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Joan Delort

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HAL Id: tel-04904285

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Vulnerability and adaptation potential of high variable renewable energy penetration electricity systems to socioeconomic scenarios of heating electrification and air conditioning adoption coupled to climate change: the case of France.

Thèse de doctorat de l'Institut Polytechnique de Paris
préparée à l'École polytechnique

École doctorale n°626 École doctorale de l'Institut Polytechnique de Paris (EDIPP)
Spécialité de doctorat: Sciences de l'Environnement

Thèse présentée et soutenue à Palaiseau, le 18 Septembre 2024, par

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Acknowledgments

Si la thèse peut s'avérer être un exercice parfois solitaire, il n'en est pas moins le fruit d'un travail collectif, ou du moins s'appuyant sur et s'enrichissant de l'interaction avec de nombreuses personnes. Il convient ici de remercier en premier les deux personnes sans qui cette aventure n'aurait pas été possible, et qui m'ont fait confiance dès le début: Philippe, Alexis, merci d'avoir voulu tenter cette aventure avec moi, et merci pour votre accompagnement tout au long de ce chemin, chacun à votre manière, dans et autour de la thèse. En deuxième lieu, il me semble important de remercier ces chercheurs et chercheuses qui ont pris un peu de temps pour lire, écouter et juger ce travail. Je remercie donc ici chaleureusement mon jury de thèse pour leur attention, leur intérêt et leurs remarques toujours enrichissantes. Merci également aux membres de mon comité de thèse Hiba et Tanguy, pour leur suivi, leurs remarques et leurs suggestions. Enfin, il ne m'est pas possible de conclure ces remerciements sans mentionner toutes ces personnes, qui n'ayant pas contribué au travail de thèse à proprement parler, l'ont malgré tout accompagné, dans et en dehors du laboratoire. Dans le laboratoire d'abord, merci à toutes celles qui avez fait, faites et allez faire de ce laboratoire l'endroit si accueillant qui m'a donné envie d'y travailler. En dehors du laboratoire ensuite, mes amis, camarades, parfois les deux à la fois, qui ont fait de ces quatre années une aventure remplie de sens et de vie. À mes plus proches relations, parents, famille, ami.e.s, compagnes et compagnons, qui m'avez supporté dans tous les sens du terme, vous revient le dernier et plus personnel remerciement, qu'il me revient d'écrire ici, bien qu'il vous appartienne entièrement: merci, gracias.

*A partir de les dues llengües que em van aprendre a descriure el nostre món,
i de les que van seguir.
A tot.es vosaltres, camarades.*

“Il ne faut être ni optimiste ni pessimiste, mais déterminé.”

Hubert Reeves (1932 - 2023)

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Résumé

Nous partons du constat que les systèmes énergétiques en Europe sont en pleine mutation. Cette mutation est due à l'intégration croissante depuis les années 2000 pour certains pays d'Europe, 2010 pour les autres, d'une part de plus en plus importante d'énergies renouvelables variables (ERVs) que sont l'énergie solaire et éolienne. Les causes de cette mutation sont multifactorielles, bien qu'en premier lieu nous pourrions noter la volonté politique de décarboner la production d'électricité qui comptait en 2010 pour environ 25 % des émissions totales européennes de gaz à effet de serre, contre environ 20 % en 2021, afin de réduire l'impact de la production d'électricité sur le climat et l'accélération du changement climatique d'origine anthropique. À ces considérations d'ordre écologique s'ajoutent des décisions d'ordre politique, comme la sortie ou la limitation du nucléaire dans certains pays européens, d'ordre industriel, les ERV permettant potentiellement de créer une filière industrielle et de créer de l'emploi et de l'activité économique, et d'ordre géostratégique enfin, les ERV solaire et éolienne permettant potentiellement de reconfigurer les relations de collaboration et d'interdépendance à l'échelle globale.

Il est possible que cette transformation se poursuive dans un futur proche, et que la part d'ERV dans le mix de production continue d'augmenter. L'introduction d'une large part d'ERV dans le mix énergétique européen soulève des questions de faisabilité technique et économique. La question du potentiel technique est relativement consensuelle et il ne fait pas de doute quand à la possibilité de s'approvisionner en grande partie à partir d'ERV, ou même quand à la possibilité d'en intégrer une grande partie dans le système électrique: tous les problèmes techniques associés ont en effet des solutions technologiques éprouvées. Si la question de la faisabilité économique faisait encore débat récemment, les études les plus récentes font état de peu d'impacts économiques pour des pénétrations en-deça de 35 % et vont même jusqu'à proposer des optimums économiques de pénétration de 75 % à 98 % de toute l'électricité produite selon les scénarios. Nous considérerons donc que des scénarios de pénétration compris entre 40 % et 90 % sont alors tout à fait plausibles à la fois techniquement et économiquement. En parallèle de la potentielle augmentation de la part d'ERV dans le mix de production, l'ambition de décarbonation du système énergétique dans son ensemble, incluant donc les secteurs du transport, l'industrie, les secteurs du résidentiel et du tertiaire et l'agriculture amène à considérer la possibilité d'une plus grande électrification de ces secteurs économiques, qui, couplés à la décarbonation du secteur de la production d'électricité, permettent de s'affranchir de vecteurs énergétiques à émissions positives. Nous nous focalisons dans cette étude sur la demande de chaud et de froid et nous concentrons plus précisément sur l'électrification de la demande de chauffage dans les bâtiments (résidentiels et tertiaires) couplée à l'adoption de climatiseurs (qui est une demande exclusivement électrique). Le potentiel d'électrification de la demande de chauffage d'une part et d'adoption de climatiseurs d'autre part sont très importants. Du côté de la demande de chauffage on estime que dans le cas de la France, seuls 20 % de la demande de chaud et de froid du secteur du bâtiment (constituée majoritairement de la demande de chauffage) sont satisfaits par le vecteur électricité. Pour la climatisation, des études suggèrent que la demande pourrait être multipliée par 6 si tous les besoins de climatisation étaient satisfaits en Europe. L'ampleur du potentiel d'électrification apparaît également lorsque l'on regarde les taux d'équipement des bâtiments en chauffages électriques ou en climatiseurs. En France on estime que ces taux d'équipement atteignent respectivement 35 % et 23 %. S'il existe de nombreuses études sur les scénarios futurs d'électrification du chauffage et d'adoption de climatiseurs, peu d'entre elles étudient l'impact de ces scénarios sur les investissements optimaux en ERV. Ces travaux ne sont donc pas capables

d'estimer le potentiel d'adaptation du système électrique à des scénarios d'électrification de la demande de chauffage ou d'adoption de climatiseurs. Nous nous attachons à étudier ce point dans ce travail. Bien-sûr, il existe d'autres facteurs affectant le devenir des systèmes énergétiques: parmi eux nous pouvons mentionner la population, l'activité économique ou les comportements individuels et collectifs. Nous ne cherchons pas ici à être exhaustifs mais plutôt à étudier deux phénomènes qui nous semblent pertinents, parmi tant d'autres. Nous avons présenté jusqu'ici deux phénomènes d'ordre socio-économique pouvant impacter le système énergétique dans le futur. Cependant le fonctionnement du système énergétique dépend grandement de l'état du climat, et ce d'autant plus que la pénétration d'ERV est grande. Nous discutons ce point dans le paragraphe suivant.

Si le système énergétique lié au système économique actuel est une des causes majeures du changement climatique d'origine anthropique, et impacte donc le climat actuel, celui-ci est également affecté par l'état du climat et donc le changement climatique confirmé et potentiel. Nous nous focalisons ici sur l'impact sur le système électrique. Cet impact se traduit d'abord au niveau des composantes du système électrique. Les impacts peuvent être classés entre ceux affectant la demande, ceux affectant la production et ceux impactant les infrastructures physiques. Nous nous intéressons dans cette étude au deux premiers et laissons de côté les impacts sur les infrastructures qui concernent principalement des capacités de transmission réduites en cas de forte température. En France, les impacts au niveau de la demande dus au seul changement climatique sont de faible amplitude dans les différents scénarios étudiés dans la littérature. La diminution de la demande de chauffage est majoritaire comparée à l'augmentation de la demande de climatisation, ce qui se traduit par une diminution de l'ordre de 5 % de la demande totale. En ce qui concerne les moyens de production, ceux-ci voient leur capacité de production changer de manière modérée, i.e. dans une fourchette de $\pm 20\%$. Ces études au niveau des composantes du système électrique ne sont pas suffisantes pour étudier les impacts du changement climatique sur les systèmes électriques: l'intégration de toutes les composantes est nécessaire pour déterminer les impacts finaux. Nous étudions la littérature correspondante et trouvons plusieurs limites aux travaux réalisés jusqu'à aujourd'hui. Comme pour les scénarios d'électrification du chauffage et d'adoption de la climatisation mentionnés plus haut, toutes les études ne prennent pas en compte les impacts des changements futurs sur l'investissement optimal en ERV, et ne peuvent donc pas étudier le potentiel d'adaptation du système électrique au changement climatique. Parmi les études qui prennent en compte les effets du changement climatique sur les décisions d'investissement optimales, nous trouvons qu'aucune ne prend en compte à la fois l'effet du changement climatique sur la ressource en ERV et celui sur la demande électrique. Nous étudions donc ce point précis dans cette étude. Nous notons finalement qu'il existe peu d'études sur l'impact couplé du changement climatique et de scénarios socioéconomiques sur des systèmes énergétiques à forte pénétration d'ERV.

Comment réagir face à ces changements futurs? Quels sont leurs impacts? Peut-on s'y adapter? À quel coût? Quels mixes de production en résultent? Voilà les questions qui structurent notre thèse et motivent notre travail. L'approche de modélisation permet de donner des points de vue pertinents pour le décideur sur ces questions. Elle permet soit de tester des mixes donnés (présents ou futurs) face à de futurs changements potentiels, soit d'optimiser les mixes de production aux conditions futures potentielles. À ce titre là, l'approche de modélisation permet de tester les capacités d'adaptation du système électrique à des changements futurs, et les coûts induits associés. Nous nous focalisons dans cette étude sur l'impact couplé du changement climatique et de l'électrification. Nous nous demandons en particulier comment le changement climatique et l'électrification du chauffage additionné à l'adoption de climatiseurs impactent les décisions optimales d'investissement en ERV et les coûts associés. Nous avons vu que cette question générale est partiellement traitée dans la littérature. Nous nous focalisons donc sur des sous-questions englobées dans cette problématique générale, qui ne sont pas ou peu traitées. Dans un premier temps nous nous demandons quel est l'impact de scénarios d'électrification du chauffage et d'adoption de la climatisation sur les décisions optimales d'investissement en ERV. Nous explorons donc de ce fait la capacité d'adaptation du mix électrique à ces scénarios. Dans un second temps, nous nous attaquons au problème de l'impact du changement climatique sur le système électrique et étudions plus

précisément l'effet du changement de ressource en ERV couplé à un changement de demande sur les décisions optimales d'investissement et le potentiel d'adaptation. Dans un troisième temps nous étudions ces deux phénomènes de manière couplée et nous demandons si ces deux phénomènes peuvent être étudiés de manière séparée.

Afin de répondre à ces questions nous créons des scénarios d'états futurs de demande avec un modèle de demande prenant en entrée des données climatiques et paramétré par les conditions socioéconomiques d'électrification et d'adoption de climatiseurs. Nous créons en parallèle des scénarios d'états futurs de ressource en ERV à partir de données climatiques. Nous modélisons ensuite les décisions d'investissement optimales ainsi que les coûts associés sous ces différents scénarios avec un modèle de système électrique. Ce travail de thèse se décompose en trois temps.

Dans un premier temps, nous étudions les impacts de scénarios d'électrification via l'électrification de la demande de chauffage et l'adoption de climatiseurs. Nous nous concentrons donc sur des effets liés à la demande exclusivement. Nous montrons d'abord que les scénarios d'adoption de climatiseurs sans modification de l'usage de la climatisation n'ont d'impact significatif ni sur les mixes optimaux, ni sur les coûts totaux système à climat actuel. Des impacts plus importants à climat futur ne sont pas à exclure, même à usage constant. Nous recommandons cependant l'exploration de scénarios d'adoption et d'usage de la climatisation à climat présent et futur dans de futurs travaux. Nous explorons donc principalement des scénarios d'électrification de la demande de chauffage, que nous comparons à des scénarios d'augmentation moyenne de la demande afin d'exclure les effets d'augmentation moyenne de la demande. Nous montrons que l'électrification de la demande de chauffage augmente les coûts totaux système en même temps qu'elle favorise la pénétration d'ERV. L'énergie éolienne est installée préférentiellement par rapport au solaire qui lui est préféré dans le cas d'une augmentation moyenne de la demande. Cependant, ces différences sont du second ordre par rapport à l'impact des coûts d'installation et des capacités maximales installables par région, qui déterminent la composition du mix au premier ordre. Nous nous attendons donc à ce que la sensibilité des mixes optimaux aux scénarios d'électrification augmente si les contraintes maximales d'installation venaient à être relaxées. Nous obtenons ces résultats dans un cadre idéalisé où l'investissement dans les moyens de production conventionnels n'est pas pris en compte. Nous nous attendons à ce que la prise en compte de ces processus favorise la pénétration d'ERV, fasse augmenter les coûts système et accentue de ce fait les effets observés dans le cadre idéalisé. Nous laissons cependant la confirmation de ces conclusions à de futures recherches.

Dans un deuxième temps nous montrons que l'effet du changement climatique sur la ressource en ERV et la demande électrique tend à faire baisser les coûts système tout en faisant diminuer la quantité optimale d'ERV dans le mix. La variable d'ajustement est l'éolien, dont la proportion tend à diminuer avec l'intensité du changement climatique, alors que les capacités de solaire photovoltaïque restent constantes. Nous montrons que le lien entre les effets du changement climatique sur la demande et la ressource en ERV, et les mixes optimaux correspondants n'est pas trivial, et ce même en tenant compte de la corrélation entre la demande et les facteurs de charge des ERV. Les effets sur cette dernière, couplés à des effets de demande moyenne permettent cependant d'avancer une explication plausible sur les causes des effets que nous observons dans nos expériences numériques, confirmant que la corrélation entre demande et facteurs de charge joue un rôle prépondérant dans la détermination de l'évolution des mixes optimaux. Nous montrons que cette corrélation est peu dépendante aux effets de changement de ressource. Les impacts du changement climatique sur les mixes optimaux seraient donc majoritairement lié à des effets de changement de demande plutôt qu'à des effets sur la ressource en ERV, dans le cas de la France. Des études dans d'autres régions seraient nécessaires pour généraliser ce constat, la France étant un pays avec une forte thermosensibilité et des changements attendus modérés de ressource éolienne et solaire (n'excédant pas $\pm 20\%$). Nous montrons également qu'avec nos hypothèses de travail, le changement climatique n'induit pas de surcoûts, que ce soit avec ou sans adaptation du mix de production. Les surcoûts entraînés par le changement de mix et les actifs échoués rendent même l'adaptation au changement climatique moins attractive économiquement. Ces résultats ne doivent cependant pas être sortis du contexte idéal dans lequel ils ont été produits: d'un côté nous ne prenons pas en compte les coûts

d'investissement dans les capacités de production des producteurs conventionnels, de l'autre, nous ne prenons en compte que l'impact du changement climatique sur la demande et la ressource en ERV et laissons de côté tout les impacts sur les producteurs conventionnels et en particulier les conséquences d'un changement de la disponibilité de la ressource en eau pour le refroidissement des centrales thermiques et la production hydroélectrique. Prendre en compte les coûts d'investissement en capacité conventionnelle devrait amener à investir plus en capacité d'ERV. Ces dernières étant de moins en moins corrélées à la demande, cela devrait entraîner une augmentation des coûts totaux système. La prise en compte de l'impact du changement climatique sur les producteurs conventionnels dépend majoritairement de l'évolution de la ressource en eau (disponibilité, température) et est potentiellement un facteur de surcoûts. Nous soulignons donc l'importance de conduire les études d'impact du changement climatique de manière intégrée, en prenant en compte tous les éléments du système de production et tout les processus susceptibles de les impacter. Nous laissons de tels travaux, nécessitant des développements méthodologiques, pour de futures recherches.

Nous étudions finalement les impacts de l'électrification et du changement climatique de manière couplée. Nous montrons que pour les scénarios considérés, qui s'appuient sur des changements plausibles d'électrification et de changement climatique, les changements liés à l'électrification sont de premier ordre comparés aux changements liés au changement climatique. L'électrification entraîne une augmentation de la demande thermosensible et non thermosensible. L'électrification du chauffage entraîne un couplage plus important entre le climat et la demande et rend le système plus sensible au changement climatique. Les effets de l'adoption de la climatisation, amplifiés par le changement climatique, restent toutefois toujours minoritaires du fait de la non prise en compte des changements potentiels d'usage. Nos scénarios sont donc conservateurs du point de vue de l'augmentation de la demande causée par l'effet couplé du changement climatique et l'électrification, et des coûts système que cela pourrait entraîner. Nous montrons que les effets du changement climatique sur la demande thermosensible de chauffage ne contrebalancent pas l'augmentation de la demande liée à cette électrification ainsi qu'à l'augmentation de la demande non thermosensible. L'impact couplé de l'électrification et du changement climatique entraîne donc des surcoûts pour le système dans son ensemble, principalement dûs à des effets sur la demande, les effets du changement de la ressource en ERV étant encore plus marginaux qu'avec le changement climatique seul. Dans ce cadre, il devient plus intéressant économiquement de s'adapter aux potentielles conditions futures: le potentiel d'adaptation est positif et implique l'ajout de capacité d'ERV solaire et éolienne en proportions variables en fonction du scénario d'électrification et de changement climatique considéré. Nous montrons finalement qu'il est nécessaire de prendre en compte le changement climatique et l'électrification de manière couplée dans l'étude du potentiel d'adaptation des mixes aux changements futurs. L'étude de ces processus de manière séparée, puis la somme de leurs effets entraîne une mauvaise quantification du potentiel d'adaptation et peut même conduire à des conclusions erronées quand à l'impact du changement climatique sur ce potentiel d'adaptation. Nous montrons donc dans un cadre idéalisé que la prise en compte des processus socioéconomiques impliquant une modification de la sensibilité du système électrique au climat doivent être étudiés de manière couplée au changement climatique dans les exercices de modélisation des systèmes énergétiques pour produire des résultats pertinents pour les parties prenantes. Nous nous attendons qu'une telle conclusion soit valide pour des études plus complètes allant au delà du seul effet sur la ressource en ERV couplé à la demande électrique.

Bien que partant d'un cadre idéalisé, nous montrons que l'électrification des usages et le changement climatique impactent significativement les systèmes électriques. L'effet de ces deux processus sur la demande électrique est majoritaire par rapport à celui du changement climatique sur la future ressource en ERV. Ces changements de demande guident donc la capacité du système électrique à s'adapter: nous montrons que des changements de demande thermosensible chaude sont plutôt liés à l'ajout ou la suppression de capacités de production éoliennes, alors que les capacités de production solaire réagissent quant à elles plutôt à des changements de demande non thermosensible. Les changements de demande thermosensible froide ont été peu explorés dans cette étude. Nous montrons finalement la valeur de l'approche intégrée énergie-climat, et l'importance de prendre en

compte tous les éléments du secteur de la production électrique ainsi que les processus les affectant de manière couplée, pour produire des résultats significatifs au niveau opérationnel.

Nous recommandons donc le développement d'une approche le plus intégrée possible pour informer la décision sur la planification du système énergétique face aux changements potentiels futurs. Cela pourra commencer par l'intégration de plus d'éléments du système électrique dans les exercices de modélisation, la prise en compte de plus de processus de manière couplée ou la considération du système énergétique dans son ensemble. D'autres processus pouvant affecter la demande comme le potentiel de sobriété ou de flexibilité de la demande n'ont pas été considérés dans cette étude et mériteraient d'être pris en compte dans de futurs travaux.

Chapter 1

Introduction

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1.1 Socio-ecological context

The European electricity systems have been undergoing profound transformations over the last two decades. A major axis of transformation corresponds to the introduction of large shares of Variable Renewable Energies (VREs) in the electricity generation sector, as shown in Figures 1.1 and 1.2.

Determining the drivers of such a transformation is a piece of work in itself, belonging to history and political science books, and not the goal of this study. The causes of these transformations are nonetheless very probably multifactorial, with the primary factor being the political will to deal with the stringent ecological crisis humanity is facing (Bonneuil and Fressoz 2016; Bonneuil 2016). A part of mankind is currently operating outside of the safe operating space for humanity (Rockström et al. 2009; Persson et al. 2022; Wang-Erlandsson et al. 2022; Richardson et al. 2023), while all of humanity and other living collectives around the globe face the consequences of the collapse of biodiversity (Pimm et al. 2014; Ceballos et al. 2015; IPBES 2019b; IPBES 2019a) and climate change (IPCC 2021; IPCC 2022a; IPCC 2022b), both issues being intimately entangled (Pörtner et al. 2021). European energy systems accounted in 2019 for 5.3% of all referenced anthropogenic Greenhouse Gas (GHG) emissions¹ (without Land Use, Land Use Change and Forestry (LULUCF)), while the electricity generation sector (including heat generation) was responsible for 1.5% of the total GHG emissions². These figures correspond to respectively 0.6% and 0.06% for the case of France³. Although these figures might seem small, for the case of France in particular, the decarbonization of the European energy system and the electricity generation sector in particular is crucial to reduce the contribution of these sectors to climate change, and commit to Paris agreement targets in terms of climate change mitigation⁴. To give an idea of the importance of such reductions, the emissions by the electricity generation sector account for about a third of the yearly remaining carbon budget for the case of France⁵.

Aside from these ecological drivers other processes are potentially favoring the penetration of VREs in the electricity generation sector. Among these we can cite all political processes pushing for the integration of these energy sources, such as nuclear phaseout or limitation plans (McCauley et al. 2018; Johnstone and Stirling 2020; Faber 2023), or sociological effects going in the same direction (Hermwille 2016). VRE also represent a strategic and industrial opportunity. First a strategic one, as albeit not being exempt from geopolitical tensions, the increased development of the VRE sector might reconfigure the geopolitical interdependencies associated to supply chains, international trade and cooperation, a typical example of which is the reconfiguration of the European to Russian gas imports dependency (Blondeel et al. 2021; Ah-Voun, Chyong, and C. Li 2024). The introduction of large shares of VRE can also represent an industrial opportunity through the creation of economic activity (IPCC 2022b, Chapter 6)(IEA 2023b).

How these trends will unfold in the future is uncertain. In the case of France, assuming the installed renewable capacity remains at least at its current levels, taking into account the decommissioning of historical nuclear power plants, and further assuming that the total installed capacity remains constant to that of 2023 results in about 64 GW (i.e. nearly 43%) of electricity generation capacity to be allocated by 2050 (see Figure 1.2). From this point on, many possible futures are possible. We discuss some of the potential future unfoldings in the next section.

¹Data from https://di.unfccc.int/detailed_data_by_party and (IPCC 2022b, Figure 2.5).

²Ibid.

³Ibid.

⁴These targets correspond to the ambition of keeping climate change “well below 2 °C above pre-industrial levels” and to pursue efforts to limit this warming to 1.5 °C.

⁵This is computed from (IPCC 2021, Table 5.8) for 1.5 °C of warming. Without uncertainty, the median remaining carbon budget is of 500 Gt_{CO₂eq}. Supposing that we have 50 years to reach carbon neutrality and that the remaining carbon budget is equally divided between all those years, this amounts to a remaining carbon budget of 10 Gt_{CO₂eq} per year. This is about 20 times the total GHG emissions of France in 2019. However, if we weight the remaining carbon budget by total population, then as France is about 1% of the world's population, its remaining carbon budget for the next 50 years before reaching a carbon-neutral economy is of 0.1 Gt_{CO₂eq}.

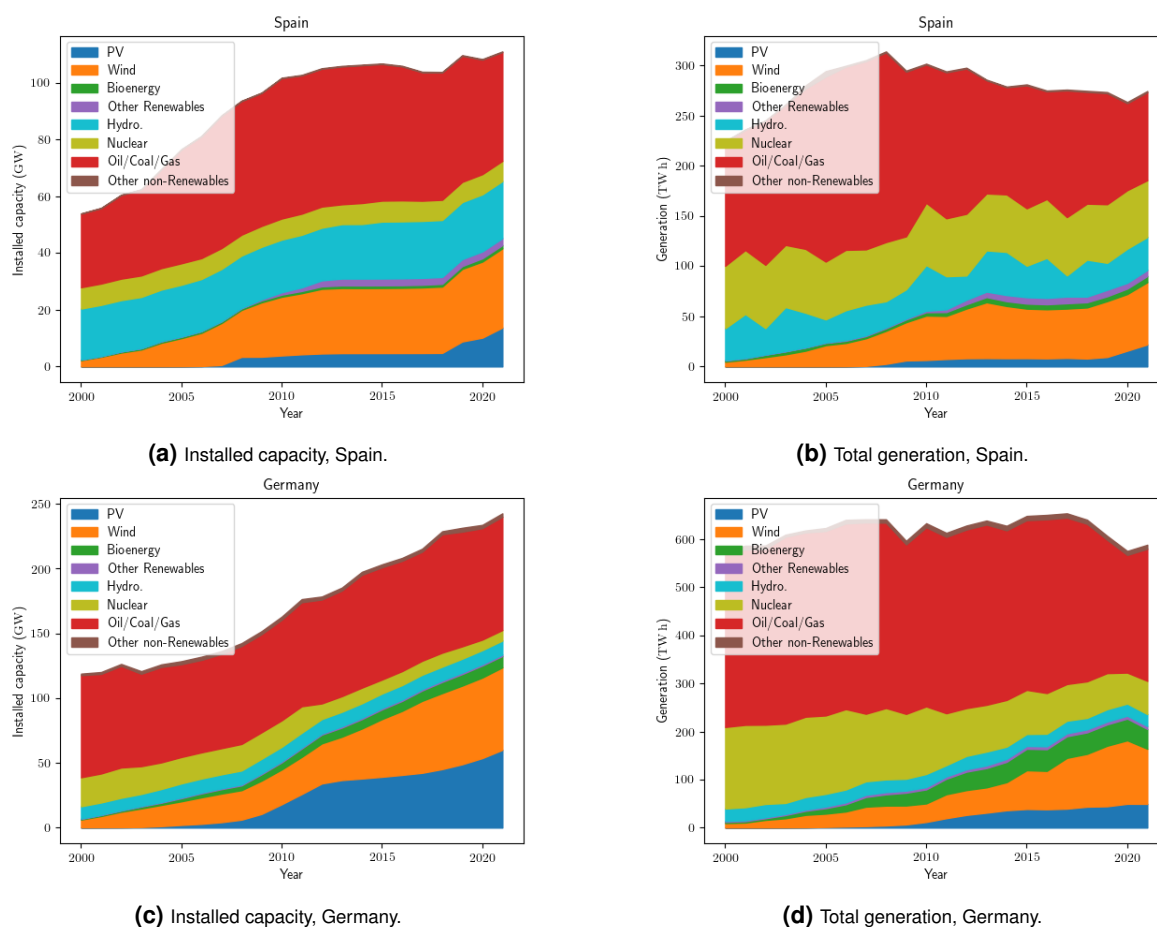


Figure 1.1. Cont.

1.2 The future state of the energy sector

Before discussing the future state of the European energy system, we give a brief contextualization. We first discuss some aspects of what we define as a suitable energy system and then discuss very briefly how this work articulates with what we know of the history of energy systems.

Based on (IIASA 2012), Pfenninger, Hawkes, and Keirstead (2014) define energy systems as “the process chain [...] from the extraction of primary energy to the use of final energy to supply services and goods”. This definition is large and quite suitable as it encompasses all sectors of the energy system, from the fossil-fueled transportation sector to the electricity generation one. If this definition can be deemed as objective, what services and goods should this energy system provide and how it should provide them is necessarily subjective. In this work, we adopt the broad consensus in the scientific literature that energy systems should be able to guarantee this supply of services and goods in a secure and affordable manner. Secure is a broad term, which is most often understood as the adequate and reliable supply of critical services and goods: we can think of the supply of fuel for mobility, or the supply of electricity to power pumps that provide drinking water. Affordable is more specific and directly relates to the economic cost of the energy system, which in a welfare maximization perspective is directly linked to the price of the goods and services provided. Affordability is a key challenge to tackle the issue of energy poverty and inequity (Bednar and Reames 2020; Huang et al. 2023) in a world with increasing inequalities (Piketty 2019; Millward-Hopkins 2022). Ensuring a secure and affordable energy system while addressing the environmental concerns at stake presented earlier is deemed to be one of the challenges of the 21st century (Pfenninger, Hawkes, and

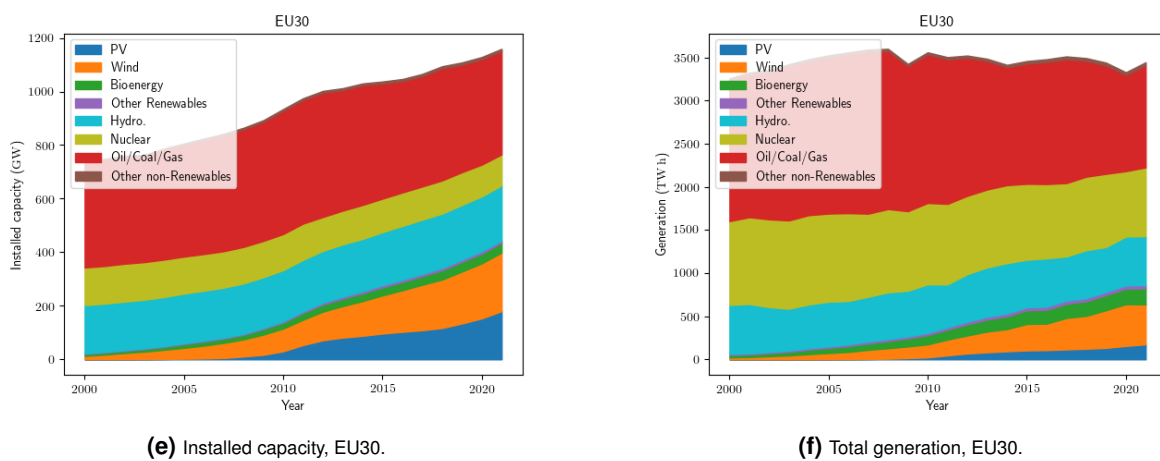


Figure 1.1. Historical VRE penetration for Spain, Germany and the EU30 (EU27 + Norway, Switzerland and the UK). Data from (<https://www.irena.org/Data/Capacity-building/Data-Collection-Guide>). Note that pumped hydro is not considered as renewable, but is included in the Hydro. field.

Keirstead 2014). Some authors mention these challenges as the energy trilemma, as energy systems must deal at the same time with the security of supply, environmental concerns and affordability (Qadrdan et al. 2019). Energy systems can be designed with other constraints or objectives, thus potentially expanding the energy trilemma. We can cite, among others, social justice (Burke 2020; Carley and Konisky 2020; Lonergan, Suter, and Sansavini 2023), or energy sufficiency (Steinberger and Roberts 2010; Millward-Hopkins et al. 2020; Okushima 2024). Tackling all these aspects at once can be challenging, especially in modeling studies (Lonergan, Suter, and Sansavini 2023). However, the focus on a sole aspect of an energy system functionality in energy system policy design may lead to adverse consequences in the other aspects, as shown in (Vázquez-Rowe et al. 2015) for the case of climate change-centrism. This highlights the need for an integrated approach to policy-making in this regard. In the following we will greatly simplify what a suitable energy system should be, by simply considering that it should supply energy at all times when required, and at minimal economical cost. The complexity of energy system design should however not be reduced to these considerations.

The history of energy systems is complex and non-linear (Jarrige and Vrignon 2020). It would be a mistake to consider that the sole incentive to decarbonize has led to the emergence of alternative sources of energy such as wind and solar. As early as in the second half of the 19th century the search for alternatives to coal (and later oil) was motivated by the foreseen finitude of the resources and the concerns about the environmental problems (air pollution mainly). If locally energy transitions could be observed, these were not homogeneous across human societies. In fact, globally, the history of energy is more a history of material additions than that of transitions (Bonneuil and Fresoz 2016; Bonneuil 2016; Fresoz 2024). In this piece of work we somehow adopt the opposite point of view compared to the historian. If the historian produces narratives about the past, we aim at proposing narratives about the future of energy systems. The objective is obviously not to guess what will happen, but rather what could: i.e. to unfold storylines about desirable or nondesirable futures which make sense starting from today. The ultimate goal of these narratives being to inform the present-day decision-making. Producing narratives to explore the future, also coined as the storylines approach, is a widespread approach in the energy economics (Siddiqui and Marnay 2008; Trutnevyte, Barton, et al. 2014; Cao et al. 2016) and climate change community (Nakicenovic, Lempert, and Janetos 2014; Vuuren and Carter 2014; Shepherd et al. 2018; Shepherd 2019; Guivarch et al. 2022). The main limitations of this approach lie in the fact that (i) scenarized futures appear as more plausible as unscenarized ones and (ii) scenarios are strongly constrained by the perception of the future in present-day conditions, and extreme events or radical changes are often neglected (Trutnevyte, McDowall, et al. 2016; McCollum et al. 2020; Hickel et al. 2021). We thus try in the

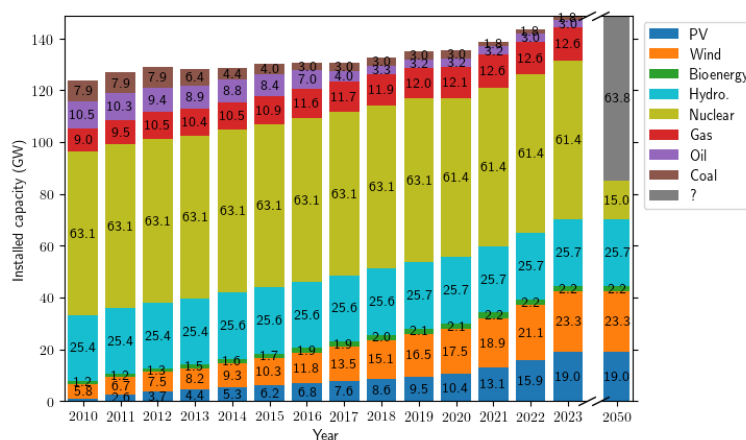


Figure 1.2. Historical and future electricity generation mix for France. Data from RTE (<https://opendata.reseaux-energies.fr/>).

following to explicit our scenario choice, and to explore a broad range of possibilities, even if they might seem improbable or extreme in some regard.

We discuss in this section two of the possible paths the european energy system could take in the near future: the transition to high-VRE penetration electricity generation systems and the electrification of other sectors of the energy system.

1.2.1 VRE penetration

We explore first the feasibility of high-VRE electricity generation systems. High-VRE penetration scenarios receive a lot of credit for the attention that has been and is currently given to them at the level of intergovernmental organizations such as the International Energy Agency (IEA), or at the state level: high-VRE electricity systems are becoming a cornerstone of climate change mitigation and energy policies across Europe (MTES 2020; BEIS 2020; OFEN 2020; BMWK 2022).

Projections at the global level from the IEA have evolved through the different World Energy Outlooks (WEOs). Early projections for 2035 in the New Policies scenario (middle ground decarbonization) reached 20% for the whole European Union (EU) (IEA 2010). The projected penetration increased in later reports with VRE generation projected to reach 26% of total electricity generation globally in the New Policies scenario, and 40% of total electricity generation in the EU in the 450 scenario (high ground decarbonization). (IEA 2018) projected a penetration of up to 40% in 2040 at the EU level and 21% at the global level, in the New Policies Scenario as well. From the 2021 WEO onwards, scenarios changed and penetrations were projected to reach between 40% to 68% in 2050 globally depending on the scenario considered (IEA 2021). These projections were reconsidered and increased to between 46% and 68% in the 2022 WEO (IEA 2022), and between 55% to 70% in the 2023 WEO (IEA 2023b) for 2050 at the global level. We can see how the increase in VRE in the present pushed for more optimistic projections in the future.

At the level of France, electricity system actors such as the french Transmission System Operator (TSO) Réseau de Transport de l'Électricité (RTE) or the Agence de l'Environnement et de la Maîtrise de l'Énergie (ADEME) also projected the state of the electricity generation sector in accordance with french legislation regarding GHG emissions and energy policy. Early projections by the ADEME envisioned penetrations between 52% to 80% of total electricity generation in 2050, associated to 110 GW to 165 GW of installed capacity (ADEME 2015). These projections were later revised to 50% to 67%, with associated capacities of 135 GW to 210 GW (ADEME 2018). The french TSO issued in 2021 projections in the same range, with penetrations reaching between 38% to 88% (RTE 2021). However, these were associated to much higher installed capacities, ranging from 135 GW to 344 GW in 2050. The popularity of high VRE futures, perceived as desirable by a certain share of

the population, and as we saw, important energy agencies, and the political incentive to reach higher penetration levels than currently, e.g. see (MTES 2020; IEA-RTE 2021) for the case of France, do not ensure that such increased VRE penetration scenarios will unfold with certainty. It does however give them some credit, which makes them certainly worth studying.

Envisioning a future with a high penetration of VREs in the electricity generation sector requires first that such a future is technically feasible. Technical potential is evaluated as the resource that can be extracted with the current technological capabilities (Edenhofer et al. 2013). It has been assessed that technical potential for renewable energies and VRE in particular will not constrain their development, see e.g. (IPCC 2011) for a global assessment and (Dupré la Tour 2023) for an assessment at the level of France and the EU. VRE electricity generation sources are however technically different from historical hydrothermal generators that supply the vast majority of the generated electricity currently. The most marked difference lies in their variability and unpredictability: to the contrary of dispatchable generators, the output of VRE generators cannot be controlled at all (dispatchable generators are not controllable at will and instantaneously either) or programmed. This increases the needs for operating reserves (or system flexibility). A second salient feature of VRE generators is that they are grid-following as opposed to grid-forming. The fact that VRE generators do not provide inertia as opposed to hydrothermal generators requires additional measures to be taken to ensure frequency and voltage control in the grid. High penetrations of decentralized VRE might also pose congestion issues in the distribution and transmission networks. Finally, because of their daily and seasonal variability, VRE output does not necessarily correlate with periods of high demand, forcing backup hydrothermal generation to be kept, or increasing the need for operating reserves. These technical issues have proven and mature technical solutions (T. W. Brown et al. 2018). However this leads to the question of the cost of such accommodations. This relates to the economic feasibility of the integration of VREs in the electricity generation sector (Edenhofer et al. 2013). The economic feasibility of VRE integration was first assessed through the estimation of specific integration costs (Hirth 2012; Ueckerdt et al. 2013; Sijm 2014; Hirth, Ueckerdt, and Edenhofer 2015; Heptonstall and Gross 2021). However this approach has been superseded by integrated approaches modeling the whole energy/electricity system that focused directly on the optimal levels of VRE integration rather than on the associated costs for different levels of penetration (Edenhofer et al. 2013; Heptonstall and Gross 2021).

Studies exploring economic optima of VRE penetration are often decarbonization studies. The literature is very rich in this regard. The majority of studies tackle either the decarbonization of the energy (Henrik Lund 2007; Brian Vad Mathiesen, Henrik Lund, and Karlsson 2011; J. Weyant et al. 2013; David Connolly and Brian Vad Mathiesen 2014; Fernandes and Ferreira 2014; Hooker-Stroud et al. 2014; Jacobson, Delucchi, Ingrassia, et al. 2014; Kriegler et al. 2014; Jacobson, Delucchi, Bazouin, et al. 2015; Jacobson, Delucchi, Cameron, et al. 2015; D. Connolly, H. Lund, and B. V. Mathiesen 2016; T. Brown et al. 2018; Traber, Hegner, and Fell 2021; Williams et al. 2021; Pickering, Lombardi, and Pfenninger 2022; Hainsch 2022) or electricity (Amorim et al. 2014; Elliston, MacGill, and Diesendorf 2014; T. Mai et al. 2014; Riesz, Vithayasrichareon, and MacGill 2015; Frew et al. 2016; Krakowski et al. 2016; Mileva et al. 2016; Heuberger et al. 2017; Pleßmann and Blechinger 2017; D. P. Schlachtberger, T. Brown, Schramm, et al. 2017; D. P. Schlachtberger, T. Brown, Schäfer, et al. 2018; Sepulveda et al. 2018; Zeyringer et al. 2018) system. Some target specifically the optimal VRE mixes to satisfy an electricity demand with (Heide et al. 2010; Eichman et al. 2013; Becker et al. 2014; Rodríguez et al. 2014; Safaei and W. Keith 2015; Brouwer et al. 2016; Després, Mima, et al. 2017) or without (Budischak et al. 2013) considering balancing capabilities (such as storage or a generic form of dispatchable producers), or grid developments (MacDonald et al. 2016). Some other studies explore the decarbonization of the whole economy (Bibas and Méjean 2014), the specific role of certain technologies, such as storage (Sisternes, Jenkins, and Botterud 2016; M. T. Craig, Jaramillo, and Hodge 2018), or other socioeconomic trajectories not specifically targeted at decarbonization or VRE penetration (Maïzi and Assoumou 2014; Alimou et al. 2020). Most recent studies show economically optimal VRE penetrations on the order of 75 % (T. Brown et al. 2018), 92 % to 98 % (Williams et al. 2021) or 93 % (Pickering, Lombardi, and Pfenninger 2022).

What is high VRE penetration then? From (Heptonstall and Gross 2021) we could give a value of 35 %, which is the value above which integration costs start to increase significantly. It however appears from the most recent energy system modeling studies that, most often under a decarbonization constraint, VRE penetration could reach more than 90 % in an economically viable way. Of course, the hypothesis of the modeling studies arriving to those figures, and in particular their handling of the flexibility mix of the energy system, could be discussed. We however consider that penetrations comprised between the broad range of 40 % to 90 % are representative of what is feasible technically and economically, and thus considered valid hypothesis in the construction of plausible future scenarios.

1.2.2 Electrification

In parallel to renewable energies, and in particular VRE, penetration, electrification of the energy sector is considered to be a serious candidate for decarbonization, and was featured in early decarbonization studies (MacKay 2009; Schellekens et al. 2010; Committee on Climate Change 2011; IIASA 2012; Pfenninger, Hawkes, and Keirstead 2014; Dennis 2015). Electrification is in general envisioned through a sectoral approach: either the building (commercial and residential), industrial or transportation sector are seen as potential electrification candidates. If the transportation (Muratoro 2018; Khalili et al. 2019; Kapustin and Grushevenko 2020; Ferdousee 2022; IEA 2023a) and industrial (Lechtenböhmer et al. 2016; Palm, Nilsson, and Åhman 2016; Vogl, Åhman, and Nilsson 2018) sectors show a certain potential for electrification, we choose in this study to focus on the building sector. More specifically, we focus on the electrification of the space heating demand and the adoption of Air Conditioning (AC) to satisfy the potentially growing cooling demand in the building sector.

Heating and cooling demand represents a significant share of the total final European energy demand. This heating and cooling demand (comprising other end-uses than space heating and cooling) accounted for 51 % of the final energy demand in 2012 (Fleiter, Steinbach, and Ragwitz 2016) and 50 % of the final energy demand in 2015 (Fleiter, Elsland, et al. 2017) for the EU28. Space heating accounted at this time for 27 % of the total final energy demand while process heating and water heating accounted for 16 % and 4 % of the total final demand respectively, making the most of the total final heating and cooling energy demand to all three end-uses. The building sector accounted in 2015 for 62.5 % of the final energy demand for heating and cooling, of which about 75 % was associated to the space heating end-use (space cooling is very minority). Space heating demand in the building sector is thus the major end-use associated to the heating and cooling energy demand. Considering now that only 12 % of the final heating and cooling demand is supplied by electricity in the residential sector and 19 % of it is supplied by electricity in the tertiary sector, we can see straight away that there is a huge electrification potential for space heating demand in the building sector in the EU. In the case of France, about 20 % of both the residential and tertiary sector heating and cooling demand is supplied through electricity. Supposing that a similar share of end-uses holds as for Europe, this shows similar electrification potential for the space heating demand electrification in the building sector. Cooling demand is not completely an analogue of heating demand, since all of the former is supplied through electricity. However estimates of the electrification potential exist in the literature. (Werner 2016) argue that if all cooling needs were to be satisfied in Europe, then cooling demand would increase sixfold. This is due to the fact that most cooling needs as of today are not met since people are keen to accept some discomfort during the hot summer days (D. Connolly 2017).

Another way to look at the electrification potential of space heating and AC adoption in the building sector is to look at the equipment rates of the sector. For example, the share of households using electric heating amounts to 35 % in the US as of 2015 (White et al. 2021) according to the United States (US) Energy Information Administration (EIA) RECS⁶ from 2015. In Germany and the UK,

⁶<https://www.eia.gov/consumption/residential/index.php>. Note that other surveys focusing on the commercial buildings sector <https://www.eia.gov/consumption/commercial/>, the industry sector <https://www.eia.gov/consumption/manufacturing/> and transportation <https://www.eia.gov/energyexplained/use-of-energy/transportation.php> also exist.

this share amounts to 4 % and 10 % respectively as of 2015 (Bossmann and I. Staffell 2015). We can estimate the current percentage of equipment of electric heating in France to be of 35 % and 23 % for the equipment of AC in the building sector (see Chapter 3 for more details on this estimation). This shows the huge potential for space heating demand electrification and AC adoption as well.

This state of things is related in France to the different thermal regulations that have been issued since the 1970s (RTE/ADEME 2020), creating path-dependency effects that make it harder to switch from one technical solution to another (Bertelsen and Brian Vad Mathiesen 2020). The short-term evolution, i.e. until 2050, will however not be determined by thermal regulations that only apply to new buildings (the renovation of the building stock is of only 1 % per year). Instead, policy packages designed for building retrofit and renovation as well as switching from one heating solution to another will be crucial for near-term system transformation (RTE/ADEME 2020). This shouldn't prevent research studies as this one to study extreme cases of electrification.

The literature on future scenarios of electricity demand related to heating demand electrification and AC adoption is rich and diverse, and we refer the reader to Chapter 3 for a detailed overview. We can here nonetheless underpin that most of these studies do not consider the impacts of such scenarios on the electricity system investment decisions: studies that consider the impacts on a prescribed mix (current or projected) are more numerous, but if they allow to compute the vulnerability of these mixes to future demand scenarios, they are unable to assess the adaptation potential to future changes. Studies that incorporate this latter feedback are scarce and not well-suited to account for combined high VRE penetration scenarios. We tackle this gap in the literature in this work.

The future changes in the energy system considered so far consist of socioeconomic changes. However this is not the sole determinant of future conditions. We saw that the ecological context and in particular climate is changing and will potentially do so even more markedly than what is currently observed. We explore the impacts of a changing climate on energy system operations in the next section.

1.3 Climate change impacts on the energy system

Energy systems are a key component in climate change mitigation policies because of their impact on the climate system. They are however vulnerable to changing climatic conditions as well. The literature on the impacts of climate change on the energy system is quite exhaustive. We review here briefly its most salient features but refer the reader to Chapter 4 for a more detailed overview. Energy systems will be impacted at all component levels: on the supply side, the demand side and at the level of physical infrastructure (M. T. Craig, S. Cohen, et al. 2018; Cronin, Anandarajah, and Dessens 2018; Yalew et al. 2020). This component-level impacts need to be assessed but are not sufficient by themselves to assess the compound impacts of climate change on the energy system (Chandramowli and Felder 2014; Miara, Macknick, et al. 2017; M. T. Craig, S. Cohen, et al. 2018). For this last purpose, integrated studies are necessary. We thus briefly review first component-level studies found in the literature and then briefly summarize the main limitations of the integrated assessment literature.

Component-level studies can be classified into demand-side impacts, supply-side impacts and physical infrastructure-related impacts. Numerous reviews exist on this topic (Schaeffer et al. 2012; Chandramowli and Felder 2014; Bonjean Stanton, Dessai, and Paavola 2016; M. T. Craig, S. Cohen, et al. 2018; Cronin, Anandarajah, and Dessens 2018; Sara C. Pryor et al. 2020; Yalew et al. 2020). The demand-side component-level studies reviewed in this work address the impact of climate change at different geographical scales: either at the regional or country/state scale (Ruth and A.-C. Lin 2006; Davis and Gertler 2015; Ralston Fonseca, Jaramillo, et al. 2019), at the continental scale (Eskeland and Mideksa 2010; M. D. Bartos and Chester 2015; Auffhammer, Baylis, and Hausman 2017; Damm et al. 2017) or at the global scale (Isaac and Vuuren 2009; Levesque et al. 2018; Enrica De Cian and Ian Sue Wing 2019; Ruijven, Enrica De Cian, and Ian Sue Wing 2019). Demand evolutions due to climate change are region-specific, although there are robust trends on the reduction

of the space heating demand and the increase of the space cooling demand with the sole effect of climate change. Socioeconomic factors are sometimes explored in the aforementioned studies and are found to have a greater impact on demand than climate change alone. In the case of France a net decrease on the order of 5% is attributed to climate change *ceteris paribus*. On the supply-side studies vary in scope and geographical area considered. In the studies we reviewed, the impact of climate change on thermal power plants has been studied for the US and Europe (Vliet, Yearsley, et al. 2012), Europe alone (Förster and Lilliestam 2010; I. Tobin et al. 2018), China (Zheng et al. 2016) and globally (Vliet, Wiberg, et al. 2016; Gernaat et al. 2021). Impacts on hydropower generation have been studied for Europe and the US (Vliet, Yearsley, et al. 2012), Europe (Lehner, Czisch, and Vassolo 2005; I. Tobin et al. 2018), Sweden (Bergström et al. 2001), Switzerland (Schaeffli, Hingray, and Musy 2007) and globally (Vliet, Wiberg, et al. 2016; Gernaat et al. 2021). Assessments of VRE resource change have also been conducted in different regions and at different spatial scales. For solar, we reviewed studies over Europe (I. Tobin et al. 2018; Jerez et al. 2015), South-Africa (Fant, Adam Schlosser, and Strzepek 2016) and the whole world (Gernaat et al. 2021), while for wind, studies reviewed included Europe (S. C. Pryor, Schoof, and Barthelmie 2005; Isabelle Tobin, Vautard, et al. 2015; Isabelle Tobin, Jerez, et al. 2016; Reyers, Moemken, and Pinto 2016; Soares et al. 2017; Moemken et al. 2018; I. Tobin et al. 2018), Finland (Venäläinen et al. 2004), South-Africa (Fant, Adam Schlosser, and Strzepek 2016) and the whole world (Gernaat et al. 2021). It can be drawn from these studies, that at the level of Europe, projected changes on the supply-side are of moderate intensity (comprised within a $\pm 20\%$ evolution). Finally, impacts of climate change on the electricity systems physical infrastructure are mainly related to decreased transmission capacity due to high temperatures (M. Bartos et al. 2016; Loew, Jaramillo, and Zhai 2016; M. T. Craig, S. Cohen, et al. 2018; Cronin, Anandarajah, and Dessens 2018) but we do take this phenomena into account in this work.

We review in this work a set of 15 studies on the integrated assessment of the impacts of climate change on the energy or electricity system. We refer the reader to Chapter 4 for a detailed overview. Among these studies, a single one addresses the vulnerability of current mixes to climate change for the case of the US (Miara, Macknick, et al. 2017). Considering plausible future power system configurations (e.g. increased VRE penetration or electrification) has however been shown to be crucial in climate change studies: it is not enough to consider the current mainly hydrothermal systems (M. T. Craig, S. Cohen, et al. 2018). The rest of the reviewed studies do consider a changed energy/electricity system either by prescribing it to some educated guess (M. T. Craig, Carreño, et al. 2019; Kozarcenin, Liu, and Andresen 2019; Turner et al. 2019; Bloomfield, D. J. Brayshaw, Troccoli, et al. 2021), or by optimizing it to future conditions (Ciscar and Dowling 2014; Jaglom et al. 2014; Mima and Criqui 2015; McFarland et al. 2015; Schlott et al. 2018; Miara, S. M. Cohen, et al. 2019; Peter 2019; Khan et al. 2021; Ralston Fonseca, M. Craig, et al. 2021b; Ralston Fonseca, M. Craig, et al. 2021a). We find however several limitations in the existing literature. First no study assesses the combined impact of a VRE resource change coupled to a change in demand caused by climate change on the optimal investment decisions. Secondly there are only scarce assessments of the impact of climate change coupled to socioeconomic change on high VRE electricity systems. Both these issues are addressed in this work.

1.4 Main questions and approach

How to react facing those potential future changes? What are the impacts of such changes? Can we adapt to them? To what cost? What are the resulting mixes? These are the questions that structure our thesis and motivate our work. The goal of this work is not to give a definite answer to all these overarching questions, but rather to contribute to the building of scientific knowledge and make progress in the understanding of those questions.

We focus in this study on the coupled impact of climate change and electrification scenarios on electricity systems. We ask in particular **how vulnerable are electricity systems to scenarios of**

climate change coupled to the electrification of heating demand and the adoption of AC, and how do these changes impact economically optimal investment decisions in VRE capacity.

We have seen that this question has been partially addressed in the literature. We thus focus on three more precise research questions that have not been addressed previously. These questions structure our work and are as follows:

- **Q1** — What are the impacts of scenarios of heating demand electrification and AC adoption on optimal investment decisions in VRE capacity, and what are the associated system costs?
- **Q2** — What are the impacts of climate change induced modifications of demand and VRE resource on high VRE mixes and on the optimal investment decisions in VRE capacity, and what is the associated adaptation potential?
- **Q3** — Can we study both drivers of change separately or should we do so in a compound way to get relevant adaptation potential policy advice?

We address these questions by developing an innovative methodological framework that allows us to proceed to scenarization of potential future outcomes: of heating demand electrification and AC adoption on the one side, of climate change impacts on the demand and on the VRE resource on the other side. These scenarios are then considered separately to tackle questions **Q1** and **Q2** or used in combination to tackle question **Q3**, by using the different separated or compound scenarios as input to an electricity system model to study the optimal allocations of VRE capacity and the necessary balancing needs.

1.5 Thesis outline

The thesis is structured as follows. Chapter 2 presents the methodological developments put into place to address the research questions. We detail in particular the model of demand we use to scenarize climate change impacted demand and socioeconomic scenarios of electrification. We then present the methodology employed to derive climate sensitive VRE resource time series. After that, climate data used throughout this thesis is presented. After giving a brief introduction to energy system modeling, we present the electricity system model used in this thesis for the different applications.

In Chapter 3 we present the analysis developed around question **Q1**. After giving an introduction on the scenarization of heating demand electrification and AC adoption, and giving an overview of the literature associated to the corresponding impacts on the energy system, we present the different scenarios considered in this study and their associated impacts on the demand. We show that AC adoption scenarios do not have a significant impact at constant climate given that the intensive margin is not modified. We then proceed in a last section to the investigation of the impact of heating demand electrification on the optimal investment decisions in VRE capacity and the associated system costs. This last work was the subject of an article submitted for publication in a peer-reviewed journal, whose preprint is reproduced in this thesis and serves as a presentation of the conducted work.

Then, in Chapter 4 we tackle question **Q2**. The content of this chapter consists in an article submitted to a peer-reviewed journal.

Finally, the results of addressing question **Q3** are presented in Chapter 5. These results are also presented in the form of a paper in preparation to be submitted to a peer-reviewed journal as well.

We finally conclude in Chapter 6.

Chapter **2**

Methods

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We develop a framework to be able to derive cost optimal VRE mixes that fulfill hourly system adequacy with optimal dispatch under different scenarios and test the resilience of those mixes to different scenarios. To do so we develop a minimal temperature-sensitive demand model that we use for scenarization, which we present in Section 2.1. We then adapt a methodology to obtain VRE capacity factors at the regional level, which we present in Section 2.2. Both demand and VRE capacity factors models depend on weather data, which can be obtained for reference conditions or different levels of projected climate change. This is presented in Section 2.3. We finally present the energy system model that we adapted to fulfill our numerical experiments objectives in Section 2.4.

2.1 Development of a minimal temperature sensitive demand model

2.1.1 A review on the modeling of electricity demand

Electricity demand depends on the weather

The electricity demand relationship to weather has been studied for more than 50 years and it is now well established that the heating temperature sensitive demand depends to the first order on temperature, whereas the cooling electricity demand depends to the first order both on temperature and humidity. Early studies in academic literature tackled the question with a variety of purposes: to study the potential of temperature modification via contrails to reduce electricity demand in the US (S. R. Johnson, McQuigg, and Rothrock 1969), study the impacts of rare extreme heat waves on the cooling electricity consumption in the US (Karl and Quayle 1981) or study the potential impacts of climate change on gas and electricity consumption in the US (David J. Sailor and Muñoz 1997). (Dubin 1985) is a typical example of a bottom-up approach (or engineering model) relating demand to temperature to answer economically focused problematics related to households electricity consumption (e.g. the response to price signals), while (Henley and Peirson 1997) discuss the relevance of parametric and non-parametric statistical methods to represent the demand-temperature relationship in the United Kingdom (UK). Studies vary in the geographical area considered, at the scale of national grids or regions, with studies focusing on Spain (Valor, Meneu, and Caselles 2001), the UK (Hor, Watson, and Majithia 2005), Europe (Bessec and Fouquau 2008), Ireland (P. G. Leahy and Foley 2012) or India (Harish, Singh, and Tongia 2020); or at the scale of cities such as Athens (Greece) or London (UK) (Psiloglou et al. 2009). Most studies focus on the single demand vs. temperature relationship. Among studies that explore the impacts of other meteorological variables, some consider wind speed, rainfall, relative humidity and sunshine (Hor, Watson, and Majithia 2005), wind speed, relative humidity and cloud cover (Apadula et al. 2012), or humidity alone (Maia-Silva, Kumar, and Nateghi 2020). What stands out from these studies is that temperature is the main driver of electricity demand, at least for heating, whereas humidity plays also a crucial role for cooling.

The quasi-linear regime of demand as a function of temperature in the heating and cooling temperature ranges allows to compute so-called temperature sensitivity coefficients. These measure the linear response of demand to a change in temperature, in units of $\text{GW h h}^{-1} \text{ } ^\circ\text{C}^{-1}$. Typical values of heating temperature sensitivities are e.g. $0.4 \text{ GW h h}^{-1} \text{ } ^\circ\text{C}^{-1}$ to $0.5 \text{ GW h h}^{-1} \text{ } ^\circ\text{C}^{-1}$ for the UK (H. E. Thornton, Hoskins, and Scaife 2016), $2.4 \text{ GW h h}^{-1} \text{ } ^\circ\text{C}^{-1}$ in the case of France (RTE 2021) (this high value is due to high levels of electric heating in the building sector, as discussed in Chapter 3) or $4.2 \text{ GW h h}^{-1} \text{ } ^\circ\text{C}^{-1}$ for Europe (Wiel et al. 2019). A value of $0.8 \text{ GW h h}^{-1} \text{ } ^\circ\text{C}^{-1}$ for the cooling temperature sensitivity of Europe is also given in (Wiel et al. 2019).

Can we forecast electricity demand ?

Electricity demand is a weather-dependent process, and as such is unpredictable with perfect accuracy since the initial conditions are never perfectly known and the governing equations are chaotic. If socioeconomic behavior exhibits a typical pattern that confers some predictability to the demand

(e.g. more demand on weekdays than sundays, more demand during the day than at night), some unpredictable short-term socioeconomic behavior adds to the weather uncertainty. Short-term hourly demand forecasting is an already well-established field of research with mature theoretical background and a diverse panel of available models: see e.g. (Chan et al. 2012; Tao Hong 2014) for reviews on point-forecasting, (Tao Hong and Fan 2016; Wang et al. 2019) for reviews on probabilistic load forecasting or (Weron 2007; Tao Hong, Pinson, et al. 2020) for a global overview. At longer lead times (typically more than a year), socioeconomic factors dominate and demand forecasting is a different exercise, where demand is forecast at a coarser time granularity (typically yearly demand). Future demand is then projected according to forecasts on socioeconomic factors such as population, GDP, fuel prices, etc.

Both types of forecast are used by system operators, although for different purposes: short-term forecast is used for system operation, while long-term forecasts are mainly used to evaluate the future security of supply and discuss potential capacity expansion decisions. An example for each case are given in Figure 2.1 for short-term forecast and Figure 2.2 for long-term forecast. Each figure presents the forecast absolute and relative error depending on the type of forecast for the short-term forecast and as a function of the lead times for the long-term forecast. Figure 2.1 is obtained by comparing the J and J-1 types of forecast from the french TSO RTE to observed hourly national demand data (RTE 2024). Both forecasts have a different lead time that cannot be exactly determined due to an untransparent methodology. We can however suppose that the J type of forecast has a smaller lead time than the J-1 forecast. This is why the error of the J type of forecast is smaller than that of the J-1 type. State-of-the-art operational forecast models thus have forecast errors on the order of 1% (i.e. a few hundreds of MW) for the shorter lead times. Figure 2.2 presents the forecast absolute and relative errors from the long-term forecast exercises of the US EIA, as a function of the forecast lead time (USEIA 2022). We can see that if for lead times below ten years it can happen that forecasts are correct (almost zero relative error), it can also happen that forecasts are way off (up to 20% relative error). On average, the absolute and relative error increase with increasing lead time. Note that the convergence of the min. max. and mean errors for lead times above 17 years is simply due to a lack of data, so that the error distribution at those lead times is not properly sampled.

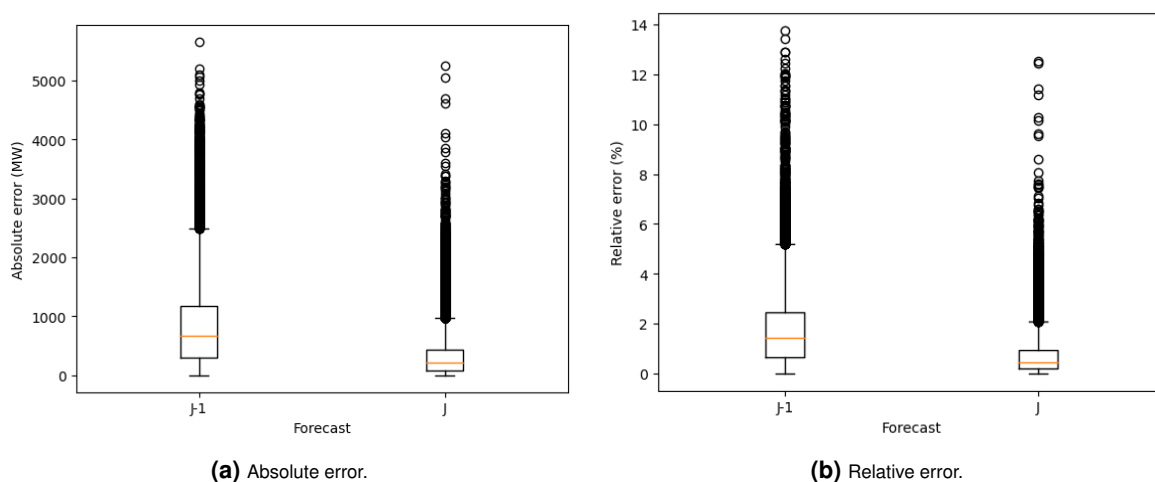


Figure 2.1. Example of short-term forecast error. Panel (a) gives the absolute error and panel (b) the relative error. Errors are represented as box plots, with the median represented in orange, the box representing the interquartile range between the first and third quartile, with the whiskers extending to 1.5 times the interquartile range outside of the box. The forecast lead time is not perfectly clear since the methodology is not transparent, but it can be estimated to be between 1h and 48h for the J-1 forecast and 1h to a few hours for the J forecast. Data and forecast from RTE (<https://opendata.reseaux-energies.fr/>) (RTE 2024).

Electricity demand cannot be forecast with certainty at any lead time. However, similarly to the difference in paradigm between weather forecasts and climate simulations, we aim at producing plausible time-series of demand given a stationary climate and a set of socioeconomic conditions.

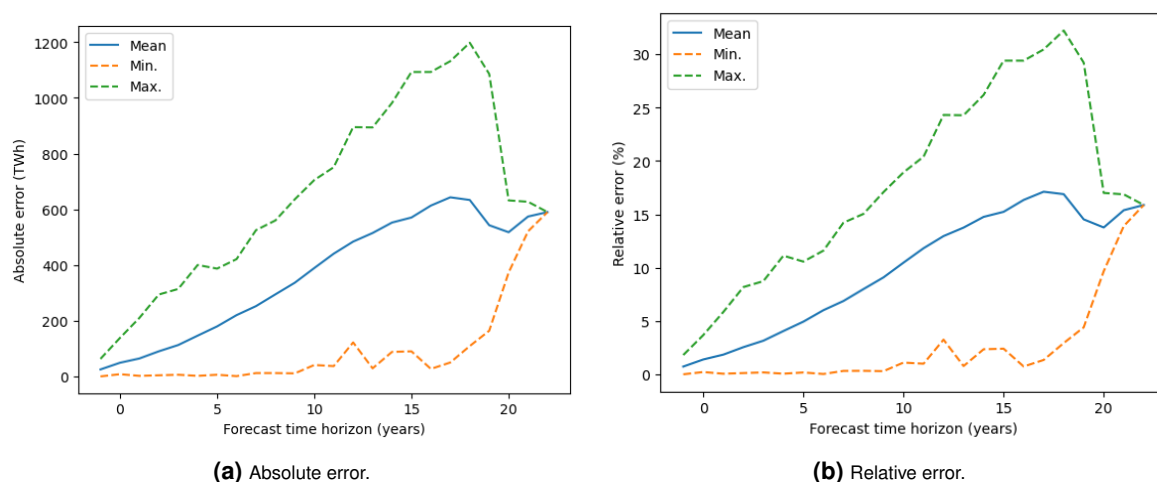


Figure 2.2. Example of long-term forecast error as a function of lead time. Panel (a) gives the absolute error and panel (b) the relative error. Data and forecast from US EIA (<https://www.eia.gov/>) (USEIA 2022).

As such, retrospectively modelling the observed electricity demand or trying to forecast what the future electricity demand could be is not the focus of this study. We instead focus on producing long multi-year time series of electricity demand at a sufficient time granularity so that typical features of the observed electricity demand can be reproduced. We review in the following section the different modelling approaches developed to this end.

Modelling electricity demand

Modelling the electricity demand as a function of the weather follows two main paradigms (M. T. Craig, S. Cohen, et al. 2018): top-down models deriving more or less complex relations between spatially and sectorally aggregated electricity demand and weather variables (most often temperature), and bottom-up approaches that usually derive electricity demands by sector or end-use, often from the physical simulation of a set of buildings representative of a larger ensemble. Such a distinction is similar to that of (D. H. W. Li, Yang, and Lam 2012) that differentiate modelling approaches based on the Heating Degree Days (HDD)/Cooling Degree Days (CDD) approach and building energy simulation methods, although the top-down category encompasses more models than just the HDD/CDD approach and some models that qualify themselves as bottom-up are not strictly speaking physical building simulation models, see e.g. (Ruijven, Vuuren, et al. 2011; Daioglou, Ruijven, and Vuuren 2012; Eom et al. 2012; Chaturvedi et al. 2014; Levesque et al. 2018).

Still, most top-down models use the HDD/CDD approach (Hargy 1997; Spinoni, Vogt, and Barbosa 2015; Mistry 2019) or similar (Auffhammer, Baylis, and Hausman 2017; Enrica De Cian and Ian Sue Wing 2019; Ruijven, Enrica De Cian, and Ian Sue Wing 2019; Ralston Fonseca, Jaramillo, et al. 2019), to represent the electricity demand relationship to temperature, although the details of the HDD/CDD calculation may differ, see e.g. (Hargy 1997) vs. (David J Sailor 2001). This approach consists in general in a regression of observed electricity demand against the HDD and CDD variables to determine temperature sensitivities. Some models however use directly the temperature variable (Hor, Watson, and Majithia 2005; Damm et al. 2017; Wiel et al. 2019), or an effective temperature parameter to account for the lag between outer and inner temperature equilibration (J. W. Taylor and Buizza 2003; Bloomfield, D. J. Brayshaw, Shaffrey, et al. 2016; Bloomfield, D. J. Brayshaw, Shaffrey, et al. 2018; Ruhnau, Hirth, and Praktijnjo 2019; Peacock, Fragaki, and Matuszewski 2023; Iain Staffell, Pfenninger, and N. Johnson 2023). Population weighted temperature is also sometimes used to account for the heterogeneous distribution in population across the area(s) studied (Ruth and A.-C. Lin 2006; Isaac and Vuuren 2009; Klein et al. 2013; E. De Cian and I. Sue Wing 2014). Other top-down models that rely on the HDD/CDD quantities are not properly speaking regression models, as in (Isaac and Vuuren 2009), or (Bossmann and I. Staffell 2015), the latter scaling typical daily

hourly demand profiles for each sector to total yearly sectoral demand (which is closer to a bottom-up approach). Finally, some top-down regression models do not use a meteorological variable at all (Alberg Østergaard, Møller Andersen, and Kwon 2015). Note that regression models deriving demand vs. temperature relationships, depending on their design (this comment applies mainly to models of total electricity demand), are not exactly speaking models of space heating/cooling demand: as noted in e.g. (Iain Staffell, Pfenninger, and N. Johnson 2023), other temperature sensitive end-uses like cooking, hot water heating, lighting, or increased appliances cooling needs are captured as well. This is discussed further in the introduction of Chapter 3. Furthermore, as noted in (Ruth and A.-C. Lin 2006; H. E. Thornton, Hoskins, and Scaife 2016; Cozian 2021), fitting a model to temperature also captures other seasonal phenomena not necessarily related to but correlated to temperature: this is typically the case for lighting, which is related to the seasonal variation in daylight hours.

Bottom-up models do not necessarily rely on the HDD/CDD approach (Eom et al. 2012; Chaturvedi et al. 2014; Dirks et al. 2015), although some incorporate it in their heating/cooling demand modules (Ruijven, Vuuren, et al. 2011; Daioglou, Ruijven, and Vuuren 2012; Levesque et al. 2018). Energy-Plus (Crawley et al. 2001) is an example of a bottom-up, physical building simulation model, whose use is so widespread that it is worth mentioning. The power of bottom-up models lies in the precise description of energy demand at the end use level coupled to a fine description of demand drivers, allowing for the testing of precise socioeconomic scenarios, like for example the replacement of resistive heaters by heat pumps. This precision usually comes at the computational cost of being able to simulate only a limited number of buildings and for a limited time range. As such, although they are relevant to assess changes in demand characteristics (e.g. total or peak demand), most bottom-up studies lack the accurate representation of demand aggregated over the different energy sectors, simply because modelling studies focus on a sector, most often the building (Dirks et al. 2015; Levesque et al. 2018) or residential sector (White et al. 2021), or an end-use (Viguié et al. 2020) in particular. Some bottom-up approaches however model the total electricity demand from computed sectoral demands, often with the addition of a final calibration step (Eggimann, J. W. Hall, and Eyre 2019; Eggimann, Usher, et al. 2020).

The HDD/CDD family of approaches typically requires the determination of a single or multiple threshold temperatures, sometimes also called base or balance point temperatures. These correspond to ambient temperatures below resp. above which some heating resp. cooling occurs. When multiple values are defined, a threshold temperature is usually given for heating and cooling. Typical values of those threshold temperatures are 11.7 °C to 15.6 °C for the state of Maryland (US) (Ruth and A.-C. Lin 2006), 12.6 °C to 24.1 °C for Europe (Damm et al. 2017), 18 °C for the whole world or India (Isaac and Vuuren 2009; Ruijven, Vuuren, et al. 2011), 18.3 °C for the US (David J Sailor 2001; D. J Sailor and Pavlova 2003), when a unique threshold temperature is set, whereas values in the literature for the heating threshold temperature are 15.5 °C for Ireland (Hargy 1997; P. G. Leahy and Foley 2012), 15.5 °C over England and Wales (Hor, Watson, and Majithia 2005), 18 °C for Europe (Eskeland and Mideksa 2010), 18 °C for the whole world (Levesque et al. 2018) while typical values found in the literature for the cooling threshold temperature are 18.3 °C for Mexico (Davis and Gertler 2015), 20 °C over England and Wales (Hor, Watson, and Majithia 2005), 21 °C for the US (Auffhammer, Baylis, and Hausman 2017) or the whole world (Levesque et al. 2018), 22 °C for Europe (Eskeland and Mideksa 2010).

Electricity demand models are developed for various purposes, the most salient ones being to project future demand and its characteristics under the impact of climate change in top-down (Ruth and A.-C. Lin 2006; Isaac and Vuuren 2009; Eskeland and Mideksa 2010; M. Bartos et al. 2016; Auffhammer, Baylis, and Hausman 2017; Damm et al. 2017; Ralston Fonseca, Jaramillo, et al. 2019) or bottom-up (Dirks et al. 2015) studies, the impacts of socioeconomic drivers in top-down (Alberg Østergaard, Møller Andersen, and Kwon 2015; Bossmann and I. Staffell 2015; Iain Staffell and Pfenninger 2018; Deakin et al. 2021; Peacock, Fragaki, and Matuszewski 2023) and bottom-up (Eom et al. 2012; Chaturvedi et al. 2014; Eggimann, J. W. Hall, and Eyre 2019; Eggimann, Usher, et al. 2020; White et al. 2021) studies, or a combination of the two, in top-down (D. J Sailor and Pavlova 2003; Davis and Gertler 2015; Levesque et al. 2018; Enrica De Cian and Ian Sue Wing 2019; Ruijven,

Enrica De Cian, and Ian Sue Wing 2019) and bottom-up (Ruijven, Vuuren, et al. 2011; Levesque et al. 2018; Tarroja et al. 2018) studies as well. Other studies focus on studying the relationship of demand to weather variables (Hor, Watson, and Majithia 2005; Tianzhen Hong, Chang, and H.-W. Lin 2013) or weather patterns (Bloomfield, D. J. Brayshaw, Shaffrey, et al. 2018). Finally, some of the reviewed studies focus on the resulting impacts of a modified demand on the power system, through the use of key power system indicators (demand, demand net of VRE) (Bloomfield, D. J. Brayshaw, Shaffrey, et al. 2016; Bloomfield, D. J. Brayshaw, Shaffrey, et al. 2018; Wiel et al. 2019; Viguié et al. 2020), or by using state-of-the-art power system models (Tarroja et al. 2018; Ralston Fonseca, M. Craig, et al. 2021b; Ralston Fonseca, M. Craig, et al. 2021a).

We can finally note that demand models vary in their space and time granularities, although the time resolution and length of the modelled time frame are determining. Top-down approaches can be split between those models that project yearly demand changes usually at large spatial scales, such as the whole world or main world regions (Europe, China, etc.) (Isaac and Vuuren 2009), or Europe/european countries (Eskeland and Mideksa 2010), and those models that compute demand at a finer time resolution, the latter increasing as available data and computational resources allowed it. Among these we find e.g. (David J Sailor 2001; Ruth and A.-C. Lin 2006) that compute monthly statewide (US) demand, or (Hor, Watson, and Majithia 2005) for the monthly demand at the level of England and Wales. Later studies usually reach the hourly time resolution for a whole year, see e.g. (Alberg Østergaard, Møller Andersen, and Kwon 2015) for Denmark or (Bossmann and I. Staffell 2015) for the UK and Germany, for tens of years at the state or country level for the UK (Bloomfield, D. J. Brayshaw, Shaffrey, et al. 2016; Bloomfield, D. J. Brayshaw, Shaffrey, et al. 2018; Iain Staffell and Pfenninger 2018; Peacock, Fragaki, and Matuszewski 2023) or the US (Ralston Fonseca, Jaramillo, et al. 2019) or globally (Iain Staffell, Pfenninger, and N. Johnson 2023), and up to thousands of years at the European level (Wiel et al. 2019), despite only daily average demand being considered. Among bottom-up approaches, the same splitting applies, principally because of the distinction between physical building simulation bottom-up models and the other approaches, the former typically having a higher time resolution. Examples of the former include (Tianzhen Hong, Chang, and H.-W. Lin 2013), which compute hourly demand at the city level, (Dirks et al. 2015), which compute hourly year long demand at the multistate (US eastern interconnection) level, (Tarroja et al. 2018), computing hourly year long demand at the state level in California (US), (Eggimann, J. W. Hall, and Eyre 2019; Eggimann, Usher, et al. 2020), which compute the hourly demand at the scale of local authority districts in the UK, (Viguié et al. 2020) computing subhourly resolution demand for a month at the scale of Paris (France), or (White et al. 2021), which compute the hourly year long demand at the county level for a whole state interconnection (ERCOT, US). Other bottom-up approaches usually focus on the yearly demand at the country (Ruijven, Vuuren, et al. 2011; Daioglou, Ruijven, and Vuuren 2012; Eom et al. 2012; Chaturvedi et al. 2014) or global (Levesque et al. 2018) level. While time resolution is of crucial importance for some applications, like energy system impacts assessment or modeling (Bloomfield, D. J. Brayshaw, Shaffrey, et al. 2016), some models focus exclusively on the demand vs. temperature relationship, leaving aside the time dimension (Davis and Gertler 2015; M. Bartos et al. 2016; Auffhammer, Baylis, and Hausman 2017; Damm et al. 2017; Enrica De Cian and Ian Sue Wing 2019; Ruijven, Enrica De Cian, and Ian Sue Wing 2019).

We showed that a great variety of electricity demand models exist, going from high time resolution residential building energy demand simulation to yearly global total electricity demand estimates. Our ultimate goal is to be able to produce synthetic realistic long (20-30 years) time series of hourly electricity demand at the regional level under stationary climate and socioeconomic conditions, to be used in power system modeling tools. Our model should be sensitive to climate, such that the impacts of climate change can be assessed. We are interested in methodologies that are able to capture the change in shape of electricity demand as well as its temporal correlation with VRE generation. Interannual variability related to weather dependence should also be captured. This implies being able to produce long (multi year, typically ten) time series of national/regional total electricity demand (and not just sectoral demand) at fine time resolution (typically hourly). Finally, we want a

minimal model that gives us access to the temperature sensitivity coefficients and allows us to modify them without compromising electricity demand signatures, so that scenarios of heating demand electrification can be derived straightforwardly. The model developed to this end is presented in the rest of this section.

2.1.2 Model description

We develop a probabilistic linear regression model of electricity demand adapted from (Tantet, Stéfanon, et al. 2019). We present in the following sections the general and detailed formulation of the model, as well as some theoretical background on the fitting and estimation procedure.

Model formulation

Let $L(t)$ be the hourly electricity demand, and $T(t)$ the hourly outdoor surface temperature. The model can be generally formulated as a probabilistic linear model, i.e.

$$L(t) = \omega^0 + \boldsymbol{\omega} \cdot \mathbf{X}(t, T(t)) + \eta(t), \quad (2.1)$$

where ω^0 is the intercept of the model, $\boldsymbol{\omega}$ is the vector of model coefficients, \mathbf{X} is a well chosen vector of features that depends both on time t and temperature $T(t)$, and η is a residual that accounts for all stochastic processes affecting the demand that are not captured by the model (typically short-term unpredictable changes in behavior). We assume this residual to be a Gaussian white noise with variance $\sigma^2(t)$. This general formulation will be used to describe the fitting and prediction procedure in next section. We give now a detailed formulation that explicits the models architecture and design principles.

At its core, our model is a piecewise linear model of demand as a function of temperature, which, drawing inspiration from the HDD/CDD approach, assumes that there exist two temperature thresholds T_H and T_C , below resp. above which electricity demand increases linearly with temperature, and is thus proportional to a heating (ω^H) resp. cooling (ω^C) temperature sensitivity coefficient. Demand is supposed to remain constant between those two thresholds and is equal to a baseline coefficient ω^B . To account for the characteristic hourly daily demand profile and weekly variations in demand, we introduce two dummy variables $h(t) \in \llbracket 0, 23 \rrbracket$ and $j(t) \in \{0, 1, 2\}$ (discriminating between calendar days, $j(t) = 0$, saturdays $j(t) = 1$, and sundays/holidays $j(t) = 2$) that factorize our coefficients such that our model can be written in its detailed form as

$$L(t) = \omega^0 + \omega_{h(t),j(t)}^B \cdot X^B(t) + \omega_{h(t),j(t)}^H \cdot X^H(t) + \omega_{h(t),j(t)}^C \cdot X^C(t) + \eta(t), \quad (2.2)$$

where X^B , X^H and X^C are given by

$$X^B(t) = 1 \quad (2.3)$$

$$X^H(t) = (T_H - \bar{T}(t))\Theta[T_H - \bar{T}(t)] \quad (2.4)$$

$$X^C(t) = (\bar{T}(t) - T_C)\Theta[\bar{T}(t) - T_C] \quad (2.5)$$

where $\bar{T}(t)$ is the average daily temperature at time t and Θ is the Heaviside step function. In Equation 2.2, $\omega_{h(t),j(t)}^B$, $\omega_{h(t),j(t)}^H$, and $\omega_{h(t),j(t)}^C$ are the factorized baseline, heating and cooling coefficients respectively, which collected together form the vector of 216 model coefficients $\boldsymbol{\omega}$. Similarly, $X^B(t)$, $X^H(t)$ and $X^C(t)$ can be factorized by our dummy variables to wit

$$(X_{h',j'}^B(t), X_{h',j'}^H(t), X_{h',j'}^C(t)) = \begin{cases} (X^B(t), X^H(t), X^C(t)) & \text{if } h' = h(t) \text{ and } j' = j(t) \\ (0, 0, 0) & \text{otherwise,} \end{cases} \quad (2.6)$$

and then collected into a single feature vector $\mathbf{X}(t)$ (the explicit dependence on temperature has been dropped here for clarity). The model then translates back to the general formulation given in Equation 2.1.

This model design has several implications. First, using the average daily temperature over the hourly temperature will tend to increase the average daily demand in heating and cooling days without modifying too much the characteristic demand profile. Using the average daily temperature rather than hourly temperature is motivated by the fact that heating and cooling processes have some inertia and that the temperature variations within a day will not impact the building's inner temperature as much as average temperature. The second motivation is that the characteristic daily demand cycle, whether it is associated to heating, cooling or baseline days, is determined by socioeconomic behavioral factors rather than by the temperature variations within the day (although the daily mean temperature influences its shape some). As such, using the hourly temperature would introduce artificial intraday demand variations that would not correspond to any observed behavior.

Second, factorizing the coefficients by hour of the day has the advantage of generating a characteristic intraday demand variation, or daily demand profile, for each type of day (any combination of heating/cooling/baseline daytype with workday/saturday/sunday and holiday daytype), that is directly learnt from the data. No external intraday parametrization is thus needed. The demand profiles for each daytype can further be split between the baseline contribution and the heating/cooling contribution. This allows us to directly derive from the data typical daily temperature sensitive (heating or cooling) demand profiles. Note finally that as these temperature sensitive demand profiles are multiplied by a temperature difference in the case of heating/cooling daytypes, the resulting demand profile (heating/cooling + baseline) will be slightly modified: the latter will have a higher amplitude in the days where the temperature difference is more important. We discuss further these daily demand profiles in Section 2.1.4.

Fit and estimation

We use a Bayesian regression framework (MacKay 1992; Tipping 2001; Bishop 2006) to determine the optimal model coefficients, while also being able to estimate the posterior noise on the model estimates (i.e. the $\sigma^2(t)$ parameter introduced in Equation 2.1). The Bayesian framework is a regularization method and as such prevents the model from overfitting (Bishop 2006, Chapter 3.3). We use a sparse version of the Bayesian regression framework to prune coefficients of poor quality (those that are very close to zero or those for which not enough data is available): the Automatic Relevance Determination (ARD) bayesian framework (Tipping 2001; Wipf and Nagarajan 2007) and (Bishop 2006, Chap. 7.2), also coined as sparse Bayesian learning or relevance vector machine (Tipping 2001). The regression procedure is streamlined through a scikit-learn pipeline (Pedregosa et al. 2011): a linear model is created for each geographical area (french administrative regions), while the ARD hyperparameters are empirically set to the same small values for all regions to make the priors non-informative. Model hyper-parameters T_H and T_C are determined jointly for all regions through grid search with k-fold cross-validation. We develop briefly some aspects of the regression framework, to introduce the parameters of the model and to give visibility on the inference of the posterior noise $\sigma(t)$.

We use for simplification the general formulation of our model, where ω is the vector of model coefficients, of size M (216 in our case). Given a set of training data \mathbf{u} of size N (equivalent to N observations of hourly demand in our case) and a training feature matrix $\hat{\mathbf{X}}$ of size $(N \times M)$, the prior over the data is given by

$$p(\mathbf{u}|\omega, \beta) \sim \mathcal{N}(\mathbf{u}|\hat{\mathbf{X}}\omega, \beta^{-1}), \quad (2.7)$$

i.e. by a normal distribution with mean $\hat{\mathbf{X}}\omega$ and variance β^{-1} . β is also called noise precision. Note that we omit $\hat{\mathbf{X}}$ in the conditional probabilities for clarity (i.e. $p(\mathbf{u}|\omega, \beta) = p(\mathbf{u}|\hat{\mathbf{X}}, \omega, \beta)$). A particularly interesting feature of ARD is that a different prior can be given to each coefficient. This allows the pruning of coefficients that should be zero (this is discussed later) and thus allows the reduction of the effective number of model parameters (Tipping 2001). The prior over the weights is given by a

centered elliptical gaussian:

$$p(\boldsymbol{\omega}|\boldsymbol{\alpha}) = \prod_{i=0}^{M-1} \mathcal{N}(\omega_i|0, \alpha_i^{-1}), \quad (2.8)$$

where $\boldsymbol{\alpha}$ is a vector of size M of precisions for each coefficient.

Parameters β and $\boldsymbol{\alpha}$ could be determined empirically or via well-chosen hyperparameter determination procedure (e.g. grid search with k-fold cross validation). However the bayesian formulation allows us to infer those parameters from the data by defining hyper-priors over them. These hyper-priors are given by

$$p(\boldsymbol{\alpha}) = \prod_{i=0}^{M-1} \text{Gamma}(\alpha_i|a, b), \quad (2.9)$$

$$p(\beta) = \text{Gamma}(\beta|c, d), \quad (2.10)$$

where $\text{Gamma}(\cdot)$ is the gamma distribution with shape and rate parameters a, c and b, d respectively. These parameters are empirically given small values so as to obtain a flat and thus non-informative prior. For general discussion on why priors are given those shapes (gaussian and gamma distributions) see (MacKay 1992; Tipping 2001; Bishop 2006).

Given the training data, we seek to determine the posterior over all unknowns $p(\boldsymbol{\omega}, \boldsymbol{\alpha}, \beta|\mathbf{u})$. This distribution is then used in the prediction step, where given a new feature vector $\mathbf{X}(t)$ the corresponding demand is given by

$$p(L(t)|\mathbf{u}) = \int p(L(t)|\boldsymbol{\omega}, \beta)p(\boldsymbol{\omega}, \boldsymbol{\alpha}, \beta|\mathbf{u})d\boldsymbol{\omega}d\beta d\boldsymbol{\alpha}, \quad (2.11)$$

where we omitted the condition over the new feature vector. Since the posterior distribution can not be analytically derived (Tipping 2001; Bishop 2006), it is decomposed as

$$p(\boldsymbol{\omega}, \boldsymbol{\alpha}, \beta|\mathbf{u}) = p(\boldsymbol{\omega}|\boldsymbol{\alpha}, \beta, \mathbf{u})p(\boldsymbol{\alpha}, \beta|\mathbf{u}), \quad (2.12)$$

where the first term can be shown to follow a gaussian distribution, $p(\boldsymbol{\omega}|\boldsymbol{\alpha}, \beta, \mathbf{u}) \sim \mathcal{N}(\boldsymbol{\omega}|\mathbf{m}_N, \mathbf{S}_N)$, with parameters

$$\mathbf{m}_N = \beta \mathbf{S}_N \hat{\mathbf{X}}^T \mathbf{u}, \quad (2.13)$$

$$\mathbf{S}_N = (\mathbf{A} + \beta \hat{\mathbf{X}}^T \hat{\mathbf{X}})^{-1}, \quad (2.14)$$

where $\mathbf{A} = \text{diag}(\alpha_0, \dots, \alpha_{M-1})$ is the diagonal matrix of precisions associated to each weight. Evaluation of the hyperparameter posterior $p(\boldsymbol{\alpha}, \beta|\mathbf{u})$ needs an approximation, e.g. see (Tipping 2001)(Bishop 2006, Chapter 3.5), and is reduced to the determination of the hyperparameter posterior modes

$$\max_{\boldsymbol{\alpha}, \beta} \{p(\boldsymbol{\alpha}, \beta|\mathbf{u}) \propto p(\mathbf{u}|\boldsymbol{\alpha}, \beta)p(\boldsymbol{\alpha})p(\beta)\}. \quad (2.15)$$

The maximization problem in Equation 2.15 must be solved iteratively since no closed form can be analytically derived for its solution $(\hat{\boldsymbol{\alpha}}, \hat{\beta})$. The update formulas depend on the chosen hyperparameters for the gamma distributions. In the general case:

$$\alpha_i^{\text{new}} = \frac{\gamma_i + 2a}{m_{N,i} + 2b}, \quad (2.16)$$

$$(\beta^{\text{new}})^{-1} = \frac{\|\mathbf{u} - \hat{\mathbf{X}}\mathbf{m}_N\|_2^2 + 2d}{N - \sum_i \gamma_i + 2c}, \quad (2.17)$$

where γ_i is the quantity defined by

$$\gamma_i = 1 - \alpha_i S_{N,ii}, \quad (2.18)$$

where the $S_{N,ii}$ are the variance/covariance matrix diagonal elements. The interpretation of parameter γ is discussed hereafter. Note that this is the step where pruning of coefficients occurs (Tipping 2001). All weights whose precision goes to infinity - and numerically beyond a certain threshold α_∞ - are set to zero. The value of α_∞ is empirically determined.

The predictive distribution is then given by

$$p(L(t)|\mathbf{u}) \simeq p(L(t)|\mathbf{u}, \hat{\boldsymbol{\alpha}}, \hat{\beta}) = \int p(L(t)|\boldsymbol{\omega}, \hat{\beta})p(\boldsymbol{\omega}|\hat{\boldsymbol{\alpha}}, \hat{\beta}, \mathbf{u})d\boldsymbol{\omega}, \quad (2.19)$$

and one can show that $p(L(t)|\mathbf{u}) \sim \mathcal{N}(L(t)|\mathbf{X}(t)\mathbf{m}_N, \sigma^2(t))$, where

$$\sigma^2(t) = \hat{\beta}^{-1} + \mathbf{X}(t)^T \mathbf{S}_N \mathbf{X}(t), \quad (2.20)$$

where $\sigma(t)$ is the standard deviation of the Gaussian white noise $\eta(t)$.

These developments allow us to discuss two important points. The main informations we want to get from our model are twofold. First we want to know how accurate are our coefficients estimations (how good are the temperature sensitivities estimates we get ?). Then we want to know what information is given by the posterior deviation σ (is this true noise, noise coming from a lack of data, noise from true temperature sensitivity coefficients ?). Model coefficients quality is given by the parameter γ . By definition, we have $\gamma \in [0, 1]$. A coefficient ω_i (with expectation value $m_{N,i}$) is of good quality when $\gamma_i \rightarrow 1$ and of bad quality otherwise. In some sense this gives an idea of how well the data available allowed to constrain the coefficients. If we look at the right part of Equation 2.18, we see that it corresponds to the ratio between the prior deviation of the coefficient i , $\hat{\alpha}_i^{-1}$, and its posterior deviation, $S_{N,ii}$. This ratio tends towards zero when the posterior deviation is much smaller than the prior deviation. We think it is important to note, as suggested by empirical numerical experiments (not shown here), that nor $\hat{\alpha}_i^{-1}$ nor $S_{N,ii}$ give an estimation of the true intrinsic/posterior noise on the coefficients. In this sense we disagree with (Tipping 2001) that states that the values of $S_{N,ii}$ can be used as errorbars for model coefficients. In fact the interpretation of α is rather counterintuitive: a high prior precision does not mean a good coefficient quality: we have that $S_{N,ii} \rightarrow 0$ when $\hat{\alpha}_i \rightarrow +\infty$, which yields $\omega_i \rightarrow 0$ (Equations 2.13 and 2.14). This property is used to prune coefficients that “we are a posteriori certain to be zero”(Tipping 2001). We thus leave aside interpretations related to the coefficients prior and posterior noise and concentrate on γ , which is a measure of how well the available data allowed to constrain the coefficient (i.e. reduce the coefficients noise compared to the prior noise). Note that we empirically observe that for the same amount of data available, coefficients close to zero have a lesser quality than more positive or negative coefficients. Further research is needed to fully explicit this mechanism.

We postulated that the posterior noise would be the result of all stochastic processes affecting the demand our model is not able to capture. By that we mean all processes that affect the load once intraday, weekly variability (including holidays) and temperature sensitivity are taken into account. From Equation 2.20 we can see there are two contributions to the predicted noise on the data. The term in $\hat{\beta}^{-1}$ is the contribution of the estimated precision of the noise to the posterior deviation. The second term is the contribution of the data to the posterior deviation. We can see that when the number of data points is very big ($N \rightarrow +\infty$), this contribution vanishes. We do also empirically observe in numerical experiments (not shown here) that the posterior deviation equals to the square root of the inverse precision of the noise when N is sufficiently big (in the order of a hundred to a thousand data points per degree of freedom). There is thus an explicit contribution of the lack of data to the posterior deviation. We can loosely see things as if the $\hat{\beta}^{-1}$ term captured the true noise of the data whereas the other term would add noise if not enough data was available. However, even with enough data available, the interpretation of the posterior deviation should be prudent. Numerical experiments (not shown here) suggest that the model in its state (Bayesian ARD) cannot differentiate noise in the data coming from true intrinsic noise or noisy coefficients. One cannot differentiate whether the data is noisy because some process were not explained by the model or if simply the true temperature sensitivity coefficients are noisy. This could be tested by running numerical experiments

with artificial data generated with an intrinsic standard deviation and/or with noisy linear coefficients, and is left for future research.

Hyperparameters selection

The rate parameters of the Gamma function that determine the hyper-priors over parameters α and β are empirically given small values to make the priors flat and non-informative. These parameters are reported in Table 2.3. We then select the best models against hyperparameters T_H and T_C , via the grid search with k-fold cross-validation procedure implemented in scikit learn (Pedregosa et al. 2011). The number of folds corresponds to the number of whole years available in the data to preserve the seasonal cycle in each fold. The metric used at each gridpoint to evaluate the quality of the model is the coefficient of determination r^2 . We implement one linear model per region/geographical area (i.e. model coefficients are region-specific). However, hyperparameters are determined over the whole geographical area and are thus the same for every regional model. We thus use the mean coefficient of determination over the whole area to select the best set of hyperparameters and as a measure of regional models quality. The motivation for this procedure is twofold: it makes the model less computation-intensive by reducing the number of hyperparameters and creates a weak correlation between regional models. The first point is motivated by the fact that numerical complexity is divided by the number of regions in the total geographical area considered. This could be tackled by model parallelization but goes beyond the scope of this study. The second point is motivated by the consideration that some correlation in electricity consumption patterns must exist between the contiguous regions constitutive of the whole geographical area.

2.1.3 Model training data

We fit a model for each one of the 12 metropolitan France administrative regions. We use weather reanalysis data to train the model (to compute the training feature matrix \hat{X}), although a different data source is used in Chapter 3 and Chapter 5. More information on weather data is given in Section 2.3. In both cases gridded values of the surface temperature field are averaged over every administrative region to yield hourly time series of surface temperature used to derive \hat{X} to train the model corresponding to a region. The training data \mathbf{u} is computed from hourly total electricity demand data at the level of each french administrative region from the french TSO RTE (<https://opendata.reseaux-energies.fr/>). The training datasets are presented in Tables 2.1 and 2.2.

Data source	Chapter	Reference
Opendata réseaux énergie	Chapter 3 and 5	https://opendata.reseaux-energies.fr/
MERRA2 reanalysis	Chapter 3	(Gelaro et al. 2017)
ERA5 reanalysis	Chapter 5	(Hersbach et al. 2020)

Table 2.1. Demand model training data sources description.

Data source	Temporal resolution	Spatial resolution	Common range
Opendata réseaux énergie	Hourly	French administrative regions	2014 – 2019
MERRA2 reanalysis	Hourly	($0.5^\circ_{\text{lat}}, 0.625^\circ_{\text{lon}}$)	2014 – 2019
ERA5 reanalysis	Hourly	31 km ($0.281^\circ_{25^\circ}$)	2014 – 2019

Table 2.2. Demand model training data sources resolution.

2.1.4 Model results

We present an overview of the resulting best model over the whole area of study for the model in its Chapter 3 version (i.e. using MERRA2 reanalysis data, see Table 2.1). We first present model

hyperparameters and then turn to model coefficients. Although the model is already validated via k-fold cross-validation over the 2014-2019 period, we conduct a final validation step over aggregated national data with the model predictions and observations for the year 2013 (which was not used for training).

Model parameters

Hyper-priors hyperparameters a , b , c and d , as well as the threshold used to prune coefficients α_∞ are empirically set and reported in Table 2.3. For parameters T_H and T_C , the grid used to conduct the grid search as well as the corresponding score for each hyperparameters pair are shown in Figure 2.3. As these hyperparameters are determined jointly for all regional models, the score corresponds to the average over the regions of the coefficient of determination r^2 of each regional model. The grid was designed based on usual values found in the literature as well as iterated score space explorations. Following this logic, the best pair of T_H and T_C hyperparameters would be $(T_H, T_C) = (15^\circ\text{C}, 18^\circ\text{C})$, for a best score of $r^2 = 0.887$. However we can observe that the best score does not change much with the values of T_C when the optimal value of T_H is considered. We thus decide to set the T_C parameter to a value of 20°C , to avoid having negative cooling temperature sensitivity coefficients (ω^C). Although a value of 18°C for the T_C parameter would perfectly fit with values found in the literature, setting $T_C = 20^\circ\text{C}$ is motivated by an increased physical meaning of the resulting model. Still, the score for the $(T_H, T_C) = (15^\circ\text{C}, 20^\circ\text{C})$ pair is of $r^2 = 0.887$ as well, and thus the loss in prediction performance is not significant up to 3 significative digits in the prediction score. The resulting coefficients and coefficient qualities do not change either to the first order, as discussed later. Increasing the T_C hyperparameter however comes to the price of having less data to constrain the ω^C coefficients, as well as missing some days where cooling actually occurs. Although the value of 20°C decreases the number of negative coefficients it does not resolve all the issues (this is discussed further in Chapter 3) related to negative coefficients. This value is thus a compromise between sticking to a value that gives the best prediction score and preventing non-physical model behavior from occurring. The best value and chosen value for the T_H and T_C hyperparameters are reported in Table 2.3. The model with chosen hyperparameters is referred to as the best model, and is the best as in the compromise between the best purely statistical model and the model that has the most physical meaning.

Parameters	Range	Best value ¹	Chosen value
Heating temperature threshold (T_H)	$[[13, 17]]^\circ\text{C}$	15°C	15°C
Cooling temperature threshold (T_C)	$[[18, 22]]^\circ\text{C}$	18°C	20°C
Hyper-priors parameters (a, b, c, d)	-	-	10^{-6}
Pruning threshold (α_∞)	-	-	10^6

Table 2.3. Demand model hyperparameters for the ARD bayesian regression framework. ¹ If applicable - parameters related to Gamma distributions (a, b, c, d) and pruning threshold α_∞ are empirically set.

Model coefficients

The best model coefficients are presented Figure 2.4 for the intercept (ω^0), Figure 2.5 for the baseline coefficients (ω^B), Figure 2.6 for the heating temperature sensitivity coefficients (ω^H) and Figure 2.7 for the cooling temperature sensitivity coefficients (ω^C). Model coefficients quality (γ) is presented Figure 2.8.

