nous considérons à la fois des infrastructures classiques, dites « grises » (tranchées infiltrantes, puits d'infiltration et d'injection...), dont la seule fonction est de favoriser la recharge maîtrisée des aquifères ; et d'autre part des SfN (noues végétalisées, bassins d'infiltration multi-usages, etc.) qui permettent à la fois la recharge, et fournissent des co-bénéfices.

Les SIGEP correspondent donc à une gestion des eaux pluviales hors réseaux, et sont assimilables ainsi aux termes de « techniques alternatives », « infrastructures vertes » et « solutions compensatoires de gestion des eaux pluviales », avec la nuance de chercher à mettre l'emphase sur l'infiltration, stockage et valorisation des eaux pluviales. Il s'agit donc aussi d'un changement de paradigme dans la gestion des eaux pluviales urbaines, à l'œuvre dans de nombreuses grandes villes européennes et mondiales. La gestion traditionnelle vise à la collecte des eaux pluviales, leur épuration et évacuation dans l'objectif de lutte contre le risque inondation et de pollution du milieu naturel.

La mise en place de SIGEP pose une problématique de décision publique. Dans un cadre de ressources budgétaires contraintes et d'espace rare en milieu urbain, le décideur public doit déterminer la localisation, l'étendue et le type de solutions permettant de maximiser le bien-être social (Bush & Doyon, 2019). Or, les coûts et les bénéfices associés aux SIGEP présentent tous une fonction de répartition spatiale (Hein et al., 2006; Naidoo & Ricketts, 2006; Tardieu, 2017). Les espaces de centre-ville et d'urbain dense concentrent des effets néfastes du changement climatique et des populations importantes (Bulkeley & Betsill, 2003), ce qui accentue les bénéfices potentiels des SfN (Bush & Doyon, 2019; Luederitz et al., 2015). En revanche, les coûts d'opportunités y sont plus élevés car la compétition entre usages des sols plus forte. Les bénéfices liés à la recharge varient également en fonction des caractéristiques pédologiques et hydrogéologiques et de la localisation de la demande pour l'eau réinfiltrée (Maréchal et al., 2020).

L'initiative de R&D comprend une étude hydrogéologique sur l'infiltration, le stockage et la réutilisation des eaux pluviales, menée en parallèle de cette thèse par une équipe d'hydrogéologues du Bureau de Recherches Géologiques et Minières (BRGM) français, qui vise à créer une cartographie de la capacité des sols urbains à infiltrer et à stocker les eaux pluviales. Le deuxième aspect de ce projet de R&D est de fournir un soutien à la prise de décision à moyen et long terme en matière d'aménagement du territoire et d'adaptation au changement climatique, et ceci est le sujet de cette thèse. Ce travail de

thèse s'attache d'une part à caractériser et évaluer les bénéfices et coûts associés aux SIGEP. Il s'agit d'en évaluer les différents bénéfices, ainsi qu'analyser leur hétérogénéité spatiale. D'autres parts, ce travail vise à proposer un support d'aide à la planification urbaine permettant de déterminer le type et la localisation de projets de recharge maîtrisée dans un contexte d'espace et de ressources contraintes, de manière à en optimiser les différents bénéfices. Comment sont répartis les coûts et bénéfices potentiels de ces infrastructures, où doivent-elles être mises en œuvre, et avec quel type de technologie (SFN, infrastructures grises)?

En résumé, les principales questions de recherche de notre travail sont les suivantes:

1. Quelle est l'hétérogénéité spatiale des coûts et bénéfices des SFN en ville ?
2. Comment prioriser le développement spatial des SFN, en tenant compte de leurs nombreux bénéfices potentiels et coûts ?

Il est important de noter que ces deux questions ont des implications à deux niveaux différents: d'une part, ce sont des questions de recherche générales qui visent à répondre aux lacunes mentionnées précédemment dans la littérature scientifique ; d'autre part, ce sont aussi des questions pratiques et opérationnelles par rapport au problème particulier rencontré dans la région métropolitaine de Bordeaux.

Pour aborder ces questions, nous avons développé deux approches générales spécifiques : une évaluation des bénéfices de la recharge des aquifères et la mise en œuvre elle-même d'une OMO. La thèse est organisée en quatre chapitres distincts qui décrivent cette approche globale. Il est important de noter que les chapitres 2, 3 et 4 sont eux-mêmes présentés comme des articles indépendants, qui ont été publiés, soumis ou doivent être soumis à des revues scientifiques au moment de la rédaction de cette thèse. Ces chapitres développent leurs propres questions de recherche, mais servent également nos questions de recherche globales, et ils se nourrissent mutuellement pour servir la mise en œuvre de l'OMO. Cette thèse est organisée comme suit :

Le Chapitre 1 présente le cadre méthodologique général de la thèse. Ce chapitre fournit une description plus détaillée de l'étude de cas, ainsi qu'une vue d'ensemble des méthodes principales employées pour mettre en œuvre l'OMO, en particulier dans son application à l'étude de cas de la région métropolitaine de Bordeaux. Nous précisons que ce chapitre se concentre sur la présentation des approches de l'OMO développées dans la thèse, à l'exclusion de l'approche de l'expérience de choix discrets du chapitre 2 et de l'approche de l'OMO de la ville modèle du chapitre 3, qui ont leurs propres sections dédiées aux méthodes. Ce chapitre fournit une description générale de la mise en œuvre de l'OMO, de sa conception à sa mise en œuvre, ainsi que de sa connexion avec l'initiative de R&D générale. La deuxième partie de ce chapitre fournit aux lecteurs des informations fondamentales sur les

algorithmes évolutionnaires, couvrant les concepts clés, les processus algorithmiques et les composants de prise de décision, et spécifiant les choix méthodologiques faits dans notre OMO.

