



Structural transformation and weather extremes : essays on agricultural impacts and adaptive strategies in low-income countries

Kristin Muthui

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Structural transformation and weather extremes: essays on agricultural impacts and adaptive strategies in developing countries

La transformation structurelle et les événements météorologiques extrêmes : Essais sur les impacts agricoles et les stratégies d'adaptation dans les pays en développement

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Titre: La transformation structurelle et les événements météorologiques extrêmes : Essais sur les impacts agricoles et les stratégies d'adaptation dans les pays en développement

Mots clés: Agriculture, changement climatique, transformation structurelle, emploi, développement économique, pays à faible revenu

Résumé: Cette thèse étudie l'impact des extrêmes météorologiques, de la biodiversité et des pratiques agricoles soutenables sur la transformation structurelle dans les économies à faible revenu et émergentes. La transformation structurelle, définie comme le passage d'une dépendance économique principalement à l'égard d'une agriculture à faible productivité à des secteurs à plus forte productivité tels que l'industrie et les services, a toujours été le moteur de la croissance économique dans les pays à revenu élevé. Toutefois, dans les pays en développement, des facteurs tels que la faible productivité des terres agricoles et de la main-d'œuvre, les effets des réformes du Consensus de Washington, l'essor des matières premières, l'urbanisation rapide et l'évolution démographique ont entravé ce processus. Le changement climatique et la dégradation de la biodiversité remettent encore plus en question la faisabilité des stratégies d'industrialisation passées. Le premier chapitre examine les effets des extrêmes météorologiques - sécheresses, inondations et vagues de chaleur - sur la transformation structurelle. À l'aide d'un modèle de panel dynamique et d'équations simultanées, il constate que les extrêmes météorologiques réduisent la productivité de la main-d'œuvre agricole et augmentent la dépendance à ce secteur pour l'emploi à court et à long terme. Plus précisément, les sécheresses sévères et les inondations réduisent la productivité de la main-d'œuvre agricole et augmentent la part de l'emploi dans l'agriculture, tandis que les vagues de chaleur et les sécheresses extrêmes réduisent la part de l'emploi dans l'agriculture. Les effets varient considérablement d'une région à l'autre : les conditions météorologiques favorables dans certaines parties de l'Amérique latine et de l'Asie ont favorisé une transformation structurelle propice à la croissance, tandis que la détérioration des conditions dans certaines parties de l'Afrique a encore affaibli l'agriculture, retardant ou compromettant les perspectives de transformation structurelle. Le deuxième chapitre prolonge cette anal-

yse en explorant le rôle de la biodiversité dans le soutien de la croissance de la productivité totale des facteurs (PTF) agricoles et dans l'amélioration de la résistance aux extrêmes météorologiques. Les résultats montrent que la biodiversité stimule la croissance de la PTF agricole, tandis que les événements météorologiques extrêmes, en particulier les sécheresses, ont un impact négatif à la fois sur la croissance de la PTF agricole et sur la biodiversité. La perte de biodiversité qui en résulte affaiblit encore son rôle de soutien à la croissance de la PTF agricole, ce qui soulève des inquiétudes quant à la pérennité du secteur face à des phénomènes météorologiques de plus en plus fréquents et graves. Le troisième chapitre examine l'impact des pratiques agricoles soutenables sur la productivité des terres agricoles, en utilisant les données du recensement agricole 2020-2021 du Sénégal. Les exploitations agricoles sont regroupées en trois catégories: les exploitations intensives à haut niveau d'intrants, les exploitations adaptées au climat et les exploitations traditionnelles avec des pratiques soutenables. Les exploitations à forte intensité d'intrants affichent la productivité des terres la plus élevée, tandis que les exploitations adaptées au climat obtiennent des résultats modérés. Les taux d'adoption des pratiques agricoles soutenables restent faibles et dépendent de facteurs tels que l'alphabétisation des ménages, le soutien à l'agriculture et les événements météorologiques extrêmes. Des pratiques telles que l'agriculture de conservation sont liées à la réduction des impacts négatifs des extrêmes météorologiques et de la dégradation de l'environnement. La thèse préconise des stratégies intégrées et localisées pour stimuler la productivité des terres agricoles, améliorer les conditions d'emploi et renforcer la résistance aux extrêmes météorologiques et la transition vers d'autres voies de développement face à des conditions météorologiques plus fréquentes et plus extrêmes.

Title: Structural Transformation and Weather Extremes: essays on agricultural impacts and adaptive strategies in developing countries

Keywords: Agriculture, climate change, structural transformation, employment, development economics, low-income countries

Abstract: This thesis investigates the impact of weather extremes, biodiversity, and sustainable agriculture practices on structural transformation in low-income and emerging economies. Structural transformation, defined as the shift from economic dependence primarily on low-productivity agriculture to higher-productivity sectors like industry and services, has historically driven economic growth in high-income countries. However, in developing nations, factors such as low agricultural land and labour productivity, the effects of Washington Consensus reforms, commodity booms, rapid urbanisation, and demographic change have impeded this process. Climate change and biodiversity degradation further challenge the feasibility of past industrialisation strategies. The first chapter examines the effects of weather extremes—droughts, floods, and heatwaves—on structural transformation. Using a dynamic panel model and simultaneous equations, it finds that extreme weather reduces agricultural labour productivity and increases reliance on agriculture for employment in the short and long-run. Specifically, severe droughts and floods reduce agricultural labour productivity and increase agriculture employment shares, while heat waves and extreme drought reduce agriculture employment shares. Effects vary significantly across regions: favourable weather in parts of Latin America and Asia has supported growth-enhancing structural transformation, whereas worsening conditions in parts of Africa have further weakened agriculture, delaying or undermining prospects for structural transformation. The second chapter extends

this analysis by exploring the role of biodiversity in supporting agricultural total factor productivity (TFP) growth and enhancing resistance to weather extremes. Findings demonstrate that biodiversity boosts agricultural TFP growth, while extreme weather events, particularly droughts, have a negative impact on both agricultural TFP growth and biodiversity. The resulting loss in biodiversity further weakens its role in supporting agricultural TFP growth, raising concerns about the sector's sustainability in the face of increasingly frequent and severe weather events. The third chapter examines the impact of sustainable agriculture practices on agricultural land productivity, using data from Senegal's 2020-2021 agriculture census. Farms are grouped into three categories: high-input intensive, climate-adapted, and traditional farms with sustainable practices. High-input farms demonstrate the highest land productivity, while climate-adapted farms show moderate results. Adoption rates of sustainable practices remain low, shaped by factors such as household literacy, agricultural support, and extreme weather events. Practices like conservation agriculture are linked to reduced negative impacts from weather extremes and environmental degradation. The thesis advocates for integrated, localised strategies to boost agricultural land productivity, improve employment conditions and enhance resistance to weather extremes and transition to alternative pathways to development in the face of more frequent and extreme weather.

*To all the researchers and practitioners committed to bringing about a more just and equitable
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Chapter 1

General Introduction

The end of a period of rapid growth that significantly raised incomes and reduced poverty in low-income and emerging countries in the 2010s sparked renewed interest in the determinants of economic growth and development. This interest gained greater relevance as recent trends—such as technological change, shifts in global demand, and the reconfiguration of global supply chains—challenged the viability of labour-intensive, export-led industrialization strategies that once fueled growth in today's high-income countries (Rodrik, 2012). At the core of this renewed focus is the process of structural transformation, where economies shift from low-productivity agricultural activities to higher-productivity sectors like industry and services. Although this transition has historically driven rising incomes and economic development, growing concerns about climate change, biodiversity loss, and demographic shifts have made it more critical than ever to adopt development strategies that integrate social and environmental goals.