The intercept corresponds to the part of the training data independent from temperature. It thus corresponds roughly to the average demand on the baseline days. Regions do not contribute equally to this baseline part of the national energy demand: the greatest intercept is about 4 to 5 times higher than the lowest one (Figure 2.4, by reading the values at the extremities of the box's whiskers), while half of the regions have an intercept between 2 GW and 4 GW. The baseline part of the demand is the result of the addition between the intercept ω^0 and the baseline coefficients ω^B ,

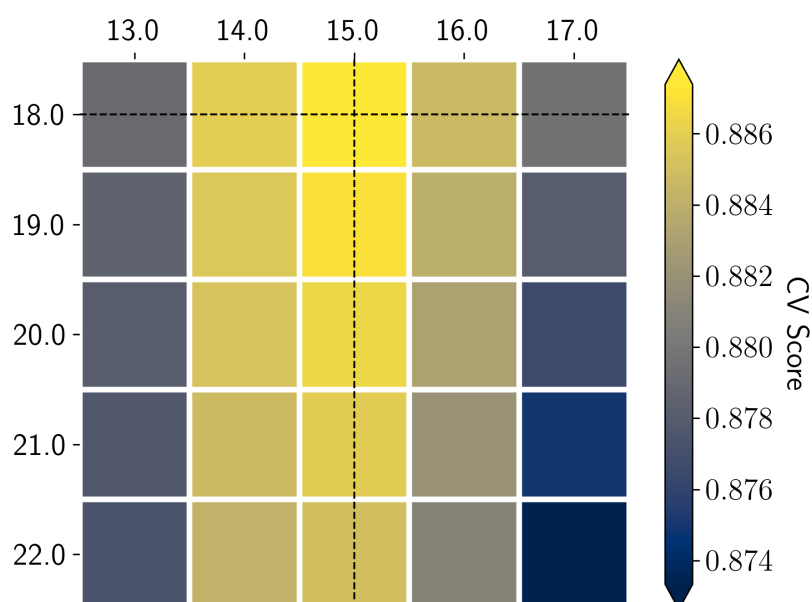


Figure 2.3. Grid and scores for the T_H and T_C hyperparameters determination. The cross-validation score (CV Score) corresponds to the coefficient of determination r^2 . Values of the T_C parameter are given on the y axis on the left, and values of the T_H parameter are given on the x axis on the top (see also Table 2.3).

which represent variations around the intercept. As such here coefficients can be negative without any issue regarding the physical meaning. The baseline daily demand profile (or daily cycle) is thus encoded in the baseline coefficients. It corresponds to the demand profile when there is no heating nor cooling, to which the heating/cooling demand profiles are added on the heating/cooling days. We can observe from Figure 2.5 that the baseline coefficients are higher during workdays (Cal. Daytype = 0) than Saturdays or Sundays/holidays (Cal. Daytype = 1 or Cal. Daytype = 2). The baseline demand profile presents the usual main features, e.g. (Créti and Fontini 2019): a broad peak during the day and an evening peak between 17h and 19h (Coordinated Universal Time (UTC)), followed by a late evening peak at around 22h (UTC). Baseline coefficients are overall well constrained by the data, except for those that are close to zero. This is evidenced by looking at coefficients quality γ , which is shown in Figure 2.8, between indices 72 and 143. Although all coefficients have the same amount of data to be constrained, those close to zero exhibit a lower quality (γ closer to 0). This hints at the fact that the model cannot distinguish those coefficients that should actually be zero from the coefficients that should be zero because they cannot be satisfactorily constrained by the data. Further exploration of the model is needed to explicit this behavior and its impact on the modeling results.

Heating and cooling coefficients encode the heating and cooling temperature sensitive demand variations within the day. They vary across regions due to probable differences in population, level of electric heating equipment and other socioeconomic factors. Heating coefficients ω^H give the hourly demand profile of heating temperature sensitive demand, which to first order can be considered to be that of electric heating (this is discussed later). The heating demand profile is roughly constant throughout the day (even at night) with light peaks in the morning during workdays and in the evening throughout the week. This daily profile will be added to the baseline profile during heating days with as much intensity as the day is colder than the heating threshold temperature: increased peaks in the morning and in the evening are thus expected in the demand profile of heating days. The heating demand profile is quite homogeneous through the different regions (with variations in magnitude) with the notable exception of two regions with very flat profiles and one region (corresponding to Île-de-France) with a notably higher and more variable profile. Heating coefficients quality are very good ($\gamma \rightarrow 1$) throughout the day and for every region (see Figure 2.8, between indices 0 and 71). This is expected since the amount of occurrences of heating days — and the associated amount of data available to constrain the coefficients — is relatively important in France, compared to that

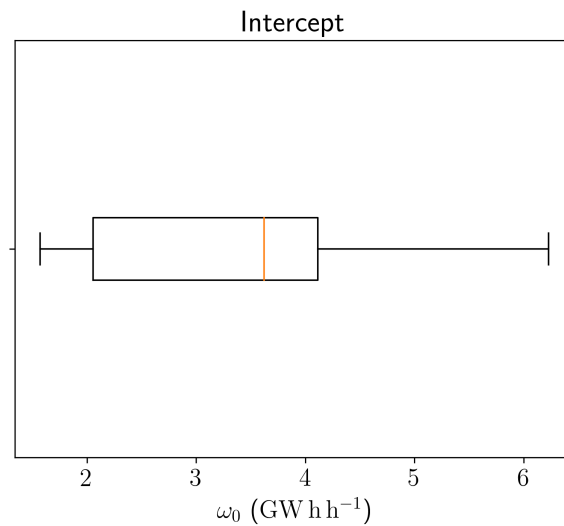


Figure 2.4. Intercept of the linear model. The box represents the distribution over the study area (metropolitan France). The orange line represents the median while the box represents the interquartile range between first quartile and third quartile. Whiskers extend to the farthest point within 1.5 times the interquartile range.

of exclusively baseline or cooling days. Compared to the baseline coefficients, here no coefficients should naturally be zero.

Cooling coefficients ω^C encode the cooling demand profile. The latter is more variable than the heating demand profile with a broad daylight peak followed by an evening peak around 20h-21h (UTC). A notable feature of cooling temperature sensitivity coefficients is the occurrence of negative coefficients, around 6h-7h and 18h (UTC), Figure 2.7. This is discussed later. The cooling demand profile is more heterogeneous than the other profiles across regions. Two groups of regions can be distinguished: those with positive coefficients and a marked daily profile and those with a rather flat and almost zero demand profile. This translates the fact that only some regions in France use the AC as of the 2014-2019 period. This will have consequences in the design of AC adoption scenarios and is further discussed in Chapter 3. Cooling coefficients quality is much worse ($\gamma \rightarrow 0$) than for the heating coefficients, with the notable exception of regions Nouvelle-Aquitaine, Auvergne-Rhône-Alpes, Occitanie and PACA (see Figure 2.8, between indices 143 and 215). This due to those coefficients being close to zero or due to a lack of data to constrain these coefficients satisfactorily. The occurrence of cooling days in France is indeed much less than that of baseline or cooling days.

Two important points merit further discussion. The first is the fact that not all temperature sensitive demand is related to space heating (for space cooling the hypothesis is more accurate). This is further discussed in Chapter 3. In fact, it can be inferred from available data that the ratio of space heating demand to temperature sensitive demand amounts to about $2/3$. However, this is true for daily average demand data. The relative distribution of space heating throughout the day is not evidenced by the available data. This could pose a problem in our scenarization exercise where we project scenarios of heating demand electrification by multiplying the temperature sensitivity coefficients (see Chapter 3). It could be that other end-uses not related to space heating with a minority average daily contribution still concentrate on a few hours of the day, thus significantly modifying the daily demand profile that is later to be multiplied in the scenarization exercise. An example of such an end-use would be lighting, which is typically cited as a temperature sensitive end-use, and whose usage — at least in the residential sector — is very probably concentrated in the morning and the evening when people are awake but there is no daylight. This could explain the morning and evening peaks that we observe in the heating temperature sensitive demand profile (Figure 2.6) in particular for workdays (Cal. Daytype = 0). However some studies suggest that these peaks are meaningful (Peacock, Fragaki, and Matuszewski 2023). Further research with data disaggregated by end-use at

a high time resolution (hourly rather than daily) would be needed to better characterize the contribution of each end-use to the observed temperature sensitive demand profile aggregated at the level of a french administrative region or France. We thus here point out — and this should be kept in mind — that even if we scale our scenarios of heating electrification by the contribution of electric heating to the current temperature sensitivity (2/3), we cannot disentangle the relative importance of space heating at each hour of the day. The resulting demand profiles in the increased heating electrification scenarios will thus keep the same shape, scaled by a coefficient.

The second point necessitating further discussion is the occurrence of negative coefficients. This behavior poses no problem in the case of baseline coefficients since the baseline part of the demand is the addition of the intercept ω^0 and the baseline coefficients ω^B , and as such is always positive. This behavior can however pose problems in the case of heating and cooling coefficients, and as only the latter are affected, we will focus our discussion on the cooling coefficients case. It can make physical sense that some cooling coefficients ω^C are negative: this can represent a modification of the baseline demand profile during cooling days where, e.g. less demand is needed over a certain hour. However it should be that the daily average of the cooling coefficients is positive or zero. Indeed if some cooling via AC occurs during cooling days, then the average demand over the day should be larger in the end. This is not the case for each region, and this issue is further discussed in Chapter 3. To prevent this from happening we increase the T_C threshold. As already discussed this does not change model prediction performance significantly. We can also show that the intercept, baseline and heating coefficients are not significantly affected either. This is shown qualitatively by comparing Figures 2.4, 2.5 and 2.6 to Figures A.1, A.2 and A.3 in Appendix A. We can however observe that increasing the T_C threshold has the desired effect: cooling coefficients are increased and less coefficients are non-zero (compare Figure 2.7 to Figure A.4, or Figure 2.8 to Figure A.5). As was already discussed, while increasing the cooling threshold tends to reduce the undesired model behavior, it also reduces the amount of data available to constrain the coefficient. We empirically find that $T_C = 20^\circ\text{C}$ is a good tradeoff. The impacts of such model behavior is further discussed in Chapter 3.

Final validation & summary

We focus in this section on the predicted demand aggregated at the national level, since this is the input to the power system model, and compare it to observations from the year 2013. The observed and predicted demand for France for the year 2013 are shown Figure 2.9a. We can see that the overall seasonal trend is well represented by our model: a higher demand in the winter and a lower demand in the summer. The weekly cycle is also well represented (shown by the high frequency oscillation in the figure, most visible in the summer). There are some periods however where the demand is either overestimated (in late spring, between days 100 and 150) or underestimated (e.g. during early summer, between days 150 and 200). A notable phenomena that we do not capture is the summer holidays, between days 200 and 250. Nonetheless our model has a good predictive power: the daily average Root Mean Square Error (RMSE) is of 3.26 GW (from 3.8% to 9.1% of the observed demand) and the coefficient of determination (0.927) is close to a value of one. For the hourly values, both indicators are a bit worse but still very good: the hourly RMSE is of 3.81 GW, i.e. from 4.1% to 12.8% of the observed demand, while the coefficient of determination (0.914) is also close to a value of one. These values compare well to other state-of-the-art demand models with a similar approach to ours (Iain Staffell, Pfenninger, and N. Johnson 2023).

The demand response to temperature is well represented by our model. This is qualitatively shown in Figure 2.9b. This figure evidences how France is a heating dominated country, with little cooling temperature sensitivities and only a few excursions above 20°C . A notable feature of our model is to be able to discriminate between workdays, Saturdays and Sundays, which explains a sensible share of the vertical spread of demand for a given temperature. We can however observe that the spread predicted from our model is much lower than that of the actual demand. Note that the notion of heating and cooling days is a bit ambiguous here since we are dealing with french national

averages (i.e. averages over the different administrative regions) and it can happen that on the same day one region experiences a cooling day whereas the other will experience a baseline or even a heating day. We thus speak in this section of cold, mild and hot days instead of heating, baseline and cooling days.

If the seasonal behavior of demand, associated to the temperature dependence of the former, is well represented, so are the hourly variations. We show this by comparing the modeled and observed demand profiles at the national aggregated level and for mild, Figure 2.10a, cold, Figure 2.10b, and hot days, Figure 2.10c. We can see that these differing demand profiles are qualitatively well reproduced by our model. We give as an indication the count for each type of day, to make clearly visible that cold days are much more frequent in France than hot days or purely mild days.

We thus work with a demand model capable of reproducing the main features of the electricity demand aggregated at the national level: from the seasonal cycle to the daily demand profiles, our model has a good prediction power that translates in average errors on the order of 5 % to 10 % of the observed demand, while more than 90 % of the demand variability is explained. This model allows us to generate long (from 10 to 30 years long) time series of hourly demand representative of a given set of socioeconomic conditions. Scenarios of electrification can also be designed from the model by multiplying its coefficients. It should however be kept in mind that these scenarios of electrification will retain demand profiles with similar shapes to those learnt during the training process, and as such will keep a signature of given socioeconomic conditions.

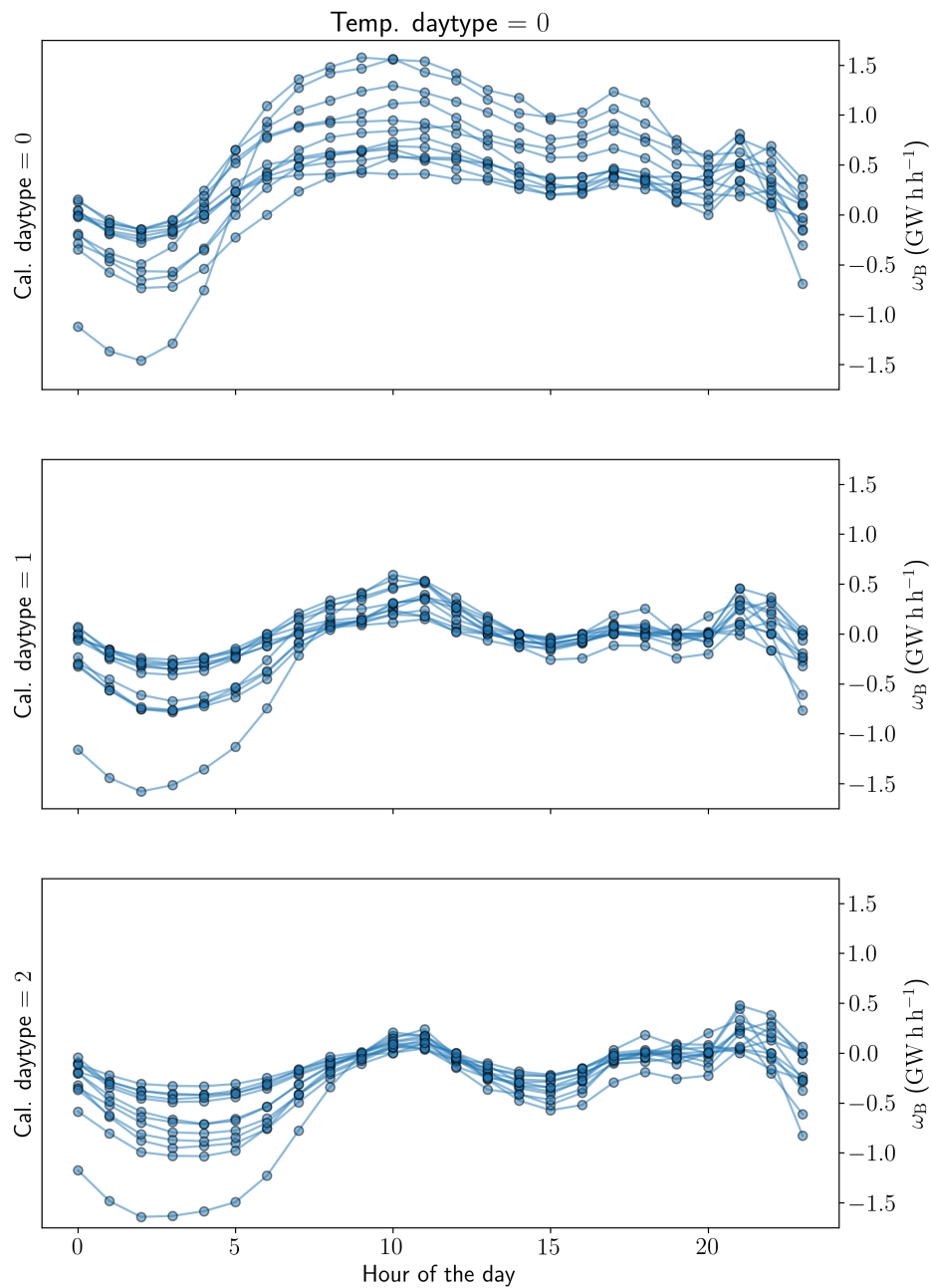


Figure 2.5. Baseline coefficients of the linear model. Model coefficients are represented throughout the day (to each hour of the day corresponds a coefficient). The different lines correspond to the different french administrative regions.

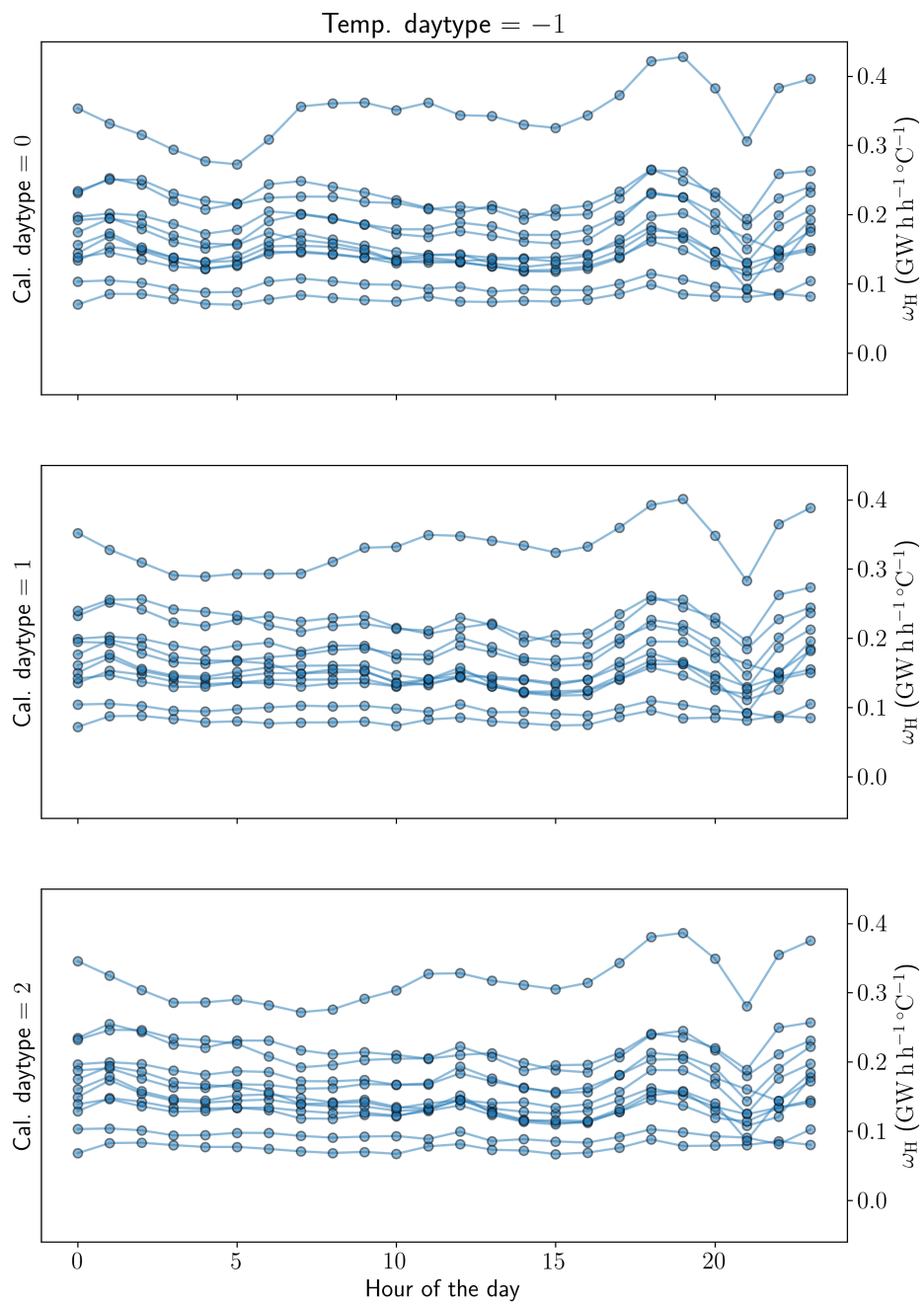


Figure 2.6. Heating temperature sensitivity coefficients of the linear model. Model coefficients are represented throughout the day (to each hour of the day corresponds a coefficient). The different lines correspond to the different french administrative regions.

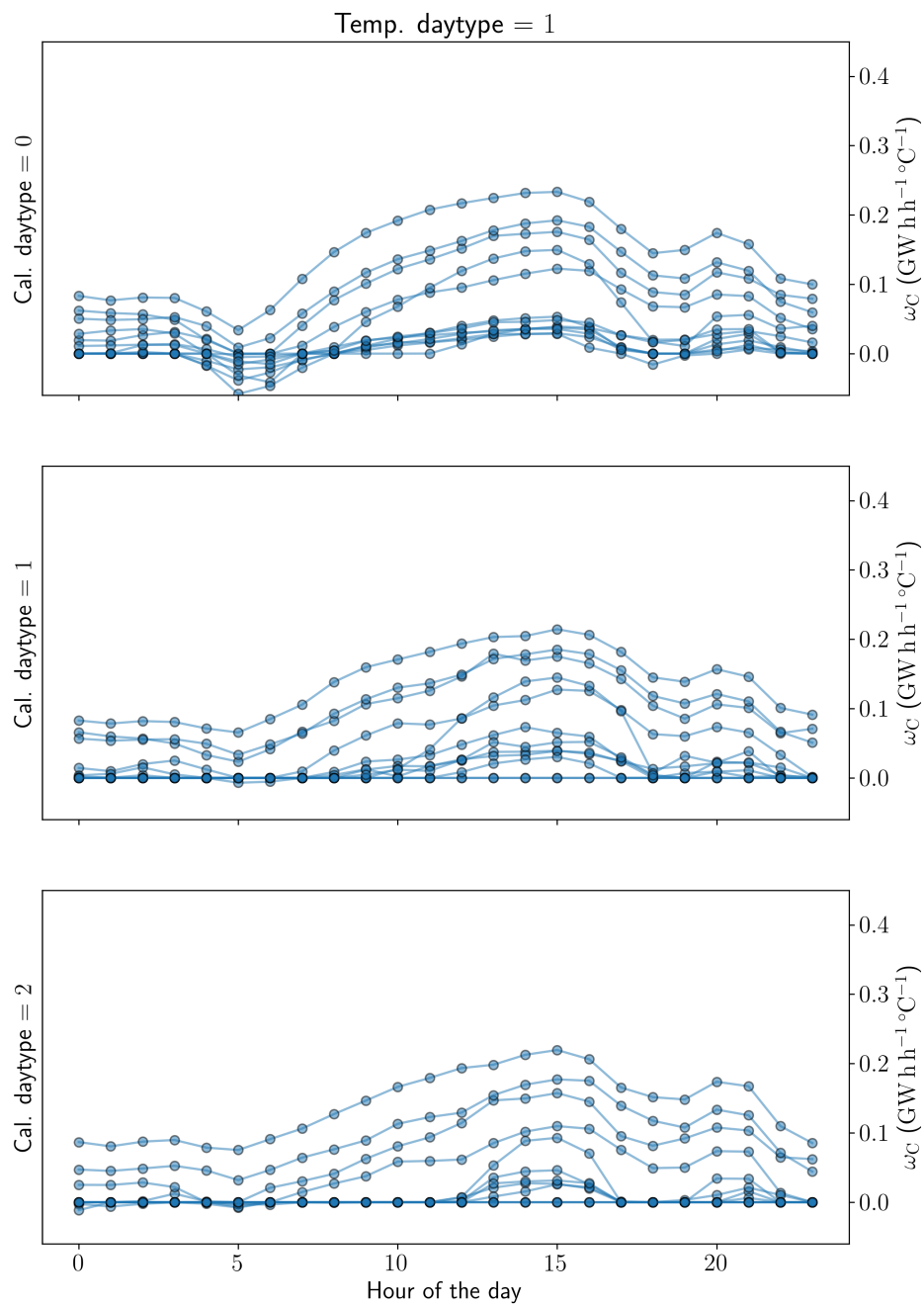


Figure 2.7. Cooling temperature sensitivity coefficients of the linear model. Model coefficients are represented throughout the day (to each hour of the day corresponds a coefficient). The different lines correspond to the different french administrative regions.

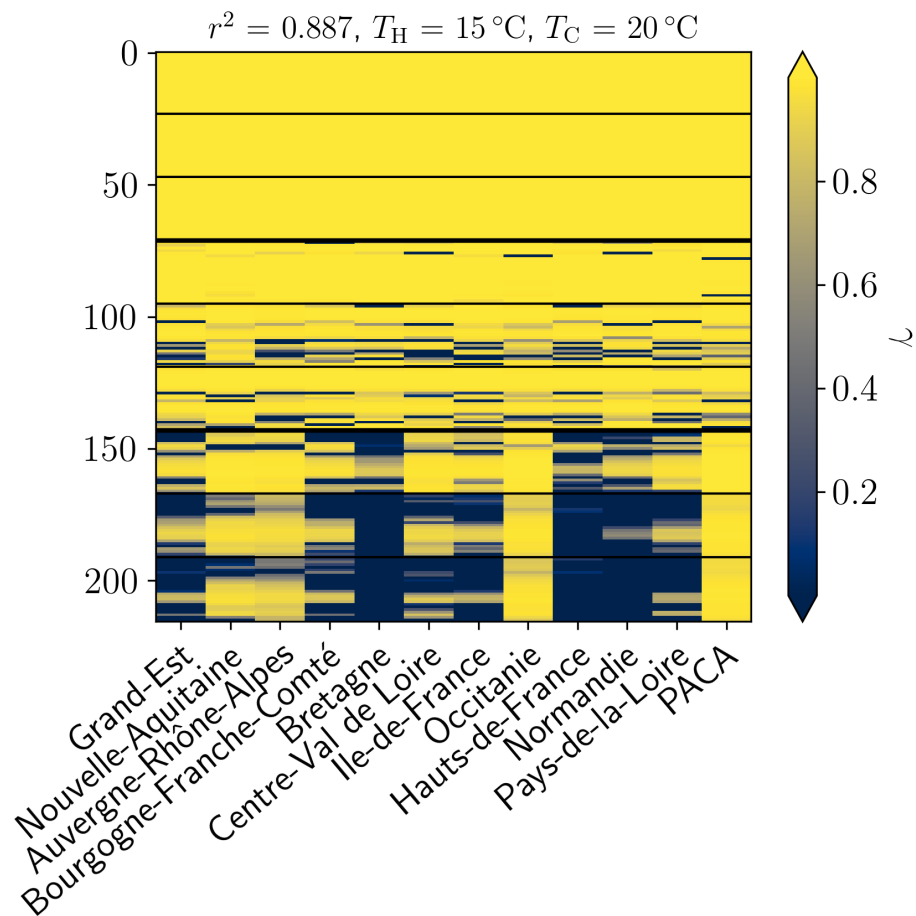


Figure 2.8. Model coefficients quality (γ). Heating coefficients ω^H are indexed between 0 and 71, baseline coefficients ω^B between 72 and 143, and cooling coefficients ω^C between 144 and 215.

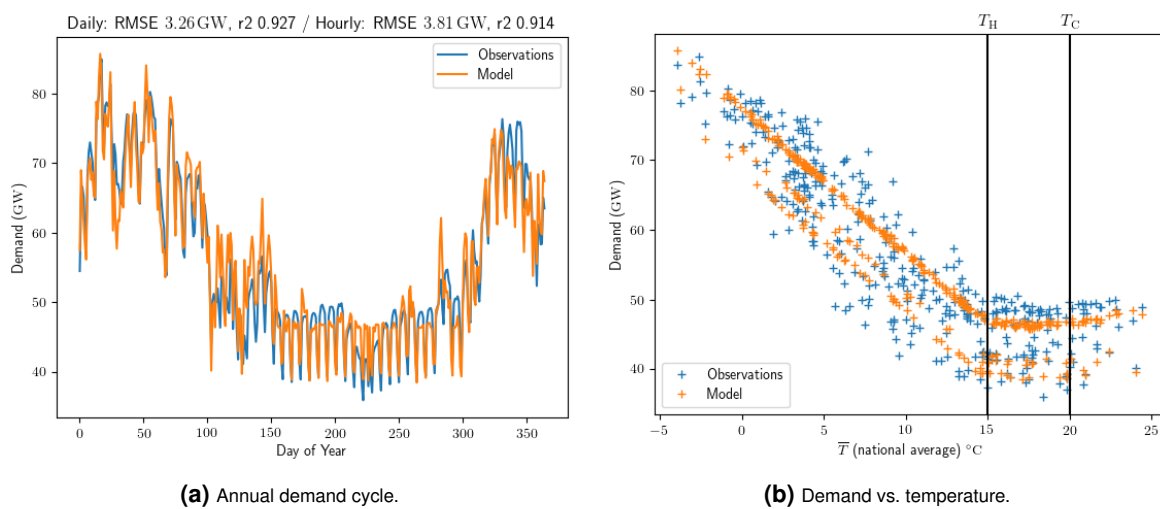
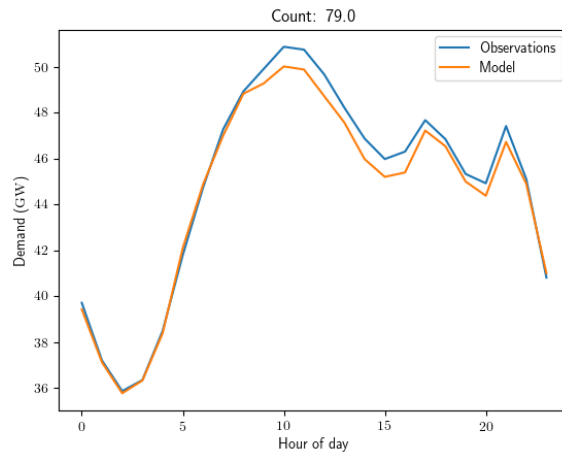
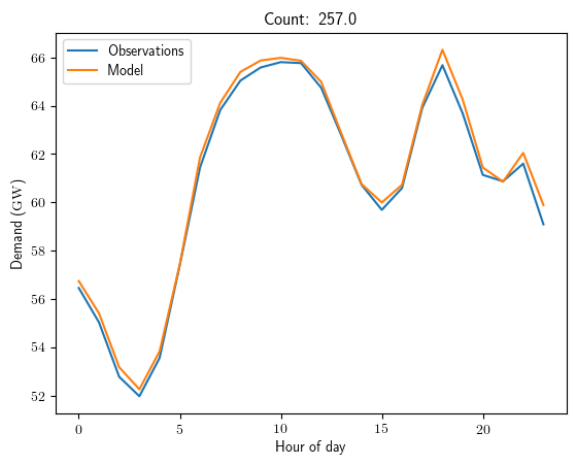


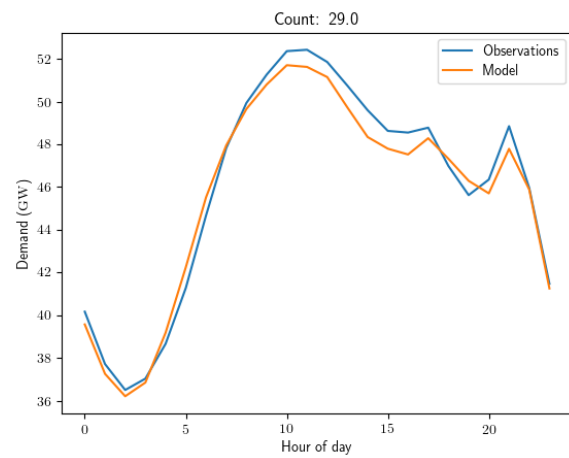
Figure 2.9. Model validation: annual demand and temperature dependence. Seasonal (annual) variations of demand, panel (a), and demand as a function of daily average temperature, panel (b), for the observed and modeled demand in 2013.



(a) Mild days demand profile.



(b) Cold days demand profile.



(c) Hot days demand profile.

Figure 2.10. Model validation: demand profiles. Daily demand profiles for rather cold, hot or mild days over France for the observed and modeled demand in 2013.

2.2 Determination of VRE capacity factors

To determine long (tens of years) time series of VRE capacity factors to be used as input for our power system model, we rely on the methodology presented in (Tantet, Stéfanon, et al. 2019) to which we add some extra features. We briefly summarize the methodology here.

2.2.1 VRE capacity factors computation

Wind capacity factors

Wind capacity factors are computed by passing the total wind speed through a power curve transfer function and dividing by the turbine nominal power. We use a reference power curve extrapolated from the Siemens SWT-2.3 MW-101m model specifications (Tantet, Stéfanon, et al. 2019) that we reproduce in Figure 2.11.

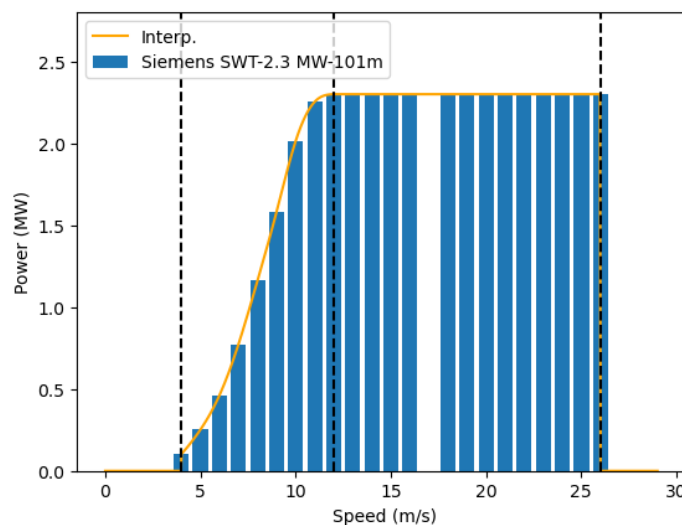


Figure 2.11. Reference wind turbine power curve. The vertical dotted lines mark the cut-in, nominal power and cut-out wind speeds.

Zonal and meridional wind speeds components are first extrapolated at hub height (101 m) using a power law with exponent $1/7$ according to (Justus and Mikhail 1976), which is a satisfactory approach, as discussed in (Tantet, Stéfanon, et al. 2019, Section A.3.1-). We assume that the turbine is always facing the wind and we neglect wake losses, so that total wind speed is used.

In Chapter 3 wind speeds at height are directly passed to the power curve transfer function. As a consequence, the influence of temperature, pressure and humidity on air density and thus power output are neglected. In Chapter 5 the influence of temperature is accounted for by correcting wind speeds for deviating air densities for which the power curve has been established before passing it through the power curve transfer function. Wind speeds are thus multiplied by a factor $(\rho/\rho_0)^{1/3}$, with ρ the corrected density and ρ_0 the reference density. This allows to preserve the cut-in and cut-out behavior of the turbine. Density is corrected for a deviation from the reference temperature following (Dupré 2020), such that

$$\rho = \rho_0 \frac{1}{1 + \frac{\Delta T}{T_0}}, \quad (2.21)$$

where

$$\rho_0 = \frac{MP_0}{RT_0}, \quad (2.22)$$

and

$$\Delta T = T_h - T_0, \quad (2.23)$$

with P_0 the reference pressure (1013.25×10^2 Pa), T_0 the reference temperature (288.15 K or 15 °C), M is the dry air molar mass ($0.028\,964\,4$ kg mol⁻¹), and T_h is the temperature at hub height. The latter is extrapolated from the temperature at surface following

$$T_h = T - L(z_h - z), \quad (2.24)$$

where T is the surface temperature, L is the lapse rate (0.0065 K m⁻¹), z_h is the hub height in m, z is the height of the surface temperature field in m. Only the effect of temperature is taken into account as it is the main factor affecting density, compared to pressure and humidity (Dupré 2020). Including other variables would be computationally expensive compared to the gains in accuracy.

We thus obtain hourly wind capacity factors at every weather variables grid point, that we then average at the level of french administrative regions for bias correction. In Chapter 5, wind capacity factors will be impacted by climate change via the potential changes in wind regimes as well as via the effect of increasing temperatures.

Solar capacity factors

Solar (Photovoltaic (PV)) capacity factors are computed from the cell efficiency times the incoming global tilted surface radiation (GTS), divided by the modules nominal power, following (Tantet, Stéfano, et al. 2019). We present here the main lines of the GTS derivation and cell efficiency computation.

To compute the hourly global tilted surface radiation GTS, we must first compute the hourly clearness index CI, which is the ratio of incoming global horizontal surface radiation GHS (i.e. the radiative power hitting a horizontal surface at ground level) to global horizontal extraterrestrial radiation GHET. GHET is obtained from the sun's position, that determines all angles of interest and varies as function of time, which we call s . GHS is a field from climate models and reanalyses. The hourly clearness index is then computed as

$$CI(t) = \frac{GHS(t)}{GHET(s(t))}. \quad (2.25)$$

Note that it can happen that climate models or reanalyses products used give a GHS variable which is not hourly. In this case, following (Tantet, Stéfano, et al. 2019), the hourly GHET is resampled to the coarser GHS time resolution. An average coarser clearness index is computed following Equation 2.25 and then upsampled to hourly frequency by assuming a constant value through the coarser time frequency. As an example, if GHS has a daily frequency, then the hourly CI will be constant throughout the day. This procedure has its importance since it determines whether or not processes such as changing cloud cover during the day will be accounted for or not (Tantet, Stéfano, et al. 2019).

Once the hourly clearness index has been computed, the tilted surface radiation GTS can be computed from it and the global horizontal surface radiation GHS. If GHS is not hourly then it is recomputed from the hourly clearness index and hourly extraterrestrial radiation using Equation 2.25. Following (Gueymard 2009; John A. Duffie and William A. Beckman 2013), the global tilted surface radiation is then computed as

$$GTS = \text{DirTS} + \text{DifTS} + \text{RefTS}, \quad (2.26)$$

where DirTS is the direct component of the GTS, DifTS is its diffuse component, and RefTS its reflected component. The direct component of the global tilted surface radiation DirTS is computed

as a function of the hourly global horizontal surface radiation GHS and clearness index CI as

$$\text{DirTS}(t) = \text{DirTF}(s(t), \mathbf{p}) \cdot [1 - \alpha(s(t), \text{CI}(t))] \cdot \text{GHS}(t), \quad (2.27)$$

where $\text{DirTF}(s(t), \mathbf{p})$ is the direct transposition factor, computed as a function of the sun's position at hour $s(t)$ and the panel characteristics (tilt, azimuth) \mathbf{p} that we assume to be constant through time. The coefficient $\alpha(s(t), \text{CI}(t))$ is the ratio of diffused horizontal surface radiation to global horizontal surface radiation and is a function of the sun's position and the hourly clearness index. It is computed following (Reindl, W. A. Beckman, and J. A. Duffie 1990a). Similarly the diffused component of the global tilted surface radiation is computed as the product of a diffuse transposition factor DifTF and the diffuse horizontal surface radiation to wit

$$\text{DifTS}(t) = \text{DifTF}(s(t), \mathbf{p}, \text{GHS}(t), \text{CI}(t)) \cdot \alpha(s(t), \text{CI}(t)) \cdot \text{GHS}(t), \quad (2.28)$$

where $\alpha(s(t), \text{CI}(t))$ was introduced in Equation 2.27 and $\text{DifTF}(s(t), \mathbf{p}, \text{GHS}(t), \text{CI}(t))$ is computed from the HDKR model (Reindl, W. A. Beckman, and J. A. Duffie 1990b)(John A. Duffie and William A. Beckman 2013, Equation 2.16.7). In turn, the reflected component is computed according to (Gueymard 2009) as

$$\text{RefTS}(t) = \text{RefTF}(a, \mathbf{p}) \cdot \text{GHS}(t), \quad (2.29)$$

where $\text{RefTF}(a, \mathbf{p})$ is the reflected transposition factor that depends on the albedo a and the panels characteristics (tilt and orientation). In our study the albedo is considered to be constant through time and geographical location, and equal to 0.2.

Once the hourly global tilted surface radiation GTS is computed, the hourly solar generation is computed from

$$Q_{\text{PV}}(t) = \epsilon \cdot \alpha(t) \cdot \text{GTS}(t) \cdot n \cdot a, \quad (2.30)$$

where ϵ is the circuit efficiency, n the number of modules in the array, a the area per module, and α is the cell efficiency which depends on the weather variables wind speed u and temperature T following (John A. Duffie and William A. Beckman 2013, Chapter 23.3)

$$\alpha(t) = \alpha_{\text{REF}} \cdot (1 - \theta \cdot (T_{\text{cell}}(t) - T_{\text{REF}})), \quad (2.31)$$

where α_{REF} is the cell efficiency at reference temperature $T_{\text{REF}} = 25^\circ\text{C}$, $\theta = 0.004 \text{ K}^{-1}$ is the thermal loss and T_{cell} is the hourly cell temperature defined as

$$T_{\text{cell}}(t) = T(t) + \frac{\text{GTS}(t)}{\text{GTS}_{\text{NOCT}}} \cdot (T_{\text{cell,NOCT}} - T_{\text{NOCT}}) \cdot \frac{9.5}{15.7 + 3.8u(t)}, \quad (2.32)$$

where $\text{GTS}_{\text{NOCT}} = 800 \text{ W m}^{-2}$ is the GTS at **Nominal Operating Cell Temperature (NOCT)**, $T_{\text{cell,NOCT}} = 46^\circ\text{C}$ is the cell temperature at **NOCT**, $T_{\text{NOCT}} = 20^\circ\text{C}$ is the temperature at **NOCT**, and $u(t)$ is the time dependent wind speed. The latter is set to a constant value of $u = 1 \text{ m s}^{-1}$ so that the influence of wind speed on cell efficiency and subsequent generation is not accounted for in our model. We can further notice from Equations 2.31 and 2.32 that the cell efficiency decreases with increasing temperature (and increasing GTS). The hourly capacity factor H_{PV} is then computed by dividing the array generation by the array nominal power to wit

$$H_{\text{PV}}(t) = \epsilon \cdot \frac{\alpha(T(t)) \cdot \text{GTS}(t) \cdot a}{q_{\text{PV}}^*}, \quad (2.33)$$

where $q_{\text{PV}}^* = 250 \text{ W m}^{-2}$ is the nominal power per module. Note that the value of the circuit efficiency (Equation 2.33) does not matter in our case because of the subsequent bias correction step (Tantet, Stéfanon, et al. 2019).

We thus obtain hourly solar PV capacity factors at every weather variables grid point, that we

then average at the level of french administrative regions for bias correction. In Chapter 5, PV capacity factors will be impacted by climate change via the effect of increasing temperatures and potential changes in global horizontal surface radiation (GHS).

2.2.2 Capacity factors bias correction

Regional average capacity factors are then bias corrected following the procedure described in (Tantet, Stéfanon, et al. 2019) by using regional observed wind and solar capacity factors training data from the french TSO RTE. The data is freely available at <https://opendata.reseaux-energies.fr/>. We hereby briefly describe the methodology.

The computed VRE capacity factors at each grid point are spatially averaged at the level of french administrative regions. This supposes that in our power system model, VREs are installed uniformly over each region, and not in the most favorable or simply possible locations. In turn, this allows for the bias correction of the computed regional capacity factors against observed regional capacity factor data. This is motivated by the fact that our generation models are simplistic in the sense that they do not account for technological diversification in the PV panels and wind turbines fleet, nor do they account for possible down time due to operation and maintenance activities. Bias correction also somehow corrects for the spatially uniform distribution of generation capacities hypothesis. We however need to assume that the bias between simulated and observed capacity factors is stationary, which is a hypothesis that can be discussed (Bakker, Van den Hurk, and Coelingh 2013; Tantet, Stéfanon, et al. 2019).

Bias correction is conducted using a linear regression with ridge regularization, using cross-validation to estimate the prediction error and conducting a grid search to estimate the best regularization parameter. The training data covers the 2014-2019 period.

2.3 Weather and climate change data

2.3.1 Reanalysis data

We use reanalysis data to train our demand model (see Section 2.1), calibrate the data from climate models that are used in Chapter 5 (see below), and run our numerical experiments under present climatic conditions in Chapter 3. Two data sources are used: MERRA-2 (Bosilovich, Lucchesi, and Suarez 2016; Gelaro et al. 2017) over the 2010 – 2020 period, and ERA5 (Hersbach et al. 2020) over the 1980 – 2020 period. Further information on both datasets is also available at <https://gmao.gsfc.nasa.gov/reanalysis/MERRA-2/> for MERRA-2 and <https://confluence.ecmwf.int/display/CKB/ERA5> for ERA5. We summarize in Tables 2.4 and 2.5 the data we extract from these reanalyses as well as the purpose they serve in our study, for MERRA-2 and ERA5 respectively.

Variable	Name	Data collection	Time resolution	Spatial resolution	Application
Surface temperature	TLML	tavg1_2d_flux_Nx	hourly	(0.5° _{lat} , 0.625° _{lon})	PV Demand
Surface radiation	SWGDN	tavg1_2d_rad_Nx	hourly	(0.5° _{lat} , 0.625° _{lon})	PV
Zonal wind	U10M	tavg1_2d_slv_Nx	hourly	(0.5° _{lat} , 0.625° _{lon})	Wind
Meridional wind	V10M	tavg1_2d_slv_Nx	hourly	(0.5° _{lat} , 0.625° _{lon})	Wind

Table 2.4. MERRA-2 reanalysis data and applications in this study.

Variable	Short name	Time resolution	Spatial resolution	Application
Surface temperature	t2m	hourly	31 km (0.281 25°)	Calibration
Surface radiation	msdwsrf	hourly	31 km (0.281 25°)	Calibration
Zonal wind	u100	hourly	31 km (0.281 25°)	Calibration
Meridional wind	v100	hourly	31 km (0.281 25°)	Calibration

Table 2.5. ERA5 reanalysis data and applications in this study.

2.3.2 Climate change data

In Chapter 5 we study the effect of climate change on the optimal VRE investments by using climate change projections from state of the art Global Climate Models (GCMs) and Regional Climate Models (RCMs) forced with widely used emission scenarios (we use CMIP-5 Representative Concentration Pathways (RCPs) (Moss et al. 2010)). We present here briefly the models that we select for our analysis, the data we extract from the modeling exercises, and the data post-processing steps that we needed to apply to get ready-to-use data fit for our purposes.

Model and data selection

We use climate data from the EURO-CORDEX initiative¹ (Jacob et al. 2014; Coppola et al. 2021), which is based on diverse RCMs driven by CMIP-5 GCMs (K. E. Taylor, Stouffer, and Meehl 2012) forced with the same CMIP-5 RCPs (Moss et al. 2010) for climate change projections. We use six different (GCM, RCM) model pairs available from the initiative, which we summarize in Table 2.6, together with the associated experiment and period covered. The references for each GCM and RCM are given in Tables 2.7 and 2.8. The reader is further referred to (Kotlarski et al. 2014; Vautard et al. 2021) for a review of the EURO-CORDEX RCMs, the latter including four of our six considered model pairs.

¹<https://euro-cordex.net/index.php.en>

We select four weather variables for the different applications considered in the study: demand and VRE capacity factors time series computation. These variables are reported in Table 2.9 together with their time and spatial resolution.

ID	Driving GCM	Variant	RCM	Experiment	Period
0	ICHEC-EC-EARTH	r1i1p1	COSMO-crCLIM	historical RCP 8.5	1975 – 2005 2020 – 2099
1	MOHC-HadGEM2-ES	r1i1p1	COSMO-crCLIM	historical RCP 8.5	1975 – 2005 2020 – 2099
2	MPI-M-MPI-ESM-LR	r3i1p1	COSMO-crCLIM	historical RCP 8.5	1975 – 2005 2020 – 2099
3	CNRM-CERFACS-CNRM-CM5	r1i1p1	COSMO-crCLIM	historical RCP 8.5	1975 – 2005 2020 – 2099
4	CNRM-CERFACS-CNRM-CM5	r1i1p1	ALADIN63	historical RCP 8.5	1975 – 2005 2020 – 2099
5	MOHC-HadGEM2-ES	r1i1p1	ALADIN63	historical RCP 8.5	1975 – 2005 2020 – 2099

Table 2.6. EURO-CORDEX (GCM, RCM) model pairs considered in the study.

Driving GCM	Version	References
ICHEC-EC-EARTH	2	(Wilco Hazeleger et al. 2010; W. Hazeleger et al. 2012)
MOHC-HadGEM2-ES	2	(Collins et al. 2011)
MPI-M-MPI-ESM-LR	-	(Gutjahr et al. 2019; Mauritsen et al. 2019)
CNRM-CERFACS-CNRM-CM5	5	(Voldoire et al. 2013)

Table 2.7. GCMs considered in the study. More informations on the models can be found at <https://ec-earth.org/> for ICHEC-EC-EARTH, <https://www.metoffice.gov.uk/> for MOHC-HadGEM2-ES, <https://mpimet.mpg.de/en/homepage> for MPI-M-MPI-ESM-LR and <http://www.umr-cnrm.fr/> for CNRM-CERFACS-CNRM-CM5.

RCM	Version	References
COSMO-crCLIM	4	(Leutwyler et al. 2016; Sørland et al. 2021)
ALADIN63	6	(Daniel et al. 2019; Nabat et al. 2020)

Table 2.8. RCMs considered in the study. More informations on COSMO-crCLIM can be found at <http://www.cosmo-model.org/content/default.htm>, while more informations on ALADIN63 can be found at <http://www.umr-cnrm.fr/>.

Data curation

A data curation step is necessary for some of the data obtained from the models to be fit for use. These are summarized in Table 2.10 for each (GCM, RCM) pair. The calendar conversion from 360 to 365/366 format for model pair 1 is done by splitting each 360 days year in four periods and then adding one day at the end of each period, except the last one where three days are added. Each day added takes the last value of the previous day throughout the day. If this method is fine for daily average values, it is more problematic for subdaily time resolution values as in our case. Further methodological developments should take this point in consideration. In the meantime, we should pay close attention to results obtained from model pair 1 (MOHC-HadGEM2-ES + COSMO-crCLIM).

The cutoff values procedure that needs to be applied for model pair 2 consists in identifying those EURO-CORDEX values whose magnitude is higher than 10 times the maximum ERA5 reanalysis value. Those values are then interpolated via linear interpolation when possible, and otherwise taken

Variable	Short name	Time resolution	Spatial resolution	Application
Surface temperature	tas	3h	0.11° (\approx 12 km)	Wind, PV, demand
Surface radiation	rsds	3h	0.11° (\approx 12 km)	PV
Zonal wind	ua100m	1h	0.11° (\approx 12 km)	Wind
Meridional wind	va100m	1h	0.11° (\approx 12 km)	Wind

Table 2.9. EURO-CORDEX variables considered in the study. Wind, PV and demand applications correspond to wind capacity factors, PV capacity factors and electricity demand time series computation.

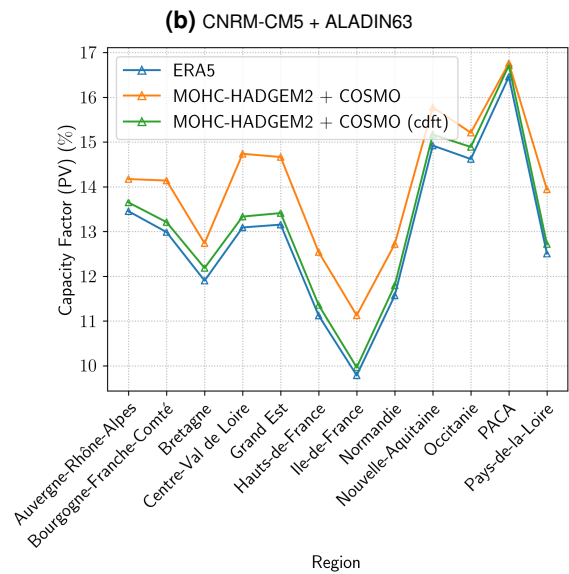
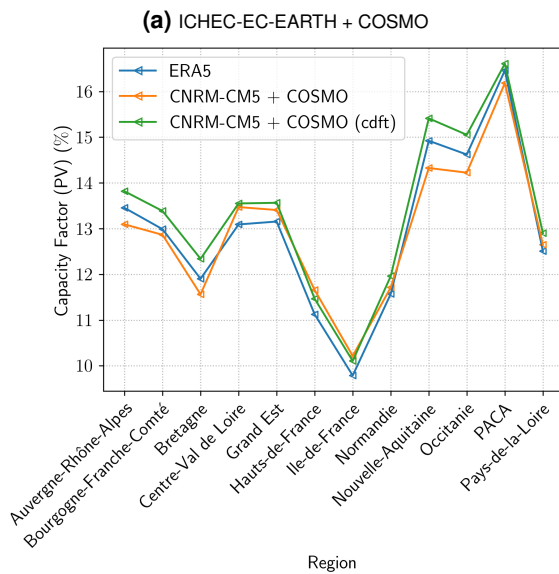
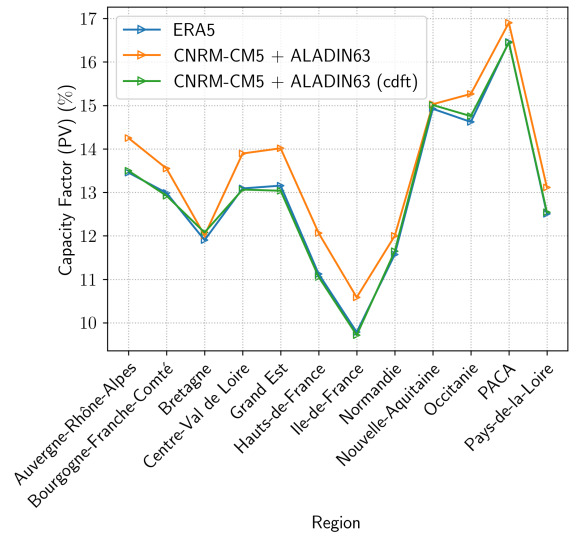
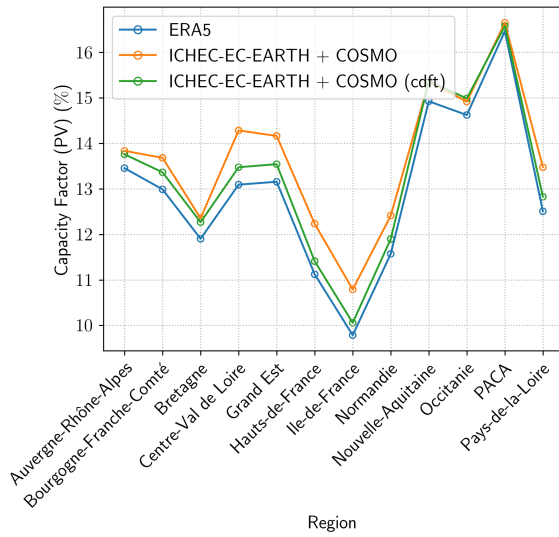
as equal to closest previous the non-aberrant value when it exists, or equal to the closest next non-aberrant value otherwise. It is not excluded that such aberrant values still remain in the final data as the cutoff procedure is only applied during the calibration step and thus applies only to historical data (1975 – 2005). Further methodological developments could focus on consistently checking the data for aberrant values and systematically applying a cutoff value procedure to the data. In the meantime, close attention should be paid to results potentially influenced by aberrant meridional wind field values (e.g. wind capacity factors) in the case of model pair 2 (MPI-M-MPI-ESM-LR + COSMO-crCLIM) for the RCP 8.5 experiment.

(GCM, RCM) pair ID	Issue	Solution
0	-	-
1	calendar is 360 days	convert to 365/366 days calendar
	downloaded va100m file for year 2093 cannot be read	replace it with year 2089
	downloaded va100m file for year 2094 cannot be read	replace it with year 2090
	downloaded va100m file for year 2095 cannot be read	replace it with year 2091
	downloaded va100m file for year 2096 cannot be read	replace it with year 2092
	downloaded va100m file for year 2097 cannot be read	replace it with year 2089
	downloaded va100m file for year 2098 cannot be read	replace it with year 2090
	year 2099 missing for ua100m, va100m, tas, rsds	replace it with year 2095 or 2091
2	downloaded va100m file for year 2099 cannot be read	replace it with year 2098
	va100m field show absurdly high magnitude values	set a cutoff value
3	downloaded ua100m file for year 2070 cannot be read	replace it with year 2066
	downloaded ua100m file for year 2092 cannot be read	replace it with year 2088
4	year 2047 missing for ua100m, va100m, tas, rsds	replace it with year 2046
5	downloaded ua100m file for year 2097 cannot be read	replace it with year 2093
	downloaded ua100m file for year 2098 cannot be read	replace it with year 2094
	downloaded ua100m file for year 2099 cannot be read	replace it with year 2095

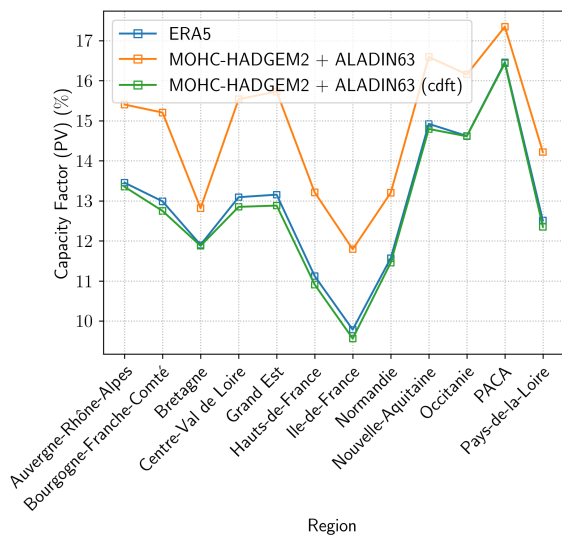
Table 2.10. Data curation steps needed in the study.

Data calibration

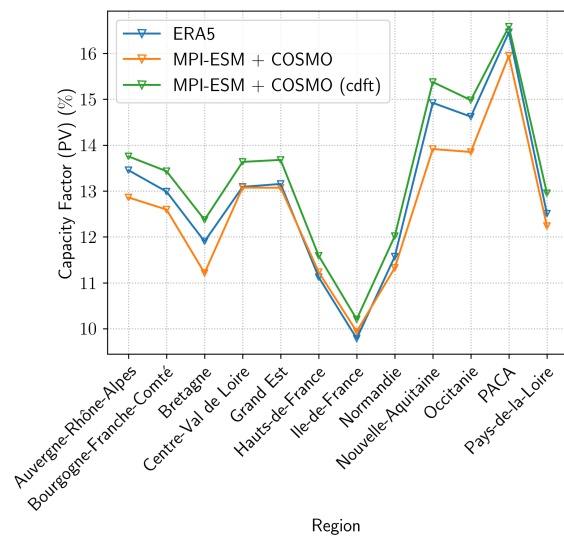
We calibrate the EURO-CORDEX models data to the ERA5 reanalysis using the CDF-t algorithm (Michelangeli, Vrac, and Loukos 2009; Lavaysse et al. 2012; Vrac et al. 2012; Vigaud, Vrac, and Caballero 2013) implemented in (Robin, Smith, and Bourgault 2023). As the ERA5 and EURO-CORDEX models grids do not necessarily match, we first interpolate the ERA5 fields at the EURO-CORDEX models grid points, using 2D linear (bilinear) interpolation. Calibration is then carried at every EURO-CORDEX model grid point using the interpolated ERA5 data. We show the effects of data calibration on VRE capacity factors and the load duration curve for each model of the EURO-CORDEX ensemble in Figures 2.12, 2.13 and 2.14 for PV capacity factors, wind capacity factors and the load duration curve respectively.



Cont.

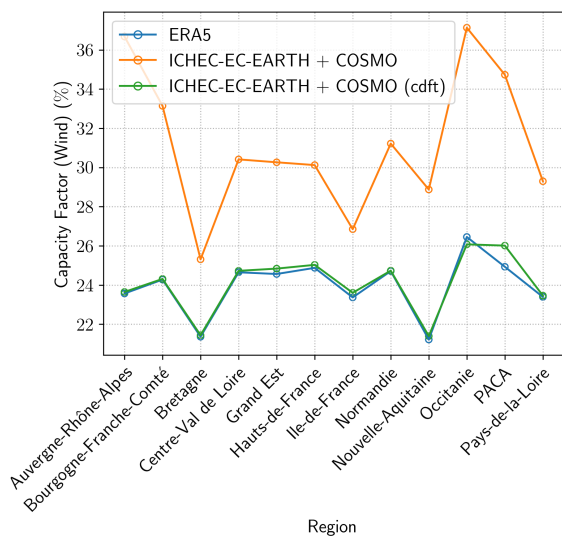


(e) MOHC-HADGEM2 + ALADIN63

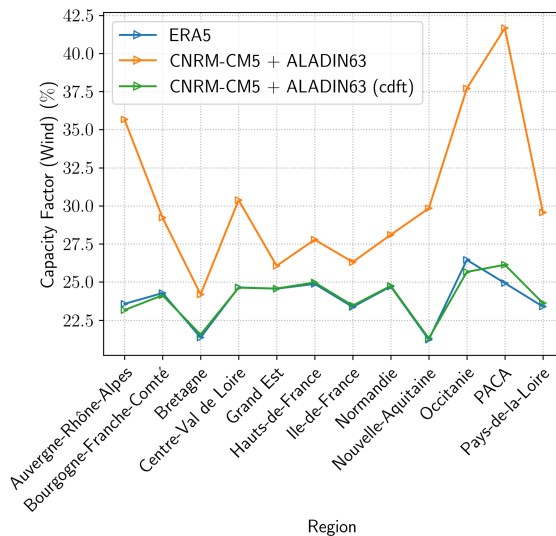


(f) MPI-ESM + COSMO

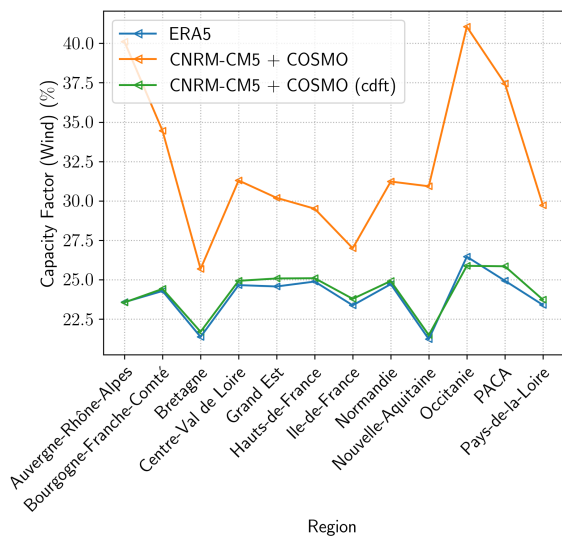
Figure 2.12. Effect of climate model data calibration on PV capacity factors.



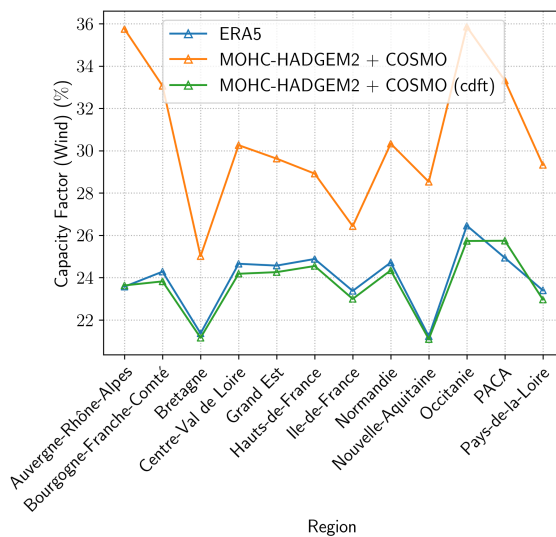
(a) ICHEC-EC-EARTH + COSMO



(b) CNRM-CM5 + ALADIN63

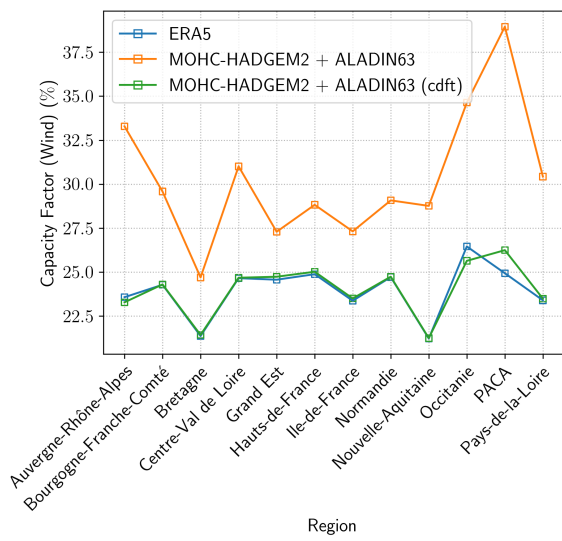


(c) CNRM-CM5 + COSMO

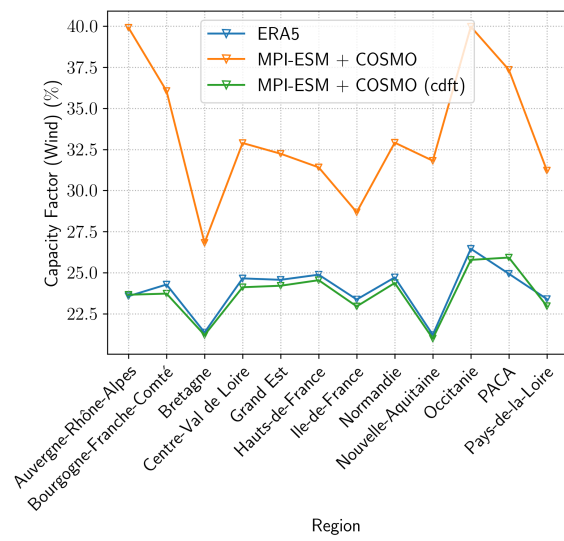


(d) MOHC-HADGEM2 + COSMO

Cont.



(e) MOHC-HADGEM2 + ALADIN63



(f) MPI-ESM + COSMO

Figure 2.13. Effect of climate model data calibration on wind capacity factors.

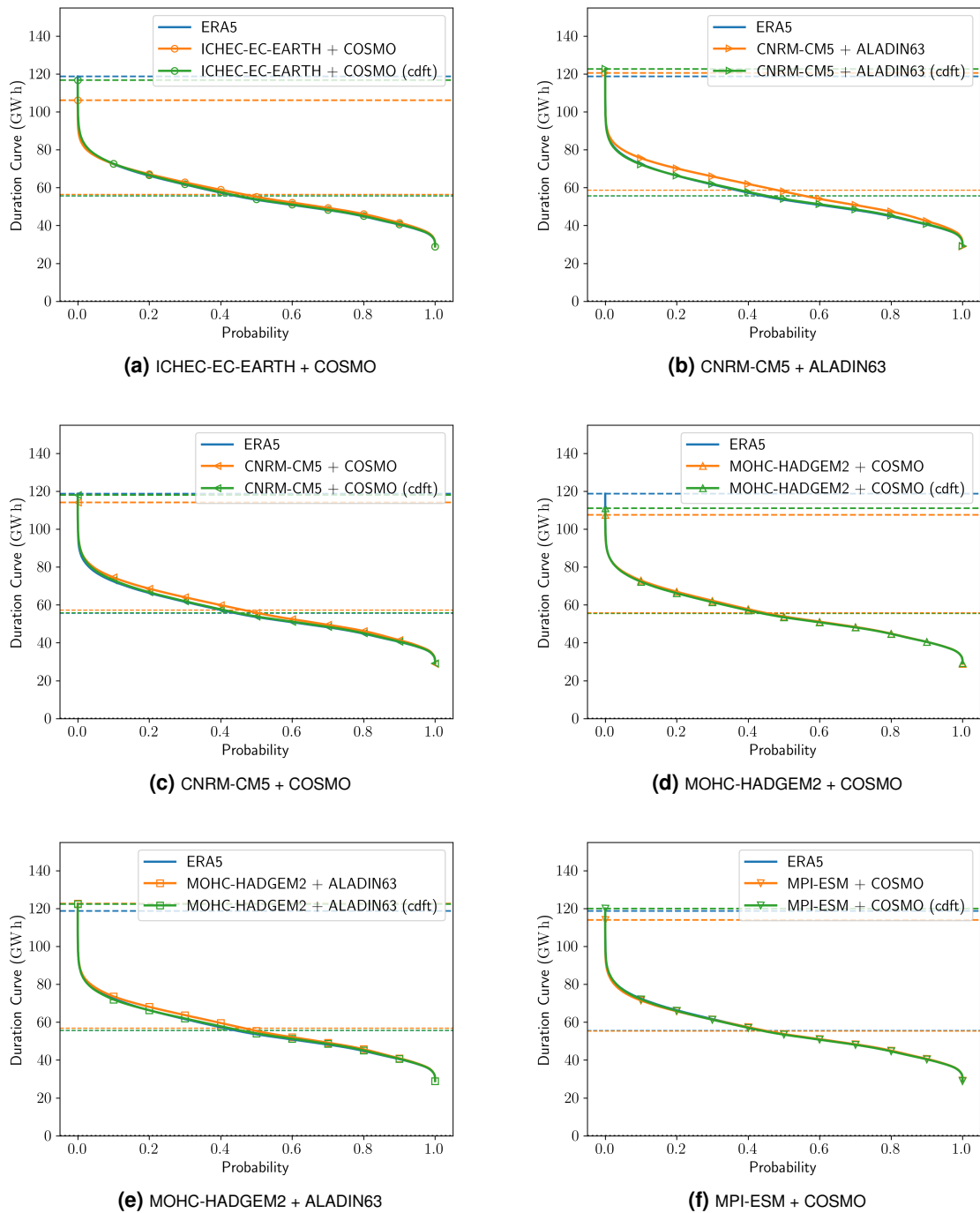


Figure 2.14. Effect of climate model data calibration on the load duration curve.

2.4 Power system model

2.4.1 Literature review and motivation

Energy system models were developed in the 70s-80s to support policy making in the energy sector, see e.g. (Fishbone and Abilock 1981). Since then, advances in computing power and sustained interest in the topic have seen the landscape of energy system modelling grow in numbers and capability (see e.g. (Fodstad et al. 2022) and the numerous reviews cited therein). As such, a variety of energy systems models exist, that can be classified according to their purpose and scope (Grubb et al. 1993; Pfenninger, Hawkes, and Keirstead 2014; Després, Hadjsaid, et al. 2015; L. M. H. Hall and Buckley 2016; Ringkjøb, Haugan, and Solbrekke 2018; Prina et al. 2020). Such classifications are mainly driven by the aim of providing assistance in the model selection process to answer specific research questions. They can also prove useful in identifying gaps and challenges in modelling capability to address a specific problem.

The first and maybe most used classification axis is the analytical approach of models, which distinguishes top-down, bottom-up and hybrid paradigms, see e.g. (Grubb et al. 1993)(Després, Hadjsaid, et al. 2015). This is a fundamental distinction in the modelling approach between top-down models that aim at capturing the interplay of energy system variables (supply, demand, etc.) with other sectors of the economy or typical economic quantities (e.g. GDP) versus bottom-up models which model technico-economical systems and aim at deriving the quantities of a system and their interplay from the modelling of their parts (e.g. the supply of energy will be derived from a set of power plants with a given operational schedule and the demand from a set of buildings whose demand depends on air temperature). Bottom-up models typically only represent the energy sector whereas top-down models may represent the interplay between different sectors of the economy. As such an analytical approach making the most of the two paradigms was developed and coined as hybrid modelling (Grubb et al. 1993; Strachan and Kannan 2008; Després, Hadjsaid, et al. 2015). Examples of models falling in each category can be found in either of the precited classification reviews. Pfenninger, Hawkes, and Keirstead (2014) classify energy system models in four categories, namely (i) energy system optimization models, (ii) energy systems simulation models, (iii) power systems and electricity market models and (iv) qualitative and mixed-methods scenarios. Two axis of classification are also identified: the first axis consisting in the predictive vs. normative paradigm, which reflects the dichotomy between simulation and optimization models, and the second axis consisting in the planning vs. operational dichotomy, the latter two corresponding to different yet not irreconcilable modelling paradigms. Widely used bottom-up energy system optimization models are e.g. the MARKAL/TIMES (Fishbone and Abilock 1981) developed by the IEA ETSAP², MESSAGE (Schratzenholzer 1981) developed by the IIASA³ or OSeMOSYS (Howells et al. 2011) models or family of models. Energy system simulation models differ fundamentally from the former in their purpose, in that they are meant to be predictive of the future state of the energy system, rather than exploring potential future states. Examples of such models include NEMS (Gabriel, Kydes, and Whitman 2001), PRIMES, developed by the E3M team⁴ or LEAP, developed by the Stockholm Environment Institute⁵. Power systems and electricity market models, as the name suggests, focus on the power system part of the energy system. The reader is referred to (Foley et al. 2010) for a review of such models as of 2010. Finally, qualitative and mixed-method scenarios encompass the type of approaches on the other hand of the quantitative-qualitative spectrum. (Després, Hadjsaid, et al. 2015) review power-sector bottom-up models that deal with the integration of variable renewables. They focus on the models PRIMES, SWITCH, REEDS, E2M2 and ELMOD. They highlight the dichotomy between these models that can give a high level of detail of the power system but fail at representing other parts of the energy system, and long-term energy system models, which lack the temporal and

²<https://iea-etsap.org/>

³<https://iiasa.ac.at/models-tools-data/messageix>

⁴<http://www.e3mlab.com/e3mlab/index.php>

⁵<https://leap.sei.org/>

spatial resolution to rigorously account for VRE integration in their studies. The latter are discriminated depending on their computational approach (simulation like MEDEE, POLES, PRIMES, WEM, Prometheus and LEAP, vs. optimization like EFOM/MARKAL/TIMES/ETSAP-TIAM, MESSAGE or OSeMOSYS), their modelling paradigm (top-down vs. bottom-up or hybrid) and introduce the categories of partial/general equilibrium models (Edmond-Reilly-Barns/SGM/Phoenix, GREEN, EPPA, MARKAL-MACRO/MARKAL-EPPA, NEMS, AMIGA, CIMS, IMACLIM, NEMESIS, which are all top-down or hybrid models with a simulation approach — except for the MARKAL family), integrated assessment models (DICE, MERGE, MESSAGE-MACRO, IMAGE, MiniCAM/GCAM, WITCH, DNE21, MIND/ReMIND, AIM/CGE which are all hybrid or top-down simulation or optimization models) and economy-energy-environment models (GEM-E3, GEMINI-E3, E3ME/E3MG, Three-ME, which are all top-down simulation models)⁶. L. M. H. Hall and Buckley (2016) propose a classification of models used in the UK energy modelling community, based on their purpose and structure (general and specific purpose of the model in plain words, i.e. forecasting/exploring/backcasting and energy demand/supply, environmental impacts, etc., model structure as in its assumptions, i.e. description of non-energy sectors, end-uses, etc., geographical coverage, sectoral coverage, time horizon and time step), their technological detail (renewable technologies, storage, demand sectors, types of costs), and their mathematical description (analytical approach, i.e. top-down, bottom-up and hybrid, methodology, i.e. simulation, optimization, etc., mathematical approach, i.e. linear programming, etc., and the data requirements). 22 energy system models are reviewed and categorized with this classification. Ringkjøb, Haugan, and Solbrekke (2018) review 75 energy and electricity system models used to study systems with large shares of VREs. They use the same classification paradigm as in (Després, Hadjsaid, et al. 2015), namely the model general logic (purpose, e.g. long-term investment vs. operation, approach, i.e. the typical top-down vs. bottom-up dichotomy, and methodology, i.e. optimization vs. simulation), the spatiotemporal resolution and the level of technico-economical detail. Finally, Prina et al. (2020) emphasize the distinction between top-down, hybrid and bottom-up models and give examples for each category. Following (Després, Hadjsaid, et al. 2015), bottom-up models are then split in static or short-term models vs. long-term models. Note that this distinction does not relate to the faculty of representing investment in capacity vs. operation of the energy system. Static or “short-term” models can solve for capacity expansion, but to the contrary of “long-term” models, do so in a once-and-for-all fashion, i.e. the investment trajectories are not represented. They thus have by definition perfect foresight, while long-term models might work under the myopic planner paradigm, i.e. have limited or no information about the future. Bottom-up models are then classified according to the energy sectors covered (specific vs. all sectors), geographical coverage (single vs. multi-node), time resolution, methodology (simulation, dispatch optimization, investment optimization) and programming technique (linear, etc.).

Challenges in energy system modelling evolved with the scientific questions tackled by modellers to support policymaking. As an example, traditional energy system models as developed until the 2000s-10s were unable to address the question of the (un)feasibility of 100% or high-VRE penetration energy systems, putting forward key challenges to be addressed (D. Connolly, H. Lund, B. V. Mathiesen, and M. Leahy 2010; Pfenninger, Hawkes, and Keirstead 2014). This led to the development of models such as in (Fripp 2012; Haller, Ludig, and Bauer 2012; Pfluger and Wietschel 2012). Ringkjøb, Haugan, and Solbrekke (2018) identified four key challenges of energy system modelling: (i) the representation of variability, (ii) consumer participation, electrification and sector coupling, (iii) impacts and links beyond the energy system and (iv) validation and transparency. The first challenge (i) is mainly presented under the scope of the temporal resolution challenge, i.e. how to get sufficient time granularity to represent well VRE generation time series in the models. Challenge (ii) is related to future system transformations and how they can be incorporated in the modelling frameworks, while challenge (iii) highlights the need for taking into account other sectors (e.g. life-cycle analysis) to draw more robust analysis on the general impacts of this or that energy system configuration. Finally challenge (iv) calls for increased openness in energy system modelling. Similarly, Prina et al.

⁶This review was conducted within the scope of a thesis that ended-up in the coupling of the long-term energy system model POLES with the power system model EUCAD (Després 2015).

(2020) identify five of them, four of which deal with the issue of resolution: either in time, in space, in techno-economical detail or in sector coupling, all of these related to the study of high shares of VRE integration. The fifth challenge, as already emphasized by (Ringkjøb, Haugan, and Solbrekke 2018), relates to model openness and transparency. On top of the time and space resolution challenge, Fodstad et al. (2022) point out the need to account for sectoral coupling (i.e. considering multi-energy systems), the rigorous treatment of uncertainty (as already mentioned in (Prina et al. 2020)) and the integration of social aspects (socio-technical transitions dynamics, behavioral models, etc.) into energy system modelling.

A central point of our study is to address the issue of high-VREs optimal mix planning while ensuring the adequacy constraint at all times (i.e. proper system operation), with a detailed description of VREs installed capacities and generation. Of particular interest to us is thus the temporal and spatial resolution challenge, which is intimately related to the study of the introduction of high levels of VREs. A high temporal resolution (typically hourly) is more important than technico-economical detail (Pina, Silva, and Ferrão 2011; Haydt et al. 2011) or model complexity regarding operational constraints (such as flexibility, stability or sector coupling) (Poncelet, Delarue, Six, et al. 2016; Heliöstö et al. 2019), when dealing with the capacity investment decision issue. If the number of available models is large in general, tackling a specific research question can quickly narrow down the list of available options. For example, among the list of 75 models in (Ringkjøb, Haugan, and Solbrekke 2018), only 30 are able to conduct coupled investment and operation of the electricity system, and 21 out of these 30 have hourly or sub-hourly time resolution. Once all technical factors of model scope and capabilities are taken into account, model choice then boils down to the stringent need for practicality of use and human resources availability, which are greatly enhanced if the model relies on an open science paradigm (Pfenninger, DeCarolis, et al. 2017). The greatest discriminant factor is then indeed the accessibility of the models to verify fitness for purpose: some models have poor documentation or contact information, while others are proprietary or rely on proprietary software (the most common being GAMS and proprietary solvers like CPLEX). Aside of these practical considerations, proceeding to such a model landscape analysis allows us to point out the strengths and weaknesses of available tools and to better understand the strengths and weaknesses of our own. We thus mention some tools whose a priori scope and capabilities would have made them tentative candidates to tackle the research questions addressed in this thesis. Those include, non exhaustively, Calliope (Pfenninger and Pickering 2018), PyPSA (Tom Brown, Hörsch, and D. Schlachtberger 2018), Eoles (Shirizadeh and Quirion 2022) or Switch (Johnston et al. 2019). We are however particularly interested in taking into account long time series (typically 20 to 30 years at hourly resolution) of weather dependent variables like electricity demand and VRE capacity factors, which allows for the rigorous study of given climatic conditions (Bloomfield, D. J. Brayshaw, Shaffrey, et al. 2016; Pfenninger 2017; Iain Staffell and Pfenninger 2018; Zeyringer et al. 2018), which in turn allows the incorporation of climate change impacts.

We adapt to this end the bottom-up, linear programming, power system model E4CLIM (Tantet, Stéfano, et al. 2019) in its most recent version (Tantet and Drobinski 2021). The model is a simple description of a power system where conventional dispatchable producers are treated as an aggregate and a variable share of PV and wind energy can be introduced. By simple we mean that the model doesn't represent a state of the art energy system with a diversity of generation technologies, accounting for operational constraints and having a high level of technico-economic detail. Instead we insert sufficient complexity for non-trivial economic impacts of VRE integration to be evidenced while keeping a problem that is mathematically conveniently tractable. This allows us to study the problem of capacity planning ensuring the adequacy constraint at all times at an hourly level⁷. The correlation of VRE generation and demand is represented at an hourly level as well. Finally, the model is capable of handling long time series (20-30 years) of demand and VRE capacity factors to smooth out low frequency climate variability and have time series representative of average climatic conditions. Spatial

⁷Implementing the adequacy constraint in capacity expansion bottom-up models is not straightforward. It is usually addressed via the Planning Reserve Margin (PRM), i.e. the installed capacity must equal the peak capacity plus the PRM, with a PRM determined in advance. However this method sometimes fails, see e.g. (Mertens et al. 2021).

resolution is of particular importance in capacity expansion decisions modelling (Krishnan and Cole 2016). The model has the advantage of representing VRE producers at a medium spatial scale (regional level, i.e. typically $250 \text{ km} \times 250 \text{ km}$) although the entire energy system is represented assuming the copper plate hypothesis, which is equivalent to a single node. As such, no network constraints are accounted for. Furthermore, our model does not incorporate operational constraints: start-up or ramping costs as well as any network stability constraints are not accounted for. Dispatchable producers are supposed to be able to instantaneously react to a change in demand and the network is supposed to remain stable no matter the penetration of grid-following generation (VRE generation in our case). Although this simplification might have an impact on model results (Poncelet, Delarue, and D'haeseleer 2020), it greatly simplifies the mathematical complexity of the problem at hand. Then, the representation of dispatchable producers is purposely simplified, to consider a single aggregate producer. If this still allows for the implementation of a variable cost function that mimicks merit-order dispatching, this simplified representation comes at the cost of not fully resolving the fixed costs of the dispatchable production. The model mathematical formulation relies on stochastic programming to account for the stochasticity of the input variables, demand and VRE capacity factors. It is however deterministic regarding other input variables, and in particular regarding costs hypothesis (which are supposed to be static, i.e. remain constant through the optimization horizon). Finally, the model focuses only on the power sector and leaves aside any sector coupling. No market mechanisms are taken into account either, which is equivalent to consider a central planner problem (Créti and Fontini 2019, Chapter 9). We furthermore neglect storage and import/export of electricity to/from the area of study. No feasibility constraints other than that explicitly mentioned are considered (economic, technical, political, social, environmental, etc.). We can see that if the model is well-suited to rigorously take into account weather-related time series and the problem of VRE capacity expansion under the hourly adequacy constraint, this is at the expense of some limitations. These limitations do not however impair our subsequent analyses. Following the “modelling for insight” philosophy (Huntington, J. P. Weyant, and Sweeney 1982), our focus is on producing sensitivity studies which could evidence non-trivial generalizable effects of VRE integration coupled to socioeconomic and climate change, rather than trying to derive plausible generation mixes, or prove the feasibility of high-VRE energy systems⁸. Last but not least, the model and the data are open-source and fully accessible upon request, to improve the transparency of the modelling exercise (Cao et al. 2016; Ringkjøb, Haugan, and Solbrenke 2018; Prina et al. 2020).

2.4.2 Problem statement

Stochasticity, cyclostationarity and convergence

In our setup, the electricity demand and VRE capacity factors are stochastic processes, because they depend on weather variables that are themselves stochastic processes following a given probability distribution related to the climatic conditions. These stochastic processes have however the particular characteristic to exhibit some cyclicity. Indeed we expect the value of the demand to be more or less the same every year on some hour of the year in winter, compared to another given hour of the year in summer, simply because temperature follows a seasonal pattern. Similarly, solar irradiance and wind speed are expected to exhibit a similar cyclicity because of the seasons. These cyclic stochastic processes are supposed to be cyclostationary processes (Gardner, Napolitano, and Paura 2006), which require a particular mathematical setup to be dealt with, presented in detail in (Tantet and Drobinski 2021, Appendix A).

Furthermore, on top of the cyclostationarity hypothesis, we must suppose that correlations over the years for a given hour decay fast enough. This is not completely true for the climate system, and we must thus verify numerically that the sample means converge to the expectation value for

⁸This follows the early criticism on the fitness for purpose of energy system models and the fact that energy system models cannot be properly validated by a physical measure, see e.g. (Pfenninger, Hawkes, and Keirstead 2014) and references therein or (J. Beckman, Hertel, and Tyner 2011).

the number of years N present in the data. This is, we must verify that for a cyclostationary process $(X(t))_{t \in \mathbb{T}}$, the yearly average of the expectation over the outcomes ω ($\omega \in \Omega$) of a sample $(X(t, \omega))_{t \in \mathbb{T}_0}$ equals the sample average, i.e.

$$\mathbb{E} \left(\frac{1}{T_0} \sum_{t=0}^{T_0-1} X(t, \omega) \right) = \frac{1}{NT_0} \sum_{t=t_0}^{t_0+NT_0-1} X(t). \quad (2.34)$$

Tantet and Drobinski (2021) show that convergence is satisfactory for ten years of data, which we will use in the following.

Dispatchable producers

Dispatchable producers are treated as a single aggregated producer with maximum generation capacity x_{Di} . This producer is an idealized producer that can generate power instantaneously when needed at no extra costs, i.e. it has no start-up or ramping costs, nor operational constraints. Its generation is thus a non-negative (no storage) cyclostationary process $(G_{\text{Di}}(t))_{t \in \mathbb{T}}$. We further suppose in this work that the maximum capacity x_{Di} of this dispatchable producer is always in excess compared to the demand to be served. This strong hypothesis is necessary to safely discard the dispatchable production fixed costs from the following analyses. We however anticipate that this hypothesis will have a strong impact on the model results, which is something that will be discussed in every subsequent analysis. In particular, it implies that the adequacy constraint will always be verified. Anticipating that introducing VRE will reduce system total costs, we are thus not so much solving for the problem of optimal mix dimensioning than solving for the problem of optimal VRE mix dimensioning to satisfy the adequacy constraint at the least cost.

We further suppose that dispatchable generation comes at a variable cost of production VC_{Di} given by

$$\text{VC}_{\text{Di}} := \alpha q^2, \quad (2.35)$$

where q is the generation in MWh, and α is the Dispatchable Variable-Cost Coefficient (DVCC) in € MWh^{-2} . The motivation for this form of the dispatchable variable costs is twofold: it has the right mathematical properties (Tantet and Drobinski 2021) at the same time as it mimicks merit order dispatching. Even if only one dispatchable producer is taken into account, the cost of dispatchable generation will increase as the generation q increases. The generation to meet peak demand thus comes at a higher cost than that of meeting base demand. The cost of no generation is zero. The variable costs of the dispatchable generation depend on the DVCC. This parameter, that can be assimilated to a carbon tax, can be tuned to increase or decrease the variable costs of the dispatchable generation, which will in turn determine the optimal levels of VRE penetration.

VRE producers

We then introduce m VRE producers indexed by $i \in \{0, \dots, m-1\}$ into the mix. Two technologies distributed across a set of geographical areas are considered: onshore wind and solar PV. Each producer i is thus referred to as a technology-region.

In the same way as for dispatchable producers a cost function for VRE producers is designed. VRE producers are supposed to incur no variable costs and thus only fixed costs are taken into account. This is motivated by the fact that PV or wind-onshore plants are capital intensive assets that do not however incur any costs related to fuel utilization, nor much operation and maintenance costs. It is also common practice in the literature to count discounted operation and maintenance costs as fixed costs (Tsiropoulos, Zucker, and Tarvydas 2018). The cost function of a single VRE producer is thus constant in time and entirely determined by its hourly rental cost hRC_i (€ GW^{-1}) and installed capacity x_i (GW), following

$$C_i(x_i) := \text{hRC}_i x_i. \quad (2.36)$$

The total cost of VRE producers over a year, C , is simply given by the sum over all technology-regions,

$$C_x := T_0 \mathbf{hRC}^T \mathbf{x}, \quad (2.37)$$

where \mathbf{hRC}^T is the transpose of $\mathbf{hRC} = (\text{hRC}_0, \dots, \text{hRC}_{m-1})$ the vector of VRE producers hourly rental costs and $\mathbf{x} := (x_0, \dots, x_{m-1})$ the vector of VRE installed capacities.

To the contrary of dispatchable producers VRE producers are not supposed to be able to produce at all times. Their generation depends on weather variables. As such, as for the demand $(L(t))_{t \in \mathbb{T}}$, the generation of VRE producers is given by the non-negative cyclostationary stochastic process $(H_i(t))_{t \in \mathbb{T}}$, where H_i is the time-dependent capacity factor of technology-region i . It corresponds to the fraction of energy that the producer is generating over the maximum energy that the producer could generate over an hour. We thus have $H_i(t) \in [0, 1]$ for every technology-region i . It is assumed that the probability density function of $H_i(t)$ has the right mathematical properties (Tantet 2021) for subsequent developments. We define $\mathbf{H} := (H_0, \dots, H_{m-1})$ the vector of capacity factors. The total generation of VRE producers is thus given by

$$Q_x(t) := \mathbf{x}^T \mathbf{H}(t), \quad (2.38)$$

where \mathbf{x}^T is the transpose of the vector of VRE capacities.

Long term investment problem

We derived so far the cost functions for dispatchable and VRE producers. Some further assumptions are needed to derive a system total cost that will be used in the long term investment problem. The first one is related to network costs. In our setup, we work under the ideal copper plate hypothesis, i.e. we suppose that no transmission capacities limits exist. As such our model can be considered as a single spatial node with distributed VRE generation that can be aggregated at no extra cost. Network costs are thus zero. Secondly, operational constraints are neglected: dispatchable producers have no start-up or ramping costs and grid stability is supposed to be met at any time. Our system is thus perfectly flexible at no extra costs. Finally, curtailment of VRE generation is allowed and assumed to come at no extra cost, while imports and exports are not accounted for. These hypothesis yield the following one year system total cost, given a sample of the dispatchable generation over one year $(G_{\text{Di}}(t, \omega))_{t \in \mathbb{T}_0}$:

$$\text{STC}(\mathbf{x}, (G_{\text{Di}}(t, \omega))_{t \in \mathbb{T}_0}) := C_x + \sum_{t=0}^{T_0-1} \text{VC}_{\text{Di}}(G_{\text{Di}}(t, \omega)), \quad (2.39)$$

for a given $\omega \in \Omega$. In plain words, the system total cost over a year is the sum of the VRE producers total costs (Equation 2.37) and the dispatchable producers total costs (Equation 2.35) over a year. This cost function is of interest since it implements formally the tradeoff between the cost of installation of new VRE capacities and the avoided costs of dispatchable generation. It thus allows an economical analysis - yet simple - that goes beyond the sole analysis of the Levelized Cost of Electricity (LCoE) per technology, or the simple consideration of the residual demand.

The long term investment problem then corresponds to finding the mix of VRE producers \mathbf{x} that minimizes the expectation of the system total cost over a year, while ensuring optimal dispatch of electricity at every time step. In other words, given a load $(L(t))_{t \in \mathbb{T}}$, we want to minimize the system total cost presented in Equation 2.39 so as to serve the demand at all times (adequacy constraint) at a minimum total cost. The problem is twofold: at the same time we want to find the optimal VRE capacities to be installed and we want to determine what is the best way to dispatch the conventional producers generation over the period considered. For the latter is expected: the producers with the least marginal costs, in this case the VRE producers, should produce first, and dispatchable generation occurs only when all VRE producers are producing at full capacity. For the former, we expect that

introducing VREs will tend to increase the total fixed costs of the system (as enough dispatchable generation is installed to be able to cover the load at all times) but to decrease the variable costs of satisfying the load. Finally it must be highlighted that because of the cyclostationary and stochastic nature of the load $(L(t))_{t \in \mathbb{T}}$ and VRE capacity factors $(H(t))_{t \in \mathbb{T}}$ processes, we compute the expectation over all periods of one year (that each represent a given outcome $\omega \in \Omega$) of the one-year system total cost. Note that this is only valid under the hypothesis of a stationary climate, which we already discussed in Section 2.4.2. Formally, this optimization problem translates into the following program (Tantet and Drobinski 2021):

$$\begin{aligned} \min_{\mathbf{x}} \quad & \mathbb{E}(\overline{\text{STC}}(\mathbf{x})) \\ \text{s.t.} \quad & x_i \leq x_i^{\max} \text{ for } i \in \{0, \dots, m-1\}, \\ & x_i \geq 0 \text{ for } i \in \{0, \dots, m-1\}, \end{aligned} \quad (2.40)$$

with $\overline{\text{STC}}(\mathbf{x}, \omega)$ the optimal solution of:

$$\begin{aligned} \min_{(G_{\text{Di}}(t, \omega))_{t \in \mathbb{T}_0}} \quad & \text{STC}(\mathbf{x}, (G_{\text{Di}}(t, \omega))_{t \in \mathbb{T}_0}) \\ \text{s.t.} \quad & G_{\text{Di}}(t, \omega) + Q_{\mathbf{x}}(t, \omega) \geq L(t, \omega), \\ & G_{\text{Di}}(t, \omega) \leq x_{\text{Di}}, \\ & G_{\text{Di}}(t, \omega) \geq 0. \end{aligned} \quad (2.41)$$

The first problem (Equation 2.40) corresponds to the problem of long-term investment in VRE capacities. The second problem (Equation 2.41) corresponds to the problem of optimal dispatch and is referred to as the scheduling problem. The first and second constraints of problem (Equation 2.40) ensure that the installed capacities of VRE producers are capped by maximum installable capacities x_i^{\max} for each technology-region, and that they should be positive. The constraints on the decision variable of the scheduling problem are the same as previously stated: the aggregated dispatchable generation should always be positive (no storage) and not exceed a maximum capacity x_{Di} . Note however that the adequacy constraint of the scheduling problem (Equation 2.41) does not impose that the sum of dispatchable and VRE generation be strictly equal to the demand. It can occur instead that the total generation exceeds the demand for some hours. This formally translates the fact that we assume in this setup that the demand can be curtailed at no extra cost. We can observe that the optimal solution of the second problem (2.41), depends on the optimal value of the decision variable of the first problem $\bar{\mathbf{x}}$ (2.40). Inversely, the optimal solution to the first problem depends on the the uncertain values of $L(t, \omega)$ and $Q_{\mathbf{x}}(t, \omega)$ that determine the optimal solution to the second problem.

The necessary conditions satisfied by the optimal solutions to the long-term investment and scheduling problems are detailed in (Tantet and Drobinski 2021).

Scheduling problem For the scheduling problem (Equation 2.41), the optimal primal/dual solutions $\overline{G_{\text{Di}}}$ (dispatchable generation, MWh) and $\bar{\lambda}$ (system marginal cost, € MWh^{-1}) must verify, for all $t \in \mathbb{T}_0$, and for some *residual load* $RL(t, \omega)$,

$$\begin{aligned} - \text{ when } x_{\text{Di}} > RL(t, \omega) > 0 : \\ \begin{cases} \overline{G_{\text{Di}}}(t, \omega) = RL(t, \omega), \\ \bar{\lambda}(t, \omega) = c_{\text{Di}}(RL(t, \omega)), \end{cases} \end{aligned} \quad (2.42)$$

$$\begin{aligned} - \text{ when } RL(t, \omega) < 0 : \\ \begin{cases} \overline{G_{\text{Di}}}(t, \omega) = 0, \\ \bar{\lambda}(t, \omega) = 0, \end{cases} \end{aligned} \quad (2.43)$$

where $RL(t, \omega) := L(t, \omega) - Q_x(t, \omega)$ is a certain realization of the cyclostationary stochastic process $(RL(t))_{t \in \mathbb{T}}$ (note that it is not necessarily positive) which corresponds to the net demand (or residual load), i.e. the demand to be served after all generation by VRE producers has been accounted for. These conditions ensure merit-order dispatching between dispatchable and VRE producers: dispatchable producers only generate if the net demand is positive. Otherwise they are idle and the system marginal cost is zero. The form of the cost function of dispatchable producers (Equation 2.35) ensures overall merit-order dispatching within the system.

Long-term investment problem Before presenting the necessary conditions given by the investment problem (Equation 2.40), we must introduce some notions about VRE producers profits. Let P_i (€ GW⁻¹) be the one year potential profits per unit of installed capacity of VRE producer i ,

$$P_i = T_0 \mathbb{E} \left(\frac{1}{T_0} \sum_{t=0}^{T_0-1} \lambda(t) H_i(t) \right) - T_0 \text{hRC}_i, \quad (2.44)$$

where $\mathbb{E}(1/T_0 \sum_{t=0}^{T_0-1} \lambda(t) H_i(t))$ is the expectation of the yearly average of producer's i revenue, that we will later denote $\langle \lambda H_i \rangle$. Dividing by the capacity factor $H_i(t)$ one obtains the potential profits per unit generation (€ MWh⁻¹):

$$P_i = \langle \lambda \rangle \nu_i - \text{LCoE}_i, \quad (2.45)$$

where ν_i and LCoE_i are respectively the *value factor* and the *LCoE* (€ MWh⁻¹) of VRE producer i . They are defined by

$$\nu_i = \frac{\langle \lambda H_i \rangle}{\langle \lambda \rangle \langle H_i \rangle}, \quad (2.46)$$

and

$$\text{LCoE}_i = \frac{\text{hRC}_i}{\langle H_i \rangle}. \quad (2.47)$$

Theorem 1 in (Tantet 2021) then states that if the VRE mix \bar{x} is an optimal solution to the investment problem (Equation 2.40) then only producers with non-negative potential profits have some capacity installed. While maximum installable capacity x_i^{\max} is not reached producer i makes zero profits. Profits only become positive when $\bar{x}_i = x_i^{\max}$. These positive profits are equivalent to an economic rent.

Impact of VREs

Given a load $(L(t))_{t \in \mathbb{T}}$ to be satisfied at all times, a mix of dispatchable producers with maximum capacity x_{Di} and optimal dispatching schedule $(\overline{G_{\text{Di}}}(t))_{t \in \mathbb{T}}$, and an optimal mix of VRE producers \bar{x} , we want to estimate the economic impact of introducing VRE producers in the system. Costs and challenges associated to the introduction of large shares of VREs in electricity systems were already discussed in Chapter 1. We will hereafter focus on the estimation of the VRE total and marginal value. VRE total and marginal value are defined as in (Tantet and Drobinski 2021). The expected system total value over a year for a given VRE mix x is given by:

$$\mathbb{E}(\text{STV}_x) = \mathbb{E}(\overline{\text{STC}}(0)) - \mathbb{E}(\overline{\text{STC}}(x)) \quad (2.48)$$

$$= T_0 (\langle \text{VC}_{\text{Di}}(L) \rangle - \langle \text{VC}_{\text{Di}}(\overline{G_{\text{Di}}}) \rangle) - C_{\bar{x}}. \quad (2.49)$$

Similarly, the marginal system value of VREs is given by:

$$\mathbb{E}(\text{SMV}_x) = \langle \lambda(0) \rangle - \langle \lambda(\bar{x}) \rangle. \quad (2.50)$$

2.4.3 Model parameters: the case of France

Maximum dispatchable capacity (x_{Di}) In the adapted version of the E4CLIM model we use, the maximum capacity of the aggregated dispatchable producer x_{Di} is set to a level high enough so that the adequacy constraint without VREs can be satisfied at all times. The exact value depends on the study considered and is of 200 GW in Chapter 3 and of 300 GW in Chapter 5. This has no impact on the evaluation of system total costs, since the dispatchable producer fixed costs are not taken into account in our studies (see Equation 2.39).