Le chapitre 2 est intitulé "Les inégalités environnementales urbaines influencent-elles la demande en SFN ?". Il présente une expérience de choix discrets menée dans la région métropolitaine de Bordeaux. Cette approche sert deux objectifs : enquêter sur ses propres questions de recherche concernant les co-bénéfices des SFN et produire des données spatiales à utiliser dans l'OMO. Ce travail examine les préférences de la population pour des scénarios contrastés de recharge des aquifères, y compris les SFN. Il vise à analyser l'hétérogénéité spatiale des préférences. Il examine également une problématique spécifique: comment divers types d'inégalités environnementales (exposition aux risques environnementaux, inégalité d'accès aux espaces verts et inégalité relative aux impacts négatifs des politiques environnementales) impactent-ils la demande des individus pour les SFN ? Le but de ce travail est également de nourrir le chapitre 3 en fournissant des estimations de la demande pour les bénéfices des SFN, et d'identifier la distribution spatiale de la demande en matière de rafraîchissement urbain, afin de servir l'OMO.

Le chapitre 3 est intitulé "Optimisation multi-objectifs le long d'un gradient urbain-rural". Dans cette section, nous examinons deux points principaux. D'une part, nous examinons la viabilité de l'OMO pour résoudre un problème de localisation des SFN. D'autre part, cet article vise à résoudre un problème générique qui va au-delà des études de cas individuelles : dans le cas d'un gradient urbain-rural de coûts et de bénéfices des politiques SFN : où les décideurs doivent-ils mettre en œuvre leurs projets de recharge (les SIGEP), et de quel type doivent-ils être, afin de maximiser la production de recharge, de maximiser le rafraîchissement urbain et de minimiser les coûts d'opportunité des terrains utilisés ? L'article développe une OMO sur une ville modèle ad hoc, conçue pour répondre à ces questions. Ce travail nourrit également le chapitre 3 en 1) fournissant un test pour la méthode de l'OMO dans un cadre contrôlé avant sa mise en œuvre sur l'étude de cas réelle 2) fournissant des lignes directrices spatiales à tester dans la mise en œuvre finale.

Le chapitre 4 est intitulé "Une approche d'optimisation multi-objectifs pour les ouvrages de recharge maîtrisée des aquifères à bénéfices multiples en ville". Dans ce chapitre, nous appliquons l'OMO à l'étude de cas de la région métropolitaine de Bordeaux. Ce travail vise à développer une approche approfondie, depuis la conception, jusqu'à la mise en œuvre et l'exploitation des résultats de l'OMO. Il s'agit d'une étude qui lie les différentes facettes de l'initiative de R&D, en tenant compte des enseignements de l'étude hydrogéologique réalisée dans la région métropolitaine ainsi que des résultats spatialisés du chapitre 2 dans le cadre de l'OMO. Ce travail est basé sur plusieurs volets de consultation des principaux acteurs et décideurs, et vise à fournir des méthodes pour l'exploration des fronts de Pareto et leur exploitation en vue de prodiguer des éléments de recommandations exploitables aux décideurs.

Conclusion générale

En résumé, cette thèse examine divers défis liés à la mise en œuvre d'infrastructures multifonctionnelles de SFN pour l'adaptation des villes au changement climatique. Cette thèse est également le fruit d'un projet de recherche spécifique, lancé par les autorités en charge de l'assainissement et de la gestion des eaux pluviales des communes de Bordeaux Métropole, en France. Les décideurs locaux cherchent à développer des projets de recharge des aquifères en ville, dans le but de préserver les eaux souterraines, en contribuant en même temps à la lutte contre les îlots de chaleur et à d'autres co-bénéfices, tout en opérant sur un espace limité.

Les deux principaux objectifs de cette thèse sont d'analyser la distribution spatiale des co-bénéfices fournis par les SIGEP y compris les SFN, et de fournir une approche novatrice d'aide à la décision adaptée à la planification opérationnelle des SFN dans les villes et adaptée à une approche multidisciplinaire. Dans ce contexte, cette recherche aborde des questions scientifiques spécifiques inhérentes aux SFN, à l'économie des services écosystémiques, à la planification urbaine, à la gestion des eaux pluviales urbaines et à l'adaptation au changement climatique. L'objectif parallèle de cette thèse est également de fournir des outils d'aide à la décision adaptés à notre étude de cas spécifique, dans le cadre du projet de recherche et développement en cours.

Dans ces dernières remarques de conclusions, nous mettons d'abord en évidence les principales conclusions de notre recherche. Ensuite, nous tirons des conclusions générales concernant la planification des SFN dans les villes. Enfin, dans la troisième section, nous exposons les limites de ce travail et quelques perspectives de recherche future.

1. Résultats principaux

Dans le chapitre 2, nous avons développé une expérience de choix discrets qui explore les préférences de la population pour les bénéfices et les effets négatifs générés par la mise en place de SFN. Notamment, cette étude innove dans la littérature sur les préférences déclarées en analysant l'impact de trois types d'inégalités environnementales sur les préférences pour les bénéfices et les effets des SFN. Il s'agit également de l'une des premières études à examiner l'impact sur les préférences de l'utilisation d'espaces de voiries pour le développement des SFN dans une ville.