Building on existing literature, this thesis expands the analysis of barriers to growth-increasing structural change by examining the impact of weather extremes on structural transformation in low-income and emerging economies. Next, it explores the role of biodiversity and ecosystems in increasing agricultural total factor productivity, and the role they play in maintaining stability of production the face of weather extremes. Finally, the thesis concludes with an exploratory analysis that transitions from a macroeconomic approach using aggregate data to a microeconomic investigation, utilising agriculture survey data from Senegal to explore the implications of sustainable agriculture practices on the process of structural transformation.

Structural transformation, as defined by early scholars like Lewis (1954) and Kuznets (1966), involves economies transitioning away from low-productivity agricultural activities toward higher-productivity sectors, such as industry and services. This process typically results in a decline in the proportion of

employment in agriculture, a temporary rise in industrial employment, and a long-term shift towards services (Duarte and Restuccia, 2010). Scholars such as Schultz (1953) argue that structural transformation begins when countries successfully address the "food problem." Once staple food production exceeds subsistence levels, food prices decline, crop production diversifies, and commercial farming expands. This shift, combined with the adoption of new inputs and services, creates backward and forward linkages with non-agricultural sectors, driving demand for non-agricultural goods and services (Johnston and Mellor, 1961). Consequently, these linkages provide raw materials for non-agricultural industries, facilitating the movement of labour from agriculture to higher-productivity secondary and tertiary industries. As a result, rural labour productivity rises, wages increase, and poverty declines. Ultimately, as this process unfolds, the share of agriculture in total employment and value-added typically falls to 2-3%, while income and labour productivity in both agricultural and non-agricultural sectors converge (Larson and Mundlak, 1997).

This process, also known as the "Lewis Path" (Dorin et al., 2013), has historically resulted in rapid industrialisation in today's OECD countries and the 'Newly Industrialized Countries in Asia'¹. It underpins much of the theoretical understanding of structural transformation for both development economists (Lewis, 1954; Kuznets, 1966; Chenery et al., 1986) who initially developed the theory and more recent works integrating neoclassical assumptions of capital accumulation and technological change (McMillan et al., 2014; Duarte and Restuccia, 2010; Herrendorf et al., 2014).

However, recent experiences in low-income and emerging economies have called into question the viability of this path to sustained growth. As demonstrated by Sen (2019), between 1960 and 2010, structural transformation in low-income economies has often resulted in less prosperous trajectories. Although the share of employment in agriculture has steadily declined, as the theory predicts, this process has been particularly sluggish in low-income, agricultural economies, where workers have primarily transitioned to the non-tradable services sector, leading to lower overall labour productivity gains than if they had moved to higher-value-added manufacturing and service sectors. Conversely, emerging economies have experienced rapid declines in agricultural employment shares, accompanied by significant growth in the services sector and manufacturing. Overall, labour productivity gains have fallen short of predictions, with some countries facing premature deindustrialisation as well (Rodrik, 2016).

These atypical growth trajectories can be attributed to various factors, including the growth of small-scale, artisanal manufacturing in low-income countries, which has led to modest labour productivity increases (Kruse et al., 2022). Dabla-Norris et al. (2013) show that Washington Consensus reforms, which promoted liberalisation and deregulation, shifted demand toward non-tradable goods and services, expanding the non-manufacturing sector at the expense of manufacturing. Similarly, commodity

¹ South Korea, Taiwan, Singapore and Hong Kong

booms driven by natural resource exports spurred urbanisation and the rise of "consumption cities," dominated by non-tradeable services (Gollin et al., 2016). This rapid urbanisation has occurred without a corresponding increase in industrial growth, resulting in limited labour productivity gains in agriculture and manufacturing, as well as only modest improvements in overall labour productivity. In Latin America, dependence on commodities and deindustrialisation following market liberalisation have hindered the expected benefits from labour and capital reallocation (McMillan et al., 2014). In Sub-Saharan Africa, structural transformation came at the expense of declining labour productivity in the more modern sectors of the economy (Rodrik et al., 2019).

Meanwhile, agriculture in low-income countries lags, accounting for most of the output gap between rich and poor countries (Fuglie et al., 2019; Gollin et al., 2014). Dorin et al. (2013) propose that agricultural labour productivity growth is fundamentally determined by land productivity and availability. Historically, land productivity was raised through better agricultural practices and technologies, which resulted in the intensification of production through innovation and input intensification. In contrast, higher land availability was driven by agricultural labour out-migration and intensive use of heavy motorised equipment to replace farmers. In high-income countries, these processes were facilitated by historical factors that no longer exist today, namely the expansion of labour-intensive industries and out-migration to the 'new world'. These factors allowed for the expansion of land per worker and rendered the strategy of boosting agricultural labour productivity through fossil energy-intensive, 'labour-saving' technology possible.

Moreover, unmitigated fossil fuel use, which powered agricultural modernisation and industrialisation, has raised greenhouse gas concentrations, driving climate change (Allan et al., 2023). The vulnerability of the agriculture sector to climate change is already well-established, with extreme weather events such as floods, droughts, and heatwaves, alongside soil acidity and salinity, expected to intensify crop stress. These factors could reduce staple crop yields by up to 24% by 2030 (Jägermeyr et al., 2021). High temperatures also limit worker productivity by reducing outdoor working hours and diminishing performance (Shayegh et al., 2021). Additionally, rising temperatures negatively impact health, educational outcomes, and cognitive function, compounding the challenges for agriculture (Deschenes et al., 2009a). However, while much research has focused on the direct effects of extremes like droughts and floods on GDP growth and sectoral labour productivity, studies on their impact on structural transformation are scarce. Yet extreme weather events can drive labour migration from rural to urban areas (Barrios et al., 2006), disrupt financial markets, and shift capital away from agriculture toward manufacturing and services (Bansal et al., 2016; Krueger et al., 2020). Hence, these dynamics affect labour and land productivity, warranting a deeper analysis from a structural transformation perspective.

Therefore, this thesis begins by interrogating how extreme weather events impact the process of struc-

tural transformation, linking variables related to structural transformation, namely agricultural labour productivity and employment shares, with extreme weather events, including droughts, floods, and heat-waves. Precise weather indicators are used to analyse short-run effects with a system of simultaneous equations and long-run effects with a linear dynamic panel data model. Findings show that extreme weather events negatively impact this process in the short run by reducing agricultural labour productivity and increasing reliance on agricultural employment when droughts and extreme precipitation occur. On the other hand, extreme temperatures result in a premature exit of labour from the agricultural sector without a corresponding increase in agricultural labour productivity in the short run. Further, long-term effects are significantly pronounced for droughts, as well as when multiple weather extremes occur. Effects are highly disparate across continents and countries. Positive trends, thanks to a reduction in weather extremes, have sustained growth-increasing structural transformation in some countries, notably in Latin America and, to some extent, in Asia. Conversely, worsening conditions, especially for some African countries, have further hindered development and agricultural labour productivity growth, thus compromising any prospects of structural transformation.