Dispatchable costs and DVCC (α) Fixed costs of dispatchable producers are not accounted for in our studies. In turn, variable costs of the dispatchable production are assumed to be quadratic with respect to the generated amount (see Equation 2.35) and are parametrized via the DVCC (α). This parameter is tuned to allow for different levels of optimal VRE penetration. In Chapter 3 the DVCC is varied between $1.0 \times 10^{-6} \text{ € MWh}^{-2}$ and $6.0 \times 10^{-3} \text{ € MWh}^{-2}$ with steps of $1.0 \times 10^{-4} \text{ € MWh}^{-2}$. In Chapter 5 only two values of the DVCC are considered to emulate a low penetration ($\alpha = 0.5 \times 10^{-3} \text{ € MWh}^{-2}$) and a high penetration scenario ($\alpha = 1.5 \times 10^{-3} \text{ € MWh}^{-2}$).

Maximum installable VRE capacities (x_i^{\max}) Maximum installable VRE capacities are a crucial parameter of the model (see Chapter 3). In Chapter 3, maximum installable capacities per french administrative region for wind-onshore and utility-scale solar PV are taken from (ADEME 2015). In Chapter 5, maximum installable capacities per french administrative region for wind-onshore are taken from (ADEME 2015) as well, whereas maximum installable solar PV capacities correspond to those in (ADEME 2015) multiplied by a factor 4, to get values of the national installable potential closer to those in (RTE 2021), knowing that some estimates are much larger (Dupré la Tour 2023).

VRE fixed costs VRE fixed costs are computed from (Tsiropoulos, Zucker, and Tarvydas 2018; Shirizadeh, Perrier, and Quirion 2020). They are shown in Table 2.11.

	Wind	PV
Overnight cost (€/kWe)	1130	423
Lifetime (year)	25	25
Annuity (€/kWe/year)	81.2	30.7
Operation and maintenance (€/kWe/year)	34.5	9.2
Rental costs (€/kWe/year)	115.7	39.9

Table 2.11. VRE fixed costs data for the E4CLIM model.

Chapter **3**

Socioeconomic scenarios of electric heating and cooling and their impacts on optimal mixes and power system costs

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We proceed in this section to a detailed analysis of the impacts of heating and cooling demand scenarios on the electricity system optimal VRE mixes and associated costs. We suppose in this section that the climate is stationary and equivalent to that of 2010 to 2020 in France.

3.1 Introduction

As introduced in Chapter 1, electric heating and cooling demand are expected to change in the near future because of climatic and socioeconomic drivers. In this chapter, we focus on the socioeconomic drivers of a changing electric heating and cooling demand and leave the analysis of coupled socioeconomic and climate change for Chapter 5. These changes will mainly happen in the residential and tertiary sector — often regrouped as the building sector — which concentrate the majority of the temperature sensitive part of the electricity demand. Industrial heating and cooling processes are thus left aside in this analysis. It is also important to note that electric heating and cooling demand corresponds to a fraction of the energy demand related to the space heating/cooling and hot water provision end uses. This electric heating/cooling demand does not necessarily match the temperature sensitive electricity demand: typical examples are that some heating demand will always be present for hot water no matter the daily temperature, whereas lighting demand tends to correlate with temperature even though it is not related to heating and cooling. We present first the drivers of the electric heating and cooling demand and discuss later its relation to the temperature sensitive electricity demand, that we use for scenarization.

Following (Davis and Gertler 2015; Enrica De Cian and Ian Sue Wing 2019), socioeconomic drivers of the heating and cooling electricity demand can be decomposed between those affecting the extensive or intensive margin. Changes along the extensive margin relate to changes in the stock of devices used to supply heat and cold in the building sector. Changes in population and the subsequent change in the building stock can also fall in this category. Given a fixed number of buildings, changes along the extensive margin are typically measured by the percentage of buildings that rely on an electricity-based technology for heating and cooling services, without discriminating by technology type. They correspond for example to changes in the percentage of buildings that rely on some form of electric device for space heating, whether it is through a heat pump or a resistive heater, or the percentage of buildings that rely on AC for cooling, or the percentage of buildings equipped with an electric rather than a gas water boiler. Changes along the intensive margin relate to how the stock of devices is used to provide a given heating or cooling service. In plain words, it gives us the level of electricity demand given a level of electrification. Changes along the intensive margin are impacted by changes in the technological diversification of the stock of devices used to provide heating and cooling services, changes in the level of building retrofitting and floor space, and changes in user behavior. Changes in technological diversification of the heating and cooling stock impact the demand along the intensive margin as they impact the efficiency with which heating or cooling is provided given a certain electricity consumption. A typical example is the transition from a resistive heater stock to a heat pumps stock and the associated gains in efficiency for space heating. A given technological diversification of the heating and cooling appliances stock gives us the amount of electricity that needs to be consumed to give an extra degree of heating/cooling. It relates a given level of heating/cooling demand to the necessary electricity demand to provide it. Changes in building retrofitting and floor space mainly apply to space heating/cooling. They impact the level of heating/cooling demand needed to maintain a given temperature difference between the inside and the outside. A given floor space and a given level of building retrofit — and associated insulation — gives us the need for heating/cooling, i.e. the magnitude of the heating/cooling demand needed to maintain a certain temperature difference between the inside and the outside. Finally, changes in heating and cooling behavior along the intensive margin are related to changes in the heating/cooling comfort temperature: they give us the relation between the temperature difference imposed by the user as a function of the outside temperature. Other drivers that do not fall into this two categories but still worth mentioning are the potential changes in user behavior regarding the heating and cooling

strategy, i.e. whether the heating profile is flat throughout the day or more marked at certain periods of the day, etc. These different drivers will impact the electricity demand in magnitude and in shape (Bossmann and I. Staffell 2015; Iain Staffell and Pfenninger 2018; Eggimann, Usher, et al. 2020; Peacock, Fragaki, and Matuszewski 2023). In particular, the demand variability at short sub-daily time scales, which characterizes the demand daily cycle (also called load profile in some studies), will be strongly impacted by the heating and cooling appliances technological stock¹ (Peacock, Fragaki, and Matuszewski 2023) and the heating and cooling behavior of users. If these drivers can add up to yield potentially strongly challenging impacts (more interannual variability, higher peak demands and increased ramps), they can also combine to enhance the potential for demand side efficiency, sufficiency and flexibility measures.

Studies that project potential electricity demand changes are numerous and we focus here on those that account for the previously introduced socioeconomic drivers of the electricity demand and thus leave aside those that focus exclusively on external drivers such as climate change, e.g. (Burillo et al. 2019). Changes in demand due to socioeconomic drivers have been studied for at least 20 years (Henrik Lund 2005) but most of the reviewed studies concentrate from the 2010s up until today. Although they do not specifically focus on changes in future demand, (Henrik Lund 2005) study the potential for wind power integration in Denmark. They conclude that the potential for large-scale integration of wind power in the danish energy sytem is very weak and that such an integration would present high challenges, unless some investments are made in flexibility options such as investment in heat pumps by using them as a flexibility option. Some studies focus exclusively on changes in the heating and cooling demand. (Hedegaard et al. 2012) study the impacts of heat pump adoption and subsequent gains in flexibility on wind power integration in Denmark. (Wilson et al. 2013) qualitatively discuss the impacts on the energy system of transferring the heating demand from gas to electricity in the UK. (Waite and Modi 2014) study the potential for wind power integration through the penetration of heat pumps (in urban areas) with a case study in New York City (US). (Zhang et al. 2016) study the potential for wind power integration via electric boilers installation in West Inner Mongolia (China). (Henrik Lund 2018) compare the impacts on the energy system of scenarios of heating electrification via resistive heaters, heating electrification via heat pumps and sector coupled district heating and heat pumps installation. (Tarroja et al. 2018) study of coupled heating electrification and climate change, and its impacts on building energy and subsequent impacts on GHG emissions and grid capacity expansion requirements in California. (Eggimann, J. W. Hall, and Eyre 2019) analyze the potential impacts of demand-side management policies under scenarios of 50 % penetration of heat pumps. (White et al. 2021) conduct a qualitative analysis of the potential impacts of heating electrification (100 % heat pump adoption with different levels of heat pump efficiencies) on the ERCOT grid, Texas (US). (Deakin et al. 2021) characterize the impacts of switching to heat pumps for the heating demand on the loss of load expectation and subsequent additional capacity to secure, given prescribed VRE capacities. (Peacock, Fragaki, and Matuszewski 2023) proceed to a detailed analysis of heat pump introduction under two scenarios: one where all heating demand is provided by heat pumps and another one where 41 % of the demand is provided by heat pumps.

Other studies proceed in a more integrated way, where changes in heating and cooling demand are usually coupled to changes in electricity demand due to technological changes in the transport sector (mainly plug-in electric vehicles adoption). These are usually aimed at studying the impacts of future demand changes on the energy system. (Kiviluoma and Meibom 2010) study the potential for wind integration in Finland via the extra flexibility brought to the system by plug-in electric vehicles, heat pumps and electric boilers. (Bossmann and I. Staffell 2015) project Load Duration Curve (LDC) changes for the UK and Germany following a socioeconomic scenario of a transition to a low carbon energy system by 2050 (for each country). They test the sensitivity of the obtained LDCs to the charging profile of electric vehicles and to the degree of electrification (i.e. adoption fraction of electric heating devices, heat pumps in this study, and electric vehicles). (Alberg Østergaard, Møller Andersen, and Kwon 2015) study scenarios of transportation demand electrification and heat

¹In particular, if the heating and cooling supply stock is mainly composed of heat pumps, the way heat pumps are programmed will impact the shape of the demand daily cycle.

pumps adoption, and the associated impacts on wind power integration in Denmark. (Iain Staffell and Pfenninger 2018) use the Two Degrees scenario from the UK National Grid FES2016 (ESO 2016) to project electrification of heating as well as transportation (among other socioeconomic changes). (Eggimann, Usher, et al. 2020) model levels of heat pump penetration between 20 % to 60 %, coupled to industry electrification and changes in heating behavior (shape of the daily load profile) as well as population. (Murphy et al. 2020) study the impacts on the energy system of two demand-side scenarios following (T. T. Mai et al. 2018): a reference electrification scenario is considered where the electrification of space and water heating goes from 12 % and 26 % in 2018 to 17 % and 26 % respectively in 2050, and a high electrification scenario where these levels go up to 61 % and 52 % respectively in 2050. In parallel electrification of transport (in both scenarios) and industry (in the high electrification scenario only) are considered. The former is the main driver of electricity demand increase in the high electrification scenario.

All these studies vary in time and spatial resolution. Some studies consider the aggregated demand over a country (Henrik Lund 2005) or a state (Tarroja et al. 2018) whereas others disaggregate it at finer levels (e.g. county level in the US (White et al. 2021) or local authority districts in the UK (Eggimann, Usher, et al. 2020)). Similarly, the changes in demand are accounted for on yearly values or on full hourly time series over multiple years (Eggimann, Usher, et al. 2020; Peacock, Fragaki, and Matuszewski 2023), while some studies focus exclusively on peak demand changes (Cooper et al. 2016; Love et al. 2017). It is finally interesting to note that all these studies account exclusively for changes along the extensive margin, and that changes along the intensive margin (typically building retrofit or lowering the comfort temperature) are not accounted for in the projected scenarios.

From all the reviewed studies, about only a half consider the subsequent impacts of a change in shape and magnitude of the electricity demand on the energy system. Among those that do, VRE capacities are most of the time prescribed (Henrik Lund 2005; Hedegaard et al. 2012; Waite and Modi 2014; Alberg Østergaard, Møller Andersen, and Kwon 2015; Zhang et al. 2016; Henrik Lund 2018; Tarroja et al. 2018; Deakin et al. 2021) and only some studies focus on capacity expansion decisions due to changes in demand (Kiviluoma and Meibom 2010; Murphy et al. 2020). We find several limitations to the remaining studies. (Kiviluoma and Meibom 2010) use the sector coupled (heat + electricity) model Balmorel. The model is able to optimize capacity expansion decisions while also ensuring system adequacy at every hour. As such, they are able to study the tradeoff between installing wind and using dispatchable production to supply the necessary demand. However two main limitations remain in the fact that (i) PV is not included in the study (the effects of PV introduction are unclear since it is not clear whether it will displace wind or dispatchable capacity), and (ii) the study lacks accounting for multi-year time series, which can lead to under or overestimation of the optimal wind fleet depending on the weather-year selected (Hilbers, David J. Brayshaw, and Gandy 2019). (Murphy et al. 2020) are not able as per their protocol design to disentangle the effects of heating and transportation electrification, although both will impact the demand in different ways (in particular one is temperature sensitive while the other is not). Furthermore, the model architecture prevents it from fully capturing the electricity demand and VRE generation correlation, as well as the inter-annual variability of both these quantities and subsequent impacts on the VRE and dispatchable stock dimensioning.

We address these gaps by specifically studying the impact of heating and cooling demand electrification on VRE capacity investment decisions using an electricity system model designed to take into account the year-to-year variability of demand and VRE generation time series in the capacity investment decisions while ensuring system adequacy at all times. We first present in Section 3.2 several heating and cooling electrification scenarios and their impacts on the electricity demand under current climatic conditions that we suppose stationary. We find that the impacts of heating electrification are much larger than those of cooling electrification, due to both a little number and intensity of cooling days under current climate conditions, and the fact that we did not account for modifications along the intensive margin. Thus, in a second time, we focus on the impacts of heating electrification scenarios on optimal regional VRE mixes and associated costs, which we present in Section 3.3.

3.2 Socioeconomic scenarios of electric heating and cooling

3.2.1 Scenario design

We build on the model of hourly electricity demand developed and presented in Chapter 2 to build our scenarios of heating and cooling demand electrification. We recall that the model can be written as

$$L(t) = \omega^0 + X(t) \cdot \omega + \epsilon(t), \quad (3.1)$$

where ω^0 is the intercept of the data, $X(t)$ a feature vector that potentially depends on the weather conditions at time t , ω the coefficients of the model and $\epsilon(t)$ a white noise with standard deviation computed as a function of the prior noise on the model coefficients (also called noise precision) and the quality of the data. For a day where the average daily temperature \bar{T} is below a certain threshold T_H , the feature vector has the right form such that the demand is given by

$$L(t) = \omega^0 + \omega^B(t) + \omega^H(t)(T_H - \bar{T}), \quad (3.2)$$

where $\omega^B(t)$ is the baseline coefficient in GW h h^{-1} and $\omega^H(t)$ is the heating temperature sensitivity coefficient in $\text{GW h h}^{-1} \text{ } ^\circ\text{C}^{-1}$. The dependence in time is here to signify that these coefficients vary with the hour of the day and calendar daytype (whether the considered day is a working day, Saturday or holiday). ω^0 and ω^B represent the temperature insensitive part of the demand, that we also call baseline demand. Then $\omega^H(t)(T_H - \bar{T})$ corresponds to the temperature sensitive part of the demand. The same reasoning holds for a day where the average temperature is above a certain threshold T_C . The cooling temperature sensitivity coefficient is then $\omega^C(t)$.

Assuming the building stock is in fact composed of the same average building with a given average heating/cooling demand, the temperature sensitivity coefficients can be further decomposed as

$$\omega^{H/C}(t) = \alpha^{H/C} \omega_{\text{tot}}^{H/C}(t), \quad (3.3)$$

i.e. into a coefficient $\alpha^{H/C}$ representing the fraction of buildings equipped with electric devices for space heating/cooling and a coefficient $\omega_{\text{tot}}^{H/C}(t)$ that then represents the total temperature sensitivity of the building stock (electric and non-electric). All other socioeconomic drivers of changes in the electric heating/cooling demand would thus affect this second coefficient.

This decomposition necessitates an important hypothesis. If $\omega^{H/C}(t)$ is the temperature sensitivity coefficient, $\alpha^{H/C}$ is the fraction of buildings that use an electric appliance for space heating/cooling. This implies that we consider that all temperature sensitive demand is related to space heating/cooling and thus neglect the share of the temperature sensitive demand that is related to other end-uses such as water heating or lighting (and probably cooking to some extent). Such a hypothesis is e.g. made in (Iain Staffell, Pfenninger, and N. Johnson 2023). The relevance of such a hypothesis is hard to verify: data aggregated over a large number of buildings at a sufficient time resolution to compute the temperature sensitivity of each end use is not easily available. We still show a figure from (Özkizilkaya 2014) in Figure 3.1a, that represents the residential monthly demand in France in 2005 disaggregated by end-uses. We can qualitatively see from the figure that most of the heating temperature sensitive demand (that demand that varies seasonally in the figure) is due to space heating. Thus to the first order (variations on the order of 6 TWh) space heating is the sole driver of the demand heating temperature sensitivity. To the second order (variations on the order of 1 TWh or less), lighting, domestic hot water and cooking to a lesser extent, also vary seasonally (and thus are correlated to temperature variations) and are drivers of the demand heating temperature sensitivity. The demand cooling temperature sensitivity is visibly here only due to cooling. Although the data is for the residential sector only, we can suppose that a similar behavior happens for the tertiary sector as well, and even more so since domestic hot water and cooking are probably very minority. A similar graph is found in (RTE/ADEME 2020), although the data is not available, for the system-wide weekly average electricity demand (for the 2017-2018 period) disaggregated by sector

or end-use. We reproduce it in Figure 3.1b. Here about 2/3 of the heating temperature sensitivity of the demand is due to space heating alone (about 20 GW of seasonal variations due to space heating and about 10 GW for the rest). Although this is less clear from the figure, space cooling appears to be the only end-use to increase in the summer and decrease in the winter. It thus accounts for the totality of the cooling temperature sensitivity of the demand. We find again this figure of 2/3 of the heating temperature sensitive electricity demand related to space heating, when comparing the value of the temperature sensitive electricity demand computed from our model (91 TWh for the average total yearly temperature sensitive electricity demand over the 2010-2020 period) and the value of 63 TWh given in (RTE/ADEME 2020) for the year 2018. Considering that all heating temperature sensitive demand is due to space heating might thus make us overestimate the resulting demand due to electrification scenarios. The hypothesis seems to be approximately verified for space cooling.

We thus work with the alternative hypothesis that 2/3 of the heating temperature sensitive demand are due to space heating and that the totality of the cooling temperature sensitive demand is due to space cooling. We note however that the exact figures contained within this hypothesis have little consequences for the remainder of this work, as we are interested in performing a sensitivity analysis of the impact of an increased temperature sensitive demand on the electricity system. As such the exact value of the resulting electricity demand for a given level of heating/cooling electrification is not of crucial importance to us. What matters is that the values stay in the right order of magnitude, which is done by encoding these scenarios of temperature sensitive demand as space heating electrification scenarios. Even if the value of 2/3 for space heating is thus probably an approximation, the hypothesis is considered to be safe for the remainder of this work. This working hypothesis brings us to instead decompose the heating temperature sensitivity coefficients as

$$\omega^H(t) = \frac{2}{3}\alpha^H\omega_{SHtot}^H(t) + \frac{1}{3}\omega_{TS}^H(t), \quad (3.4)$$

where α^H is the fraction of buildings equipped with space heating, $\omega_{SHtot}^H(t)$ is the total temperature sensitivity of the building stock (electric and non-electric) related to space heating and ω_{TS}^H is the buildings temperature sensitivity related to other usages than space heating. The cooling temperature coefficients are still decomposed as

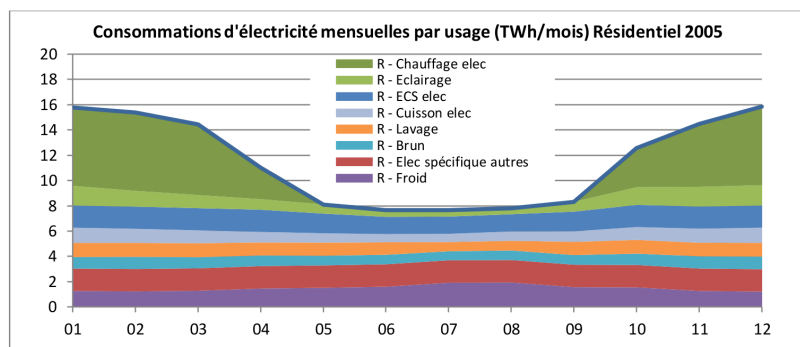
$$\omega^C(t) = \alpha^C\omega_{tot}^C(t), \quad (3.5)$$

with α^C representing the fraction of buildings equipped with electric devices for space cooling and $\omega_{tot}^C(t)$ representing the cooling temperature sensitivity of all the building stock if all buildings were equipped with AC given a certain AC usage.

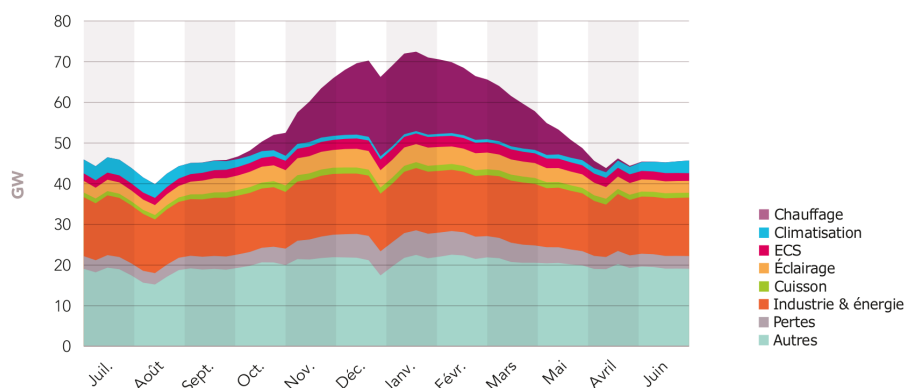
We base our scenarios on the level of building electrification by tuning the parameter $\alpha^{H/C}$. Other drivers of changes of the space heating/cooling demand, and in particular all changes related to a ω_{SHtot}^H , ω_{TS}^H or ω_{tot}^C modification are not accounted for in this study. We thus suppose that heating electrification occurs with an average technology somewhere in-between of a resistive heater and a heat pump and that AC adoption occurs with an average technology representative of the current stock. Typical values of the α^H parameter in the residential sector in Europe in 2015 are e.g. 8.5% for the UK, 15.5% for Spain, 19.6% for Italy, 8.9% for Belgium, 2.5% for Luxembourg and 3.3% for Germany², for France's neighboring countries (data unavailable for Switzerland). The values for France for the residential sector according to the same dataset are of 35.5%, while estimates from (RTE 2021) give a value on the order of 40% for 2020. Other estimates for France can be computed and a historical perspective can be given by using data from the Centre d'Études et de Recherches Économiques sur l'Énergie (CEREN)³ (CEREN 2020; CEREN 2023). The values for α^H are represented Figure 3.2a for the last 30 years in France. We can see that some electrification has

²Own computations based on the data presented in (Fleiter, Elsland, et al. 2017) and available for download at <https://heatroadmap.eu/heating-and-cooling-energy-demand-profiles/>, accessed 28 March 2024. Are considered as electric heating the fields *Heat pumps total (electric)* and *Electric Heating*.

³<https://www.ceren.fr/>, the data being freely available at <https://www.ceren.fr/publications/les-publications-du-ceren/>, accessed 30-03-2024.



(a) Adapted from (Özkizilkaya 2014, Figure 2.16).



(b) Adapted from (RTE/ADEME 2020, Figure 1.3).

Figure 3.1. Temperature sensitivity of electricity end-uses in France. Panel (a): monthly national residential electricity demand disaggregated by end-use (2005). End-uses are in french and translate as follow: Chauffage elec → electric heating, Eclairage → lighting, ECS elec → domestic hot water, Cuisson elec → cooking, Lavage → washing, Brun → electronic devices (computers, television, etc.), Elec spécifique autres → other specific electricity, Froid → cooling. Panel (b): weekly average electricity demand by sector and end-use (2017-2018). End-uses are in french and translate as follow: Chauffage → space heating, Climatisation → space cooling, ECS → domestic hot water, Éclairage → lighting, Cuisson → cooking, Industrie et énergie → industry and energy, Pertes → losses, Autres → other.

already taken place. The value for 2015 is of about 35%. Typical values of the α^C parameter cannot be computed from the (Fleiter, Elstrand, et al. 2017) dataset. The value for France as estimated from (RTE 2021) for the residential sector is of 23%⁴. Because of the way data is collected, no such estimates of $\alpha^{H/C}$ are available for the tertiary sector, where data is not given by building count but per floor space. However the two are equivalent as long as the number of buildings is kept constant and that we suppose this time that the building stock is composed of the same average building with identical average heating demand and the same average floor space. This simplification does not allow to enter in the detail of renovation policies etc. but is entirely valid as long as the total aggregated space heating/cooling demand is considered. We represent a historical perspective on the values of α^H based on CEREN data (CEREN 2020; CEREN 2023) for the aggregated⁵ residential and tertiary sectors in Figure 3.2b. We can see that some electrification has taken place over the last 30 years and that the aggregated values are close (within less than 5 percentage points) to those of the residential sector alone. Once the fraction of tertiary floor space heated via electric heating has been accounted for, the value of α^H for the aggregated building sector is of about 35% in 2015. This is the value that we will retain for our analysis. Regarding the α^C parameter in the tertiary

⁴Own computation based on the annual electricity demands for cooling given for 2020 (6 TWh) and 2050 (14 TWh), and the fraction of buildings equipped with AC in 2050 (55%). We thus assume that the average demand per household remains constant between 2020 and 2050.

⁵Aggregation is carried by considering the total residential surface assuming a surface of 65 m² for apartments and 110 m² for homes, following (RTE/ADEME 2020, Section 2.8).

sector, data equivalent to that of CEREN (CEREN 2020; CEREN 2023) does not exist to the best of our knowledge and we thus simply assume that the α^C parameter is equal to that observed in the residential sector. We will thus use the 23 % value estimated from (RTE 2021) for our analysis.

Given reference values of $\alpha^{H/C}$ for the 2010-2020 period, different levels of electric heating/cooling, are reached by multiplying the $\alpha^{H/C}$ parameter by a multiplicative factor $\epsilon'_{H/C}$. For computational simplicity the whole temperature sensitivity coefficient $\omega^{H/C}(t)$ is multiplied by an equivalent $\epsilon_{H/C}$ factor, that accounts for the 2/3 factor in the case of heating demand (for the cooling demand $\epsilon'_C = \epsilon_C$). Scenarios are built such that the level of electric heating/cooling with our approximations does not go above 100 %. The values of $\epsilon_{H/C}$ (and when relevant $\epsilon'_{H/C}$) used to explore different percentages of electrification that we describe in the following section are given in Tables 3.1 and 3.2. Scenarios of heating electrification are explored between the current value of 35 % to values of 88 % (corresponding to $\epsilon_H = 2.0$), while scenarios of AC adoption are explored between the current value of 23 % to complete adoption of AC (100 %, for $\epsilon_C = 4.35$).

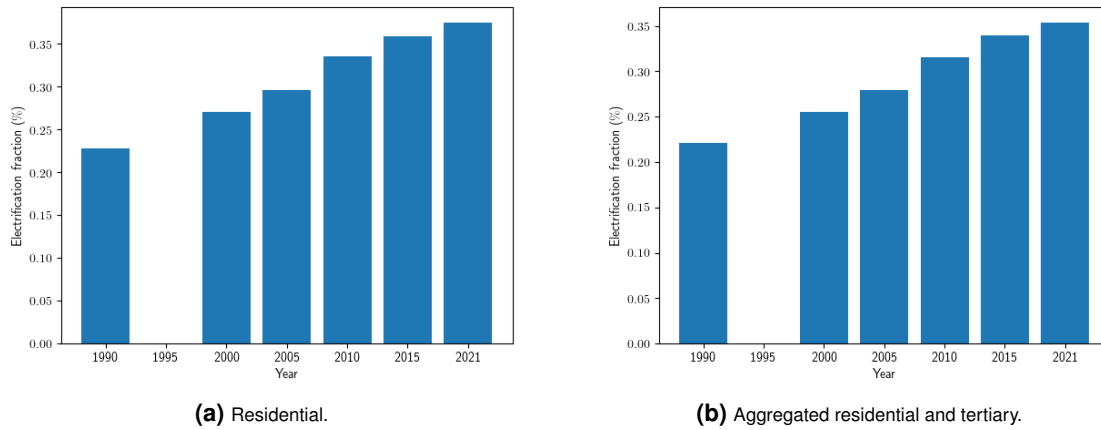


Figure 3.2. Percentage of electrification for space heating of the french building stock, according to (CEREN 2020; CEREN 2023).

% Electric heating	ϵ_H	ϵ'_H
35	1.	1.
48	1.25	1.375
61	1.5	1.75
74	1.75	2.125
88	2.	2.5

Table 3.1. ϵ_H parameter and levels of electric heating.

% Electric cooling	ϵ_C
23	1.
50	2.17
75	3.26
100	4.35

Table 3.2. ϵ_C parameter and levels of electric cooling.

We thus build a set of scenarios which are rigorously speaking scenarios of increased cooling and heating temperature sensitive demand. To design scenarios that correspond to realistic potential future changes in temperature sensitive demand, we associate changes in temperature sensitive demand to changes in the level of space heating/cooling electrification of the building stock. This equivalence is valid under one main assumption: that 2/3 of the heating temperature sensitive deman

and all of the cooling temperature sensitive demand is related to space heating/cooling. As this hypothesis is an approximation, our scenarios of electric heating/cooling will not correspond exactly to what would be expected from the actual electrification of space heating and cooling in the building stock. This is however safe for the sensitivity analysis performed here. Then, importantly, no factors other than the level of electrification $\alpha^{H/C}$ are considered. In particular electrification is supposed to occur with a constant average technology equivalent to that of the current technological mix and that users do not change any heating/cooling behavior with respect to today. These scenarios are however relevant as they still give an approximation of what the change in temperature sensitive demand could be due to an increased electrification of space heating/cooling, which is perfectly valid for the sensitivity study performed here. A finer study with more predictive power is left for future works.

3.2.2 Data and scope

We consider the period 2010-2020 in metropolitan France and use weather data from MERRA2 reanalysis (Fujiwara et al. 2017; Gelaro et al. 2017), see Chapter 2 for further details. Gridded data is then averaged at the level of french administrative regions (12 in total) to compute the average daily temperature for each day of the 2010-2020 period. A map of the different regions is given in the presented paper, Section 3.3, Figure A.6. A model of regional electricity demand is computed for each french administrative region, following the methodology presented in Chapter 2, Section 2.1. Each model is trained against observations from the 2014-2019 period⁶ and then applied to the 2010-2020 temperature time-series. The demand is then aggregated at the national level by simply summing over the resulting regional demands. We consider the fraction of electric heating/cooling to be the same in each region and equal to the one at the national level, which we discuss throughout the analysis.

3.2.3 Electric heating scenarios

We present in this section the different scenarios of electric heating considered, as shown in Table 3.1. We first assess the impact on model coefficients and then discuss the impacts of the different scenarios on the electricity demand.

Model coefficients

Model coefficients for each region and as modified for each scenario of electric heating are presented in Appendix B, Figure B.1. The figure shows the coefficients of the model for each region per hour of the day and for each daytype, which is a combination of a day's temperature daytype, i.e. whether a day is a heating day (space heating is turned on), a cooling day (space cooling is turned on) or none of the former, and a day's calendar daytype, i.e. whether a day is a working day, a saturday or a sunday/holiday. Since we focus on heating demand scenarios, only heating daytype coefficients should be modified by our protocol, as the ϵ_H coefficient multiplies only the ω^H coefficients. We thus plot the coefficients corresponding to other temperature daytypes as a control measure. We can effectively see that they are not modified in our different heating demand scenarios. We focus in the following on the heating temperature daytype coefficients only.

Two observations can be drawn from the figure. The first one is that the way heating temperature sensitivities are modified yields an offset electric heating daily cycle with an increased variability: the amplitude of the daily cycle is more important for higher levels of electric heating. This is best seen in Figures B.1g and B.1a, corresponding to administrative regions Île-de-France and Auvergne-Rhône-Alpes respectively, by comparing the curves associated to $\epsilon_H = 1.0$ and $\epsilon_H = 2.0$.

⁶Data is from the french TSO and freely available at <https://opendata.reseaux-energies.fr/>, accessed 31-03-2024.

The second important observation is that although the same multiplicative coefficient is applied to all regions, the impact of electrification is regionally differentiated. This can be seen by e.g. comparing Figure B.1g and Figure B.1h, where we can observe a greater difference between model coefficients for the different scenarios in the former than in the latter. This is simply due to some regions having higher reference temperature sensitivities (i.e. for $\epsilon_H = 1.0$). Those regions contributing the most to the nationally aggregated temperature sensitivity will thus in proportion contribute even more in the increasing electrification scenarios. This model behavior doesn't have to be the case in what could actually be observed, since regions with an already high temperature sensitivity could be more electrified than others. This approximation could be refined by deriving regional levels of electrification and then applying a regionally differentiated ϵ_H coefficient. Such a refinement could be of interest since the contribution of each region to the aggregated national electricity demand can also be differentiated depending on the weather patterns affecting the whole area of study: we can imagine weather conditions where the mediterranean part of France experiences mild temperatures whereas the northern part of France experiences colder temperatures. The regional differentiation of temperature sensitivities then plays an important role in the resulting nationally aggregated electricity demand. We however leave such analyses for future works and consider the model behavior to be safe for the sensitivity analysis performed here.

We thus expect that such modified model coefficients will lead to an increased and increasingly variable electricity demand during heating days with a similar response to weather patterns as for the reference electrification scenarios.

Impacts on the demand

We study how the different scenarios impact the resulting electricity demand. We first look at how the demand seasonal and daily variability are modified. We then focus on key quantities that characterize the electricity demand: base, mean and peak demand. We finally assess the impacts of the different scenarios on the load duration curve.

Demand variability Demand daily variability is represented Figure 3.3. The daily cycle is represented for each electrification scenario and each daytype. We expect only the daily cycles corresponding to a heating temperature daytype (Temp. daytype = -1) to change across the scenarios since only the heating temperature sensitivity coefficients were modified. The other daytypes are thus represent for control purposes. As expected from the coefficients modifications, the daily cycle is offset and more variable with increasing electrification (compare e.g. the curves for $\epsilon_H = 1.0$ and $\epsilon_H = 2.0$). This is true for all calendar daytypes. We can furthermore notice that the heating daily cycle general features are conserved: a trough during the night and early morning, a morning peak with a subsequent plateau, an evening peak between 17h and 19h (UTC) and finally a late evening plateau around 23h to 1h or 2h in the morning. This latter plateau is not observed in the baseline and cooling daytypes where the night trough starts right after a secondary evening peak around 21h (UTC) (we can also note that the 17h-19h evening peak is much less pronounced in these daytypes).

Yearly variability of demand aggregated at the national level for all scenarios of electrification is represented in Figure 3.4. As expected, demand is more pronounced in winter with increasing electrification, and demand in summer is left unchanged. The seasonal variations of demand are thus much more pronounced in increased electrification scenarios. In short, electrification of space heating causes the electricity demand to be more variable, both at the daily level, where features of the typical daily cycle are exacerbated, and at the yearly level, where the typical seasonal cycle is more pronounced as well.

Base, mean and peak demand We now assess the impacts of the electrification scenarios considered on key aspects of the electricity demand: base demand, average demand and peak demand. We define here base demand as that demand that is observed 95% of the time: demand is lower

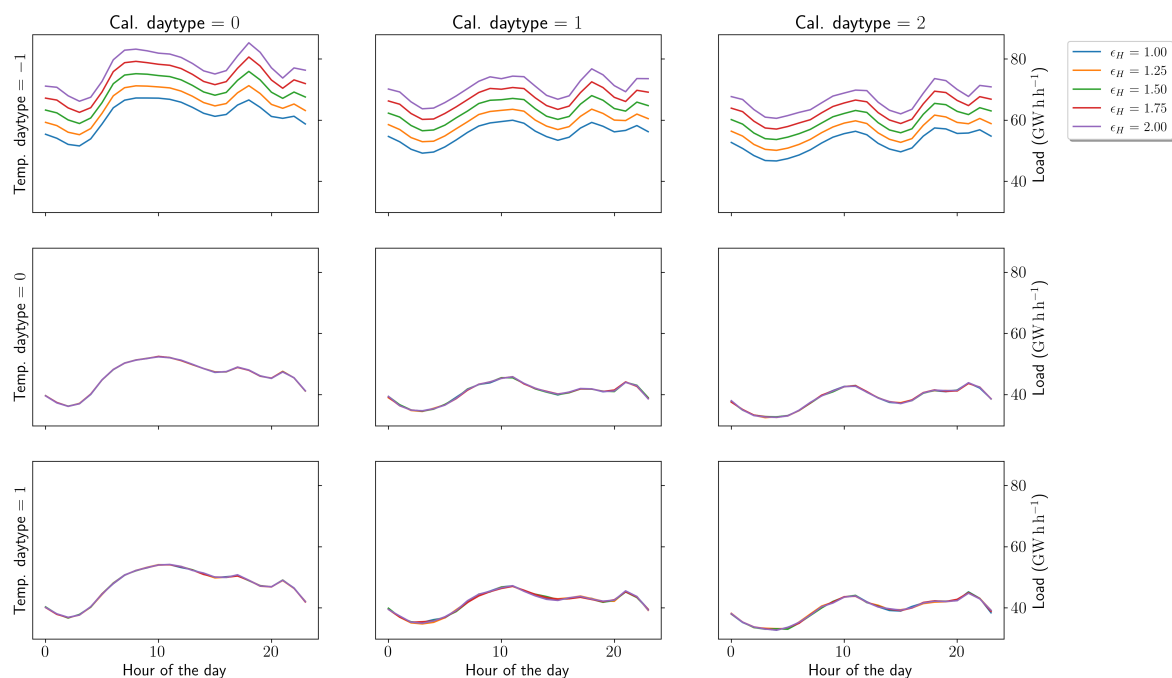


Figure 3.3. Daily variability of the heating demand scenarios considered. Load is a synonym for electricity demand. Temp. daytype corresponds to whether the day is a heating day (-1), cooling day (1) or none of the two (0). Cal. daytype corresponds to whether the day is a working day (0), saturday (1) or sunday/holiday (2).

than that value only 5 % of the time. Base demand changes across the different scenarios are represented Figure 3.5a for the aggregated national demand and in Appendix B, Figure B.2 for a regional picture. Base demand is little affected by changes in space heating electrification. Although it steadily increases with increasing electrification, the changes are kept within 1.0 % of the reference value. At the regional level, no notable difference can be noticed. Base demand thus remains stable with increasing electrification.

Mean demand is a proxy for the yearly total demand. Mean demand changes across the different electrification scenarios are represented Figure 3.5b for the aggregated national demand and in Appendix B, Figure B.3 for the regionally disaggregated impacts. At the national level, average demand, and thus the yearly total energy demand, increases markedly with increasing electrification. Reaching a 50 % electrification rate ($\epsilon_H = 1.25$) causes a 5 % increase in the yearly total demand, and demand increases up to 19 % for the most extreme scenario. At the regional level, the contribution to that increase is regionally differentiated with a higher contribution of the upper west coast regions (Bretagne, Normandie, Île-de-France and Centre-Val-de-Loire).

Finally, peak demand changes across the different scenarios are presented Figure 3.5c for the nationally aggregated demand and in Appendix B, Figure B.4 for regional changes. We define here peak demand as the demand observed 5 %⁷ of the time: i.e. demand is lower than that value 95 % of the time. At the national level, peak demand increases strongly with increasing electrification. Reaching a 50 % electrification rate ($\epsilon_H = 1.25$) causes a 9 % increase in peak demand, and it increases up to 38 % for the most extreme scenario. Not all regions contribute equally to peak demand. An East-West gradient is observed, with a greater contribution of the western regions to the peak demand increase.

To summarize, heating electrification has a differentiated impact on the demand: base demand remains roughly constant, whereas peak and total demand increase significantly. Peak demand increases more than average demand with the electrification of space heating, with increases roughly

⁷This is equivalent to 438 hours in a year which is much more than the allowed hours of adequacy failure allowed in national regulations (in France it is 2 to 3 hours). As such the peak demand so defined is lower than the peak demand values usually given by TSOs.

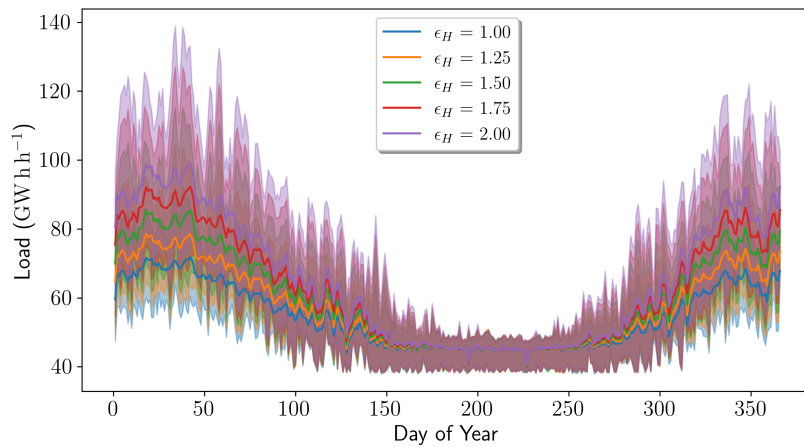


Figure 3.4. Yearly variability of the heating demand scenarios considered, as given by the average daily load (electricity demand) throughout a year. The shaded area represents the daily average demand minimum-maximum range over the 2010-2020 period.

2 times higher than for the average demand. The contribution to those changes is regionally differentiated with different patterns for different parts of the demand. The reasons and impacts of such a variable regional contribution are not studied here, mainly since only the national aggregated demand is of importance to us. This could however be the focus of further studies, in particular if the transmission network is considered in the electricity system modelling step (typically some regions in France are at higher risk of experiencing blackouts than others).

Load duration curve We finally study the impacts of the different electricity demand scenarios on the Load Duration Curve (LDC). The LDC for the different electrification scenarios is represented Figure 3.6. The way the LDC evolves with increasing electrification summarizes what has been said earlier: base demand is little affected whereas the demand increases even more so that we are close to peak demand. The demand is also more variable, in the sense that it covers a wider range of values, with increasing electrification. We can see that there is a particular threshold around the 60% probability above which the curves clearly separate from each other whereas they are mixed together below this point. This emphasizes the fact that heating demand electrification has a differentiated impact on the demand, with demand above the median (50% probability) being more impacted than below.

3.2.4 Electric cooling scenarios

We present in this section the considered scenarios of electric cooling as summarized in Table 3.2. We first discuss the impacts on model coefficients of the change in the rate of AC adoption and then present the subsequent impacts on the nationally aggregated and regional electricity demand.

Model coefficients

The modified model coefficients for the different scenarios of AC adoption are presented in Appendix B, Figure B.5. The graphical representation follows what has already been introduced in Section 3.2.3. As for the heating electrification scenarios, here only the cooling temperature sensitivity coefficients ω^C are multiplied by ϵ_C . The other coefficients thus shouldn't change and are plotted as a control measure.

The first important thing to notice is that AC adoption scenarios exacerbate the cooling daily cycle. This is best seen in e.g. Figures B.5g, B.5j or B.5k, where the magnitude of the coefficients in the afternoon is increased. A regional trend exists in the distribution of cooling coefficients: southern regions of France (Auvergne-Rhône-Alpes, Nouvelle-Aquitaine, Occitanie, PACA) have higher cooling

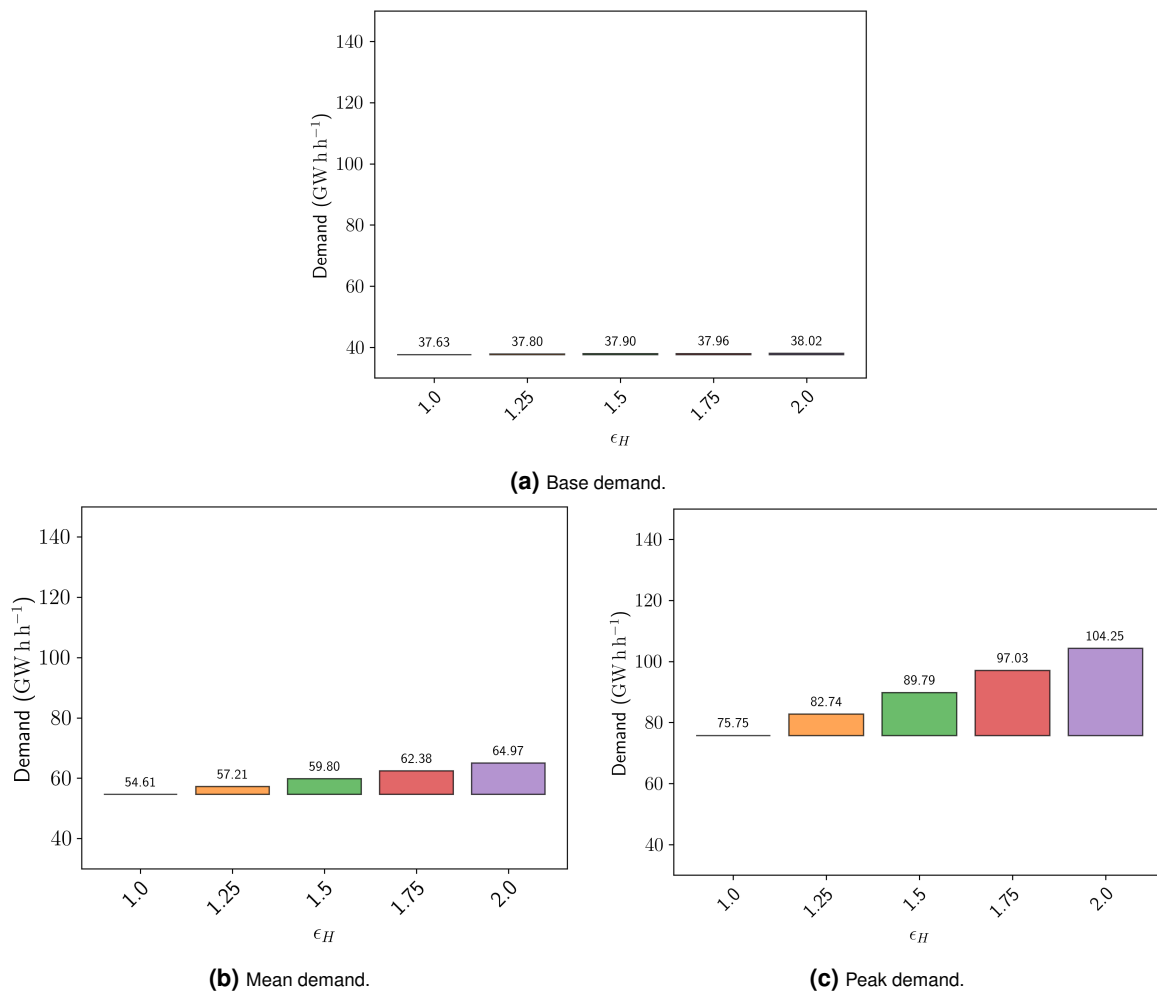


Figure 3.5. Base, average and peak demand for the heating demand scenarios considered. The values correspond to the height of the bars.

coefficients than the rest with the notable exception of Île-de-France. As for the heating electrification scenarios, because of our scenario building method, the regions that contribute the more to the cooling demand in the reference case ($\epsilon_C = 1.0$) will have a relatively even higher contribution in the scenarios considered. This model behavior stems from the hypothesis that all regions have the same level of AC adoption, which can be discussed. It is however left for further studies to represent regionally differentiated scenarios of AC adoption.

Finally we should note that the model has sometimes an erratic behavior as some cooling coefficients ω^C are negative. Negative coefficients can still have a physical meaning if we consider that the daily cycle is the sum of the coefficients ω^0 , $\omega^B(t)$ and $\omega^C(t)$. As such it can be that a different shape of the daily cycle during cooling daytypes is encoded in the cooling coefficients: typically the early morning (5h-6h UTC so 6h-7h UTC+1 in wintertime and 7h-8h UTC+1 in summertime) peak is lower, as e.g. seen in Figure B.5g or B.5e. However the average over the day should be positive so that cooling coefficients have a physical meaning. Demand integrated over the whole day should be higher when there is some cooling than when there is neither cooling nor heating. Regions and daytypes for which this is not the case are marked with a red circle in Figure B.5. This behavior can be avoided by increasing the cooling temperature threshold T_C (see Chapter 2). However there is a tradeoff between increasing this threshold and avoiding having negative cooling coefficients, capturing all days where some cooling takes place and following the mathematical logic of choosing the best set of hyperparameters according to the best r^2 metric: a too high threshold would miss some days where cooling occurs, whereas increasing the cooling threshold decreases the value of r^2 . Furthermore,

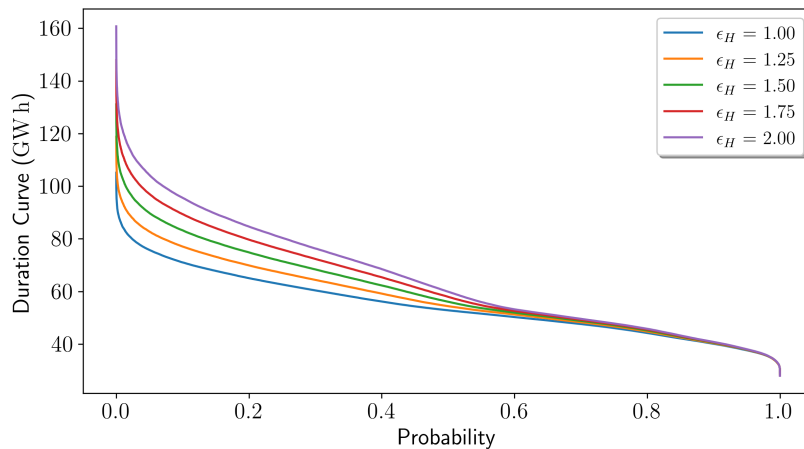


Figure 3.6. LDCs for the heating demand scenarios considered.

increasing the cooling threshold reduces the data available to constrain the ω^C coefficients. The most problematic case is that of region Hauts-de-France (Figure B.5f) where coefficients are clearly negative and non-zero. However the mean over the day is close to zero ($-7.5 \times 10^{-4} \text{ GW h h}^{-1} \text{ }^\circ\text{C}^{-1}$ for the reference case and $-3.3 \times 10^{-3} \text{ GW h h}^{-1} \text{ }^\circ\text{C}^{-1}$ for $\epsilon_C = 4.35$) and we can expect this region to have a negligible impact in the nationally aggregated demand. The choice of hyperparameters as presented in Chapter 2 is thus a good compromise, and the model behavior safe for our analysis. This however points out one main limitation of our model, which is not to consider changes in the use of electric heating and AC in particular.

We thus expect a modified daily cycle during days of cooling with a majoritary contribution of the southern regions to the national electricity demand. Northern regions are not expected to be the cause of demand increases since most of them are lowly to not sensitive to increases in the daily mean temperature.

Impacts on the demand

We study in this section how the modified coefficients impact the regional and nationally aggregated demand. We focus first on the impacts on demand variability and then focus on the key indicators of the demand main characteristics introduced before (base, mean and peak demand) and finally present the resulting LDCs for each scenario.

Demand variability The demand daily cycle for each daytype and across all scenarios of AC adoption is shown in Figure 3.7. We show the daily cycle for all daytypes as a control measure, as only the one corresponding to the cooling temperature daytype should be modified by our experimental protocol. As expected from the model coefficients modifications, the variability of the demand over the day increases with increasing AC adoption. To the contrary of the heating electrification scenarios, here the shape of the daily cycle during cooling daytypes is notably altered: the midday peak and plateau increases and merges with the early evening peak to yield a broad late daytime peak going from 7h (UTC, equivalent to 9h UTC+1 in summertime) to around 18h. This broad peak is then followed by a late evening peak around 21h, which increases in magnitude with increasing AC adoption. Increasing the share of buildings equipped with AC causes the shape of the demand to change during those days where some cooling occurs, with an increased broad daytime peak that peaks around 13h-14h (UTC+1), when the sun is at its zenith.

The seasonal variations of the demand are in turn shown in Figure 3.8. Summer demand increases with increasing AC adoption, with daily average demand reaching more than 60 GW in the 10 years considered for the most extreme scenario ($\epsilon_C = 4.35$). Otherwise demand is still dominated by the winter seasonal peak with daily average values reaching on average more than 70 GW. The

variability — in the sense of the range of values covered — of demand is thus not affected by the considered scenarios of AC adoption. However, the seasonal cycle is altered with the appearance of a summertime secondary peak. By summarizing the effects on the daily and seasonal cycles we can conclude that in our case AC adoption does not so much increase the variability of the demand than it alters the shape of the daily and seasonal cycles: a broader daytime peak appears at the daily scale while a summertime peak appears at the yearly level.

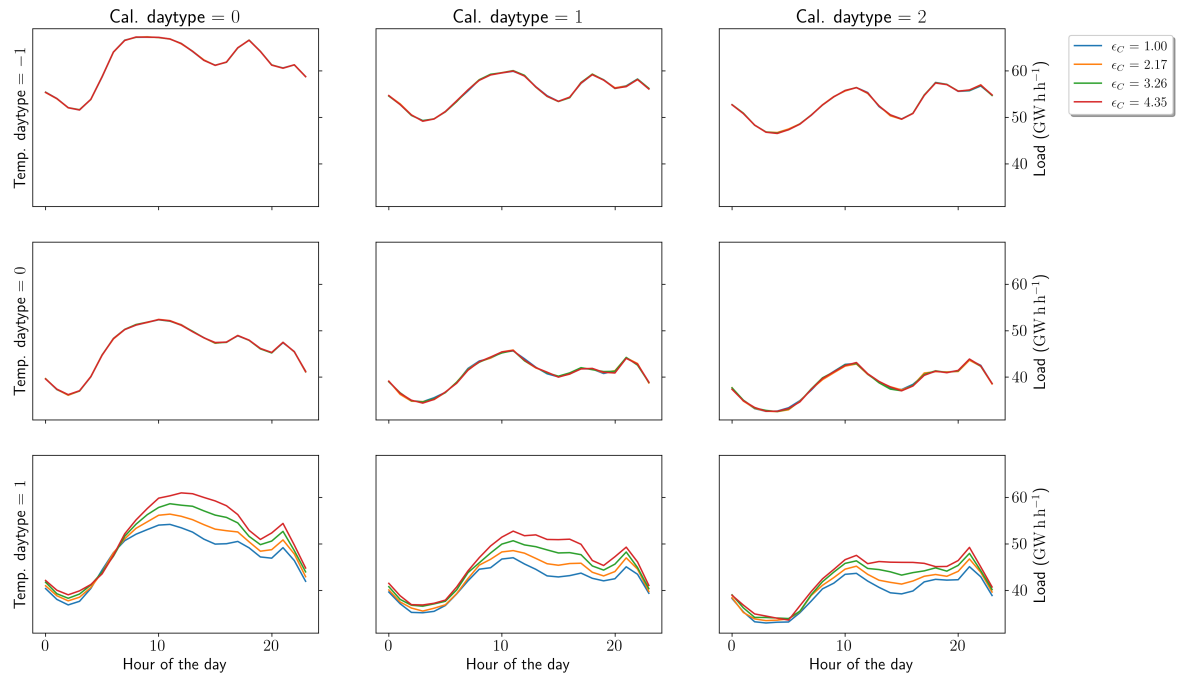


Figure 3.7. Daily variability of the cooling demand scenarios considered. Load is a synonym for electricity demand. Temp. daytype corresponds to whether the day is a heating day (-1), cooling day (1) or none of the two (0). Cal. daytype corresponds to whether the day is a working day (0), saturday (1) or sunday/holiday (2).

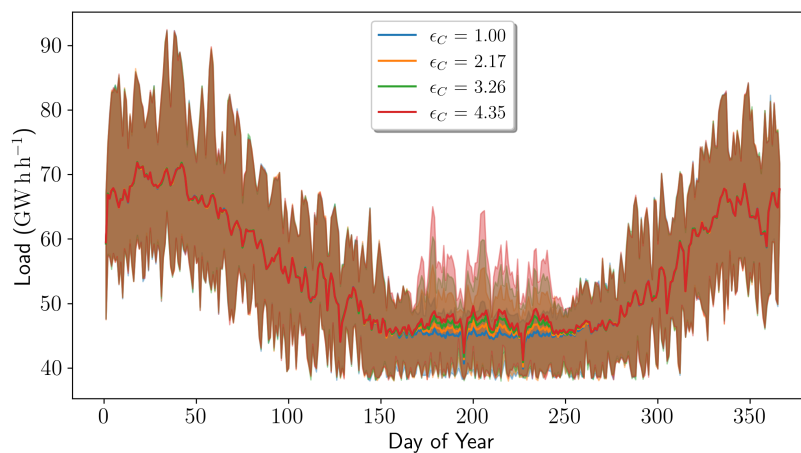


Figure 3.8. Yearly variability of the cooling demand scenarios considered, as given by the average daily load (electricity demand) throughout a year. The shaded area represents the daily average demand minimum-maximum range over the 2010-2020 period.

Base, mean and peak demand We now turn to the analysis of key features of the demand, base, mean and peak demand, as introduced in Section 3.2.3. Impacts of the different scenarios on base

demand are represented Figure 3.9a for the nationally aggregated demand and in Appendix B, Figure B.6 for the regional demands. At the national levels, increasing AC adoption has a mild but consistent impact on base demand: base demand increases with increasing levels of AC adoption. However this impact is minor as the increase remains below 1.1 % for the most extreme scenario ($\epsilon_C = 4.35$). At the regional level there is a clear distinction between the two southernmost regions (Occitanie, PACA) and the rest, the former contributing more than the latter to the base demand increase.

Average demand across the different scenarios is represented Figure 3.9b for the national demand and Appendix B, Figure B.7 for the regional demand. Similar to base demand, increasing AC induces a mild but consistent increase in the average demand. The impact is slightly more important in absolute terms (a few hundreds of MW) but decreases in relative terms as it remains below 1.0 %. The same pattern as for base demand is observed at the regional level, with what seems to be a slightly higher heterogeneity in the contribution to mean demand increase. This is evidenced by the fact that Occitanie and PACA contribute more to the relative increase in mean demand, whereas the total relative contribution is slightly less than for the base demand. The other regions must thus contribute less.

The same effect is observed at the regional level for peak demand (Figure B.8, Appendix B). The two southernmost regions of France contribute each to up to 5 % in relative increase of the peak demand. Surprisingly enough, at the national level, peak demand remains stable across the scenarios. The inconsistent trend of peak demand with increasing electrification, as shown in Figure 3.9c, gives us low confidence that the observed changes in peak demand are significant.

All in all, AC adoption scenarios have a low impact on the national electricity demand. This is a direct consequence of our working hypothesis since only AC adoption is considered and an increased usage is not envisioned. As such those regions that did not have any cooling habits so far (most northern regions) do not change those habits, and as a result demand increase is mostly due to two regions (Occitanie, PACA) over the twelve that constitute metropolitan France, even in the most aggressive scenarios of AC adoption. We leave for future works to tackle this issue, by e.g. propagating the cooling coefficients from one neighbor region to the other to mimic the onset of AC usage increase. Another factor of explanation for this low overall impact on the nationally aggregated demand is the relatively low occurrence of cooling days throughout the year compared to heating days. The intensity of the experienced hot days or heatwaves will also play a role. Both these factors will be affected by climate change, which we will account for in the next Chapter 5.

Load duration curve We finally analyze the impacts of the different scenarios on the LDC. These are represented Figure 3.10. As for the impacts on the different key indicators considered, the impacts of AC adoption as modelled in our study on the LDC are minor. The greatest impact is observed around the median demand (50 % probability), while the rest of the Figure confirms our previous interpretations: base demand is more affected than peak demand, which remains the same throughout the scenarios.

3.2.5 Summary and discussion

We have shown that space heating electrification increases the total and peak demand. We find that reaching a 50 % rate of electrification increases the yearly total demand by 5 % and by twice as much for the peak demand. Space heating electrification increases the demand variability as well: demand has a higher spread over the period considered as a result of both the daily and seasonal cycle having higher amplitudes. We have shown that our AC adoption scenarios do not change notably the total demand, nor any part of the demand on the LDC (all changes are on the order or below 1 %). However the daily and seasonal variations are strongly affected by an increased AC adoption: the typical midday plateau turns into a broad peak during a typical cooling day, whereas electricity demand increases in the summer. We put in perspective those scenarios with existing prospective exercises for the case of France or similar countries in the (grey) literature.

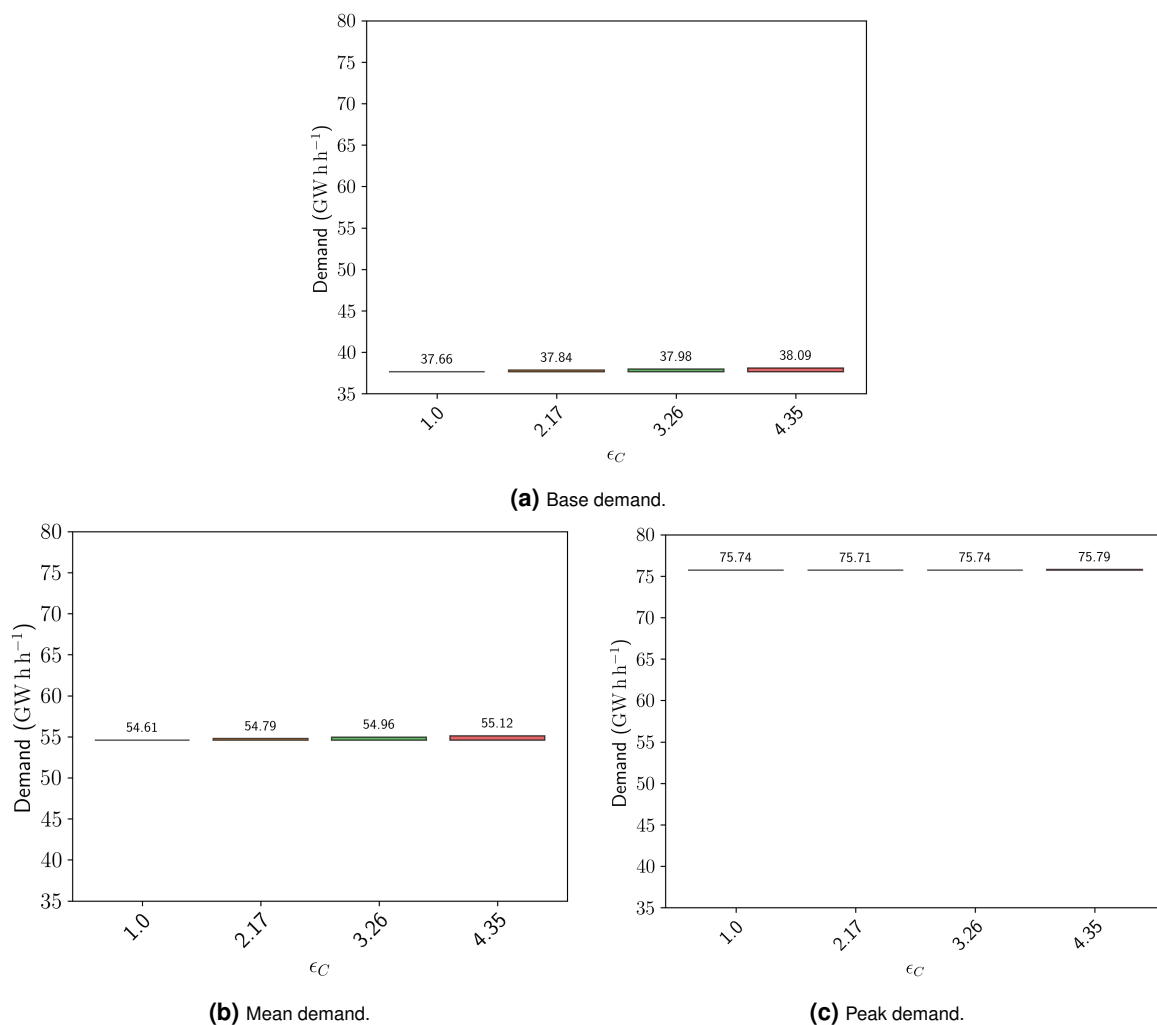


Figure 3.9. Base, average and peak demand for the cooling demand scenarios considered.

Prospective exercises vary in their projected demands for heating and cooling depending notably on the time horizon considered, their underlying assumptions regarding efficiency and whether or not they account for climate change effects. In their special focus on the electricity system in the WEO 2018, the IEA projects heating and cooling demand increases on the order of 1 % for advanced economies (IEA 2018). These estimates are quite far off to what we project for heating demand and quite in accordance with our cooling demand projections, if it weren't that in our case the cooling demand increase due to AC adoption is probably much underestimated. However, these projections rely on the FPS (Future Policies) scenario assumptions, which are conservative with respect to electrification compared to e.g. the FiES (Future is Electric) scenario assumptions. However no estimates of the heating and cooling demand growth are available for the latter. Furthermore, their projections are a mean over all advanced economies and do not focus on the specific case of France, which can also explain the discrepancy.

In their prospective exercise about the potential future state of the french electricity system in 2050, the french TSO RTE project a 20 % decrease in heating electricity demand and a 40 % increase in the cooling electricity demand (RTE 2021, Chapter 3). Their projections however account for efficiency measures and the effect of climate change, which could explain the discrepancy between our projected increase and their projected decrease in heating demand (efficiency measures and climate change will both tend to reduce this share of the demand). Their increase in cooling demand related to AC adoption — although it accounts for the climate change effects — seems more reasonable than our projections, given the levels of AC adoption that they consider (55 %) and that we consider (up to

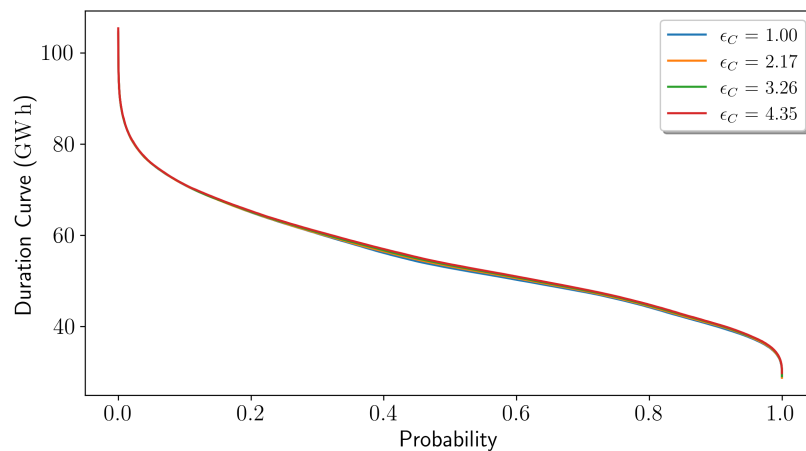


Figure 3.10. LDCs for the cooling demand scenarios considered.

100%). This reinforces our belief that our electric cooling scenarios are not really representative of such levels of electrification. Still, the effect of climate change could enhance the overall impacts of the cooling scenarios considered. A more representative model of AC adoption and usage is left for future works.

In their specific focus on the future of heating in buildings in 2035 the french energy transition agency ADEME, in collaboration with the french TSO RTE, projected the impact of efficiency and electrification policies on the building sector heating energy demand (RTE/ADEME 2020). From a total heating demand of 61 TWh (value that we use to calibrate our heating electrification scenarios, see Section 3.2.1) associated to a peak demand of 99 GW in 2018, they project a 8 % to 20 % space heating demand and a 4 % to 7 % peak demand increase in 2035, depending on whether electrification occurs with heat pumps or resistive heaters only. These projections correspond to their scenarios C and D, and do not account for any efficiency measures. The total demand increase corresponds to half of what we project in our 50 % electric heating scenario, whereas it corresponds to a rate of electric heating of 49 % for the residential sector and 41 % in the tertiary sector in their case. Our scenarios of electrification thus yield a higher total demand increase than what is estimated in their case. Regarding peak demand, a 20 % total space heating demand increase results in a 7 % peak demand increase in their case (a ratio of $7/20 = 0.35$), whereas in our case peak demand increase to total space heating demand increase has a ratio of $9/38 = 0.23$. We thus tend to underestimate the peak demand increase resulting from space heating electrification compared to what they find. This discrepancy probably comes from the way the daily cycle is encoded in the model and modified by future electrification, as e.g. described in (Peacock, Fragaki, and Matuszewski 2023), but as the methodology in (RTE/ADEME 2020) is not clearly explicited it makes it difficult to compare it with our own.

Other studies on heating electrification in Europe are harder to compare to our scenarios since the reference levels of electrification can differ. We can however compare the ratio of peak demand increase to total demand increase, which has a value of 2 in our case. (D. Connolly 2017) show ratios of peak demand to total demand increase close to what we find: e.g. from 1.8 to 2.6 in Italy or from 1.3 to 1.6 in the UK, based on a methodology detailed in (David Connolly, Drysdale, et al. 2015) (HDD approach). This gives us confidence that our projections are relevant for a sensitivity study. Given this perspective on the projected scenarios, we now assess what are the expected impacts on the electricity system and on the optimal VRE mix in particular.

We give here a qualitative analysis of how the different scenarios considered might impact the optimal VRE mix. In particular, we assess whether any of the aforementioned features of our heating and cooling scenarios might favor VRE penetration or favor one type of VRE technology over another. We do not however discuss any impacts related to storage technologies, network expansion or flexibility needs. For this analysis we rely on the nationally averaged typical daily and yearly capacity

factors profiles of VRE sources as modelled in our study (see Chapter 2) for the 2010-2020 period. These are presented Figure 3.11 for PV and in Figure 3.12 for Wind.

The changes in daily cycle due to AC adoption will probably favor the installation of PV generation capacity. PV generation is always zero at night and has a marked daytime peak that follows the average daily cycle of incoming solar radiation (Figure 3.11a). As such there is a good complementarity between the daily cycle during the cooling days and PV average generation, and even more so when AC adoption levels are increased. The complementarity between heating electrification and PV generation is not so evident, although we can suppose that as heating electrification scenarios tend to offset the daily cycle, which has a morning to early afternoon plateau, this will also favor the installation of PV generation capacity. However it should be noted that PV generation will never be correlated to the increased early and late evening peaks observed during the cooling days. It is hard to predict whether wind energy will be correlated to those peaks increase. The average daily wind generation profile (Figure 3.12a) is similar in shape to that of solar, but the min and max envelope indicates that wind can generate most of the time and even at night, all the same as it can not generate at all. A detailed study of the hourly correlation of wind power to electricity demand as in (Hazel E. Thornton et al. 2017) would be needed to further conclude. The average profile of wind generation however hints at the fact that there can be a good complementarity between wind generation and an increased AC adoption. If both energy sources have a good complementarity with demand during cooling days, then they enter in competition to satisfy the demand. This issue must be tackled. We however considered an average daily cycle over the whole period (2010-2020) regardless of the season the day belongs to. This is a limitation, since wind and PV capacity factors exhibit a strong seasonal variability.

The changes in seasonal cycle due to heating electrification will probably be favorable to wind generation. Wind capacity factors exhibit a moderately strong seasonal variability with generation peaking in winter time, as shown Figure 3.12b: the daily average capacity factor varies between about ~ 0.1 in summer and ~ 0.3 in winter. This variability is however small compared to the interannual variability for a given day of the year (from almost 0 to ~ 0.9 for a given day of the year). We can notice that if the minimum average daily capacity factor is roughly constant throughout the year, the maximum capacity factor tends to follow the same seasonal cycle as the average capacity factor. This is not the case for the PV capacity factors seasonal variations where the interannual variations of average daily capacity factor (~ 0.1 spread) are smaller than the seasonal variations (~ 0.15 spread), as shown Figure 3.11b. To the contrary of wind seasonal cycle, the more definite PV seasonal cycle peaks in summer. The changes in seasonal cycle due to AC adoption will thus be probably favorable to PV generation.

We qualitatively analyzed possible synergies between the demand derived from our scenarios and VRE capacity factors. We have the intuition that heating electrification scenarios will tend to favor both wind and PV installation, although from the seasonal cycle analysis we infer that wind will be preferred. It is hard to tell how AC adoption scenarios will impact wind energy integration, although from the seasonal cycle analysis it seems that PV capacities will be preferred in that case. However, the analysis presented here has several inherent limitations. The main one being that the actual hourly correlation between demand and VRE capacity factors is not accounted for. Then, we considered so far national averages whereas weather patterns can be regionally differentiated and as such the hourly correlation of demand to VRE capacity factors may not be the same from one region to another. We also discussed the potential synergies of each VRE technology separately, while competition or complementarity effects can be observed when both are considered at the same time. Finally, as averages were considered, we missed the inherent interannual variability due to the stochasticity of the demand and capacity factors (let aside the low frequency internal climate variability). To fully account for the regional hourly correlation between demand and VRE capacity factors, their stochasticity, as well as the wind and PV technological complementarity, we use the E4CLIM framework (Tantet, Stéfanon, et al. 2019; Tantet and Drobinski 2021) presented in Chapter 2, Section 2.4. We showed that the impacts on the demand of scenarios of AC adoption are limited with the climate conditions of reference. They are expected to be higher in the future due to climate

change. We thus focus exclusively in this chapter on heating demand electrification and its impacts on the obtained VRE mixes and their economic properties. We assess in the following section what are the impacts of our different heating demand scenarios on the choice of the optimal VRE mix.

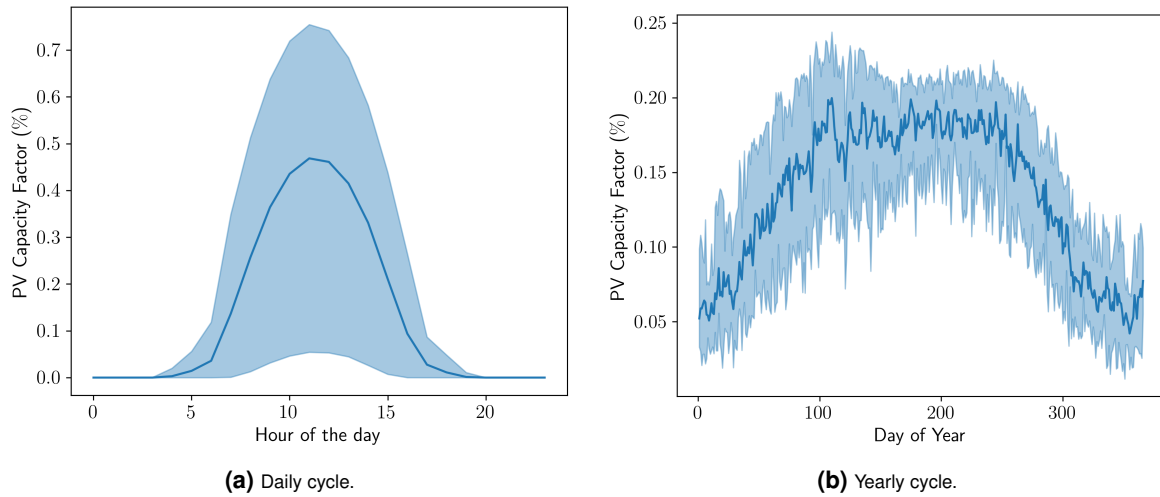


Figure 3.11. PV capacity factor daily and yearly cycles. The shaded area corresponds to the minmax envelope.

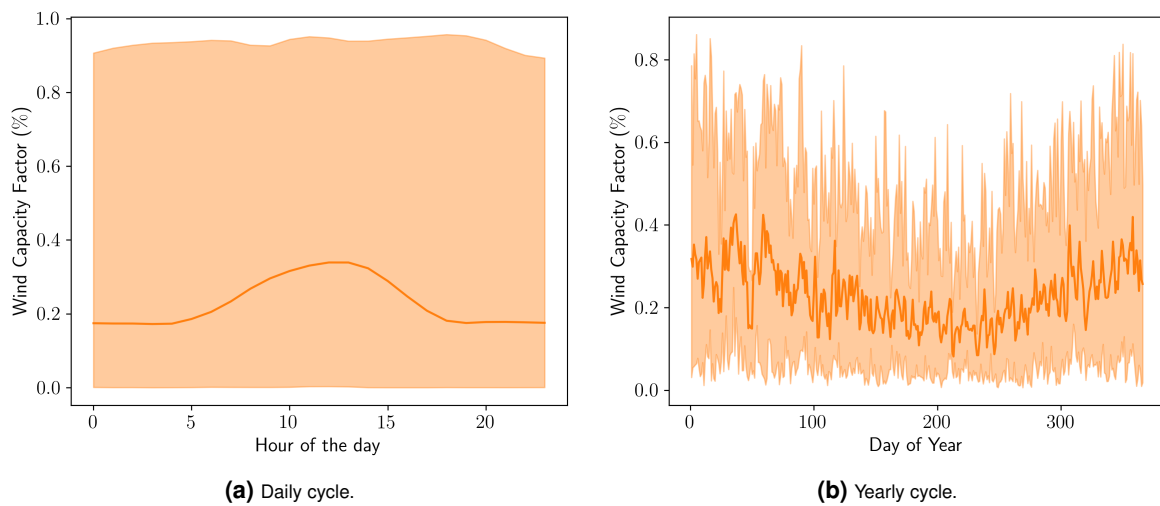


Figure 3.12. Wind capacity factor daily and yearly cycles. The shaded area corresponds to the minmax envelope.

3.3 Impacts of socioeconomic scenarios of electric heating on VRE optimal mixes and system costs

Highlights

Impacts of space heating electrification on variable renewable energies regional mixes and system total costs

Joan Delort Ylla, Alexis Tantet, Philippe Drobinski

- A minimal model of temperature-sensitive electricity demand was developed;
- Space heating electrification favors the penetration of Variable Renewable Energies (VREs);
- Increases in system total costs are moderately compensated by VRE value;
- Optimal energy mixes are governed by the LCoE and maximal installable VRE capacities;

Impacts of space heating electrification on variable renewable energies regional mixes and system total costs

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Abstract

Decarbonising heating demand is a necessary step towards meeting the Paris Agreement goals. We study the decarbonisation of the former in the case of France, where an electrification of the heating demand seems plausible. We design to this end a temperature-sensitivity model of demand and use the E4CLIM electricity system model to study a variety of heating electrification scenarios in an electricity system with high shares of VREs. We find that the electrification of heating demand favors the installation of VRE capacities at the same time that it increases the system total cost. We find also that increasing heating demand electrification is not the main driver for the determination of optimal VRE mixes. These are mainly driven by the technologies LCoEs and maximal installable capacities. We suggest to perform a similar sensitivity study within the context of climate change in future works.

Keywords: Decarbonisation, VRE, Heating, Temperature-sensitive demand

1. Introduction

Current and projected climate change impacts are a threat to the well-being of numerous human and non-human populations around the globe. This is particularly true for the already most vulnerable ones [1, Executive Summary, B.1]. Mitigation of climate change is a necessary but not sufficient

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step in ensuring a livable environment for all [2]. The objectives to mitigate climate change impacts as defined by the Paris agreement¹ cannot be reached without reduction of the carbon emissions of the world energy systems [3, Chapter 6]. Reduction of Greenhouse Gas (GHG) emissions of the electricity generation sector is key to reaching low carbon energy systems [3, Chapter 6]. Aside from other low carbon energy technologies, Variable Renewable Energies (VREs) like solar Photovoltaic (PV) and wind energy will be key players in the decarbonisation of the electricity generation sector. Although debated [4, 3], some studies strongly support that a fully renewable low carbon electricity generation mix based on wind, solar PV and hydroelectricity is feasible and viable [5]. Such mixes have already been incorporated into states' energy policies and industrial stakeholders projections. These projections and roadmaps define energy mixes that contain a high share of VREs: from 60 % to 90 % of installed capacity and up to 90 % in production according to 2050 scenarios from the french Transmission System Operator (TSO) [6, Chapter 5]. Studying the properties of such mixes is key to understand processes that might compromise their social, environmental or economical viability.

Tackling the decarbonisation of the heating sector is also key to reduce global carbon emissions. In France, emissions from the heating demand supply accounted for 15 % to 20 % of the total emissions in 2019 [7], whereas in Europe they accounted for at least 10 % to 15 %² in 2020 [8]. Space heating accounts for the majority of the heating demand (54 %), in particular in the residential and services sectors, in the case of Europe [9]. It alone accounts for 80 % of the heating demand in the residential sector and 10 % of the global European Union (EU)-28 GHG emissions in 2015³. Decarbonisation of the heating sector has received much attention at the national and international levels, with commissioned reports from EU-funded projects [11, 12] — part

¹<https://unfccc.int/process-and-meetings/the-paris-agreement/the-paris-agreement>

²Own computation based on data from https://di.unfccc.int/detailed_data_by_party and considering the sum of sectors 1.A.4.a and 1.A.4.b as corresponding to the actual residential and tertiary heating. Note that electric and district heating contributions are in this case not taken into account, which would in general increase the estimation by a few percent.

³Own computation based on data by [10] for sectoral emissions and [8] for total GHG emissions with Land Use, Land Use Change and Forestry (LULUCF).

of the Heat Roadmap Europe (HRE) project — and national reports like [7] in the case of France, for the most recent ones. Apart from gains in energy efficiency, use of low carbon fuels — including the parsimonious use of biomass [13] — or connection to local decarbonated district-heating systems, electrification of services and residential sectors heating demand will play an important part in their decarbonisation [3]. In the case of France, 40 % of households rely on electric heating (heat pumps or resistive heaters) as of 2020. This number is projected to rise to 70 % in 2050 [6], although the overall electricity demand is expected to remain stable. In the case of Europe, the transition to heat pumps to satisfy the heating and cooling demand could increase the electricity demand by 30 % to 50 % for some countries, and by 100 % in the case of resistive heaters [14].

Before considering the impact of heating demand⁴ electrification on the electricity system, an electricity system with high shares of VRE already implies multiple challenges to be tackled. In particular, high shares of VREs in the mix induce (positive or negative) extra costs related to their intrinsic characteristics IEA-RTE [15]. If introducing high shares of VREs has an impact on the energy system from the production side of things, increasing the electricity demand due to heating electrification will also affect the electricity system considered. In the literature, the most mentioned impacts consist of an increase in average demand and peak demand [14] and an increased temperature-sensitivity [6, Section 6.4.4]. The effects on other components of the electricity system, e.g. the need for greater flexibility or the need for network expansion [14, 16, 6], although mentioned, are not well characterized. In particular the effects of heating demand electrification on the optimal generation mixes are — to the best of our knowledge — not well documented.

We ask in this study what are the impacts of increased heating demand electrification on optimal VRE mixes and system total costs. This allows us to identify and discuss the possible synergies between an increase of the rate of electric heating and the integration of large shares of VRE. We focus on the techno-economical impacts of a transition from low to high heating demand electrification in the case of France.

⁴We denote in the following as heating demand this share of the demand that comprises space heating in the residential and services sectors. The former are often regrouped into the more generic term of building sector and we will not differentiate the two terms in the following.

We use a modified version of the open-source E4CLIM model [17] as a tool to study coupled investment and optimal dispatch of demand in a power system with high shares of VRE. The model architecture allows for the modelling of capacity factors and demand from climate and energy data at a regional scale, which allows us to study demand scenarios corresponding to various rates of electric heating and different levels of VRE penetration. One originality of this model is its mathematical simplicity, allowing for straightforward analysis of the phenomena at play. In particular, it is technology agnostic: no assumptions on the mix that supplies the heating electricity demand, nor on the mix of dispatchable producers that complement VRE producers in supplying the electricity demand are needed. Finally, the exact definition of VRE integration costs being subject to discussion [18], we base our techno-economical analysis on the optimisation of a system total cost [19], rather than the simple use of an Levelized Cost of Electricity (LCoE)-like metric or the decomposition into VRE integration costs.

A more detailed description of the methods is presented in Section 2. In Section 3, we present the main results of the study, some of which are discussed in Section 4. We finally present the main conclusions in Section 5.

2. Methods

In order to analyze the effect of heating demand electrification on an electricity system with high shares of renewables, we use a temperature-sensitive electricity demand model to estimate hourly variations of the demand in response to temperature variations, in which the temperature-sensitivity can be controlled according to different electrification scenarios. The resulting demand is then fed to electricity systems with varying penetrations in VRE modeled in E4CLIM at the regional scale with a minimal representation of dispatchable producers. In this section, the temperature-sensitive demand model, the heating electrification scenarios and the electricity system model are presented.

2.1. Temperature-sensitive demand model

We are interested in modeling the impact of climate and meteorological variability on electricity demand for a given geographical region. The demand model presented by Tantet et al. [20] is adapted to this end. We design a probabilistic generalized linear regression model of demand taking

temperature as input. The main purpose of this model is to give one access to the temperature-sensitivity coefficients and to allow one to modify them without compromising the demand statistical features (yearly, weekly and daily variability). The hour of the day, h in $\llbracket 0, 23 \rrbracket$, and the calendar daytype, j in $\{0, 1, 2\}$, are included as dummy variables, to account for the daily and weekly variability. The calendar dummy j discriminates work days ($j = 0$), saturdays ($j = 1$) and holidays ($j = 2$).

Let $L(t)$ be the hourly demand for a particular region and $T(t)$ be the surface temperature for time t . We also note $h(t)$ and $j(t)$ the hour of the day and the daytype for t , respectively. The factorized temperature-sensitive model may be written as

$$L(t) = \omega^0 + \omega_{h(t),j(t)}^B X^B(t) + \omega_{h(t),j(t)}^H X^H(t) + \omega_{h(t),j(t)}^C X^C(t) + \eta(t), \quad (1)$$

where ω^0 is an intercept and $\omega_{h,j}^B$, $\omega_{h,j}^H$ and $\omega_{h,j}^C$ are respectively the Base, the Heating temperature-sensitivity and the Cooling temperature-sensitivity coefficients for the hour of day h and daytype j . The corresponding input features X^B , X^H and X^C are given by

$$\begin{aligned} X^B(t) &= 1 \\ X^H(t) &= (T_H - \bar{T}(t))\Theta(T_H - \bar{T}(t)), \\ X^C(t) &= (\bar{T}(t) - T_C)\Theta(\bar{T}(t) - T_C) \end{aligned} \quad (2)$$

where T_H and T_C are the heating and cooling threshold temperatures and Θ is the Heaviside step function. Note that we must have $T_H < T_C$. The quantity $\bar{T}(t)$ is the daily-mean surface air temperature of the region considered; it is kept constant throughout the day. The term η is a residual which accounts for all processes other than changes in air temperature that influence the demand as well as variations in the demand in response to temperature changes that cannot be captured by the model (1). We assume this residual to be a Gaussian white noise with variance σ^2 . Given T_H and T_C , the model (1) can be turned into a linear model by replacing the inputs (2) by the factorized inputs,

$$\left(\hat{X}_{h',j'}^B(t), \hat{X}_{h',j'}^H(t), \hat{X}_{h',j'}^C(t) \right) = \begin{cases} (X^B(t), X^H(t), X^C(t)) & \text{if } h' = h(t) \text{ and } j' = j(t) \\ (0, 0, 0) & \text{otherwise,} \end{cases} \quad (3)$$

for all h' in $\llbracket 0, 23 \rrbracket$ and j' in $\{0, 1, 2\}$. The factorized coefficients and inputs can then be collected into a vector $\boldsymbol{\omega}$ and a random vector $\mathbf{X}(t)$ to wit,

$$L(t) = \omega^0 + \mathbf{X}(t) \cdot \boldsymbol{\omega} + \eta(t). \quad (4)$$

The coefficients of the linear model (4) are fitted using a training set of input temperatures and target demands for each region (see Sect. 2.1.1). To avoid overfitting we apply a regularization method instead of simply estimating the coefficients via an ordinary least-squares regression. We choose a method that is both Bayesian and sparse: the Automatic Relevance Determination (ARD) regression (Tipping [21], Chap. 7.2 in Bishop [22] and Wipf and Nagarajan [23]) implemented in Scikit-learn [24], with small values of the hyperparameters to make the priors non-informative. The coefficients in $\boldsymbol{\omega}$ are region specific; however, to limit the number of hyperparameters and the risk of overfitting, we assume that the thresholds T_H and T_C are independent of the regions. This pair of hyperparameters is optimized in order to minimize the prediction coefficient of determination averaged over all regions. The latter is estimated via the k-fold grid-search cross-validation procedure implemented in Scikit-learn [24]. The number of folds is set to the number of years of data in order to preserve the seasonal cycle in each fold. Having estimated the coefficients for all regions, the coefficients ω^H can then be modified to account for the increased temperature-sensitivity due to the electrification of heating in the demand that is then fed to the power system model module of the E4CLIM model.

2.1.1. Temperature-sensitive model training data

The meteorological data used to compute the feature vector \mathbf{X} is from MERRA-2 reanalysis (surface temperature field, hourly resolution) following Tantet et al. [20]. The training vectors are computed from demand data from the french TSO Réseau de Transport de l'Électricité (RTE)⁵, which is also available at an hourly time resolution. The metropolitan France administrative regions considered in the study are presented in Appendix A, Figure A.6.

⁵https://opendata.reseaux-energies.fr/explore/dataset/eco2mix-regional-cons-def/information/?disjunctive.libelle_region&disjunctive.nature, accessed on 17 January 2022.

2.1.2. Electrification scenarios

From the obtained temperature-sensitivity coefficients (see Figure B.7), we design simplified scenarios of increased electrification as equivalents to the technological transition from non-electric to electric heating appliances for the case of France.

These electrification scenarios are determined by the rate of electric heating. Two families of electrification scenarios are defined. In the Uniform Electrification (UE) family, electrification occurs uniformly for all hours, so that the demand is simply multiplied by a constant. One scenario from this family will be analyzed in more details: the Uniform Electrification 65 (UE65) scenario, for which $\langle L \rangle = 65$ GW. In the Heating Temperature-sensitive Electrification (HTE) family, only the heating temperature-sensitive demand is multiplied (for all hours). In particular, the Heating Temperature-sensitive Electrification 65 (HTE65) scenario is associated with the same average demand as UE65. Last, in the Reference scenario, no electrification is performed. Those scenarios are presented in Table 1, with the Reference scenario corresponding to the french rate of electric heating as of 2015 (representative of the 2010-2020 period), that we take equal to 35 % [25, 26]. The HTE65 scenario corresponds to an increase of the temperature-sensitive demands in all regions yielding a rate of electric heating of 70 %. The UE65 scenario corresponds to a uniform increase in the demand equivalent on average to that of the HTE65 scenario. The detail of all demand scenarios is given in Appendix B, while the obtained temperature-sensitivity coefficients for each scenario are presented in Figures B.7b and B.7c.

Scenario	Average demand $\langle L \rangle$ (GW)	% electric heating
Reference	54.6	35 %
UE65	65.0	35 %
HTE65	65.0	88 %

Table 1: Main electrification scenarios of the study.

We represent the Load Duration Curve (LDC) for each of these three demand scenarios in Figure 1. We can observe that the LDC of the UE65 case is to the first order a translation of the LDC of the Reference case, whereas the shape of the LDC in the HTE65 case is altered: there is an increased demand variability and a higher probability to observe demands

above the mean than for the UE65 case. Peak demand is also higher in the HTE65 case, with a value of 162 GW, compared to the UE65 case with 124 GW. A 20% increase in the average demand is thus associated with a 60% increase of the peak demand in the HTE65 case.

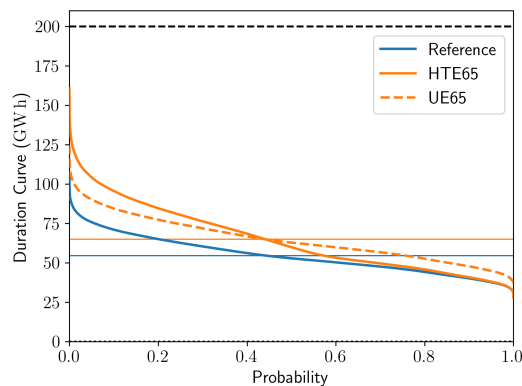


Figure 1: LDC (thick colored lines) for the Reference (plain blue), HTE65 (plain orange) and UE65 (dashed orange) scenarios.

2.2. Energy system model

In order to analyze the response of optimal VRE mixes to heating electrification we adapt the Energy System Model (ESM) E4CLIM [17]. We refer the reader to Appendix C for a summary of the main methodological developments.

2.2.1. VRE-penetration scenarios

Different levels of VRE penetration can be explored in E4CLIM by controlling the variable cost of dispatchable producers with the Dispatchable Variable-Cost Coefficient (DVCC) (α). The higher the DVCC, the more costly the dispatchable production, and so the larger the optimal penetration of VRE. This is shown Figure 2a, e.g. for the Reference case (plain blue line). Thus, for each of the electrification scenarios presented in Section 2.1.2, the VRE mix is optimized for a range of DVCC values in $[1 \cdot 10^{-6}, 6 \cdot 10^{-3}]$. This range is sufficient to explore both low and high VRE-penetration scenarios. Additionally scenarios without VRE can be considered for any DVCC value.

Three main scenarios are considered in particular in the following: Low penetration, High penetration and Max penetration, corresponding to $\alpha =$

$0.8 \cdot 10^{-3} \text{ € MWh}^{-2}$, $\alpha = 3.2 \cdot 10^{-3} \text{ € MWh}^{-2}$ and $\alpha = 6.0 \cdot 10^{-3} \text{ € MWh}^{-2}$ respectively. These VRE-penetration scenarios correspond to levels of penetration of 25 % to 35 %, 65 % to 70 %, and 70 % to 85 % for the Low-penetration, High-penetration and Max-penetration scenarios respectively (the variations being attributed to the different electrification scenarios). This is shown in Figure 2, where the total penetration of VRE (Figure 2a) corresponds to the amount of energy served by VRE per total energy served. VRE curtailment is also shown in Figure 2b, and corresponds to the amount of excess VRE generation per total energy served by VRE. The aforementioned levels of VRE penetration correspond to curtailments levels of less than 5 %, 15 % to 20 %, and 20 % to 25 % for the Low-penetration, High-penetration and Max-penetration scenarios respectively.

In summary, the electricity demand estimated in Section 2.1 for different electrification scenarios are fed to the E4CLIM model in order to estimate optimal VRE mixes at different penetrations. In the next section, the resulting VRE mixes are analyzed in order to evaluate the response of the value of VREs depending on the electrification scenario.

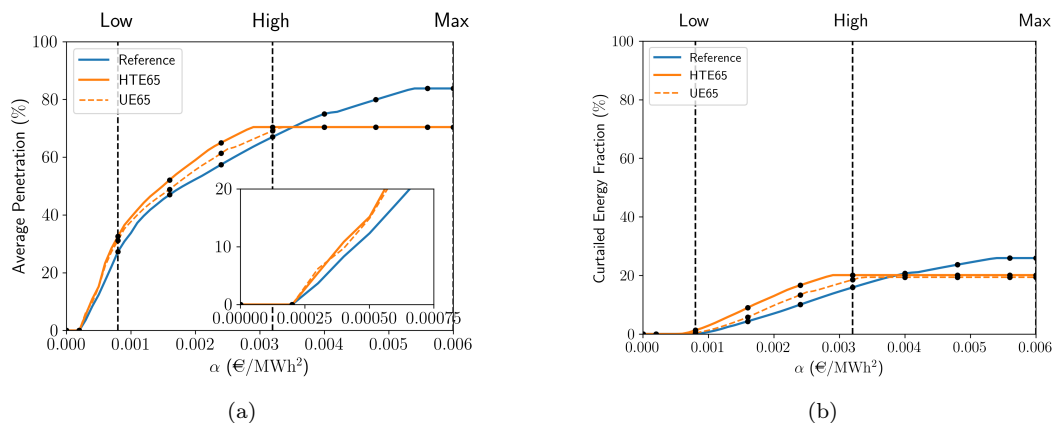


Figure 2: Global VRE penetration (left) and curtailed energy fraction (right) as a function of the DVCC for optimal VRE mixes for the three main electrification scenarios. Dashed lines correspond to the Low-, High- and Max-penetration scenarios. Inset shows both quantities for penetrations below 20 %.

3. Results

We present in this section the results of the different scenarios to study the impact of heating demand electrification on the electricity system, and

on VREs mixes value and technological diversification. In a first step, in Section 3.1, we analyse the impact of electrification on VRE mixes without discriminating VREs by technology. Then, in a second step, in Section 3.2, we analyze the regional and technological diversification of the obtained mixes.

3.1. VRE mixes

We now analyze the effect of electrification on the system for optimal VRE mixes, with VRE producers considered as a whole. A finer analysis of the VRE technological diversification is presented in Section 3.2.

3.1.1. Penetration and curtailment

In any of the considered electrification scenarios (Reference, HTE65, UE65) penetration increases with increasing DVCC up to a threshold where it remains constant (Figure 2a). This corresponds to the point where all VRE capacities have been installed and regional maximum installable capacities have been reached. Regarding the effect of an increased electrification, we observe that as long as maximal capacities have not been reached, an increased average electrification implies a higher VRE penetration in the mix (Figure 2a). At a given value of the DVCC, the penetration is higher for the HTE65 scenario than for the UE65 one. This suggests that at a given level of average electrification, a temperature-sensitive electrification tends to favor VRE capacity installation. Regarding VRE curtailment, we observe that it increases with increasing DVCC, in a similar fashion as penetration: a first phase of increase and then a plateau, once the maximal penetration has been reached (Figure 2b).

At a given variable cost of the dispatchable production (i.e. for a given DVCC), a temperature-sensitive demand electrification tends to favor installation of VREs compared to the Reference or UE scenarios. Up to 14% more VRE capacity is installed in the HTE65 scenario compared to the Reference scenario, for penetrations of $(60 \pm 5)\%$. This higher penetration of VRE is followed by an increased curtailment compared to the Reference scenario. As our mixes minimize the electricity system's total cost, this should mean that VRE are preferred over dispatchable producers when increasing the temperature sensitive electricity demand. We discuss this conclusion in the next sections by analysing the total and marginal costs for the different electrification scenarios and through the assessment of VRE value.

3.1.2. Total costs and VRE value

The System Total Cost (STC) is analyzed for mixes with optimal VRE capacities and for the values of the DVCC corresponding to the Low- ($\alpha = 8.01 \cdot 10^{-4} \text{ € MWh}^{-2}$), High- ($\alpha = 3.2 \cdot 10^{-3} \text{ € MWh}^{-2}$) and Max- ($\alpha = 6.0 \cdot 10^{-3} \text{ € MWh}^{-2}$) penetration scenarios (Figure 3a). The differences in VRE penetration for a given DVCC (α) in Figure 2a show that points in Figure 3 for the HTE and UE scenarios — for the same average demand and DVCC — may be associated with different mixes. We observe Figure 3a that an increase in average electrification yields an increase in STC. Notably, the increase in STC compared to the Reference scenario is 9 points higher in the HTE65 scenario than for the UE65 scenario (High-penetration scenario). This effect is more, resp. less, pronounced for higher, resp. lower, values of the DVCC. To summarize, a temperature-sensitive increase of the demand implies a higher STC than a uniform increase of the demand. In the next paragraph, the impacts of the different scenarios on the VRE value are assessed by comparing an energy mix without renewables and only dispatchable producers to optimal VRE mixes.

We define by System Total Value (STV) of VRE the difference in STC between a mix with optimal VRE capacities and one without VREs for a given scenario. Formally, the expected STV over a year for a given VRE mix \mathbf{x} is given by

$$\mathbb{E}(\text{STV}_{\mathbf{x}}) = \mathbb{E}(\overline{\text{STC}}(0)) - \mathbb{E}(\overline{\text{STC}}(\mathbf{x})). \quad (5)$$

The STV of VRE are given in Table 2, while the STV for all demand scenarios relative to the Reference case is plotted in Figure 3b. We first observe from the results reported in Table 2 that the VRE value is always positive for the scenarios considered: there is no scenario where disinvesting in VRE would benefit the system. This is expected since the VRE mixes are always optimal with respect to the system total cost, and as such, investment in VRE occurs only if this total cost decreases. Introducing VRE reduces notably the system costs: the STV is 2%, resp. 24%, of the STC without VRE for the Low-penetration, resp. High-penetration, scenarios (Reference electrification scenario).

We observe that VRE total value is multiplied by 1.4 to 1.8 (Figure 3b) when increasing the average demand (HTE65 scenario). This relative increase is higher for low values of the DVCC. We should however keep in

mind that VRE total value is higher for higher values of the DVCC, as shown earlier. This relative increase in STV is significantly lower for a uniform demand increase than for a temperature sensitive demand increase at high penetrations (plain vs. dashed lines). This difference between HTE and UE scenarios is not so significant at lower penetrations and gets inverted for lower values of average demand.

In conclusion, we find that increasing the average demand tends to increase the VRE value with respect to the Reference scenario. This increase is more marked for a temperature-sensitive increase of the demand (HTE scenarios) as long as maximum capacities are not reached.