L'analyse issue de l'expérience de choix indique une importante demande de la part des résidents, à la fois pour la préservation des aquifères profonds et pour la lutte contre les îlots de chaleur urbain. L'impact sur les espaces de voirie dédiés à la voiture est la principale source d'hétérogénéité au sein de

la population : il est considéré comme un impact négatif par une partie de la population, en particulier ceux qui dépendent de l'utilisation de la voiture, et comme un avantage pour une autre partie de la population. L'analyse se concentre également sur l'étude de l'hétérogénéité spatiale des préférences. Nous identifions un phénomène de dépendance spatiale globale de la demande en matière de régulation climatique locale, et nous identifions des points chauds et froids pour le consentement à payer associé à la réduction de l'espace dédié à la voiture.

L'hétérogénéité spatiale de la demande en rafraîchissement urbain est ensuite analysée comme résultant de l'impact des inégalités environnementales : une forte exposition à la chaleur augmente la demande individuelle en rafraîchissement urbain. Cette constatation indique que les inégalités en matière d'exposition aux risques environnementaux peuvent être un important moteur de l'hétérogénéité spatiale de la demande en SFN. Ce gradient de demande pour les services écosystémiques est en ligne avec les résultats d'autres études (Baró et al., 2017 ; Hérivaux & Le Coënt, 2021). Nous constatons également que la dépendance à l'égard de l'utilisation de la voiture impacte négativement la demande des individus pour des politiques susceptibles de réduire la disponibilité des espaces de voirie. Nous soutenons que cela reflète l'impact des inégalités environnementales causées par les SFN et les politiques d'embellissement urbain sur les préférences individuelles : la réduction de l'espace de voiture peut avoir un impact soit fortement négatif, soit fortement positif sur le bien-être individuel, en fonction de la mesure dans laquelle leur bien-être individuel dépend de l'utilisation de la voiture.

Enfin, la relation significative établie dans l'analyse de post-estimation entre l'exposition aux îlots de chaleur urbain et la demande en rafraîchissement permet de créer une carte de demande pour ce co-bénéfice à l'échelle de Bordeaux Métropole. La carte de demande résultante pour le rafraîchissement urbain est également un résultat en soi et peut intéresser les décideurs locaux et les services de gestion des espaces verts. Cette carte de demande est également intégrée en tant qu'élément clé dans l'optimisation multi-objectifs finale pour la planification de la recharge des aquifères dans l'étude de cas de Bordeaux.

Le chapitre 3 examine l'applicabilité de l'optimisation multi-objectifs dans un problème de décision générique. Dans le cadre de ce travail, l'accent central est mis sur les décideurs cherchant à déterminer les emplacements optimaux pour le développement d'infrastructures d'infiltration, en présence de gradients urbains-ruraux de coûts et d'avantages. Ce chapitre aspire également à relier la littérature existante sur l'optimisation spatiale des infrastructures de gestion des eaux pluviales et sur la littérature portant sur les gradients urbains-ruraux. En utilisant une optimisation multi-objectifs et une ville-modèle théorique mono-centrique simple, nous mettons en évidence des stratégies contrastées de localisation des infrastructures d'infiltration dans différents contextes caractérisés par diverses contraintes

hydrogéologiques, des effets de substitution avec les espaces verts urbains existants et la disponibilité de technologies d'infiltration alternatives.

Ce travail génère deux ensembles principaux de résultats. Tout d'abord, il établit notre positionnement méthodologique, positionnant l'optimisation multi-objectifs comme un outil robuste et pertinent d'aide à la décision, permettant la compréhension des multiples approches possibles et leurs arbitrages, pour l'adaptation au changement climatique. Deuxièmement, la simplicité de notre modèle de ville permet de fournir des conclusions générales sur les recommandations spatiales aux décideurs urbains qui vont au-delà des études de cas individuelles. D'une part, il existe un arbitrage fort entre l'introduction des SFN dans les centres-villes ou la mise en œuvre d'infrastructures grises dans les régions périphériques. De plus, l'étude met en évidence l'influence potentielle des effets de substitution, démontrant leur impact décroissant sur l'attrait des sites du centre-ville. Enfin, les règles spatiales sont modifiées lorsque les centres-villes ne sont pas adaptés aux projets de recharge des aquifères: dans ce cas, les solutions de compromis devraient plutôt viser la planification des emplacements des SFN qui mélangent les emplacements centraux avec des emplacements hors de la ville où l'infiltration est plus efficace.

Dans le chapitre 4, nous proposons une approche intégrée de la planification d'infrastructures de recharge. Ce travail est en quelque sorte la conclusion des deux approches précédentes proposées dans la thèse, ainsi que de l'étude hydrogéologique réalisée pendant le projet de recherche en parallèle de cette thèse. Nous avons proposé une nouvelle manière d'utiliser l'optimisation multi-objectifs pour relier l'adaptation urbaine au changement climatique, la gestion des eaux pluviales et la recharge des aquifères. Ce travail visait à répondre à notre deuxième question de recherche dans un contexte appliqué et interdisciplinaire : où localiser les infrastructures de recharge dans le contexte d'une distribution complexe des coûts et des bénéfices, et quel type d'infrastructure devrait être mise en place. En outre, ce résultat est une production concrète de la thèse. En effet, ces résultats ont été mis à disposition pour les services métropolitains, afin de définir leurs politiques d'aménagement du territoire et d'adaptation au changement climatique. Il faut donc aussi noter que ces travaux ont donné lieu à des livrables applicatifs, ainsi qu'à la conduite d'un atelier spécifique de rendu (14/09/2023) auprès des services métropolitains.