These findings indicate that addressing the food problem and pursuing the 'Lewis Path' to economic development is hindered by weather extremes, which disrupt agricultural activities and slow structural transformation. This is particularly concerning for low-income countries in Africa and South Asia, where a significant proportion of the workforce is primarily engaged in small-scale agriculture. They also demonstrate that it is critical to consider not only land productivity and resistance of agricultural production to weather extremes, but also working conditions and more systemic adaptation measures to maintain food production and raise standards of living.

Moreover, global agricultural total factor productivity (TFP) growth, which is a measure of agricultural efficiency, has slowed since the 2010s, particularly in developing countries (Morgan et al., 2022). Several factors contribute to this decline, including frequent climate-related weather shocks, emerging crop diseases and pests, fewer technological breakthroughs, slow diffusion of improved market technologies in low income countries, and more concerning, natural capital depletion (Fuglie and Rada, 2013; Fuglie, 2018). Furthermore, while the Green Revolution boosted global food production by increasing fertiliser use and expanding cropland (Foley et al., 2005; Tilman et al., 2002), evidence shows that it also accelerated greenhouse gas emissions, habitat destruction, and biodiversity loss (Dudley and Alexander, 2017; Tilman et al., 2002). This depletion of natural capital has reduced ecosystem services (Kremen and Miles, 2012; Reid et al., 2005), further jeopardising the long-term sustainability of agricultural total factor productivity.

Agriculture, especially in low-income countries, heavily depends on biodiversity and ecosystems, which provide essential services such as soil retention, water provision, and pollination (Vanbergen et al.,

2020). Furthermore, climate change will likely exacerbate the already large environmental impacts of agricultural production by directly and negatively affecting agricultural total factor productivity, reducing the efficacy of agrochemicals and increasing their loss to the environment; and increasing crop pests and soil erosion (Yang et al., 2024). Current trends suggest that future yield improvements rely on input intensification and cropland expansion, constrained by technological limits and diminishing returns. This trajectory could worsen deforestation and habitat loss, further depleting ecosystems and biodiversity critical to sustaining agriculture and human well-being.

While the concept of weak sustainability suggests that natural capital can be replaced by manufactured capital without reducing welfare, strong sustainability rejects this due to irreversibility, uncertainty, and 'critical' natural capital components (Turner and Pearce, 1993). Biodiversity and ecosystems are increasingly vulnerable to climate-induced weather extremes, which disrupt their structure and function (Watson et al., 2019). This is exacerbated by human-induced stressors such as defaunation, invasive species, and habitat degradation, further increasing ecosystems' sensitivity to climate change (Hjältén et al., 2016). These negative impacts are expected to worsen in the coming decades (Hoffmann and Beierkuhnlein, 2020), resulting in reductions in natural capital stock, affecting the quantity of ecosystem goods and services that agriculture depends on, and ultimately requiring fundamental changes in agricultural production. However, academic research on agricultural total factor productivity is largely focused on agricultural intensification and green growth, with little attention on how agricultural total factor productivity can be maintained or enhanced in the face of increasingly frequent and severe weather extremes.

Chapter 2 of this thesis therefore explores how biodiversity and ecosystems contribute to agricultural total factor productivity (TFP) growth, which is a measure of technological and management practices that improve the efficiency of input use, resulting in higher outputs with lower input use (Jorgenson et al., 2005). By enabling higher outputs with lower input use, TFP growth supports production and can be environmentally sustainable if it reduces reliance on polluting or emission-intensive inputs. This chapter employs a system of simultaneous equations to estimate the direct effects of biodiversity, ecosystems, and weather extremes on agricultural TFP growth, as well as the role of biodiversity in mediating the effects of weather extremes on agricultural TFP growth. Preliminary findings indicate that biodiversity and ecosystems play a direct role in enhancing agricultural TFP growth, whereas extreme weather events, particularly droughts, adversely impact both agricultural total factor productivity and biodiversity. The decline in biodiversity further diminishes its contribution to agricultural TFP growth. Hence, findings indicate that while biodiversity is essential for agricultural TFP growth, weather extremes diminish its positive contribution. Consequently, agricultural TFP growth is significantly more affected by weather extremes in countries with abundant biodiversity compared to those where biodiversity plays a lesser

role.

These results may appear somewhat unexpected, likely due to the reliance on aggregate data that does not differentiate between various agricultural production models. It is plausible that the dominant agricultural model, characterised by monoculture production underpinned by high input use and capital-intensive practices, drives these observed effects. While they may seem resistant to weather extremes in the short term due to the reliance on synthetic inputs and technology, the dependence on a limited number of crop varieties ultimately renders the system vulnerable to extreme weather events in the long term. Furthermore, the results indicate that while synthetic input use positively influences agricultural TFP growth, their indirect negative effects stemming from biodiversity loss outweigh these short-term gains. This trend suggests a long-term decline in agricultural total factor productivity as intensive agricultural practices erode biodiversity. Additionally, the analysis does not capture whether certain agricultural production models effectively utilize biodiversity and ecosystems to enhance agricultural TFP, as seen in agroecological farming systems. In this analysis, biodiversity is treated as any other input, potentially explaining the lack of a protective effect in the face of weather extremes.

By extension, this raises questions about the role of agricultural production practices, and whether individual farms put in place strategies that enhance the role of ecosystems and biodiversity, as well as if those strategies enhance agricultural land productivity and resistance to weather shocks. Sustainable agriculture has been promoted as a solution to meet growing food demand while safeguarding ecosystems. These approaches range from sustainable intensification, which aims to maximise yields while minimizing negative environmental impacts (Pretty et al., 2012), to more systemic redesigns of agricultural production systems grounded in principles of ecological intensification and agroecology (Vanbergen et al., 2020). A diverse array of sustainable agricultural practices is already in use among farmers, including agronomic measures to enhance soil fertility, vegetative practices like agroforestry, and structural interventions such as water storage systems (Liniger and Critchley, 2007). These practices affect labour and land use and are likely to influence the process of structural transformation. However, evidence regarding their impact remains mixed and context-specific; some practices increase household labour (Montt and Luu, 2020), while others show no significant difference depending on their combination (Teklewold et al., 2013). Additionally, land productivity outcomes vary based on environmental and climatic conditions (Pittelkow et al., 2015; Castle et al., 2021). The effect of changes in labour use is also contingent upon output changes, which in turn affect overall labour productivity.

Thus, understanding how the implementation of sustainable agricultural practices occurs within the contexts of weather extremes and structural transformation is vital for low-income countries, where a large share of the population relies on agriculture for employment, and thus invested in implementing strategies that create decent employment opportunities, boost food production, and improve living

standards. Moreover, small-scale farmers in low-income tropical regions are particularly vulnerable to climate change, facing socio-economic and policy barriers that hinder their adaptive capacity (Morton, 2007). The rapid demographic changes expected in the near future, coupled with declining land productivity and availability, increasing vulnerability to climate change, and the limitations of the classic "Lewis path" to development, all underscore the urgent need to reevaluate development strategies for sustainable and equitable structural transformation.