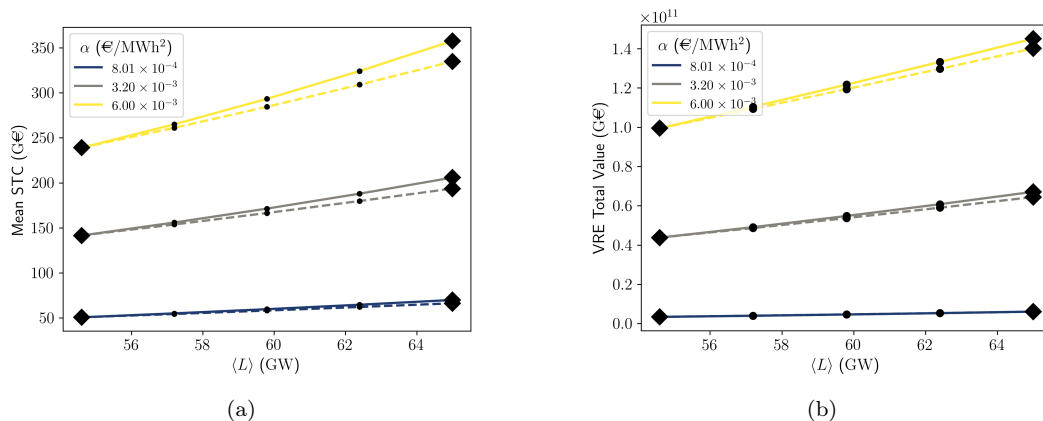


Figure 3: Mean STC (left) and mean STV with respect to the Reference case (right) as a function of the average demand (corresponding to increasing levels of electrification) and for the Low ($\alpha = 8 \cdot 10^{-4}$ €/MWh⁻²), High ($\alpha = 3.2 \cdot 10^{-3}$ €/MWh⁻²) and Max ($\alpha = 6 \cdot 10^{-3}$ €/MWh⁻²) VRE penetration scenarios. Dashed colored lines correspond to the UE scenarios while plain colored lines correspond to the HTE scenarios. Thick black diamonds show the Reference, UE65 and HTE65 electrification scenarios. The magnitude of the VRE STV for the Reference case is reported in Table 2

3.2. Technology-level assessment

We analyze the impact of heating demand electrification on the optimal VRE mixes. We expect that a change in demand will affect which VRE technology-regions will be invested in preferentially. The optimal VRE mixes per region and technology are plotted in Appendix D, Figure D.9, for the Low-penetration scenario and Figure D.10 for the High-penetration scenario.

Scenario	STV (Low %)	STV (High %)
Reference	3.4 G€	43.8 G€
HTE65	6.1 G€ ↑	67.1 G€ ↑↑
UE65	6.1 G€ ↑	64.5 G€ ↑

Table 2: System total value for the main scenarios of the study. Low % stands for low VRE penetration, while High % corresponds to the high VRE penetration scenarios. The arrows represent the evolution in magnitude with respect to the Reference scenario, between electrification scenarios only.

We observe that no matter the electrification scenario (Figures 4a and 4b), the mix is composed to the first order only of PV for values of penetration below 10 %, then is dominated by PV up to (20 ± 5) % penetration, where Wind then becomes the dominant generation source. Except for the total level of VRE penetration, which is higher in the HTE scenarios, the two investment trajectories differ only by what happens at low penetration values, where we observe that more solar PV capacity is installed sooner in the UE65 case. Inversely Wind capacity is installed earlier in the HTE65 case.

The technology-level penetrations presented here correspond to the regionally aggregated technologies. It can be shown that there is no regional diversification between the HTE65 and UE65 scenarios: the investment trajectories with increasing DVCC value are the same than for the Reference case, except that capacities are installed sooner for the higher electrification scenarios, and sooner for the HTE scenarios compared to the UE ones (see Appendix D, Figures D.9 and D.10). In particular, maximal capacities per region are reached in the same order.

We recall that investment in VRE capacity is determined by a technology-region potential profits. For VRE capacity to be installed, the potential profits of some technology-region i must be non-negative. These profits are given by

$$P_i = \langle \lambda \rangle \nu_i - \text{LCoE}_i, \quad (6)$$

where ν_i and LCoE_i are respectively the value factor and the LCoE (€ MWh^{-1}) of VRE producer i . The detail of the mathematical development is given in Appendix C. The System Marginal Cost (SMC) (λ) is the same for all producers, thus it affects the optimal VRE mixes level of penetration. The two other factors — the value factor, ν_i and the LCoE of technology-region i ,

$LCoE_i$ — control the differences in installed capacity between regions, and thus determine the mix composition per technology-region. We plot the average over all regions of the VRE value factor before VRE is installed, against the different demand scenarios in Figure 5. We observe, and this is computed in Appendix B, Equation (B.16), that the initial value factor for the UE scenarios doesn't change. However, the initial value factor of wind technology-regions is increased on the order of 2% to 3% for the HTE65 scenario compared to the Reference one. The opposite behavior is observed for solar PV, where the initial value factor of all technology-regions is decreased on the order of 5% for the HTE65 scenario compared to the Reference one. The variations in LCoE between wind energy and solar PV are on the order of 50% to 100% for the most extreme cases (see also Figure C.8). These variations are thus much higher than the variations in value factor.

These observations allow us to conclude that, to the first order, VRE mixes are not impacted by a uniform increase in the demand (UE scenarios) nor by a temperature-sensitive increase in the demand (HTE scenarios): optimal VRE mixes vary with the penetration of VREs, with solar PV dominated mixes at low penetrations and wind dominated mixes up a certain penetration threshold. However, for low penetrations — i.e. below 10% to 15% — we observe that wind energy is favored in the case of a temperature-sensitive electrification (HTE scenarios), whereas solar PV is preferred in the case of a uniform electrification (UE scenarios).

4. Discussion

We showed so far that although it had an impact on system total and marginal costs, as well as on VRE value, a temperature-sensitive electrification did not impact (to the first order) the optimal VRE mixes installed to satisfy a given demand. In particular, we show that VRE mixes were governed at low penetrations by solar PV whereas Wind energy takes up once a certain penetration threshold is reached. We discuss in this section some of the previous results, as well as put them in perspective with results from the literature.

We can compare the obtained system costs with projections from system operators. If we take for example the projected values of a decarbonated energy system at the 2050 horizon in the case of France [6], we get values for the system total cost in the order of 40 G€ per year, for the production costs only and up to 75 G€ per year for the system's total cost. These

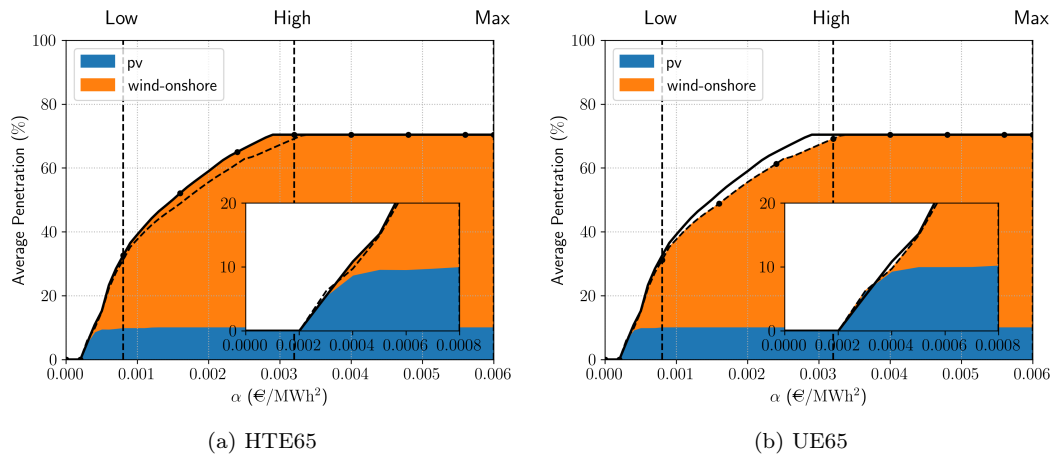


Figure 4: Penetration of Wind and PV for optimal VRE mixes at different values of the DVCC and for the HTE65 (left panel) and UE65 (right panel) scenarios. The total penetration is represented as a full black line for the HTE65 case, and as a black dashed line for the UE65 case. A zoom into what happens for low global penetrations (0 % to 35 %) is given in the insight of each panel. The vertical dashed lines mark the Low, High and Max VRE penetration scenarios.

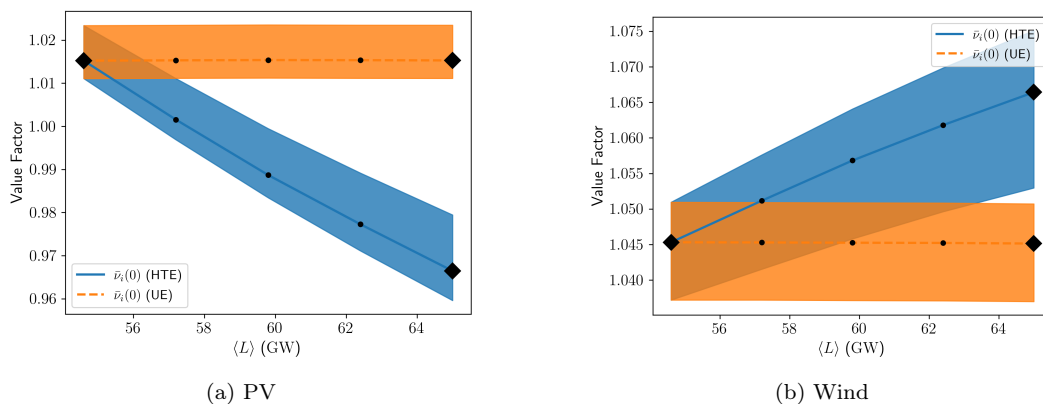


Figure 5: National median of the regional value factors — Equation (C.6) — without VRE, for PV (left), and Wind (right) panel; plotted against the average demand for each case. The plain blue line corresponds to the increased temperature-sensitive electrification scenarios (HTE scenarios), whereas the orange dashed line corresponds to the UE scenarios. The shaded area corresponds to the first and third interquartile range (linear method).

values are close to those in our Low penetration scenario — 50 G€ to 70 G€ — but lower by one order of magnitude compared to the High penetration scenarios, where the yearly average STC is on the order of 150 G€ to 200 G€. Despite these lower STC values, VRE penetration is brought to high levels, up to 88 %, in the RTE scenarios. This discrepancy might come from the internalisation of the emission costs in our model: the DVCC then becomes a proxy for the emission costs, i.e. the equivalent of a carbon tax. It is thus interesting to note that high VRE penetrations are economically optimal only under a high cost of the dispatchable production (in this study), which can be interpreted as a high carbon tax (in general).

The synergies between electrification and VRE were already explored in the case of resistive heaters [27], or in the case of heat pumps [28, 29]. Zhang et al. [27] find that resistive heaters are in good synergy with wind power in the periods of high wind power production. This is something we observe in our study, but only at low penetration values. Hedegaard et al. [28] find that a technological transition to heat pumps, causing the displacement of less efficient technologies and the subsequent electrification of heating demand, is the most effective way in their model to reduce Wind power curtailment. We would have expected a similar result in our case, however, we have shown that increasing the rate of electric heating has opposedly the effect of increasing the overall curtailment. Waite and Modi [29] presented similar results with a modelling experiment at the scale of the city of New York (USA): Wind power integration was favored by the installation of heat pumps. However, instead of optimizing VRE capacities, those were set beforehand, limiting the reach of their conclusions in terms of economically optimal mixes.

Perhaps the main limitation of this study is the extent to what the minimalism of both our demand and energy system models are able to reproduce the complex mechanisms of the electricity system as a whole. Limitations of the energy system model are well described in Tantet and Drobinski [17]. In our case the absence of storage is maybe the greatest factor of uncertainty as to the generalization of our results: indeed, the possibility of storage could weaken the effects the value factors have on optimal mixes at low penetrations. As for the demand model, the main limitation is probably its technological agnosticity, i.e. the fact that: one, the initial mix supplying the Reference heating demand is never addressed; and two, that this mix is supposed to remain the same when increasing electrification. It would be interesting to explore if technological diversification could be added into our linear model of demand, to be e.g. able to study an electrification that would be carried

out only through the installation of heat pumps. Our model can thus from this point of view be seen as a worst case scenario where no improvement in terms of heating technologies is envisioned, and only the transition from non-electric to electric heating appliances is taken into account. Further work could try to include the energy mix supplying the heating demand, for example through the use of more sophisticated energy system models accounting for sector coupling.

5. Conclusions

This study allowed us to tackle the impacts of increased heating demand electrification on optimal VRE mixes and system total costs. We conducted the analysis thanks to two minimal models, of demand on one side, and of an energy system model on the other side. From this study, we draw the following general conclusions.

We find that a temperature-sensitive increase in the demand — which is in this study an equivalent of the electrification of heating demand — favors the installation of Variable Renewable Energy (VRE) capacity compared to the actual level of heating demand electrification. This effect is more pronounced at high penetrations (60 ± 5) % of VRE, where the extra investment in VRE capacities due to an increased temperature-sensitive demand to be served reaches up to 15 %. This results confirms the synergies between increased electrification scenarios and the installation of VREs, and extends it to a temperature-sensitive increase in the demand. We show in particular that this increased penetration is higher than for a uniform increase in the demand.

In a second time, we show that although an increased electrification of heating demand increases the system total cost, the System Total Value (STV) of VRE increases as well, which tends to reduce the increase in total costs: for example, the increase in STC between the current state and the projected 80 % electrification of heating demand is reduced by 2 % due to the introduction of VRE, while its absolute value is reduced by a quarter. The major effect of introducing VRE is thus to reduce the system total costs, while a minor effect lies in an increased VRE value when increasing the rate of electric heating.

Last, we show that the composition of the optimal mixes is dominated by the technologies LCoEs and the regionally maximum installable capacities, rather than by the correlation between VRE generation and the demand to be

served. We would have expected, in accordance with the literature, that increasing the heating demand electrification would have favored Wind energy, the latter being correlated to peak demand hours in winter. Surprisingly, this effect is only observed at low penetrations — on the order of $(10 \pm 5)\%$ — while at higher penetrations it is the technology-region LCoE and the regional maximum installable capacities that determine the composition of the optimal mixes.

Finally it is worth noting that we did not take into account any other factor that could influence the electric demand. In particular, we did not take into account the effects of climate change. Regarding heating demand, in Europe, this study can thus again be considered as a worst case scenario as heating demand is expected to drop due to milder air temperatures in winter. This will be tackled in future works.

Acknowledgements

This research is conducted in the frame of the Energy4Climate Interdisciplinary Center (E4C) of Institut Polytechnique de Paris and Ecole des Ponts ParisTech and supported by the 3rd Programme d'Investissements d'Avenir [ANR-18-EUR-0006- 02] and by the Foundation of Ecole Polytechnique and ENGIE through the program "Résilience des systèmes énergétiques au changement climatique et émissions négatives".

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Appendix A. Area of study

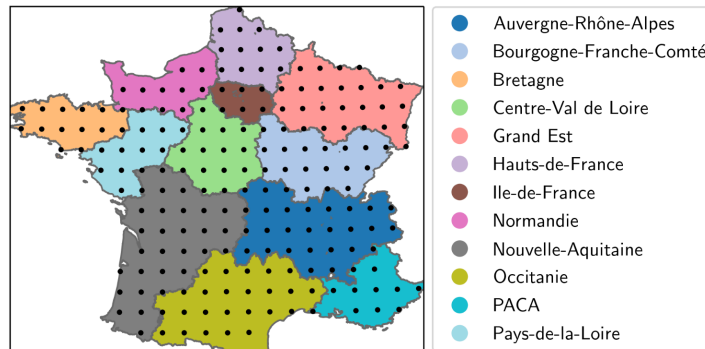


Figure A.6: Map of the french administrative regions considered in the study, adapted from [17].

Appendix B. Scenarios

We work with a set of scenarios corresponding to different levels of heating demand electrification. The scenarios are derived from a Reference scenario by multiplying the temperature-sensitivity coefficient ω^H by a factor ϵ . The temperature-sensitivity factor ϵ for each scenario is given in Table B.3. To each HTE scenario corresponds a UE scenario where all coefficients of the linear model — including the intercept ω^0 — are multiplied by a pseudo-temperature-sensitivity factor ϵ^* to yield the same average demand. These pseudo-temperature-sensitive factors, ϵ^* , are given in Table B.3 for the different scenarios.

Appendix B.1. Electrification scenarios

The obtained temperature-sensitivity coefficients are presented in Figure B.7a while the modified coefficients for the UE65 and HTE65 scenarios are presented in Figures B.7b and B.7c respectively. We can observe that the temperature-sensitivity coefficients for the UE65 scenario are close to the Reference case: this is evidenced by the similar coloring of the maps between Figure B.7b and Figure B.7a. Instead, one can also observe that the temperature-sensitivity coefficients are much higher in the HTE65 scenario, Figure B.7c: this is particularly clear for regions Ile-de-France, Aquitaine and Auvergne-Rhône-Alpes. In fact, the vectors mapped in Figure B.7b and B.7c are collinear with that mapped in Figure B.7a, but the coefficient of proportionality with respect to the Reference scenario is larger for the HTE65 scenario than for the UE65 scenario.

Appendix B.2. Implication for the demand

We compute now quantities of interest derived from the demand, for a given scenario different from the Reference one. We recall the demand model, for a given hour and calendar daytype and assuming only heating temperature-sensitivity:

$$L(t) = \omega^0 + \omega^B + \omega^H(T_H - \bar{T}(t))\Theta(T_H - \bar{T}(t)) + \eta(t), \quad (\text{B.1})$$

with the equation parameters detailed in the text. If we consider the expectation of the yearly average, i.e. we apply $\mathbb{E}(1/T_0 \sum_{t=0}^{T_0-1} (\cdot))$ to Equation (B.1) we get:

$$\langle L(t) \rangle = \omega^0 + \langle \omega^B(t) \rangle + \langle \omega^H(T_H - \bar{T}(t))\Theta(T_H - \bar{T}(t)) + \eta(t) \rangle, \quad (\text{B.2})$$

$$= \omega^0 + \omega^B + \langle E(t) \rangle, \quad (\text{B.3})$$

since ω^B is constant for a given hour and calendar daytype, and $\eta(t)$ is a gaussian white noise (with mean zero). We note $E(t)$ the temperature-sensitive part of the demand.

In a scenario where we multiply the temperature-sensitivity coefficient, ω^H , by a factor ϵ , we get the new average demand (Equation (B.4)):

$$\langle L(\epsilon) \rangle = \omega^0 + \omega^B + \epsilon \langle E(t) \rangle. \quad (\text{B.4})$$

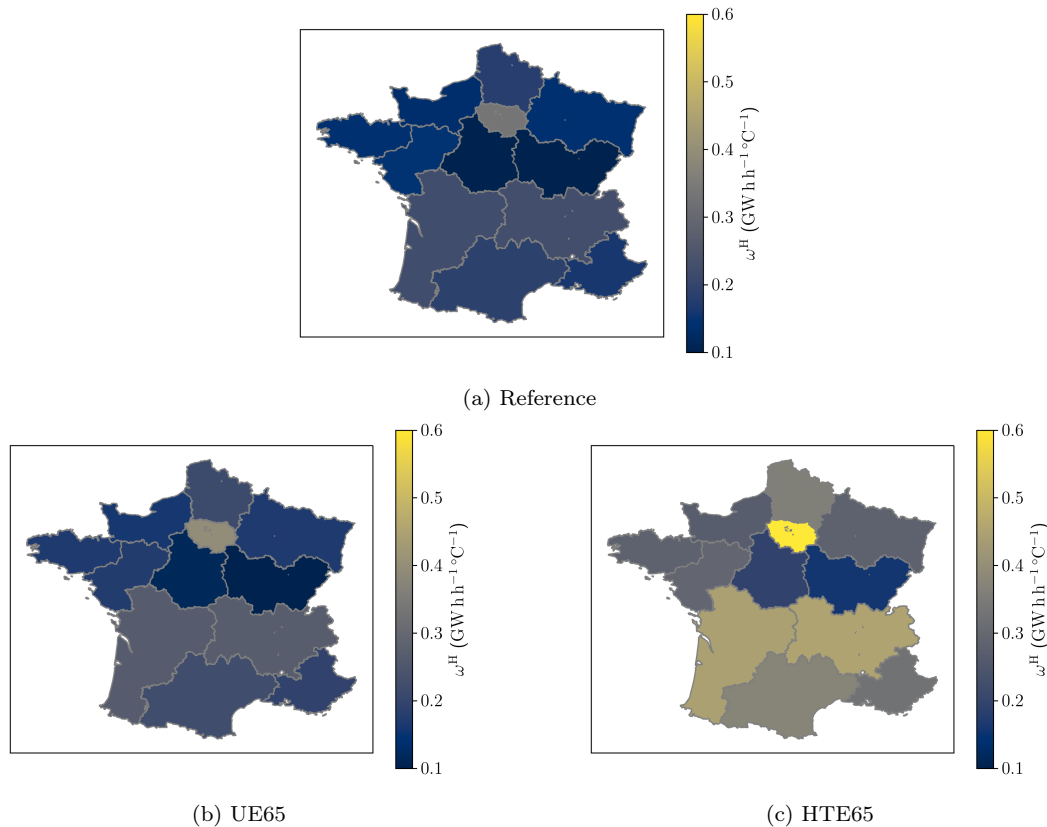


Figure B.7: Map of the computed regional temperature-sensitivity coefficients (ω^H). The plotted values correspond to the mean over the two factors hour of the day and daytime. The upper panel corresponds to the reference case. The bottom panels correspond to the magnitude of the regional temperature-sensitivity coefficients in the UE65 (left panel) and HTE65 (right panel) scenarios (Table 1).

In turn, if we multiply instead by the pseudo-temperature-sensitivity coefficient ϵ^* , the average demand is then (Equation (B.5)):

$$\langle L(\epsilon^*) \rangle = \epsilon^* \omega^0 + \epsilon^* \omega^B + \epsilon^* \langle E(t) \rangle. \quad (\text{B.5})$$

Appendix B.3. Implication for the system's total and marginal costs

Given the two modified versions of the demand (HTE vs. UE), we compute the expected system total cost and the system marginal cost without VREs for both scenarios. For the HTE scenario, the expected STC yields (Equation (B.7))

$$\mathbb{E}(\text{STC}(0, L)) = T_0 \langle \alpha L[\epsilon]^2 \rangle, \quad (\text{B.6})$$

$$= \alpha T_0 (\langle L(\epsilon) \rangle^2 + \text{Var}(L(\epsilon))). \quad (\text{B.7})$$

The computation for the offset case is the same and makes also appear the variance of the demand. For the system marginal cost, we get (Equation (B.9)):

$$\langle \lambda(0, L) \rangle = \langle 2\alpha L(\epsilon) \rangle, \quad (\text{B.8})$$

$$= 2\alpha \langle L(\epsilon) \rangle. \quad (\text{B.9})$$

where we can see that it only depends on the average of the demand.

Appendix B.4. Implication on VRE profits

We recall that a VRE technology-region potential profits are given by:

$$P_i = \langle \lambda \rangle \nu_i - \text{LCoE}_i, \quad (\text{B.10})$$

where ν_i and LCoE_i are respectively the value factor and the LCoE (€ MWh^{-1}) of VRE producer i . They are defined by

$$\nu_i = \frac{\langle \lambda H_i \rangle}{\langle \lambda \rangle \langle H_i \rangle}, \quad (\text{B.11})$$

and

$$\text{LCoE}_i = \frac{\text{hRC}_i}{\langle H_i \rangle}. \quad (\text{B.12})$$

From Equation (B.12), we can see that the LCoE_i of any technology-region i is not affected by a change in average demand, nor by the change in the shape of the demand: increasing the electrification rate or simply increasing the average demand will not change it. This is not the case for the value factor as the term $\langle \lambda H_i \rangle$ is affected by a change in the demand, through the system marginal cost factor. The value factor given some modified demand gives:

$$\nu_i(0, L(\epsilon)) = \frac{\langle \lambda H_i \rangle}{\langle \lambda \rangle \langle H_i \rangle} \quad (\text{B.13})$$

$$= \frac{\langle 2\alpha L(\epsilon) H_i \rangle}{\langle 2\alpha L(\epsilon) \rangle \langle H_i \rangle}. \quad (\text{B.14})$$

For the UE scenarios we have $L(\epsilon^*) = \epsilon^* L(\epsilon = 1.0) = \epsilon^* L_{ref}$, the latter being the reference demand (Reference scenario). With this equality, Equation (B.14) yields:

$$\nu_i(0, L(\epsilon^*)) = \frac{2\alpha\epsilon^* \langle L_{ref} H_i \rangle}{2\alpha\epsilon^* \langle L_{ref} \rangle \langle H_i \rangle} \quad (\text{B.15})$$

$$= \nu_i(0, L_{ref}), \quad (\text{B.16})$$

where $\nu_i(0, L_{ref})$ is the value factor without VREs for the Reference scenario. The initial value factor (i.e. without renewables) is thus constant in the UE scenarios. This is not true for the HTE scenarios.

scenario	$\langle L \rangle$ (GW)	ϵ (ϵ^*)	% electric heating
Reference	54.6	n.a.	35 %
HTE57.2	57.2	1.25	48 %
UE57.2	—	1.048	35 %
HTE59.8	59.8	1.5	61 %
UE59.8	—	1.095	35 %
HTE62.4	62.4	1.75	74 %
UE62.4	—	1.143	35 %
HTE65	65.0	2.0	88 %
UE65	—	1.190	35 %

Table B.3: Temperature-sensitive factors ϵ (resp. ϵ^*) for each scenario.

Appendix C. Energy-system model

The model is a minimal description of a power system where conventional dispatchable producers are treated as an aggregate represented by a single cost function and in which variable shares of PV and wind energies can

be introduced in each region of the domain. By minimal we mean that the model is not meant to represent a state of the art power system with a diversity of electricity generation technologies, network constraints and costs, different demand sectors, etc. as in Shirizadeh et al. [30] or RTE [6]. Instead we insert sufficient complexity for non-trivial economic impacts of VRE integration to be evidenced — including the cannibalization effect on the side of VRE producers and the utilization effect and wholesale price effect on the side of conventional producers — while keeping a problem that is sufficiently tractable to perform sensitivity analyses such as this one. The mathematical framework of the long term investment problem is presented in detail in Tantet and Drobinski [17]. We summarize here briefly the main points of interest.

Dispatchable producers are treated as an aggregate that is capable of delivering power instantaneously when needed. The capacity of this single aggregate producer is set to a value high enough (200 GW) to avoid any lost demand in any of the scenarios. This latter assumption would only influence fixed costs of dispatch generation, which can be safely ignored in our study, because of the focus on VRE integration effects [17]. We further assume that the variable cost of dispatchable producers is given by

$$VC_{Di}(q) = \alpha q^2, \quad (C.1)$$

where q is the amount of demand to be served by dispatchable producers and α is the DVCC in units of €MWh^{-2} . This key parameter can be tuned to modify the cost of generation for the dispatchable producers, and thus the optimal level of VRE penetration.

Then a set of m VRE producers is introduced into the mix. Only solar PV and onshore wind producers are considered, and we suppose that every region of our study area contains one producer of each technology, whose capacity can either be prescribed or optimized. We denote by x_i the generation capacity of technology-region i . The cost of a VRE producer i is given by its fixed cost of installation $\text{hRC}_i x_i$, where hRC_i is its hourly rental cost in €GW^{-1} . This allows us to compute the STC over a year, which is given by

$$\text{STC}(\mathbf{x}, (VC_{Di})_{t \in \mathbb{T}_0}) := T_0 \sum_{i=0}^{m-1} \text{hRC}_i x_i + \sum_{t=0}^{T_0-1} VC_{Di}(q(t)), \quad (C.2)$$

where \mathbf{x} is the vector of VRE producers capacities in GW, VC_{Di} the variable cost of dispatchable producers in €, \mathbb{T}_0 the set of hours in a year, T_0 the number of hours in a year, and $q(t)$ the amount of demand to be served at a given time t , in MWh. The problem considered next is the minimization of the sample-mean estimate of the annual STC expectation over a year. Investment in VRE capacities as well as the optimal dispatch of demand are optimized simultaneously for a given value of the DVCC and for a given scenario. Formally, the optimization problem translates into the following program [31, 17],

$$\begin{aligned} \min_{\mathbf{x}} \quad & \mathbb{E}(\overline{\text{STC}}(\mathbf{x})) & (\text{C.3}) \\ \text{s.t.} \quad & x_i \leq x_i^{\max} \quad \text{for } i \in \{0, \dots, m-1\}, \\ & x_i \geq 0 \quad \text{for } i \in \{0, \dots, m-1\}, \end{aligned}$$

with $\overline{\text{STC}}(\mathbf{x})$ the optimal solution of:

$$\begin{aligned} \min_{(G_{Di}(t,\omega))_{t \in \mathbb{T}_0}} \quad & \text{STC}(\mathbf{x}, (G_{Di}(t,\omega))_{t \in \mathbb{T}_0}) & (\text{C.4}) \\ \text{s.t.} \quad & G_{Di}(t,\omega) + Q_{\mathbf{x}}(t,\omega) \geq L(t,\omega), \\ & G_{Di}(t,\omega) \leq x_{Di}, \\ & G_{Di}(t,\omega) \geq 0. \end{aligned}$$

The first problem (Equation (C.3)) corresponds to the problem of long term investment in VRE capacities. The second problem (Equation (C.4)) corresponds to the problem of short term dispatch of electricity producers and is referred to as the scheduling problem. The first and second constraints of problem (Equation (C.3)) ensure that the installed capacities of VRE producers are capped by maximum installable capacities x_i^{\max} for each technology-region, and that they should be positive. The constraints on the decision variable of the scheduling problem are the same as previously stated: the aggregated dispatchable generation should always be positive and not exceed a maximum capacity x_{Di} . Note however that here we do not impose that the sum of dispatchable and VRE generation be strictly be equal to the demand. It can occur instead that the total generation exceeds the demand for some hours. We assume in this setup that the demand can be curtailed at no extra

cost: this property is a direct consequence of the hypothesis on the cost for VRE producers and the optimal solution for the scheduling problem.

We refer the reader to Tantet and Drobinski [17] for a full development of the STC minimization problem. In particular, Theorem 1 in Tantet and Drobinski [17] states that if the VRE mix \bar{x} is an optimal solution to the investment problem, then only producers with non-negative potential profits have some capacity installed. Their potential profits per unit generation, € MWh^{-1} , are given by

$$P_i = \langle \lambda \rangle \nu_i - \text{LCoE}_i, \quad (\text{C.5})$$

where ν_i and LCoE_i are respectively the value factor and the LCoE (€ MWh^{-1}) of VRE producer i . They are defined by

$$\nu_i = \frac{\langle \lambda H_i \rangle}{\langle \lambda \rangle \langle H_i \rangle}, \quad (\text{C.6})$$

and

$$\text{LCoE}_i = \frac{\text{hRC}_i}{\langle H_i \rangle}, \quad (\text{C.7})$$

where λ is the SMC in € MWh^{-1} , i.e. the cost of serving one more unit of demand [32], and H_i is the capacity factor of VRE producer i . The brackets $\langle \cdot \rangle$ denote the mean over the years of the annual-average of the quantity. The value of the LCoE per technology-region is presented in Figure C.8.

Appendix C.1. Demand, capacity factor and cost data for E4CLIM

The cost data used to compute the rental costs hRC_i in Equation (C.2) is reported in Table C.4. It is the same as in [17], and taken from [33, 30]. Annuities are computed using [30, Equation 2] and operation and maintenance (O&M) costs are taken from [30]. Capacity factors data are the same as in [17], following the model presented in [20], while the demand time series are computed using the temperature-sensitive demand model presented in Section 2.1.

	Wind	PV
Overnight cost (€/kWe)	1130	423
Lifetime (year)	25	25
Annuity (€/kWe/year)	81.2	30.7
O&M (€/kWe/year)	34.5	9.2
Rental costs (€/kWe/year)	115.7	39.9

Table C.4: Cost data for the E4CLIM model.

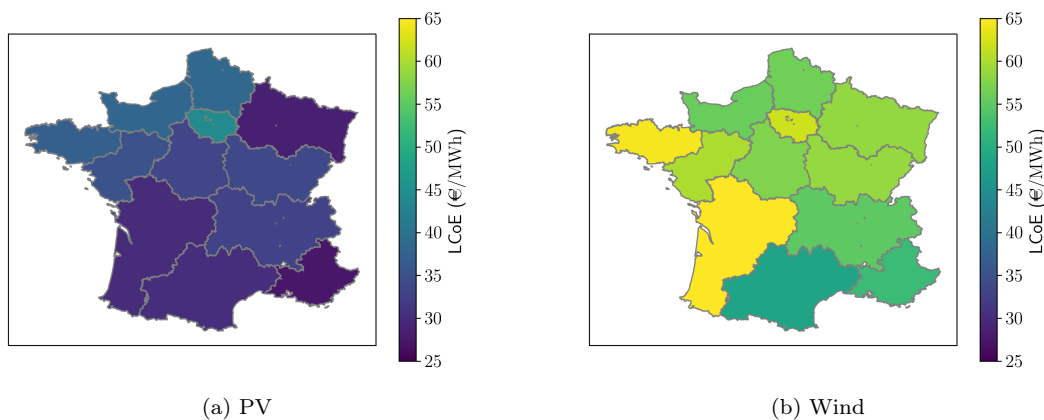


Figure C.8: Map of the LCoE — Equation (C.7) — for solar PV (left) and for Wind energy (right).

Appendix D. Regional mixes

We present in this section the regional mixes obtained for the Low- and High-penetration scenarios. We can observe for the former (Figure D.9) that PV is installed in more regions than Wind at this level of global penetration. Getting a closer look at PV shows that most capacities have been installed to their maximum (dotted regions) except in Ile-de-France region in the Reference and HTE65 scenarios. Wind capacity is installed near the Atlantic and Mediterranean coasts mainly, with an increasing installed capacity from the Reference scenario to UE65 and HTE65 scenarios. Comparing Figures D.9a and D.9e, and D.9b and D.9f shows that increasing heating demand electrification does not change the PV mix for this value of global penetration, while it slightly increases the total installed Wind capacity. For the latter (Figure D.10, High-penetration scenario) we can observe that PV

capacity is installed at its max capacities for the three demand scenarios HTE65, UE65 and Reference. We observe however that Wind capacity is not installed in Bourgogne-Franche-Comté and Île-de-France (see Figure A.6) in the Reference scenario, whereas maximum capacities are reached in the HTE65 scenario.

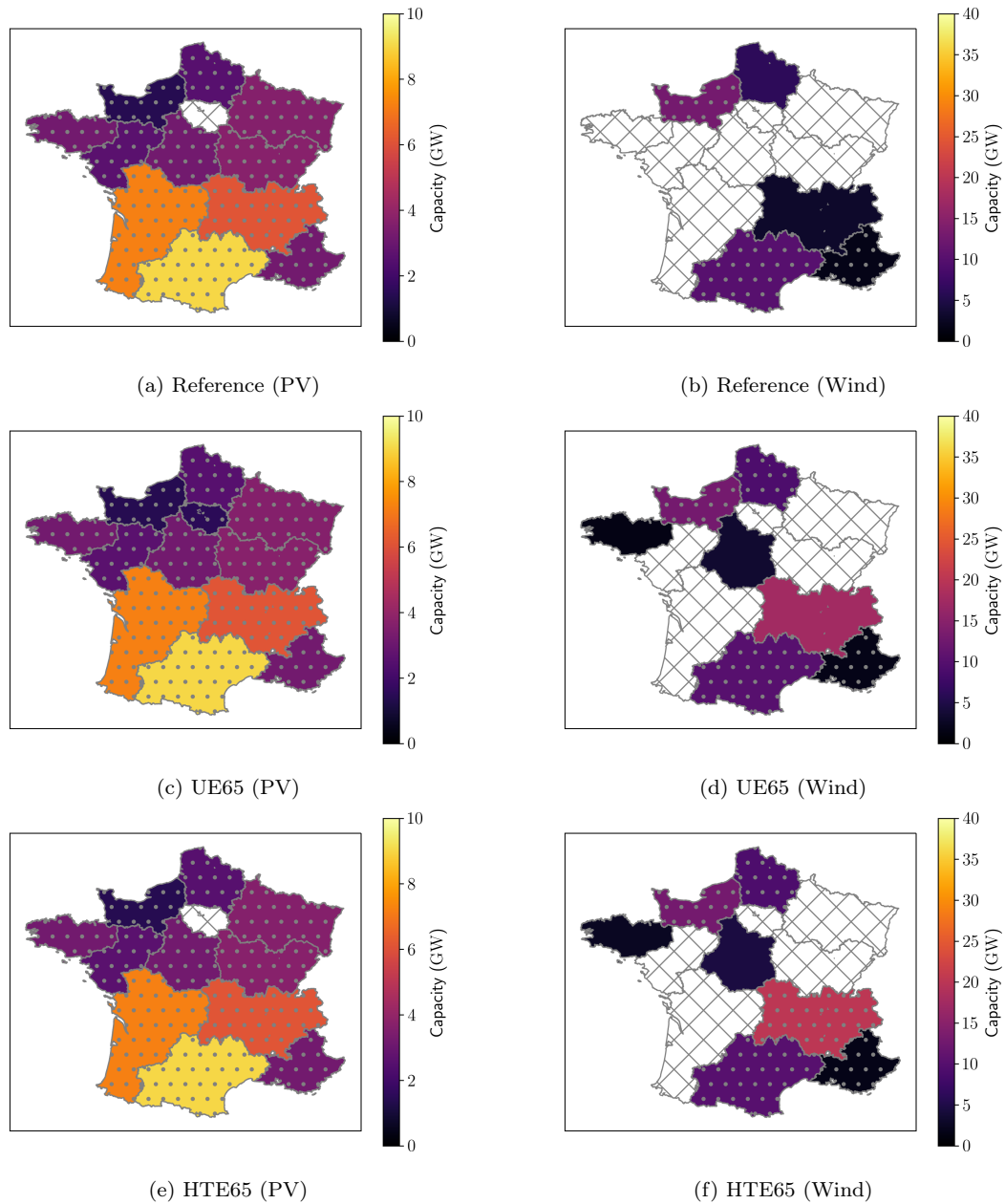


Figure D.9: Regional map of PV (left) and wind (right) capacities for the Low VRE penetration scenario ($\alpha = 8 \cdot 10^{-4} \text{€ MWh}^{-2}$) and the Reference (top), UE65 (middle) and HTE65 (bottom) scenarios. The colorbars are specific to a technology.

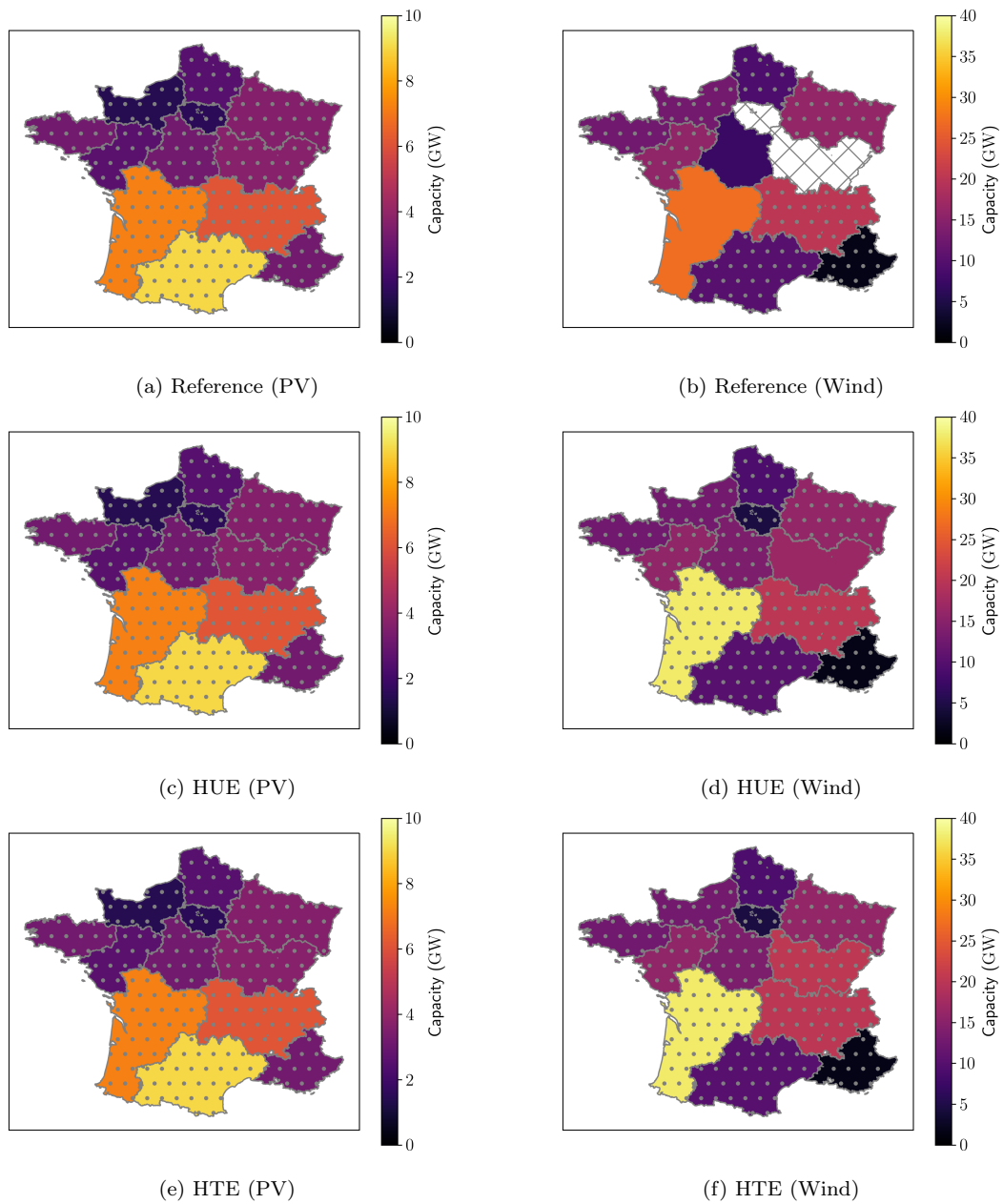


Figure D.10: Regional map of PV (left) and wind (right) capacities for the High VRE penetration scenario ($\alpha = 3.2 \cdot 10^{-3} \text{ € MWh}^{-2}$) and the Reference (top), UE65 (middle) and HTE65 (bottom) scenarios. The colorbars are specific to a technology.

Chapter **4**

Impacts of climate change on the electricity system optimal wind and solar mixes and system total costs: the case of France

Impact of climate change on high-VRE optimal mixes and system costs: the case of France.

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Abstract. The electricity generation sector is undergoing profound transformations via the introduction of variable renewable energies (VRE). If in its present state, this sector is accountable for a major share of the observed and committed climate change, it is impacted by changing climate conditions as well. These impacts are related to multiple processes both on the demand and the supply side, which have been thoroughly studied in previous literature. We find however that the impact of a change in VRE resource coupled to a change in demand has not been studied in regard of its effect on optimal investment decisions. We tackle this issue through the use of EURO-CORDEX climate projections coupled to a minimalistic electricity system modeling tool. We first assess the implied changes at the component level and find potentially degraded wind generation conditions and virtually no changes in solar generation conditions under increasing levels of climate change. Impacts on the demand lead to a higher resp. lower correlation with solar resp. wind generation. These changes lead to a constant share of solar and a reduced share of wind in optimal mixes with increasing climate change, with no trivial relation to the component-level impacts. Furthermore, the sole impact of climate change on the VRE resource and the demand is found to have no adverse consequences on system total costs, with adaptation measures in this regard being less attractive economically than their passive counterparts. This comes in contradiction with previous research exploring other processes, showing the importance of specifying the working hypotheses and phenomena taken into account when issuing policymaking advice. Further research should explore exhaustively how combining all processes related to climate change impacts all relevant elements of the electricity generation sector, to issue relevant policymaking advice for the planification issue. We also encourage continued research at the climate and energy interface, to increase the precision and interpretability of similar studies.

20 1 Introduction

The ambitious climate change mitigation goals set out under the Paris agreement¹ call for a rapid decarbonization of the world's economy and supporting infrastructures. In particular, electricity generation, which in 2021 accounted

¹To limit global warming to well below 2°C and to pursue efforts to limit global warming to 1.5°C with respect to pre-industrial level temperatures.

for 20% of total greenhouse gas emissions² is a key sector to decarbonize, potentially allowing the decarbonization of other sectors of the economy through electrification. Such decarbonization is expected to occur via the introduction of wind and solar photovoltaic generators — regrouped under the generic term of variable renewable energies (VREs). The share of VREs has been increasing in almost all European countries since the 2010s³ and is expected to surge in the coming decades, see e.g. (IEA, 2023) for projections at the world's level or (RTE, 2021) for projections at the level of France. The introduction of high shares of VREs will pose adaptation challenges from a techno-economic perspective (Sijm, 2014; Heptonstall and Gross, 2021). Even disregarding other sociopolitical factors (Carley and Konisky, 2020; Faber, 2023; Ah-Voun et al., 2024), the composition of the future generation mix and in particular the amount of installed VRE capacity thus remains uncertain. This raises the question of planning and policymaking to incentivize for the most suitable generation mix under the decarbonization constraint.

If the electricity generation sector impacts the current climate state through greenhouse gas emissions, it is impacted by the climatic conditions as well (Craig et al., 2018; Yalew et al., 2020). Historically, the dependence of demand to weather conditions — temperature in particular — makes the electricity generation sector vulnerable to weather states causing high electricity demands. On the supply side, the thermal and hydraulic dominated generation sector is mainly sensitive to the hydrologic conditions, which impact the available water for thermal power plants cooling and hydraulic power plants generation (van Vliet et al., 2012; Tarroja et al., 2016; van Vliet et al., 2016; Turner et al., 2017). Increasing the share of VREs in the electricity generation mix will increase the weather dependency of the sector (Bloomfield et al., 2016) since electricity generation will be directly conditioned to wind and surface radiation conditions. Electricity systems have been recently found to be switching from temperature dominated systems to wind dominated systems (Bloomfield et al., 2018). This important and increasing weather sensitivity makes it crucial to understand how changing climatic conditions will impact the current and future electricity generation sector. An increased understanding of these impacts will in turn help investigate the overarching question of optimal system operation and planning.

Many studies focus on a particular aspect of the impact of climate change on the electricity generation sector, see e.g. (van Vliet et al., 2016; Tobin et al., 2018; Gernaat et al., 2021) for impacts on the supply side or (Davis and Gertler, 2015; Damm et al., 2017; van Ruijven et al., 2019) for impacts on the demand side. However, if the study of the impacts of climate change at the component level is necessary, it is not sufficient and can lead to erroneous conclusions (Chandramowli and Felder, 2014; Miara et al., 2017; Craig et al., 2018; Yalew et al., 2020; Khan et al., 2021).

Assessing the impacts of a changing climate on the electricity generation sector in a systemic way via energy system modeling tools is challenging due to the number of processes to be accounted for and their relevant spatial and temporal scales. A typical example of this is the complex handling of the high intricacy of the water-energy nexus (Payet-Burin et al., 2018; Qadrdan et al., 2019; Turner et al., 2019; Ralston Fonseca et al., 2021a). These

²Own computation based on data from https://di.unfccc.int/detailed_data_by_party without LULUCF.

³See e.g. <https://www.irena.org/Data>.

challenges add up to those encountered when dealing with high VRE systems (Ringkjøb et al., 2018; Prina et al., 2020). In this last case, a particular attention must be given to the proper representation of the weather and climate dependent VRE and demand time series. The wrong representation of intraday (peak smoothing) and seasonal (e.g. by using yearly averages) variability can lead to unrealistic representations of the VRE generation and demand correlation. Not accounting for the interannual climate variability by using only a single year of climate data can lead to biased results, whereas using a typical meteorological year/mean weather year can lead to missing climate extremes and typical weather variability. As such multiple year, from 10 years to several decades (Bloomfield et al., 2016; Pfenninger, 2017; Staffell and Pfenninger, 2018; Zeyringer et al., 2018), hourly to 3-hourly time series should be used when no other time resolution reduction method is explicitly applied and tested beforehand (Pfenninger, 2017).
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65 Conclusions of modeling exercises with a high penetration of VREs failing to address, or a minima acknowledge this issue, would be highly compromised.

Historically, energy system models were not designed to deal with the issue of high resolution climate data incorporation (Ciscar and Dowling, 2014). VRE generation is typically handled at a too coarse time resolution for all its characteristics to be accounted in the modeling exercise (Jaglom et al., 2014; Mima and Criqui, 2015; McFarland et al., 2015; Miara et al., 2019). On the other hand, studies fulfilling the requirements of climate data incorporation in the study of high VRE systems are limited in their handling of the energy system modeling step: some studies focus solely on the residual demand (demand net of wind and solar generation) (Bloomfield et al., 2021) or associated indicators (Kozarcanin et al., 2019) and do not consider the feedback to energy system planning or operation, while others, albeit incorporating an energy system modeling step, work with a fixed generation mix and do not take into account the feedback of climate change impacts on the VRE and dispatchable capacity investment decisions (Craig et al., 2019; Turner et al., 2019). Finally, all reviewed studies up to date are not exhaustive in the number of processes considered. While some studies do not account for the changes in water availability (Jaglom et al., 2014; McFarland et al., 2015), others miss the effect of climate change on the VRE resource (Jaglom et al., 2014; McFarland et al., 2015; Mima and Criqui, 2015; Miara et al., 2019; Khan et al., 2021; Ralston Fonseca et al., 2021a), or neglect the impact of climate change on the electricity demand (Schlott et al., 2018; Peter, 2019). Among these limitations, we note that the compound impact of VRE resource and electricity demand changes due to climate change has up to date not been studied in regard of its effect on optimal investment decisions.
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We focus in this study on how the compound impact of climate change on the future VRE resource and electricity demand influences the optimal investment decisions in VRE capacity as well as the resulting system costs. The treatment of non-VRE (i.e. dispatchable) sources is highly idealized to reduce modeling complexity, placing us in a best case setting in this regard. This allows us to discard the added complexity of having to deal with the water-energy nexus. Storage, transmission and imports/exports are also not included to keep the problem as minimalistic as possible. We leave for further work a more thorough and complex study on the compound effect of all climate impacts on the optimal investment decisions. As climate change impacts and demand characteristics are region-specific, we tackle this question for the particular case of France. However this does not prevent our results and
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conclusions to be applicable to world regions with similar characteristics or our methodology to be applied in any other world region.

The paper is organized as follows. We detail in Section 2 the methodology employed in the study to fulfill the research objectives. In Section 3, we detail as a first step the impacts of climate change on system components for the particular case of France. We assess then in Section 4 the compound impact of a change in demand and VRE resource in optimal investment decisions for different levels of climate change. Then, in Section 5 we investigate how these impacts translate in terms of system costs and discuss different adaptation strategies. We finally discuss the obtained results and conclude in Sections 6 and 7.

2 Methods

100 We use climate projections for the 21st century to assess the impact of climate change on the electricity system. We present this climate data in Section 2.1. Modeling the impact of a change in VRE resource and demand on optimal VRE investment decisions requires then to be able to translate climate variables into associated VRE generation and electricity demand. This is presented in Sections 2.2 and 2.3. We briefly introduce the energy system model used to conduct the analysis in Section 2.4 and finally present the set of scenarios used in this study in Section 2.5.

105 2.1 Climate data

We use six different global/regional climate models pairs from the EURO-CORDEX initiative (Jacob et al., 2014; Coppola et al., 2021) for the 1975–2005 (historical) and 2020–2099 (future) periods. We use the output runs forced with the widely used CMIP-5 RCP 8.5 as a climate change scenario (Moss et al., 2010) for the future period. The detail of models used and associated references are given in Tables 1 and 2. The models were chosen for practical reasons (availability of variables at the right time resolution) and are not the result of a more elaborate selection. The choice of climate models has been shown to impact studies results (Gutiérrez et al., 2020; Wohland, 2022). This is further discussed in Section 6.1.

115 We use the near-surface air temperature (tas) and surface downward shortwave radiation (rsds) at 3h time resolution, and zonal (ua100m) and meridional (va100m) wind components variables at 1h time resolution⁴. Spatial resolution is approximately 12×12 km over the whole area of study. Data curation steps are needed to obtain a homogeneous and exploitable dataset, which we detail in Appendix A2.

To reduce model biases, each model pair output is calibrated to ERA5 reanalysis data (Hersbach et al., 2020) over the 1980–2005 period. Calibration is conducted by using the CDF-t algorithm (Michelangeli et al., 2009; Lavaysse et al., 2012; Vrac et al., 2012; Vigaud et al., 2013). As the ERA5 and EURO-CORDEX grids do not overlap, we interpolate ERA5 data on the EURO-CORDEX grid using bilinear interpolation and then calibrate the EURO-CORDEX data at every grid point. This step considerably reduces model biases (not shown here).

⁴Words in parenthesis indicate the EURO-CORDEX short variable name

Table 1. EURO-CORDEX GCM/RCM model pairs considered in the study.

ID	Driving GCM	Variant	RCM	Abbreviation
0	ICHEC-EC-EARTH	r1i1p1	COSMO-crCLIM	ICHEC-EC-EARTH + COSMO
1	MOHC-HadGEM2-ES	r1i1p1	COSMO-crCLIM	MOHC-HADGEM2 + COSMO
2	MPI-M-MPI-ESM-LR	r3i1p1	COSMO-crCLIM	MPI-ESM + COSMO
3	CNRM-CERFACS-CNRM-CM5	r1i1p1	COSMO-crCLIM	CNRM-CM5 + COSMO
4	CNRM-CERFACS-CNRM-CM5	r1i1p1	ALADIN63	CNRM-CM5 + ALADIN63
5	MOHC-HadGEM2-ES	r1i1p1	ALADIN63	MOHC-HADGEM2 + ALADIN63

GCM: Global Climate Model. RCM: Regional Climate Model.

Table 2. GCMs and RCMs considered in the study.

Driving GCM/RCM	Version	References
ICHEC-EC-EARTH	2	(Hazeleger et al., 2010, 2012)
MOHC-HadGEM2-ES	2	(Collins et al., 2011)
MPI-M-MPI-ESM-LR	-	(Gutjahr et al., 2019; Mauritsen et al., 2019)
CNRM-CERFACS-CNRM-CM5	5	(Voltaire et al., 2013)
COSMO-crCLIM	4	(Leutwyler et al., 2016; Sørland et al., 2021)
ALADIN63	6	(Daniel et al., 2019; Nabat et al., 2020)

More informations on the models can be found at <https://ec-earth.org/> for ICHEC-EC-EARTH, <https://www.metoffice.gov.uk/> for MOHC-HadGEM2-ES, <https://mpimet.mpg.de/en/homepage> for MPI-M-MPI-ESM-LR, <http://www.umr-cnrm.fr/> for CNRM-CERFACS-CNRM-CM5, <http://www.cosmo-model.org/content/default.htm> for COSMO-crCLIM, <http://www.umr-cnrm.fr/> for ALADIN63. GCM: Global Climate Model. RCM: Regional Climate Model.

2.2 VRE generation

Wind and solar generation are computed from climate time series. As generation depends on the installed capacity, which is a decision variable in our optimization problem, we focus instead on deriving time series of VRE generation per unit capacity, or capacity factors, which give the availability of the wind and solar resource for each hour of the time series. These hourly capacity factors time series — computed at each grid point — are averaged per region (see Figure A1) and then bias corrected with respect to observations of regional capacity factors following the methodology detailed in (Tantet et al., 2019) and regional capacity factors data from the french TSO RTE freely available at <https://opendata.reseaux-energies.fr/>. This bias correction step supposes that model biases are stationary with respect to observations (i.e. are the same now than they will be in the future) which is a point discussed in (Bakker et al., 2013; Tantet et al., 2019). We now briefly detail the computation of the wind and solar capacity factors.

Wind capacity factors are computed from the zonal and meridional wind, as well as surface air temperature weather variables. Both these wind speeds are extrapolated at hub height (101m) following a power law with exponent 1/7 (Justus and Mikhail, 1976; Tantet et al., 2019). Total wind speed is then corrected for temperature variations following (Dupré, 2020) by multiplying it by a factor

$$(\rho/\rho_0)^{1/3} = \left(\frac{T_0}{T - L(z_h - z)} \right)^{1/3}, \quad (1)$$

where ρ is the air density at hub height, ρ_0 the reference air density, T_0 the reference temperature (288.15K or 15°C), T is the surface temperature variable, L the lapse rate (0.0065K m^{-1}), z is the height of the surface temperature variable (2m), and z_h the hub height (101m). Because we want to obtain hourly capacity factors time series, surface temperature climate data is resampled from 3-hourly to hourly by keeping the value constant over the 3 hours. This corrected total wind speed is then passed through a standard power curve transfer function (Siemens SWT-2.3 MW-101m model, see (Tantet et al., 2019)). In doing so, we allow the power produced by wind power plants to depend on air temperature (and thus climate change) while preserving the cut-in and cut-out behavior of the turbines. Using total wind speed is a consequence of not accounting for wake losses and further supposing that the turbines are always facing the wind.

Solar capacity factors are computed from the surface downwelling shortwave radiation and surface air temperature weather variables. Because both these variables come at 3-hourly time resolution, we resample the surface temperature in a similar fashion as for wind and resample the surface radiation from the hourly global horizontal extraterrestrial radiation assuming a constant clearness index over the three hours. The global tilted surface radiation (GTS) is computed from the surface radiation according to (Reindl et al., 1990a, b; Gueymard, 2009; Duffie and Beckman, 2013) assuming fixed tilt panels facing due south, while both air temperature and surface radiation are used to compute the panels efficiency (γ) (Duffie and Beckman, 2013). Both are combined to yield a panel's generation and subsequent capacity factor (H_{PV}) according to

$$H_{PV}(t) = \epsilon a \frac{\gamma(T(t))GTS(t)}{q_{PV}^*}, \quad (2)$$

where ϵ is the circuit's efficiency, a the area of the panel, q_{PV}^* the nominal power per module. Note that these constant parameters are not of crucial importance because of the bias correction step that will rescale the capacity factors anyway.

We thus obtain hourly time series of wind and solar capacity factors for the historical (1975–2005) and future (2020–2099) periods. Wind capacity factors are impacted by climate change through any change in the wind regimes and through changes in air temperature (capacity factors decrease when temperature increases). Solar capacity factors are impacted by any change in surface radiation patterns as well as changes in air temperature (capacity factors decrease when temperature increases).

2.3 Demand model

165 Key to our study is the derivation of climate-sensitive plausible electricity demand time series for the historical and future periods. We use to this end the demand model described in (Delort Ylla et al., 2023), of which we summarize the main features here. The model is a probabilistic piecewise linear regression model of demand as a function of temperature and is thus directly linked to the surface temperature weather variable and so to the associated climate. We use electricity demand data from the french TSO RTE (freely available at <https://opendata.reseaux-energies.fr/>)
170 for the years 2014–2019 and surface temperature time series from ERA5 reanalysis data (Hersbach et al., 2020) to train the model. We then validate the model against data for the year 2013. This gives us a model of the hourly national aggregated demand for the historical and future periods with a good representation of the daily and seasonal cyclicity of the demand. The model has a mean error of 5% to 10% of the observed demand and explains 90% of its variability. Note however that because of the time span of the training data, the model corresponds to socio-economic electricity demand conditions (level of electrification, population, etc.) of the years 2014 to 2019. Such
175 socioeconomic parameters are supposed to remain constant in this study to isolate the effect of climate change, but their evolution could be explored in further works.

2.4 Energy system model

We adapt the energy system model E4CLIM (Tantet et al., 2019) in its latest version (Tantet and Drobinski, 2021)
180 to study the impacts of a changing demand and VRE capacity factors on optimal investment decisions. The model version is the one presented in (Delort Ylla et al., 2023). Our modeling domain is metropolitan France, a map of which is shown in Appendix A, Figure A1. E4CLIM is a bottom-up linear programming stochastic power system model performing greenfield optimization in a single step, while ensuring hourly adequacy for the considered time period. It minimizes a system total cost that accounts for investment in VRE capacity (fixed costs) and generation
185 of dispatchable (i.e. non-VRE) producers (variable costs).

VRE capacity can be installed in each french administrative region up until its maximum installable capacity (see Appendix A3.3). The model is minimalistic in its representation of dispatchable producers which are considered to be always available at no costs: this greatly simplifies the models mathematical formulation and places us in a best case situation where investment in VRE capacity will thus be a lower bound of what it could be if investment costs
190 in dispatchable generation were accounted for. A tradeoff between installing VRE capacity which then generate at no costs and generating via dispatchable producers at a given variable cost still remains. This variable cost of the dispatchable generation is supposed to increase quadratically compared to the amount of generation (Tantet and Drobinski, 2021) to reproduce the merit-order dispatch of producers. It is determined by a parameter α , which we call the dispatchable variable cost coefficient (DVCC), that can be tuned in our model to favor the penetration of
195 VRE and can be pictured as a cost of CO2 emissions. This parameter is however kept constant over the historical and future periods to single out the effect of climate change. Further discussion on this parameter is provided in

Appendix A3.2. Other model parameters (VRE fixed costs, maximum installable capacities) are also discussed in Appendix A3.

We finally mention that we work under a copper plate hypothesis, i.e. transmission constraints are not accounted for, nor do we account for storage or import/exports. In this study, optimization is conducted over 30 year long hourly time series of demand and VRE capacity factors.

2.5 Scenarios

The study focuses on the response of the electricity generation sector to climate change and thus relies on a set of scenarios. In this study, socioeconomic determinants of the electricity demand are kept constant and equal to the average conditions of 2014–2019 in metropolitan France. They are learnt via the training step of the demand model. VRE fixed costs are also kept constant and equal to lower values than today (in particular for solar energy) to favor VRE competitiveness, as detailed in Appendix A3.1. The parameter that determines the magnitude of the variable costs of the dispatchable producers (α) is kept constant to a value higher than that of today to favor the penetration of VREs. This is further discussed in Appendix A3.2.

The socioeconomic parameters are then combined to different levels of climate change to yield the scenarios considered in this study. The combination of the aforementioned socioeconomic parameters to the historical (1975–2005) period gives us the Reference (REF) scenario. Then different levels of climate change are considered by sampling the climate data of the future period forced with the RCP 8.5 scenario over different 30 year long time periods. Sampling the future climate around 2035 (2020–2050 period) yields an average warming of $+1.75^{\circ}\text{C}$ above pre-industrial levels, thus giving scenario REF1.75. Similarly, periods centered around 2050, 2060, 2070 and 2085 give scenarios REF2.35, REF2.80, REF3.28 and REF4.04 associated to their respective temperature increase. These scenarios are then used for the purpose of our study.

3 Impact of climate change on system components

Before assessing the systemic impact of climate change on optimal investment decisions we first focus on the component level impacts deriving from the climate models used. We analyze the impacts of climate change first on demand, at the aggregated national and regional level in Section 3.1. Then we analyze the impacts of climate change on the VRE capacity factors in Section 3.2. We finally assess how climate change influences the correlation between demand and VRE capacity factors in Section 3.3. Previous literature exists on the impacts of climate change on demand and VRE capacity factors. We discuss how our results compare to this existing literature body in Section 6.1.

3.1 Demand

We analyze in this section the impact of climate change on the french electricity demand. We focus first on the demand aggregated at the national level and then discuss the regional features of demand change. We rely on four indicators to analyze the evolution of demand: the load duration curve (LDC), the average demand (which is an equivalent of the total demand), the demand that occurs 95% of the time, hereafter denoted as base demand, and the demand that occurs 5% of the time, hereafter denoted as peak demand. This last three indicators are also analyzed at the regional level.

The LDC corresponding to each climate model pair is shown Figure 1. We can see from it that climate change impacts median to absolute peak demand — we mean by absolute peak demand the maximum demand that occurs in each scenario — more significantly than demands close to base demand. Regarding the direction of the evolution, we can see that demand decreases with increasing climate change. There is good multimodel agreement on these observations except for the ICHEC-EC-EARTH + COSMO model pair, where demands close to the absolute peak demand are higher in scenarios REF1.75 and REF2.35 than in the reference (REF) scenario. This is shown Figure 1, panel (a). This discrepancy probably comes from a bias towards cold extremes for this model pair.

Evolution of average, peak and base demand all point in the direction of a decrease of demand with increasing climate change intensity. No matter the level of climate change, total (average) demand decreases with climate change. All models agree on this trend, which in this sense is a robust result. The magnitude of the change varies between -6% to -8% for the most extreme scenario (REF4.04 vs. REF). Similarly, peak demand decreases with increasing climate change intensity, and no matter the level of climate change. There is also perfect model agreement on this trend. Note that the robustness of the result is not so strong for the absolute peak demand, as the analysis of the LDC suggests. For peak demand, the magnitude of the change varies between -8% to -11% for the highest level of climate change (REF4.04 vs. REF). We also find base demand to decrease with increasing intensity of climate change, and no matter the level of climate change. This trend is also observed in all models. The variation of base demand is comprised between -1% and -2% for the most extreme climate change scenario. Supporting figures for these results are provided in Appendix B2 (Figures B2, B3 and B1 for average, peak and base demand respectively). All these results are statistically significant (an independent t-test with an alpha threshold of 0.005 was conducted) between scenarios REF and any other scenario (some adjacent scenarios may not be statistically significantly different for some models).

At the regional level, there is a spatial heterogeneity in the changes of demand with climate change, either for total demand, peak demand or base demand (robust result). The magnitude and sign of these heterogeneities, i.e. the demand change patterns, exhibit more multimodel variability but no strong disagreement either. Overall some trends can be observed: for total demand a west-north-west–east-south-east gradient with a decrease more marked in the west can be observed. For base demand a north-west–south-east polarization with an increase or a less pronounced decrease in the south-east can be observed. Finally, for peak demand, a west-east gradient (except for the model

260 pair ICHEC-EC-EARTH + COSMO, which shows are more homogeneous decrease) with a decrease more marked in the west can be observed. Supporting figures for these results are provided in Appendix B2 (Figures B9 to B13, Figures B14 to B18, and Figures B4 to B8 for average, peak and base demand respectively).

The geographical level that matters for our modeling exercise is the national level. At this level, we observe a robust decrease of demand from peak to base. This decrease is more pronounced for peak demand (on the order of 265 10%) than base demand (on the order of 1%), probably due to the fact that climate change affects the heating temperature sensitive demand and that base demand increases in some regions due to the increase in cooling temperature sensitive demand. Heterogeneities at the regional level are not of importance in this study since the transmission network is not accounted for. They could be of importance in future works and are thus worth mentioning.

3.2 Wind and solar capacity factors

270 We analyze in this section the impacts of climate change on the VRE resource. Here, as investment in VRE capacities occurs at the regional level, the effect of climate change on the regional capacity factors is relevant. In this section, and for the sake of conciseness, we compare the average capacity factors under the different climate change scenarios, and leave for further works the detailed comparison of the whole capacity factors distributions.

To back-up and build confidence in the observed trends of regional capacity factors evolution, we perform three 275 statistical tests: the t-test (von Storch and Zwiers, 1999), a t-test with a variance inflation factor of 2.0 (that we label T-test V2) according to (Wilks, 2019), and the Wilcoxon-Mann-Whitney (WMW) U test (Mann and Whitney, 1947), as implemented in the python scipy module⁵, all with an alpha level (significance level) of 0.005. The WMW U test allows to discuss the normality hypothesis of the distribution from which the 30-year samples originate and is more robust to the presence of potential outliers. Despite this, when the normality hypothesis holds, the WMW U test is 280 almost as powerful as the t-test (Wilks, 2019). We can thus always have high confidence in distributional differences⁶ validated by the WMW test. If we suppose the normality hypothesis to hold, then we can have high confidence in the t-test and in the observed difference of the means. Both previous tests suppose that the samples within a 30-year sample are independent. It can be that because of low-frequency climate variability a time correlation exists between adjacent years. The T-test V2 allows to account for possible time correlation within the 30-year samples but reduces 285 the magnitude of the statistic and thus makes the test more complicated to pass. We finally note that discussing the significativity of the observed trends does not change how these capacity factors time series will impact the energy system modeling step. It however allows us to discuss the relevance of the modeling results: if the observed trends are not statistically significative, then modeling results will reflect artificial trends that are not grounded in any significative difference.

⁵See <https://docs.scipy.org/doc/scipy/reference/generated/scipy.stats.mannwhitneyu.html#scipy.stats.mannwhitneyu>

⁶Note indeed that to the contrary of the t-test, the WMW U test does not test for a difference of the means, but for a difference in the distributions (and the probability that a sample from one distribution would be larger than a sample drawn from the other distribution).

290 3.2.1 Wind

Wind capacity factors exhibit a trend towards a decline with increasing climate change, although this result is not perfectly homogeneous across models and regions. This is shown in Figure 2. Variations are comprised between +5% and -20% across models and regions, for capacity factors comprised between 20% and 28% in the reference scenario. With the notable exception of region PACA, and excluding model pairs MPI-ESM + COSMO and CNRM-
 295 CM5 + ALADIN63, all regions show a decrease in wind capacity factors with respect to the reference case for any level of climate change. Some models and some regions tend to show that this decrease in capacity factor is of higher magnitude with increasing climate change (e.g. region Nouvelle-Aquitaine under model MOHC-HADGEM2 + ALADIN63), whereas this is not true in others (e.g. almost all regions under model ICHEC-EC-EARTH + COSMO). Models MPI-ESM + COSMO and CNRM-CM5 + ALADIN63, together with region PACA in some models, exhibit
 300 some increases in wind capacity factors, but these increases are always below +5%.

Significativity tests also point towards a decrease of wind capacity factors. All statistically significant differences correspond to scenarios with climate change having lower capacity factors than the reference (REF) scenario. However, not all decreases in wind capacity factors are significant and this no matter the working hypothesis (normality of the sampling distribution, time correlation). No increase is found to be statistically significant.

305 Our energy system model will thus run in most cases with moderately degraded (i.e. less than -20%) wind generation conditions and in some with very mildly improved (less than +5%) conditions. However, only the changes related to a decrease in wind capacity factors should be taken as significant of changing future conditions.

3.2.2 Solar PV

Solar capacity factors exhibit no clear trend towards an increase or a decrease with increasing climate change:
 310 some models push for an increase of capacity factors, while others suggest a decrease. This is shown in Figure 3. Variations are comprised within $\pm 10\%$ across models and regions, for capacity factors between 9% and 18% in the reference scenario. All models except MPI-ESM + COSMO exhibit a consistent variability across regions. Some show a decrease with increasing climate change (ICHEC-EC-EARTH + COSMO) with a stabilization at some point (CNRM-CM5 + COSMO, MOHC-HADGEM2 + COSMO), while others suggest a clear increase (CNRM-CM5 +
 315 ALADIN63). MOHC-HADGEM2 + ALADIN63 exhibits an increase and then a decrease. Model pair MPI-ESM + COSMO is the only one exhibiting some heterogeneity across regions: solar capacity factors decrease in all regions with the exception of the southern regions Nouvelle-Aquitaine, Occitanie and PACA.

Not all observed differences are supported by statistical significance. Models CNRM-CM5 + ALADIN63 and MOHC-HADGEM2 + ALADIN63 suggest that the projected increase in capacity factors are well grounded. Pro-
 320 jected decreases are less significant statistically, except for some regions under model CNRM-CM5 + COSMO.

The energy system modeling step will thus be affected differently depending on the climate model used. Some models lead to improved solar generation conditions whereas other lead to impaired conditions. These variations are

however always comprised within $\pm 10\%$. Both this increase and decrease are suggested to be meaningful depending on the model.

325 3.3 Initial value factors

As important as changes in demand and capacity factors is the change in the correlation between the two. This correlation is measured via the value factor, as introduced in (Tantet and Drobinski, 2021; Delort Ylla et al., 2023). A value factor greater resp. lower than 1.0 indicates a correlation resp. an anticorrelation between capacity factors and demand. An increase resp. a decrease in value factor corresponds to both capacity factors and demand being
330 more resp. less positively correlated.

Wind value factor decreases with increasing climate change across all regions (see Figure 4). This result is robust across models, although discrepancies persist on the magnitude of the change across regions and models. For example, changes in value factor are more pronounced for model pair MOHC-HADGEM2 + COSMO, where heterogeneity across regions can be noted by comparing regions PACA, Occitanie and Auvergne-Rhône-Alpes to
335 others. This regional heterogeneity must come from the regional capacity factors since the demand is the same for all regions (national demand). There is thus a change in the wind regime in this three regions that is not markedly evidenced by changes in average capacity factor (see Figure 2, panel (e)). We however leave for further works the investigation of the underlying mechanisms.

Solar value factors increase with increasing climate change (see Figure 5). Furthermore, this increase follows
340 climate change intensity. Both observations are robust results, although the magnitude of the decrease is region and model specific. This is evidenced by comparing e.g. results with model pair MOHC-HADGEM2 + ALADIN63 to model pair ICHEC-EC-EARTH + COSMO, the magnitude of the increase in the former being by up to 2 percentage points higher than in the latter. A consistent heterogeneity between regions can also be observed across models, with southern regions (PACA, Occitanie, Nouvelle Aquitaine) exhibiting a milder decrease than other regions (robust
345 result). As for the wind value factors, these differences must be explained by regional changes in solar capacity factors that are not readily evidenced by average capacity factor changes depicted in Figure 3.

Overall we can conclude on the robust result that the correlation between wind generation and demand decreases with increasing climate change in most regions, while the correlation between solar generation and demand increases with increasing climate change. We suggest that these trends are explained by a displacement of the aggregated
350 national demand from winter and evening time (where wind capacity factors are higher) to summer and daytime time (where solar capacity factors are higher). A detailed analysis of the underlying processes that could also explain observed regional heterogeneities is however left for further works.

4 Systemic assessment of the impact of climate change on optimal wind and solar mixes

We showed so far that at the component level, climate change would lead to a decreased total demand (with the effect being more pronounced at the peak than at the base) on the order of 10%. In parallel, climate change will lead to mildly degraded wind generation conditions (comprised within +5% and -20%) whereas the evolution of solar generation conditions are model specific and comprised within $\pm 10\%$. These changes lead to the decrease of the correlation between demand and wind generation and the increase of the correlation between demand and solar generation. We thus expect that wind energy will be less favored under increasing climate change, to the contrary of solar energy.

We now assess how the different climate change scenarios impact the optimal investment decisions in VRE capacity. We first discuss the results at the national level and then investigate the regional detail of optimal mixes.

4.1 National level

The impact of climate change on the optimal investment decisions is presented in Figure 6 for the results aggregated at the national level. Analyzing first the obtained VRE mixes, we can observe that the installed capacities in the reference scenario are consistent across models, although exhibiting a small variability: wind installed capacity is of $86 \pm 2\text{GW}$ while solar installed capacity is of $70 \pm 2\text{GW}$ across models. The values of installed capacities under climate change scenarios are less consistent across models. Nonetheless we observe a robust consistent decrease of the installed wind capacity with increasing climate change: the former decreases monotonously with increasing climate change, from -2% to -9% for the REF1.75 scenario and up to -15% to -22% for scenario REF4.04. For solar, such a consistent trend is not observed: the optimally installed solar capacity exhibits less consistent variations across models. In some models it exhibits a non-monotonous increase with climate change (model pairs ICHEC-EC-EARTH + COSMO and CNRM-CM5 + COSMO), a decrease and then a constant value (model pairs MPI-ESM + COSMO and CNRM-CM5 + ALADIN63), a non-monotonous decrease (model pair MOHC-HADGEM2 + ALADIN63) or a monotonous increase (MOHC-HADGEM2 + COSMO). All variations are however kept within $\pm 3\%$ except for model pair MOHC-HADGEM2 + COSMO where the increase of solar PV with increasing climate change reaches +6%. This last result is probably due to the impact of climate change on the demand patterns (seasonality, daily variability) and the resulting increased correlation with demand, since changes in capacity factor point towards a decrease (Figure 3, panel (e)) and value factors points towards an increase in correlation with solar generation (Figure 5, panel (e)). Optimal investment decisions in VRE mixes are thus impacted by climate change: the higher the level of climate change and the less wind capacity is worth installing (robust result). In turn, the optimal level of investment in solar capacity remains roughly constant with climate change (robust result but for one model).

The behavior of installed dispatchable capacity with increasing climate change and across models is less consistent. Installed dispatchable capacity corresponds in our model to what is sometimes mentioned as the balancing

needs. It corresponds to the maximum of the residual demand (i.e. demand net of VRE generation) over the whole time period of optimization. As such it is strongly linked to extreme events of high residual demand in the time series: this is why we do not observe a consistent behavior of the dispatchable capacity with increasing climate change, as extreme residual demand events (e.g. a high demand for heating combined to a wind drought) can still occur in warmer climates. However some observations suggest that the need for balancing capacity decreases with increasing climate change. This is e.g. suggested by the comparison of the REF2.35 and REF2.80 scenarios in Figure 6, panel (c), where both scenarios have the same level (101GW) of dispatchable capacity but maximum demand is higher in scenario REF2.80 than in REF2.35. This increased maximum demand with less installed VREs would translate in an increased dispatchable capacity *ceteris paribus*. The fact that this is not observed is related to the effect of climate change. A similar effect can be observed by comparing scenario REF2.35 and scenario REF3.28 in in Figure 6, panel (b). Installed dispatchable capacity thus tends to decrease with increasing climate change (on average extreme events of residual demand are less frequent) although its value is strongly linked to the occurrence of extreme residual demand events in the time series considered for the optimization problem.

We conclude from these observations that wind is the adjustment variable with respect to climate change in optimal investment decisions: wind is observed to robustly decrease by -15% to -22% in the most extreme scenario. To the contrary solar PV remains roughly constant (variations are within $\pm 3\%$) except for a single model where it increases with climate change. Dispatchable capacity tends to decrease, although its exact value depends on the occurrence of extreme events of residual demand. We now discuss how these changes translate at the regional level.

4.2 Regional level

The detail of VRE mixes at the regional level are presented Figures 7 and 8 for wind and solar respectively. We observe that the mix in the reference (REF) scenario is not exactly the same across models, although some main features persist: for wind, most capacity is installed in all regions but Nouvelle-Aquitaine, Ile-de-France, Bretagne and Bourgogne-Franche-Comté ($\pm 5\text{GW}$). For solar, most installed capacity is installed in the three southern regions PACA, Occitanie and Nouvelle-Aquitaine, modulo some installed capacity in the Grand Est region (less than 10GW). The impact of climate change on regional mixes is variable depending whether solar and wind capacity are considered. For solar, changes in installed capacity at the national level are minor (less than $\pm 3\%$), which translates at the regional level by almost non noticeable changes in regional mixes. Multimodel behavior is in this regard quite consistent except for model pair MOHC-HADGEM2 + COSMO that exhibits a slightly stronger increase in region Occitanie (related to the increase of $+6\%$ at the national level). For wind, changes in installed capacity are more heterogeneous across models, although some common behavior can be observed: regions Auvergne-Rhône-Alpes and Grand Est are always involved in the installed capacity reductions observed at the national level, while Centre-Val de Loire and Pays-de-la-Loire (and to a minor extent Bretagne) may contribute depending on the model considered. The mechanisms underlying these observed regional differences across models are hard to disentangle: we find no straight answer from the distribution and evolution of initial value factors with climate change, nor from the analysis

420 of average value factors. Differences in demand or costs (which are the same across models) cannot by themselves explain those differences. The explaining factors probably reside in climate model specificities and the evolution of the correlation between demand and VRE generation as VRE capacity is installed. This could be studied via the exploration of investment trajectories (Delort Ylla et al., 2023) but goes beyond the scope of this work. We can consider that to the first order, the impact of climate change on the optimal regional mixes is the same across models.

425 **5 Impacts of climate change on system costs**

Aside from the impacts on optimal investment decisions, climate change impacts system costs. These depend on the adaptation strategy, supposing that some level of climate change will happen: either the central planner decides to adapt to climate change, and in our case it does so with perfect foresight, either it decides not to adapt, in which case climate change impacts the mix in its reference state. Since adapting to climate change with perfect foresight 430 corresponds to decreasing the share of installed wind capacity, any unperfect adaptation strategy (e.g. adapting to a level of climate change while another one happens to actually unfold) will fall between the two mentioned extremes. We discuss both these extreme adaptation strategies and associated system costs in the following. Finally, we discuss the true benefits of perfect adaptation, considering that generation portfolio transformation might come to the cost of necessary new investment or stranded assets.

435 Facing climate change with perfect foresight, a central planner has either the choice to perfectly adapt to climate change (i.e. optimize the VRE mix to a given level of climate change) or the choice not to adapt at all. In this last case, the VRE mix corresponds to the optimal mix under reference conditions put under the conditions of a changed climate (i.e. climate change happens whereas mix optimization does not). Each of these adaptation strategies yields a yearly system total cost that can be compared to the yearly system total cost in the reference scenario. We define the 440 non-adaptation costs associated to scenario S (NAC_S) as the difference between the system total cost under scenario S without adaptation and the system total cost in the reference scenario. Similarly, we define the perfect adaptation costs associated to scenario S (PAC_S) as the difference between the system total cost under scenario S with perfect adaptation (i.e. with the corresponding optimal VRE mix) and the system total cost under the reference scenario. The evolution of both indicators under the different climate change scenarios is shown in Figure 9. We observe 445 a monotonous decrease of both the NAC and the PAC with increasing climate change intensity (except between scenarios REF1.75 and REF2.35 under model pair MOHC-HADGEM2 + COSMO). This behavior is consistent across models and is thus robust in this sense. We also observe that both NAC and PAC are always negative: system total costs under some level of climate change are less than in the reference case. This is also a robust result. The magnitude of the NAC and PAC varies across models and level of climate change: from a negligible impact (less than 450 0.01bn€) per year (NAC) and a 0.03bn€ improvement (PAC) for the lowest level of climate change, to 2.67bn€ per year (NAC) and 2.9bn€ per year (PAC) improvements for the highest level of climate change. We thus show that in our experiment, no matter the future outcome (i.e. the level of climate change) and no matter the adaptation

strategy, yearly total costs will decrease with climate change, *ceteris paribus*. In this regard, and under the hypothesis of this study, climate change is found to have no adverse impacts on the electricity generation sector.

455 The previous result makes us ask whether perfect adaptation, which implies the building or decommissioning of new resp. installed capacity with respect to the VRE mix optimal under the reference scenario, is economically interesting. We discuss this question by defining a quantity that measures the benefits of perfect adaptation and that we call the cost of unpreparedness (CoU), as a measure of the extra costs incurred in the case where the central planner with perfect foresight does not adapt the VRE mix to future climate change conditions. The CoU
460 is computed as the difference between the NAC and the PAC, and is represented in Figure 9. We first observe that the CoU is positive and steadily increases with increasing climate change intensity: the higher the level of climate change the more interesting it is to adapt to it. The CoU takes values between 0.02bn€ and 0.23bn€ across models and levels of climate change. However this measure misses the fact that perfect adaptation necessitates the building resp. decommissioning of new resp. installed capacity departing from the reference mix. In the scope of this study,
465 adaptation to climate change translates in the decommissioning of wind power plants, between 2GW and 8GW across models for the lowest level of climate change and between 12GW and 18GW across models for the highest level of climate change. These decommissionings lead to stranded assets costs of 0.23bn€ to 2.08bn€ across models and levels of climate change. In fact, these stranded assets costs are consistently an order of magnitude higher than their associated CoU. We thus show that in our experiment, although yearly total system costs are smaller with a
470 perfectly adapted mix, accounting for the full adaptation path makes the perfect adaptation strategy less attractive economically than its non-adaptation counterpart.

6 Discussion

We showed so far that the component-level impacts of climate change (a decrease in total demand on the order of 10%, mildly degraded wind power generation conditions associated to a decrease in average capacity factor
475 within +5% and -20%, variations of solar capacity factors within $\pm 10\%$, a wind generation vs. demand correlation decreasing with climate change and a solar generation vs. demand correlation increasing with climate change) led to optimal mixes with less installed wind capacity with increasing climate change, while the amount of installed solar capacity remained constant. Furthermore, we showed that in the experiment detailed in this study, climate change had no adverse impacts on system total costs, and that adapting to climate change revealed more costly
480 than simply withstanding climate change effects, due to the costs related to the necessary electricity generation mix transformations. We discuss these conclusions in light of our working hypotheses and existing literature in the following sections.

6.1 Component-level results

We first discuss the obtained results on demand, wind and solar capacity factors evolution with climate change. A review of a body of existing literature on the topic is presented Appendix B. Results on wind generation found in the literature are in good agreement to what we can find in our study, with decreases up to 10% comprised in the +5% and -20% interval that we find. Regarding solar generation, compatible results are found as well, with variations observed in this analysis within $\pm 10\%$ aligning well with the worst case variations on the order of 10% mentioned in the literature. Regarding electricity demand, our study aligns well with previous works as we anticipate a decrease in demand in France with climate change only (i.e. without any socioeconomic scenario of demand increase/decrease), on the order of 10% whereas changes anticipated in the literature range within -3% to -5%. We thus expect a slightly higher total demand decrease.

If the trends of average capacity factor values are in good agreement with literature, nothing guarantees that the capacity factors variability (seasonal, intraday), derived from the calibrated climate data is representative of observed capacity factor time series. In fact some studies suggest that reanalysis products such as ERA5 are flawed in the representation of real-world capacity factors time series. This is e.g. shown in (Frank et al., 2018) for solar capacity factors derived from ERA-Interim or MERRA-2 weather data, or in (Henckes et al., 2020) which directly assess the impacts of reanalysis errors on the outputs of the full optimal investment modeling chain. More recently, the work developed in (Jiménez-Garrote et al., 2024; Pozo-Vázquez et al., 2024; Santos-Alamillos et al., 2024) arrives to similar conclusions. If we can expect the bias calibration step we perform after averaging the capacity factors over the area of study to correct for potential biases in capacity factors. We can not expect this step to reduce biases regarding wind and solar capacity factors intraday or seasonal variability. As such, further work could test the sensitivity of the obtained system-level results to the potential biases contained in capacity factors time series originating from common reanalysis products (such as ERA5) and explore/develop more realistic datasets of capacity factors time series.

Similarly, climate models used can introduce biases depending on the accounted processes. (Allen et al., 2013) showed that CMIP5 models struggled to realistically incorporate the role of aerosols. Such an issue is even more stringent in EURO-CORDEX RCMs (Gutiérrez et al., 2020), where only RCMs projecting evolving aerosols are in good agreement with GCM projections, changing the sign of the projected solar resource evolution and thus potentially altering the results of a study similar to ours. Similar biases have been shown to occur for the wind resource, with the accounting of land use changes being in cause in this case (Wohland, 2022). Further investigations could thus also tackle how system-level results respond to other climate datasets such as CMIP5 or CMIP6 GCMs downscaled with another methodology than regional climate models forcing by a GCM.

6.2 Discussion of study results and limits of the modeling approach

515 We show in this analysis that component-level trends do not easily translate into system-wide results. If the observed results for wind generation (degraded conditions with climate change and subsequent decrease of installed capacity) may seem to prove the contrary, solar installed capacity results corroborate the previous affirmation. In the case of solar, optimal installed capacity remains constant with climate change although the correlation of solar with demand increases (just as it decreased for wind). Translating capacity factor trends, or even generation/demand correlation trends into optimal investment strategies is thus not straightforward. It is even more difficult if we consider that assessing component-level impacts implies to simplify the complexity of underlying processes for the sake of the analysis or the presentation of the results: typically we discussed in this analysis the evolution of average capacity factors with climate change, when the whole capacity factors distribution, as well as the time correlation with other processes (demand in particular) is of prime importance. As in (Craig et al., 2018; Khan et al., 2021), we thus reiterate the importance to perform integrated studies of climate change impacts to correctly assess the impacts of driving processes.

If previous studies on the impact of climate change on the optimal mixes were found to be limited in some aspects a comparison of their results to our proves insightful. (Schlott et al., 2018) also find that the importance of wind in the optimal mix will shrink under climate change conditions but to the contrary of us find that the installed solar capacity will increase. They do not however account for demand changes with climate change, which we show to be of major importance when considering the correlation of VRE generation to demand, and is probably of major importance when adopting the systemic approach. In this study system total costs are found to increase or remain constant with increasing climate change (depending on the climate model). (Ralston Fonseca et al., 2021a) also find that solar generation capacity increases while installed wind capacity decreases with climate change. This increase in installed solar capacity is suggested to happen due to an increase in summer peak demand, while the decrease in installed wind capacity is not discussed. System costs impacts of climate change are more thoroughly discussed in (Ralston Fonseca et al., 2021b), where different adaptation strategies are also considered. They do find that system costs might surge if adaptation to climate change is not appropriately carried. This comes from the fact that a mix not adapted to climate change fails to supply electricity more often than a correctly adapted mix. This cannot happen in our study because of our working hypotheses and highlights a crucial limitation of our work.

The crucial hypotheses to highlight when discussing the conclusions of our work is the fact that we considered dispatchable producers to be available in the desired quantity to no other cost than that of their generation. This greatly influences the resulting effects on the optimal installed mixes. This hypothesis makes us miss a feedback between installing more dispatchable generators vs. relying on more wind and solar power. We expect that accounting for dispatchable fixed costs would lead to less dispatchable investment and in turn more VRE investment to ensure adequacy. In turn, this would increase system costs if VRE generation were to be less efficient. Furthermore, considering that dispatchable producers are always available neglects all the adverse impacts of climate change on

dispatchable generation, from availability of hydropower to thermal deratings of thermoelectric units. As such, our analysis represents an ideal case and is probably the reason why no adverse impacts of climate change on system costs are found. Such a limitation would need methodological developments to be addressed, and is left for future works. The effect of other methodological limitations such as not accounting for storage, imports/exports or transmission constraints is less clear and will also be investigated in future works.

7 Conclusions

We show in this study that in an idealized setting regarding the dispatchable production and for the case of France, accounting for the compound effect of a VRE resource and a demand change, optimal investment in wind capacity decreases, whereas the optimal investment in solar capacity is not affected.

We further show that in this idealized setting, climate change has no adverse impacts on system costs and that the costs of adaptation to climate change overcome the costs incurred in the case of no adaptation, thus not incentivizing for adaptation measures. This conclusion maybe highlights the importance of dispatchable producers as a key element in electricity system adaptation to climate change, and the importance of accounting for the effect of climate change on the whole electricity generation sector to avoid biased policymaking advice.

We suggest that further research focuses on integrating all climate change impacts in one modeling exercise to provide policy relevant advice. Other ways forward could be in the inclusion of socioeconomic scenarios of demand and costs and/or the integration of sector coupling in these prospective modeling exercises. Our study also confirms that work needs to be sustained in the energy and climate community to build a greater understanding on how weather patterns associated with climate change affect optimal investment decisions from the regional to the continental level.

Code and data availability. Code and data available upon request.

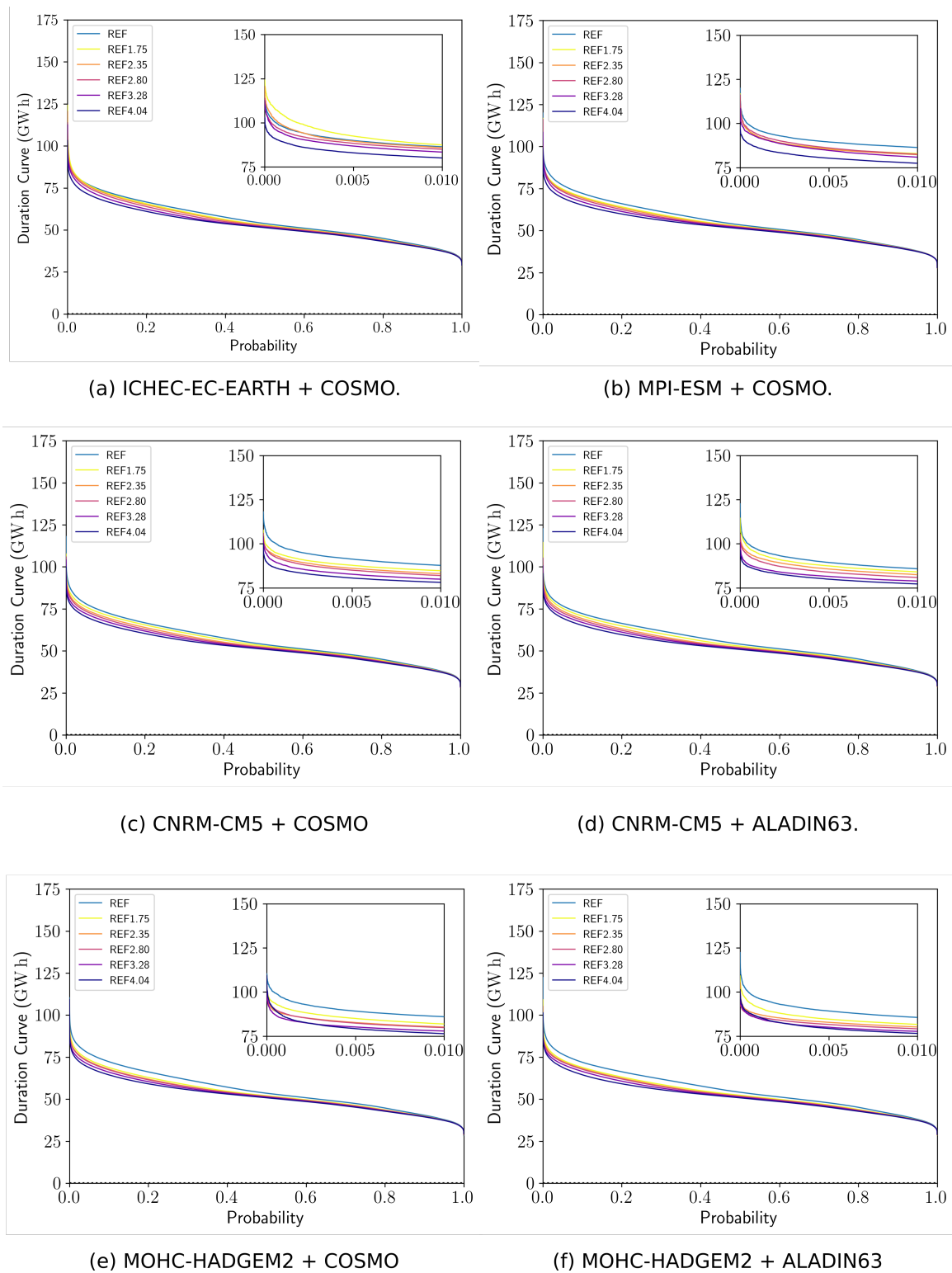
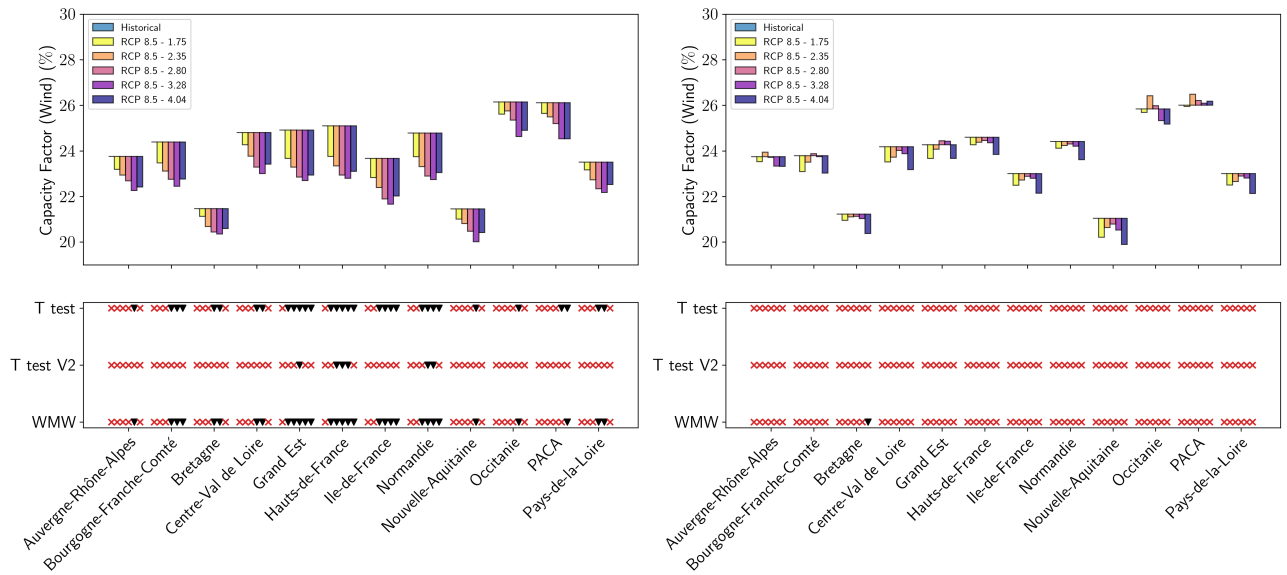
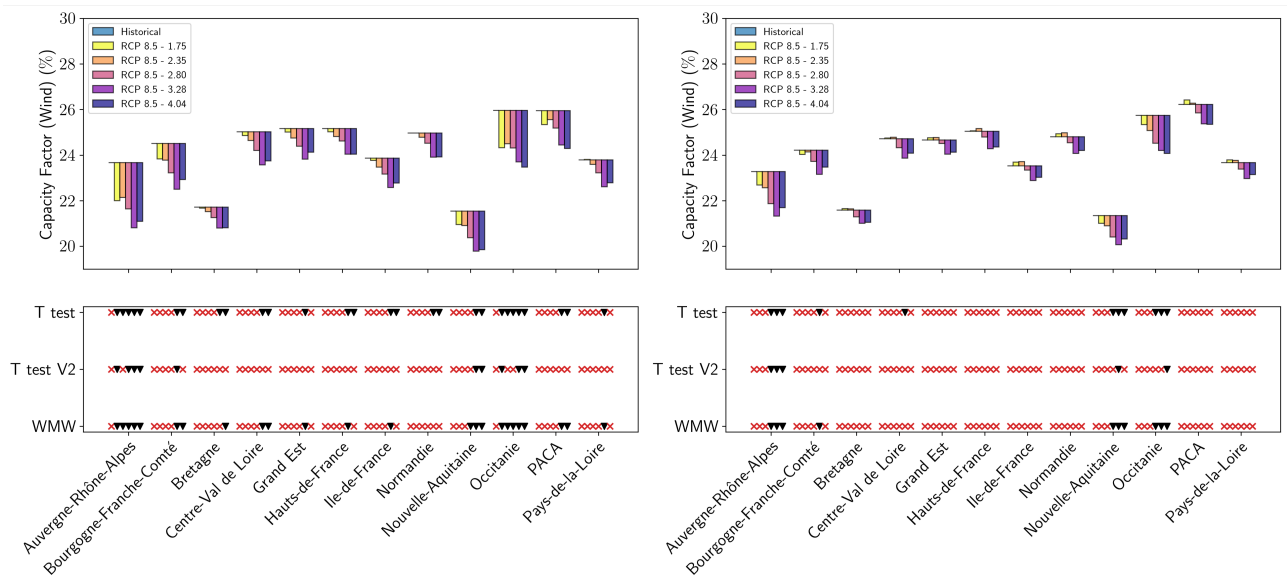


Figure 1. Load duration curves for the levels of global warming considered. Each panel (a) to (f) corresponds to a GCM + RCM pair. The inset in each panel shows the demands occurring less than 1% of the time.



(a) ICHEC-EC-EARTH + COSMO.

(b) MPI-ESM + COSMO



(c) CNRM-CM5 + COSMO

(d) CNRM-CM5 + ALADIN63

Figure 2. Cont.