Les principales conclusions de l'optimisation multi-objectifs informent les décisions concernant les zones et les quartiers à privilégier pour le développement de la recharge, ainsi que les types d'infrastructures à utiliser et les intensités de mise en œuvre à développer. Une première stratégie qui émerge de ce travail est que la priorisation de la recharge des aquifères favorise les solutions grises spécialisées, situées principalement dans des zones présentant des conditions idéales pour l'infiltration des eaux pluviales et des coûts d'opportunité faibles, principalement en périphérie de la ville. En

revanche, les solutions mettant l'accent sur le rafraîchissement urbain présentent des caractéristiques distinctes, avec des SFN concentrées dans les zones d'îlots de chaleur. Ce résultat diverge des conclusions théoriques du chapitre 3, qui n'ont pas tenu compte de la localisation des îlots de chaleur, se concentrant uniquement sur la densité de la demande. De plus, les solutions grises sont intégrées dans les deux stratégies, souvent en périphérie de la ville et dans les zones suburbaines, offrant un rendement de recharge à un coût d'opportunité moins élevé. Certains sites IRIS émergent de manière constante comme des choix préférés, quelle que soit la stratégie choisie : ce sont des choix sans regrets.

Des solutions hybrides combinant des aspects des deux stratégies sont possibles, impliquant des compromis entre les sites gris suburbains et les sites SFN centraux. De plus, l'examen du front de Pareto révèle une zone de gains élevés, où des solutions priorisant le rafraîchissement urbain offre aussi de hauts niveaux de recharge. Ce constat suggère que les décideurs n'ont pas nécessairement besoin de privilégier un bénéfice par rapport à l'autre : cette solution permet de bien performer dans les deux dimensions, bien que ces solutions s'accompagnent de coûts d'opportunité plus élevés. En conclusion pour cette étude de cas, les parties prenantes doivent tenir compte de leur priorité dans la minimisation des coûts d'opportunité lorsqu'elles agissent sur ces résultats. Si la réduction des coûts d'opportunité est primordiale, d'autres solutions alternatives peuvent être plus appropriées, tandis que ceux qui valorisent les bénéfices globaux peuvent privilégier les solutions ambitieuses priorisant le rafraîchissement urbain.

2. La planification spatiale des SFN urbains

La transformation des villes est lente, tout comme l'adoption de pratiques innovantes telles que les SFN et les nouvelles techniques, dites « alternatives », de gestion des eaux pluviales. Ces options restent des alternatives à l'aménagement urbain conventionnel, centré sur la voiture, et s'appuient sur des techniques traditionnelles de gestion de l'eau grise et centralisée. En fait, les applications des SFN et des techniques alternatives sont principalement observées dans les nouveaux développements urbains, et non dans les anciennes zones urbaines marquées par les conceptions centrées sur la voiture du XXe siècle, qui ont largement négligé les services écosystémiques. Bien que certaines grandes villes européennes, en particulier les capitales, commencent à adopter le concept de services écosystémiques et des stratégies ambitieuses d'adaptation au changement climatique, ces pratiques restent marginales. En revanche, les impacts négatifs du changement climatique augmentent rapidement, et avec d'importantes incertitudes. Les villes risquent de prendre du retard dans la course contre la montre pour s'adapter au changement climatique.

Dans cette thèse, nous avons participé à identifier des pistes en matière d'adaptation en identifiant des stratégies spatiales générales pour la planification des SFN de recharge des aquifères : compte tenu des ressources et de l'espace limités, optimiser l'impact des SFN devient un objectif impératif pour faire

face à l'écart d'adaptation. Cette thèse s'est également penchée sur les aspects spatiaux des coûts et des bénéfices associés aux SFN et de leurs implications pour l'aménagement urbain.

La première contribution majeure concerne la distribution spatiale des bénéfices. En ce qui concerne les co-bénéfices, nous avons rassemblé des informations à la fois sur la distribution spatiale de l'efficacité potentielle des SFN pour fournir des co-bénéfices, ainsi que sur la demande pour ces co-bénéfices. En termes généraux, la demande de SFN est principalement concentrée dans les zones à haut risque, qui peuvent souvent être situées dans des zones densément peuplées. Ces zones centrales sont potentiellement très rémunératrices en termes de co-bénéfices, car elles ont une demande agrégée élevée, mais les contraintes d'espace limitent souvent la mise en œuvre des SFN. En termes pratiques, il existe peu d'espaces « vides » disponibles, de zones de stationnement ou de larges rues, pouvant être transformés en SFN. Lorsqu'il existe de telles possibilités, cela se fait souvent à un coût d'opportunité très élevé. Dans de telles zones centrales, les politiques publiques peuvent envisager des types de SFN alternatifs avec une empreinte plus faible, tels que les toits et façades végétalisés, ou d'autres techniques alternatives, tels que les revêtements perméables.

Ce résultat émerge particulièrement dans la différence entre les résultats de l'approche du Chapitre 3 et du Chapitre 4. Dans le cadre de base du Chapitre 3, nous considérons toutes les localisations centriques comme des emplacements très intéressants en ce qui concerne les co-bénéfices. Cependant, dans le chapitre 4, les co-bénéfices élevés se manifestent principalement dans le quartier où il y a à la fois de nombreux terrains disponibles et une forte demande, en particulier lorsqu'on combine la demande individuelle et la demande basée sur la densité de population. Ces quartiers se trouvent plutôt en dehors du centre-ville immédiat, dans les zones péri-urbaines proches. En d'autres termes, le gradient urbain-rural des bénéfices potentiels des SFN est non linéaire dans ce cas, et présente son pic à un point médian entre les zones urbaines et rurales. Notamment, parvenir à ce résultat n'a été possible que grâce à une approche appliquée dans la thèse.