Building on this therefore, chapter 3 sheds light on the relationship between agricultural land productivity, sustainable agriculture practices, environmental degradation, and weather extremes on small-scale farms using data from the Senegal (2020-2021) agriculture census. Small-scale farmers become a focal point, as research shows that ecological farming, particularly agroecology, is most effective on smaller farms. Senegal, with its predominantly small-scale agricultural sector, high agricultural employment, frequent weather shocks, and institutional support for agroecological practices, offers an ideal context for this exploration. Additionally, robust data from the FAO-supported agricultural census, including a module dedicated to agricultural production practices, enables a deeper analysis of sustainable agriculture's role in enhancing adaptability to weather shocks. Three distinct farm typologies emerge from a hierarchical cluster analysis: high-input intensive, climate-adapted, and traditional sustainable farms. Notably, input-intensive farms exhibit the highest land productivity levels, while climate-adapted farms demonstrate moderate land productivity. A binary logistic model identifies key factors driving the adoption of sustainable practices, including household head literacy, access to agricultural support, and formal land ownership. Further, households exposed to weather extremes and environmental pressures are more likely to adopt sustainable methods. Although overall adoption rates remain low, farms employing multiple sustainable practices are better equipped to withstand extreme temperatures. Specific interventions, such as conservation agriculture and erosion control, are associated with less severe impacts of weather shocks, while other strategies, like low-cost soil fertility enhancements, show limited effectiveness.

In conclusion, findings demonstrate that weather extremes - particularly droughts and extreme precipitation, have a negative effect on the process of structural transformation in low-income and emerging economies. Secondly, while biodiversity and ecosystems positively contribute to agricultural TPF growth, they are also vulnerable to weather extremes, and under current modes of agricultural production, not adequately deployed to reduce the negative effects of weather extremes. Lastly, the partial adoption of sustainable agriculture practices limits their effectiveness in reducing the negative impacts of extreme weather events. Barriers to sustainable agriculture adoption, including limited financial resources, inadequate information and insufficient training, hinder the adoption of these practices in low-income countries. Hence, more research and investment is required in developing and deploying

technologies, practices and inputs that are more suited to local contexts, ranging from drought and heat-resistant inputs, to more comprehensive research on the redesign of agroecosystems to develop more site-specific ecological interventions, to support farmers in transitioning towards sustainable food production and pathways to structural transformation.

Introduction générale

La fin d'une période de croissance rapide qui a considérablement augmenté les revenus et réduit la pauvreté dans les pays à faible revenu et les pays émergents dans les années 2010 a suscité un regain d'intérêt pour les déterminants de la croissance économique et du développement. Cet intérêt est devenu d'autant plus pertinent que les tendances récentes - telles que les changements technologiques, l'évolution de la demande mondiale et la reconfiguration des chaînes d'approvisionnement mondiales - ont remis en question la viabilité des stratégies d'industrialisation à forte intensité de main-d'œuvre et axées sur les exportations qui ont autrefois alimenté la croissance dans les pays à revenu élevé d'aujourd'hui (Rodrik, 2012). Au cœur de ce nouvel intérêt se trouve le processus de transformation structurelle, où les économies passent d'activités agricoles à faible productivité à des secteurs à plus forte productivité, tels que l'industrie et les services. Bien que cette transition ait historiquement favorisé la hausse des revenus et le développement économique, les préoccupations croissantes concernant le changement climatique, la perte de biodiversité et les évolutions démographiques rendent plus que jamais crucial l'adoption de stratégies de développement intégrant des objectifs sociaux et environnementaux.

S'appuyant sur la littérature existante, cette thèse élargit l'analyse des obstacles au changement structurel favorisant la croissance en examinant l'impact des extrêmes météorologiques sur la transformation structurelle dans les économies à faible revenu et émergentes. Ensuite, elle explore le rôle de la biodiversité et des écosystèmes dans l'augmentation de la productivité totale des facteurs agricoles, et le rôle qu'ils jouent dans le maintien de la stabilité de la production face aux extrêmes météorologiques. Enfin, la thèse se termine par une analyse exploratoire qui passe d'une approche macroéconomique utilisant des données agrégées à une investigation microéconomique, utilisant des données d'enquête sur l'agriculture au Sénégal pour explorer les implications des pratiques agricoles soutenables sur le processus de transformation structurelle.

La transformation structurelle, telle que définie par les premiers chercheurs comme Lewis (1954) et Kuznets (1966), implique le passage des économies des activités agricoles à faible productivité vers des secteurs à plus forte productivité, comme l'industrie et les services. Ce processus se traduit générale-

ment par une diminution de la part de l'emploi dans l'agriculture, une augmentation temporaire de l'emploi industriel et une transition à long terme vers les services (Duarte and Restuccia, 2010). Des chercheurs tels que Schultz (1953) soutiennent que la transformation structurelle commence lorsque les pays parviennent à résoudre le "problème alimentaire". Lorsque la production alimentaire dépasse les niveaux de subsistance, les prix des denrées alimentaires baissent, la production se diversifie et l'agriculture commerciale s'étend. Cette transition, combinée à l'adoption de nouveaux intrants et services, crée des liens en amont et en aval avec les secteurs non agricoles, stimulant la demande de biens et services non agricoles (Johnston and Mellor, 1961). Ces liens fournissent alors des matières premières aux industries non agricoles, facilitant le déplacement de la main-d'œuvre agricole vers des industries secondaires et tertiaires à plus forte productivité de la main œuvre. En conséquence, la productivité de la main d'œuvre rural augmente, les salaires s'améliorent et la pauvreté diminue. Au fil du temps, la part de l'agriculture dans l'emploi total et dans la valeur ajoutée tend à diminuer pour atteindre environ 2-3 %, tandis que les revenus et la productivité de la main œuvre des secteurs agricoles et non agricoles convergent (Larson and Mundlak, 1997).

Ce processus, souvent appelé "voie de Lewis" (Dorin et al., 2013), a historiquement conduit à une industrialisation rapide dans les pays de l'OCDE et les "nouveaux pays industrialisés d'Asie²". Il sous-tend une grande partie de la compréhension théorique de la transformation structurelle, tant pour les économistes du développement (Lewis, 1954; Kuznets, 1966; Chenery et al., 1986) qui ont initialement développé cette théorie, que pour des travaux plus récents intégrant des hypothèses néoclassiques d'accumulation de capital et de changement technologique (McMillan et al., 2014; Duarte and Restuccia, 2010; Herrendorf et al., 2014).

Cependant, les expériences récentes dans les économies à faible revenu et émergentes ont remis en question la viabilité de cette voie vers une croissance soutenue. Comme le montre Sen (2019), entre 1960 et 2010, la transformation structurelle dans ces économies a souvent abouti à des trajectoires moins prospères. Bien que la part de l'emploi dans l'agriculture ait régulièrement diminué, comme le prévoit la théorie, ce processus a été particulièrement lent dans les économies agricoles à faible revenu, où les travailleurs ont principalement effectué une transition vers le secteur des services non échangeables, ce qui a entraîné des gains de productivité globale de la main-d'œuvre plus faibles que s'ils s'étaient orientés vers des secteurs manufacturiers et de services à plus forte valeur ajoutée. À l'inverse, les économies émergentes ont connu un déclin rapide de la part de l'emploi agricole, accompagné d'une croissance significative du secteur des services et de l'industrie manufacturière (Rodrik, 2016).