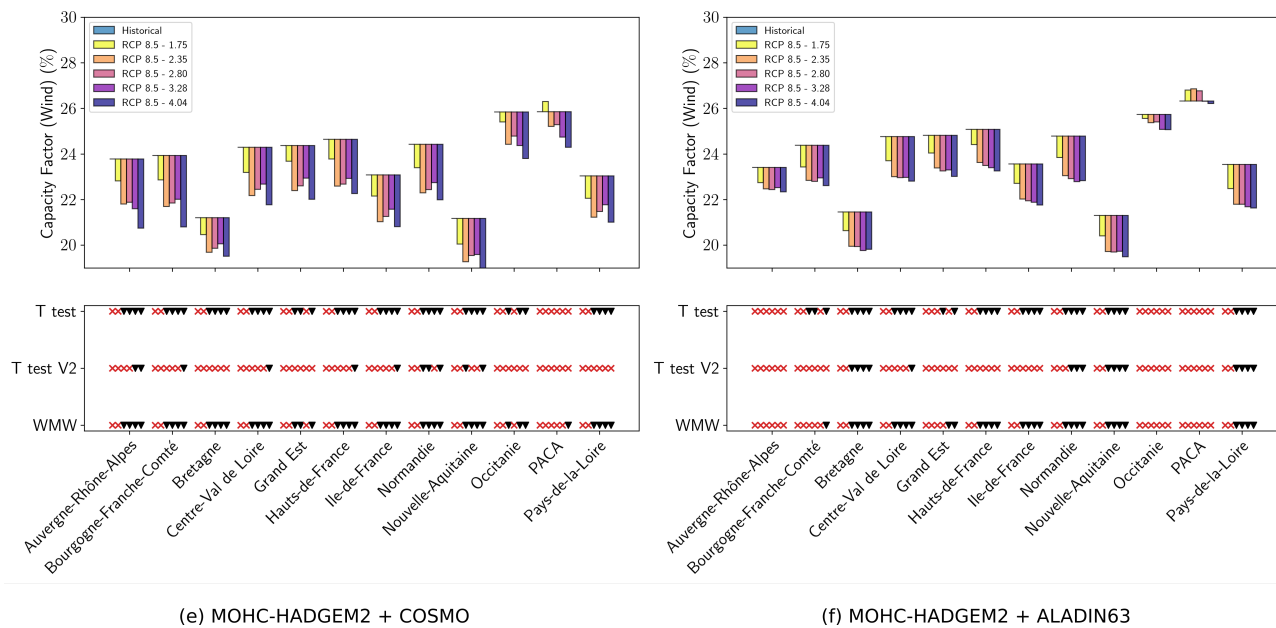
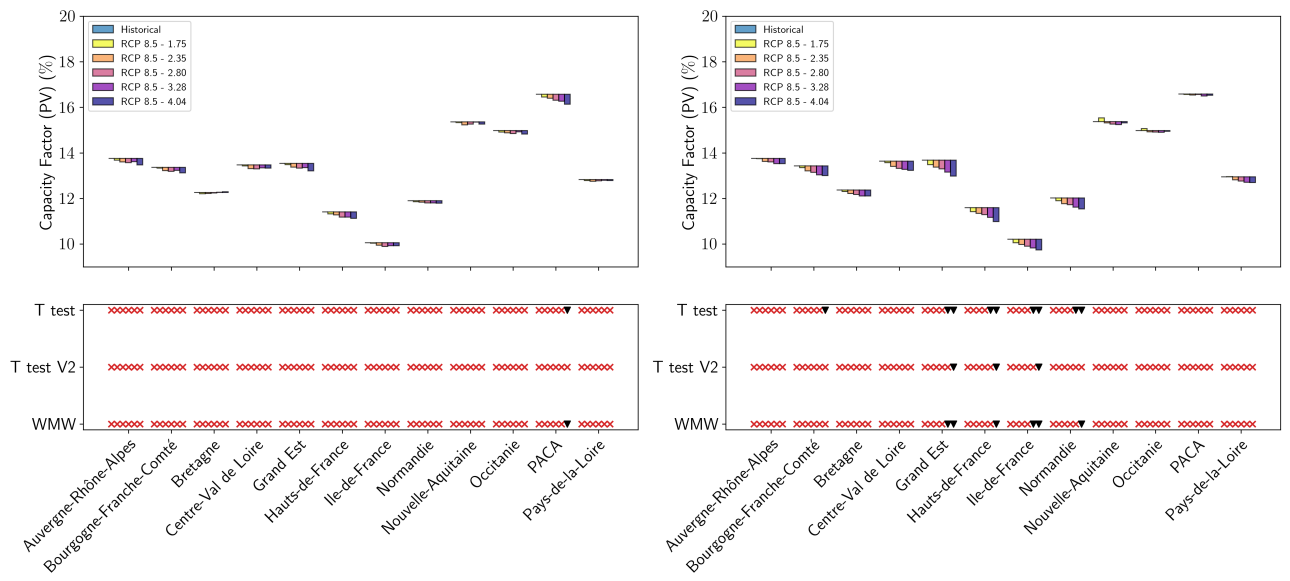
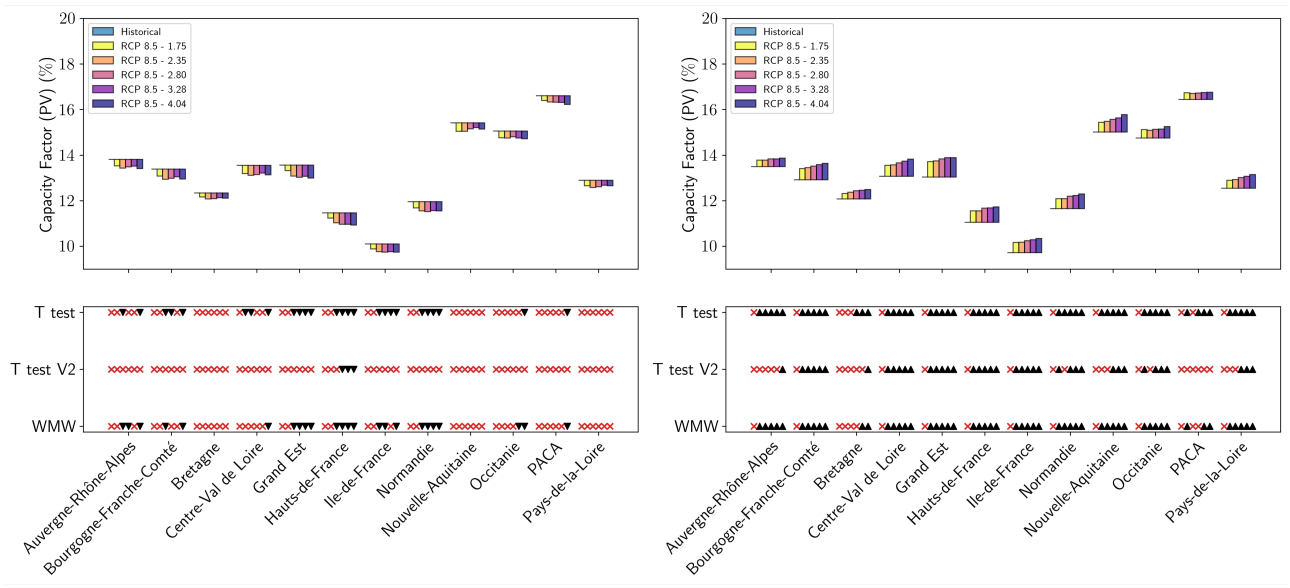


Figure 2. Wind capacity factors change for the levels of global warming considered. Each panel ((a) to (f)) corresponds to a GCM + RCM pair. In each panel, the upper part of the figure shows the evolution of capacity factors for the different climate change scenarios, while the lower part shows the corresponding statistical tests. In the lower part of the figure, a red cross stands for a non-significant difference, a square for a statistically significant difference, and an upper pointing or lower pointing arrow stands for a statistically significant increase resp. decrease with respect to the REF scenario. “T test” stands for t-test, “T test V2” stands for t-test with a variance inflation factor of 2.0, and “WMW” stands for the Wilcoxon-Mann-Whitney U test. “Historical” corresponds to the REF scenario, “RCP 8.5 - 1.75” corresponds to the REF1.75 scenario and the same logic applies to the other labels.



(a) ICHEC-EC-EARTH + COSMO.

(b) MPI-ESM + COSMO



(c) CNRM-CM5 + COSMO

(d) CNRM-CM5 + ALADIN63

Figure 3. Cont.

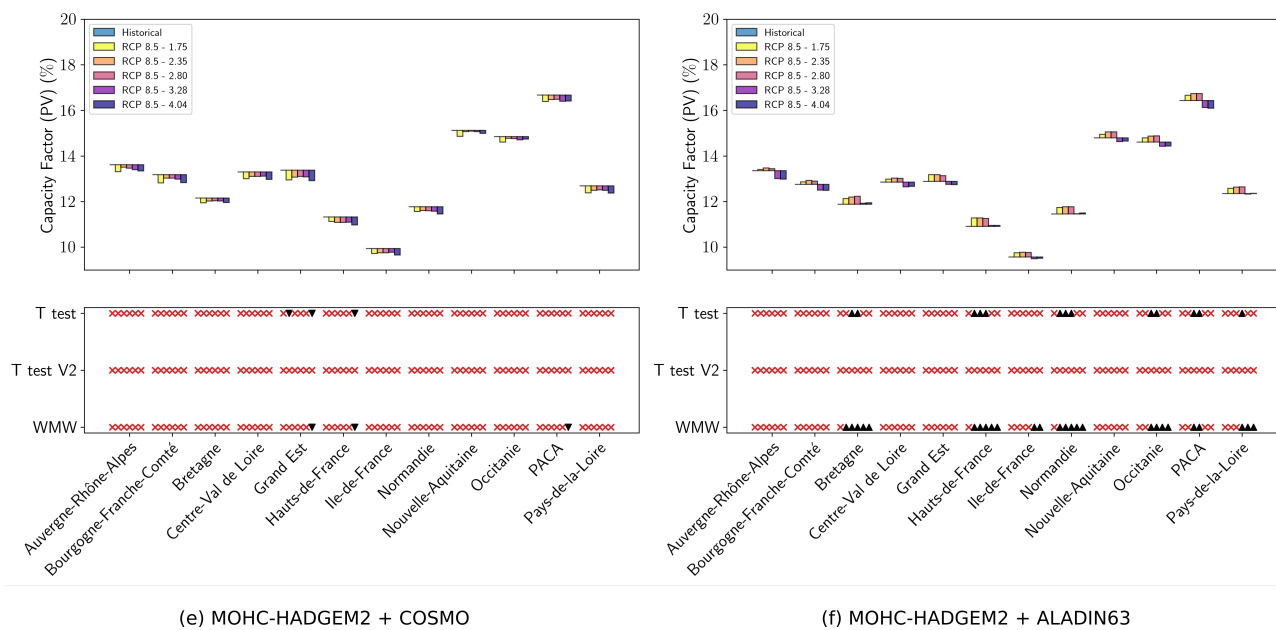
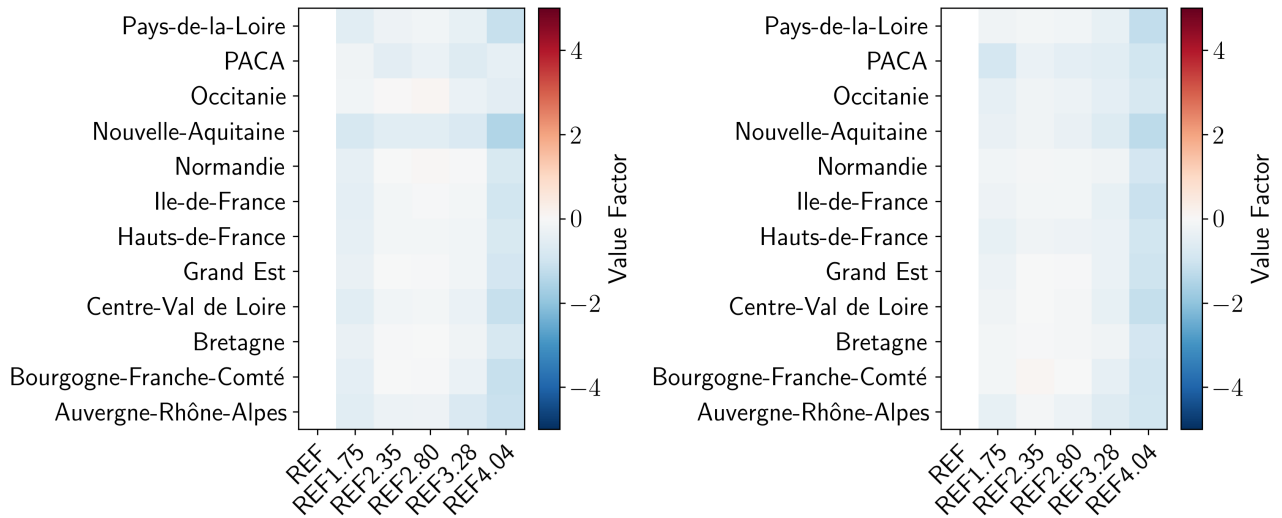
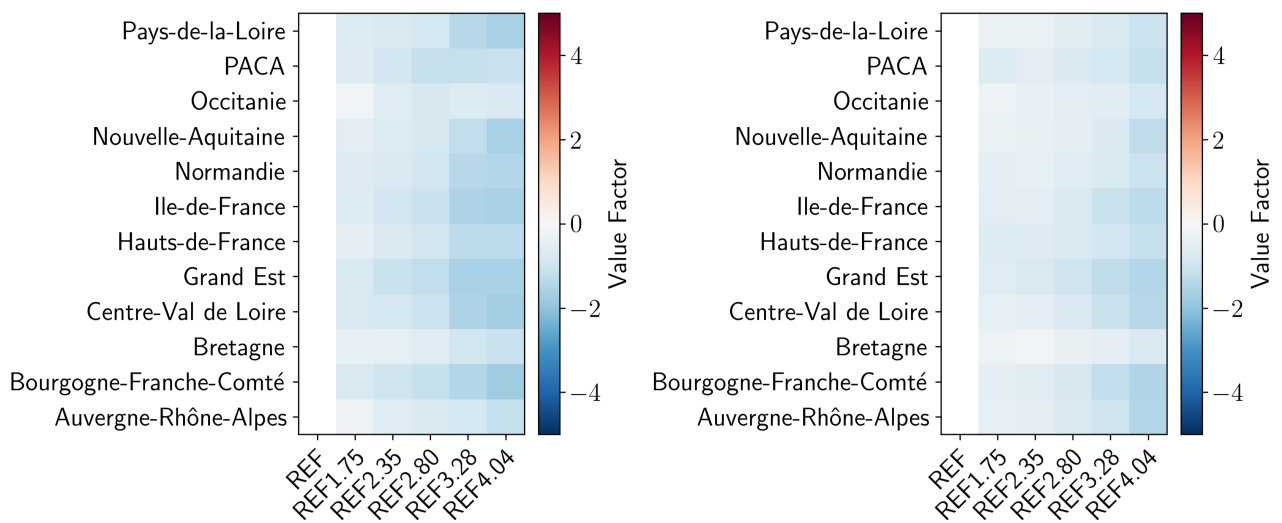


Figure 3. Solar capacity factors change for the levels of global warming considered. Each panel ((a) to (f)) corresponds to a GCM + RCM pair. In each panel, the upper part of the figure shows the evolution of capacity factors for the different climate change scenarios, while the lower part shows the corresponding statistical tests. In the lower part of the figure, a red cross stands for a non-significant difference, a square for a statistically significant difference, and an upper pointing or lower pointing arrow stands for a statistically significant increase resp. decrease with respect to the REF scenario. “T test” stands for t-test, “T test V2” stands for t-test with a variance inflation factor of 2.0, and “WMW” stands for the Wilcoxon-Mann-Whitney U test. “Historical” corresponds to the REF scenario, “RCP 8.5 - 1.75” corresponds to the REF1.75 scenario and the same logic applies to the other labels.



(a) ICHEC-EC-EARTH + COSMO.

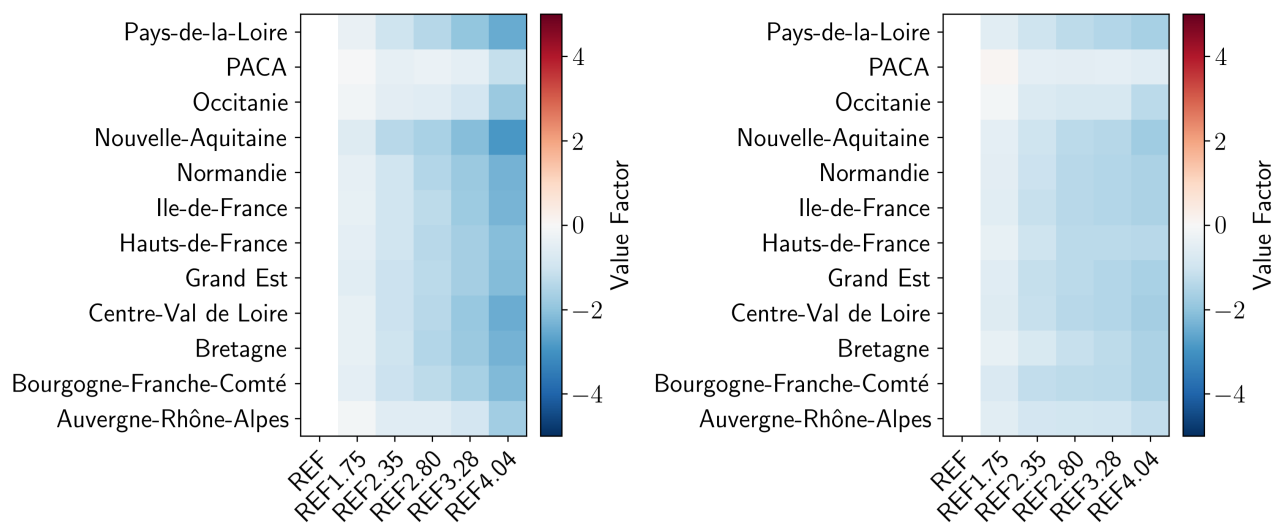
(b) MPI-ESM + COSMO



(c) CNRM-CM5 + COSMO

(d) CNRM-CM5 + ALADIN63

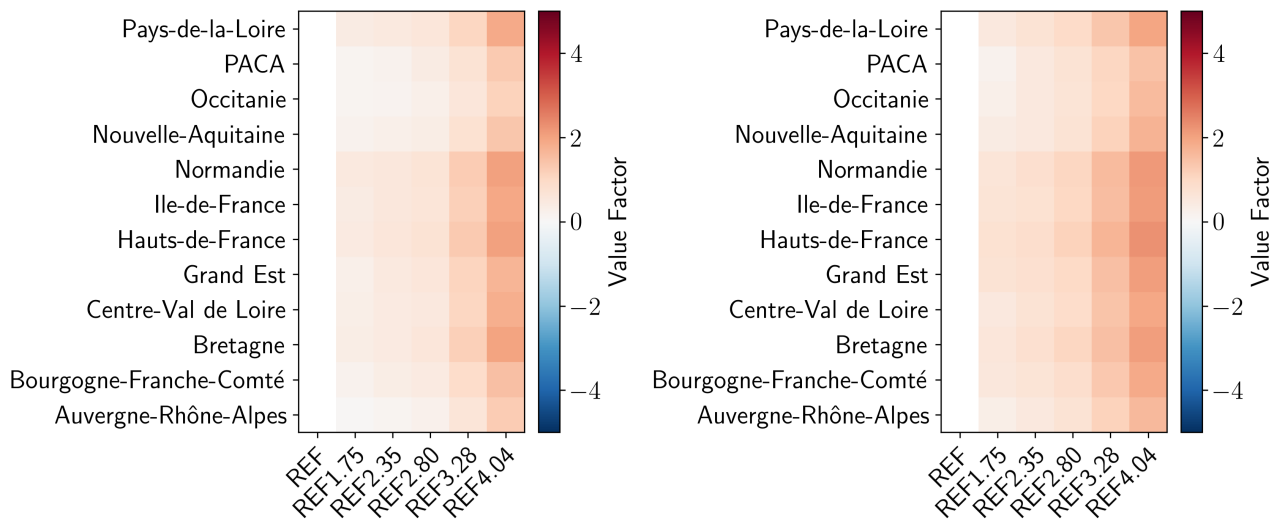
Figure 4. Cont.



(e) MOHC-HADGEM2 + COSMO

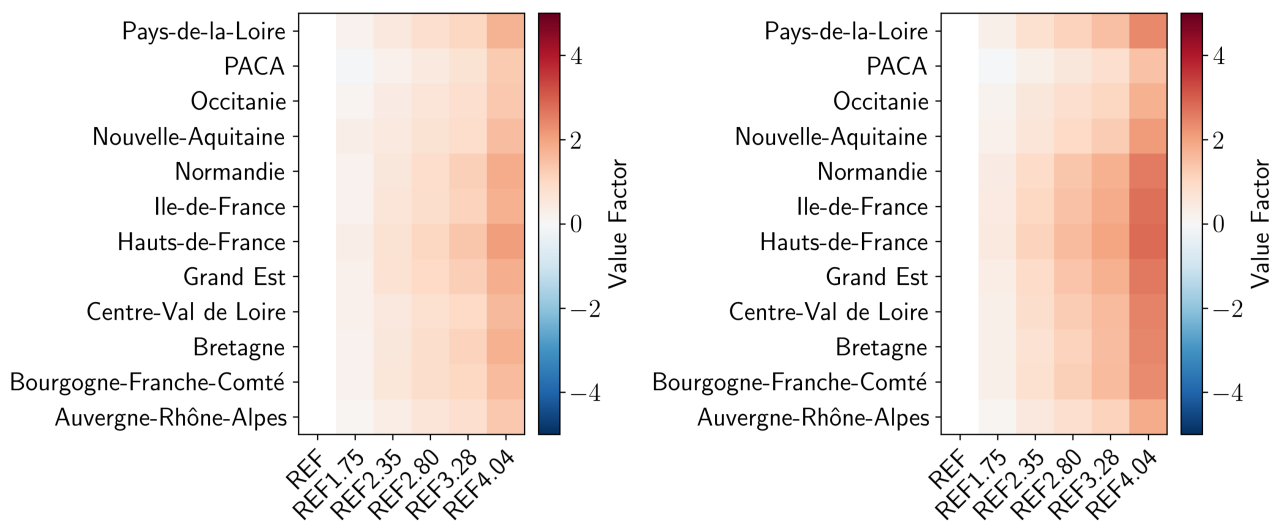
(f) MOHC-HADGEM2 + ALADIN63

Figure 4. Wind initial value factors change for the levels of global warming considered. Each panel ((a) to (f)) corresponds to a GCM + RCM pair.



(a) ICHEC-EC-EARTH + COSMO.

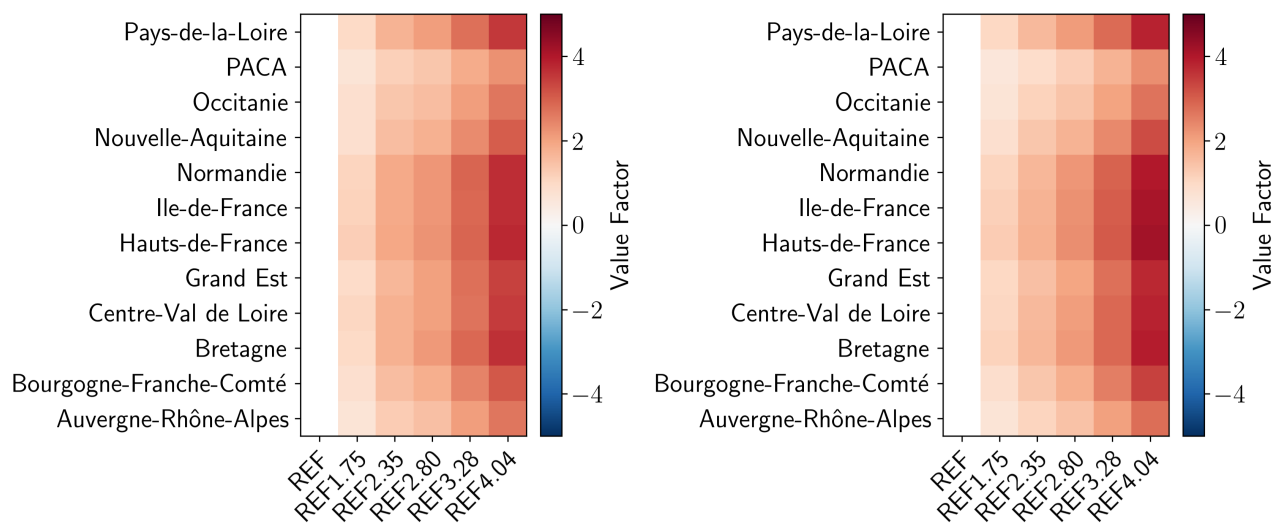
(b) MPI-ESM + COSMO



(c) CNRM-CM5 + COSMO

(d) CNRM-CM5 + ALADIN63

Figure 5. Cont.



(e) MOHC-HADGEM2 + COSMO

(f) MOHC-HADGEM2 + ALADIN63

Figure 5. Solar initial value factors change for the levels of global warming considered. Each panel ((a) to (f)) corresponds to a GCM + RCM pair.

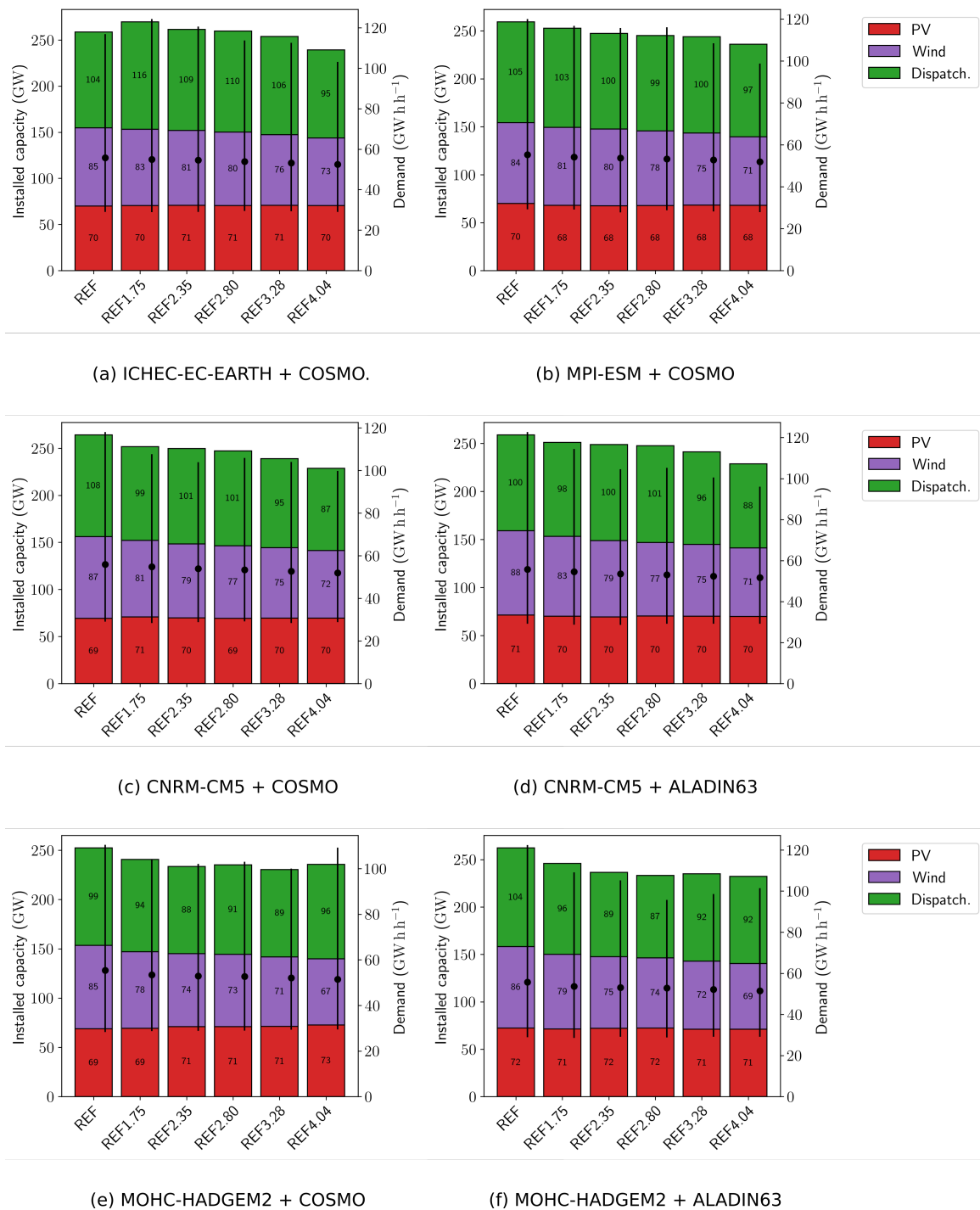
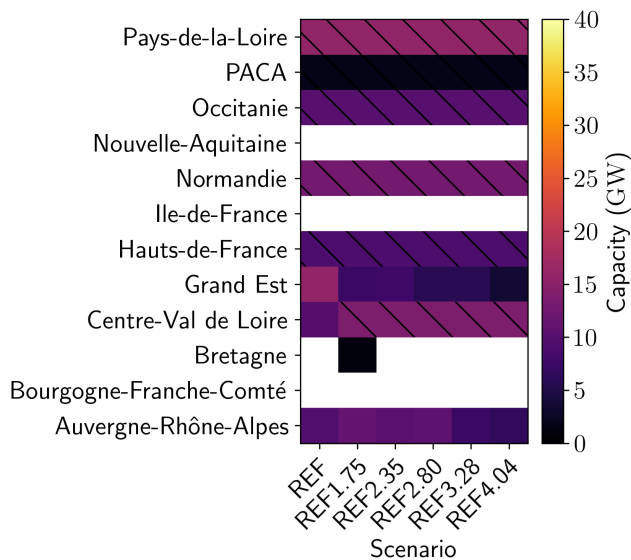
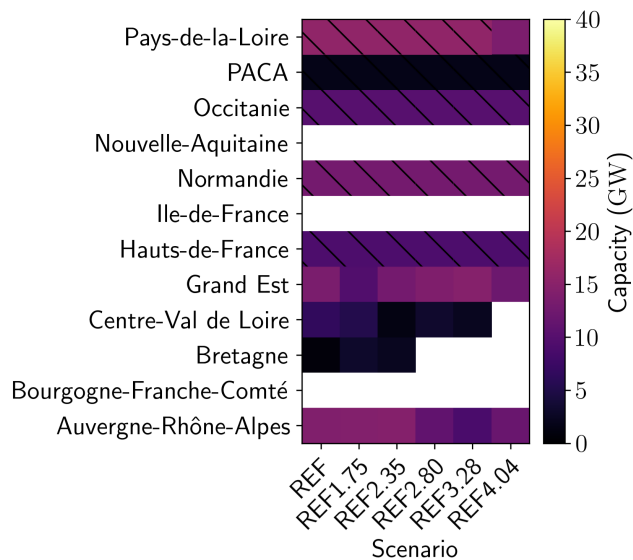


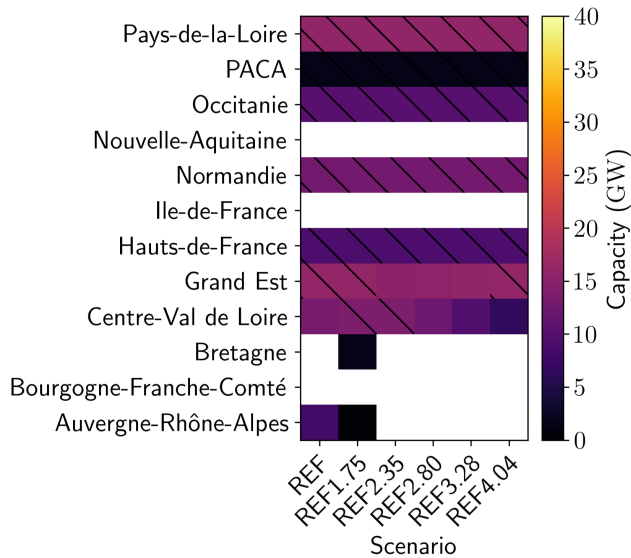
Figure 6. Optimal VRE mixes (national level) for the levels of global warming considered. Each panel ((a) to (f)) corresponds to a GCM + RCM pair. Bars correspond to the nationally installed capacity in solar PV (red), wind (purple) and dispatchable (green), and correspond to the left axis graduation. Black dots correspond to the observed average demand during the 30 year period with the errorbar corresponding to the min-max values. They are associated to the right axis graduations.



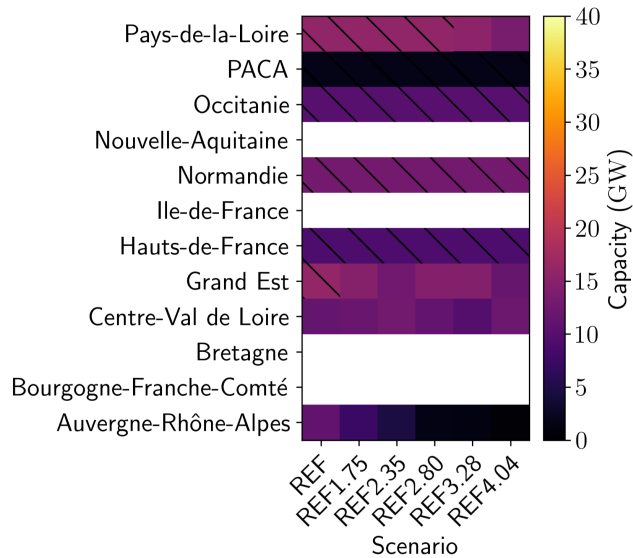
(a) ICHEC-EC-EARTH + COSMO.



(b) MPI-ESM + COSMO



(c) CNRM-CM5 + COSMO



(d) CNRM-CM5 + ALADIN63

Figure 7. Cont.

4

IMPACTS OF CLIMATE CHANGE: THE CASE OF FRANCE

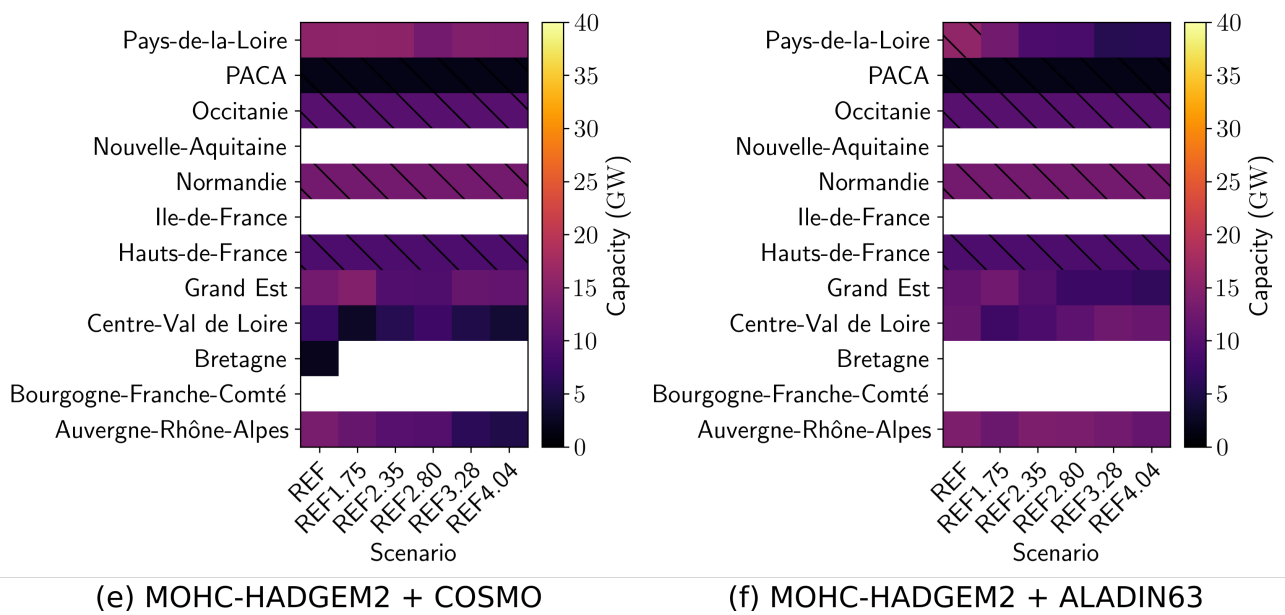
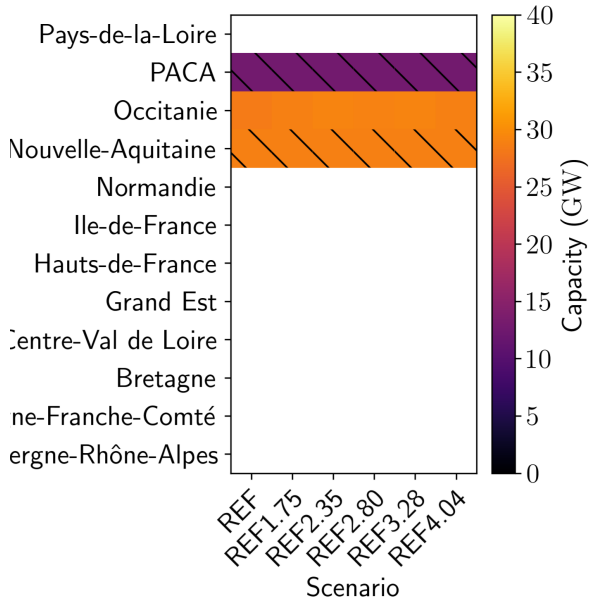
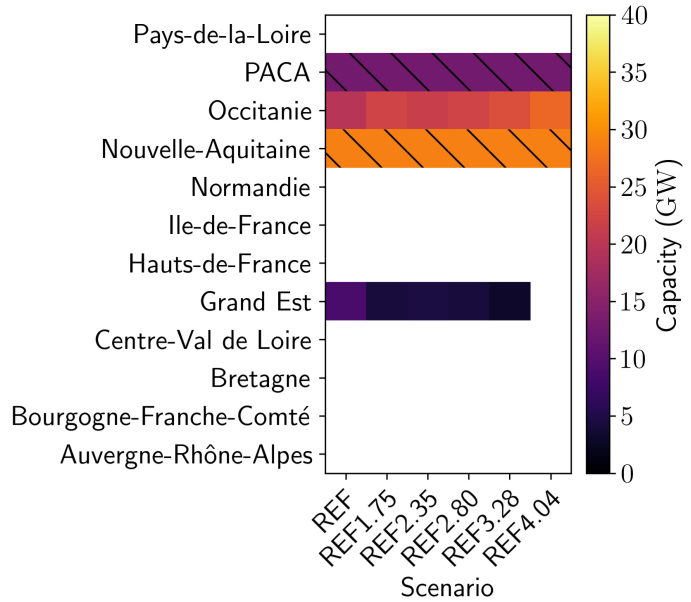


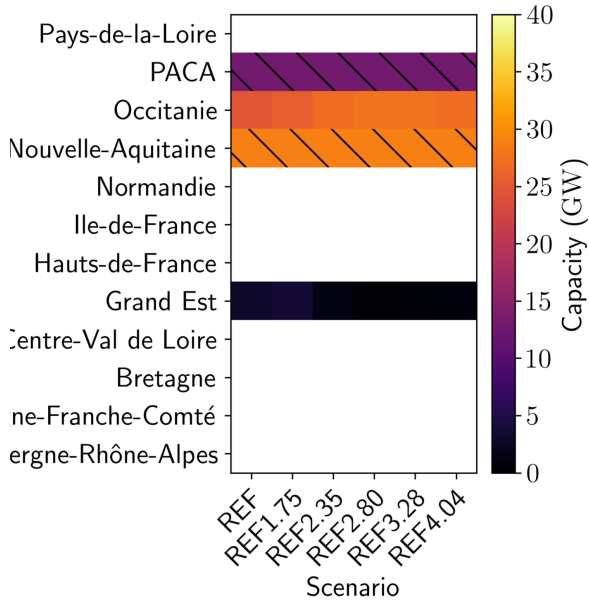
Figure 7. Optimal wind mixes (regional level) for the levels of global warming considered. Each panel ((a) to (f)) corresponds to a GCM + RCM pair. Colors are hatched when they correspond to the maximum installable capacities.



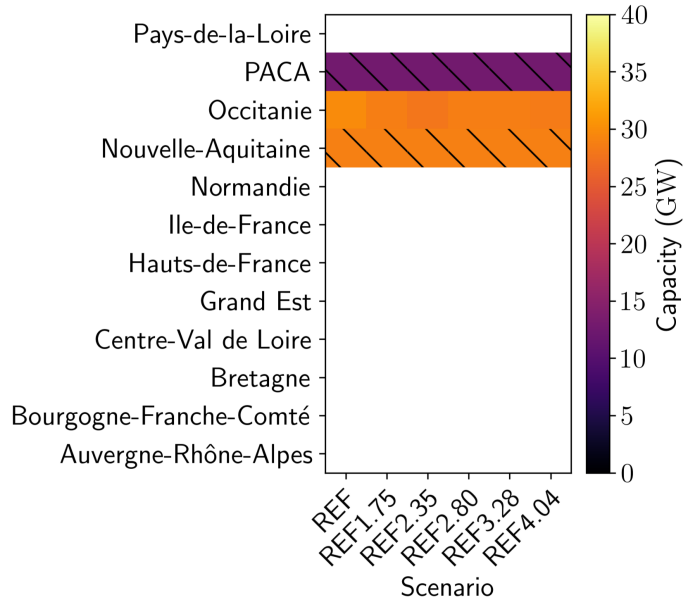
(a) ICHEC-EC-EARTH + COSMO.



(b) MPI-ESM + COSMO



(c) CNRM-CM5 + COSMO



(d) CNRM-CM5 + ALADIN63

Figure 8. Cont.

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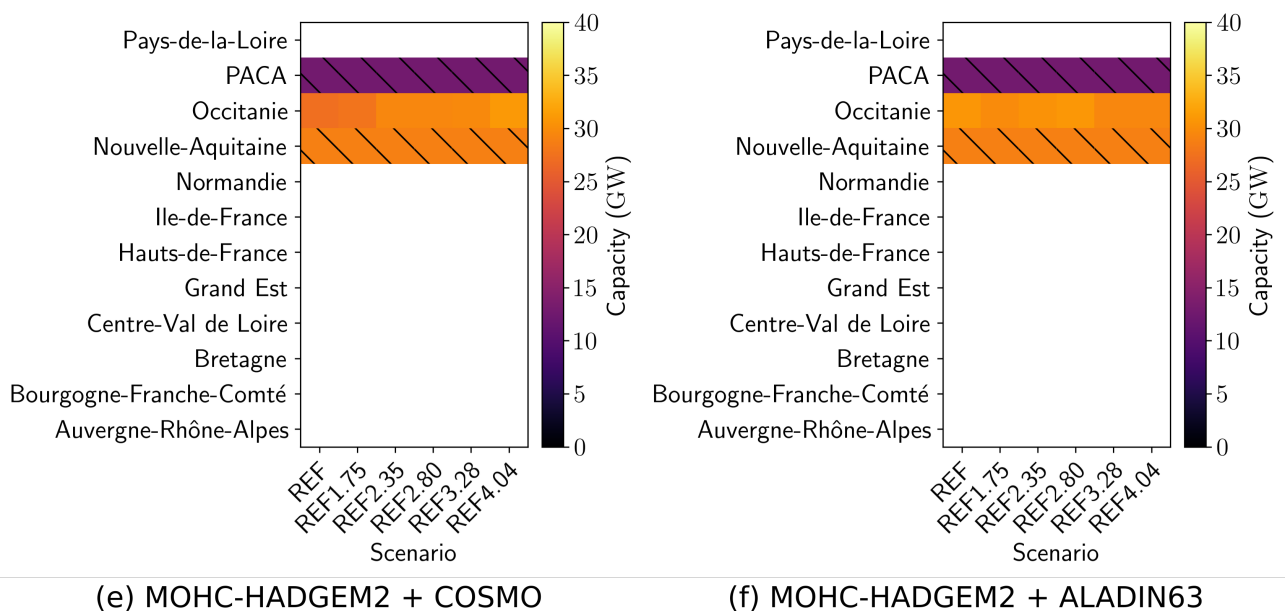


Figure 8. Optimal solar mixes (regional level) for the levels of global warming considered. Each panel ((a) to (f)) corresponds to a GCM + RCM pair. Colors are hatched when they correspond to the maximum installable capacities.

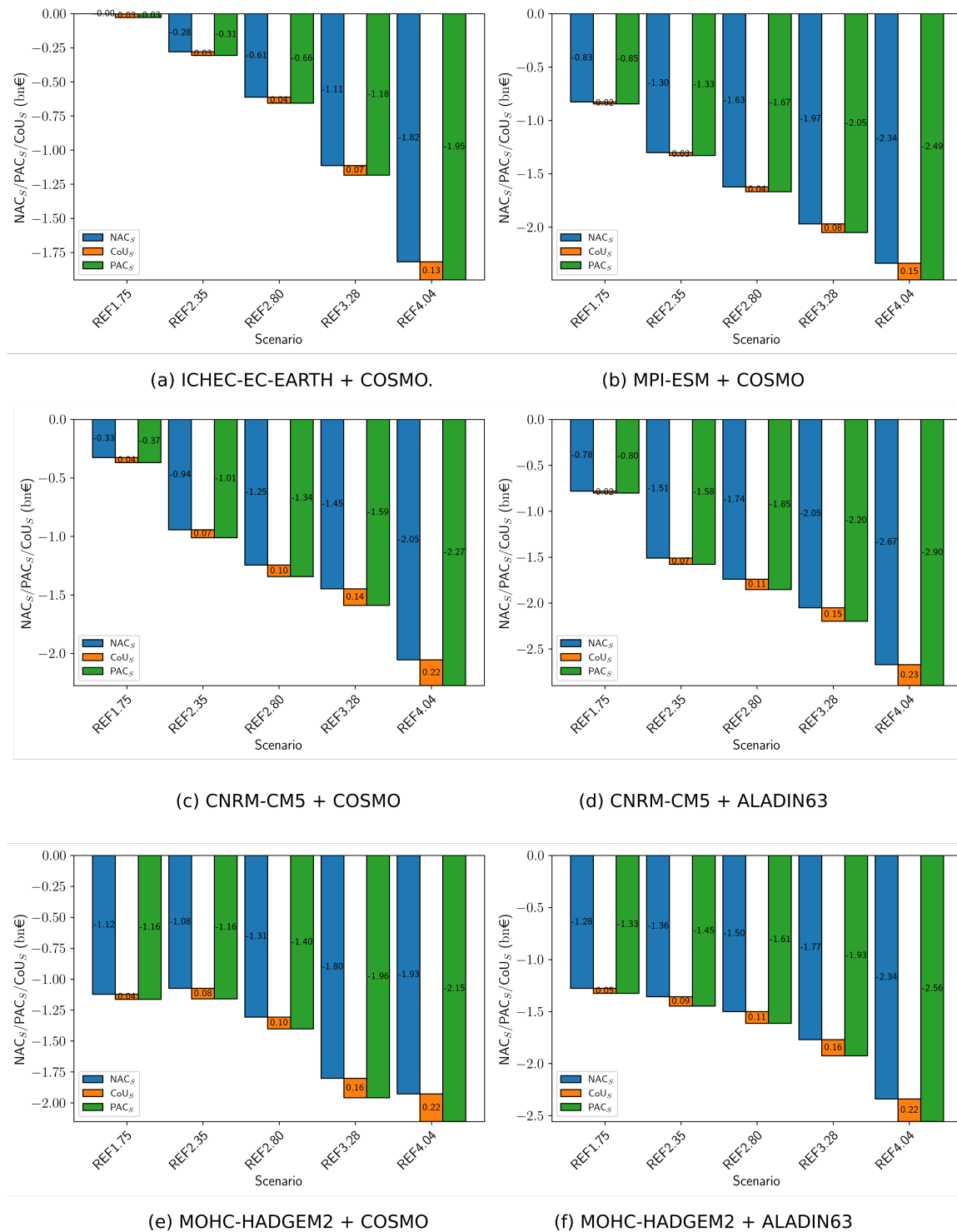


Figure 9. Non-adaptation costs (NAC), perfect adaptation costs (PAC) and cost of unpreparedness (CoU) for the levels of global warming considered. Each panel ((a) to (f)) corresponds to a GCM + RCM pair.

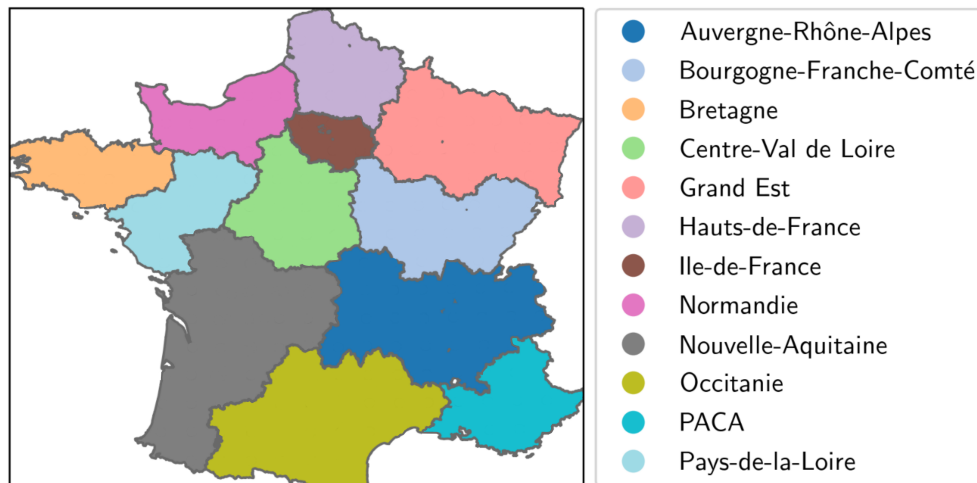


Figure A1. Area of study: detail of french administrative regions, adapted from (Tantet and Drobinski, 2021).

Appendix A: Domain and model parameters

570 A1 Area of study

The area of study corresponds to metropolitan France, subdivided into its administrative regions. A map of the area of study is presented Figure A1.

A2 Climate data curation

Climate data curation steps are needed to obtain a homogeneous and exploitable dataset. These data curation steps are reported Table A1. The calendar conversion from 360 to 365/366 format for model pair 1 is done by splitting each 360 days year in four periods and then adding one day at the end of each period, except the last one where three days are added. Each day added takes the last value of the previous day throughout the day. If this method is fine for daily average values, it is more problematic for subdaily time resolution values as in our case. Further methodological developments should take this point in consideration. In the meantime, we should pay close attention to results obtained from model pair 1.

The cutoff values procedure that needs to be applied for model pair 2 consists in identifying those EURO-CORDEX values whose magnitude is higher than 10 times the maximum ERA5 reanalysis value. Those values are then interpolated via linear interpolation when possible, and otherwise taken as equal to the closest previous non-aberrant value when it exists, or equal to the closest next non-aberrant value otherwise. It is not excluded that such aberrant values still remain in the final data as the cutoff procedure is only applied during the calibration step and thus applies only to historical data (1975 – 2005). Further methodological developments could focus on consis-

Table A1. Data curation steps needed in the study.

GCM/RCM pair ID	Issue	Workaround
0	-	-
1	calendar is 360 days	convert to 365/366 days calendar
	downloaded va100m file for year 2093 cannot be read	replace it with year 2089
	downloaded va100m file for year 2094 cannot be read	replace it with year 2090
	downloaded va100m file for year 2095 cannot be read	replace it with year 2091
	downloaded va100m file for year 2096 cannot be read	replace it with year 2092
	downloaded va100m file for year 2097 cannot be read	replace it with year 2089
	downloaded va100m file for year 2098 cannot be read	replace it with year 2090
	year 2099 missing for ua100m, va100m, tas, rsds	replace it with year 2095 or 2091
2	downloaded va100m file for year 2099 cannot be read	replace it with year 2098
	va100m field show absurdly high magnitude values	set a cutoff value
3	downloaded ua100m file for year 2070 cannot be read	replace it with year 2066
	downloaded ua100m file for year 2092 cannot be read	replace it with year 2088
4	year 2047 missing for ua100m, va100m, tas, rsds	replace it with year 2046
5	downloaded ua100m file for year 2097 cannot be read	replace it with year 2093
	downloaded ua100m file for year 2098 cannot be read	replace it with year 2094
	downloaded ua100m file for year 2099 cannot be read	replace it with year 2095

tently checking the data for aberrant values and systematically applying a cutoff value procedure to the data. In the meantime, close attention should be paid to results potentially influenced by aberrant meridional wind field values (e.g. wind capacity factors) in the case of model pair 2 for the RCP 8.5 experiment.

590 A3 ESM model parameters

A3.1 VRE fixed costs

VRE fixed costs are the same as in (Tantet and Drobinski, 2021) and taken from (Tsiropoulos et al., 2018; Shirizadeh et al., 2020). They are reported in Table A2. They correspond to 2050 projections in the “Diversified” scenario from (Tsiropoulos et al., 2018) in the “Onshore, medium specific capacity, medium hub height” category for wind energy and to the mean of the “Utility-scale PV without tracking”, “Commercial scale PV flat surface” and “Residential scale PV flat surface” categories for solar energy. This corresponds to the capex of wind and solar energy to be respectively 16% and 64% cheaper than in 2015.

Table A2. VRE fixed costs data for the E4CLIM model.

	Wind	Solar
Overnight cost (€kW ⁻¹)	1130	423
Lifetime (years)	25	25
Annuity (€kW ⁻¹ year ⁻¹)	81.2	30.7
Operation and maintenance (€kW ⁻¹ year ⁻¹)	34.5	9.2
Rental costs (€kW ⁻¹ year ⁻¹)	115.7	39.9

A3.2 Dispatchable variable cost coefficient (DVCC)

The dispatchable variable cost coefficient (DVCC) is a key parameter in our model as it determines the magnitude of the dispatchable generators variable costs following

$$VC_{Di} = \alpha q^2, \quad (A1)$$

where α is the DVCC in €MWh⁻² and q is the dispatchable generation in MWh. Intuitively, the higher the costs for the dispatchable producers, and the more competitive it is to install VRE capacity. A high DVCC thus favors VRE penetration whereas a low DVCC favors a dispatchable-only system.

We show in Figure A2 the results of the optimization for the REF scenario as a function of the DVCC. This evidences the previous intuition: the higher the DVCC and the more VRE capacity is installed. This tends to reduce the needed dispatchable capacity to ensure hourly system adequacy. The DVCC parameter is however varied in a range that yields realistic mixes. We now discuss how we can estimate the present value of this parameter.

The first method to estimate the present-day value of the DVCC is to use market and generation data. It follows from Equation A1 that the marginal cost λ is equal to

$$\lambda = \frac{dVC_{Di}}{dq} = 2\alpha q. \quad (A2)$$

The marginal cost can be approximated by the clearing price of electricity markets, such as the day-ahead one. There is thus a linear relationship between the day-ahead price and the amount of energy generated by dispatchable producers, whose coefficient corresponds to the DVCC. We gather data from <https://opendata.reseaux-energies.fr/> to get the dispatchable generation (which includes oil, coal, gas, nuclear, hydropower and bioenergies) as a function of time for the year 2018. Similarly, we gather data from <https://energy-charts.info/api.html?l=en&c=FR> to get day-ahead clearing prices for the french bidding zone of the european spot market. We plot the day-ahead price vs. dispatchable generation relationship in Figure A3, where we can see that a strict linear relationship does not hold. The reasons behind this imperfect linear relationship are beyond the scope of this work, but we can mention imperfect competition in markets which tends to invalidate the equivalence between the marginal cost and the spot

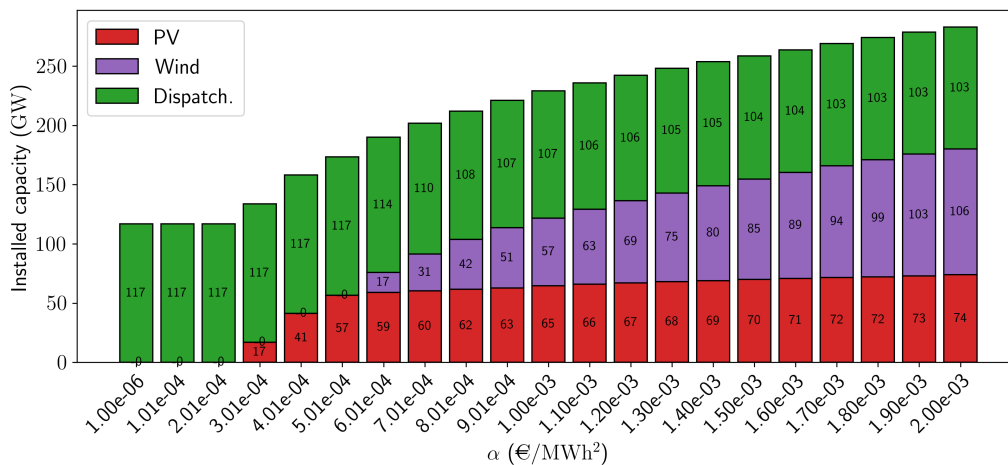


Figure A2. VRE mixes and necessary dispatchable capacity for the REF scenario as a function of the dispatchable variable cost coefficient (DVCC). Results for model pair ICHEC-EC-EARTH + COSMO.

price, and the effect of VREs on the electricity price, which tends to make prices drop. We nonetheless fit a linear model to the data, while forcing the intercept to be zero, the latter explaining the obtention of such a bad coefficient of determination (no observations exist at the (0, 0) point). This however allows us to get a rough estimate of the present day (2018) DVCC value, which should be around $4.25 \cdot 10^{-4} \text{€MWh}^{-2}$.

625 A second method relies on the comparison between modeled mixes and actual ones. Once a rough estimate of the DVCC has been made, the parameter can be varied in a range of plausible values (as shown Figure A2) to yield a series of mixes that can then be compared to actual ones. Actual installed electricity generation capacity for France from 2010 to 2023 is plotted Figure A4. The corresponding value of the DVCC would then be between $2.0 \cdot 10^{-4} \text{€MWh}^{-2}$ and $4.0 \cdot 10^{-4} \text{€MWh}^{-2}$ no matter if the total installed capacity or the installed VRE capacity
630 is taken as the element of comparison.

The present day DVCC has thus a value of around $2.0 \cdot 10^{-4} \text{€MWh}^{-2}$ to $5.0 \cdot 10^{-4} \text{€MWh}^{-2}$ to take a broad interval. To favor the penetration of VREs, this value is raised to $1.5 \cdot 10^{-3} \text{€MWh}^{-2}$ in all scenarios of this study. This leads to a system in the REF scenarios with 155GW of installed VRE capacity, which is close but still below projections from the french TSO for 2050 (RTE, 2021). A mechanism that could justify such an increase could be the
635 increase in the cost of carbon emissions, since a non negligible share of the dispatchable producers are carbonated.

A3.3 Maximum installable VRE capacity

Regional maximum installable capacities play a crucial role in our model in determining the final VRE mix, and in particular its geographical distribution (Delort Ylla et al., 2023). We set maximum installable regional VRE capacities to those determined in (ADEME, 2015). However we find that the parameters used in this study are not
640 satisfactory for utility-scale solar PV, yielding too low potentials compared to more recent estimates (Dupré la Tour,

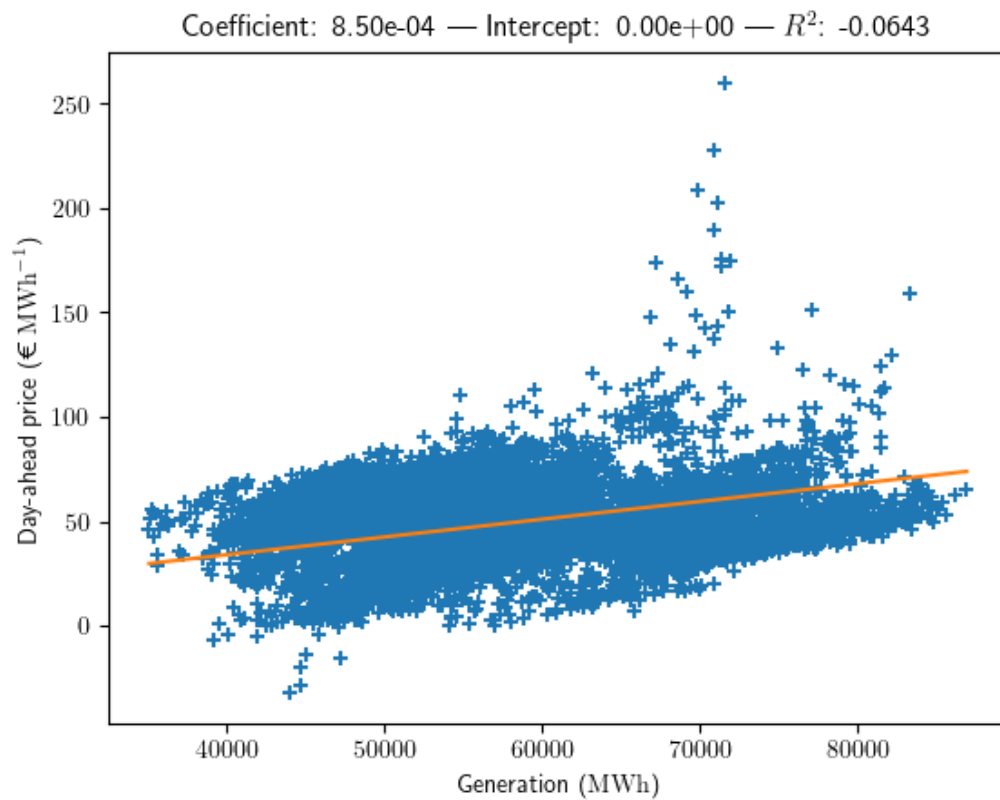


Figure A3. Estimation of the dispatch variable cost coefficient (DVCC) parameter from market and generation data. Source: <https://opendata.reseaux-energies.fr/> for the generation data and <https://energy-charts.info/api.html?l=en&c=FR> for the day-ahead market data.

2023). As such, utility-scale solar PV maximum installable capacities from (ADEME, 2015) are multiplied by a factor 4 to allow the solar installed capacity to be of the same order of magnitude than projected installed capacity in 2050 from (RTE, 2021), while remaining below the potentials presented in (Dupré la Tour, 2023). The obtained regional maximum installable capacities are shown Figure A5.

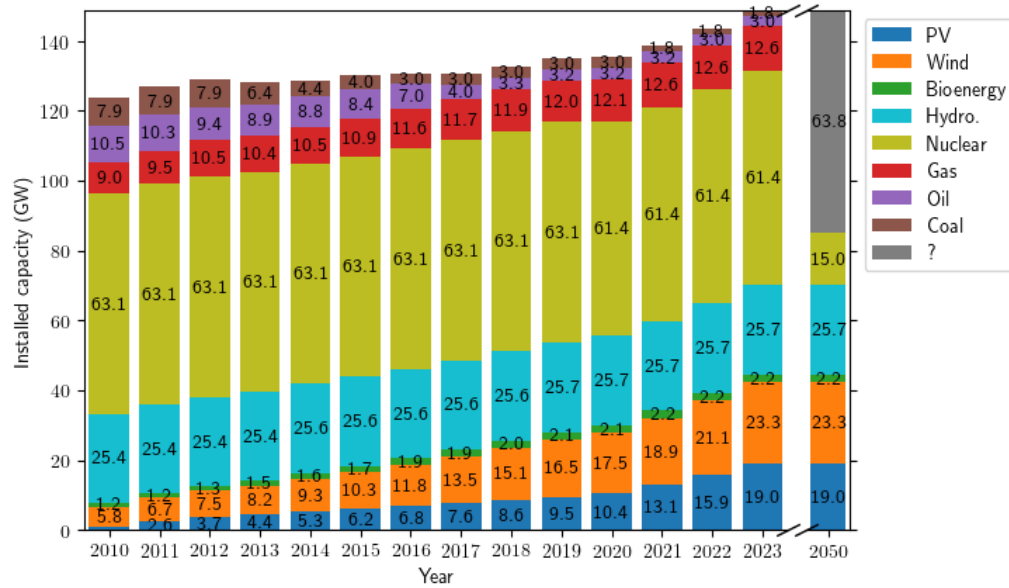


Figure A4. Installed electricity generation capacity in France, 2010 – 2023. Source: <https://opendata.reseaux-energies.fr/>. The 2050 bar represents a projection of installed capacity and capacity to be installed by that time considering that total capacity is the same as in 2023, that the installed renewable capacity is at least that of 2023, and that no new nuclear capacity has been installed while programmed decommissionings have taken place (RTE, 2021).

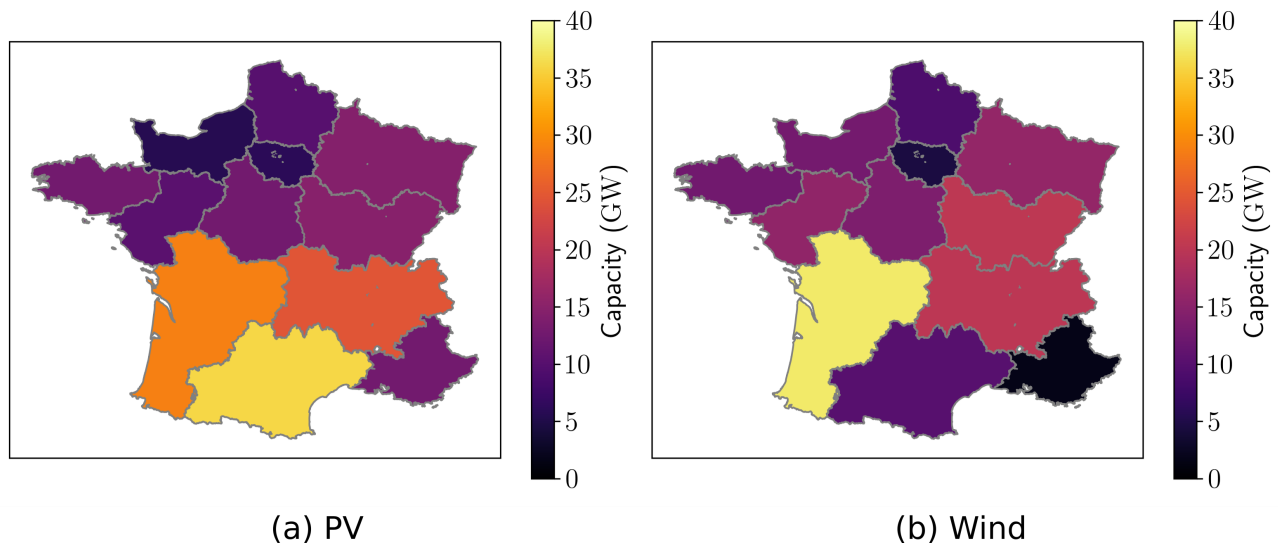


Figure A5. Maximum installable VRE capacity per region for (a) solar photovoltaic (PV) and (b) wind onshore.

645 **Appendix B: Impact of climate change on system components**

B1 Literature review

We review (IPCC, 2022, Chapter 6), (Craig et al., 2022) and references therein for studies covering the impact of climate change on the energy supply. We summarize them in Tables B1, B2 and B3 for the studies comprising France in their geographical area. A similar review over the US is presented in (Craig et al., 2018), and other studies
650 regarding the impact of climate change on the energy supply in the US can be found in (Bartos and Chester, 2015; Voisin et al., 2016; Liu et al., 2017; Miara et al., 2017). The impact of climate change on VRE, other renewable and thermoelectric production is regionally differentiated and technology-dependent. In the case of Europe, thermo-
655 electric production is expected to decrease by 20% (within 5% to 20% capacityfactor decrease in summer), wind generation is expected to decrease by less than 10% over Europe (with stability or increases by less than 10% projected locally), PV generation is expected to remain stable (changes within $\pm 2\%$ and less than 10% in the worst case) and hydropower generation is expected to decrease by up to 20% (with 5% to 20% increases locally). Overall, changes are of moderate significance over Europe, i.e. changes on the potential power output are on the order of $\pm 20\%$.

We review a set of studies on the impact of climate change on the demand-side of energy systems, which we
660 present in Tables B4, B5 and B6. These studies vary in terms of scale and geographical area considered: either at the regional, country or state scale (Ruth and Lin, 2006; Davis and Gertler, 2015; Ralston Fonseca et al., 2019), at the continental scale (Eskeland and Mideksa, 2010; Bartos et al., 2016; Auffhammer et al., 2017; Damm et al., 2017; Craig et al., 2018), or at the global scale (Isaac and van Vuuren, 2009; Levesque et al., 2018; De Cian and Sue Wing, 2019; van Ruijven et al., 2019). They vary also in terms of climate scenarios considered, although most
665 studies reviewed here comprise the use of the RCP 8.5 forcing and the resulting warming at the near 2100 time period. The studies finally vary in scope: most of them include the residential and tertiary energy demand, while some include other sectors like industry, transport or agriculture. The type of energy demand considered can also vary between all electric or including other fuels (gas, coal, oil-derived, biofuels). The global energy demand is expected to a least triple by 2100 (under RCP 8.5 forcing) mostly driven by socioeconomic factors (population rise,
670 income growth) (Isaac and van Vuuren, 2009; Levesque et al., 2018; van Ruijven et al., 2019). Some studies expect an 80% increase in electricity demand (Isaac and van Vuuren, 2009) at the global scale. The increase in peak demand should be exacerbated (Bartos et al., 2016; Auffhammer et al., 2017). At the regional scale projections vary: (Davis and Gertler, 2015) expect a 15% to 83% increase in electricity demand depending on the adoption of AC (2100, RCP 8.5) for the state of Mexico, whereas a 6% increase in electricity demand is expected in the Tennessee Valley
675 Authority region in the US. In the case of France, studies agree that a decrease in the total energy demand on the order of 3% to 5% should be observed due to climate change (Damm et al., 2017; De Cian and Sue Wing, 2019; van Ruijven et al., 2019). (Eskeland and Mideksa, 2010) project a 2.5% decrease in electricity demand whereas (De Cian and Sue Wing, 2019) project a 25% electricity demand increase. This discrepancy is explained by the fact

Table B1. Review of climate change impacts on the supply-side of energy systems: scope of the study.

Entry	Area	Scenario	Period	Models
(van Vliet et al., 2012)	US/Europe	SRES A2/B1	2050	-
(Tobin et al., 2016)	Europe	RCP 4.5/8.5	21st century	-
(Reyers et al., 2016)	Europe	RCP 4.5/8.5	2040, 2080	22 GCM, 1 RCM
(Karnauskas et al., 2018)	World	RCP 4.5/8.5	2100	10 GCM
(Tobin et al., 2018)	Europe	RCP 4.5/8.5	21st century	3 GCM, 3 RCM
(Cronin et al., 2018) *	World	-	2100	-
(Pryor et al., 2020) *	World	-	2100	-
(Gernaat et al., 2021)	World	RCP 2.6/6.0	2085	4 GCM

*: review paper. US: United States. SRES: Special Report on Emissions Scenario (IPCC, 2007). RCP: Representative Concentration Pathway (Moss et al., 2010; IPCC, 2014). GCM: Global Climate Model. RCM: Regional Climate Model.

Table B2. Review of climate change impacts on the supply-side of energy systems: elements of the energy system considered.

Entry	Wind	Solar	Hydro	Thermoelectric	Biomass
(van Vliet et al., 2012)				x	
(Tobin et al., 2016)	x				
(Reyers et al., 2016)	x				
(Karnauskas et al., 2018)	x				
(Tobin et al., 2018)	x	x	x	x	
(Cronin et al., 2018)	x	x	x		
(Pryor et al., 2020)	x				
(Gernaat et al., 2021)	x	x	x		x

680 that the former only takes into account the effect of climate change when the latter also incorporates socioeconomic effects in the study.

The impacts on the energy system physical infrastructure are mainly related to decreased transmission capacity due to high temperatures (Bartos et al., 2016; Craig et al., 2018; Cronin et al., 2018), see e.g. (Loew et al., 2016) for a case study in Texas, US.

B2 Demand

685 B2.1 National level

Table B3. Review of climate change impacts on the supply-side of energy systems: results and comments.

Entry	Results & Comments
(van Vliet et al., 2012)	6% to 19% decrease in summer (Europe)
(Tobin et al., 2016)	$\pm 5\%$; Local changes up to 15%
(Reyers et al., 2016)	Changes may occur; Uncertainties too high to quantify sign and magnitude.
(Karnauskas et al., 2018)	Decrease in northern mid-latitudes; Stability (UK); 5% to 10% decrease (Mediterranean); Stability vs. 30% decrease (Scandinavia-Finland).
(Tobin et al., 2018)	Up to 10% decrease in wind; $\pm 2\%$ for PV; Up to 20% decrease for hydro- and thermoelectric.
(Cronin et al., 2018)	$\pm 10\%$ for PV (mid- and low-latitudes); $\pm 15\%$ to $\pm 30\%$ for wind (Europe); 5% to 20% increase in hydropower (northern Europe); 5% to 20% decrease in hydropower (southern Europe).
(Pryor et al., 2020)	< 10% increase in northern Europe; slight (unquantified) decrease in southern Europe.
(Gernaat et al., 2021)	32% to 38% increase in biomass (global); 6% increase in Hydropower (global); < 1% decrease in PV (global); < 5% decrease in wind (global).

UK: United Kingdom. PV: solar photovoltaic.

Table B4. Review of climate change impacts on the demand-side of energy systems: scope of the study.

Entry	Area	Scenario	Period	Models
(Ruth and Lin, 2006)	Maryland (US)		1989 vs. 2025	1 GCM
(Isaac and van Vuuren, 2009)	World		1971 to 2100	1 IAM
(Eskeland and Mideksa, 2010)	Europe	SRES A1b	2000 vs. 2100	-
(Davis and Gertler, 2015)	Mexico	RCP 4.5/8.5	2010 vs. 2085	25 GCM
(Bartos et al., 2016)	US	RCP 2.6/4.5/8.5	2000 vs. 2050	11 GCM
(Auffhammer et al., 2017)	US	RCP 4.5/8.5	2010 vs. 2093	20 GCM
(Damm et al., 2017)	Europe	RCP 2.6/4.5/8.5	1985 vs. +2°C	11 RCM
(Craig et al., 2018)*	US			
(Levesque et al., 2018)	World	RCP 4.5/6.0/8.5	2010 vs. 2100	
(Ralston Fonseca et al., 2019)	TVA (US)	RCP 8.5	2010 vs. 2060/2095	20 GCM
(De Cian and Sue Wing, 2019)	World	RCP 4.5/8.5	2010 vs. 2050	1 GCM
(van Ruijven et al., 2019)	World	RCP 4.5/8.5	2010 vs. 2050	21 GCM

US: United States. GCM: Global Climate Model. IAM: Integrated Assessment Model. SRES: Special Report on Emissions Scenario (IPCC, 2007). RCP: Representative Concentration Pathway (Moss et al., 2010; IPCC, 2014). RCM: Regional Climate Model. TVA: Tennessee Valley Authority.

Table B5. Review of climate change impacts on the demand-side of energy systems: sector of demand considered.

Entry	Residential	Tertiary	Industry	Transport	Other
(Ruth and Lin, 2006)	x	x			
(Isaac and van Vuuren, 2009)	x				
(Eskeland and Mideksa, 2010)	x				
(Davis and Gertler, 2015)	x				
(Bartos et al., 2016)					All
(Auffhammer et al., 2017)					All
(Damm et al., 2017)	x	x			
(Craig et al., 2018)					All
(Levesque et al., 2018)	x	x			
(Ralston Fonseca et al., 2019)					Electricity
(De Cian and Sue Wing, 2019)	x	x	x	x	Agriculture
(van Ruijven et al., 2019)	x	x	x		Agriculture

Table B6. Review of climate change impacts on the demand-side of energy systems: results and comments.

Entry	Results & Comments
(Ruth and Lin, 2006)	Up to 20% to 25% yearly average demand increase; Sensitivity of changes to energy prices; Impacts differ depending on the sector.
(Isaac and van Vuuren, 2009)	Energy demand increases $\times 3$; Electricity demand increases by at least 9000TWh (2000 vs. 2100) ¹ ; Climate change \Rightarrow Net decrease (2050), increase (2100); Climate change impact < Income growth.
(Eskeland and Mideksa, 2010)	Climate change \Rightarrow $\pm 20\%$ change in electricity demand; -2.53% in the case of France.
(Davis and Gertler, 2015)	15% electricity demand increase (cooling) without AC adoption (RCP 8.5); 83% electricity demand increase (cooling) with AC adoption (RCP 8.5); Climate change impact < Income growth.
(Bartos et al., 2016)	Peak summertime (JJA) demand increase by 4% to 15% (2050) and by up to 30% in 2100 (RCP 8.5).
(Auffhammer et al., 2017)	+5% to +10% in average demand; +15% to +20% in 95th percentile peak demand.

¹ This is a 80% increase in electricity demand, based on data from <https://theshiftdataportal.org> for final electricity demand in 2000. JJA: June, July, August. RCP: Representative Concentration Pathway (Moss et al., 2010; IPCC, 2014). AC: Air Conditioning.

Table B6. Cont.

(Damm et al., 2017)	–3% in average demand (France).
(Craig et al., 2018)	+5% in average demand; +10% to +20% in peak demand.
(Levesque et al., 2018)	Building demand constant to $\times 3$.
(Ralston Fonseca et al., 2019)	6% electricity demand increase (2095).
(De Cian and Sue Wing, 2019)	17% increase in demand (RCP 8.5); < 25% rise in electricity demand (France, RCP 8.5); 5% decrease in total demand (France, RCP 8.5).
(van Ruijven et al., 2019)	$\times 2$ to $\times 3$ increase globally (socioeconomic factors); $\times 1.4$ to $\times 2.5$ increase in Europe (socioeconomic factors); 25% to 60% increase globally (climate change); within $\pm 3\%$ change in Europe (climate change).

RCP: Representative Concentration Pathway (Moss et al., 2010; IPCC, 2014).

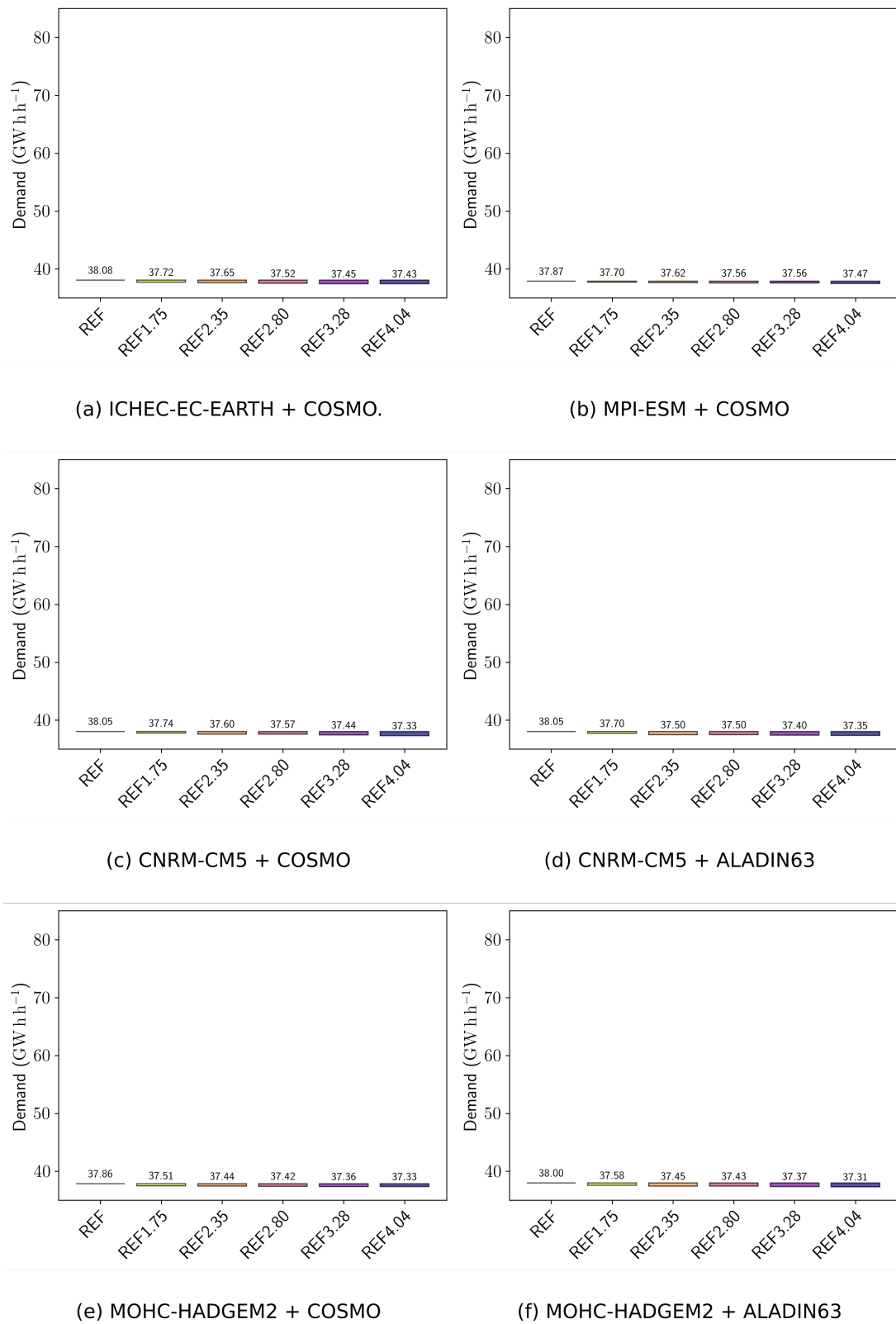


Figure B1. Base demand for the levels of global warming considered. Each panel ((a) to (f)) corresponds to a GCM + RCM pair.

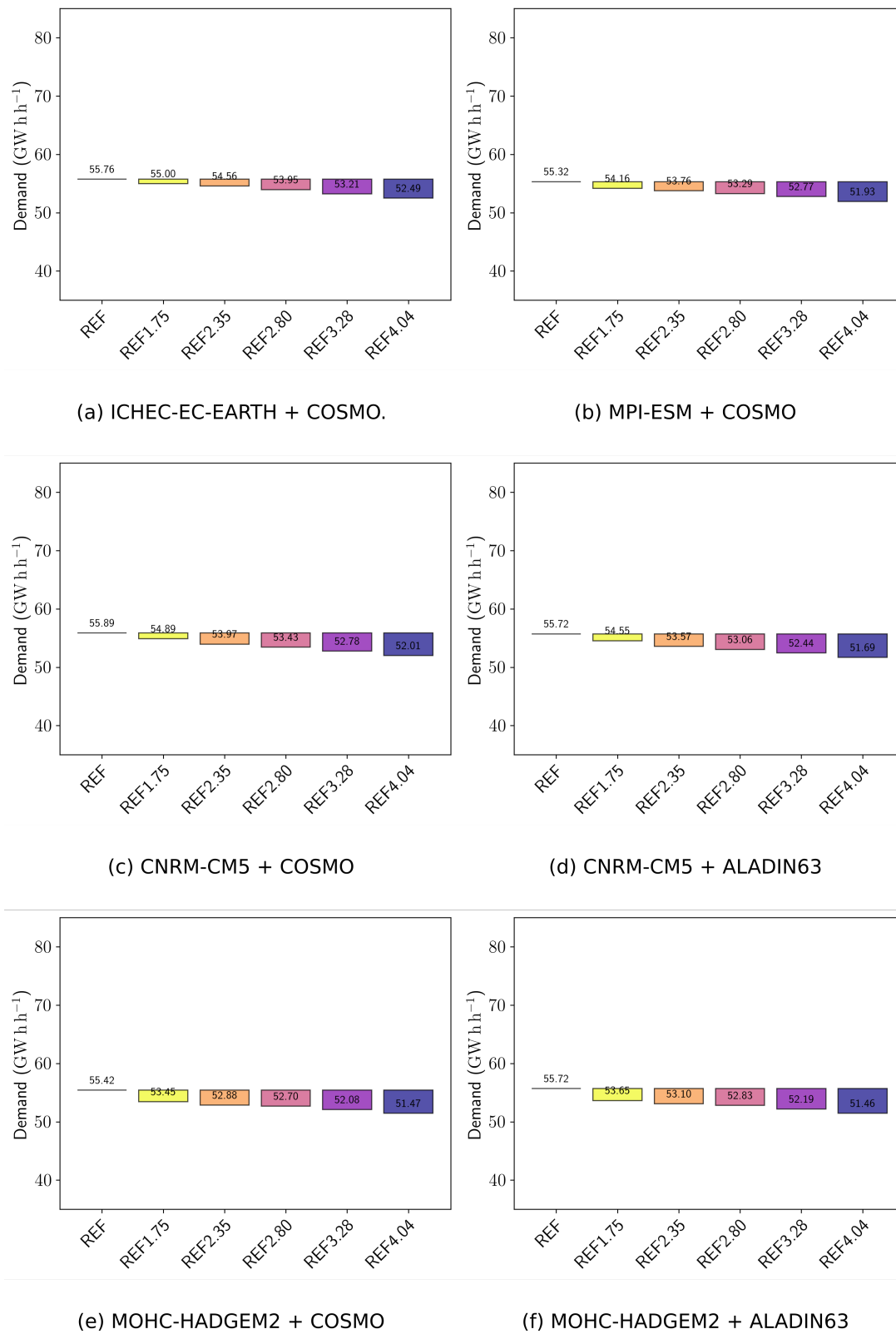


Figure B2. Average demand for the levels of global warming considered. Each panel ((a) to (f)) corresponds to a GCM + RCM pair.

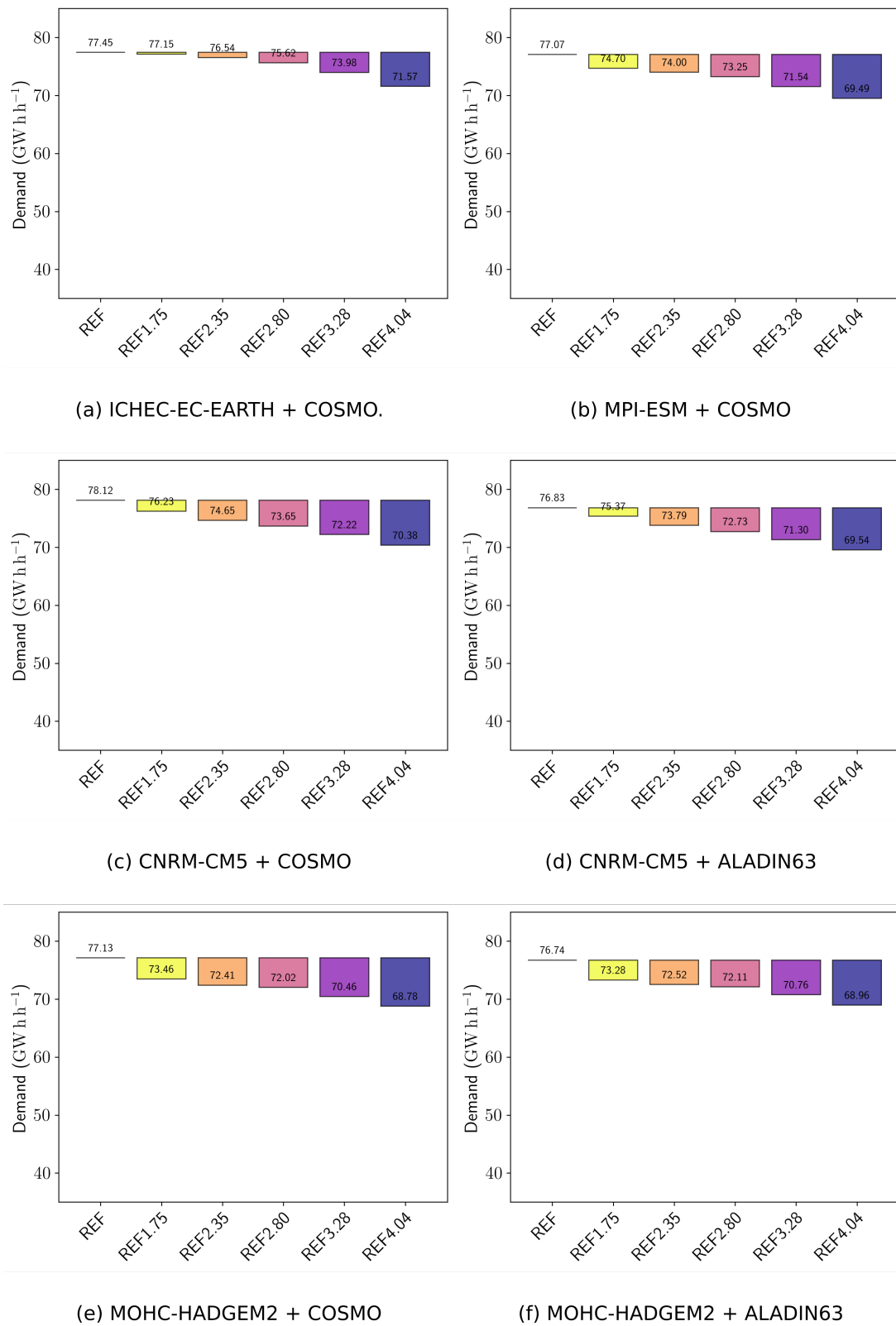


Figure B3. Peak demand for the levels of global warming considered. Each panel ((a) to (f)) corresponds to a GCM + RCM pair.

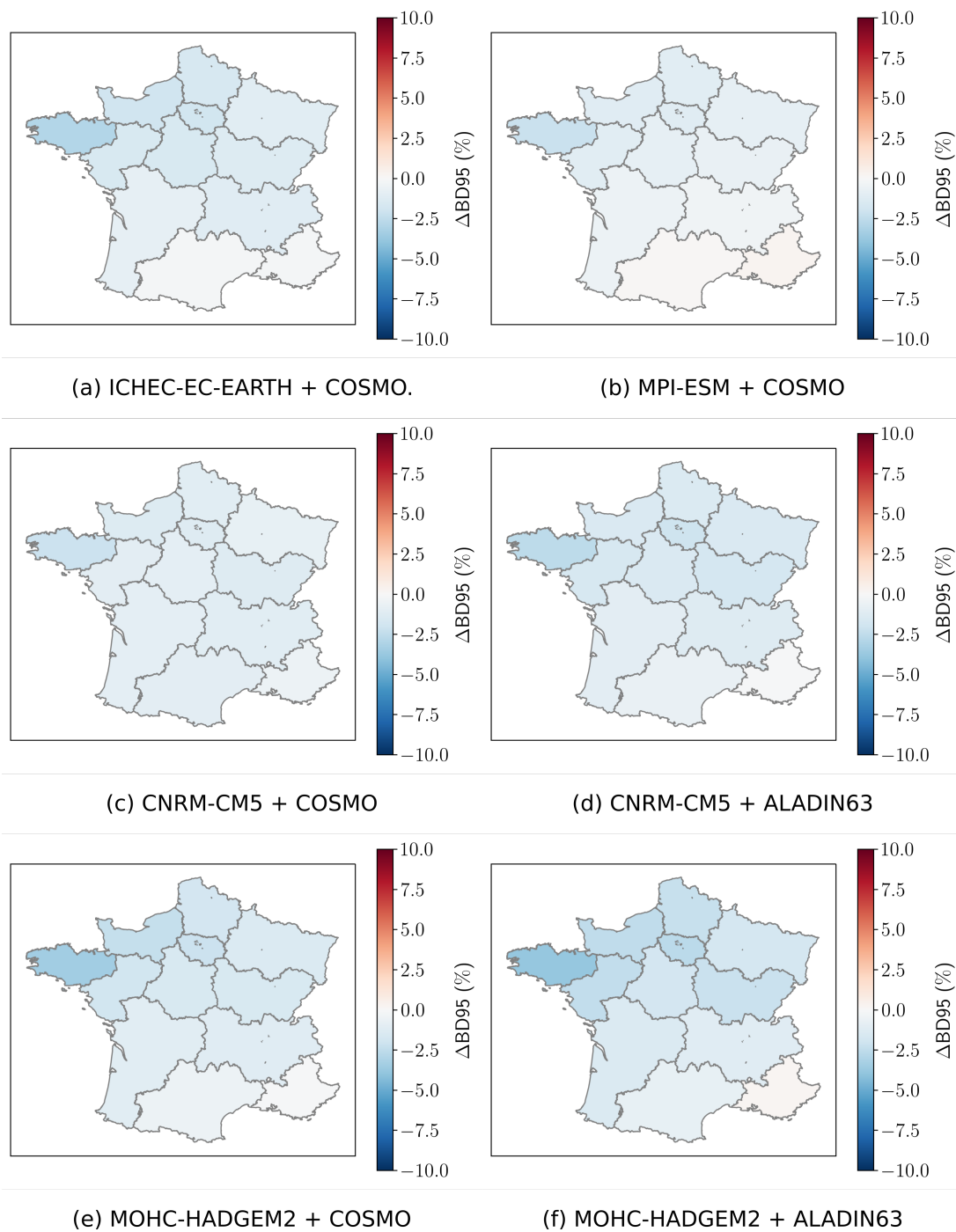


Figure B4. Difference in base demand for 1.75°C of global warming. Each panel ((a) to (f)) corresponds to a GCM + RCM pair.

B2.2 Regional level

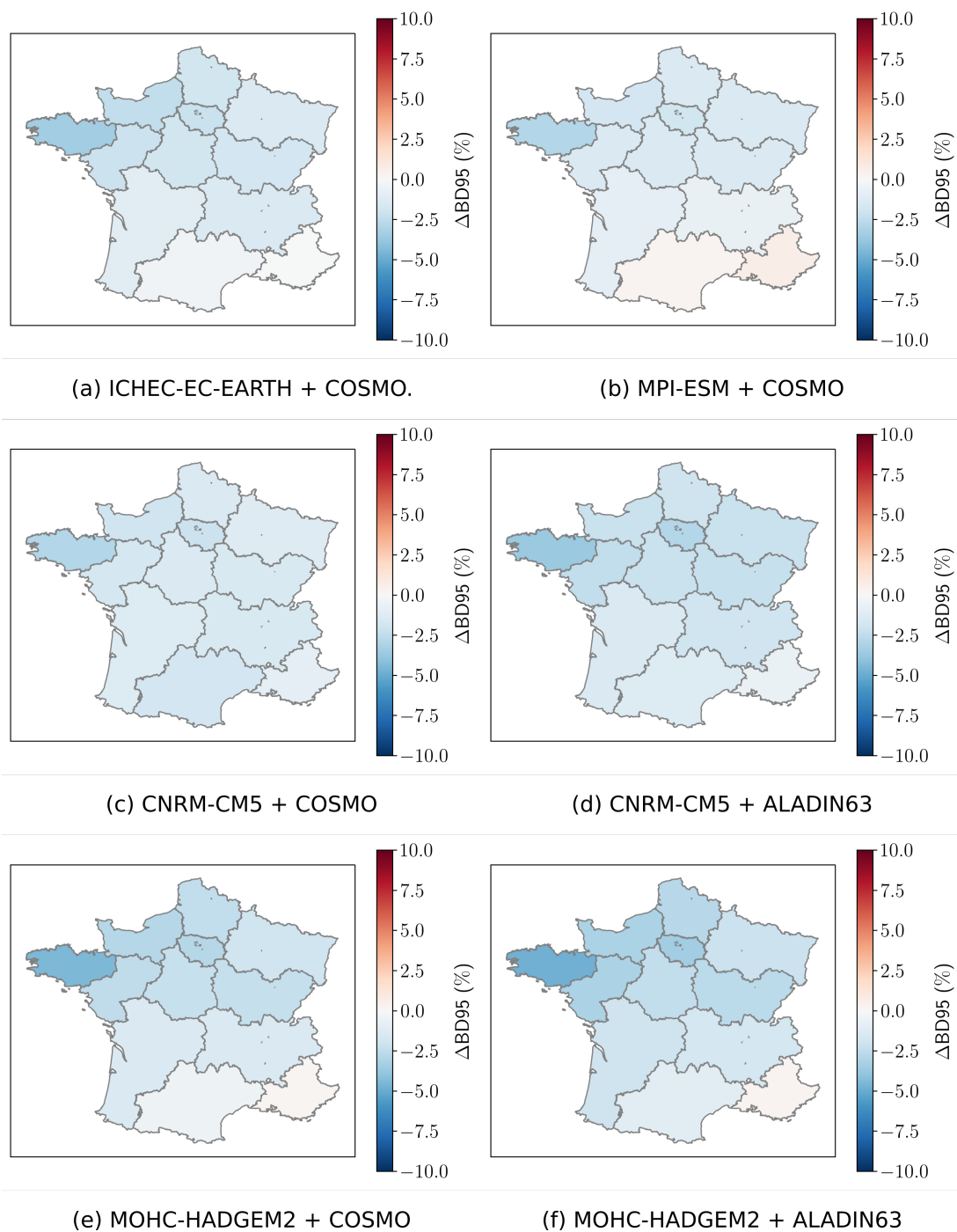


Figure B5. Difference in base demand for 2.35°C of global warming. Each panel ((a) to (f)) corresponds to a GCM + RCM pair.

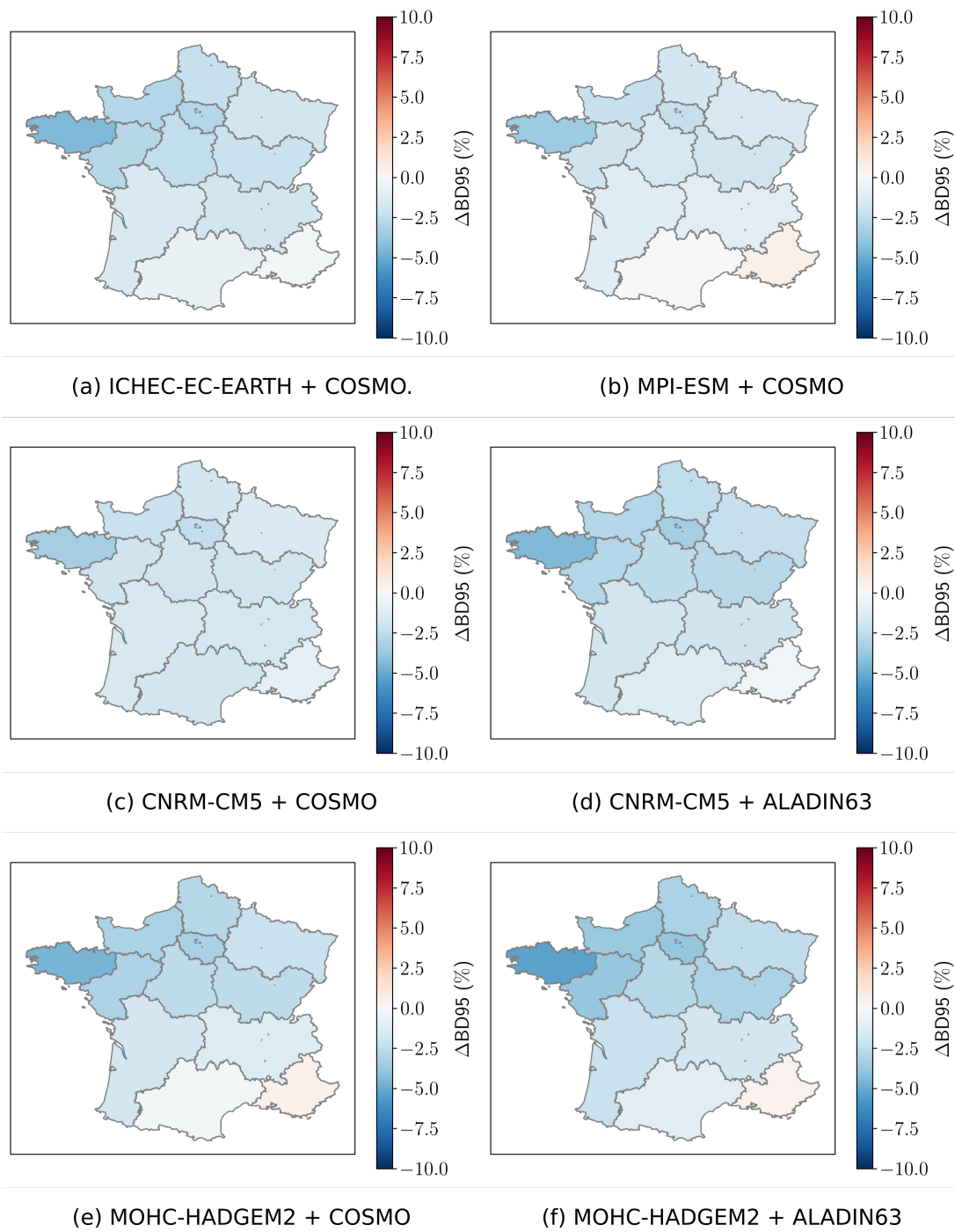


Figure B6. Difference in base demand for 2.8°C of global warming. Each panel ((a) to (f)) corresponds to a GCM + RCM pair.