L'efficacité de la recharge des aquifères ne suit pas non plus strictement un gradient urbain-rural. Bien que nous nous soyons principalement appuyés sur la recharge théorique des aquifères (pas de modélisation réelle), il semble que notre hypothèse de distribution en damier du chapitre 3 soit cohérente avec la distribution réelle du chapitre 4. En d'autres termes, il existe des zones très efficaces pour le développement de la recharge des aquifères à la fois dans le centre-ville et à l'extérieur, en théorie. L'objectif du planificateur est donc de trouver les emplacements qui offrent également de grands co-bénéfices, des zones gagnant-gagnant. De plus, il n'y a pas de phénomène spatial particulier associé à la demande de préservation des eaux souterraines, ce qui suggère qu'il n'y a pas non plus de modèle spatial particulier.

Le deuxième type de contributions de cette thèse découle de cette analyse de la distribution spatiale des bénéfices de la recharge des aquifères, et concerne les modèles spatiaux pour optimiser l'emplacement des infrastructures de recharge des aquifères. Le premier modèle suggère de mettre en œuvre des SFN près des zones qui présentent les conditions suivantes : des zones densément peuplées avec des services écosystémiques gravement dégradés, une forte demande individuelle pour les SFN, et beaucoup d'espace disponible pour développer les SFN. Ces zones peuvent être des points chauds potentiels des inégalités environnementales, de sorte que cette approche peut apporter une amélioration substantielle du bien-être des villes, et elles ne se trouvent pas nécessairement dans les centres-villes. Dans notre cas, elles se trouvent principalement dans les quartiers périurbains.

Ce modèle contraste avec la dynamique des politiques actuelles de végétalisation à l'œuvre dans de nombreuses villes – pas nécessairement dans le cas de la Métropole de Bordeaux - qui visent principalement soit les quartiers relativement aisés du centre, soit les développements urbains récemment construits ou en construction (Kato-Huerta & Geneletti, 2022). En d'autres termes, la répartition actuelle des projets de végétalisation tend souvent à perpétuer les inégalités socio-économiques (Calderón-Argelich et al., 2021). Par conséquent, maximiser les emplacements des SFN pour fournir des co-bénéfices est intrinsèquement lié aux considérations de justice environnementale en matière de distribution : les perspectives spatiales résultant de notre OMO pourraient potentiellement contribuer à atténuer les inégalités environnementales.

En ce qui concerne les infrastructures spécialisées, telles que les infrastructures d'infiltration grises, nos résultats indiquent qu'elles devraient plutôt être développées dans les rares zones péri-urbaines qui remplissent les conditions suivantes : avoir les meilleures conditions hydrogéologiques pour la recharge et présenter un espace abondant et bon marché pour développer les infrastructures de recharge. La mise en œuvre de telles stratégies offre potentiellement des économies d'échelle élevées et un ratio coût-efficacité élevé en ce qui concerne la recharge. De plus, dans de nombreuses villes, il s'agit souvent de zones moins peuplées, ce qui se traduit par moins de co-bénéfices potentiels, de sorte que ces stratégies se concentrent davantage sur la recharge que sur la fourniture de multiples bénéfices. Peut-être aussi, dans de nombreux contextes, ces habitants péri-urbains sont peut-être mieux pourvus en jardins privés ou en accès à des espaces verts naturels et publics, ce qui entraîne une demande moindre de bénéfices individuels. Cet effet particulier reste à étudier, car nous n'avons pas réussi à identifier avec succès des effets de substitution entre les SFN et les jardins privés ou les parcs existants dans l'expérience de choix.

Ce modèle spatial ne constitue pas un contraste net par rapport aux pratiques existantes - la création de grandes infrastructures monofonctionnelles en dehors des zones urbaines. Cependant, la comparaison de ce modèle avec le premier - lié aux SFN - est d'une grande importance. Potentiellement, les mêmes zones péri-urbaines peuvent apparaître comme optimales soit pour développer des SFN

multifonctionnels, comme mentionné précédemment, soit pour des infrastructures grises spécialisées. Une interprétation de ce résultat est que les parcelles péri-urbaines qui peuvent sembler initialement intéressantes pour développer des infrastructures grises hautement spécialisées peuvent, dans les bonnes conditions, être également optimales pour développer des SFN. Dans cette situation, opter pour des SFN plutôt que des infrastructures grises pourrait contribuer à réduire les inégalités environnementales, apportant de grandes améliorations au bien-être public. En conclusion, les décideurs doivent absolument adopter une approche spatiale pour planifier les stratégies d'adaptation et de gestion des eaux pluviales : cela peut permettre de révéler ces solutions synergiques qui ne se manifesteraient pas nécessairement autrement.

Notre deuxième question de recherche dans cette thèse concernait également les outils pour optimiser l'emplacement et le type d'infrastructures de recharge des nappes. En conclusion de cette thèse, nous pouvons affirmer que l'OMO est une approche précieuse pour la planification spatiale urbaine. Cette méthode s'inscrit dans une niche spécifique en matière de prise de décision : elle fournit un cadre robuste pour la création et la comparaison de stratégies spatiales, lorsque la conception de telles stratégies à grande échelle avec des objectifs conflictuels est une tâche difficile. En tant que telle, cette approche a une portée légèrement différente de l'analyse coûts-bénéfices et de l'AMC, qui ne fournissent pas d'outils pour élaborer des plans spatiaux.