Ces trajectoires de croissance atypiques peuvent être attribuées à différents facteurs, notamment la

²(Corée du Sud, Taïwan, Singapour et Hong Kong)

croissance de l'industrie manufacturière artisanale à petite échelle dans les pays à faible revenu, qui a entraîné de modestes augmentations de la productivité de la main-d'œuvre (Kruse et al., 2022). (Dabla-Norris et al., 2013) montrent que les réformes du Consensus de Washington, qui ont favorisé la libéralisation et la déréglementation, ont déplacé la demande vers les biens et services non échangeables, développant le secteur non manufacturier au détriment de l'industrie manufacturière. De même, les booms des matières premières, tirés par les exportations de ressources naturelles, ont favorisé l'urbanisation et l'émergence de "villes de consommation" dominées par les services non échangeables (Gollin et al., 2016). Cette urbanisation rapide s'est produite sans une augmentation correspondante de la croissance industrielle, ce qui a entraîné des gains de productivité de la main-d'œuvre limités dans l'agriculture et l'industrie manufacturière, ainsi que des améliorations modestes de la productivité globale de la main-d'œuvre. En Amérique latine, la dépendance aux matières premières et la désindustrialisation après la libéralisation des marchés ont entravé les bénéfices attendus de la réallocation de la main-d'œuvre et du capital (McMillan et al., 2014). En Afrique subsaharienne, la transformation structurelle s'est faite au prix d'une baisse de la productivité du travail dans les secteurs les plus modernes de l'économie (Rodrik et al., 2019).

Pendant ce temps, l'agriculture dans les pays à faible revenu est à la traîne, représentant une grande partie de l'écart de production entre les pays riches et pauvres (Fuglie et al., 2019; Gollin et al., 2014). Dorin et al. (2013) proposent que la croissance de la productivité de la main d'œuvre agricole soit fondamentalement déterminée par la productivité et la disponibilité des terres. Historiquement, la productivité des terres a été augmentée grâce à de meilleures pratiques agricoles et technologies, ce qui a permis l'intensification de la production via l'innovation et l'intensification des intrants. En revanche, une plus grande disponibilité des terres a été obtenue par l'émigration de la main d'œuvre et l'utilisation intensive de matériel motorisé lourd pour remplacer les agriculteurs. Dans les pays à revenu élevé, ces processus ont été facilités par des facteurs historiques qui n'existent plus aujourd'hui, à savoir l'expansion des industries intensives en main-d'œuvre et l'émigration vers le "nouveau monde". Ces facteurs ont permis l'expansion des terres par travailleur et ont rendu possible la stratégie d'augmentation de la productivité de la main d'œuvre agricole grâce à une technologie intensive en énergie fossile dite "économe en main-d'œuvre".

De plus, l'utilisation non maîtrisée des combustibles fossiles, qui a alimenté la modernisation agricole et l'industrialisation, a augmenté les concentrations de gaz à effet de serre, provoquant le changement climatique (Allan et al., 2023). La vulnérabilité du secteur agricole au changement climatique est déjà bien établie, avec des événements météorologiques extrêmes tels que les inondations, les sécheresses et les vagues de chaleur, ainsi que l'acidité et la salinité des sols, qui devraient intensifier le stress des cultures. Ces facteurs pourraient réduire les rendements des cultures de base de jusqu'à

24% d'ici 2030 (Jägermeyr et al., 2021). Les températures élevées limitent également la productivité de la main-d'œuvre en réduisant les heures de travail en plein air et en diminuant les performances (Shayegh et al., 2021). En outre, l'augmentation des températures a des effets négatifs sur la santé, les résultats scolaires et les fonctions cognitives, aggravant les défis pour l'agriculture (Deschenes et al., 2009a). Cependant, bien que de nombreuses recherches se concentrent sur les effets directs des extrêmes tels que les sécheresses et les inondations sur la croissance du PIB et la productivité de la main-d'œuvre, les études sur leur impact sur la transformation structurelle sont rares. Pourtant, les événements météorologiques extrêmes peuvent entraîner des migrations de main-d'œuvre des zones rurales vers les zones urbaines (Barrios et al., 2006), perturber les marchés financiers et détourner le capital de l'agriculture vers l'industrie et les services (Bansal et al., 2016; Krueger et al., 2020). Ces dynamiques affectent donc la productivité de la main-d'œuvre et des terres, nécessitant une analyse plus approfondie sous l'angle de la transformation structurelle.

Par conséquent, cette thèse commence par s'interroger sur l'impact des événements météorologiques extrêmes sur le processus de transformation structurelle, en reliant les variables liées à la transformation structurelle, à savoir la productivité de la main-d'œuvre agricole et la part de l'emploi, aux événements météorologiques extrêmes, y compris les sécheresses, les inondations et les vagues de chaleur. Des indicateurs météorologiques précis sont utilisés pour analyser les effets à court terme à l'aide d'un système d'équations simultanées et les effets à long terme avec un modèle de données de panel dynamique linéaire. Les résultats montrent que les événements météorologiques extrêmes ont un impact négatif sur ce processus à court terme en réduisant la productivité de la main-d'œuvre agricole et en augmentant la dépendance à l'emploi agricole lors de sécheresses et de précipitations extrêmes. En revanche, des températures extrêmes entraînent une sortie prématurée de la main-d'œuvre du secteur agricole sans augmentation correspondante de la productivité de la main-d'œuvre agricole à court terme. Les effets à long terme sont particulièrement prononcés pour les sécheresses ainsi que lorsque plusieurs extrêmes météorologiques se produisent. Les effets varient considérablement selon les continents et les pays. Des tendances positives, grâce à une réduction des extrêmes météorologiques, ont soutenu la transformation structurelle axée sur la croissance dans certains pays, notamment en Amérique latine et dans une certaine mesure en Asie. À l'inverse, la détérioration des conditions, notamment dans certains pays africains, a encore freiné le développement et la croissance de la productivité de la main-d'œuvre agricole, compromettant ainsi toute perspective de transformation structurelle.

Ces résultats montrent que résoudre le problème alimentaire et emprunter la "voie de Lewis" vers une croissance économique soutenue est entravée par les extrêmes météorologiques, qui perturbent les activités agricoles et ralentissent la transformation structurelle. Cela est particulièrement préoccupant

pour les pays à faible revenu d'Afrique et d'Asie du Sud, où une proportion importante de la main-d'œuvre est principalement engagée dans l'agriculture à petite échelle. Ils montrent également qu'il est essentiel de prendre en compte non seulement la productivité des terres et la résistance de la production agricole aux extrêmes météorologiques, mais aussi les conditions de travail et les mesures d'adaptation plus systémiques pour maintenir la production alimentaire et améliorer les niveaux de vie. Cependant, les recherches académiques sur la productivité totale des agriculteurs se concentrent principalement sur l'intensification agricole et la croissance verte, avec peu d'attention portée à la manière dont la productivité totale des facteurs agricoles peut être maintenue ou améliorée face à des extrêmes météorologiques de plus en plus fréquents et graves.

De plus, la croissance de la productivité totale des facteurs (PTF) agricoles, qui mesure l'efficacité de l'agriculture, a ralenti depuis les années 2010, en particulier dans les pays en développement (Morgan et al., 2022). Plusieurs facteurs expliquent cette baisse, notamment les chocs climatiques fréquents, les nouvelles maladies des cultures et les ravageurs, le manque de percées technologiques, la lente diffusion des technologies améliorées dans les pays à faible revenu et, plus inquiétant, l'épuisement du capital naturel (Fuglie and Rada, 2013; Fuglie, 2018). Alors que la révolution verte a permis d'augmenter la production alimentaire mondiale en augmentant l'utilisation d'engrais et l'expansion des terres cultivées (Foley et al., 2005; Tilman et al., 2002), elle a également accéléré les émissions de gaz à effet de serre, la destruction des habitats et la perte de biodiversité (Dudley and Alexander, 2017; Tilman et al., 2002). Cet épuisement du capital naturel a réduit les services écosystémiques (Kremen and Miles, 2012; Reid et al., 2005), compromettant encore davantage la soutenabilité à long terme de la productivité totale des facteurs agricole.