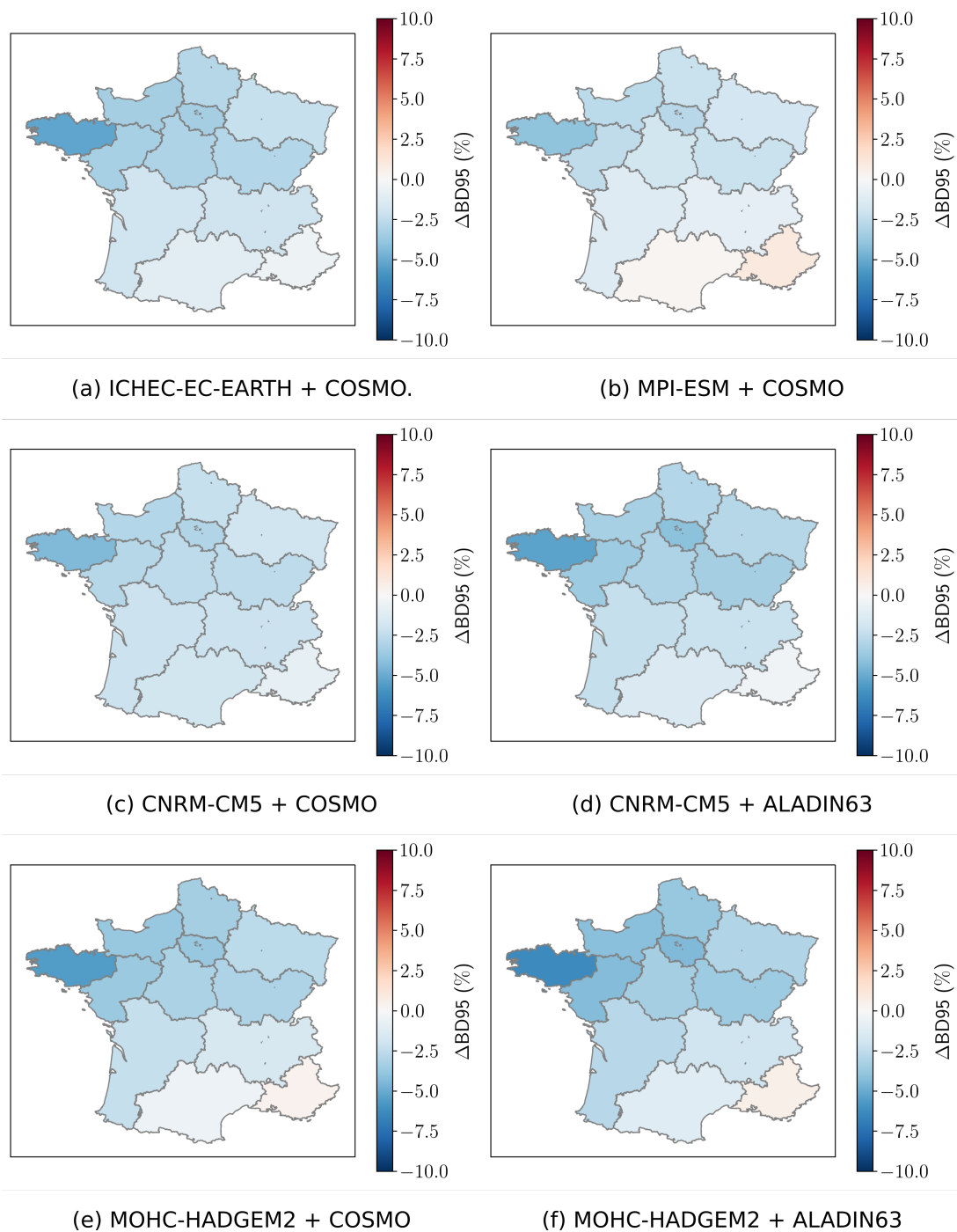


Figure B7. Difference in base demand for 3.28°C of global warming. Each panel ((a) to (f)) corresponds to a GCM + RCM pair.

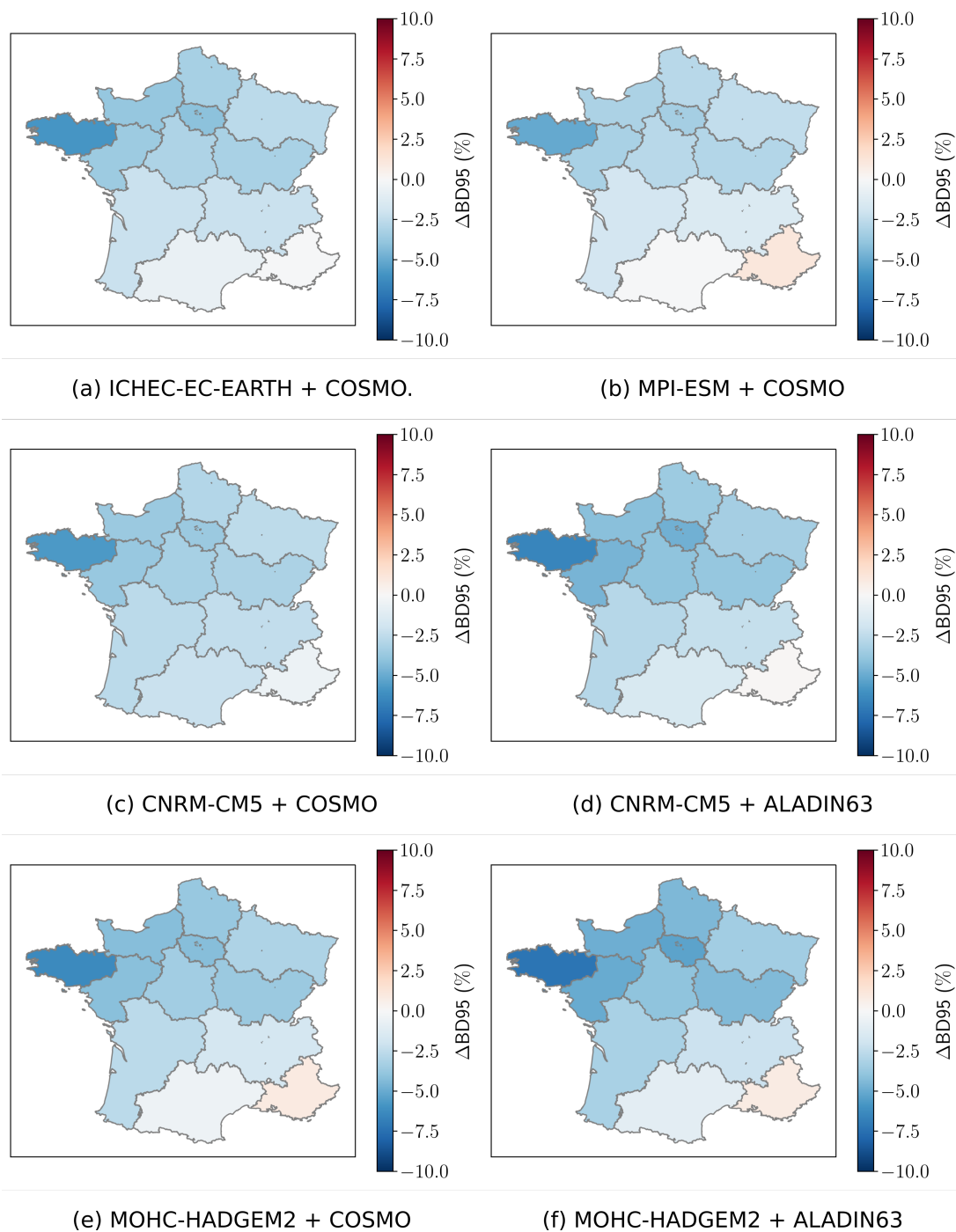


Figure B8. Difference in base demand for 4.04°C of global warming. Each panel ((a) to (f)) corresponds to a GCM + RCM pair.

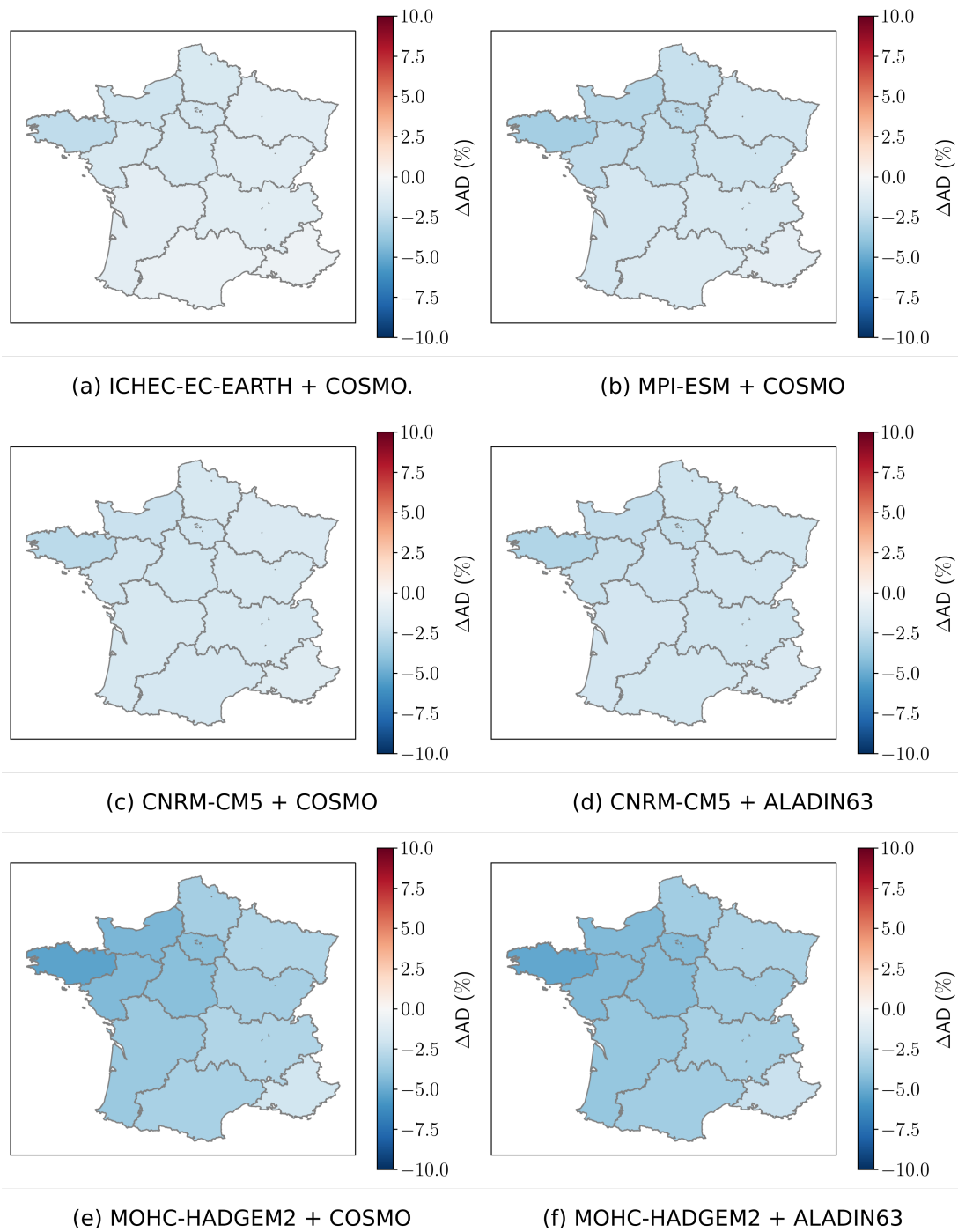


Figure B9. Difference in average demand for 1.75°C of global warming. Each panel ((a) to (f)) corresponds to a GCM + RCM pair.

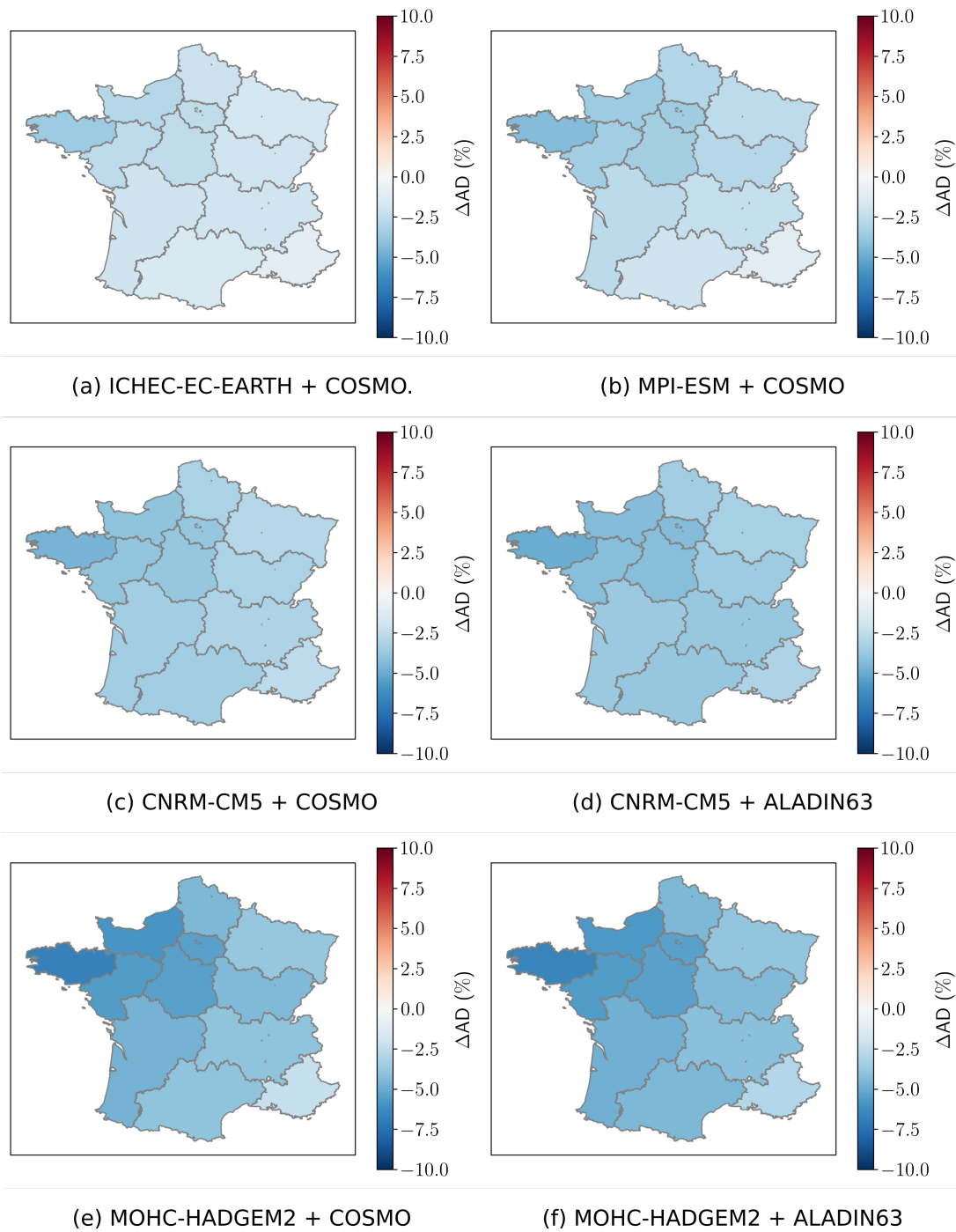


Figure B10. Difference in average demand for 2.35°C of global warming. Each panel ((a) to (f)) corresponds to a GCM + RCM pair.

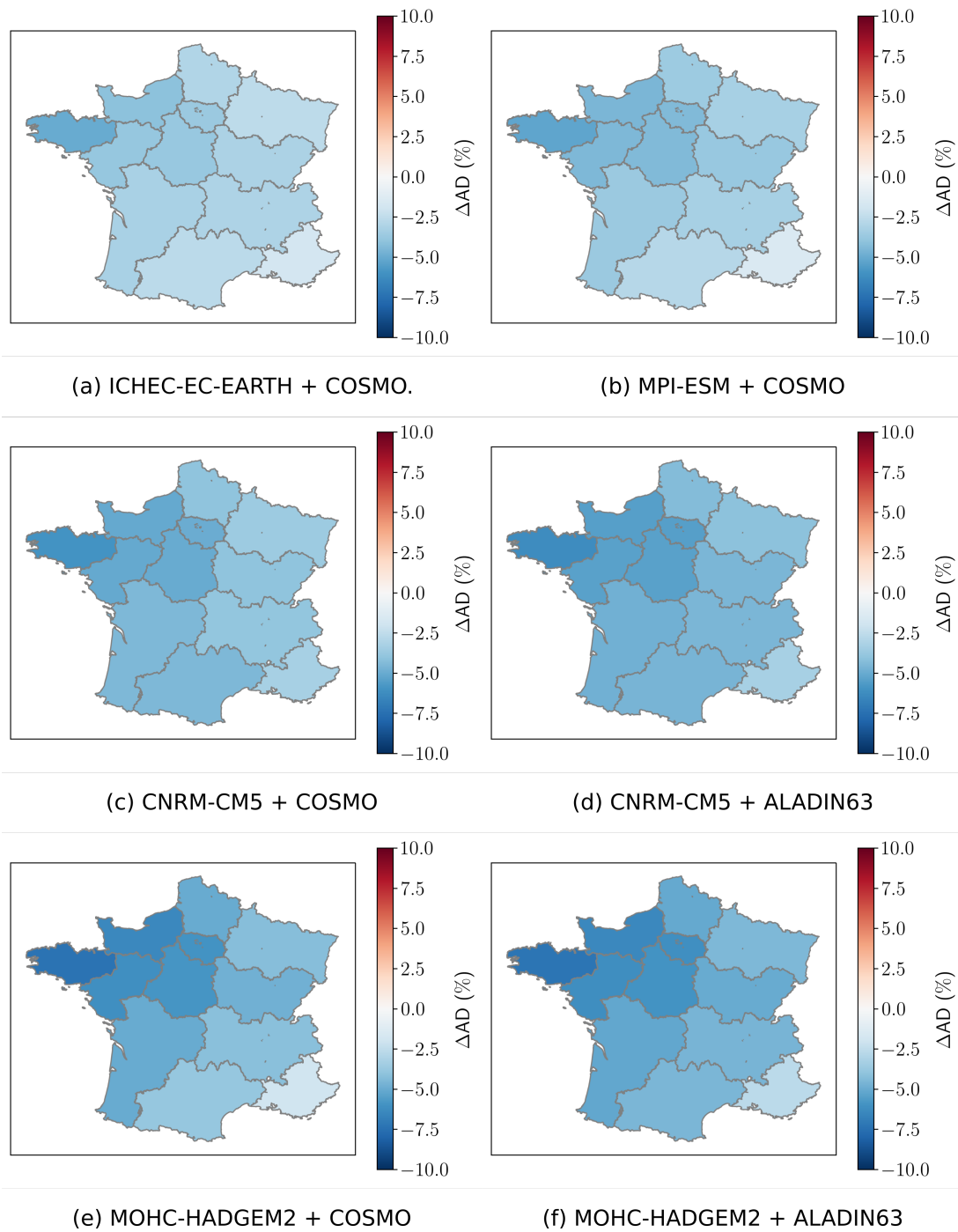


Figure B11. Difference in average demand for 2.8°C of global warming. Each panel ((a) to (f)) corresponds to a GCM + RCM pair.

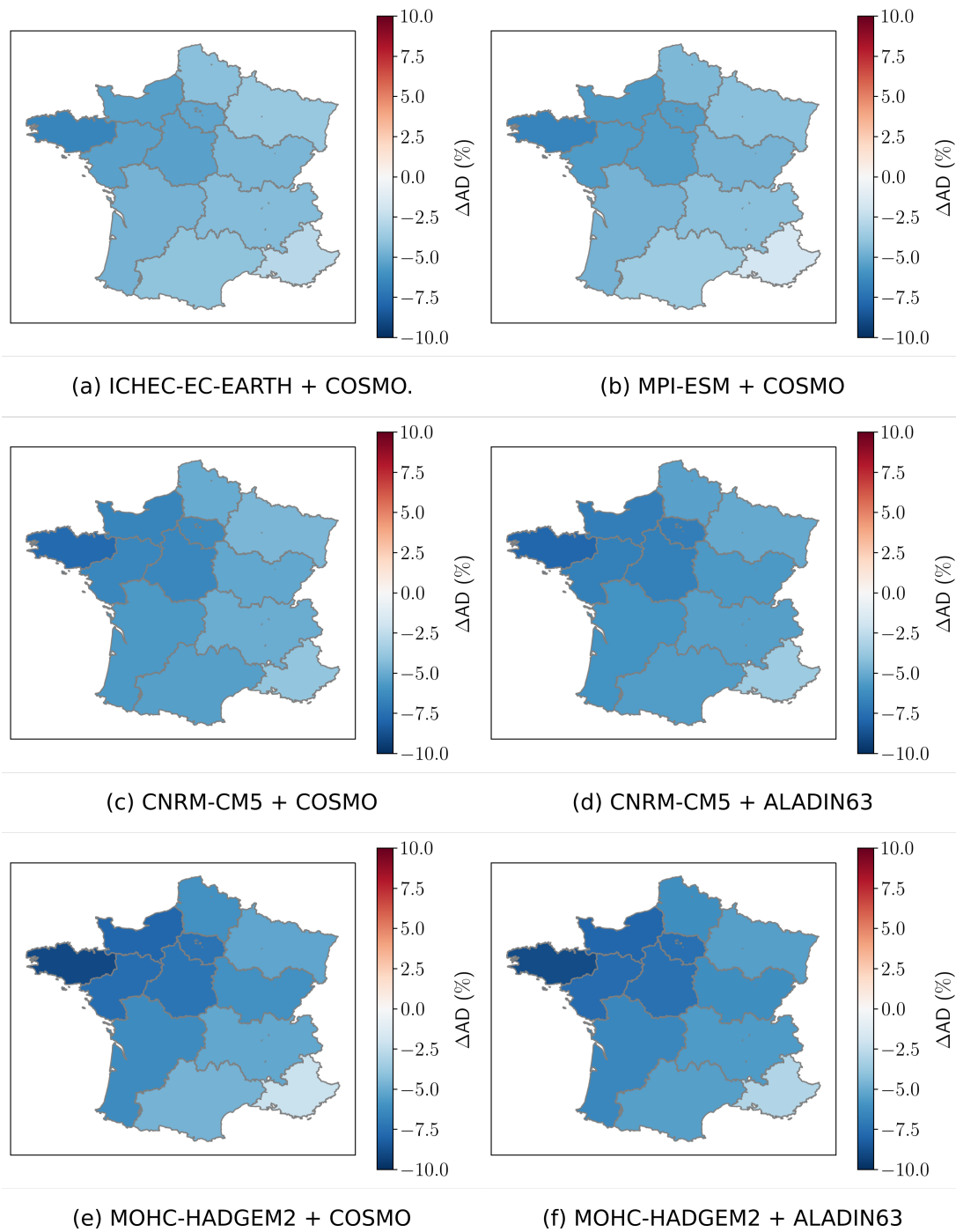


Figure B12. Difference in average demand for 3.28°C of global warming. Each panel ((a) to (f)) corresponds to a GCM + RCM pair.

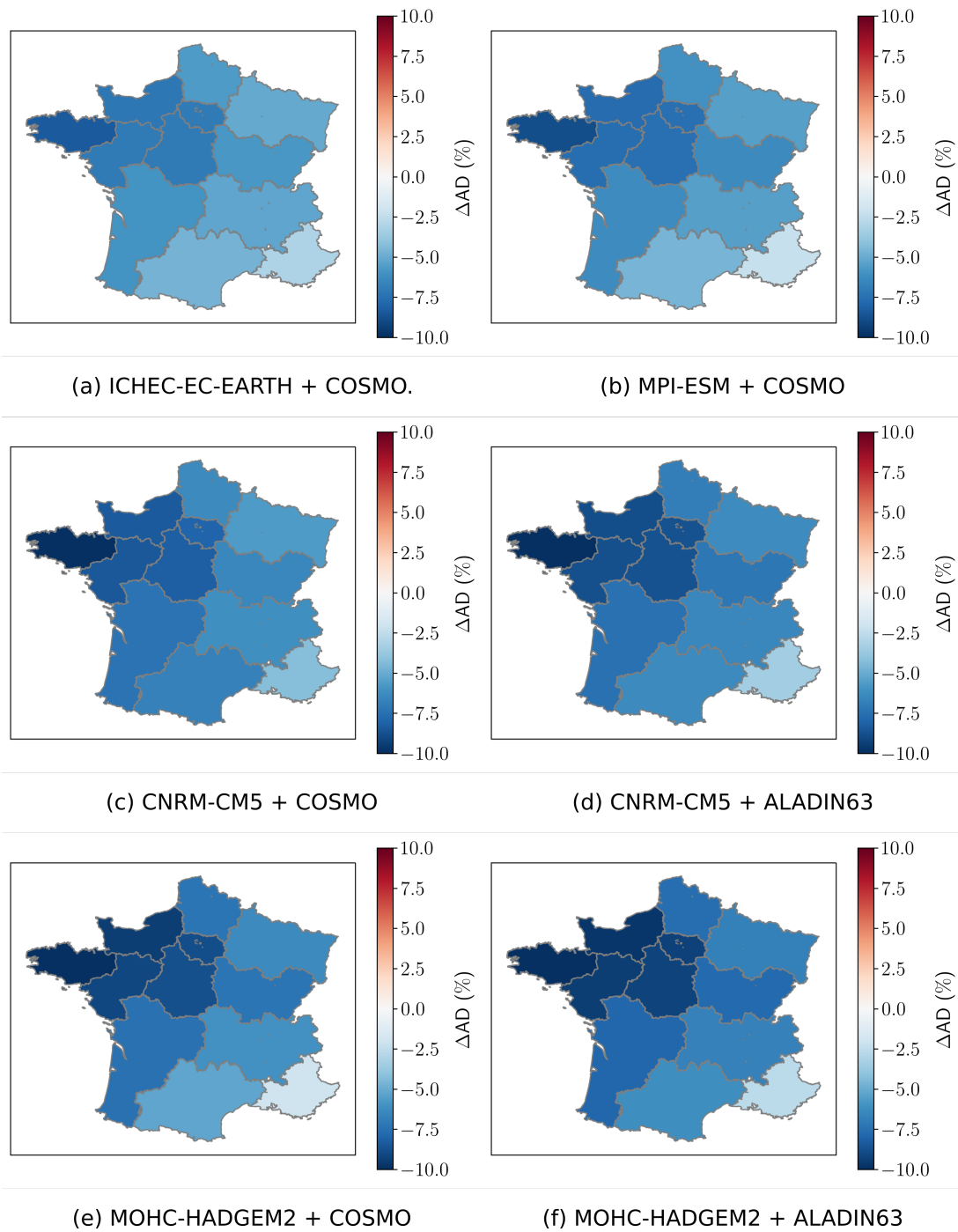


Figure B13. Difference in average demand for 4.04°C of global warming. Each panel ((a) to (f)) corresponds to a GCM + RCM pair.

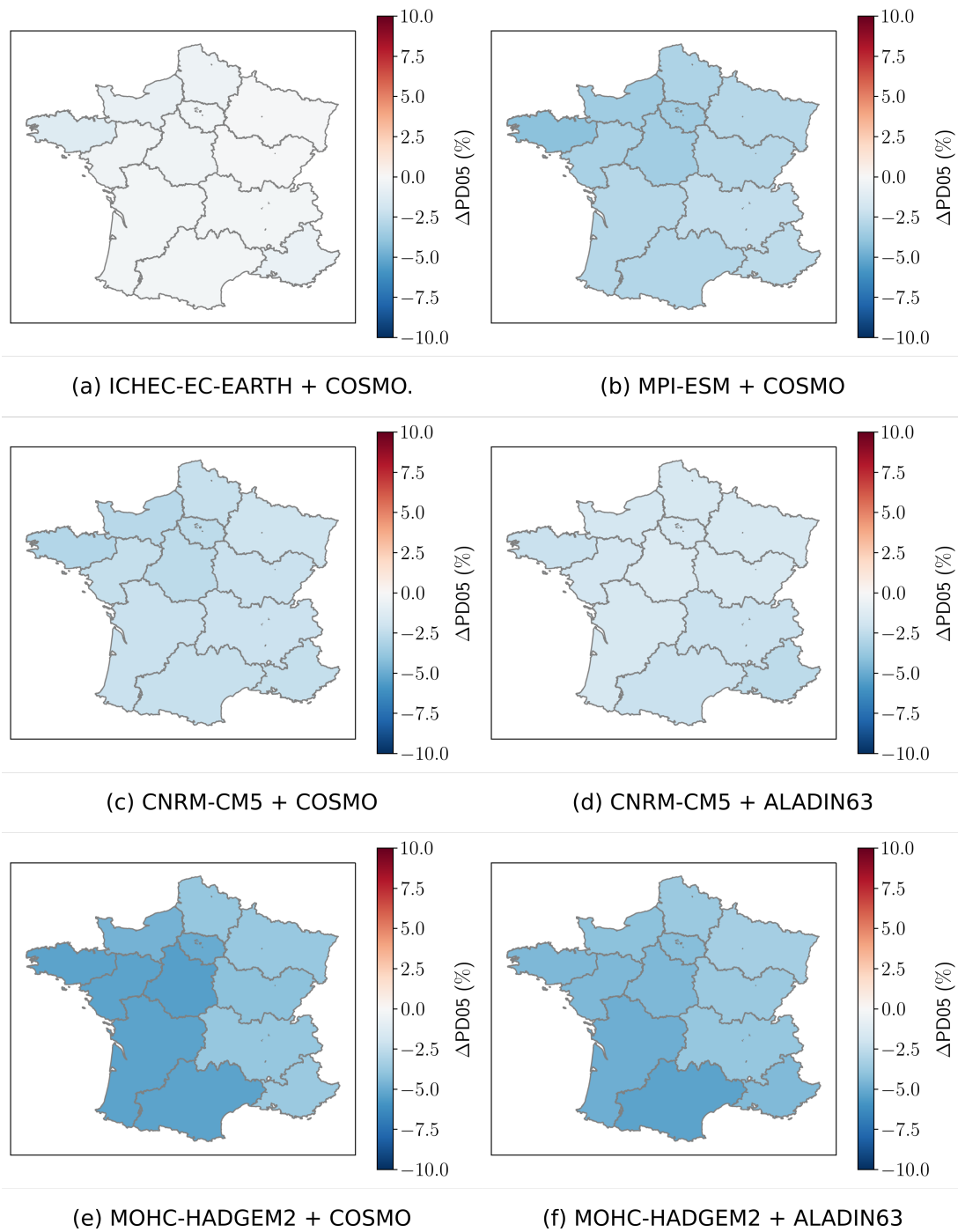


Figure B14. Difference in peak demand for 1.75°C of global warming. Each panel ((a) to (f)) corresponds to a GCM + RCM pair.

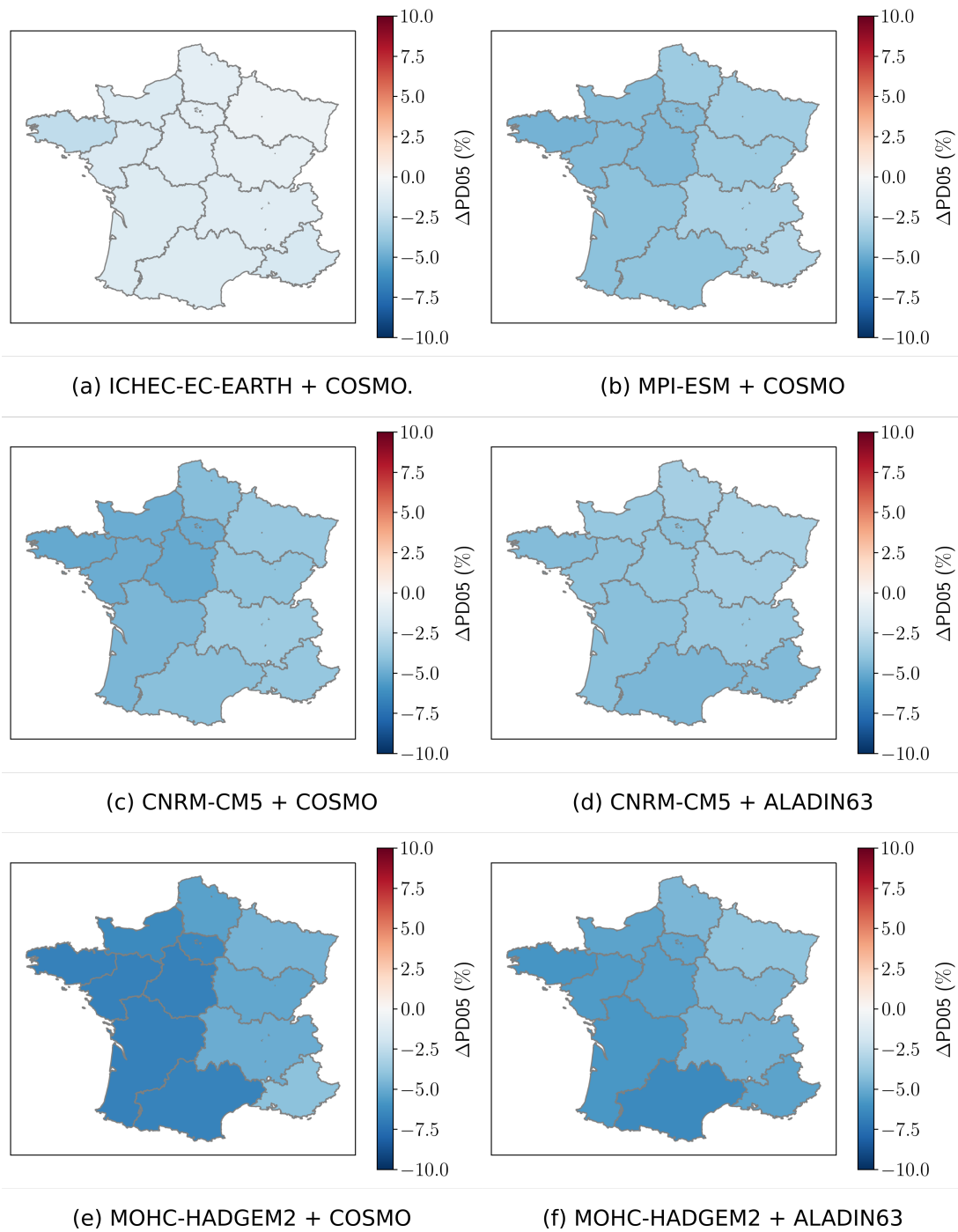


Figure B15. Difference in peak demand for 2.35°C of global warming. Each panel ((a) to (f)) corresponds to a GCM + RCM pair.

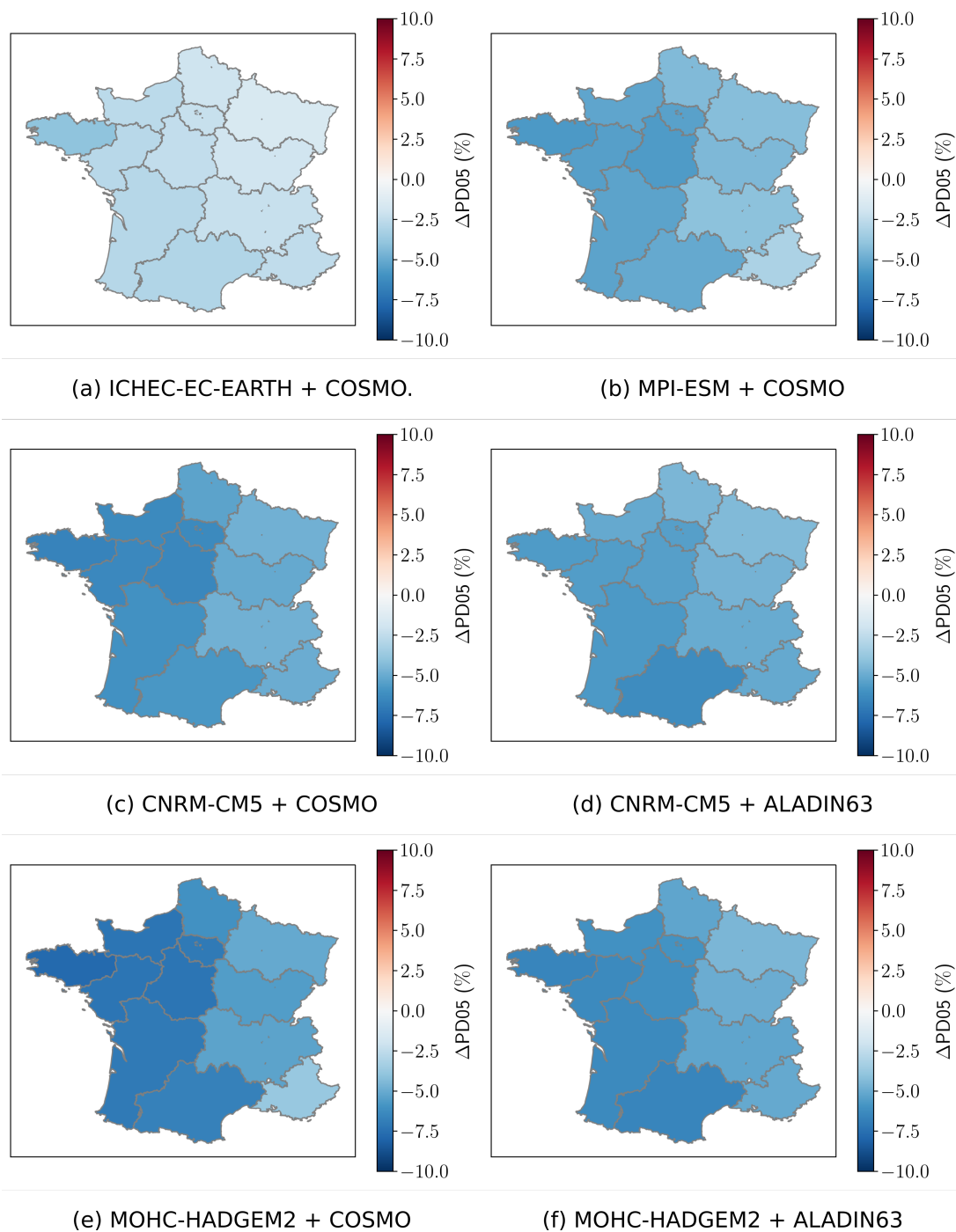


Figure B16. Difference in peak demand for 2.8°C of global warming. Each panel ((a) to (f)) corresponds to a GCM + RCM pair.

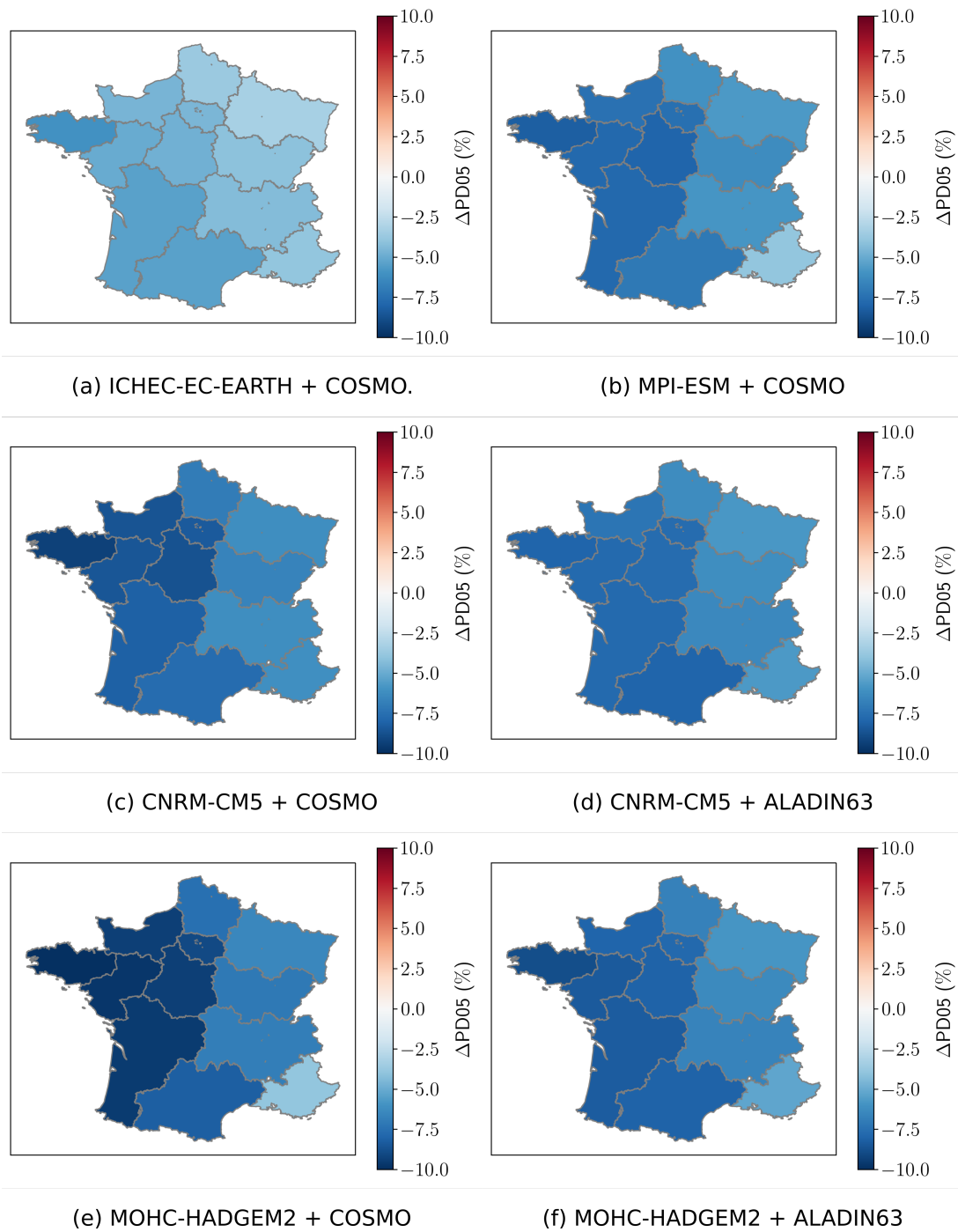


Figure B17. Difference in peak demand for 3.28°C of global warming. Each panel ((a) to (f)) corresponds to a GCM + RCM pair.

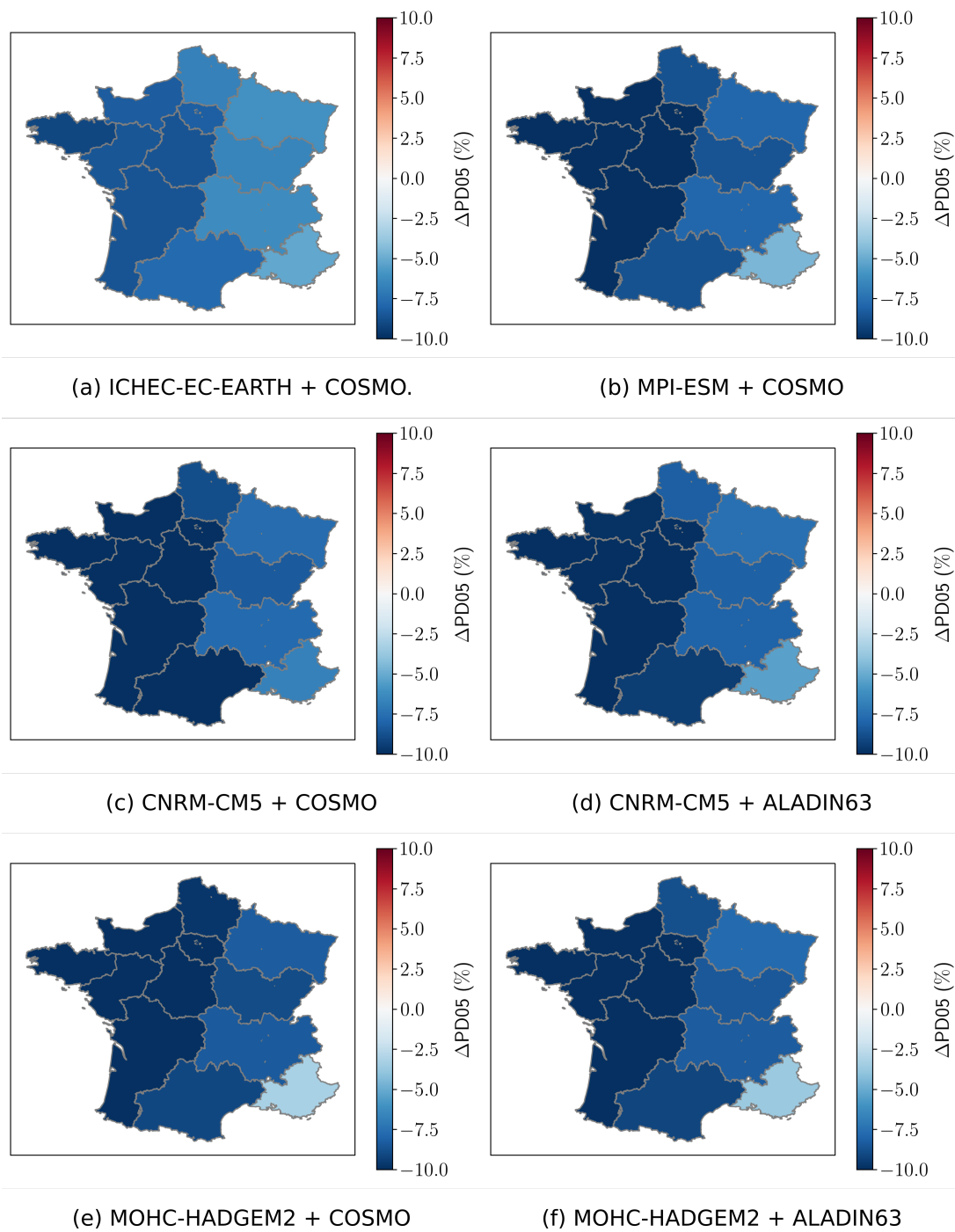


Figure B18. Difference in peak demand for 4.04°C of global warming. Each panel ((a) to (f)) corresponds to a GCM + RCM pair.

Author contributions. Joan Delort Ylla: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Software, Validation, Visualization, Writing — original draft preparation, Writing — review & editing. Alexis Tantet: Conceptualization, Data curation, Methodology, Project administration, Software, Supervision, Validation, Writing — review & editing.
690 Philippe Drobinski: Conceptualization, Funding acquisition, Project administration, Supervision, Validation, Writing — review and editing.

Competing interests. The authors declare that they have no conflict of interest.

Acknowledgements. This research is conducted in the frame of the Energy4Climate Interdisciplinary Center (E4C) of Institut Polytechnique de Paris and Ecole des Ponts ParisTech and supported by the 3rd Programme d'Investissements d'Avenir [ANR-
695 18-EUR-0006- 02] and by the Foundation of Ecole Polytechnique and ENGIE through the program “Résilience des systèmes énergétiques au changement climatique et émissions négatives”.

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Chapter **5**

Compound effect of socioeconomic and climate change

1 The cost of unpreparedness: adaptation potential
2 facing compound socioeconomic and climate
3 change in wind and solar mix planning exercises.

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11 **Abstract**

12 Electricity systems are expected to undergo profound transformations both in
13 the supply and demand side in the coming decades. We focus in this study on the
14 problem of solar and wind mix dimensioning facing socioeconomic and climate
15 change. We use an integrated electricity system model to assess what is the
16 resilience of a high wind and solar penetration mix to increasing electrification
17 and climate change intensity, and compare its performance to cost-optimal mixes
18 to compute the adaptation potential. We find that accounting for the compound
19 impact of socioeconomic and climate change is necessary to get good qualitative
20 and quantitative measures of the adaptation potential and other adaptation-
21 related metrics. We thus recommend the continued incorporation of plausible
22 socioeconomic scenarios in future climate change studies to improve the accuracy
23 of policymaking recommendations.

24 **Keywords:** Energy system modelling, Climate change, Electrification, Policymaking

25 Introduction

26 Climate change is a threat to human and non-human collectives around the globe,
 27 threatening the worlds political and ecological equilibrium [1, 2]. A key lever of mit-
 28 igation policies for the Paris Agreement parties is the reduction of greenhouse gas
 29 emissions from energy systems as a whole and electricity systems in particular [3].
 30 Because they also represent a strategic [4, 5] and industrial [3, 6] opportunity, low
 31 carbon solar and wind energy sources are expected to surge globally in the coming
 32 decades (see e.g. [6]). In all advanced economies with centralized interconnected elec-
 33 tricity systems, the transition from fully dispatchable to high wind and solar electricity
 34 systems will pose adaptation challenges [7].

35 From the policymakers point of view, designing public policies to implement a
 36 suitable solar and wind mix to fulfill Paris agreement’s targets at the same time as
 37 ensuring an affordable and secure electricity provision is a complex problem involving
 38 entangled social [8, 9], political [10–12] and economical [7, 13] considerations, along the
 39 precited ecological ones. At the same time, committed and potential climate change
 40 [14] will impact electricity systems both on the demand and supply side [15, 16],
 41 affecting the capacity of planned or resulting mixes to supply electricity reliably [17]
 42 and at the lowest cost. This capacity to perform well will also be affected by socioe-
 43 conomic changes, mainly via impacts on the demand: wether it is through changes
 44 in population [18–20], air conditioning or electric heating adoption [21–24], industry
 45 electrification [25–27] and electric vehicles adoption [28–30], or efficiency [31–33] and
 46 sufficiency [34–36] measures.

47 How these climatic and socioeconomic changes will combine and impact the elec-
 48 tricity system is uncertain. Planning or designing public policies to incentivize for
 49 the right wind and solar mix is thus submitted to this uncertainty. The resilience of
 50 future mixes and the underlying planning question is a widely addressed problematic
 51 (see e.g. [37] for an overview). Studies in the literature can be broadly divided into
 52 four categories: those that tackle the question at constant climatic and socioeconomic
 53 conditions [38–40], those that take into account at the same time socioeconomic and
 54 climate change [41–45], and those that fall in-between the two by working with a con-
 55 stant parameter and another variable one see e.g. [46–52] for the most recent ones.
 56 Among those studies not all optimize decision making to changing climate and socioe-
 57 conomic conditions, and instead rely on prescribed mixes [47, 48, 50]. Those studies
 58 that do consider optimal investment often fail to consider the combined impact of
 59 socioeconomic and climate change [51], or suffer from limitations in addressing high
 60 wind and solar mixes feasibility [41–44]. A recent study [45] tackled these points by
 61 proposing a novel methodology more adapted to high wind and solar energy pene-
 62 tration, and insisted on the importance to take socioeconomic scenarios into account
 63 in climate change studies to inform mix planning. We go a step further by assess-
 64 ing whether or not these two processes can be studied separately and their effects
 65 additioned, and, in the opposite case, to what extent crucial policymaking support
 66 indicators can be over or underestimated. This is assessed by comparing the adapta-
 67 tion potential, hereby denoted as the cost of unpreparedness, under various scenarios
 68 of socioeconomic and climate change.

69 We use to this end the bottom-up stochastic capacity expansion model E4CLIM
 70 in its latest version [53, 54]. In comparison to e.g. [43, 45] our approach is limited
 71 in its optimal mix planning capabilities as our methodology is voluntarily minimal-
 72 istic (this is discussed further in the Methods section). We do however fully account
 73 for the impacts of a changing climate by considering the hourly correlation of wind
 74 and solar generation and demand over the whole year, and for long time periods to
 75 include the influence of interannual variability [46, 55, 56]. Our methodology is thus
 76 an interdisciplinary compromise between the usual approaches of the weather and cli-
 77 mate community that often limit their energy systems study to the impacts on the
 78 demand net of wind and solar generation [50, 57], and that of the energy system mod-
 79 eling community that often restrict their analysis to subsampled or yearly averages
 80 of demand and generation [41–44], hampering their planning skills [58]. This method-
 81 ological framework is situated in the lineage of those models contributing to bridging
 82 the gap between climate and energy system modeling [56, 59, 60].

83 The uncertainty related to climate and socioeconomic change is accounted for
 84 using a storylines approach [61], i.e. by deriving a set of plausible future scenarios.
 85 Different levels of climate change are accounted for through an ensemble of six climate
 86 model pairs from the latest EURO-CORDEX (CMIP5) initiative [62] to ensure suffi-
 87 cient space and time granularity, whereas three socioeconomic scenarios are designed
 88 according to grey literature [63–65] to encompass a broad range of possible electri-
 89 fication futures. The present methodology is applied to the example of France, an
 90 advanced economy with a highly heating temperature sensitive electricity demand, a
 91 moderate cooling temperature sensitive electricity demand, and an important wind
 92 and solar resource. We expect our results to be generalizable even if the magnitude
 93 of the impacts are necessarily region and context specific.

94 Our results show that taking into account the compound effect of socioeconomic
 95 and climate change is key to correctly evaluate the performance of given solar and
 96 wind mixes under future potential outcomes, and to obtain a good qualitative and
 97 quantitative description of policy relevant metrics such as the adaptation potential.
 98 We thus recommend the continued implementation of plausible future socioeconomic
 99 scenarios in future climate change studies aiming to provide relevant policy advice.

100 Approach

101 We start from a reference mix (*REF*), which is cost-optimal under the reference
 102 scenario (*REF*)¹. This could correspond to a state where because of economic com-
 103 petitiveness and some decarbonization efforts, a large share of wind and solar energy is
 104 already present. In our case, (156 ± 2) GW of wind and solar capacity are installed and
 105 penetration reaches $(53 \pm 1)\%$ of total generation. This is shown in Figures 1 and 2a
 106 for outputs of model CNRM-CM5 + ALADIN63 and Supplementary Information
 107 Figures 2 and 7 for the results of other models. Facing future socioeconomic and cli-
 108 mate changes, and assuming perfect foresight, a policymaker can make two extreme
 109 choices: either to adapt to the foreseen future conditions or not to adapt to them.

¹In the text body, mixes are denoted in italics whereas scenarios are written in upright capital letters.

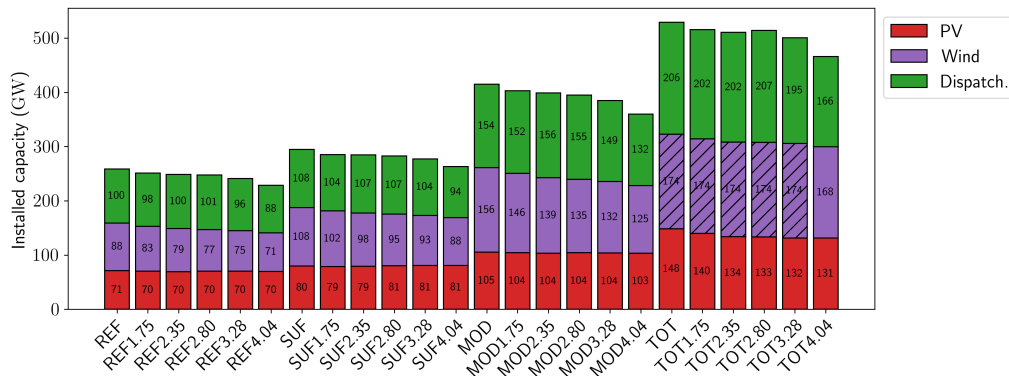


Fig. 1: Optimal wind and solar mixes and necessary dispatchable capacity aggregated at the national level and for model pair CNRM-CM5 + ALADIN63. Bars are hatched when maximal installable capacities are reached. PV stands for solar photovoltaic.

110 Non-adaptation costs

111 Not adapting to future changes is equivalent to ensuring the adequacy constraint with
 112 mix *REF* under future climate and socioeconomic conditions defined by a given scenario.
 113 In our setting, and since we assume an infinite amount of dispatchable producers
 114 to be available at no costs (see the Methods section), solving for the economically
 115 optimal dispatch while ensuring the hourly adequacy constraint is equivalent to satisfying
 116 all the residual demand, this is, the demand net of wind and solar generation, via
 117 the dispatchable producers. This entails generation costs, also referred to as variable
 118 costs, on the dispatchable producers side. These generation costs evolve quadratically
 119 with the amount of generated energy. As such, as the amount of energy generated by
 120 dispatchable producers changes with the corresponding scenario, the variable costs
 121 and the associated system total cost change as well. This change in generation patterns
 122 with changing scenario is evidenced by comparing Figure 2a and 2c for the total
 123 generation and Figure 2b for how this generation is distributed between peak and
 124 base demand. Note that no changes in the fixed costs of the solar and wind producers
 125 occur since the mix remains fixed. These extra variable costs, that can be positive or
 126 negative, are referred to as the non-adaptation costs associated to scenario *S* (NAC_S).
 127 They correspond to the difference in expected yearly system total costs between the
 128 case with mix *REF* under scenario *S* and the reference case, i.e. the case with mix
 129 *REF* under the reference scenario (REF).

130 The non-adaptation costs are represented by the height of the left bars in Figure 3
 131 for model CNRM-CM5 + ALADIN63 and in Figures 8 to 12 of the Supplementary
 132 Information for the other models of the ensemble. Their values are comprised
 133 between 1.6 bn€ to 2.8 bn€ (scenario SUF4.04) and 40.3 bn€ to 48 bn€ (scenario
 134 TOT1.75), ranging from 6.25 % to 10.9 % (scenario SUF4.04), to 157 % to 186 % (scenario
 135 TOT1.75) of the system total cost in the reference case. They are thus always
 136 positive for the compound scenarios considered. We also show that they decrease with
 137 increasing levels of climate change and increase with increasing levels of electrification

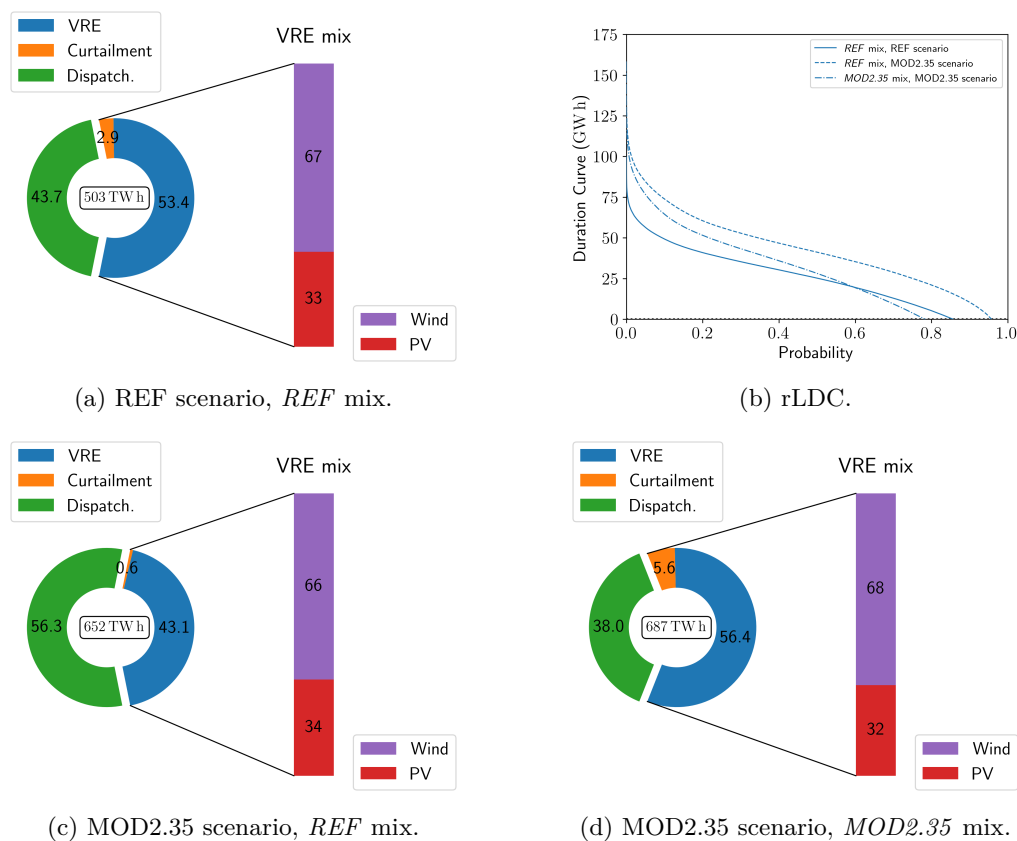
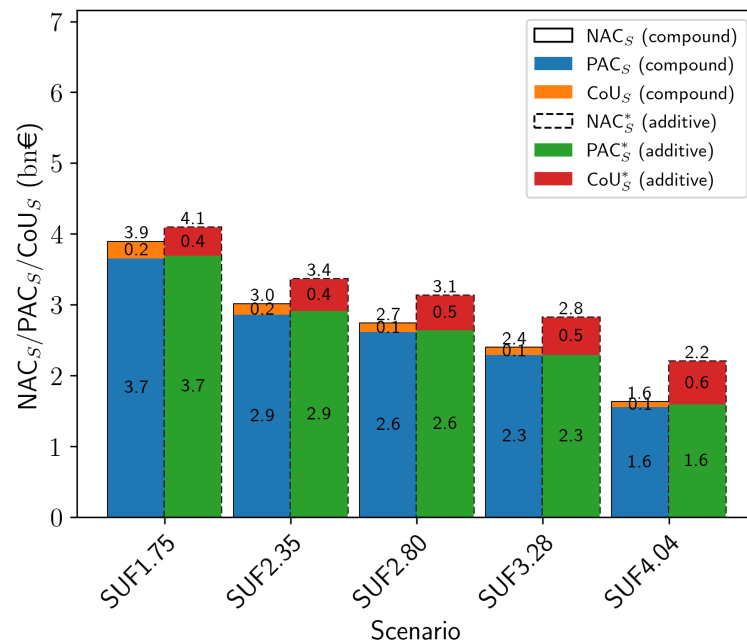


Fig. 2: Panels (a), (c), (d): Total generation over the 30 year period for (a) the reference conditions (REF scenario, *REF* mix) and two cases showing either (c) non-adaptation (MOD2.35 scenario, *REF* mix), and (d) perfect adaptation (MOD2.35 scenario, *MOD2.35* mix) strategies. All results for model CNRM-CM5 + ALADIN63. The number within the pie chart corresponds to the average yearly generation. All other numbers are percentages. Panel (b): Load duration curve of the residual demand under in the reference case, in the cases with non adaptation and perfect adaptation to scenario MOD2.35. rLDC: residual load duration curve.

138 (from SUF to MOD to TOT family). These conclusions are robust to the choice of climate
 139 model but for model MOHC-HADGEM2 + COSMO between scenarios SUF1.75
 140 and SUF2.35, which we deem not to be a significant deviation from the conclusions.

141 Perfect adaptation costs

142 The perfect adaptation strategy (i.e. adapt with perfect foresight) corresponds to
 143 changing the mix from its reference state to a new generation mix that is cost-optimal
 144 under the foreseen future conditions. In our setting, we assume greenfield optimization
 145 and thus do not account for stranded assets: wind and solar capacity can be removed



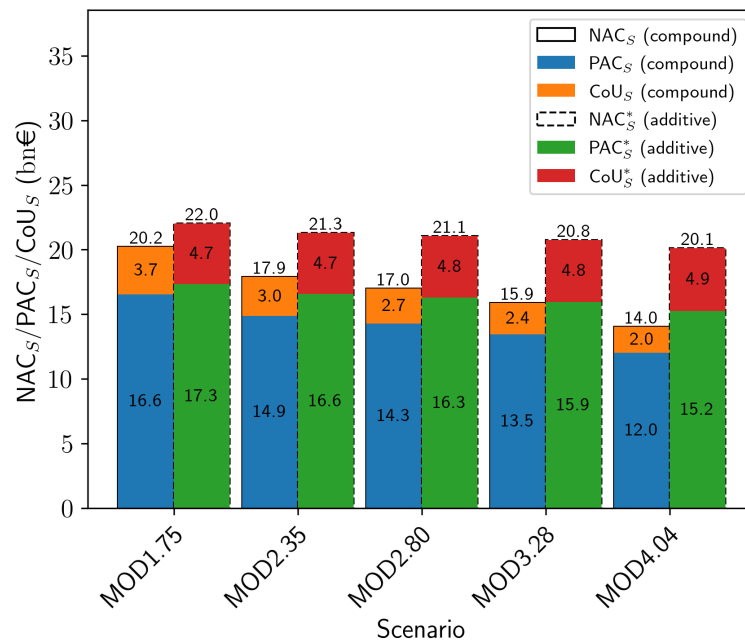
(a) SUF family.

Fig. 3: Cont.

146 at no cost and is installed at a given fixed cost (see Methods section). Changes in
 147 system total cost are thus related to changes in installed wind and solar capacity and
 148 associated fixed costs, and changes in dispatchable generation and associated variable
 149 costs.

150 We show the computed optimal mixes for each scenario in Figure 1 for model
 151 pair CNRM-CM5 + ALADIN63. Other models are shown in Supplementary Informa-
 152 tion, Figure 2. A detail of wind and solar mixes at the regional level are given
 153 in Figures 3 to 6 in Supplementary Information. How changing socioeconomic and
 154 climate conditions impact the optimal wind and solar mix is not the focus of this
 155 study and will be the topic of future works. We can nonetheless highlight that wind
 156 capacity tends to decrease with increasing climate change while wind and solar capac-
 157 ity increase with increasing electrification. This behavior is consistent across models.
 158 Changes in optimal installed capacity due to climate change are in general smaller
 159 than those caused by a change in electrification level for the scenarios considered here.

160 As with non adaptation, perfect adaptation can lead to a change in generation.
 161 An example of changing generation with perfect adaptation is shown in Figure 2, for
 162 model pair CNRM-CM5 + ALADIN63. Comparing panels (a) (reference case) and
 163 (d), we show that the share of wind and solar generation increases together with
 164 curtailment, while albeit decreasing in relative terms, the total dispatchable gener-
 165 ation increases. These changes in total dispatchable generation are the result of a change
 166 in the residual demand distribution as shown in Figure 2, panel (c). These changes

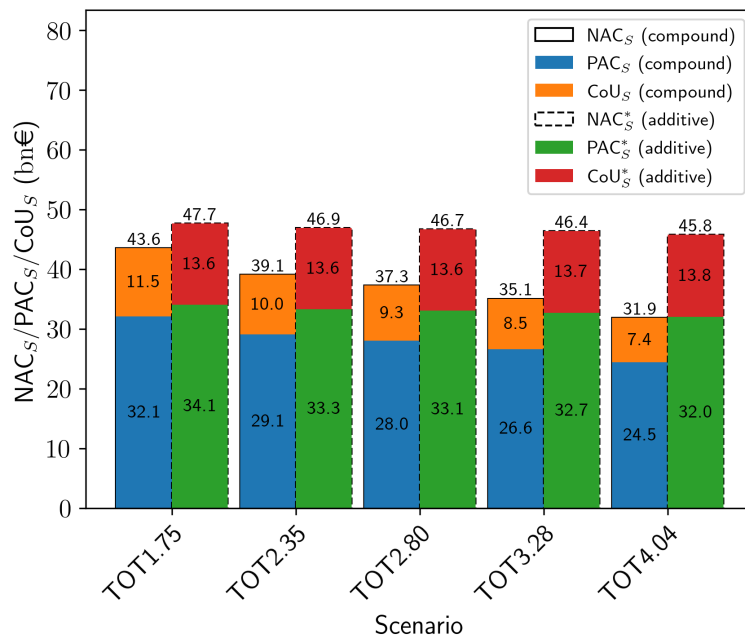


(b) MOD family.

Fig. 3: Cont.

167 in dispatchable generation can lead to changes in variable costs and together with
 168 changes in fixed costs associated to investment in wind and solar capacity, to a change
 169 in the system total cost.

170 The extra costs, positive or negative, related to perfect adaptation to a changing
 171 future S are referred to as the perfect adaptation costs (PAC_S). They correspond to
 172 the difference in expected yearly system total cost between the case with the optimal
 173 mix associated to scenario S under scenario S and the reference case. For example the
 174 perfect adaptation costs associated to scenario MOD2.35, $PAC_{MOD2.35}$, correspond
 175 to the system total cost associated to the optimal dispatch of mix $MOD2.35$ under
 176 scenario MOD2.35 minus the system total cost associated to the reference case. These
 177 perfect adaptation costs are represented by the blue bars in Figure 3 for model CNRM-
 178 CM5 + ALADIN63 and Figure 8 to 12 in Supplementary Information for the other
 179 models of the ensemble. They are comprised between 1.6 bn€ to 2.7 bn€ (scenario
 180 SUF4.04) and 29.8 bn€ to 34.9 bn€ (scenario TOT1.75), ranging from 6.25 % to
 181 10.5 % (scenario SUF4.04), to 116 % to 135 % (scenario TOT1.75) of the system total
 182 cost in the reference case. We expect the PAC to be smaller than the NAC, since the
 183 former correspond to the case with a cost-optimal mix, thus minimizing the system
 184 total cost. This is indeed what we observe: the PAC are systematically lower than their
 185 NAC counterparts. We show that under our hypothesis, similarly to the NAC, the PAC
 186 are always positive for the scenarios considered in this study: all scenarios induce extra
 187 costs, even with perfect adaptation. We further show, that the perfect adaptation costs



(c) TOT family.

Fig. 3: Adaptation metrics under the compound or additive impact of socioeconomic and climate change. Non-adaptation costs (NAC) are shown as full (compound effect) or dashed (additive effect) empty bars, perfect adaptation costs (PAC) are shown in blue (compound effect) or green (additive effect) bars, while the cost of unpreparedness (CoU) is shown in orange (compound effect) or in red (additive effect). All results for model pair CNRM-CM5 + ALADIN63.

188 decrease with increasing climate change and increase with increasing electrification.
 189 These results are robust across models, but for model MOHC-HADGEM2 + COSMO
 190 between scenarios SUF1.75 and SUF2.35, an exception that we do not consider to be
 191 significant.

192 Adaptation potential: the cost of unpreparedness

193 If the non-adaptation costs (NAC) give the extra costs resulting from not adapting
 194 to a foreseen future change and the perfect adaptation costs (PAC) the extra costs
 195 incurred even when perfectly adapting to these future changes, then the difference
 196 between the two yields the adaptation potential. We refer to the adaptation potential
 197 as the cost of unpreparedness (CoU), since it represents the costs related to not being
 198 prepared to future changes. The cost of unpreparedness for scenario S is computed as
 199 the difference between the non-adaptation costs and the perfect adaptation costs as

$$\text{CoU}_S = \text{NAC}_S - \text{PAC}_S. \quad (1)$$

200 Note that because in our case the mixes are optimal with respect to the system total
 201 cost, the NAC are always larger than the PAC, and as such the cost of unprepared-
 202 ness has the property to be positive: it is always more interesting to adapt to future
 203 conditions than to remain passive.

204 The cost of unpreparedness is represented by the orange bars in Figure 3 for model
 205 CNRM-CM5 + ALADIN63 and Figure 8 to 12 in Supplementary Information for the
 206 other models of the ensemble. It is comprised between 0.1 bn€ to 0.2 bn€ (scenario
 207 SUF4.04) and 10.2 bn€ to 13.1 bn€ (scenario TOT1.75). It ranges from 0.4 % to 0.8 %
 208 (scenario SUF4.04), to 40 % to 51 % (scenario TOT1.75) of the reference case system
 209 total cost. We show that the cost of unpreparedness decreases with increasing climate
 210 change, while it increases with increasing electrification. Both these results are robust
 211 across models. We further show that the share of the non-adaptation costs that can be
 212 recovered through adaptation decreases with increasing climate change and increases
 213 with the level of electrification. This relative adaptation potential corresponds to the
 214 cost of unpreparedness (CoU) relative to the non-adaptation costs (NAC). It ranges
 215 from 3 % to 5 % (scenario SUF4.04), to 25 % to 27 % (scenario TOT1.75). The observed
 216 trends are also robust across models.

217 Compound vs. additive impacts

218 We analyzed so far the compound impact of changing climate and socioeconomic
 219 conditions on adaptation metrics related to two extreme strategies a planner can adopt
 220 under perfect foresight. This analysis however required $nm + 1$ optimal investment
 221 computations and $2nm + 1$ solvings of the optimal dispatch problem, with n the
 222 number of socioeconomic scenarios and m the number of climate change scenarios.
 223 We now ask whether we could have alleviated this computational burden by studying
 224 both impacts separately and then adding them back to infer their compound effect.
 225 This would significantly reduce the computation costs to respectively $n+m+1$ optimal
 226 investment computations and $2(n+m) + 1$ optimal dispatch problems.

227 For the analysis of this study we perform both approaches and thus compute the
 228 aforementioned adaptation indicators for scenarios of socioeconomic changes alone
 229 (SUF, MOD, TOT), scenarios of climate change alone (REF1.75, REF2.35, REF2.80,
 230 REF3.28, REF4.04), and all compound scenarios. The results of these computations
 231 are shown in Supplementary Information, Figures 13, 14 and 15. We then compute
 232 the additive impacts of socioeconomic and climate change by adding the two separate
 233 effects, i.e. for a quantity X and a scenario $S = \text{SES} \times \text{CCS}$ computed from a socioe-
 234 conomic scenario SES and a climate change scenario CCS, we compute the additive
 235 quantity X^* as

$$X_{\text{SES} \times \text{CCS}}^* = X_{\text{SES}} + X_{\text{CCS}}. \quad (2)$$

236 We show that for all adaptation indicators (NAC, PAC, CoU and relative adap-
 237 tation potential), the additive quantity wrongly captures the compound impact of
 238 socioeconomic and climate change. Across all compound scenarios, adding the sep-
 239 arate effect of socioeconomic and climate change leads to the overestimation of the
 240 non-adaptation costs (NAC), the cost of unpreparedness (CoU), and the relative

241 adaptation potential. This effect is more pronounced with increasing levels of cli-
 242 mate change: no matter the socioeconomic scenario considered, the estimation error
 243 is higher both in relative and absolute terms with increasing levels of climate change.
 244 This result is consistent across models. The magnitude of this overestimation however
 245 depends on the level of electrification: if for the NAC the overestimation increases with
 246 increasing electrification, the opposite holds true for the CoU and relative adaptation
 247 potential indicators. All these observations are robust across models. The comparison
 248 of the additive method to the compound estimation for the perfect adaptation poten-
 249 tial (PAC) is more complex: the same observations as for the NAC hold true for the
 250 MOD and TOT family of scenarios, but the additive method tends to underestimate
 251 the NAC in the SUF family of scenarios. This result is less robust across models since
 252 the trend is not observed for one of them (MPI-ESM + COSMO).

253 If relying on the addition of socioeconomic and climate change effects can miss
 254 the adequate quantification of adaptation indicators, it can also miss the trend of
 255 these indicators with the intensity of the studied phenomena. The evolution of the
 256 non-adaptation and perfect adaptation costs (NAC and PAC) with increasing climate
 257 change is correctly given by the additive approach. This is however not the case for the
 258 (relative) adaptation potential, where the additive method would suggest an increase
 259 of both absolute (CoU) and relative adaptation potential with increasing climate
 260 change, whereas the compound estimation shows that both these quantities tend to
 261 decrease with increasing climate change. The trend of all indicators with increasing
 262 electrification is however well described by the additive method.

263 Discussion and conclusions

264 We showed that socioeconomic and climate change induced extra costs in the electric-
 265 ity generation sector. For the compound climate change and electrification scenarios
 266 considered, these extra costs were always positive. The analysis of two extreme
 267 adaptation strategies allowed us to compute the adaptation potential, or cost of unpre-
 268 paredness, of the electricity generation sector facing plausible future changes. We show
 269 that although the qualitative behavior of some of the adaptation indicators we com-
 270 pute is conserved and well reproduced when studying the effects of climate change
 271 and electrification separately, the compound effect of both these factors needs to be
 272 taken into account to obtain quantitatively accurate results.

273 Our results suggest that in this simplified idealized setting, the system's behavior
 274 is strongly affected by the level of demand, and to a minor extent by the correlation
 275 of demand with wind and solar generation. Because in our scenarios electrification
 276 translates into more extreme demand changes than climate change, a result shared
 277 by e.g. [24], the non-adaptation and perfect adaptation costs are always positive:
 278 the increase in demand due to electrification is not compensated by a decrease in
 279 demand due to climate change. The coupling between climate change and demand is
 280 suggested to be the cause of the discrepancy between the additive and compound
 281 impact methods. This is evidenced by the fact that most indicators are overestimated
 282 with the additive method that misses the increased reduction in heating temperature
 283 sensitive demand due to climate change.

Table 1: EURO-CORDEX GCM/RCM model pairs considered in the study.

ID	Driving GCM	Variant	RCM
0	ICHEC-EC-EARTH	r1i1p1	COSMO-crCLIM
1	MOHC-HadGEM2-ES	r1i1p1	COSMO-crCLIM
2	MPI-M-MPI-ESM-LR	r3i1p1	COSMO-crCLIM
3	CNRM-CERFACS-CNRM-CM5	r1i1p1	COSMO-crCLIM
4	CNRM-CERFACS-CNRM-CM5	r1i1p1	ALADIN63
5	MOHC-HadGEM2-ES	r1i1p1	ALADIN63

GCM: Global Climate Model. RCM: Regional Climate Model.

284 Some behavior remains however unexplained. In particular, we could not provide
 285 good suggestions as to why the perfect adaptation costs were underestimated by the
 286 additive method only in the SUF family of compound scenarios (although the result
 287 is less robust across models). A natural extension of this study is to complexify the
 288 modeling of the energy system to include dispatchable fixed costs and diversify the
 289 mix of dispatchable producers. The impacts of climate change on the water-energy
 290 nexus should also be considered as well.

291 We have however high confidence that the results of this study will transpose to
 292 any energy system modeling study aiming at understanding the impacts of climate
 293 change on the optimal investment planning question. We thus strongly recommend,
 294 in line with [45], that plausible future socioeconomic scenarios are included in any
 295 climate change study aiming at producing reliable and accurate policymaking advice.

296 Methods

297 Climate data

298 We use climate data from the EURO-CORDEX initiative [62, 66]. Six global/regional
 299 model pairs are considered in this study, whose details are given in Tables 1 and 2. We
 300 use both data from the historical (1975–2005) and future (2020–2099) periods, the lat-
 301 ter being forced with RCP 8.5 [67]. Considered variables are 2m air temperature (tas),
 302 surface downward shortwave radiation (rsds), both at 3h time resolution, and zonal
 303 (ua100m) and meridional (va100m) wind, both at 1h time resolution. The acronym
 304 in parenthesis corresponds to the short variable name in EURO-CORDEX. Spatial
 305 resolution is approximately 12×12 kilom over the whole area of study, a map of which
 306 is shown in Supplementary Information, Figure 1. Data curation steps are needed to
 307 ensure the data is ready-to-use for our modeling purposes. These are recapitulated
 308 in Supplementary Information, Section 1.2. We use the CDF-t algorithm [68–71] to
 309 calibrate the EURO-CORDEX data to ERA5 reanalysis data [72]. ERA5 data is first
 310 interpolated at every EURO-CORDEX grid point using bilinear interpolation, and
 311 then calibrated at each grid point.

Table 2: GCMs and RCMs considered in the study.

Driving GCM/RCM	Version	References
ICHEC-EC-EARTH	2	[73, 74]
MOHC-HadGEM2-ES	2	[75]
MPI-M-MPI-ESM-LR	-	[76, 77]
CNRM-CERFACS-CNRM-CM5	5	[78]
COSMO-crCLIM	4	[79, 80]
ALADIN63	6	[81, 82]

GCM: Global Climate Model. RCM: Regional Climate Model.

312 Wind and solar generation

313 We compute time series of wind and solar generation per unit capacity (i.e. capacity
314 factors) from climate data. Wind and solar capacity factors are computed following
315 [53, 54, 83]. This entails that wind turbines are supposed to be always facing the
316 wind and that we neglect wake losses. In turn, solar panels are supposed to be facing
317 due south and have a fixed tilt. We add a temperature dependency to wind capacity
318 factors [84] by multiplying the total wind speed by a coefficient

$$(\rho/\rho_0)^{1/3} = \left(\frac{T_0}{T - L(z_h - z)} \right)^{1/3}, \quad (3)$$

319 where ρ is the air density at hub height, ρ_0 the reference air density, T_0 the reference
320 temperature (288.15 K or 15 °C), T is the surface temperature variable, L the lapse
321 rate (0.0065 K m⁻¹), z is the height of the surface temperature variable (2 m), and z_h
322 the hub height (101 m). We thus obtain wind capacity factors that depend on the wind
323 regimes as well as the ambient temperature, and solar capacity factors that depend
324 on surface solar radiation patterns and temperature as well.

325 These capacity factors are then averaged per region of the area of study (see Sup-
326plementary Information, Figure 1) and bias corrected to observations from the french
327 transmission system operator (freely available at <https://opendata.reseaux-energies.fr/>)
328 according to [83].

329 Demand model

330 We use the temperature sensitive demand model presented in [54] to generate plau-
331sible time series of hourly demand for France. We train the model with electricity
332 demand data from the french transmission system operator (freely available at
333 <https://opendata.reseaux-energies.fr/>) for the years 2014–2019 and surface tempera-
334 ture time series from ERA5 reanalysis data [72]. We then validate the model against
335 data for the year 2013. We find that our model explains 90% of the demand’s vari-
336 ability, with a mean error of 5% to 10% of the observed demand. Model coefficients
337 are modified as in [54] to generate different socioeconomic scenarios of demand. For
338 each scenario, 30 year long hourly demand time series are then obtained by applying
339 the modified demand model to the different periods (historical and future) of climate
340 data.

341 Energy system model

342 We use the bottom-up linear programming stochastic power system model E4CLIM
343 [83] in its most recent version [53, 54] to solve for the optimal investment problem
344 in wind and solar capacity while ensuring hourly adequacy through the optimization
345 period. The model performs a one-step greenfield optimization based on a system total
346 cost comprising wind and solar fixed costs and dispatchable producers variable costs.
347 Fixed costs of the dispatchable producers are not accounted for in this version of the
348 model which is equivalent to having an unlimited stock of available dispatchable pro-
349 ducers at no costs. This places us in an idealized setting in this regard, but should not
350 affect the conclusions of the study since this behavior is consistent throughout scen-
351 arios. We solve our optimization problem for 30-year long periods of hourly demand
352 and wind and solar capacity factors.

353 Scenarios

354 This study aims at disentangling the compound vs. additive affect of socioeconomic
355 and climate change on the adaptation potential of the electricity generation sector.
356 This implies the design of future plausible scenarios both of socioeconomic evolution
357 and climate change.

358 In this study, socioeconomic scenarios only relate to the demand side of the elec-
359 tricity generation sector. As such, cost data remains fixed throughout the different
360 scenarios: wind and solar fixed costs are kept constant and equal to those in [54].
361 This translates to capex lower by 16 % and 64 % compared to 2015 values [85] for
362 wind and solar respectively. The parameter that determines the variable costs of the
363 dispatchable production in our model (see [54]) is kept constant as well, but set to a
364 higher value than what is observed at present (2018) to guarantee a high penetration
365 of wind and solar energy in cost-optimal mixes. In our study, socioeconomic scenar-
366 ios are determined by the level of heating demand electrification, AC adoption and
367 baseline demand increase. They are summarized in Table 3. Current levels of heating
368 demand electrification, AC adoption and baseline demand make up for the reference
369 (REF) scenario. They are determined from [65] and [64]. The sufficiency (SUF) fam-
370 ily of scenarios comes from the energy and climate plan of the french government [86]
371 that projects the increase in electricity demand in 2050. We suppose in this case that
372 the share of electric heating and AC appliances remains constant to that of REF.
373 In the moderate electrification (MOD) family of scenarios, the rate of electric heat-
374 ing and AC equipment, as well as the amount of baseline demand are increased to
375 reach projections for 2050 from the transmission system operator [65]. Finally, the
376 total electrification (TOT) family of scenarios explores extreme electrification levels,
377 with baseline demand increase based on electricity demand growth projections from
378 [63] up until 2085. These socioeconomic scenarios are then combined to six different
379 scenarios of climate change to yield the 24 scenarios considered in this study.

380 Climate change scenarios are derived from the sampling of the RCP 8.5 experi-
381 ment at different 30 year long periods in the 21st century. We choose to sample the
382 80 year long simulation on periods centered around 2035, 2050, 2060, 2070 and 2085,
383 corresponding to a global warming above pre-industrial levels of respectively 1.75 °C,

Table 3: Socioeconomic scenarios considered in the study.

Scenario family	Electric heating (%)	AC adoption (%)	Increase in baseline demand (%)
REF	35	23	-
SUF	35	23	15
MOD	88	55	30
TOT	100*	100	45

AC: Air Conditioning.

* This scenario involves some increased usage as well, so that the equivalent level of heating demand electrification would be of 113.75% instead of 100%.

384 2.35 °C, 2.80 °C, 3.25 °C and 4.04 °C [14]. Any socioeconomic scenario combined to a
 385 level of climate change is referenced by the socioeconomic scenario family acronym
 386 followed by the level of global warming: e.g. the MOD scenario combined to 2.35 °C
 387 of global warming is thus referred to as the MOD2.35 scenario. The reference climate
 388 is set to be the historical (1975–2005) period. Any socioeconomic scenario combined
 389 to the historical period keeps its acronym, e.g. the MOD socioeconomic scenario com-
 390 bined to the reference climate is simply denoted as the MOD scenario. This yields
 391 $4 \times 6 = 24$ scenarios that combine either a socioeconomic change from the REF sce-
 392 nario (e.g. MOD), a climate change from the REF scenario (e.g. REF2.35), or both
 393 (e.g. MOD2.35).

394 **Supplementary information.**

395 **Acknowledgments.**

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Chapter **6**

Conclusions and perspectives

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We tackled in this work the question of the vulnerability and the potential of adaptation of electricity systems facing socioeconomic and climate change. We found that this question was partially tackled in the literature, and that several gaps remained. In particular, we identified that (i) the impacts of scenarios of heating demand electrification and AC adoption on the optimal investment decisions in VRE capacity were not satisfactorily addressed, (ii) some aspects of the impacts of climate change on the vulnerability and the adaptation potential of the electricity system had not been tackled, and (iii) if some studies assessed the impacts of socioeconomic and climate change jointly, many did not, despite the fact that the effects of studying both effects separately had not been tested. We contributed to filling these gaps in the literature in this work. We summarize hereafter the main findings.

6.1 Main contributions

We divided our work in three main chapters, tackling each one of the research questions identified in Chapter 1. The methodological aspects of this work are presented in Chapter 2.

6.1.1 An increase of the heating temperature sensitive demand favors wind penetration, the modification of the cooling demand along the extensive margin only has no effect in France.

In Chapter 3 we studied the impacts of scenarios of heating demand electrification and AC adoption on the optimal investment decisions in VRE capacity.

We first assessed the impact of scenarios corresponding to different levels of electric heating and AC adoption on the demand. We showed that modifications of the cooling demand along the extensive margin (adoption) only had a negligible effect on the total demand. Without effects on the intensive margin (usage), AC adoption is shown to induce very minor modifications to the demand under the present-day climate in France. These minor have no consequences on the optimal investment decisions (not shown). If more important effects are not excluded under future climates, we recommend incorporating scenarios of AC usage in future studies. Modifications of the electric heating demand along the extensive margin (adoption) without modifications along the intensive margin (usage) are shown to have much more significant effects on the electricity demand than for the cooling demand. Furthermore, these demand modifications are shown to be heterogeneous across the different levels of demand: peak demand is more affected than base demand. We then explored in more detail the effects of these demand modifications on the optimal investment decisions in VRE capacity.

To do so, we set up a protocol where changes in demand due to electric heating adoption are compared to equivalent changes in average demand, to remove any effects related to a bulk demand increase. This is equivalent to comparing an increase in temperature sensitive demand to an increase in baseline demand (i.e. that demand which is non temperature sensitive). We show that increasing the temperature sensitive demand favors the penetration of VRE: if increasing the average demand tends to increase the optimal installed VRE capacity, more VRE capacity is installed in the temperature sensitive increase case than in the baseline case. We further show that this increase in temperature sensitive demand increases system costs compared to a baseline increase. Regarding optimal investment decisions, we show that an increase in temperature sensitive demand tends to favor wind energy penetration compared to solar. This effect is however of second order compared to the impacts of technology costs and regional maximum installable capacity: cheaper technologies (solar in our case) are installed first and in regions where their LCoE is highest. This study was however conducted using quite restrictive maximal installation capacities for solar, thus causing investment in wind capacity to occur because all the solar capacity was already installed. We expect that if these constraints were relaxed, then the observed effects of preferred investment in wind capacity with higher temperature sensitive demand increase would become more significant.

As for all results in this work regarding optimal investment decisions, the results obtained in this chapter are so under an idealized framework regarding dispatchable (i.e. non-VRE) producers. We did not take into account the investment costs of the dispatchable production. We expect that accounting for these extra costs would favor investment in VRE capacity and thus exacerbate the effects observed so far. Further work is however needed to confirm this hypothesis.

6.1.2 Climate change has no adverse impacts if impacts on the dispatchable producers are not accounted for, changes in demand are the driving factor of changes in France.

In Chapter 4 we focused on the impact of climate change on a french electricity system with high penetration of VREs. We addressed more precisely what are the impacts of the combined change in VRE resource and electricity demand due to climate change.

We find that increasing levels of climate change tend to reduce the optimal levels of installed VRE capacity as well as its optimal penetration. Wind is the adjustment variable as its installed capacity decreases with increasing climate change intensity whereas solar capacity remains constant. We show that the direct relation between the changes in VRE resource and demand on the one side, and the resulting optimal VRE mixes on the other side are not straightforward. We however suggest that the evolution of the demand to capacity factors correlation with climate change might be a good predictor of the expected changes, given that average demand effects are accounted for. We further show that the evolution of this correlation is little sensitive to the changes in VRE resource, changes in demand patterns being the main driver of this evolution. We thus suggest that the effects of climate change on the optimal investment decisions are thus mainly related to changes in demand rather than changes in the VRE resource in the case of France. This conclusion might well be region-specific, as France is a country with a high temperature sensitivity for the electricity demand and climate change impacts on the VRE resource are moderate (at most $\pm 20\%$). Further works on other world regions are necessary to see if this conclusion can be generalized. Further studies should also couple these assessments to socioeconomic scenarios of demand, as we showed that e.g. heating demand electrification or AC adoption could influence the temperature sensitivity of the electricity demand of a country.

We further show in this chapter that the effects of climate change alone tend to decrease system total costs, whether it be with or without adaptation. We show that the adaptation potential however remains positive since system total costs are still lower with an optimal mix that with a mix optimal under reference climate conditions. Still, we show that accounting for the costs of stranded assets can make this adaptation step less attractive economically than non-adaptation. This positive impact of climate change regarding total costs is related to the overall decrease in total demand. These results need not be taken outside of the ideal case under which they are produced: on the one side we did not consider the investment costs in dispatchable capacity, and on the other side, impacts of climate change on other system components than the VRE resource and the demand were not considered. In particular, the impacts of climate change on the dispatchable producers were not accounted for. The impact of considering investment costs of the dispatchable producers should favor the investment in VRE capacity and increase system total costs. It should not however impact the observed trends with climate change. Opposedly, considering the impacts of climate change on the dispatchable producers might strongly influence the results obtained in this study. These impacts are mainly related to water availability for the cooling of thermoelectric power plants and for the operation of hydropower generation. Reduced water availability due to deteriorated hydrologic conditions and increased water temperatures are two phenomena that might reduce the availability of hydrothermal power plants and thus increase the need for more investment in VRE or the need for more balancing capacity, thus increasing system total costs with increasing climate change. This highlights the need to approach climate change studies in an integrated way to provide relevant policy-making advice and relevant assessments of climate change impacts. We thus recommend

that further studies incorporate as much climate change effects and on as many components as possible.

We finally note that in this chapter, we proceeded in an integrated way to identify bulk effects of climate change impacts. A more detailed protocol could have been set up to differentiate climate change impacts from average demand effects, or to specifically address the effects of a change in VRE resource or a change in demand induced by climate change. This is however left for further works.

6.1.3 Socioeconomic change is potentially the driving force but socioeconomic and climate change impacts should be assessed jointly to issue relevant policy-making advice

In Chapter 5 we studied the compound impact of socioeconomic and climate change. Here electrification of other end-uses than just space heating or AC adoption was considered in the form of an increase of the baseline demand. These increases were derived from projections in the grey literature on the electrification potential of the energy sector. Socioeconomic scenarios explored in this chapter explore at the same time a wide range of electrification futures and a wide range of climate change futures.

We found that the coupling of our socioeconomic scenarios of electrification with climate change led to an overall increase of the demand compared to the present state. Our scenarios impact the electricity demand in two ways. On the one side, heating and cooling temperature sensitive demand are increased due to electric heating and AC adoption, and baseline demand increases due to electrification. On the other side, climate change tends to either decrease on average the heating temperature sensitive demand because of milder average air temperatures in the winter, or increase on average the cooling temperature sensitive demand because of warmer temperatures in the summer. This second effect is even more pronounced in either directions that the increase in temperature sensitive demand is pronounced. However we showed that even for the most extreme scenarios of climate change found in the literature, the decrease in demand related to climate change was smaller than the associated increase due to either a baseline demand or temperature sensitive demand increase. We further showed that demand never increased with climate change in our scenarios, evidencing that the decrease in heating temperature sensitive demand was still majoritary compared to the increase in cooling temperature sensitive demand. Modifying the cooling demand along the extensive margin only, even when coupled with climate change, was not enough to make cooling sensitive demand majoritary in our scenarios. We thus worked with conservative scenarios in this regard and highlight here again the fact that further studies should incorporate modifications of the cooling demand along both margins to capture potentially important demand increases and further adverse impacts in the case of France.

We also showed that for all the scenarios considered in this study, climate change had a lesser impact on the demand than socioeconomic change. As we stated in previous section, we showed in Chapter 4 that climate change impacts on the VRE resource were of second order compared to changes in demand. When adding socioeconomic scenarios of electrification, these impacts on the VRE resource thus become negligible. The driving force of change is socioeconomic change in our case, even when comparing the smallest socioeconomic change considered with the greatest climate change scenario available in the literature. This shows the importance of considering socioeconomic scenarios in studies about the future of energy systems: accounting for climate change alone is not enough. Moreover, if only socioeconomic scenarios that led to an increase in the demand were considered in this study, scenarios leading to a demand decrease could be envisioned as well. Such scenarios could for example correspond to the implementation of individual or collective efficiency or sufficiency measures. Finally, it is important to notice that if socioeconomic change is the driving force in our setup, this might not be the case once climate change impacts are accounted for in a more integrated way (we think of climate change impacts on the dispatchable producers in particular). Further studies would be needed to conclude on this point.

We then computed the adaptation potential of the electricity system to future changes assuming perfect foresight. We set up a protocol where we assessed the impacts of socioeconomic change only and then of climate change only. These two estimates were then added and compared to the compound assessment of both impacts. We thereby showed that it is necessary to take into account the compound impact of socioeconomic and climate change when assessing a policy-making relevant metric such as the adaptation potential. Not doing so can lead to erroneous quantitative and qualitative results on the impacts of climate or socioeconomic change on these metrics. We believe that this result holds no matter the modeling setup, as long as coupled processes exist between the two driving forces taken into account: here the coupling between the temperature sensitivity of the electricity demand and the impacts of climate change on this demand are in cause. Further research could concentrate on identifying whether this hypothesis holds and if for example cost scenarios can be studied independently of climate change.

6.1.4 General conclusions and policy advice

Despite working in an idealized setting, we showed in this work that both socioeconomic and climate change have a significant impact on the vulnerability and adaptation potential of high VRE electricity systems. We showed that the impacts of both processes on the demand were of first order compared to the impacts on the VRE resource. Climate change was also found to be of secondary importance compared to socioeconomic change, although this might be discussed in light of a more thorough accounting of climate change impacts. If we found that electricity systems were more vulnerable to socioeconomic scenarios of electrification than to climate change, it should however be kept in mind that we considered very conservative scenarios of cooling demand increase as we did not consider modifications of AC usage. Regarding the adaptation potential, we show that how both processes impact the demand guides the adaptation strategy: changes in the heating temperature sensitive demand are related to the installation or removal of wind capacity, whereas changes in baseline demand are related to changes in the installed solar capacity. Changes of cooling temperature sensitive demand have been little explored in this work. We finally showed the importance of the climate and energy integrated approach, and the importance to account for all elements of the electricity system and all processes impacting them in a coupled way to produce relevant results from the policy-making perspective.

This work is a modest contribution to the understanding of how future changes might impact high VRE penetration electricity systems and what is their adaptation potential in this regard. We were able to issue generalizable conclusions that go beyond the strict hypothesis and the framework of the different research studies conducted. These general conclusions would however need further verification and exploration to be consolidated, offering many perspectives to the work performed in this thesis, which we discuss in next section. The question of the policy advice that could be issued from this work is more delicate. We think that relevant policy advice should come from a meta-analysis of distributed scientific knowledge in the model of the Intergovernmental Panel on Climate Change (IPCC) reports, and that a single piece of research work is not capable of encapsulating all dimensions of such a complex problem as policy-making in the energy sector facing such stringent issues as climate change (among others). Because energy system policy-making is more region-specific, we do not see the need for the creation of an intergovernmental panel such as the IPCC, although international cooperation will certainly be beneficial to foster energy sector transformation. We do however think that a regional, e.g. european or french, panels of experts proceeding to critically review the state of scientific knowledge could be beneficial to build more consensus or at least inform the debate on the energy question.

6.2 Perspectives

This piece of work paves the way for many exciting continuations and further research.

We first discuss some minor modifications and questions that could have been addressed in this work, without the need for further methodological developments or the setup of additional heavy research protocols. Although this question was reviewed in the introduction, Chapter 1, the feasibility of very high, i.e. from 90 % to 100 % VRE mixes could have been addressed with the tools and data at hand. It would have been interesting, in a toy model perspective, to analyze what ratio of average marginal cost of generation to an average VRE LCoE would have given a 100 % VRE mix. Maybe this limit cannot be reached even for an infinite ratio, highlighting the fact that 100 % VRE mixes are not feasible without a minimum amount of balancing capacity available. This would have been an original way to study the economical cost of very high VRE penetration. Additionally, we think it would be interesting to reconsider the results presented in Chapter 3 in the light of relaxed constraints on the maximum solar installable capacities. As previously stated, we would expect the same results to be found but in a more pronounced way. Performing such an extension to this work would however give us confidence in this conjecture. Finally, minor protocol changes in Chapter 4 would have allowed to better disentangle (i) the climate change effects from average demand effects, (ii) a change in VRE resource alone, and (iii) a change in demand alone compared to the combination of both effects in the context of climate change impacts. All these minor modifications are left for further works, but could be undertaken rather straightforwardly from the work done so far.

On top of the aforementioned minor modifications, this work has rather natural extensions. The first one would be to explore scenarios of AC use coupled to our scenarios of AC adoption. This could be rather straightforwardly implemented in our demand model and would only require adequate scenarization hypothesis. Such hypothesis could for example consist in assuming that all regions in France adopt the same AC usage as the southern regions currently, or setting the usage level to some average plausible value in all regions. Another way of doing so could be to use a more sophisticated econometric model based on e.g. income, discomfort levels, etc. A second natural extension of this work would be to use an energy system modeling that can handle other components of the electricity system, such as, in the order of importance, dispatchable producers, storage or transmission constraints. Such an extension of our work would however necessitate methodological developments or the use of other modeling tools, thus requiring some methodological development time. We can finally note that our questioning integrates well into an energy system perspective, i.e. considering the whole energy system rather than the electricity system separately. This would avoid having to design socioeconomic scenarios of demand electrification as the electricity demand would be determined endogenously. This would however greatly increase the complexity of the model used, hampering in this way the interpretability of modeling results, which we showed to be already quite complex in a minimal setting such as our own.