Néanmoins, l'OMO pose des enjeux de visualisation en raison de la quantité de données et de résultats générés. Impliquer les parties prenantes dès le début et élaborer des méthodes efficaces pour visualiser et explorer les résultats du front de Pareto sont des aspects impératifs pour utiliser efficacement l'OMO. En fait, cette approche n'est pas encore une méthode entièrement opérationnelle et pratique pour soutenir la planification urbaine des SFN. Outre le fait que la mise en œuvre de l'OMO nécessite une connaissance technique assez élevée, nous soutenons que cette méthode manque encore de directives appropriées pour diffuser sa mise en œuvre auprès des décideurs urbains. En particulier, il reste encore beaucoup à faire pour incorporer cet outil issu des sphères académiques dans les cadres de prise de décision des SFN. Plusieurs éléments seraient nécessaires pour favoriser une meilleure diffusion de cet outil. En premier lieu, l'analyse des fronts de Pareto et l'analyse des perspectives spatiales résultant des fronts de Pareto manquent encore de directives claires, et il est nécessaire que les praticiens et experts de l'OMO investiguent et proposent des directives pratiques pour améliorer ses aspects. Deuxièmement, cette méthode nécessite un niveau important de programmation informatique et de gestion de données spatiales, et sa mise en application pourrait être grandement facilitée par l'élaboration d'outils non-experts (par exemple en les intégrant aux outils de gestion de données géographiques, type ArcGIS).

Cependant, nous soutenons qu'il y a dans cette approche une opportunité pour les chercheurs, et en particulier les économistes de l'environnement : il s'agit indéniablement d'un outil précieux qui peut

combler les lacunes entre l'économie des services écosystémiques et les sciences de la prise de décision, et un outil qui fournit une interface multidisciplinaire pour tous les multiples domaines liés à l'adaptation au changement climatique et à la planification de l'usage des sols.

3. Limites et perspectives pour de futures recherches

Cette thèse présente diverses limites. Dans cette section, nous mettons en évidence en premier lieu deux limitations inhérentes à la portée de la recherche, ainsi que des suggestions pour améliorer ces limitations. Ensuite, nous présentons deux perspectives intéressantes pour de futures recherches qui ont émergé des enseignements de cette thèse.

Commençons par les limites de ce travail, le premier élément, peut-être le plus notable, est l'absence presque totale de considérations financières. Notamment, l'OMO s'est uniquement concentrée sur les coûts d'opportunité et les contraintes spatiales générales, en excluant d'autres dimensions des coûts tels que les coûts opérationnels traditionnels et les coûts d'investissement. En fait, nous avons adopté une approche de planification urbaine à long terme, en omettant délibérément les notions de coûts des infrastructures de recharge et en nous concentrant uniquement sur les incitations à la gestion du foncier urbain, dans le but de minimiser le coût d'opportunité.

L'objectif de cette approche était de limiter notre perspective sur les coûts à la dimension la plus spatialement distribuée, ceux qui peuvent être le mieux représentés sous forme de gradients urbains-ruraux, en nous appuyant sur une hypothèse de coûts d'investissement spatialement constants. Dans ce cas, lorsqu'il s'agit du défi de la planification urbaine et de la priorisation spatiale des politiques publiques dans une ville, il est apparu que le coût inhérent à l'utilisation d'un espace rare et disputé était la meilleure représentation de la dimension du gradient urbain-rural à l'étude. En d'autres termes, décider de prendre en compte uniquement les coûts d'opportunité spatiale était un choix de modélisation que nous avons fait afin de modéliser au mieux le cœur du défi spatial en cours : la complexité spatialement hétérogène de la mise en œuvre des SFN, le long des gradients urbains-ruraux.

En conséquence de ce choix, notre approche omet une partie significative des problèmes liés à la planification urbaine des SFN : comment exploiter et optimiser la planification des SFN dans les villes, compte tenu des contraintes budgétaires et des ressources publiques limitées ? Par conséquent, de futures recherches pourraient renouer avec les travaux menés sur l'analyse des éléments de coûts des SFN et des techniques alternatives. De telles approches pourraient inclure une modélisation des coûts tout au long du cycle de vie dans le cadre de l'OMO, tout en tenant compte des contraintes budgétaires financières, établies avec les parties prenantes, afin de représenter au mieux la réalité du problème. Cette approche viserait à travailler avec les parties prenantes publiques pour estimer les niveaux de budget en fonction

de leur réalité opérationnelle. Un tel travail pointerait également vers l'adoption d'une perspective temporelle dans l'optimisation, en actualisant les coûts et les bénéfices sur une période donnée, par exemple. Dans une telle approche, l'OMO aurait une approche encore plus opérationnelle et servirait à la fois d'approche de soutien à la décision pour la planification des stratégies des SFN, mais aussi pour la gestion de ces actifs à long terme.

Une autre piste de recherche concernant les coûts consisterait à relier ces éléments de coûts à leurs différents porteurs, et donc à faire le lien entre cette recherche et les récentes enquêtes sur la répartition des coûts des SFN entre différents acteurs dans le contexte de la planification urbaine (Le Gat et al., 2023 ; Thebault et al., 2020). Par exemple, les propriétaires de parcelles, les promoteurs immobiliers urbains, les services publics de gestion des espaces verts, les services de traitement de l'eau peuvent supporter diverses parties différenciées des coûts des scénarios découlant de l'OMO. Dans de nombreux cas les services d'espaces verts supporteraient les coûts de l'entretien des SFN, tandis que les entreprises de traitement de l'eau et des eaux usées et l'administration publique pourraient supporter davantage les coûts de l'entretien des infrastructures souterraines de filtration grise. Une telle approche fournirait encore plus de détails opérationnels pour la planification organisationnelle de ces scénarios de planification urbaine.