L'agriculture, en particulier dans les pays à faible revenu, dépend fortement de la biodiversité et des écosystèmes, qui fournissent des services essentiels tels que la rétention des sols, la provision en eau et la pollinisation (Vanbergen et al., 2020). De plus, le changement climatique devrait exacerber les impacts environnementaux déjà importants de la production agricole en affectant directement et négativement la productivité totale des facteurs agricoles, en réduisant l'efficacité des produits agrochimiques et en augmentant leur perte dans l'environnement, tout en augmentant les ravageurs des cultures et l'érosion des sols (Yang et al., 2024). Les tendances actuelles suggèrent que les futures améliorations des rendements reposeront sur l'intensification des intrants et l'expansion des terres cultivées, contraintes par les limites technologiques et les rendements décroissants. Cette trajectoire pourrait aggraver la déforestation et la perte d'habitats, épuisant encore davantage les écosystèmes et la biodiversité, qui sont essentiels à la soutenabilité de l'agriculture et au bien-être humain.

Alors que le concept de soutenabilité faible suggère que le capital naturel peut être remplacé par du capital manufacturé sans réduire le bien-être, la soutenabilité forte rejette cette idée en raison des ir-

réversibilités, de l'incertitude et des composants "critiques" du capital naturel (Turner and Pearce, 1993). La biodiversité et les écosystèmes sont de plus en plus vulnérables aux événements météorologiques extrêmes, qui perturbent leur structure et leur fonctionnement (Watson et al., 2019). Cette vulnérabilité est exacerbée par des pressions d'origine humaine telles que la défaunation, les espèces envahissantes et la dégradation des habitats, ce qui accroît encore la sensibilité des écosystèmes au changement climatique (Hjältén et al., 2016). Ces impacts négatifs devraient s'aggraver dans les décennies à venir (Hoffmann and Beierkuhnlein, 2020), entraînant une réduction du stock de capital naturel, ce qui affectera la quantité de biens et de services écosystémiques dont dépend l'agriculture, nécessitant ainsi des changements fondamentaux dans les modes de production agricole.

Le chapitre 2 de cette thèse explore donc comment la biodiversité et les écosystèmes contribuent à la productivité totale des facteurs agricoles (PTF), une mesure des pratiques technologiques et de gestion qui améliorent l'efficacité de l'utilisation des intrants, entraînant une production plus élevée avec une utilisation réduite des intrants (Jorgenson et al., 2005). En permettant d'obtenir des résultats plus élevés tout en utilisant moins d'intrants, la croissance de la PTF soutient la production et peut être durable sur le plan environnemental si elle réduit la dépendance à l'égard d'intrants polluants ou à forte intensité d'émissions. Ce chapitre utilise un système d'équations simultanées pour estimer les effets directs de la biodiversité, des écosystèmes et des extrêmes météorologiques sur la croissance de la PTF agricole, ainsi que le rôle de la biodiversité en tant que médiateur des effets des extrêmes météorologiques sur la PTF agricole. Les résultats préliminaires indiquent que la biodiversité et les écosystèmes jouent un rôle direct dans l'amélioration de la PTF agricole, tandis que les événements météorologiques extrêmes, en particulier les sécheresses, ont un impact négatif à la fois sur la PTF et sur la biodiversité. La diminution de la biodiversité réduit encore sa contribution à la croissance de la PTF agricole. Par conséquent, bien que la biodiversité soit essentielle à la croissance de la PTF agricole, les événements météorologiques extrêmes diminuent sa contribution positive. En conséquence, la croissance de la PTF agricole est plus significativement affectée par les extrêmes météorologiques dans les pays où la biodiversité est abondante que dans ceux où la biodiversité joue un rôle moindre.

Ces résultats peuvent sembler quelque peu inattendus, probablement en raison de l'utilisation de données agrégées qui ne font pas de distinction entre les différents modèles de production agricole. Il est plausible que le modèle agricole dominant, caractérisé par une production en monoculture étayée par une utilisation élevée d'intrants et des pratiques à forte intensité de capital, soit à l'origine des effets observés. Bien qu'ils puissent sembler résistants aux extrêmes météorologiques à court terme en raison de la dépendance aux intrants synthétiques et aux technologies, la dépendance à un nombre limité de variétés de cultures rend finalement le système vulnérable aux événements météorologiques extrêmes à long terme. En outre, les résultats indiquent que, bien que l'utilisation d'intrants synthétiques ait un

effet positif sur la croissance de la PTF agricole, leurs effets indirects négatifs, dus à la perte de biodiversité, l'emportent sur ces gains à court terme. Cette tendance suggère une baisse de la PTF à long terme à mesure que les pratiques agricoles intensives érodent la biodiversité. De plus, l'analyse ne permet pas de déterminer si certains modèles de production agricole utilisent efficacement la biodiversité et les écosystèmes pour améliorer la PTF, comme c'est le cas dans les systèmes de production agroécologiques. Dans cette analyse, la biodiversité est traitée comme tout autre intrant, ce qui pourrait expliquer l'absence d'un effet protecteur face aux extrêmes météorologiques.

Par extension, cela soulève des questions sur le rôle des pratiques de production agricole et sur le fait que les exploitations agricoles mettent en place des stratégies qui renforcent le rôle des écosystèmes et de la biodiversité, et si ces stratégies améliorent la productivité des terres agricoles et la résistance aux chocs météorologiques. L'agriculture soutenable a été promue comme une solution pour répondre à la demande croissante de nourriture tout en protégeant les écosystèmes. Ces approches vont de l'intensification soutenable, qui vise à maximiser les rendements tout en minimisant les impacts négatifs sur l'environnement (Pretty et al., 2012), à des refontes plus systémiques des systèmes de production agricole fondées sur les principes de l'intensification écologique et de l'agroécologie (Vanbergen et al., 2020). Un éventail diversifié de pratiques agricoles soutenables est déjà utilisé parmi les agriculteurs, notamment des mesures agronomiques pour améliorer la fertilité des sols, des pratiques végétales comme l'agroforesterie et des interventions structurelles telles que les systèmes de stockage d'eau (Linger and Critchley, 2007). Ces pratiques influencent l'utilisation de la main-d'œuvre et des terres et sont susceptibles d'affecter le processus de transformation structurelle. Cependant, les preuves concernant leur impact restent mitigées et dépendent du contexte ; certaines pratiques augmentent le travail des ménages (Montt and Luu, 2020), tandis que d'autres ne montrent aucune différence significative selon leur combinaison (Teklewold et al., 2013). De plus, les résultats en termes de productivité des terres varient en fonction des conditions environnementales et climatiques (Pittelkow et al., 2015; Castle et al., 2021). L'effet des changements dans l'utilisation de la main-d'œuvre dépend également des changements de production, qui influencent à leur tour la productivité globale de la main-d'œuvre.