Based on the current insight we could gain from conducting this work, we think several research questions would be worth exploring in the future. The first one maybe consists in evaluating the impact of extreme events on the design of energy systems. Although we did consider some year to year variability in this study, we did not account for extreme events with high return times. The extent to which such extreme events would impact the optimal investment decisions after the introduction of a reliability criteria would be of great interest. The second question that could be considered is that of the impact of demand-side measures on the optimal investment decisions. Demand-side measures such as flexibility of sufficiency have the potential to decrease the tension put on the grid either temporarily or in a durable way, and as such would impact the necessary balancing capacity needed to accommodate a high penetration of VRE. A third question could relate to expanding the criteria on which the optimality of the mix is considered. Throughout our study an electricity generation mix was considered to be optimal if it was able to supply electricity when needed at all times at the lowest system total cost. This misses the fact that electricity generation systems, and more broadly energy systems can be thought of as having to ensure other functions and under certain other conditions. Among the main factors that we did not consider in this study we can mention all environmental-related impacts other than the decarbonization target, such as land-use and the sustainable use of biomass. Another aspect that we think should be tackled in further studies is the sociological aspect of energy system development. These questions go probably beyond the

discipline of climate and energy system modeling and we do not think that a definite answer should come from modeling exercises alone. Valuable research at the interface of various disciplines could however be undertaken to rigorously explore these questions with an integrated point of view.

Appendices

Appendix **A**

Methods — Supplementary information

A.1 Model results for the best statistical demand model

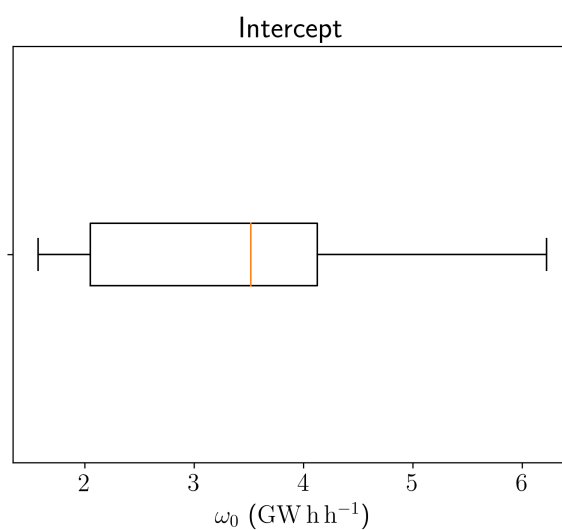


Figure A.1. Intercept of linear model. The box represents the distribution over the study area (metropolitan France). The orange line represents the median while the box represents the interquartile range between first quartile and third quartile. Whiskers extend to the farthest point within 1.5 times the interquartile range.

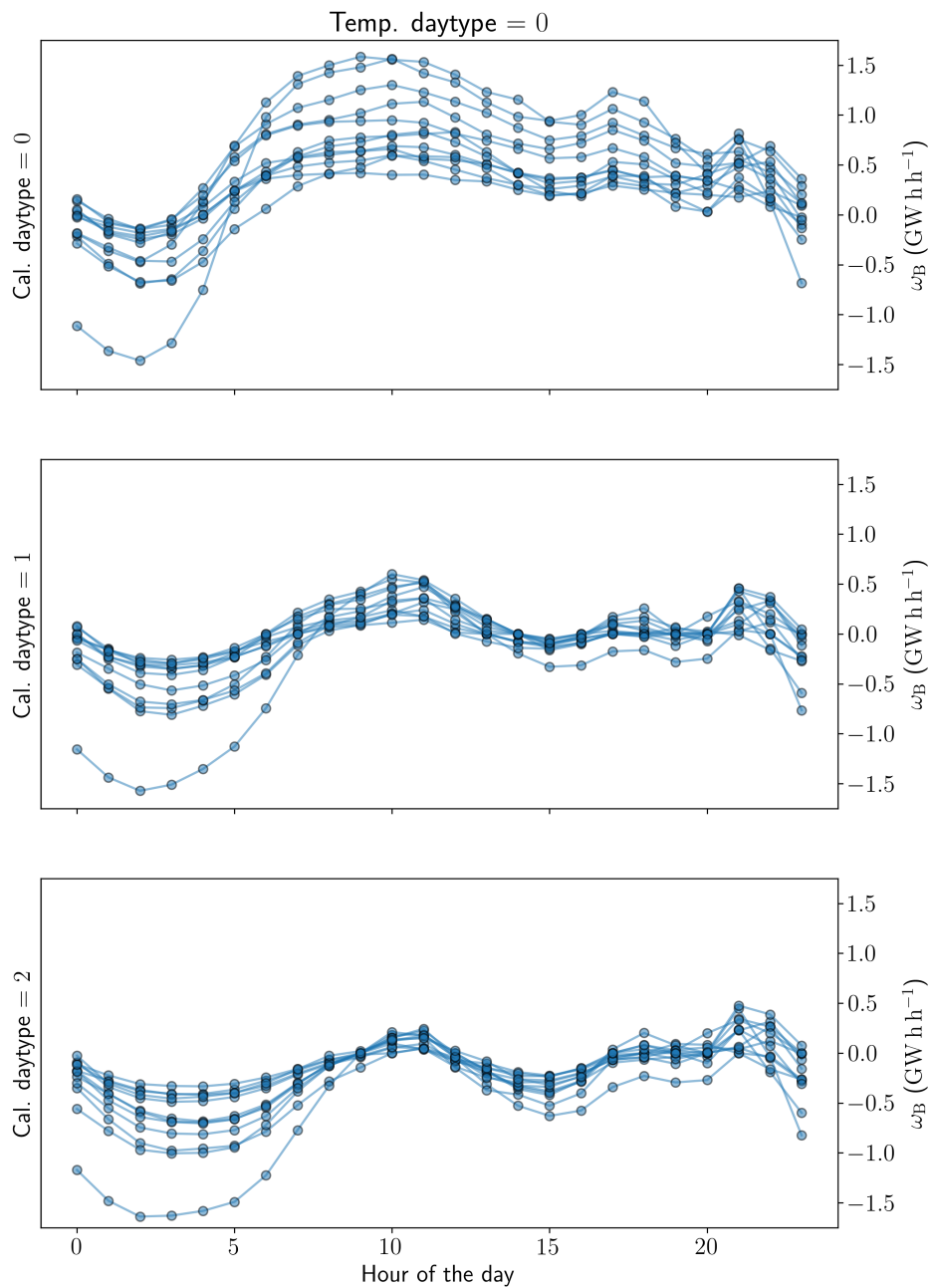


Figure A.2. Base coefficients of the linear model. Model coefficients are represented throughout the day (to each hour of the day corresponds a coefficient). The different lines correspond to the different french administrative regions.

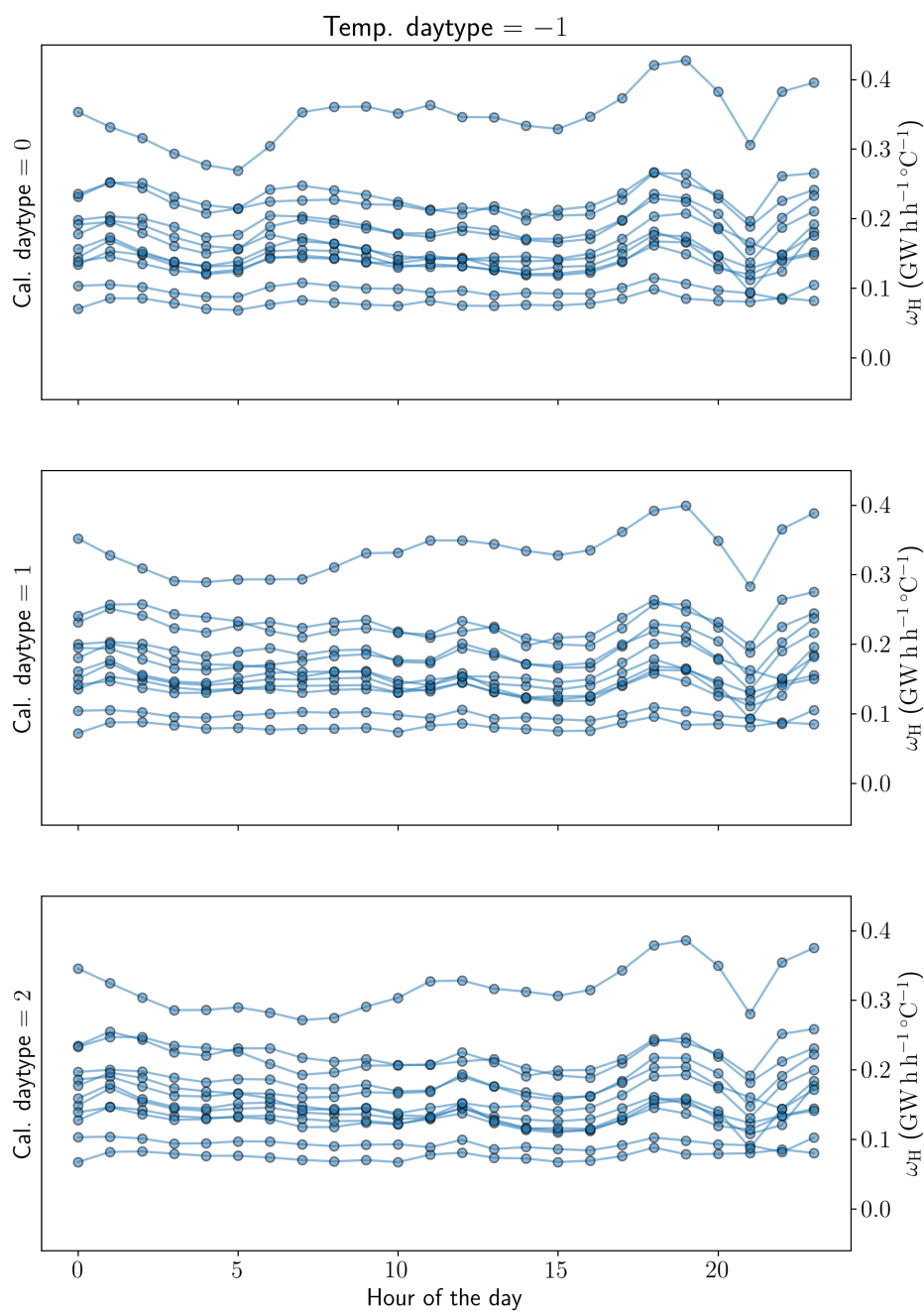


Figure A.3. Heating temperature sensitivity coefficients of the linear model. Model coefficients are represented throughout the day (to each hour of the day corresponds a coefficient). The different lines correspond to the different french administrative regions.

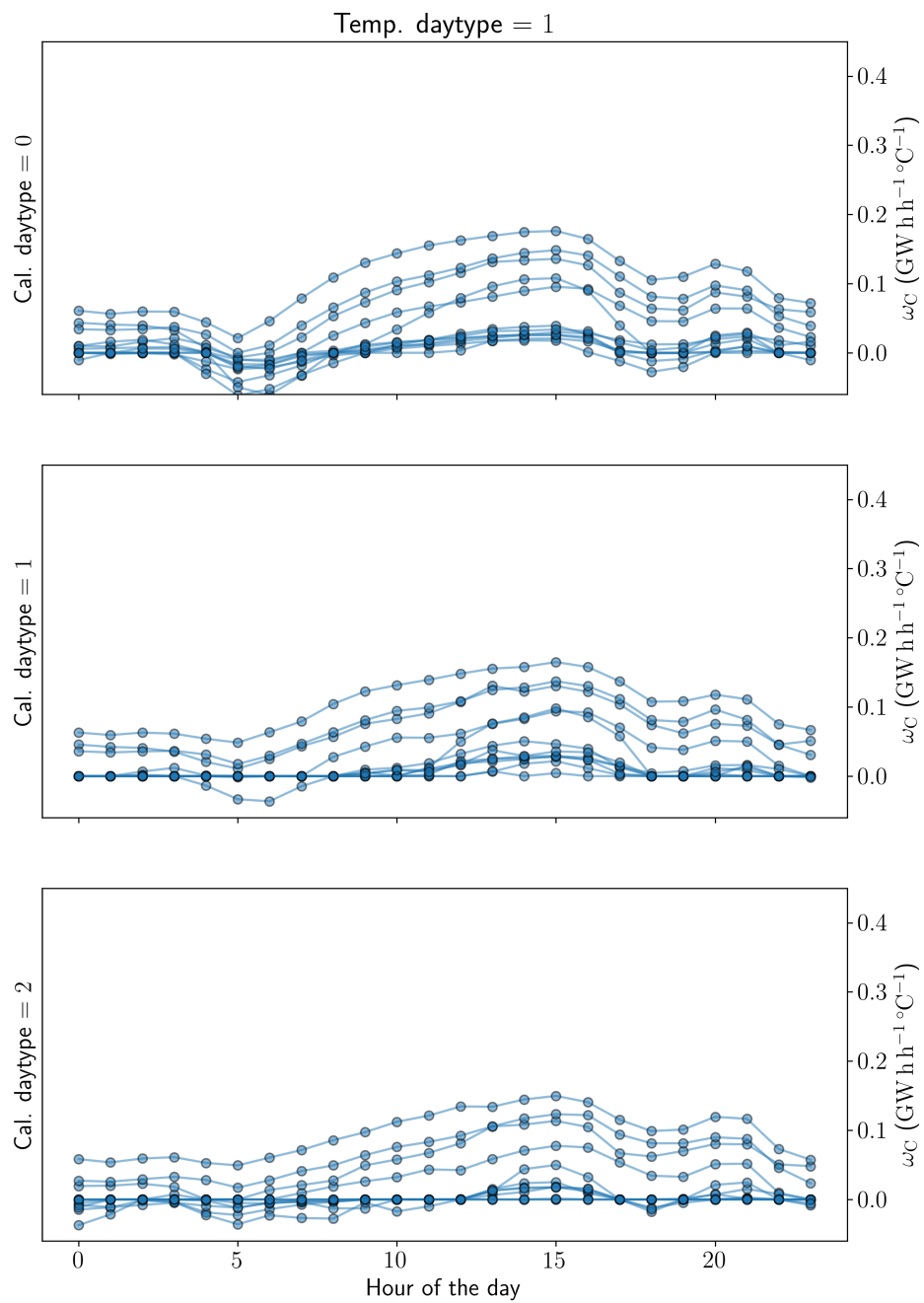


Figure A.4. Cooling temperature sensitivity coefficients of the linear model. Model coefficients are represented throughout the day (to each hour of the day corresponds a coefficient). The different lines correspond to the different french administrative regions.

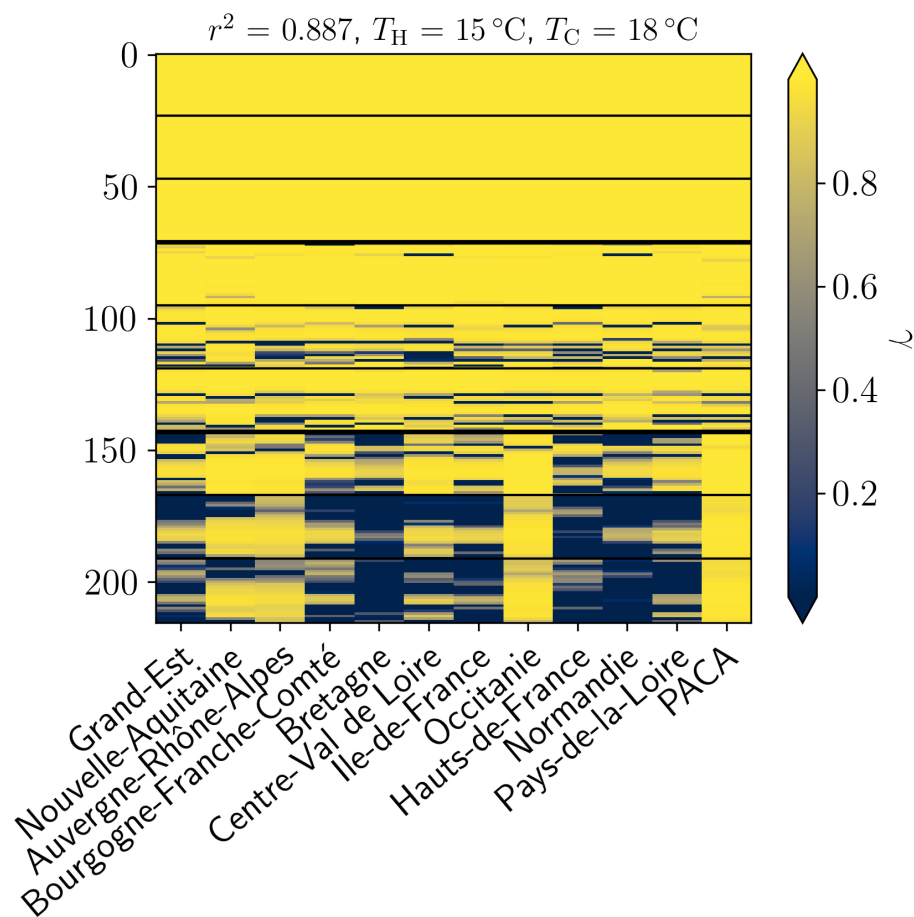


Figure A.5. Model coefficients quality (γ). Heating coefficients ω^H are indexed between 0 and 71, baseline coefficients ω^B between 72 and 143, and cooling coefficients ω^C between 144 and 215.

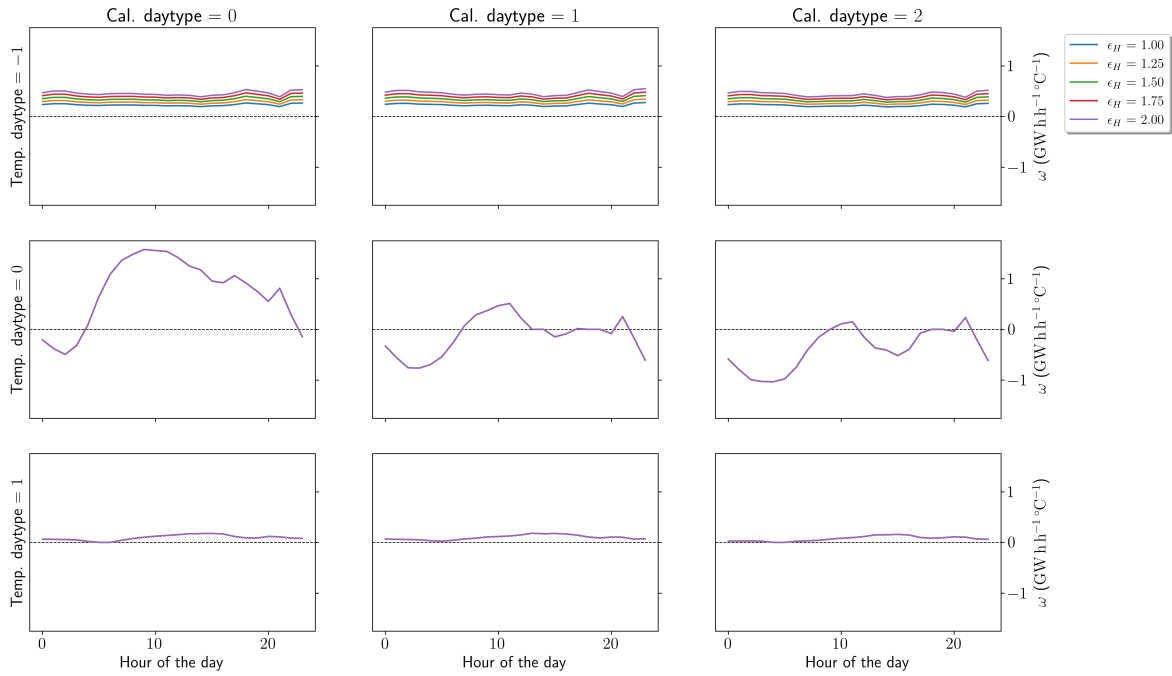
Appendix **B**

Socioeconomic scenarios of electric heating and cooling and their impacts on optimal mixes and power system costs — Supplementary information

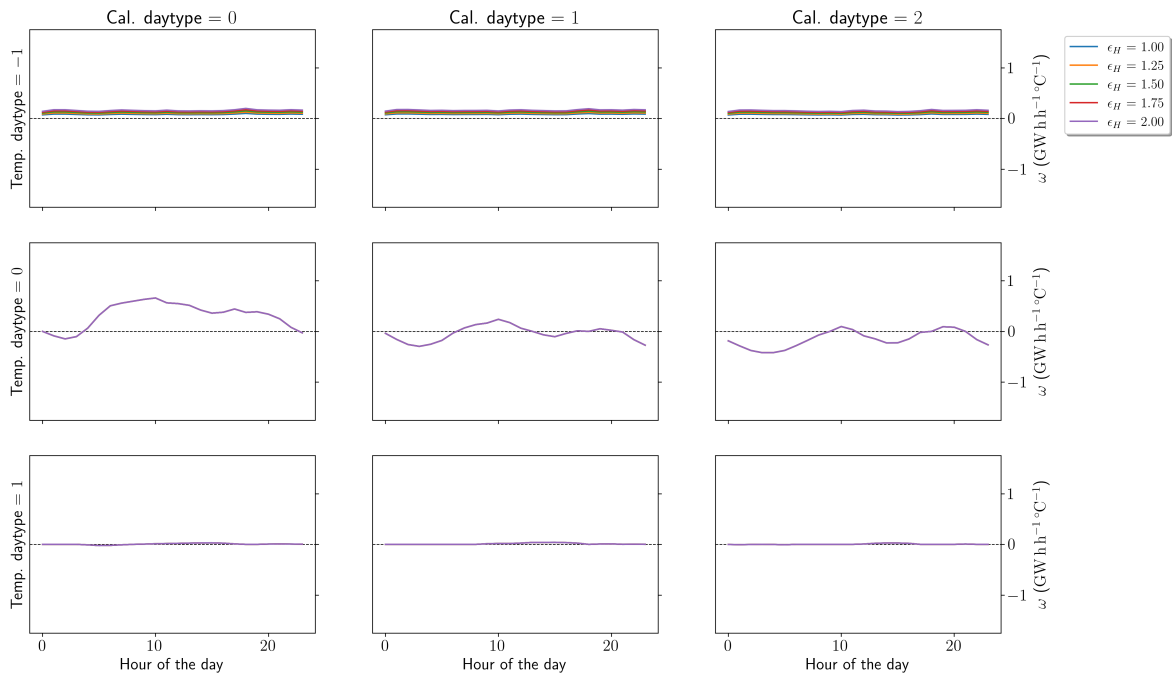
B.1 Socioeconomic scenarios of electric heating and cooling

B.1.1 Electric heating scenarios

Model coefficients

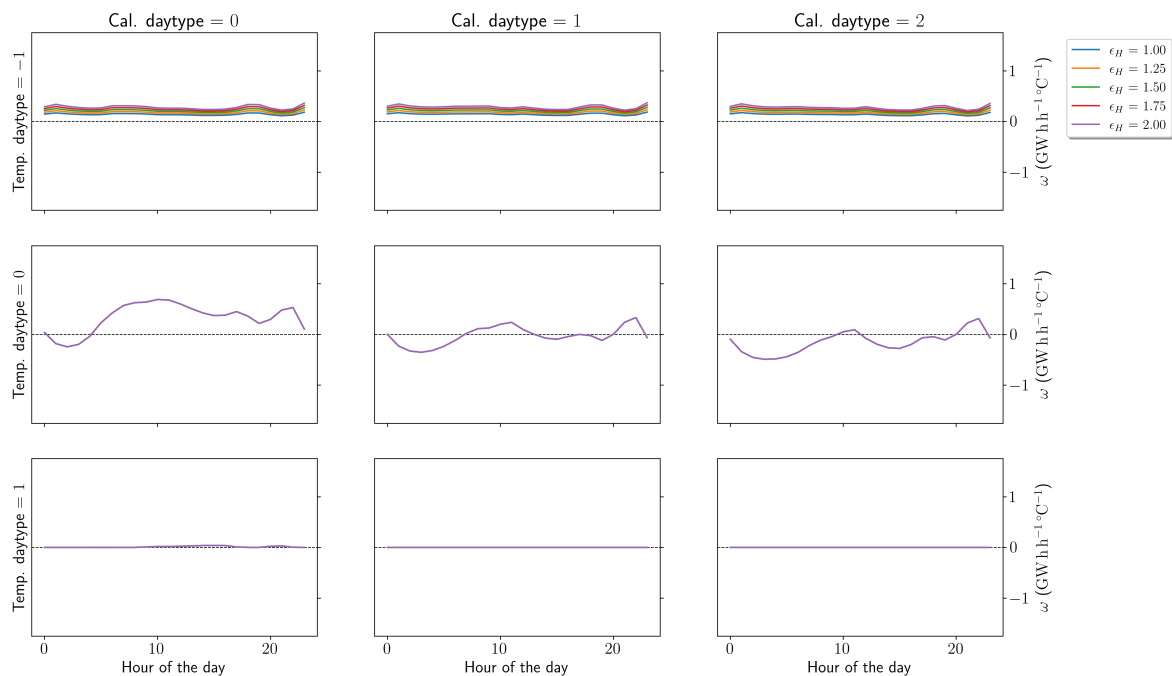


(a) Auvergne-Rhône-Alpes.

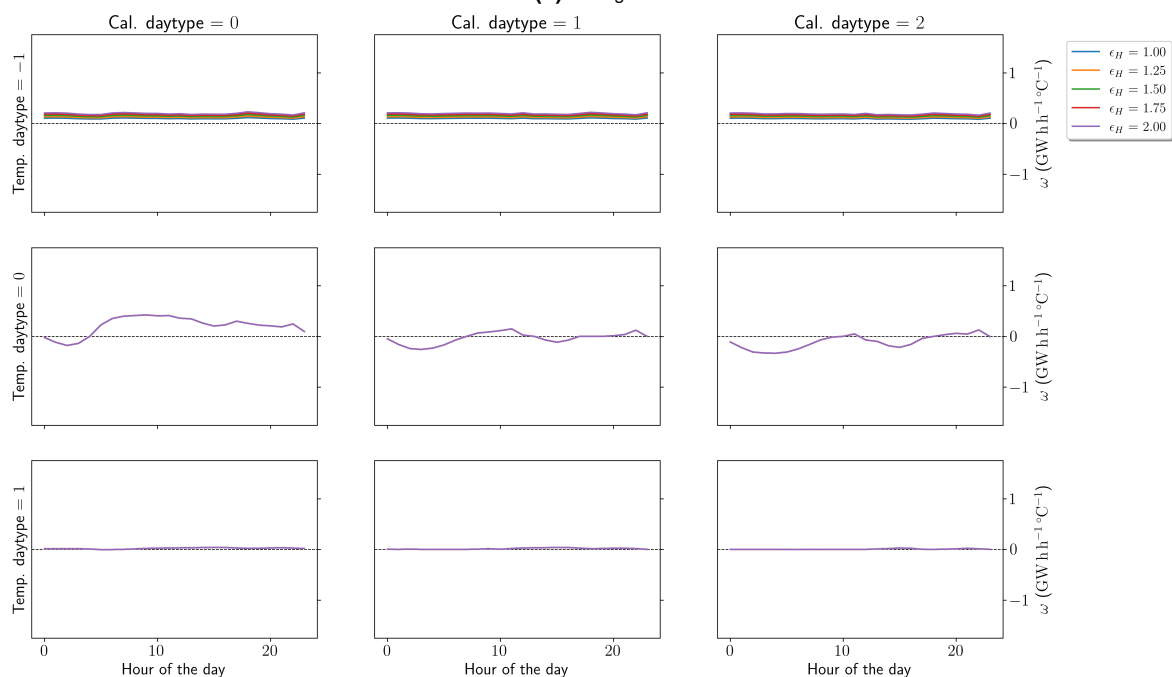


(b) Bourgogne-Franche-Comté.

Cont.



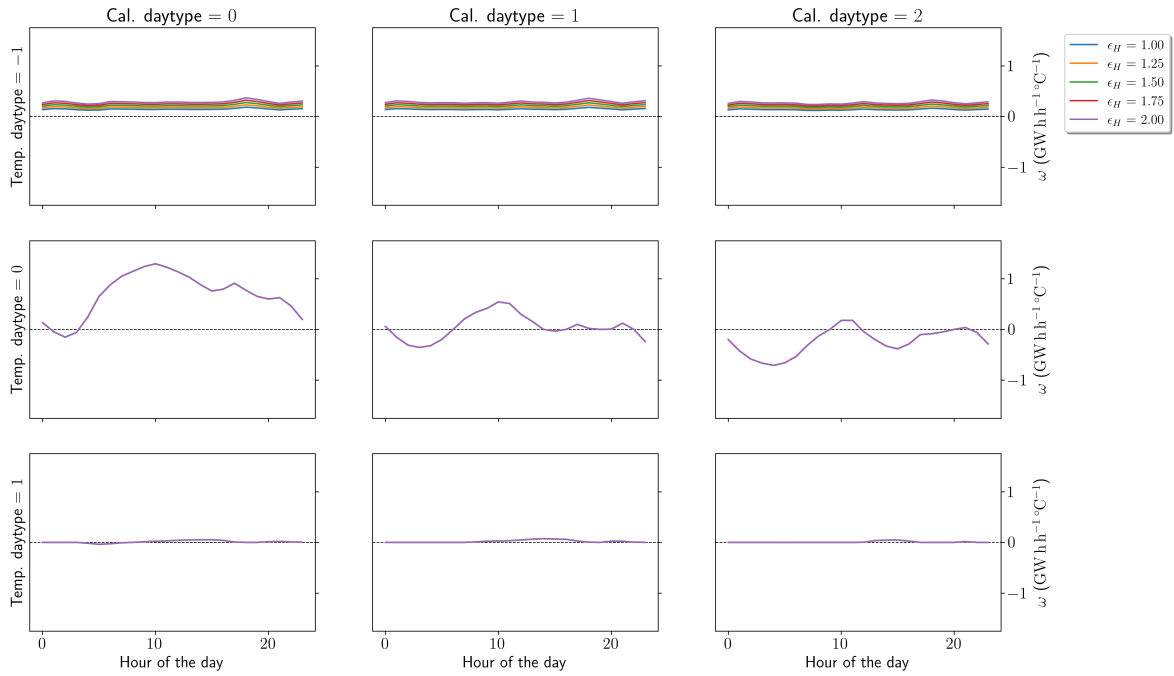
(c) Bretagne.



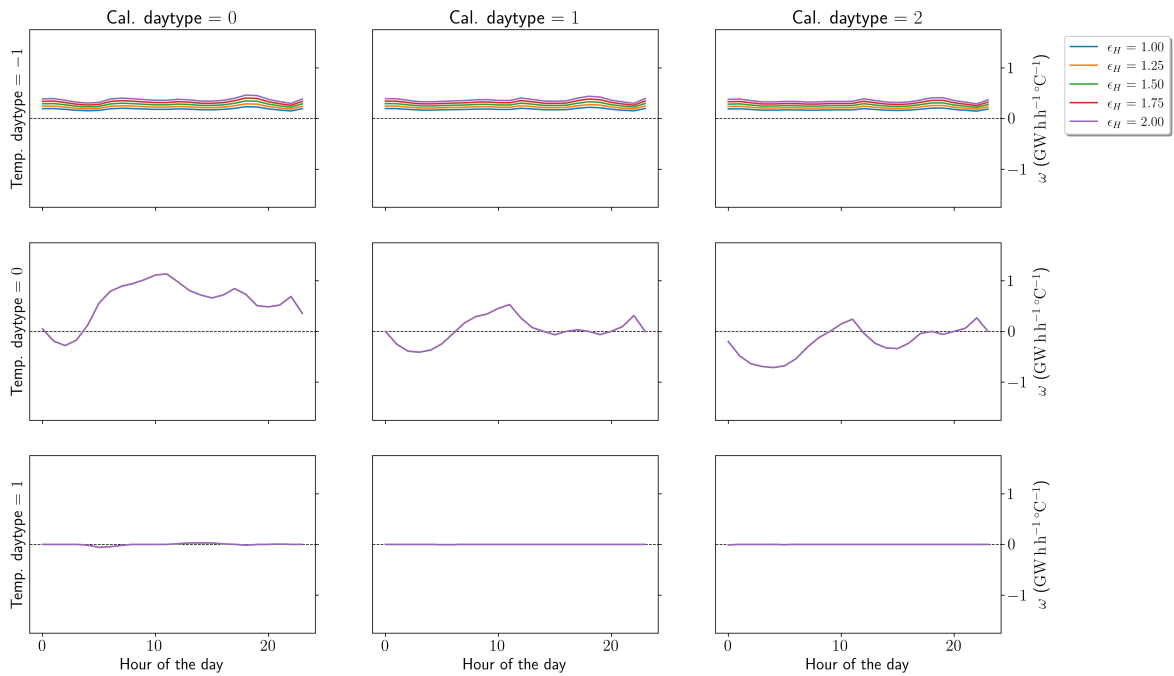
(d) Centre-Val de Loire.

Cont.



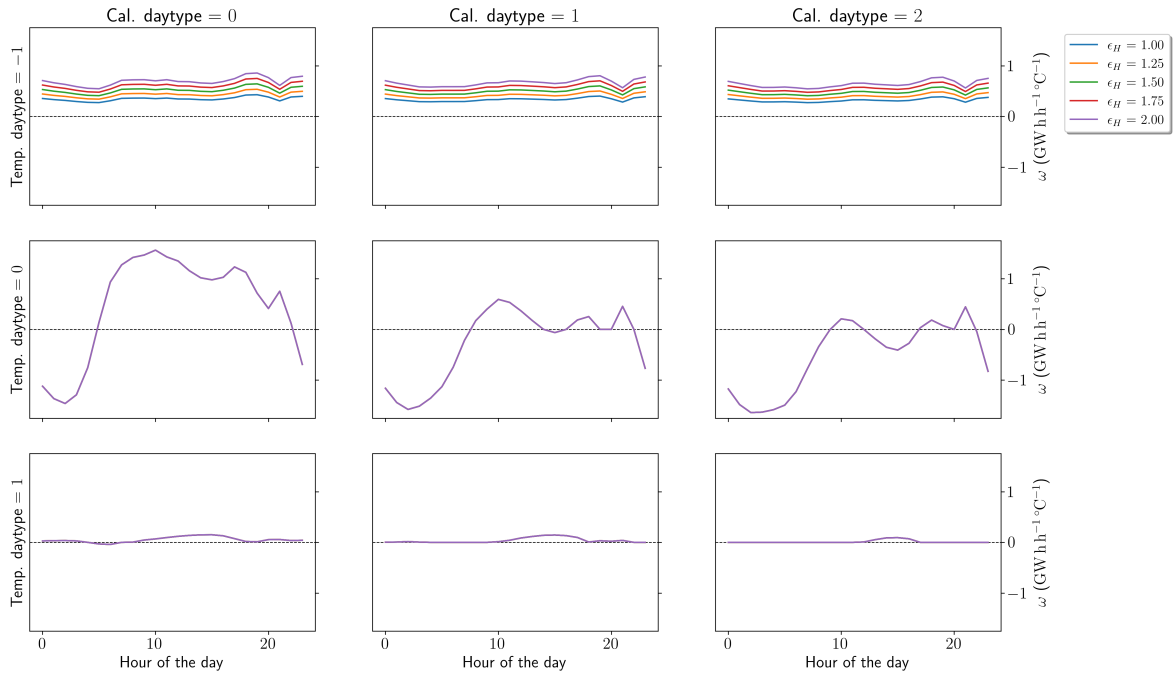


(e) Grand-Est.

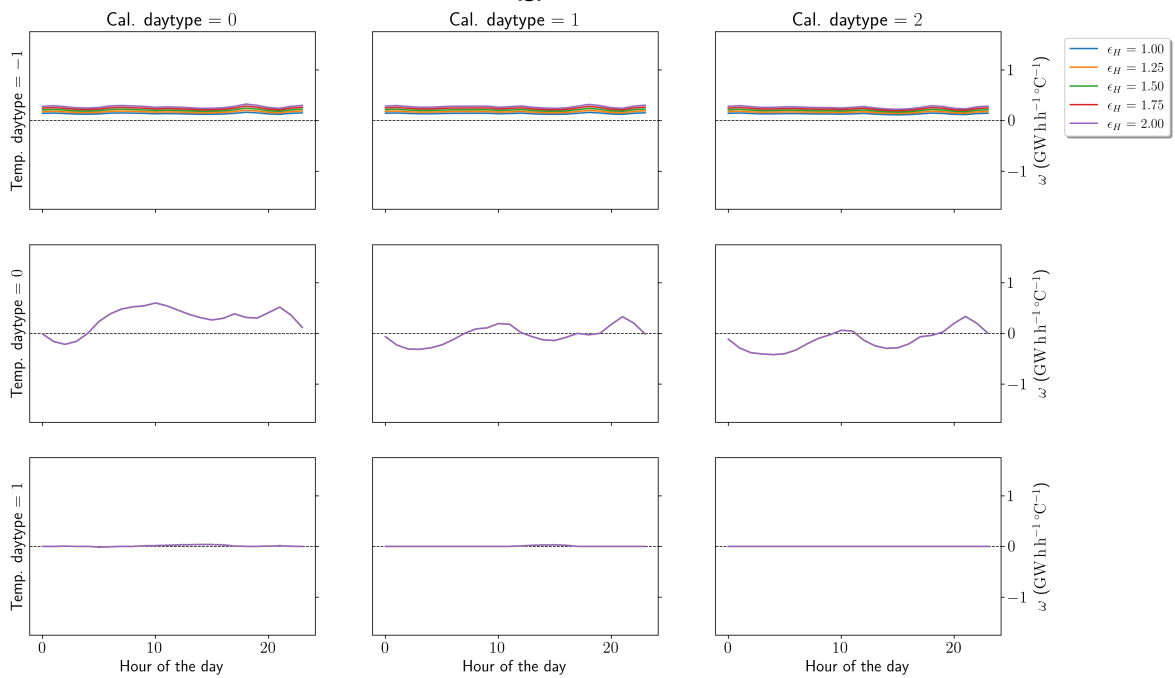


(f) Hauts-de-France.

Cont.

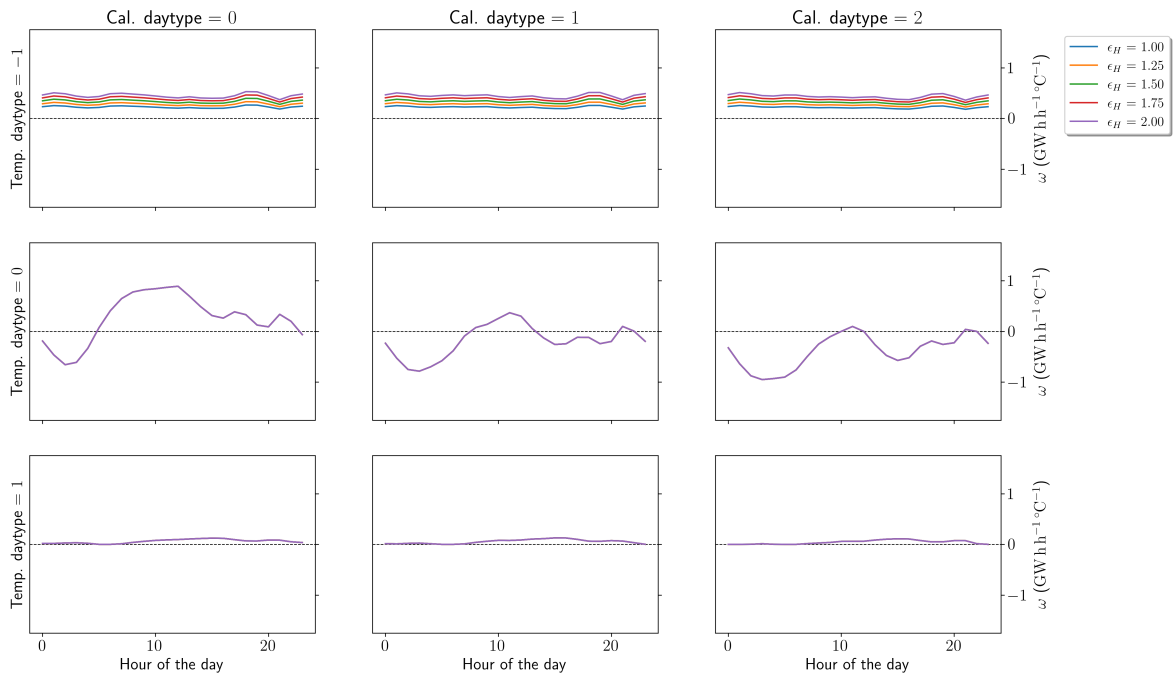


(g) Ile-de-France.

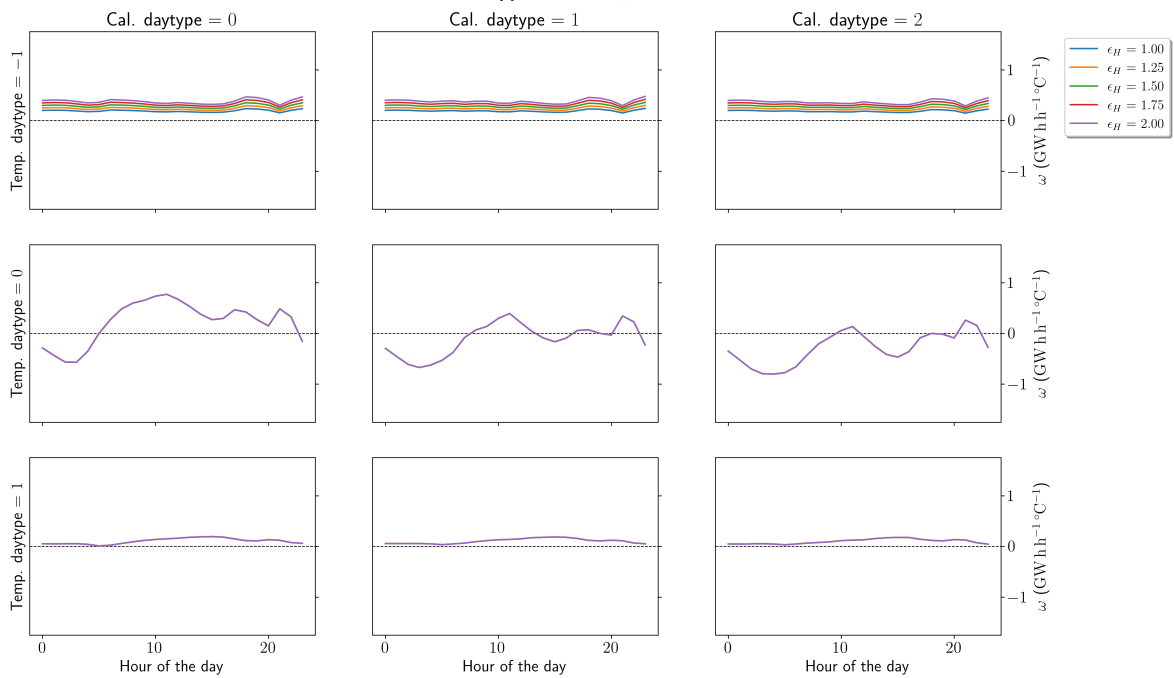


(h) Normandie.

Cont.



(i) Nouvelle-Aquitaine.



(j) Occitanie.

Cont.

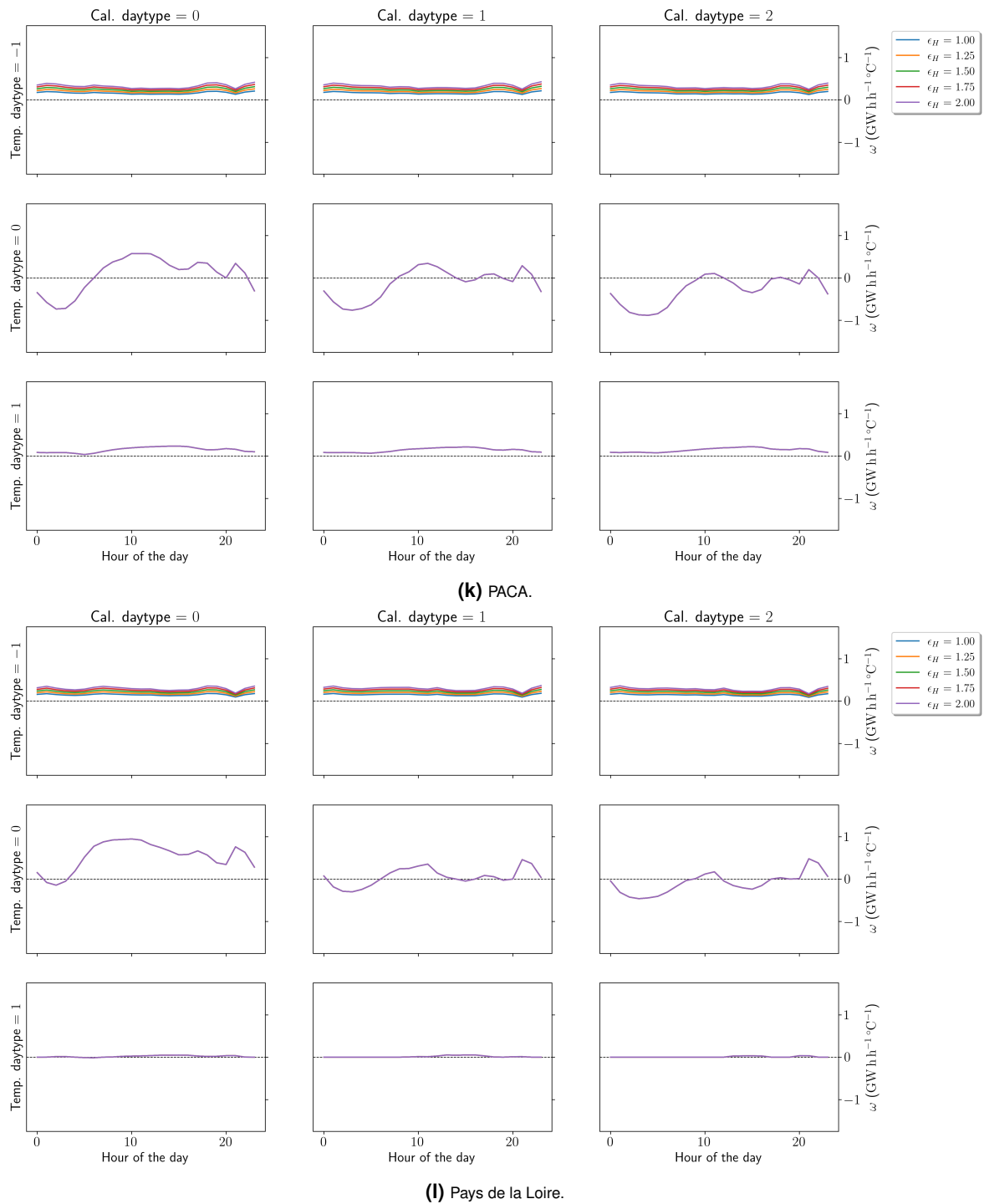


Figure B.1. Coefficients of the model for the heating demand scenarios considered. Temp. daytype corresponds to whether the day is a heating day (-1), cooling day (1) or none of the two (0). Cal. daytype corresponds to whether the day is a working day (0), saturday (1) or sunday/holiday (2).

Impacts on the demand

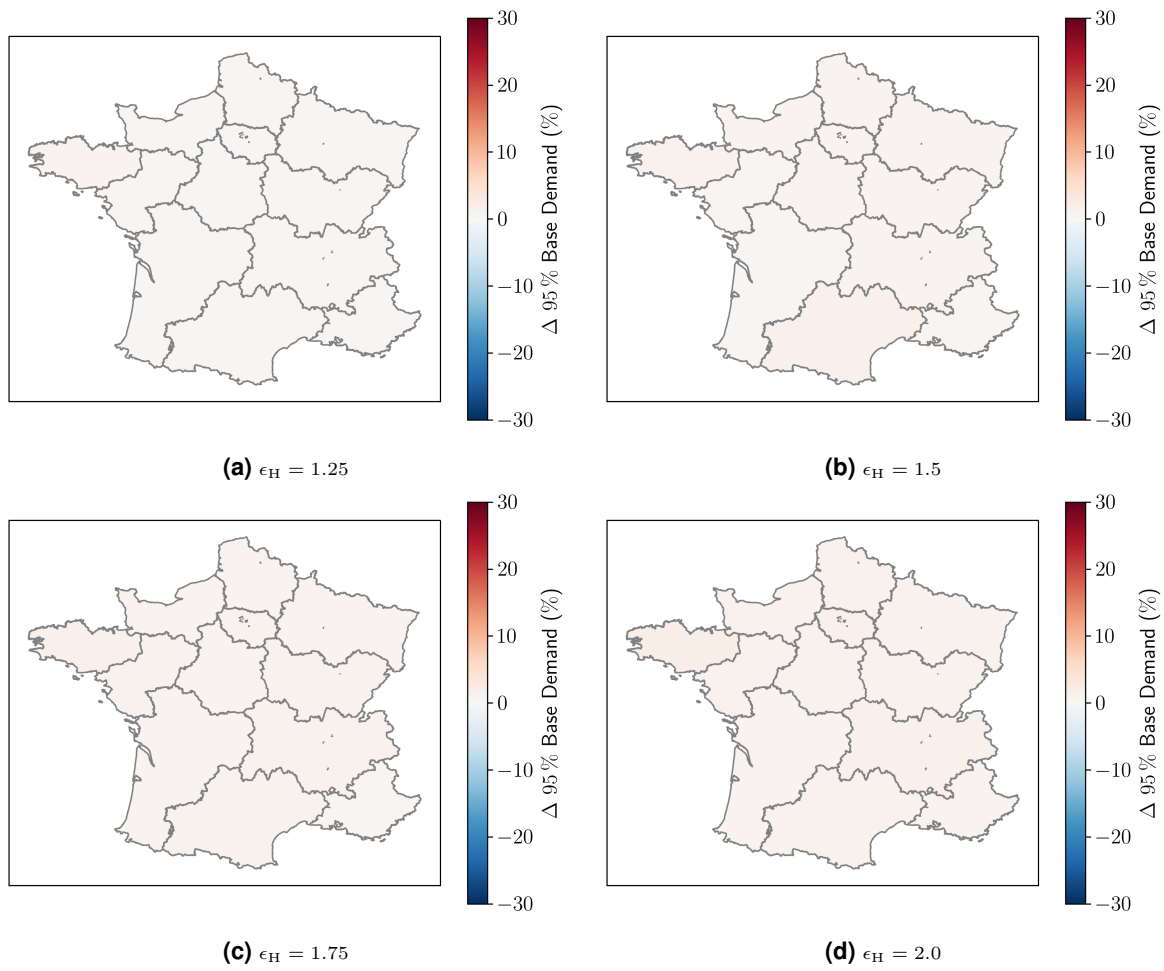


Figure B.2. Base demand relative difference for the heating demand scenarios considered, per region.

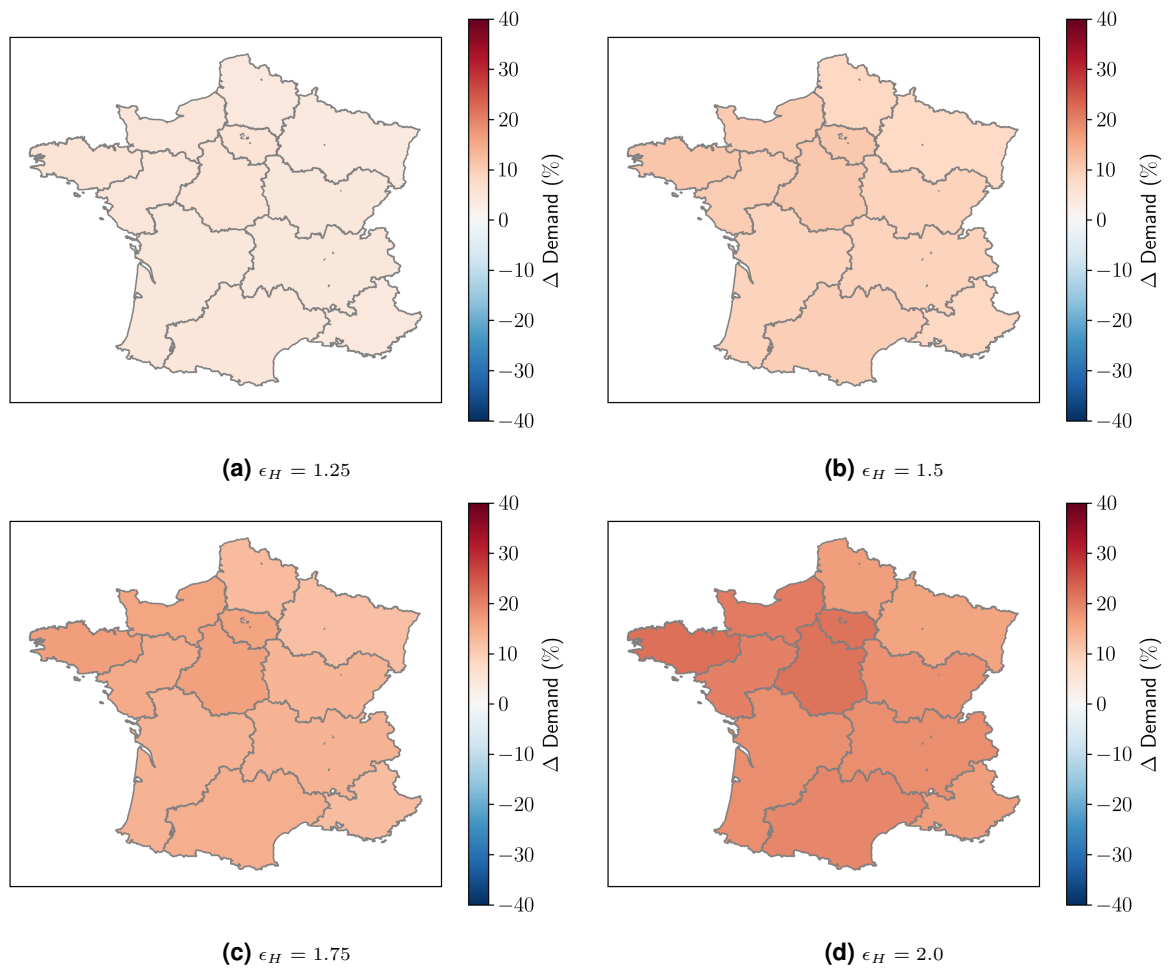


Figure B.3. Mean demand relative difference for the heating demand scenarios considered, per region.

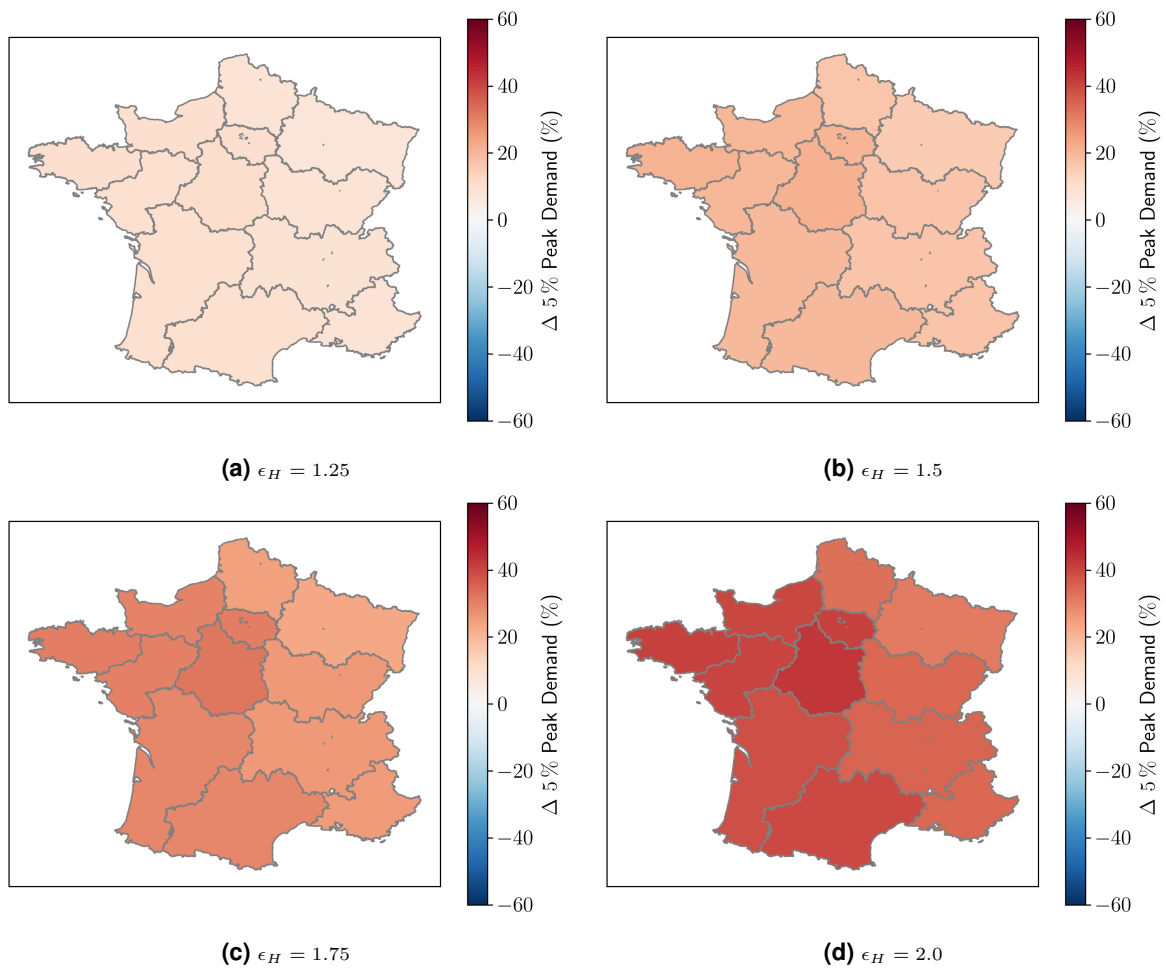
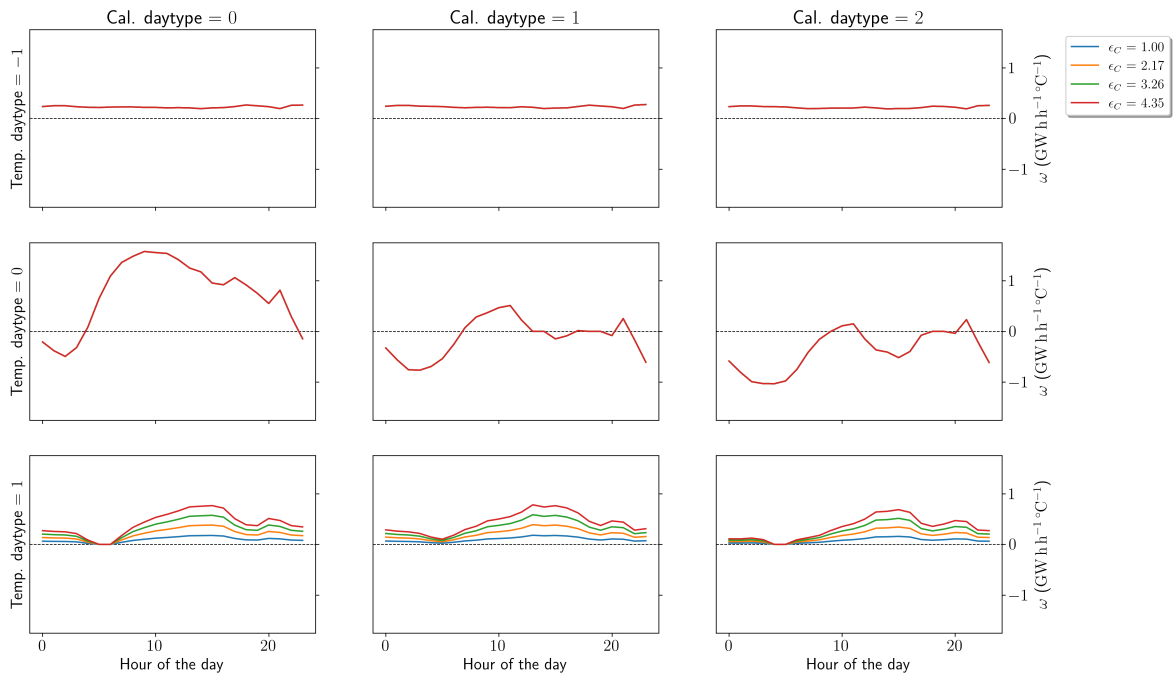


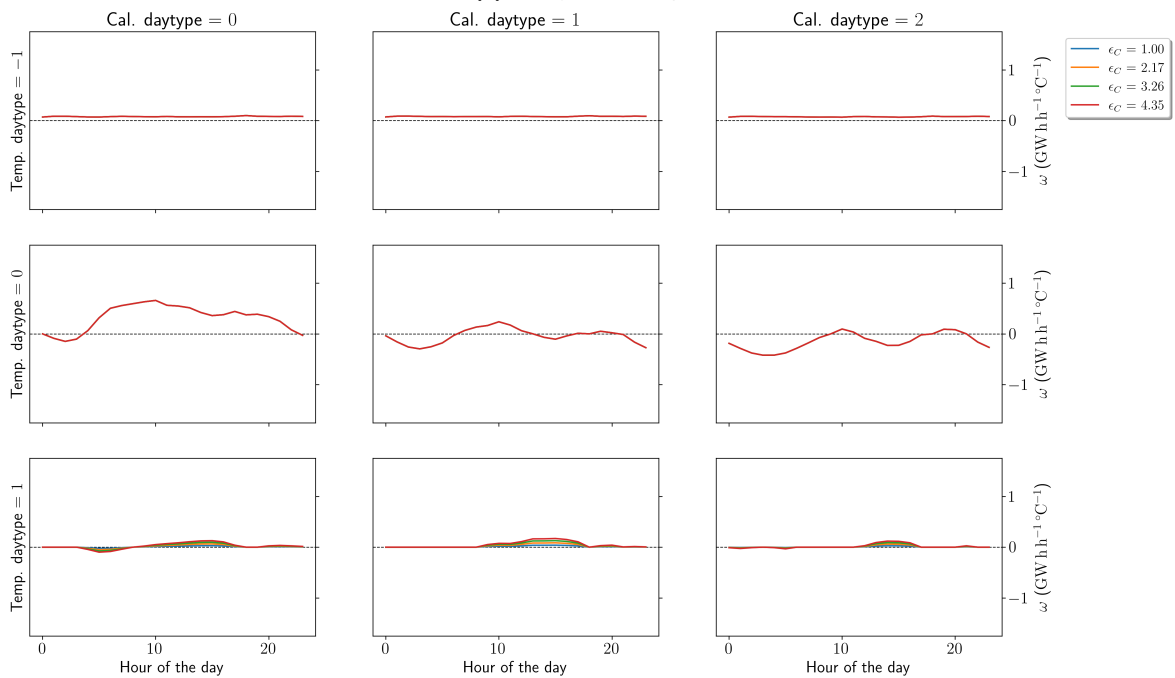
Figure B.4. Peak demand relative difference for the heating demand scenarios considered, per region.

B.1.2 Electric cooling scenarios

Model coefficients

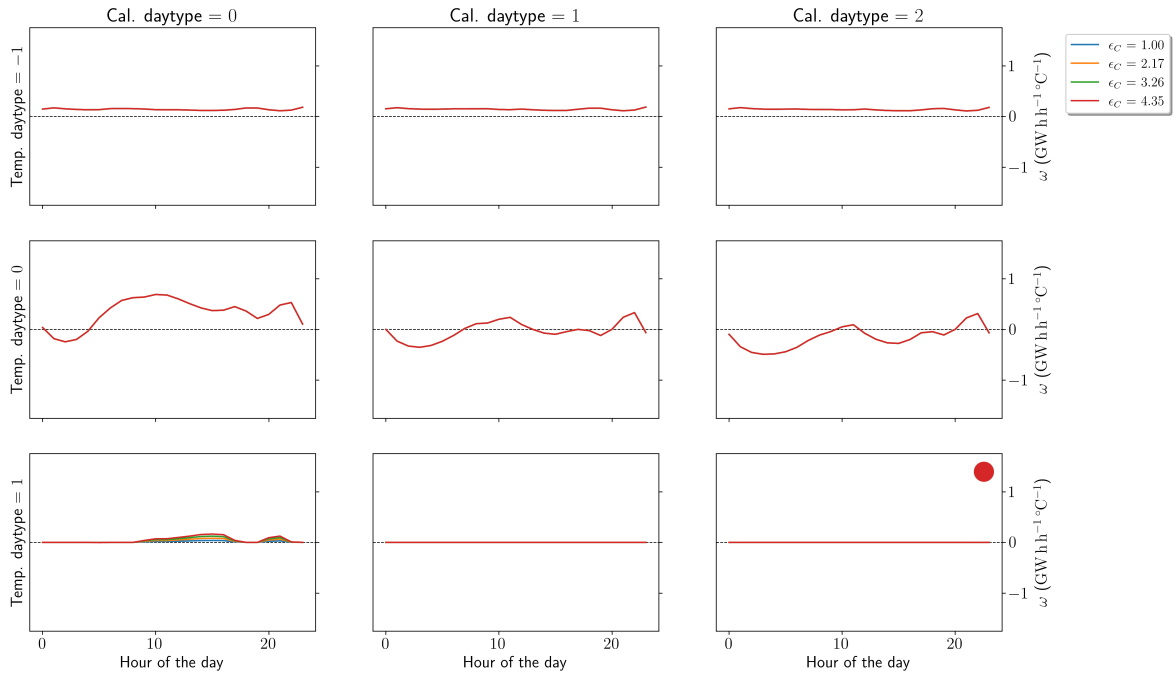


(a) Auvergne-Rhône-Alpes.

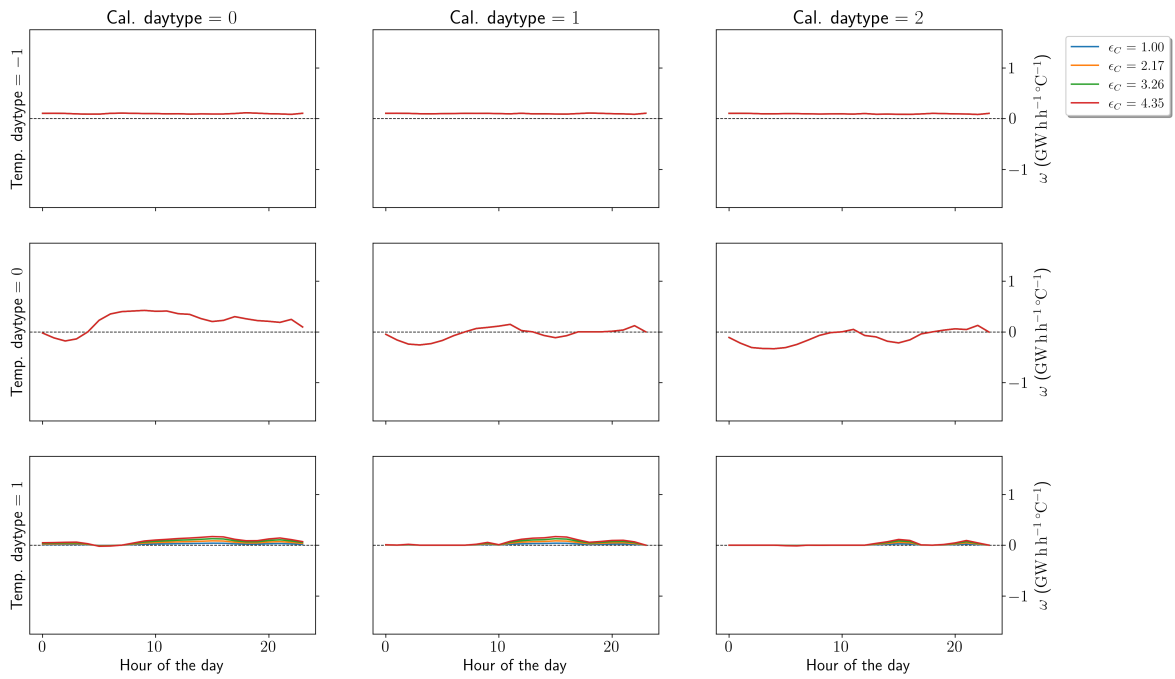


(b) Bourgogne-Franche-Comté.

Cont.

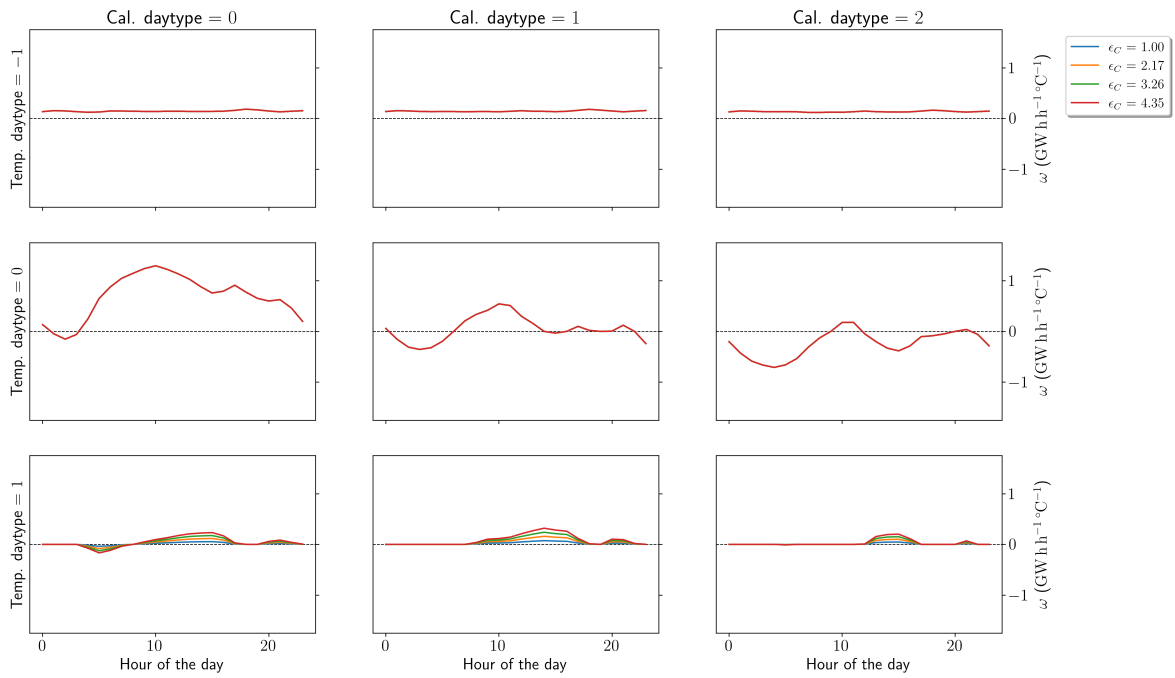


(c) Bretagne.

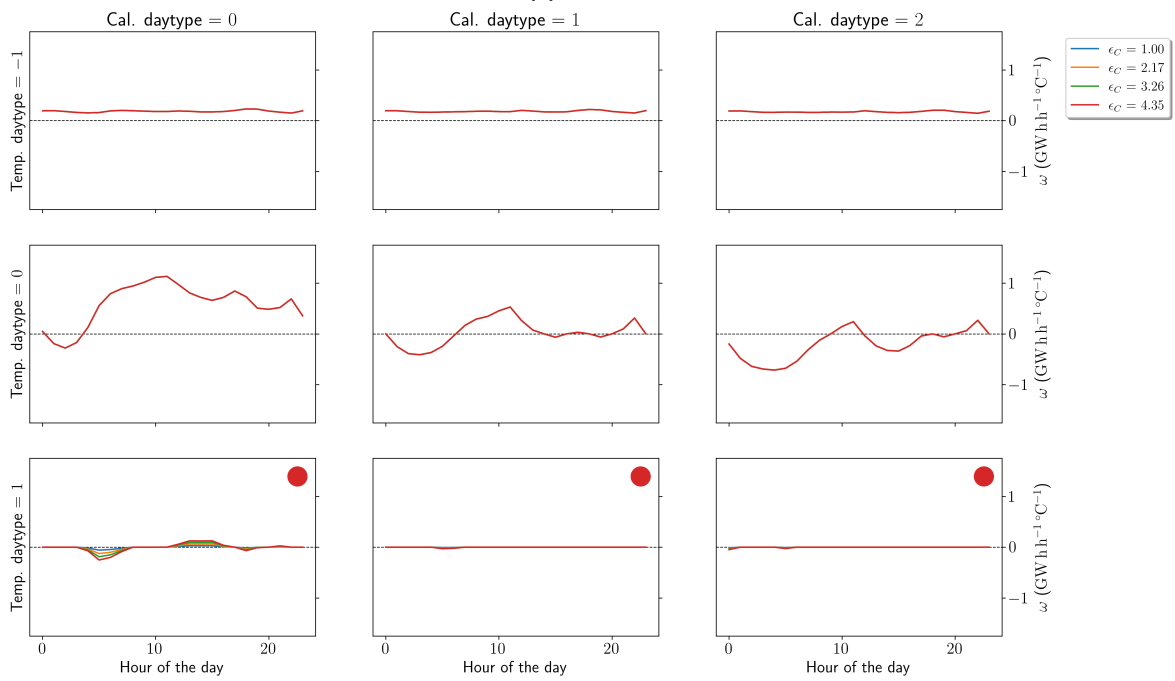


(d) Centre-Val de Loire.

Cont.

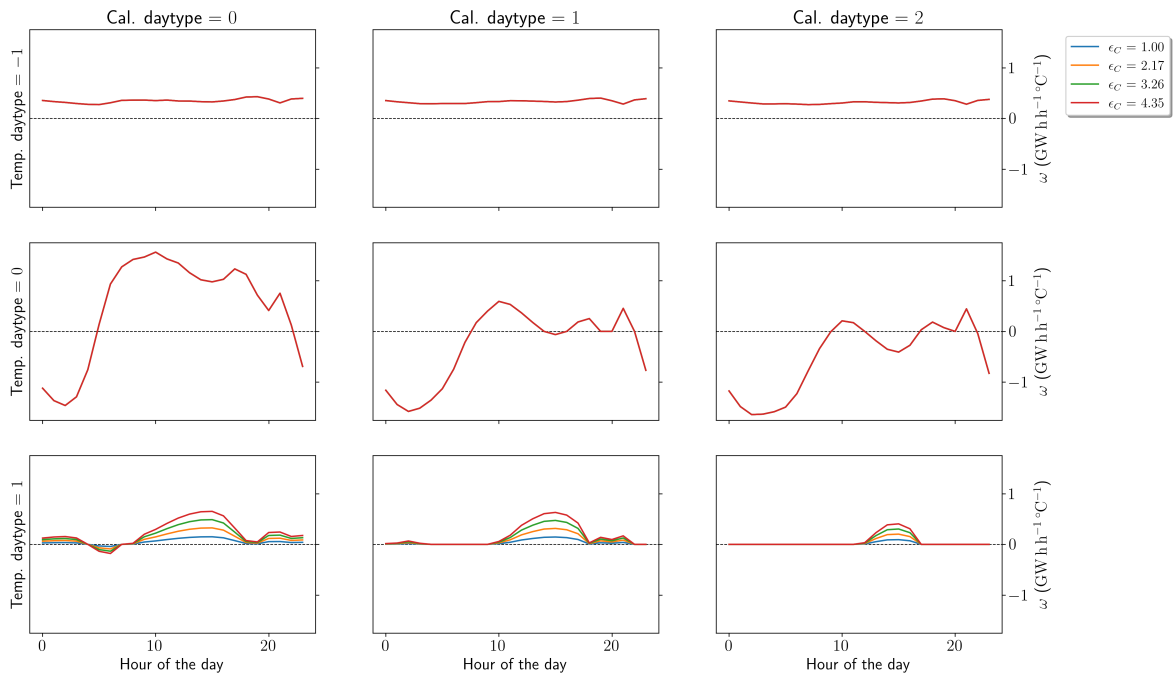


(e) Grand-Est.

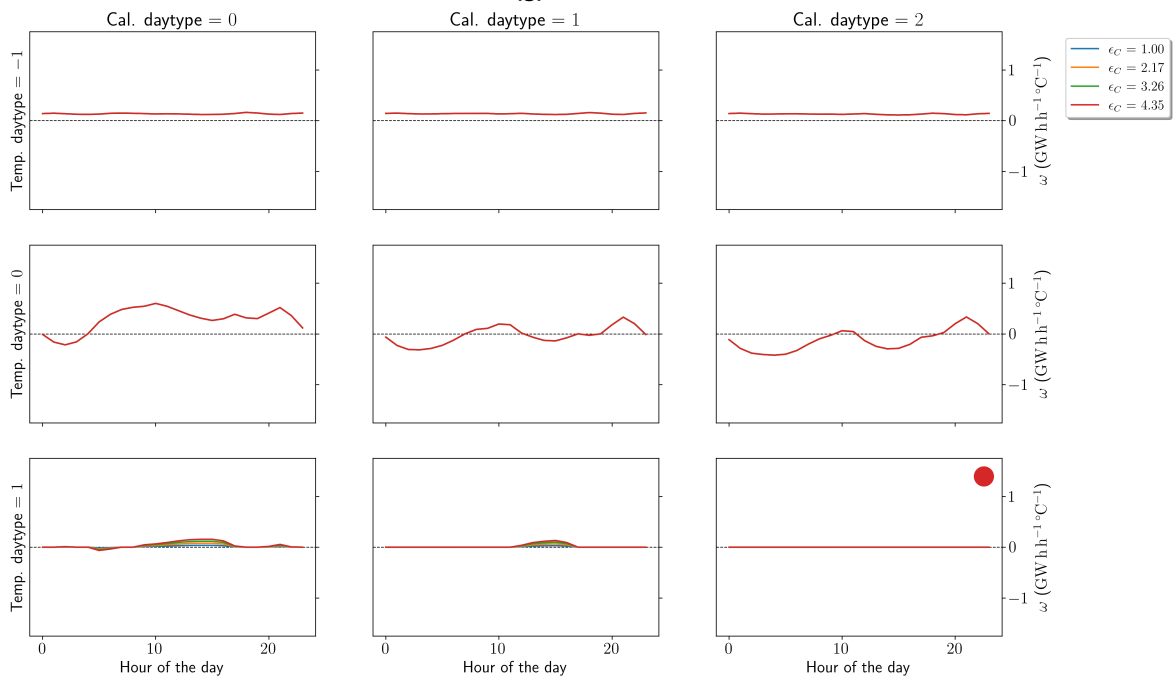


(f) Hauts-de-France.

Cont.

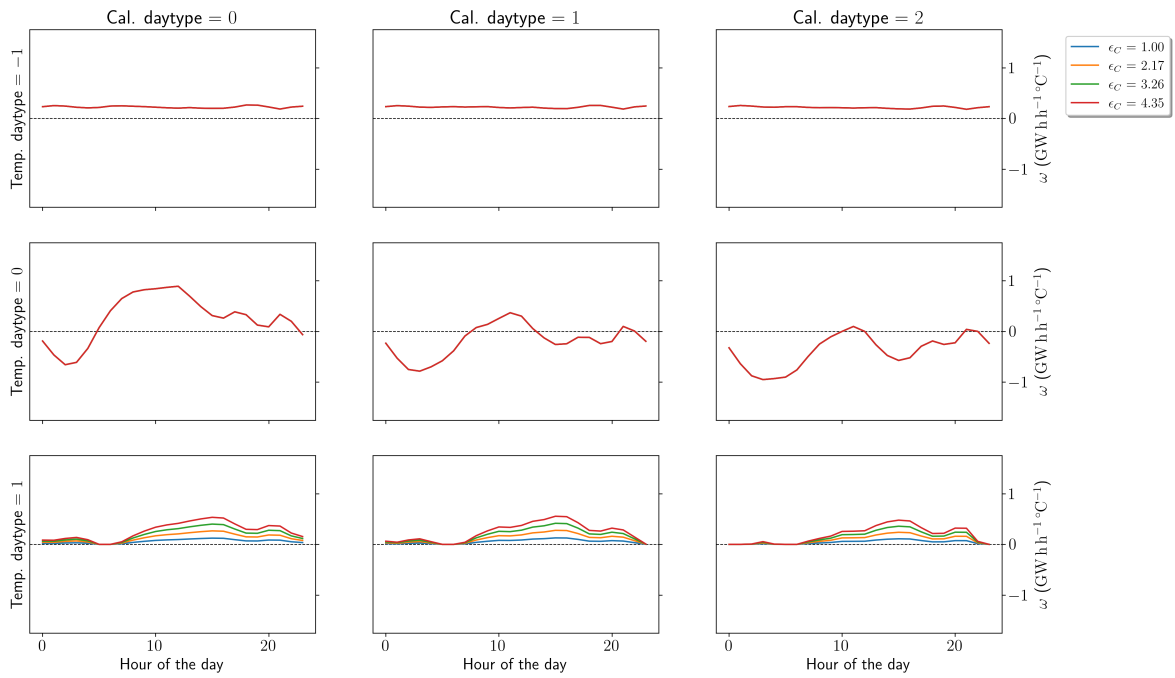


(g) Ile-de-France.

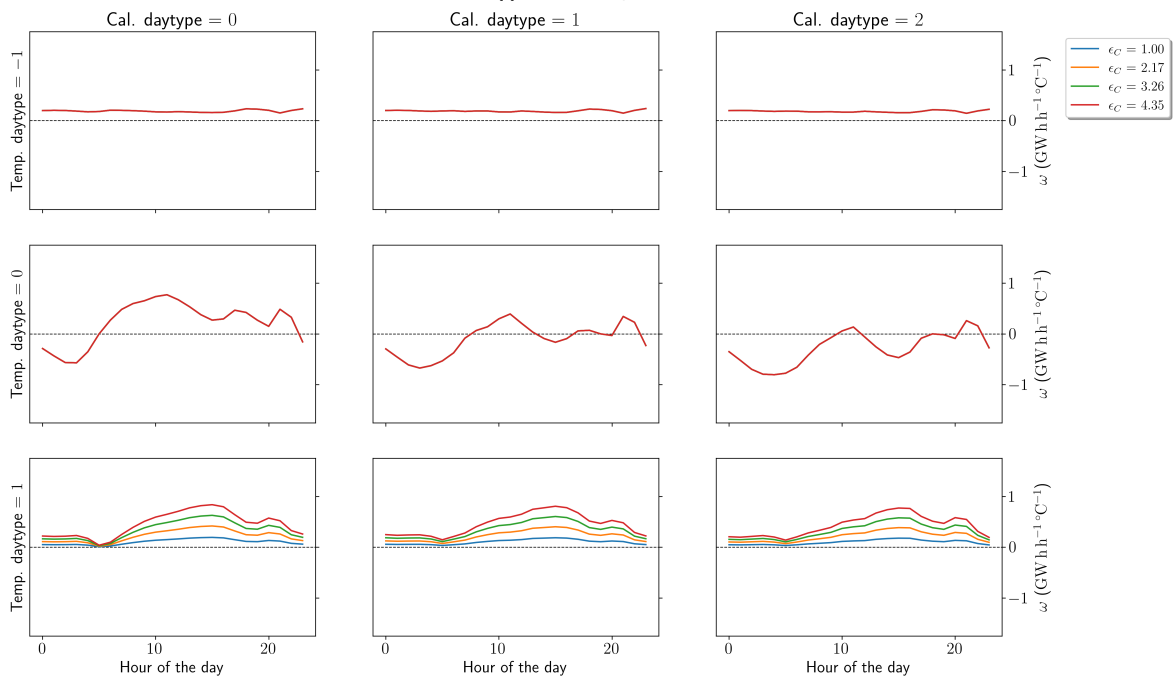


(h) Normandie.

Cont.



(i) Nouvelle-Aquitaine.



(j) Occitanie.

Cont.

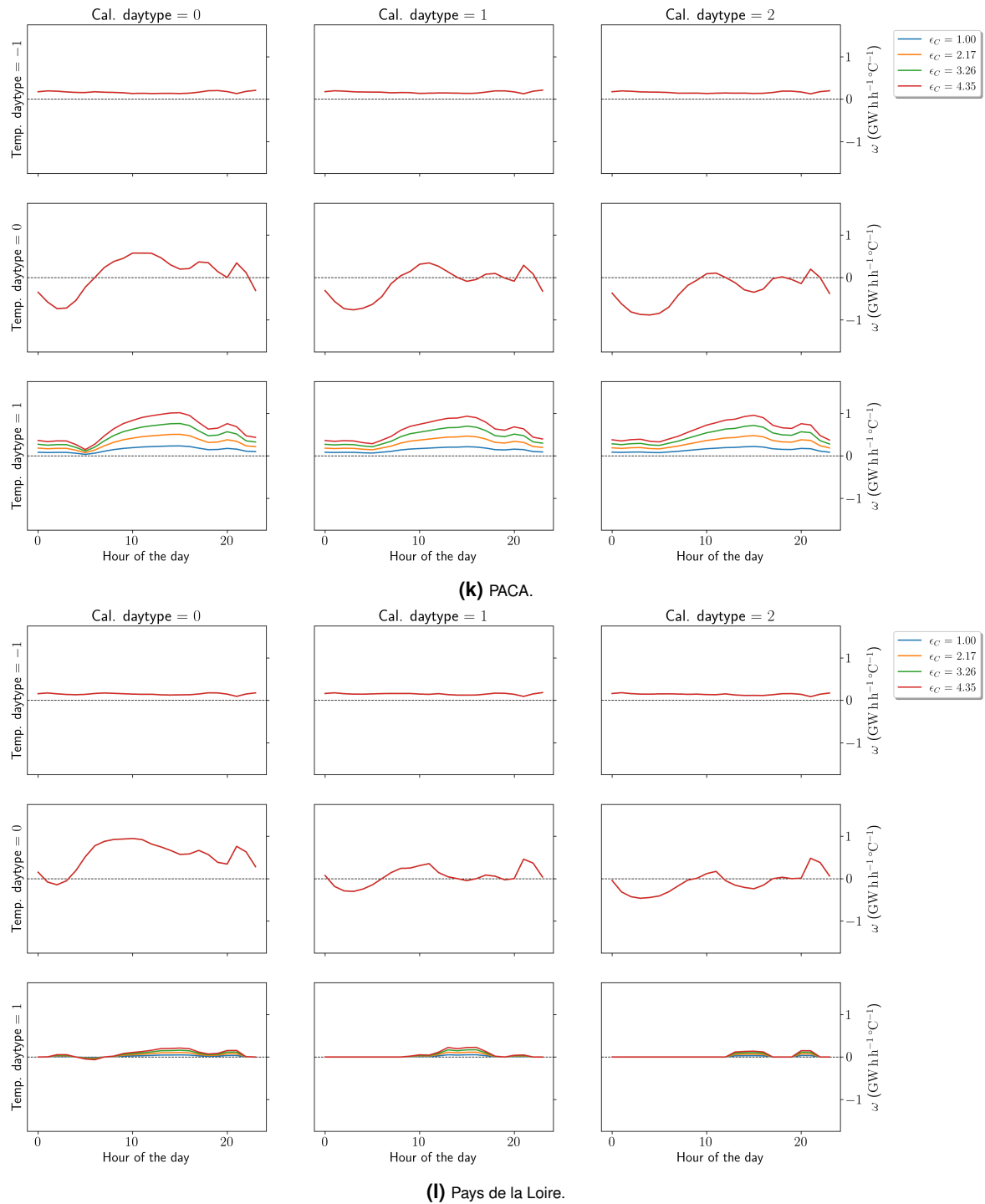


Figure B.5. Coefficients of the model for the cooling demand scenarios considered. Temp. daytype corresponds to whether the day is a heating day (-1), cooling day (1) or none of the two (0). Cal. daytype corresponds to whether the day is a working day (0), saturday (1) or sunday/holiday (2). Red dots on the upper right of the figure indicate an undesired model behavior (that the average over the hours of the day is negative).

Impacts on the demand

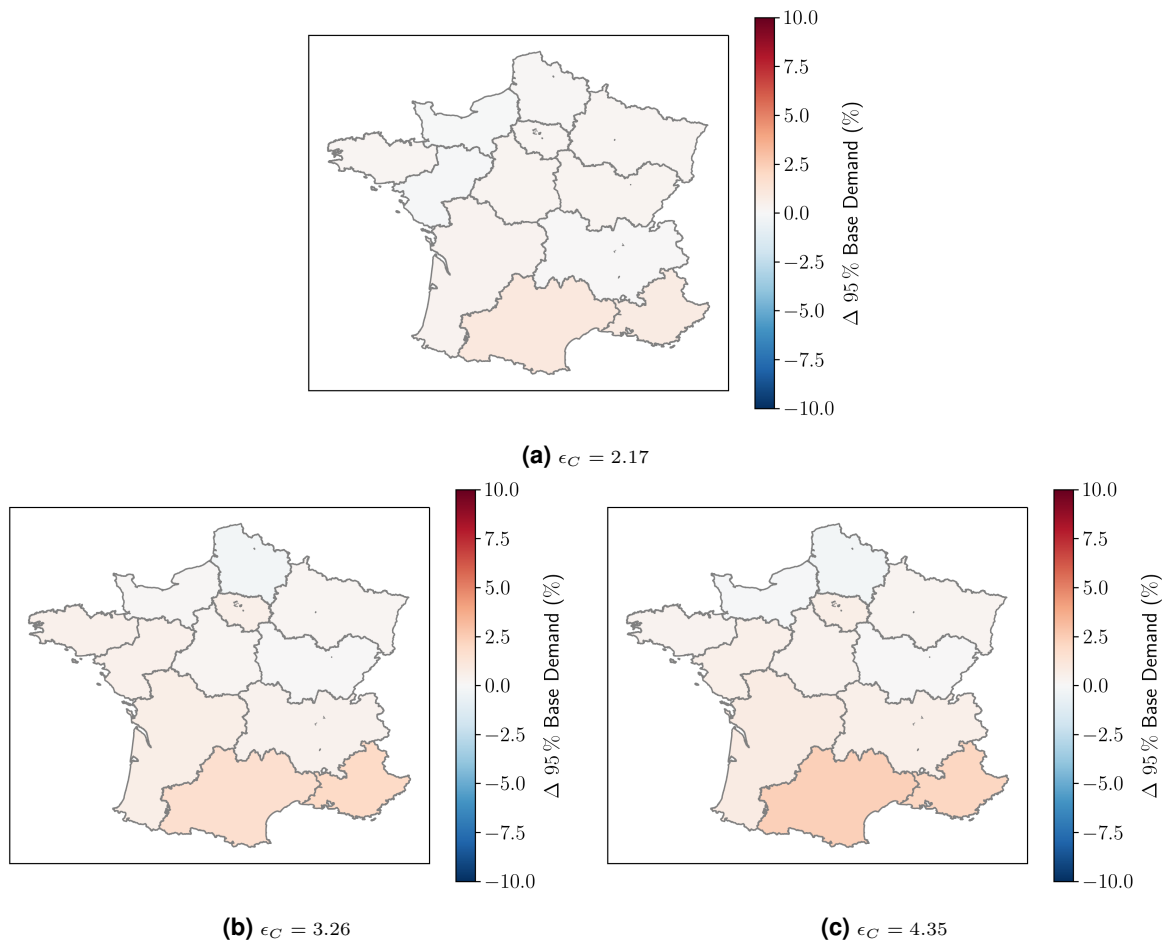


Figure B.6. Base demand relative difference for the cooling demand scenarios considered, per region.

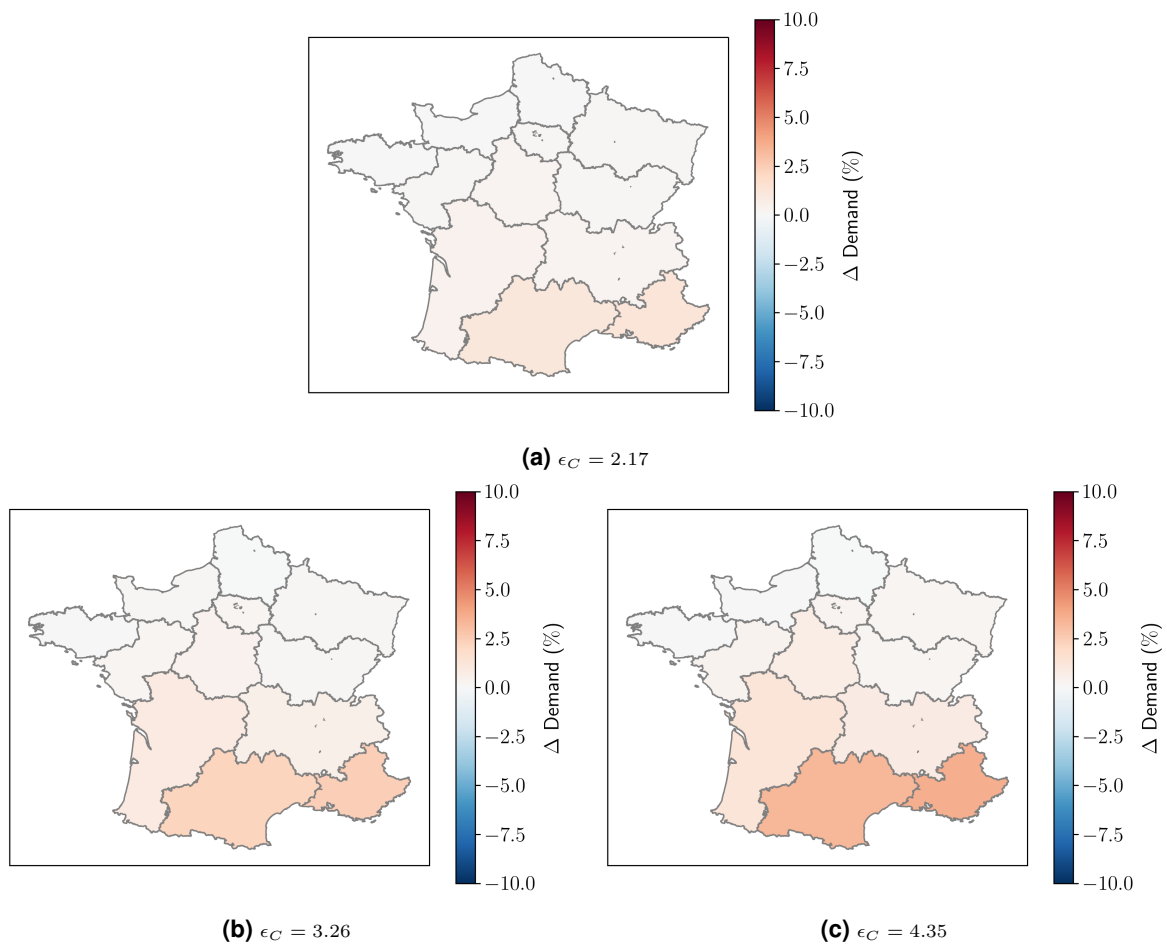


Figure B.7. Mean demand relative difference for the cooling demand scenarios considered, per region.

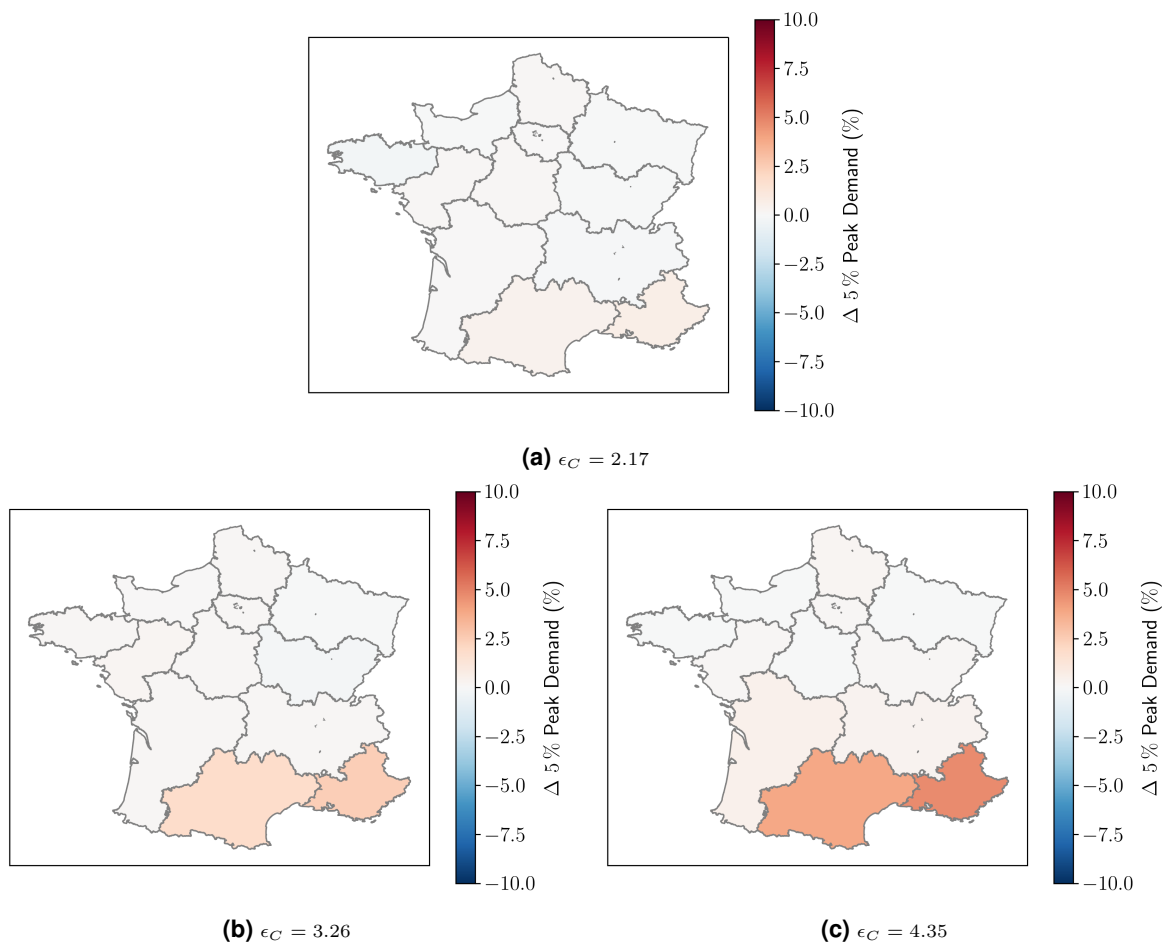


Figure B.8. Peak demand relative difference for the cooling demand scenarios considered, per region.

Appendix **C**

**Compound effect of socioeconomic
and climate change —
Supplementary Information**

The cost of unpreparedness: adaptation potential
facing compound socioeconomic and climate
change in wind and solar mix planning exercises —
Supplementary Information.

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philippe.drobinski@lmd.ipsl.fr;

1 Model domain and setup

1.1 Area of study

The area of study corresponds to metropolitan France, subdivided into its administrative regions. A map of the area of study is presented Figure 1.

1.2 Climate data curation

Climate data curation steps are needed to ensure a consistent dataset. They are recapitulated in Table 1.

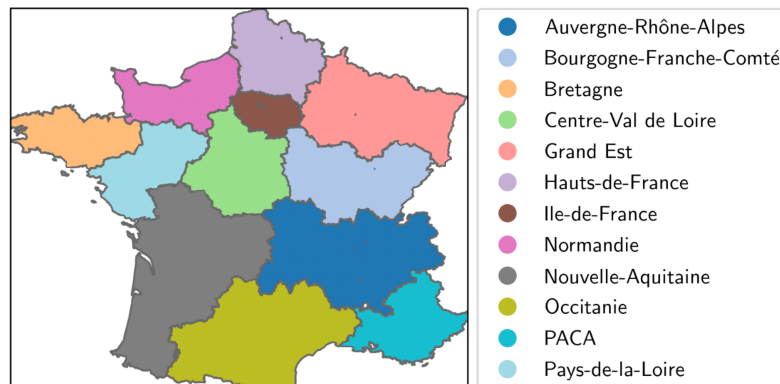


Fig. 1: Area of study: detail of french administrative regions.

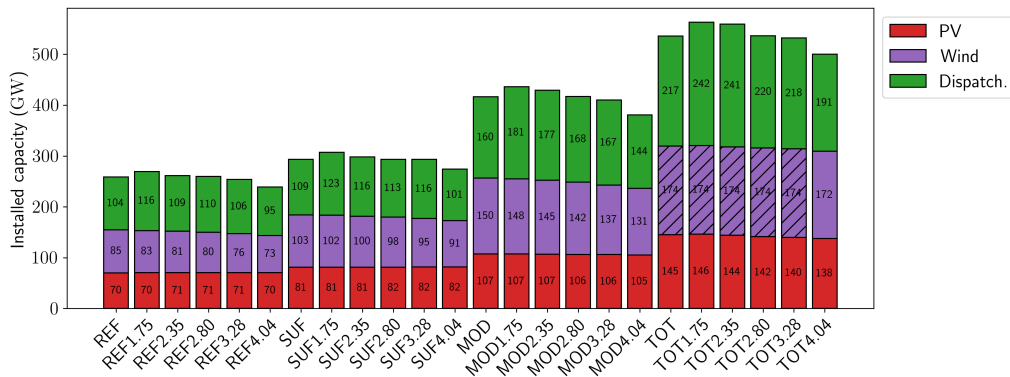
Table 1: Data curation steps needed in the study.