En tenant compte de ces considérations, il serait possible d'illustrer un autre type de compromis dans l'OMO : les compromis entre les différentes entités de gestion et les départements d'une grande ville. En poussant cette logique plus loin, on peut imaginer que de telles considérations permettraient de voir comment les entités publiques et privées seraient mobilisées avec une intensité relative différente pour mettre en œuvre des stratégies des SFN. Avec une telle addition, l'OMO serait également un moyen d'étudier plus avant les instruments politiques nécessaires pour développer des stratégies des SFN, par exemple, les approches de transfert monétaire nécessaires pour inciter les acteurs à développer des SFN.

Un deuxième point crucial qui est sorti du cadre de cette thèse est la prise en compte de la raison la plus courante derrière l'incitation à développer des SFN et des SuDS dans les villes : la réduction du risque d'inondation. Ce travail s'est vraiment concentré sur l'innovation politique du projet de R&D spécifique initié dans la métropole bordelaise : la recharge des eaux souterraines dédiée à la préservation des stocks d'eau profonde, par le biais du mécanisme du remplacement de l'utilisation de l'eau, en utilisant des infrastructures SFN et grises qui facilitent la recharge des eaux souterraines. Mais malgré cette nouveauté, l'objectif de réduction du risque d'inondation dans la métropole est toujours présent et central - c'est en fait l'objectif principal de la gestion des eaux pluviales. La réduction du risque d'inondation est également l'un des objectifs de l'intérêt du gouvernement métropolitain de Bordeaux pour la recharge des eaux souterraines, bien qu'il s'agisse d'un objectif secondaire dans ce cas particulier. En effet, l'infiltration des eaux pluviales peut réduire les ruissellements de surface, et donc contribuer à

réduire le risque d'inondation. Dans le cas de la métropole bordelaise, l'intégration de telles extensions sur la réduction du risque pourrait être une perspective intéressante, identifiée par les services de gestion des eaux pluviales.

La réduction du risque d'inondation est le principal levier des politiques d'adaptation au changement climatique dans la plupart des villes, et relier notre approche de soutien à la décision à la réduction du risque d'inondation pourrait étendre l'applicabilité et la valeur de ce travail. Une telle approche pourrait également étendre la manière dont les bénéfices de l'infiltration des eaux pluviales sont représentés dans cette thèse. Prendre en compte à la fois les bénéfices de la préservation des eaux souterraines et de la réduction du risque d'inondation pourrait conduire à une meilleure appréciation de la nature des bénéfices multiples liés à la préservation des eaux souterraines (Hérivaux & Rinaudo, 2016).

Une possibilité d'étendre ce travail pour inclure de telles considérations pourrait consister à lier l'OMO à une approche de modélisation des risques. Il consisterait à interfacer un modèle hydrologique de ruissellement de surface et à simuler la réduction du risque ajoutée par les différents scénarios de recharge. Cela permettrait de mettre encore plus l'accent sur l'hétérogénéité spatiale des bénéfices potentiels des infrastructures de recharge : la distribution des bénéfices potentiels dépendrait non seulement des caractéristiques hydrogéologiques des sols urbains - illustrées dans notre approche par le score multicritère de la carte de favorabilité de la recharge - mais aussi d'autres facteurs variant spatialement tels que les caractéristiques du ruissellement de l'eau ou le placement particulier des infrastructures de recharge dans le bassin hydrologique. Des avancées récentes dans l'OMO ont réussi à atteindre de tels objectifs en incorporant la modélisation du risque d'inondation, bien qu'elle nécessite une expertise plus approfondie en matière de modèles de ruissellement de l'eau (Alves et al., 2020 ; Behroozi et al., 2018 ; Majidi et al., 2019).

Enfin, cette thèse présente également des perspectives intéressantes pour de futures recherches.

Le premier domaine d'exploration potentielle découle de l'approche de l'expérience de choix utilisée dans le chapitre 2, qui a examiné le lien entre les inégalités environnementales et les préférences pour les bénéfices et les impacts des infrastructures urbaines de recharge des eaux souterraines. L'objectif principal de cette étude était d'investiguer la variabilité spatiale des préférences et les dimensions spatiales des co-bénéfices associés aux SFN, en éclairant leur distribution dans les zones urbaines. Cette approche a été élaborée pour formuler une série d'hypothèses sur l'influence des différentes inégalités environnementales sur la demande de SFN. L'objectif était de mettre en lumière les déterminants spatiaux de la demande de co-bénéfices des SFN. Nous avons notamment identifié des relations significatives entre les inégalités et la demande de SFN, un domaine de recherche relativement nouveau dans les études de préférence déclarée, offrant de nombreuses pistes pour de futures investigations.

Tout d'abord, de futures recherches pourraient approfondir les trois types d'inégalités environnementales abordées dans cette étude. En ce qui concerne les inégalités liées aux risques environnementaux, la recherche pourrait se concentrer particulièrement sur les risques d'inondation, et sur la manière dont l'exposition perçue ou réelle aux risques d'inondation impacte la demande de politiques visant à réduire de tels risques. Cette exploration pourrait révéler des disparités entre les zones à forte demande de mitigation des inondations et celles où la mise en œuvre de mesures de mitigation, telles que les SuDS, serait la plus efficace. De plus, en ce qui concerne le deuxième type d'inégalité examiné dans le chapitre 2 (l'accès aux espaces verts), de futures recherches pourraient approfondir ce thème. La littérature existante a identifié d'importantes disparités socio-démographiques en matière d'accès aux espaces verts, mais notre étude n'a pas trouvé d'impact notable sur la demande de SFN. Les recherches ultérieures en matière de préférence déclarée pourraient se pencher sur les pratiques des individus en ce qui concerne les espaces verts urbains (Bülow et al., 2022), afin de mieux déterminer la nature de ce type d'inégalité environnementale et sa relation avec la demande de SFN urbains. Cette enquête pourrait révéler la relation entre ces pratiques et la demande de SFN.