Ainsi, comprendre comment la mise en œuvre des pratiques agricoles soutenables se déroule dans les contextes des extrêmes météorologiques et de la transformation structurelle est crucial pour les pays à faible revenu, où une grande partie de la population dépend de l'agriculture pour l'emploi et est donc investie dans la mise en œuvre de stratégies qui créent des opportunités d'emploi décent, augmentent la production alimentaire et améliorent les niveaux de vie. De plus, les petits agriculteurs des régions tropicales à faible revenu sont particulièrement vulnérables au changement climatique, faisant face à des barrières socio-économiques et politiques qui entravent leur capacité d'adaptation (Morton, 2007). Les changements démographiques rapides attendus dans un avenir proche, associés à la baisse de la pro-

ductivité et de la disponibilité des terres, à la vulnérabilité croissante au changement climatique et aux limites de la "voie de Lewis" classique vers le développement, soulignent tous l'urgence de réévaluer les stratégies de développement pour une transformation structurelle soutenable et inclusive.

En s'appuyant sur cela, le chapitre 3 met en lumière la relation entre la productivité des terres agricoles, les pratiques agricoles soutenables, la dégradation de l'environnement et les extrêmes météorologiques dans les petites exploitations agricoles, en utilisant les données du recensement agricole du Sénégal (2020-2021). Les petits exploitants deviennent un point focal, car les recherches montrent que l'agriculture écologique, en particulier l'agroécologie, est plus efficace sur les petites exploitations. Le Sénégal, avec son secteur agricole principalement constitué de petites exploitations, une forte proportion d'emplois agricoles, des chocs météorologiques fréquents et un soutien institutionnel aux pratiques agroécologiques, offre un contexte idéal pour cette exploration. En outre, les données solides du recensement agricole soutenu par la FAO, y compris un module consacré aux pratiques environnementales, permettent une analyse plus approfondie du rôle de l'agriculture soutenable dans l'amélioration de la capacité d'adaptation aux chocs météorologiques.

Trois typologies distinctes d'exploitations agricoles émergent d'une analyse de classification hiérarchique : les exploitations intensives en intrants, les exploitations adaptées au climat et les exploitations traditionnelles soutenables. Notamment, les exploitations intensives en intrants présentent les niveaux de productivité des terres agricoles les plus élevés, tandis que les exploitations adaptées au climat affichent une productivité modérée. Un modèle logistique binaire identifie les principaux facteurs déterminant l'adoption de pratiques soutenables, notamment le niveau d'alphabétisation du chef de ménage, l'accès au soutien agricole et la propriété foncière formelle. En outre, les ménages exposés aux extrêmes météorologiques et aux pressions environnementales sont plus susceptibles d'adopter des méthodes soutenables. Bien que les taux d'adoption globaux restent faibles, les exploitations employant plusieurs pratiques soutenables sont mieux équipées pour faire face aux températures extrêmes. Des interventions spécifiques telles que l'agriculture de conservation et le contrôle de l'érosion sont associées à des impacts moins graves des chocs météorologiques, tandis que d'autres stratégies, telles que les améliorations de la fertilité des sols à faible coût, montrent une efficacité limitée.

En conclusion, les résultats démontrent que les extrêmes climatiques - en particulier les sécheresses et les précipitations extrêmes - ont un effet négatif sur le processus de transformation structurelle dans les économies émergentes et à faible revenu. Deuxièmement, si la biodiversité et les écosystèmes contribuent positivement à la croissance du secteur agricole, ils sont également vulnérables aux extrêmes climatiques et, dans le cadre des modes de production agricole actuels, ils ne sont pas suffisamment déployés pour réduire les effets négatifs des extrêmes climatiques. Enfin, l'adoption partielle de pratiques agricoles soutenables limite leur efficacité dans la réduction des effets négatifs des événe-

ments météorologiques extrêmes. Les obstacles à l'adoption de l'agriculture soutenable, notamment les ressources financières limitées, les informations inadéquates et la formation insuffisante, entravent l'adoption de ces pratiques dans les pays à faible revenu. Il est donc nécessaire d'intensifier la recherche et les investissements dans le développement et le déploiement de technologies, de pratiques et d'intrants mieux adaptés aux contextes locaux, qu'il s'agisse d'intrants de base tels que des intrants résistants à la sécheresse et à la chaleur, ou de recherches plus approfondies sur la reconfiguration des agroécosystèmes en vue de mettre au point des interventions écologiques plus spécifiques à chaque site, afin d'aider les agriculteurs à passer à une production alimentaire soutenable et à emprunter les voies de la transformation structurelle.

Chapter 1

Weather extremes and agricultural labour productivity: impacts on structural transformation in low-income and emerging economies^{*}

^{*} This chapter was co-authored with Natalia Zugravu-Soilita and has been submitted for publication under the title "Agricultural Dynamics and Structural Transformation: Can They Withstand Weather Extremes?"

1.1 Introduction

As outlined in the introduction, a series of factors have been advanced and studied in the literature to explain the limited progress toward structural transformation. These include liberalisation and deregulation amidst weak institutions that hinder innovation and modernisation, commodity booms, reliance on natural resource exports, urbanisation, the expansion of small-scale and informal manufacturing, and challenges in land allocation often leading to migration (Rodrik et al., 2019; Gollin et al., 2016; Dabla-Norris et al., 2013; Kruse et al., 2022; Dorin et al., 2013). One could thus suppose that overcoming these challenges should enable the replication of a universal model of agricultural development (characterised by input intensification, modernisation and mechanisation to achieve economies of scale and labour productivity gains) and structural transformation. Indeed, standard growth models assume that productivity growth in each sector is mainly constrained by capital, labour, and land (for agriculture), as well as the rate of technological change and friction in reallocating factors between sectors. However, climatic and environmental conditions can affect stocks and land, labour, and capital returns and may even endogenously influence technological change (Barrett et al., 2021). Moreover, these conditions call for more specific and localised development solutions. However, they are still under-explored in the context of structural transformation, especially in low-income and emerging economies that are among the most exposed to extreme weather events.

Recent research by Ortiz-Bobea et al. (2021) has revealed that anthropogenic climate change has resulted in a significant reduction of approximately 21% in global agricultural total factor productivity since 1961, with even more severe impacts in warmer regions such as Africa, Latin America, and the Caribbean, where the reductions range from 26 to 34%. As the frequency and intensity of extreme weather events are projected to increase due to climate disruption, it is crucial to assess the potential implications for economic growth, particularly for low-income and emerging economies that need to create employment opportunities and improve welfare to better withstand climate change impacts. Effectively addressing these challenges will require exploring alternative pathways to the conventional understanding of structural transformation.

This chapter aims to extend the existing literature through several key contributions. First, it links variables related to structural transformation—such as agricultural labour productivity and employment shares—with extreme weather events, including droughts, floods, and heat waves. By affecting agricultural labour productivity and employment, we hypothesise that these weather extremes may slow the pace of structural transformation. Second, we use precise weather indicators from ERA5 ERGCS and CRU-TS data to measure the impact of extreme weather on the agricultural sector, enhancing our understanding of its effects in low-income and emerging economies. We analyse short-run effects us-

ing a system of simultaneous equations and long-run effects using a linear dynamic panel data model. This research is novel in its international comparative approach, focusing on agricultural employment shares and labour productivity within a unified framework. It distinguishes between the direct, indirect, immediate, and long-term impacts of extreme weather events on structural transformation.

Following this brief introduction, Section 2 explores the stylised facts concerning structural transformation and extreme weather events, providing essential background information. Section 3 presents the theoretical assumptions underpinning the empirical analysis. Section 4 discusses the estimation results, and Section 5 concludes by drawing insights from the empirical findings.