GCM/RCM pair ID	Issue	Workaround
0	-	-
1	calendar is 360 days downloaded va100m file for year 2093 cannot be read downloaded va100m file for year 2094 cannot be read downloaded va100m file for year 2095 cannot be read downloaded va100m file for year 2096 cannot be read downloaded va100m file for year 2097 cannot be read downloaded va100m file for year 2098 cannot be read year 2099 missing for ua100m, va100m, tas, rsds	convert to 365/366 days calendar replace it with year 2089 replace it with year 2090 replace it with year 2091 replace it with year 2092 replace it with year 2089 replace it with year 2090 replace it with year 2095 or 2091
2	downloaded va100m file for year 2099 cannot be read va100m field show absurdly high magnitude values	replace it with year 2098 set a cutoff value
3	downloaded ua100m file for year 2070 cannot be read downloaded ua100m file for year 2092 cannot be read	replace it with year 2066 replace it with year 2088
4	year 2047 missing for ua100m, va100m, tas, rsds	replace it with year 2046
5	downloaded ua100m file for year 2097 cannot be read downloaded ua100m file for year 2098 cannot be read downloaded ua100m file for year 2099 cannot be read	replace it with year 2093 replace it with year 2094 replace it with year 2095

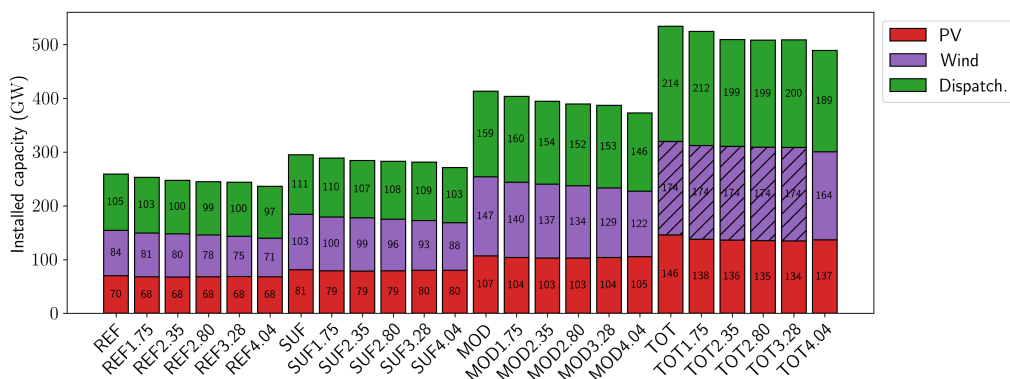
GCM: Global Climate Model. RCM: Regional Climate Model.

2 Computed optimal wind and solar mixes

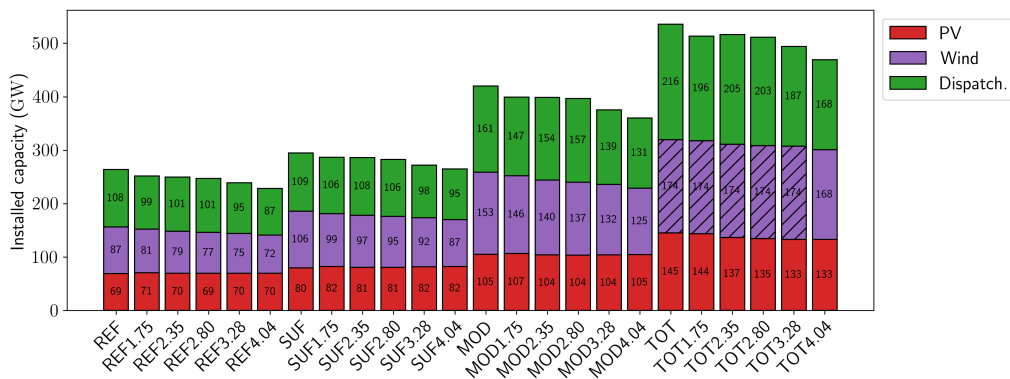
2.1 National level



(a) ICHEC-EC-EARTH + COSMO.

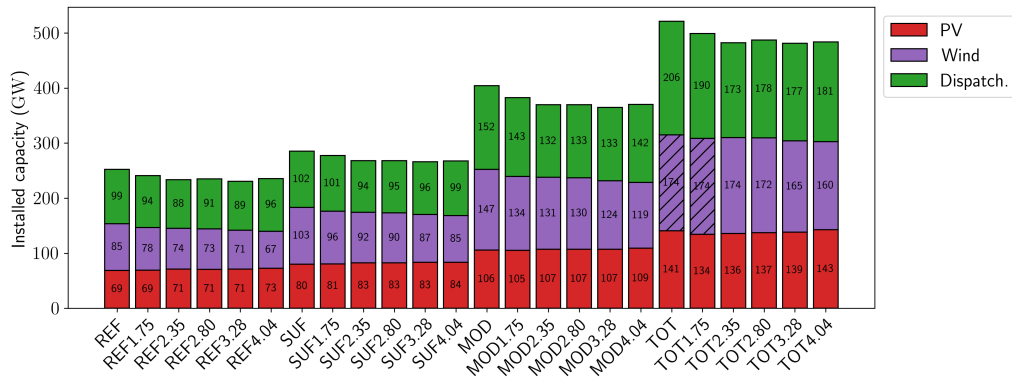


(b) MPI-ESM + COSMO.

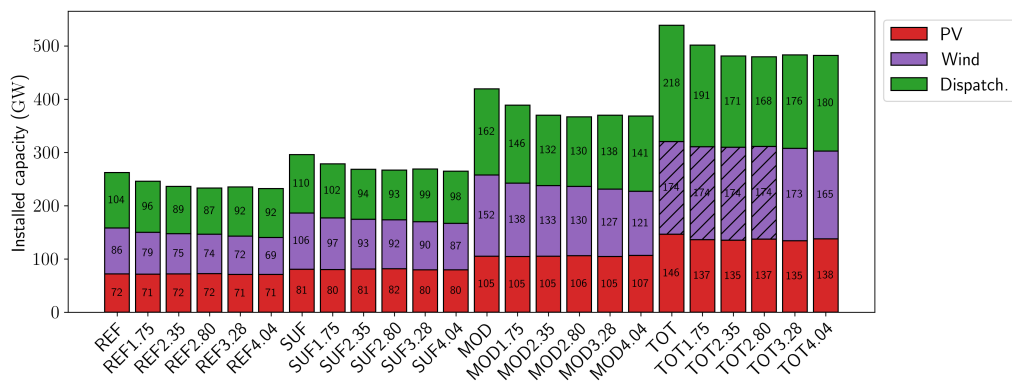


(c) CNRM-CM5 + COSMO.

Fig. 2: Cont.



(d) MOHC-HADGEM2 + COSMO.



(e) MOHC-HADGEM2 + ALADIN63.

Fig. 2: Optimal wind and solar mixes and necessary dispatchable capacity aggregated at the national level for all models of the ensemble (but CNRM-CM5 + ALADIN63). Bars are hatched when maximal installable capacities are reached. PV stands for solar photovoltaic.

2.2 Regional level

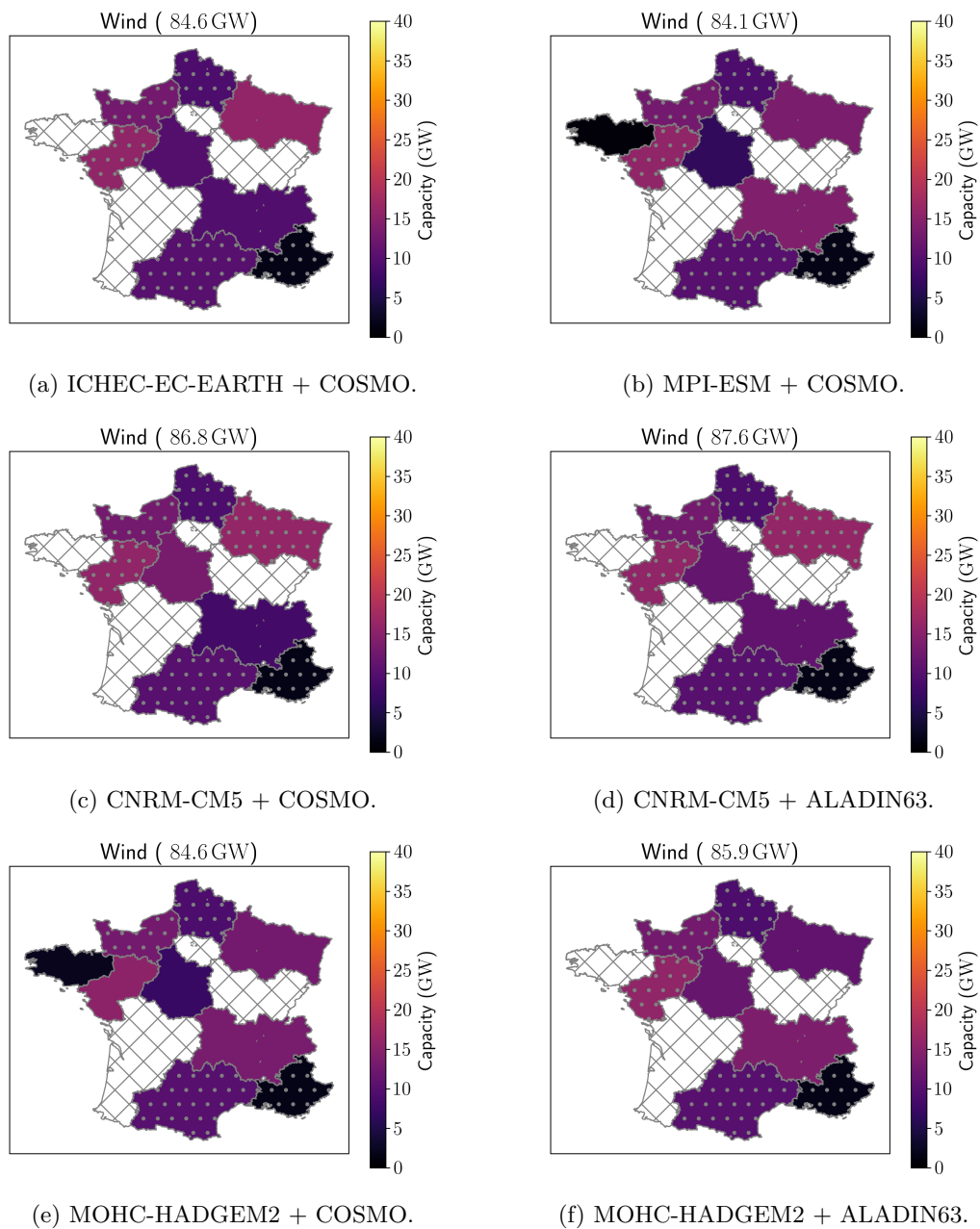


Fig. 3: Optimal wind installed capacity for the REF scenario. Regions where no capacity is installed are hatched while regions where maximum installable capacity is attained are dotted.

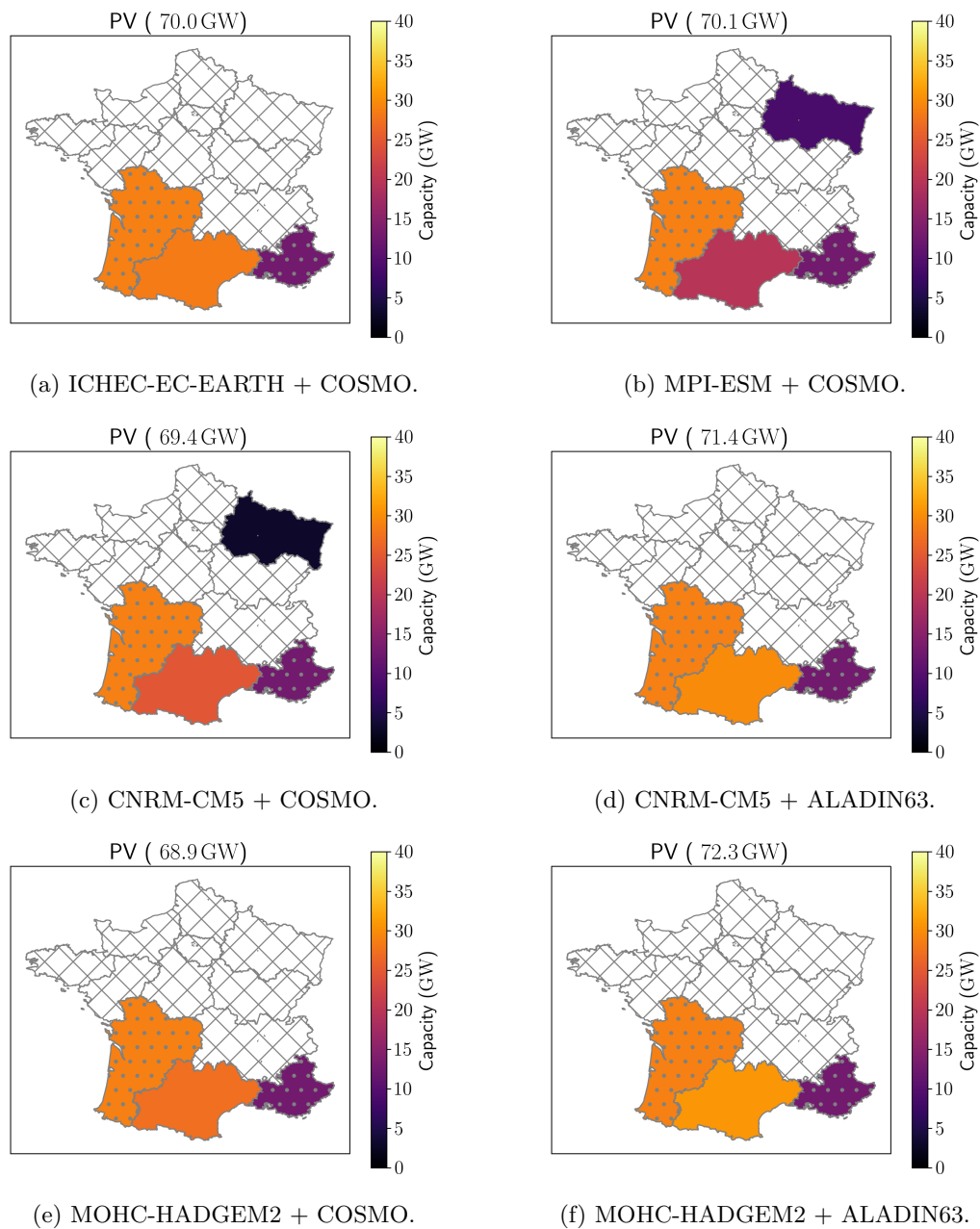
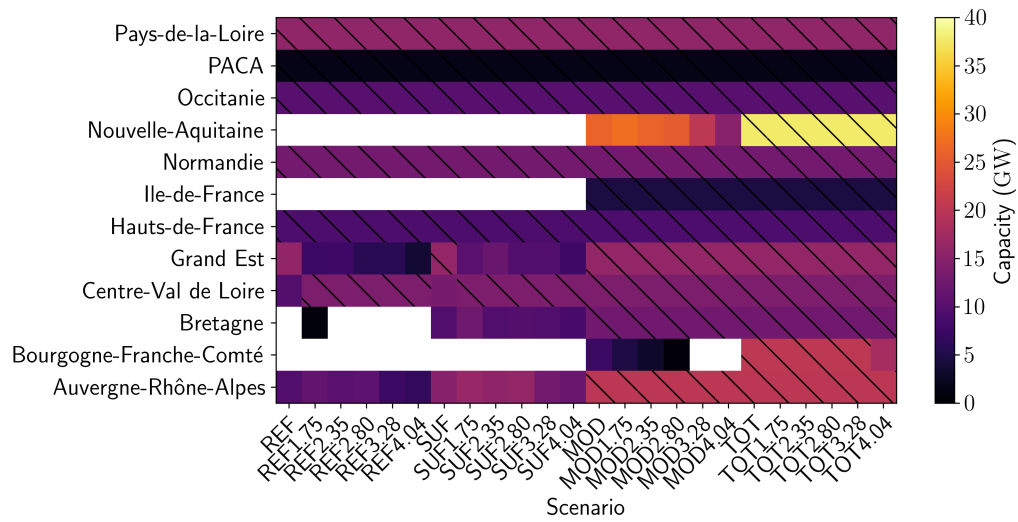
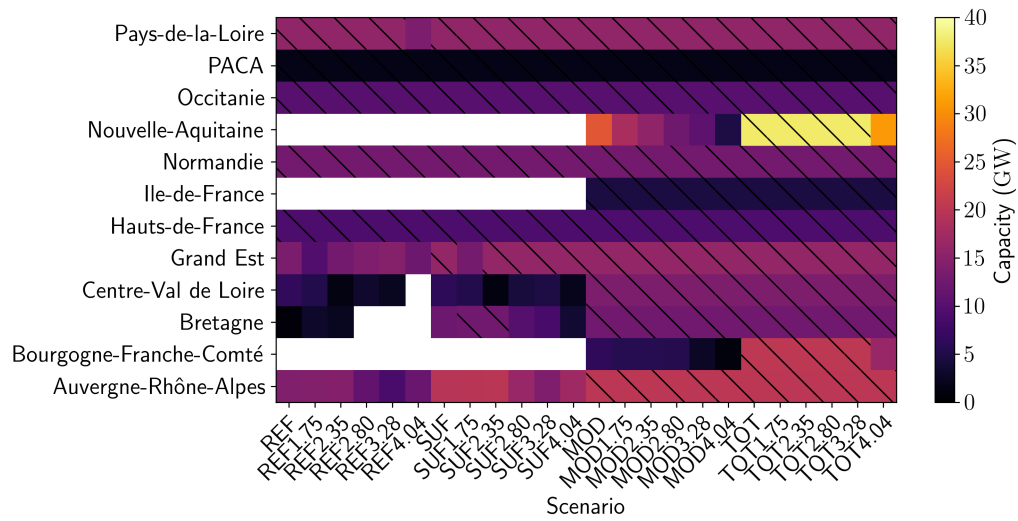


Fig. 4: Optimal solar installed capacity for the REF scenario. Regions where no capacity is installed are hatched while regions where maximum installable capacity is attained are dotted.

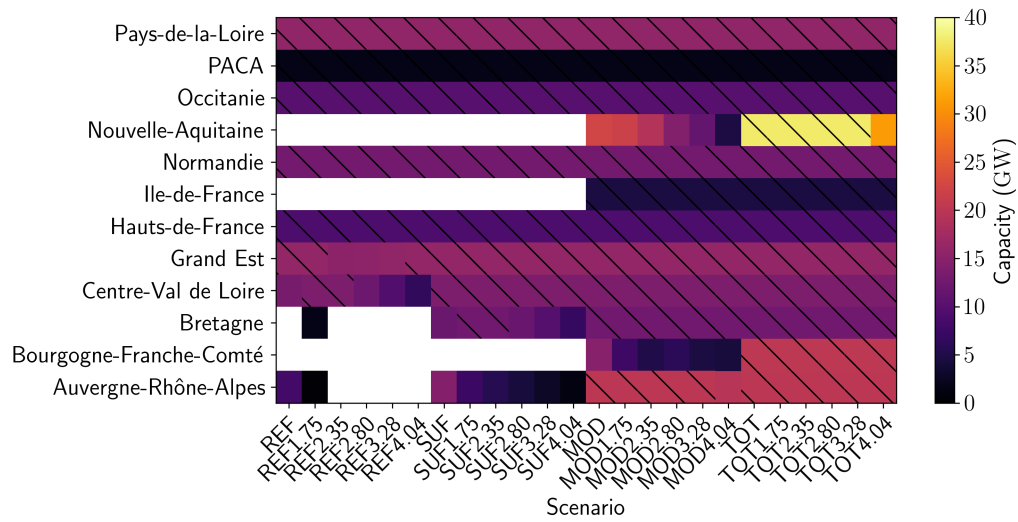


(a) ICHEC-EC-EARTH + COSMO.

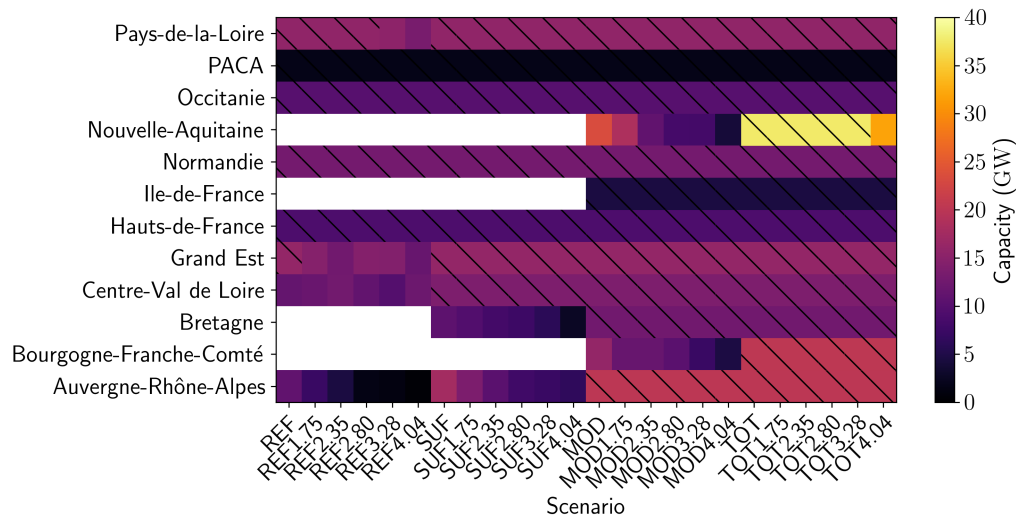


(b) MPI-ESM + COSMO.

Fig. 5: Cont.

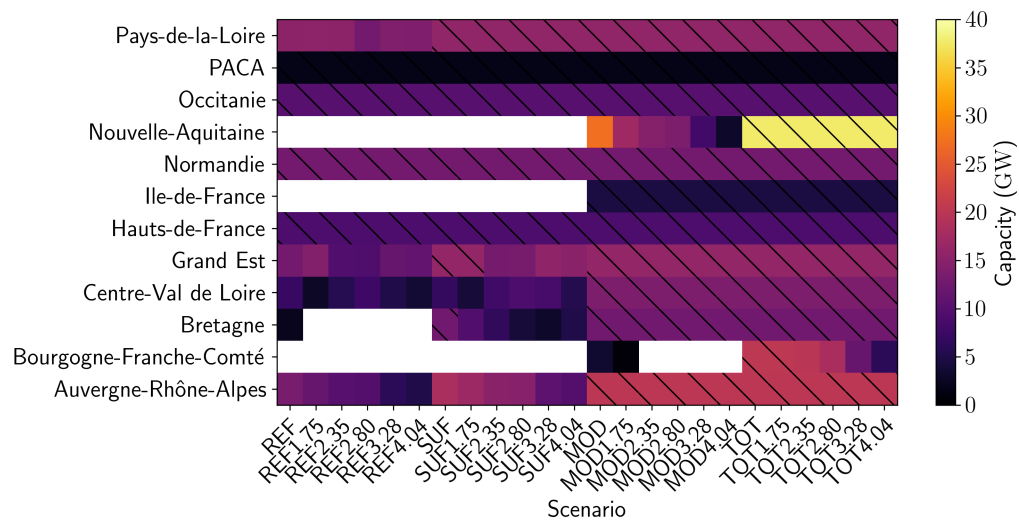


(c) CNRM-CM5 + COSMO.

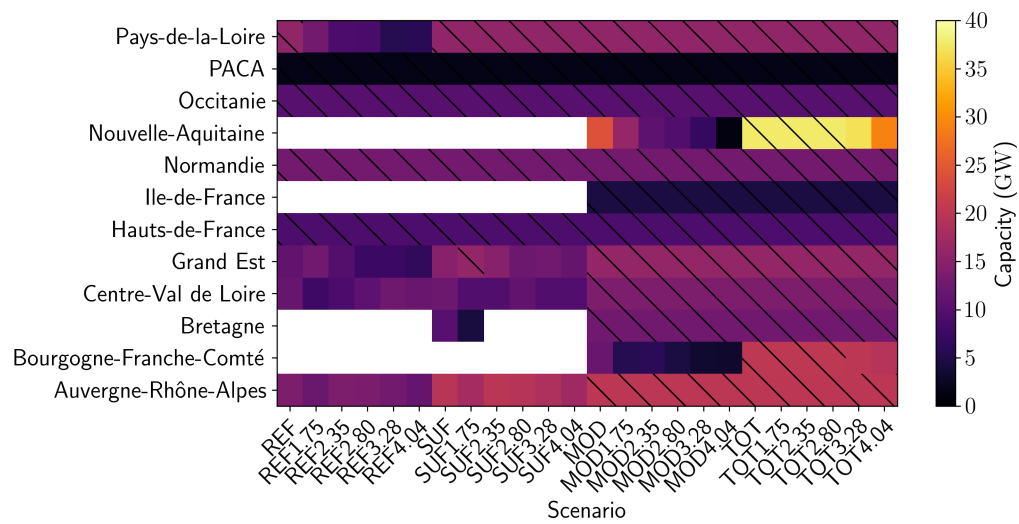


(d) CNRM-CM5 + ALADIN63.

Fig. 5: Cont.

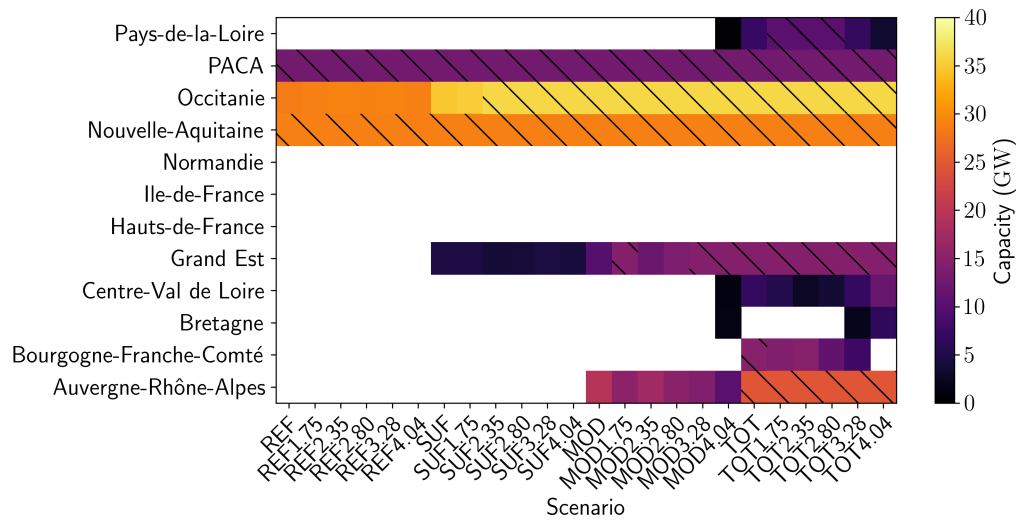


(e) MOHC-HADGEM2 + COSMO.

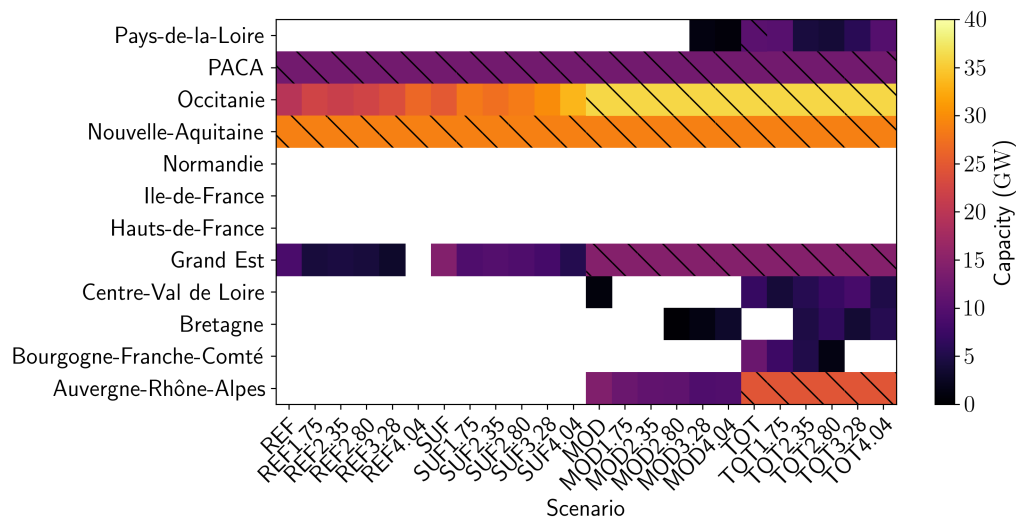


(f) MOHC-HADGEM2 + ALADIN63.

Fig. 5: Optimal wind installed capacity per region and scenario. White regions indicate that no capacity is installed, whereas hatched areas indicate that a region's maximum installable capacity has been reached.

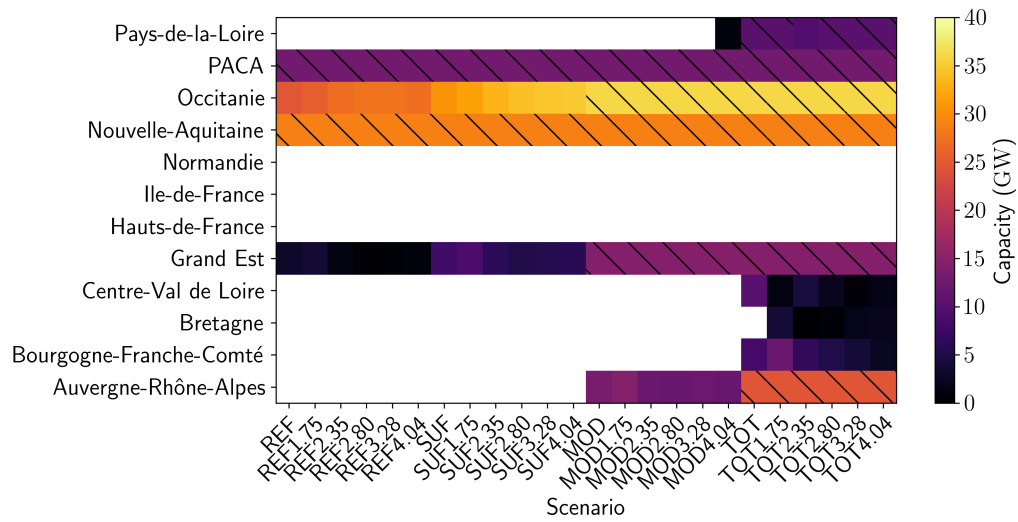


(a) ICHEC-EC-EARTH + COSMO.

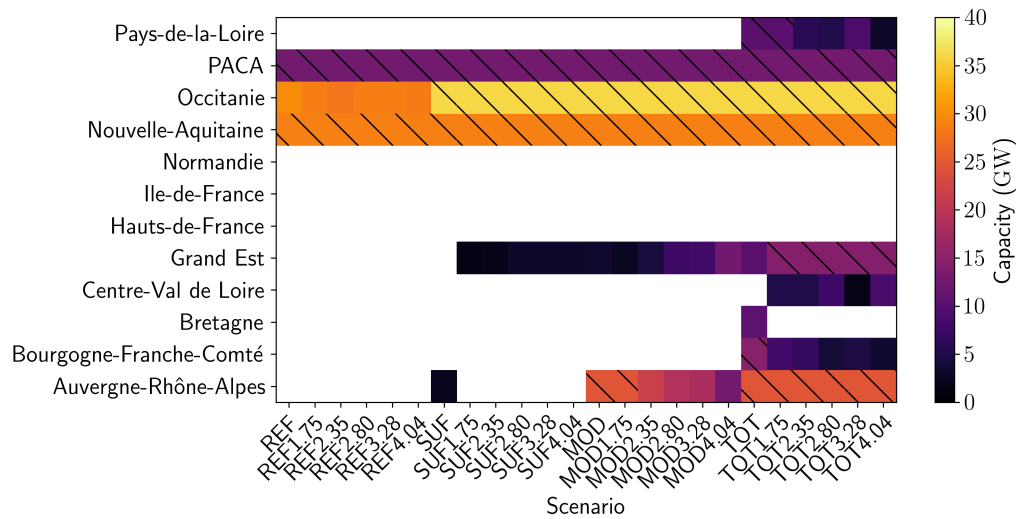


(b) MPI-ESM + COSMO.

Fig. 6: Cont.

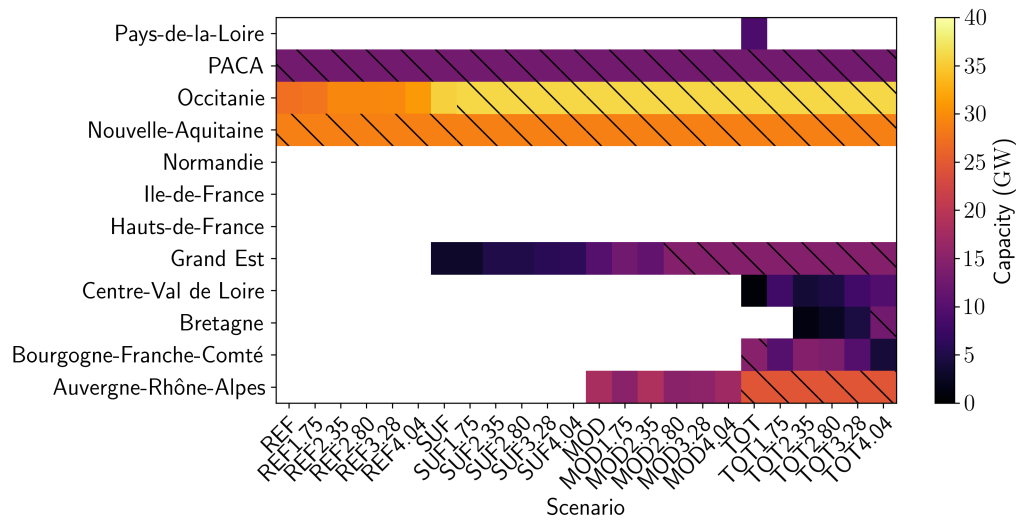


(c) CNRM-CM5 + COSMO.

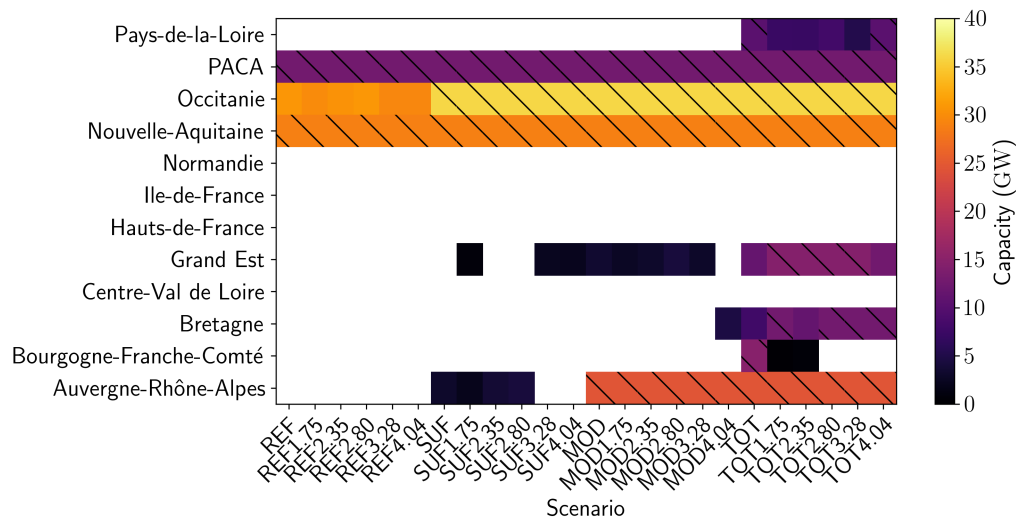


(d) CNRM-CM5 + ALADIIN63.

Fig. 6: Cont.

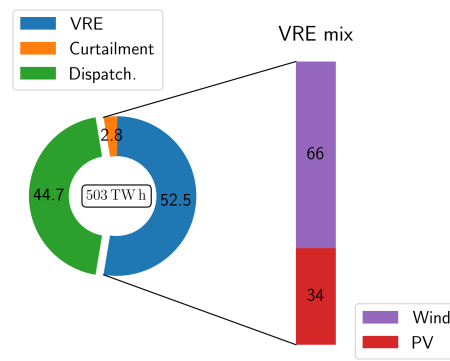


(e) MOHC-HADGEM2 + COSMO.

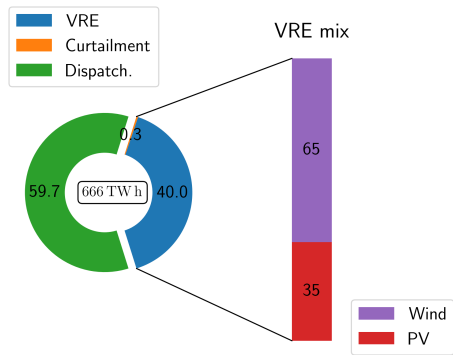


(f) MOHC-HADGEM2 + ALADIN63.

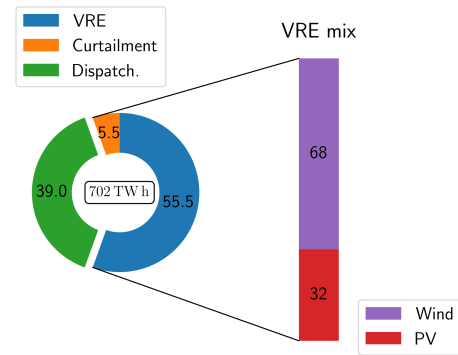
Fig. 6: Optimal solar installed capacity per region and scenario. White regions indicate that no capacity is installed, whereas hatched areas indicate that a region’s maximum installable capacity has been reached.



(a) REF scenario, *REF* mix (ICHEC-EC-EARTH + COSMO).



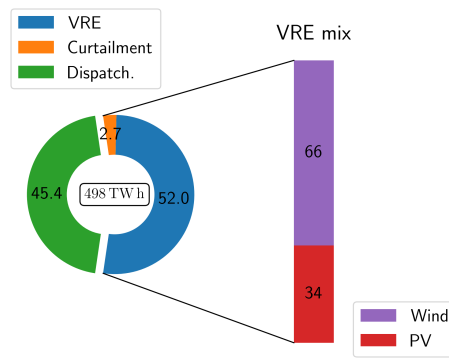
(b) MOD2.35 scenario, *REF* mix (ICHEC-EC-EARTH + COSMO).



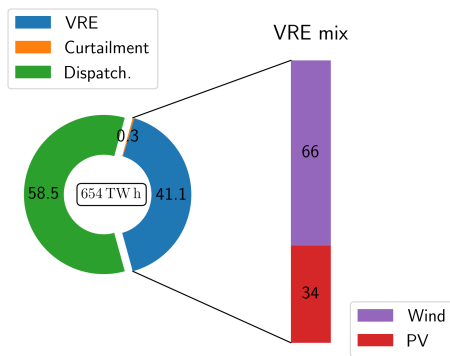
(c) MOD2.35 scenario, *MOD2.35* mix (ICHEC-EC-EARTH + COSMO).

Fig. 7: Cont.

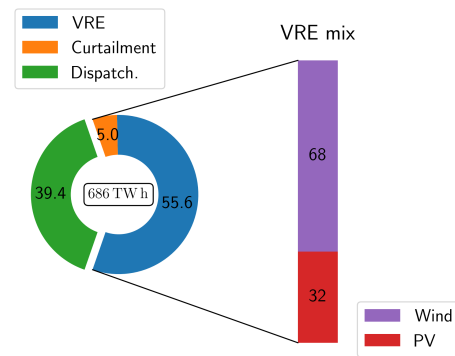
3 Impacts on generation



(d) REF scenario, *REF* mix (MPI-ESM + COSMO).

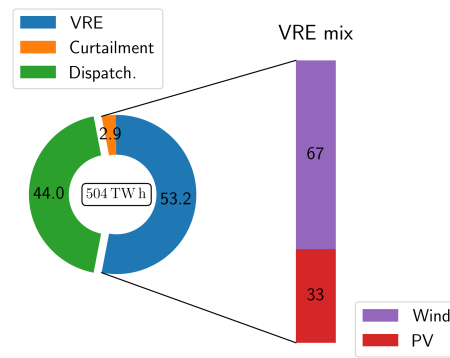


(e) MOD2.35 scenario, *REF* mix (MPI-ESM + COSMO).

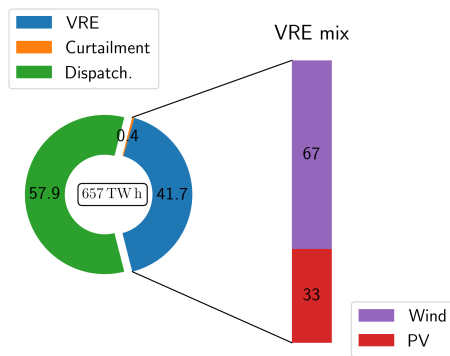


(f) MOD2.35 scenario, *MOD2.35* mix (MPI-ESM + COSMO).

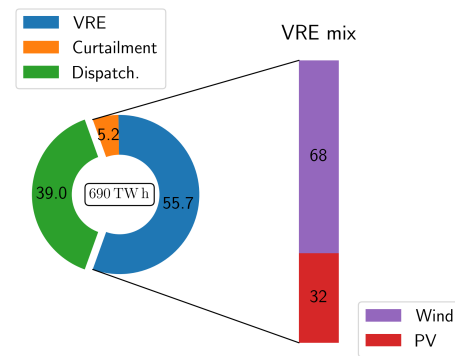
Fig. 7: Cont.



(g) REF scenario, *REF* mix (CNRM-CM5 + COSMO).

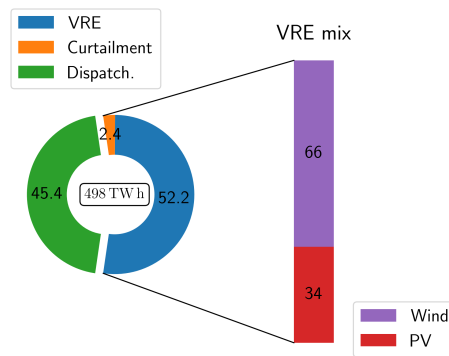


(h) MOD2.35 scenario, *REF* mix (CNRM-CM5 + COSMO).

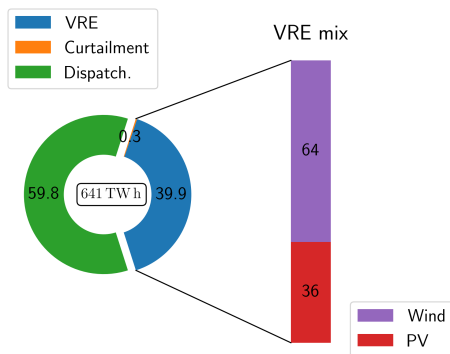


(i) MOD2.35 scenario, *MOD2.35* mix (CNRM-CM5 + COSMO).

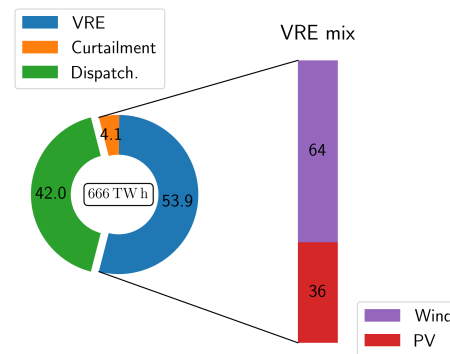
Fig. 7: Cont.



(j) REF scenario, *REF* mix (MOHC-HADGEM2 + COSMO).

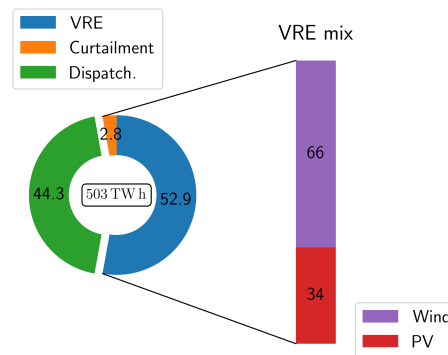


(k) MOD2.35 scenario, *REF* mix (MOHC-HADGEM2 + COSMO).

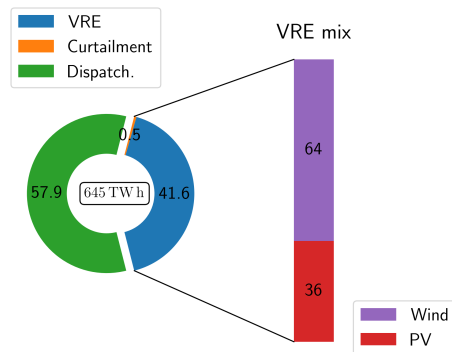


(l) MOD2.35 scenario, *MOD2.35* mix (MOHC-HADGEM2 + COSMO).

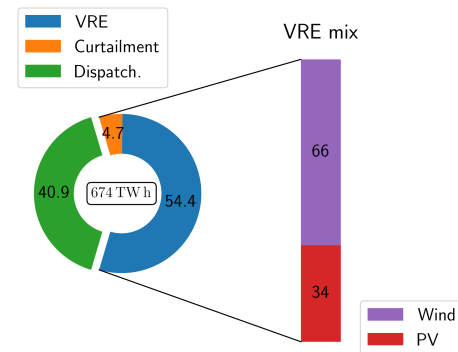
Fig. 7: Cont.



(m) REF scenario, *REF* mix
(MOHC-HADGEM2 + ALADIN63).



(n) MOD2.35 scenario, *REF* mix
(MOHC-HADGEM2 + ALADIN63).

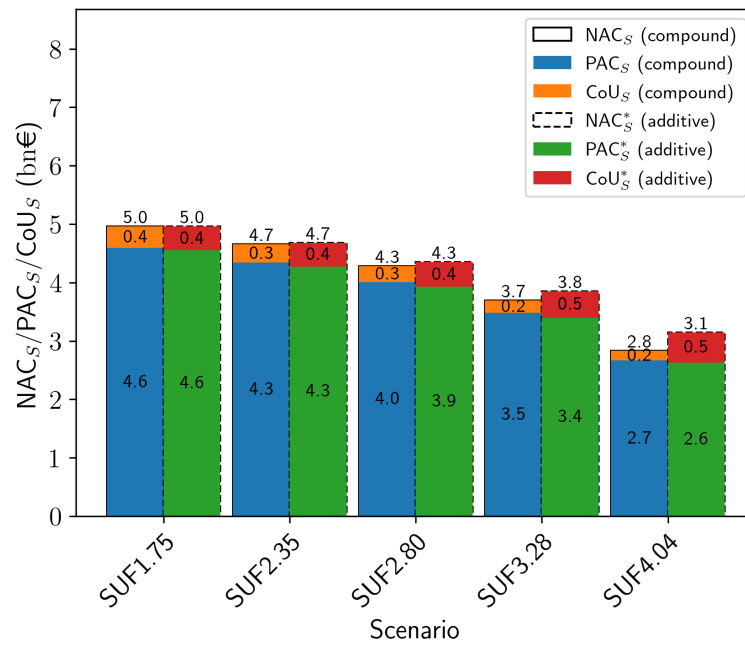


(o) MOD2.35 scenario, *MOD2.35* mix
(MOHC-HADGEM2 + ALADIN63).

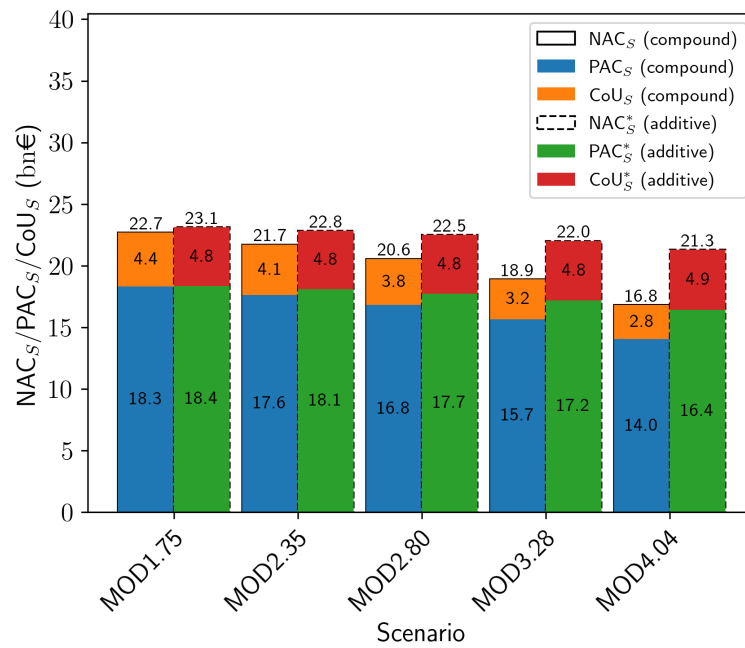
Fig. 7: Total generation over the 30 year period for (a, d, g, j, m) the reference conditions (REF scenario, *REF* mix) and two cases showing either (b, e, h, k, n) non-adaptation (MOD2.35 scenario, *REF* mix), and (c, f, i, l, o) perfect adaptation (MOD2.35 scenario, *MOD2.35* mix) strategies. Results for all models of the ensemble but CNRM-CM5 + ALADIN63. The number within the pie chart corresponds to the average yearly generation. All other numbers are percentages.

4 Additive vs. compound effect



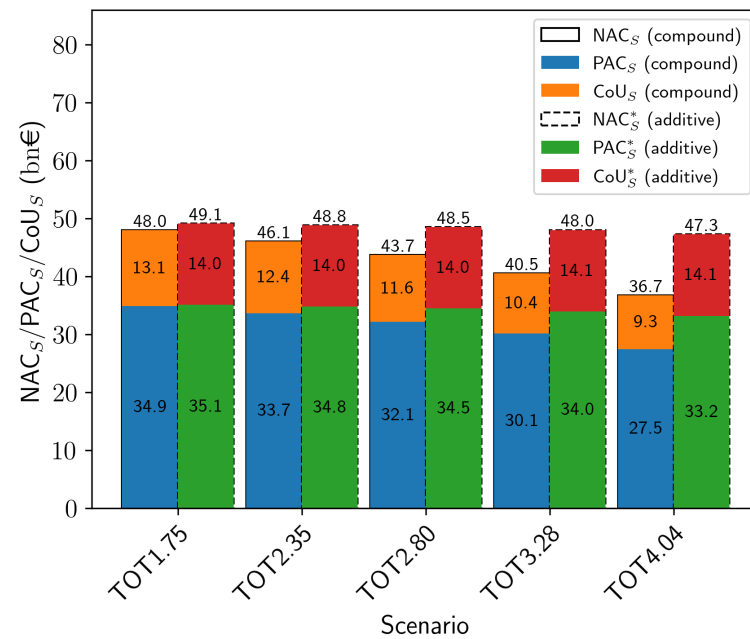


(a)



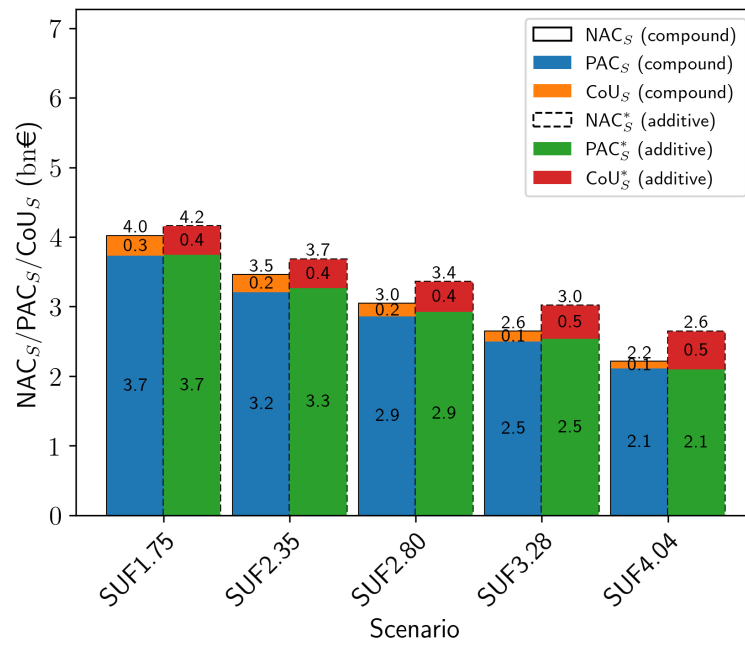
(b)

Fig. 8: Cont.

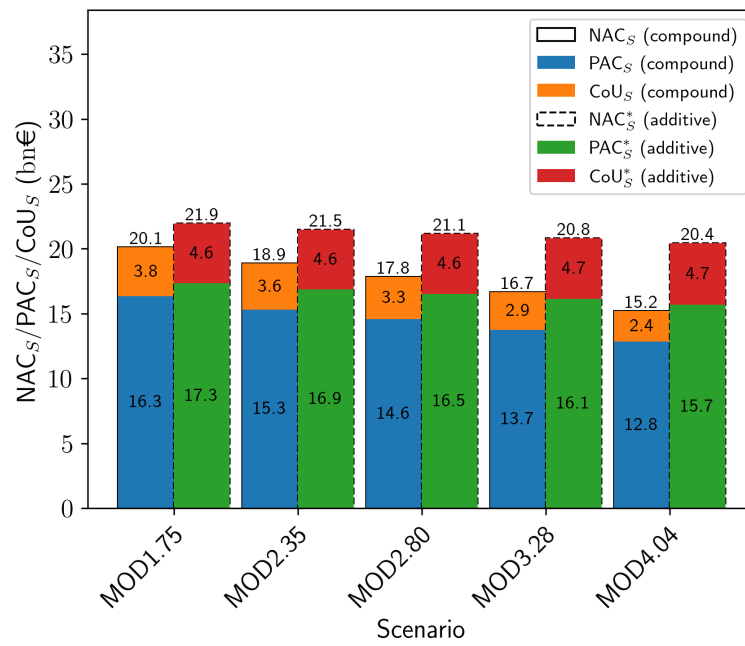


(c)

Fig. 8: Adaptation metrics under the compound or additive impact of socioeconomic and climate change. Non-adaptation costs (NAC) are shown as full (compound effect) or dashed (additive effect) empty bars, perfect adaptation costs (PAC) are shown in blue (compound effect) or green (additive effect) bars, while the cost of unpreparedness (CoU) is shown in orange (compound effect) or in red (additive effect). All results for model pair ICHEC-EC-EARTH + COSMO.

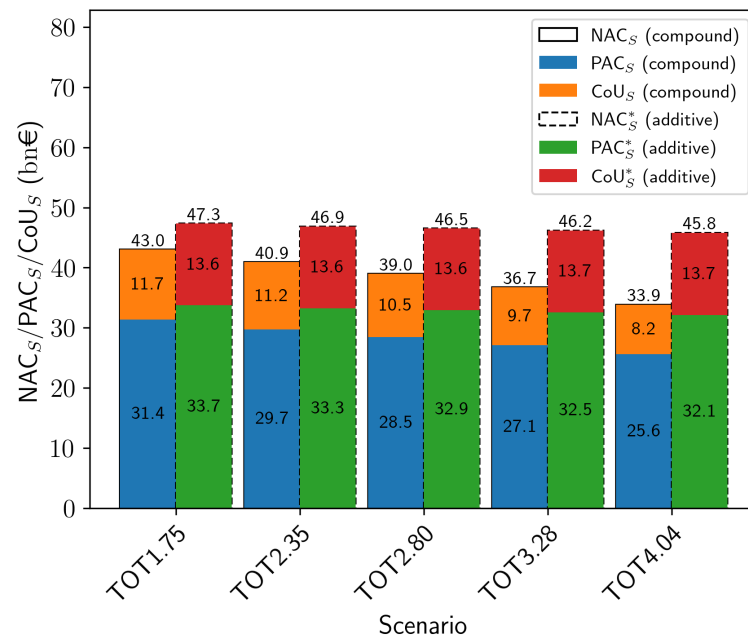


(a)



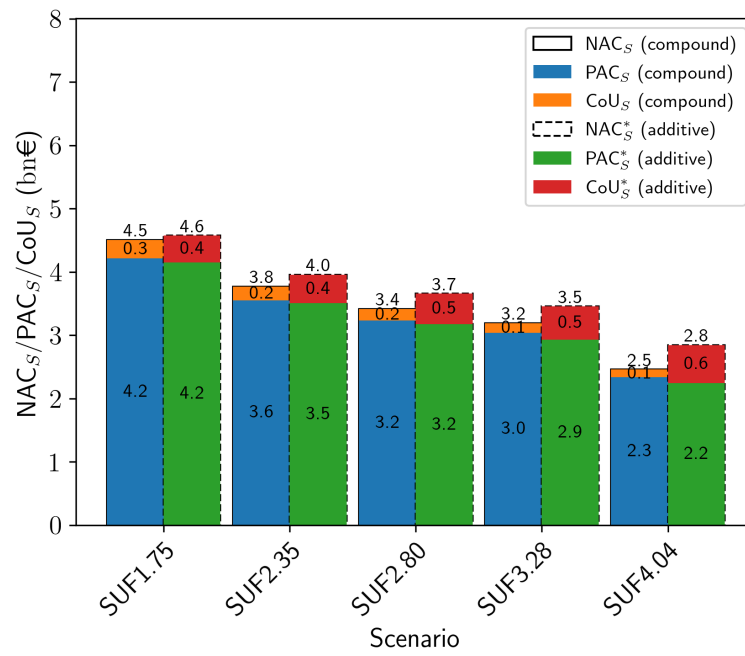
(b)

Fig. 9: Cont.

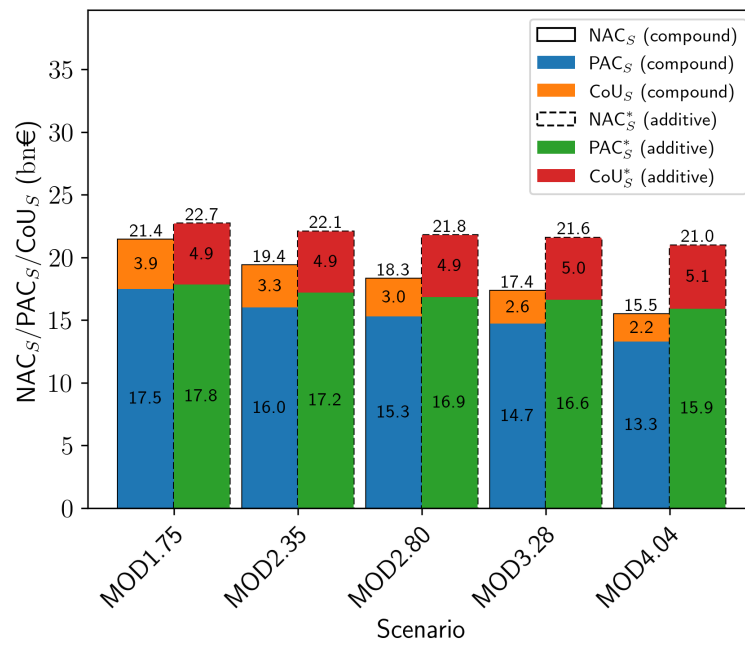


(c)

Fig. 9: Adaptation metrics under the compound or additive impact of socioeconomic and climate change. Non-adaptation costs (NAC) are shown as full (compound effect) or dashed (additive effect) empty bars, perfect adaptation costs (PAC) are shown in blue (compound effect) or green (additive effect) bars, while the cost of unpreparedness (CoU) is shown in orange (compound effect) or in red (additive effect). All results for model pair MPI-ESM + COSMO.

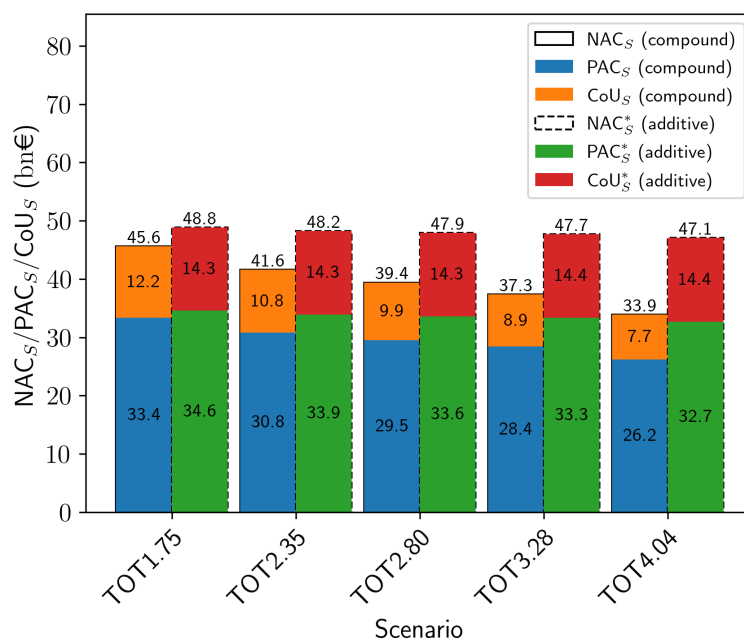


(a)



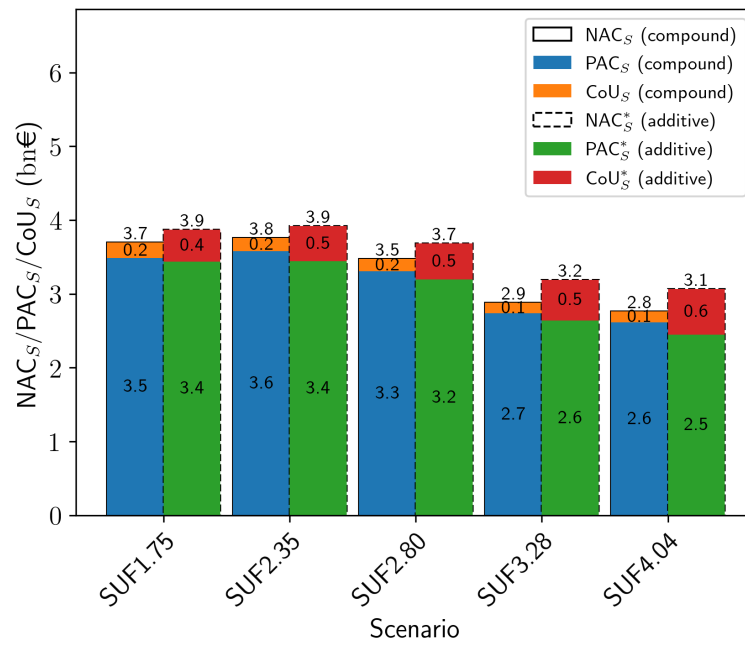
(b)

Fig. 10: Cont.

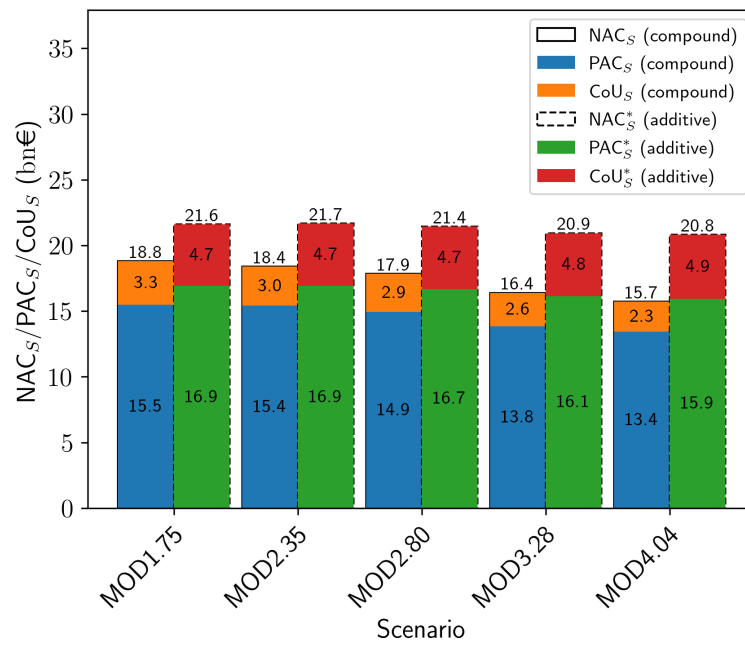


(c)

Fig. 10: Adaptation metrics under the compound or additive impact of socioeconomic and climate change. Non-adaptation costs (NAC) are shown as full (compound effect) or dashed (additive effect) empty bars, perfect adaptation costs (PAC) are shown in blue (compound effect) or green (additive effect) bars, while the cost of unpreparedness (CoU) is shown in orange (compound effect) or in red (additive effect). All results for model pair CNRM-CM5 + COSMO.

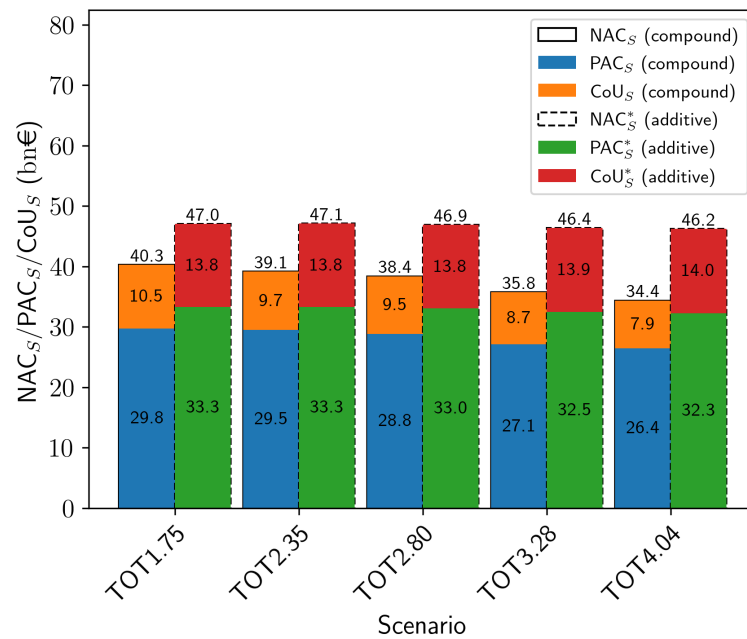


(a)



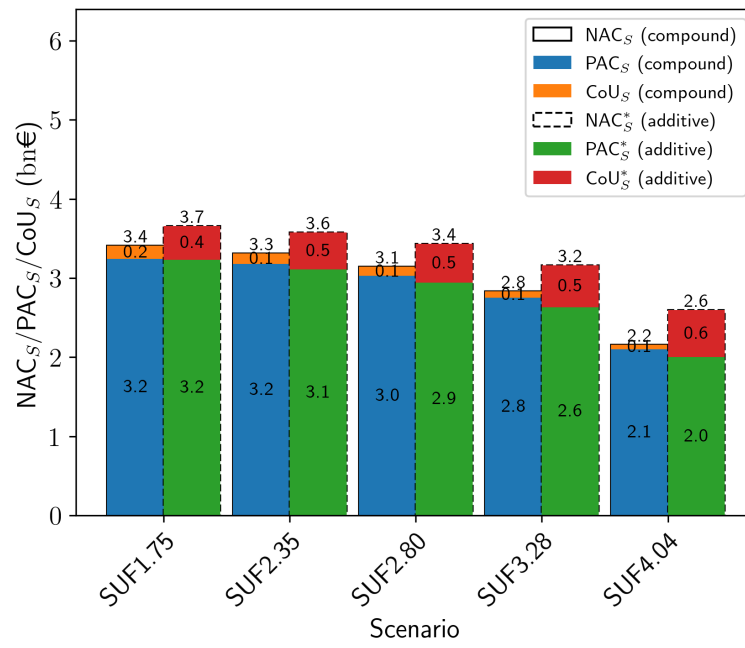
(b)

Fig. 11: Cont.

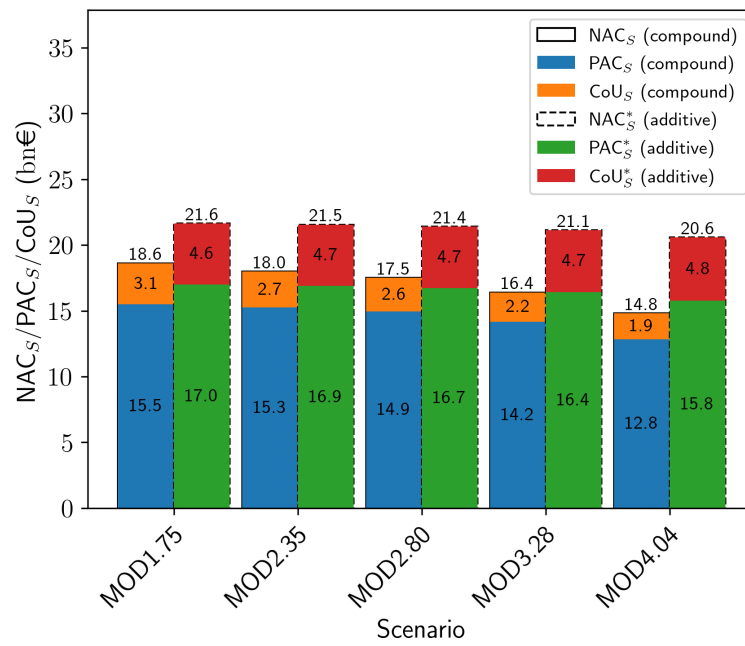


(c)

Fig. 11: Adaptation metrics under the compound or additive impact of socioeconomic and climate change. Non-adaptation costs (NAC) are shown as full (compound effect) or dashed (additive effect) empty bars, perfect adaptation costs (PAC) are shown in blue (compound effect) or green (additive effect) bars, while the cost of unpreparedness (CoU) is shown in orange (compound effect) or in red (additive effect). All results for model pair MOHC-HADGEM2 + COSMO.

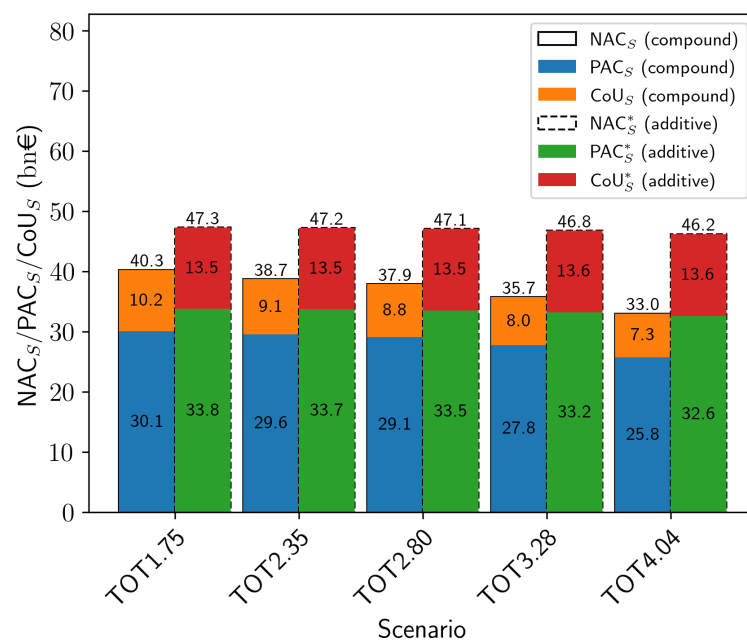


(a)



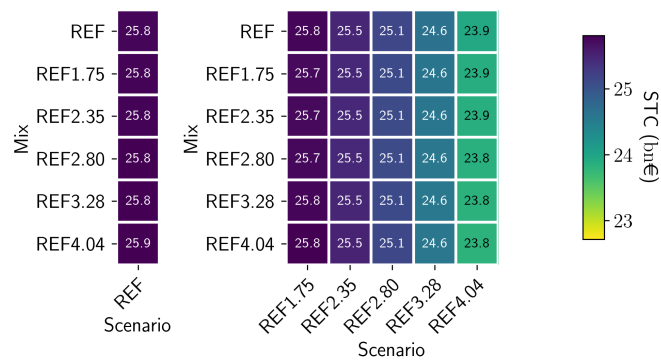
(b)

Fig. 12: Cont.

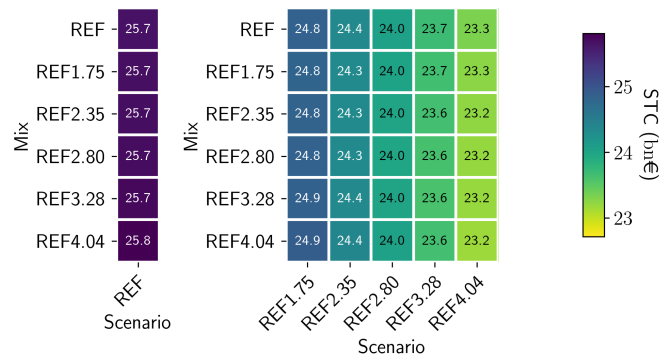


(c)

Fig. 12: Adaptation metrics under the compound or additive impact of socioeconomic and climate change. Non-adaptation costs (NAC) are shown as full (compound effect) or dashed (additive effect) empty bars, perfect adaptation costs (PAC) are shown in blue (compound effect) or green (additive effect) bars, while the cost of unpreparedness (CoU) is shown in orange (compound effect) or in red (additive effect). All results for model pair MOHC-HADGEM2 + ALADIN63.



(a) ICHEC-EC-EARTH + COSMO

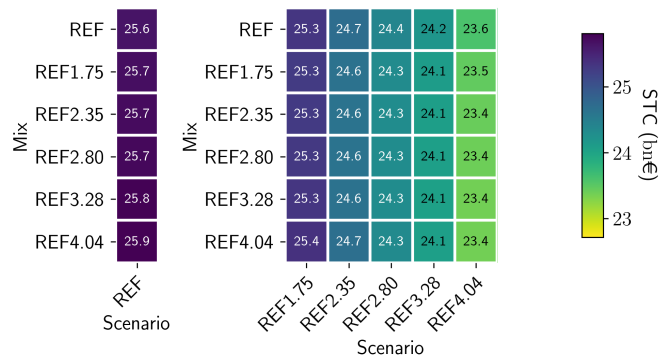


(b) MPI-ESM + COSMO

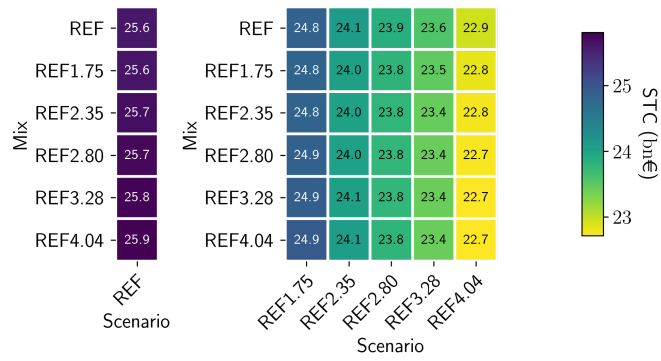
Fig. 13: Cont.

5 System total costs for all mixes and scenarios

5.1 Climate change only scenarios

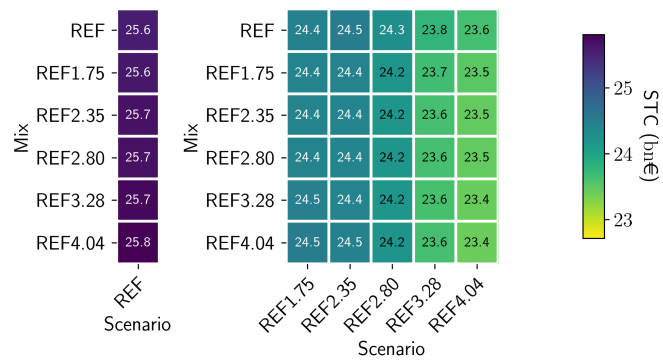


(c) CNRM-CM5 + COSMO

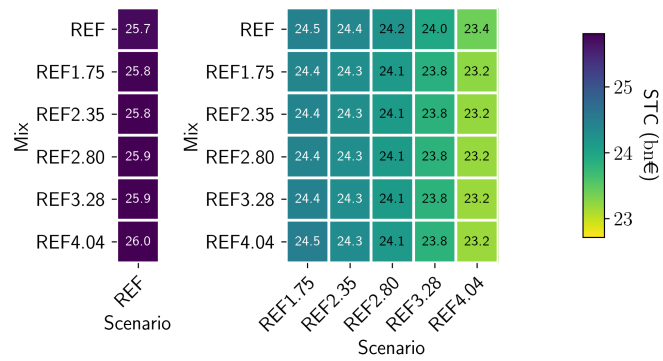


(d) CNRM-CM5 + ALADIN63

Fig. 13: Cont.

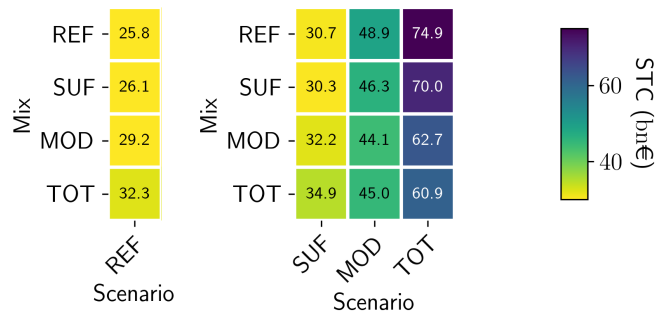


(e) MOHC-HADGEM2 + COSMO

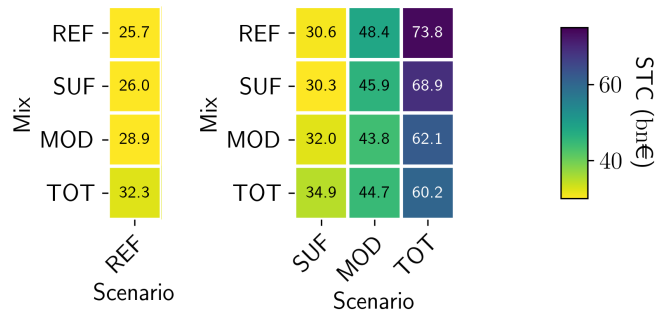


(f) MOHC-HADGEM2 + ALADIN63

Fig. 13: System total cost (STC) per scenario and per mix (climate change scenarios only), for all models of the ensemble.



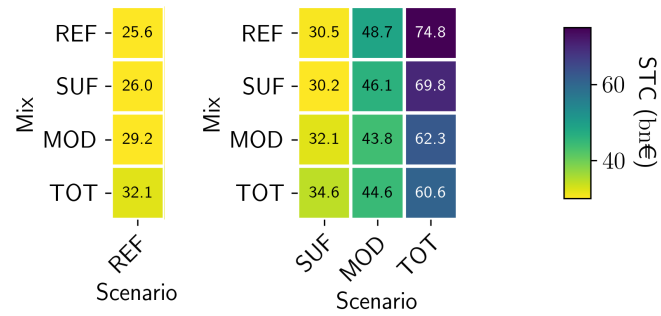
(a) ICHEC-EC-EARTH + COSMO



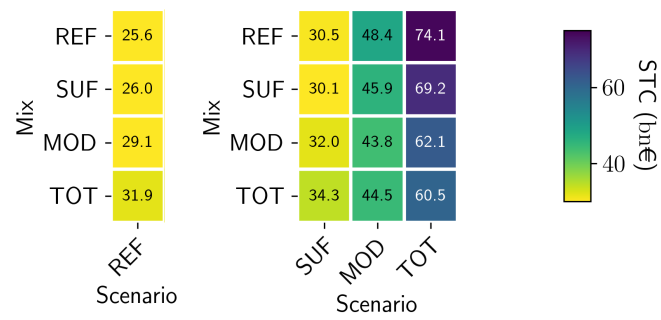
(b) MPI-ESM + COSMO

Fig. 14: Cont.

5.2 Socioeconomic change only scenarios

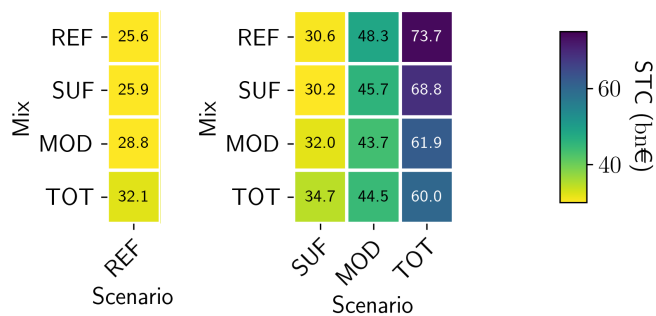


(c) CNRM-CM5 + COSMO

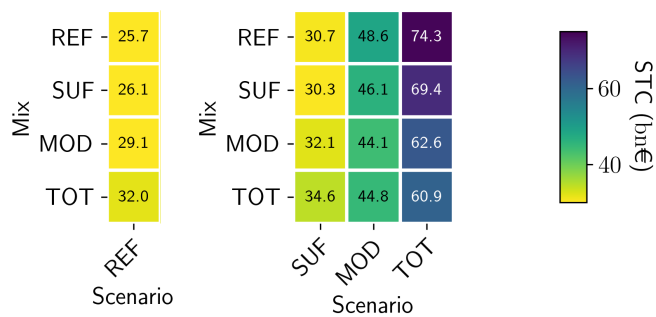


(d) CNRM-CM5 + ALADIN63

Fig. 14: Cont.

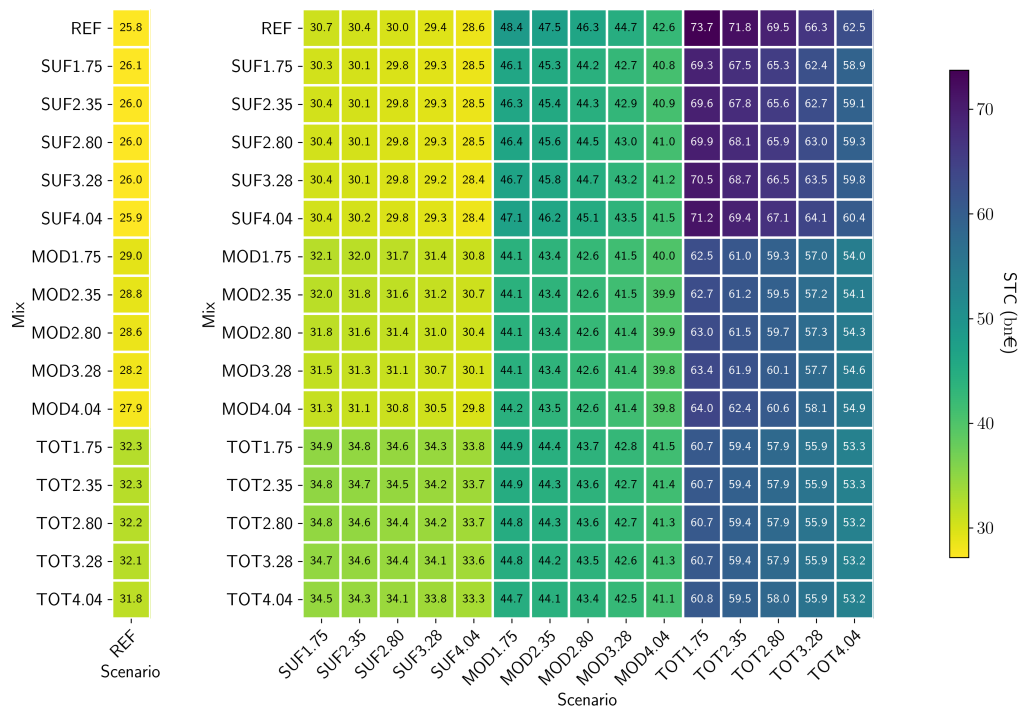


(e) MOHC-HADGEM2 + COSMO



(f) MOHC-HADGEM2 + ALADIN63

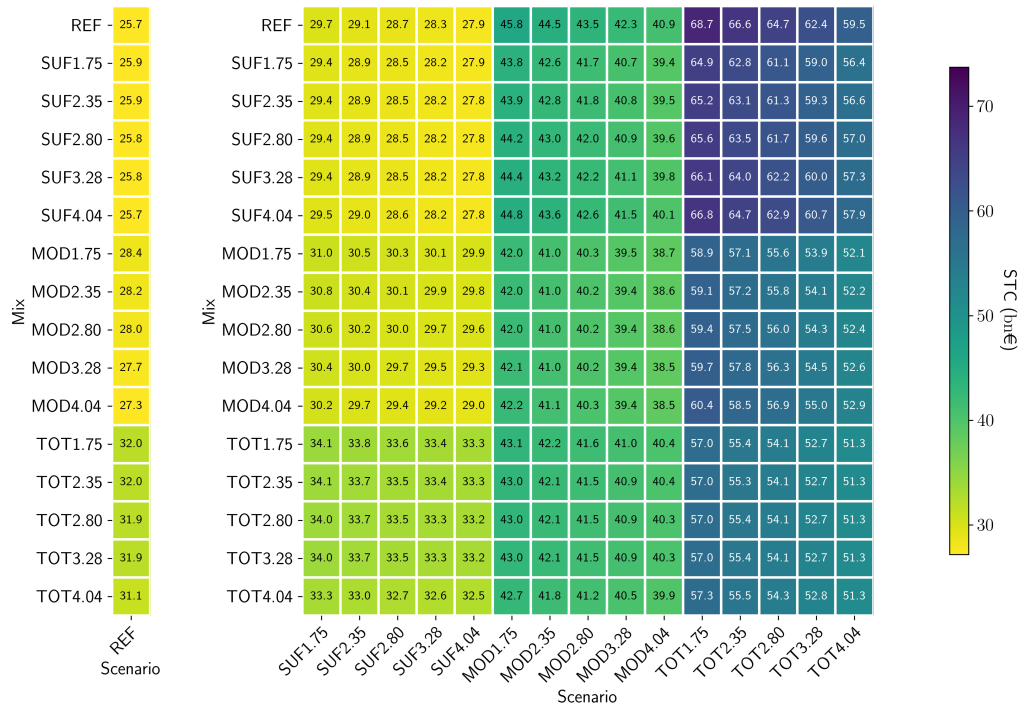
Fig. 14: System total cost (STC) per scenario and per mix (socioeconomic scenarios only), for all models of the ensemble.



(a) ICHEC-EC-EARTH + COSMO

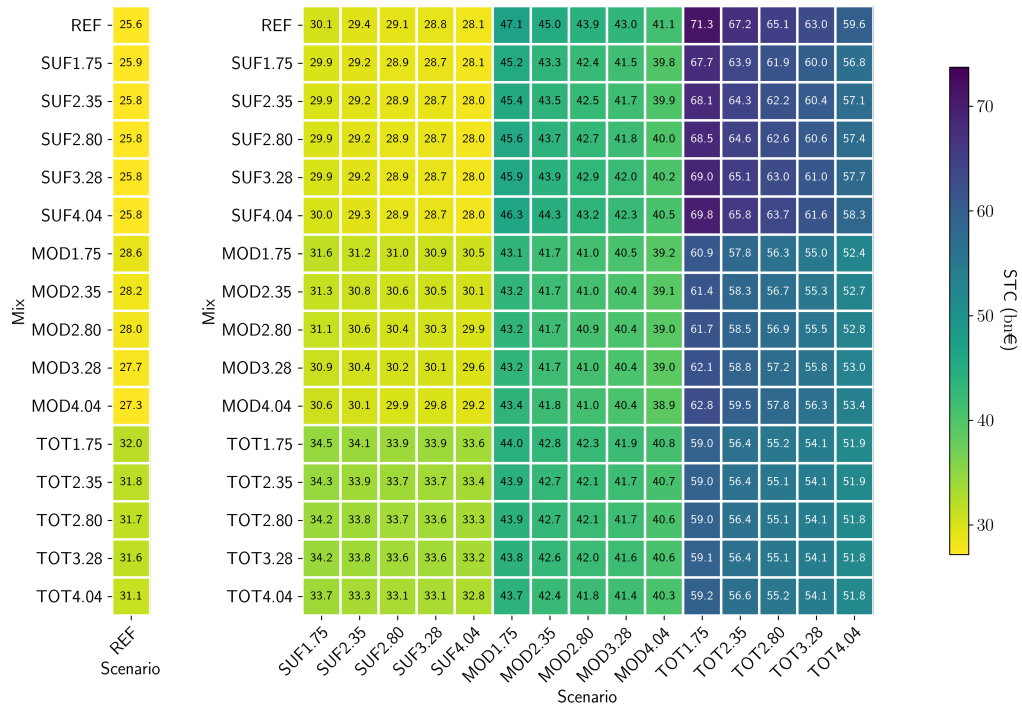
Fig. 15: Cont.

5.3 Socioeconomic and climate change scenarios



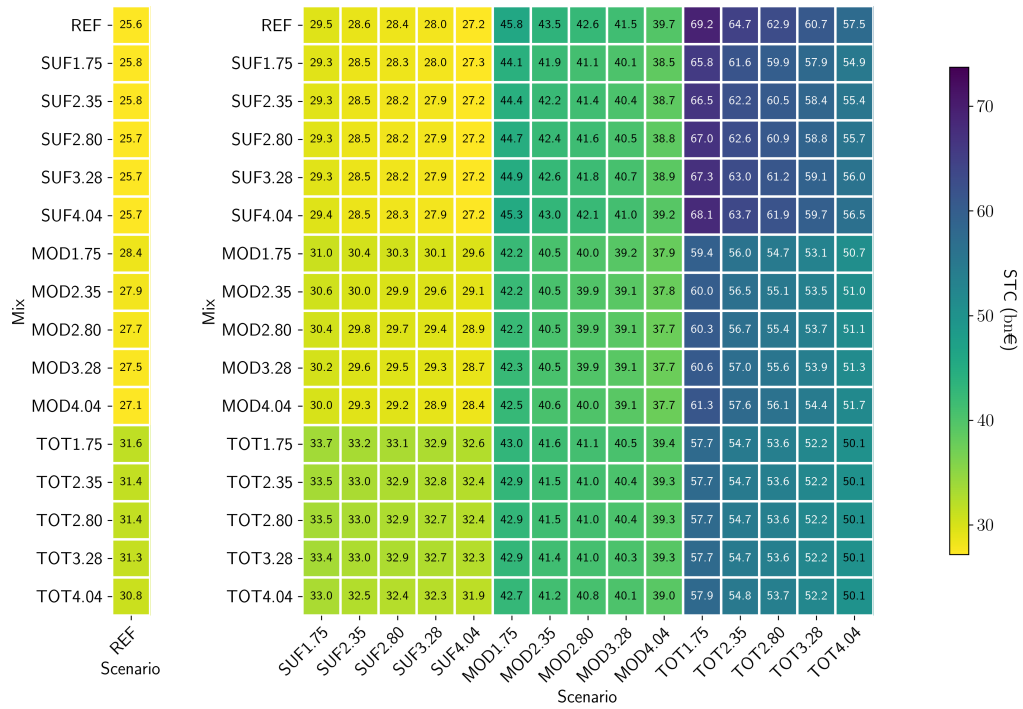
(b) MPI-ESM + COSMO

Fig. 15: Cont.



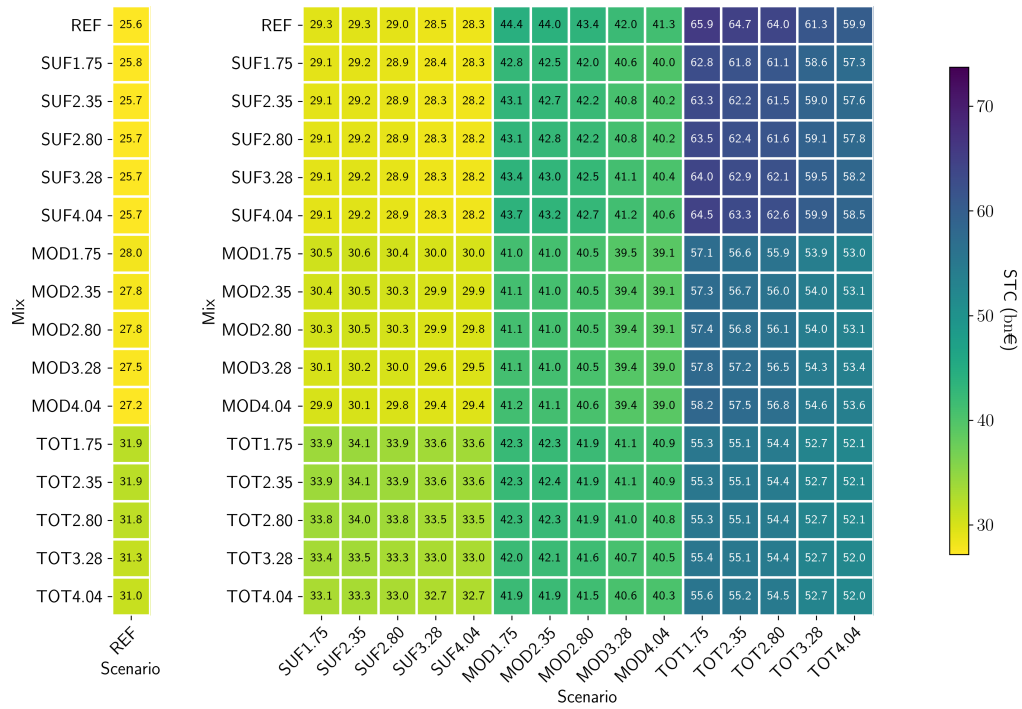
(c) CNRM-CM5 + COSMO

Fig. 15: Cont.



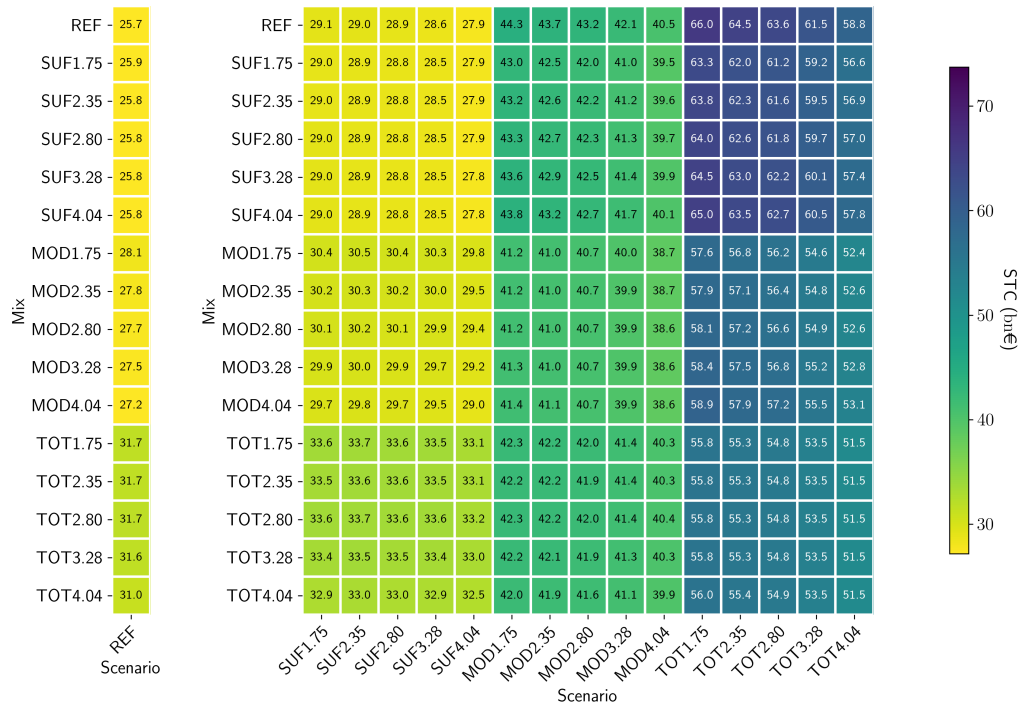
(d) CNRM-CM5 + ALADIN63

Fig. 15: Cont.



(e) MOHC-HADGEM2 + COSMO

Fig. 15: Cont.



(f) MOHC-HADGEM2 + ALADIN63

Fig. 15: System total cost (STC) per scenario and per mix, for all models of the ensemble.

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Titre: Vulnérabilité et potentiel d'adaptation des systèmes électriques à forte pénétration d'énergies renouvelables variables à des scénarios socioéconomiques d'électrification du chauffage et d'adoption de la climatisation couplés au changement climatique: le cas de la France.

Mots clés: Énergie, Climat, Demande électrique, Chauffage, Climatisation, Adaptation

Résumé: Le secteur de la production d'électricité est en pleine mutation. Dans toutes les économies européennes, la pénétration d'énergies renouvelables variables (ERVs) augmente et est attendue à la hausse dans un futur proche. Ces mixes futurs doivent être capables de fournir une électricité sûre et abordable tout en étant soumis à des contraintes écologiques fortes. Nous étudions dans ce travail deux processus affectant le secteur économique de la production d'électricité: le changement climatique et l'électrification des usages à travers l'électrification du chauffage et l'adoption de climatiseurs. Nous nous demandons en particulier comment ces deux processus affectent la vulnérabilité du secteur de la production d'électricité et comment ces deux processus impactent les décisions optimales d'investissement en ERV. Comme le changement climatique et l'électrification des usages sont ancrés géographiquement, nous nous focalisons sur le cas particulier de la France. Nous montrons qu'une augmentation de la demande thermosensible de chauffage favorise la pénétration de l'éolien tandis qu'une modification de l'adoption de la climatisation sans modification de son usage n'a pas d'impacts en

France. Nous montrons également que le changement climatique n'a pas d'impacts négatifs si l'impact sur les producteurs conventionnels n'est pas pris en compte, et que les changements de demande dus au changement climatique sont le vecteur principal de changements en décisions d'investissement optimales. Nous montrons finalement que les changements socioéconomiques sont potentiellement le facteur dominant affectant la vulnérabilité des systèmes électriques et impactant les décisions optimales d'investissement en ERV. Cependant ces changements socioéconomiques doivent être étudiés de manière conjointe avec le changement climatique pour produire des estimations correctes du potentiel d'adaptation. En tout et pour tout, les mixes optimaux et les coûts associés changent de manière substantielle en fonction de l'évolution des conditions socioéconomiques ou climatiques, les premières ayant un impact potentiellement plus grand que les secondes. Nous suggérons que les recherches ultérieures se focalisent dans la production d'études d'impacts plus intégrées, incorporant tous les éléments du système électrique et l'ensemble des processus les affectant.

Title: Vulnerability and adaptation potential of high variable renewable energy penetration electricity systems to socioeconomic scenarios of heating electrification and air conditioning adoption coupled to climate change: the case of France.

Keywords: Energy, Climate, Electricity demand, Heating, Air conditioning, Adaptation

Abstract: The electricity generation sector is undergoing profound changes. In all European economies, the penetration of variable renewable energies (VREs) is rising and is expected to reach important levels in the near future. These future mixes need to be able to provide secure and affordable electricity while subject to stringent ecological constraints. We investigate in this work two processes affecting the electricity generation sector: climate change, and electrification through heating electrification and air conditioning adoption. In particular, we ask how vulnerable is the electricity generation sector to these processes and how both these processes affect the optimal investment decisions in VRE capacity. Because climate change and the electrification potential are region-specific, we focus in the particular case of France. We show that an increase of the heating temperature sensitive demand favors wind penetration while the modification of the cooling demand along the extensive margin only has no effect in the case of France. We further

show that climate change has no adverse impacts if impacts on the dispatchable producers are not accounted for, and that changes in demand are the driving factor of impacts on the optimal investment decisions. We finally show that socioeconomic change is potentially the driving force influencing vulnerability and investment decisions, but that socioeconomic and climate change impacts should be assessed jointly to issue relevant policy-making advice. Overall optimal mixes and associated costs change substantially with changing socioeconomic and climate conditions, with the former having a potentially greater impact than the latter. We suggest that further research focuses on producing more integrated assessments of potential future changes impacts on the electricity generation sector, by being exhaustive at the same time on the elements of the electricity generation sector considered and on the processes impacting them.