Enfin, une opportunité de recherche plus innovante réside dans une exploration plus approfondie du troisième type d'inégalité. Notre étude a proposé une analyse préliminaire de la fréquence d'utilisation de la voiture et de son influence sur la demande de politiques de SFN affectant l'espace dédié aux voitures, en posant que cela reflète des inégalités liées aux effets indésirables des politiques. Les politiques publiques actuelles de végétalisation impliquent souvent la restriction de l'accès des voitures aux centres-villes, suscitant des débats et des controverses. En termes très généraux, ces politiques ont été critiquées pour exclure potentiellement les populations à faibles revenus et suburbaines des zones du centre-ville. Analyser la dépendance à l'égard de la voiture à l'échelle urbaine plus large et son impact sur l'acceptation des SFN urbains et des politiques de végétalisation pourrait fournir des informations précieuses aux urbanistes. Pour approfondir cette enquête, une analyse plus détaillée des pratiques de transport et de la dépendance individuelle à la voiture dans le cadre d'une expérience de choix discrète pourrait éclairer la nature de cette inégalité. Un aspect essentiel de cette enquête consisterait à examiner la relation avec les caractéristiques socio-démographiques, en particulier le revenu.

La deuxième extension potentielle de la recherche développée dans cette thèse concerne les innovations dans les méthodes de soutien à la décision. Une zone prometteuse d'investigation pourrait être l'interface entre l'OMO et l'Analyse de Décision Multi-Critères, pour relier la mise en œuvre de l'OMO à l'exploration ultérieure de ses résultats avec les parties prenantes. Ces deux méthodes ont en effet des bénéfices qui peuvent se combiner. En essence, l'une des forces de l'OMO dans un tel contexte est de réduire un ensemble potentiellement presque infini de solutions à seulement quelques solutions. Cependant, cette méthode comporte la limite de ne pas nécessairement fournir des clés de décision pour

sélectionner ces solutions. L'OMO expose les parties prenantes à un grand front de Pareto, souvent constitué d'une myriade de solutions complexes. L'exploration et la visualisation de ces solutions sont en elles-mêmes un défi et une limite à la diffusion plus large de cette méthode, et c'est un défi que nous avons commencé à relever en intégrant de nouvelles méthodes d'exploration participative au chapitre 3. De plus, une fois que ces solutions sont visualisées et comprises par les parties prenantes, et une fois que les principaux compromis sont identifiés, décider d'une seule meilleure solution est une tâche complexe, et c'est une tâche qui a été relativement moins étudiée.

L'Analyse de Décision Multi-Critères, en revanche, fournit une manière claire, participative et compréhensible, pour réaliser une décision collectivement, lorsqu'on est confronté à quelques options bien définies. À cet égard, cette méthode de prise de décision offre potentiellement une bonne solution aux limites de l'OMO. Une telle approche consisterait à mélanger une approche « experte » descendante - ici l'OMO - et une approche ascendante - l'Analyse de Décision Multi-Critères - dans le processus de prise de décision (Girard et al., 2015). Elle pourrait permettre de choisir quelles parties du front de Pareto et quelle solution sont privilégiées par les parties prenantes, et même de fournir des informations sur les différentes valeurs et opinions entre les parties prenantes, et sur la manière dont ces différences se matérialisent en termes de solutions privilégiées. Cette approche pourrait même être développée jusqu'au point d'analyser une analyse multicritères avec des schémas de pondération émanant du public (Estévez & Gelcich, 2015).

En conclusion, nos investigations ont montré qu'il existe des synergies précieuses à exploiter dans le développement de la recharge des eaux souterraines en milieu urbain. Ces synergies dépendent de la distribution spatiale des potentiels bénéfiques des SfN. En répondant à notre première question de recherche, nous avons découvert que la distribution de ces bénéfices peut différer des pratiques actuelles en matière de NBS et de mise en œuvre de la recharge des eaux souterraines. Notamment, les initiatives de végétalisation ne produisent pas toujours des résultats optimaux dans les centres-villes, et de grands sites suburbains ne sont pas systématiquement les zones les plus efficaces pour la recharge des eaux souterraines, en particulier dans le contexte de la substitution de l'utilisation de petites quantités d'eau, comme c'est le cas dans l'agglomération bordelaise.

Les stratégies urbaines visant une adaptation efficace au changement climatique doivent prendre en compte ces dimensions spatiales, car une action environnementale proactive nécessite entre autre une exploration globale des compromis spatiaux, la prise en compte des demandes des citoyens, l'anticipation de l'acceptation des politiques par les populations, et l'optimisation des ressources spatiales. Les méthodologies émergentes, telles que l'Optimisation Multi-Objectif, pourraient revêtir une plus grande importance dans les outils futurs d'économie environnementale pour relever ces défis spatiaux complexes.

Les effets du changement climatique sur les villes et sur leurs approvisionnements en eau sont trop nombreux et trop graves pour que les chercheurs et les décideurs politiques négligent l'exploration de toutes les approches de soutien à la décision existantes. Cette ligne d'investigation offre le potentiel de découvrir de nouvelles méthodologies de formulation des politiques qui pourraient contribuer à favoriser l'adoption généralisée de stratégies d'adaptation climatique intégrées, précises et efficaces, avant que la fenêtre d'opportunité pour mettre en œuvre l'adaptation ne se referme.