1.2 Understanding structural transformation: stylised facts, literature insights, and the role of weather extremes

The conventional view of structural transformation in economic development is characterized by three stylized facts: a decline in agricultural employment due to rising agricultural labour productivity, a hump-shaped pattern in industrial employment, and an increase in service sector employment, perceived to offer higher labour productivity. Figure 1.1 illustrates these trends in labour productivity (LP) across different sectors.¹ The data, from the GGDC/UNU-WIDER Economic Transformation Database (GGDC/UNU-WETD), covers 1990-2018 for 18 sub-Saharan African, 20 Asian, 4 Middle East and North African, and 9 Latin American countries.² Notably, although labour productivity has grown across sectors, growth rates vary significantly, with low-income developing countries often lagging behind.

As expected, the manufacturing sector shows the highest increase in labour productivity, followed by services, and then agriculture. This pattern reflects structural transformation, where economies typically shift from agriculture to industry and services with development. The high labour productivity in manufacturing is due to advanced technology, increased capital, and higher value-added production. The services sector's growth stems from a rising middle class, urbanisation, and increased service demand.³ However, this trend is prominent in advanced and emerging economies, while less evident in low-income countries.

Figure 1.2 shows the trend of declining agricultural employment shares in our sample of countries,

¹Industry & Manufacturing LP includes ISIC Rev 4 categories: Mining, Manufacturing, Utilities, Construction. Services LP includes: Trade services, Transport services, Business services, Financial services, Real estate, Government services, and Other services. Data are in gross value added at constant 2015 prices (millions, USD).

²The GGDC/UNU-WIDER Economic Transformation Database covers sub-Saharan Africa: Botswana, Burkina Faso, Cameroon, Ethiopia, Ghana, Kenya, Lesotho, Malawi, Mauritius, Mozambique, Namibia, Nigeria, Rwanda, Senegal, South Africa, Tanzania, Uganda, Zambia; Middle East & North Africa: Egypt, Morocco, Tunisia, Turkey; Latin America: Argentina, Bolivia, Brazil, Chile, Colombia, Costa Rica, Ecuador, Mexico, Peru; Asia: Bangladesh, Cambodia, China, India, Indonesia, Lao PDR, Malaysia, Myanmar, Nepal, Pakistan, Philippines, Sri Lanka, Thailand, Vietnam, Hong Kong (China), Israel, Japan, Korea (Rep. of), Singapore, Chinese Taipei.

³At the start of the study, the service sector had the highest labour productivity levels, but its growth has slowed, trailing behind manufacturing in recent years.

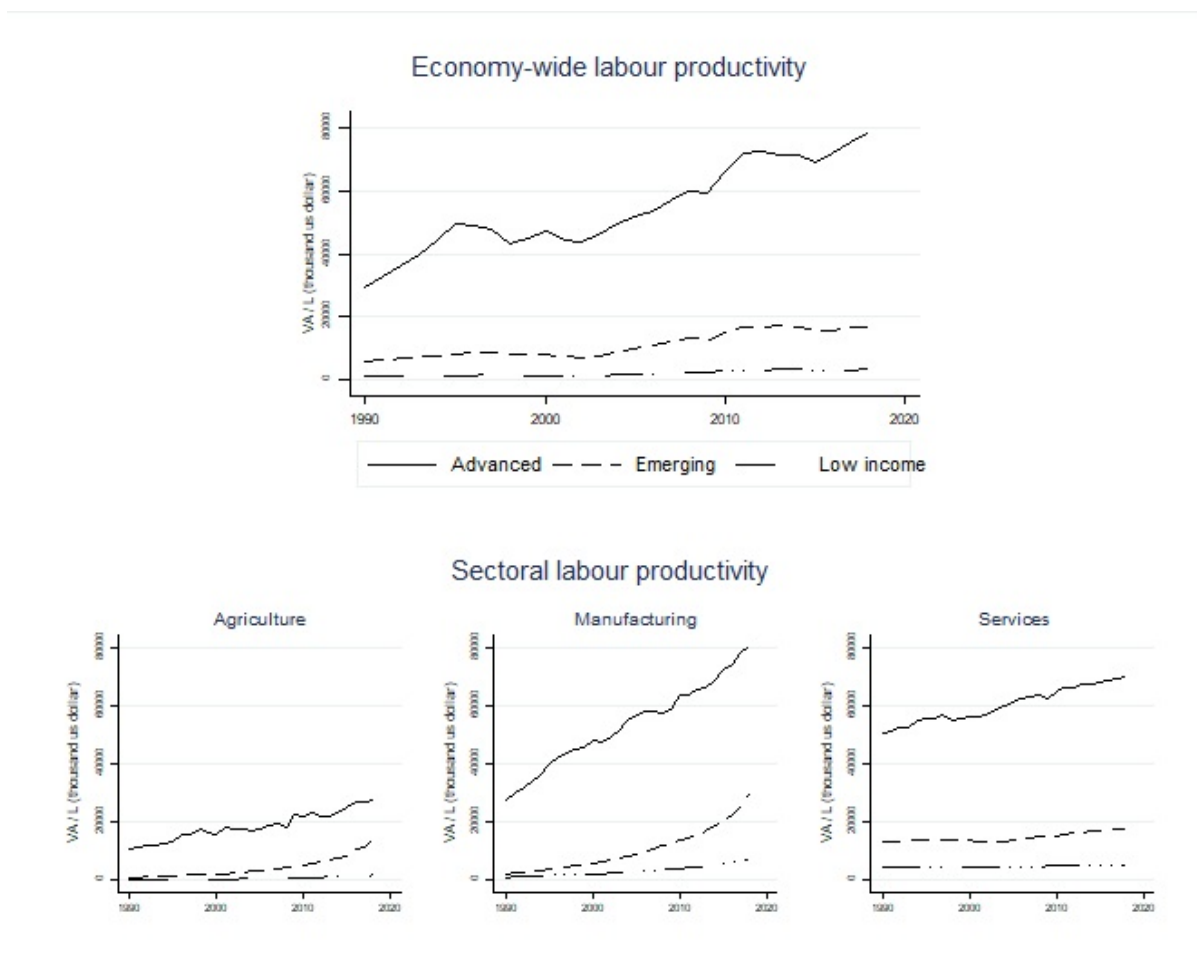


Figure 1.1: Economy-wide and sectoral labour productivity in the GGDC/UNU-WETD sample of countries (1990 - 2018)

Sample data consists of 22 emerging economies and 15 low-income countries.

Source: Economic Transformation Database, calculations, authors' own

alongside a rise in service sector employment. Notably, low-income economies exhibit a sharp drop in agricultural employment, but only modest gains in high-value-added sectors. These countries seem to have transitioned directly to the services sector without significantly revitalising their industrial sectors. Despite this shift, low-income countries still have much higher agricultural employment shares—two to four times higher—compared to other country groups.

As noted by Kruse et al. (2022), the modest rise in manufacturing shares in low-income economies is due to the growth of small-scale, domestic manufacturing. Thus, labour productivity gains from shifting workers from agriculture to non-agricultural sectors have been less significant in low-income African countries than in emerging East Asian countries (Sen, 2019). One explanation for this limited labour productivity gain in manufacturing could be the impact of Washington consensus structural reforms, which promoted liberalisation and deregulation. These reforms may have shifted aggregate demand toward non-tradable goods and services, expanding the non-manufacturing sector at the expense of manufacturing (Dabla-Norris et al., 2013). Commodity booms have similarly influenced growth pat-

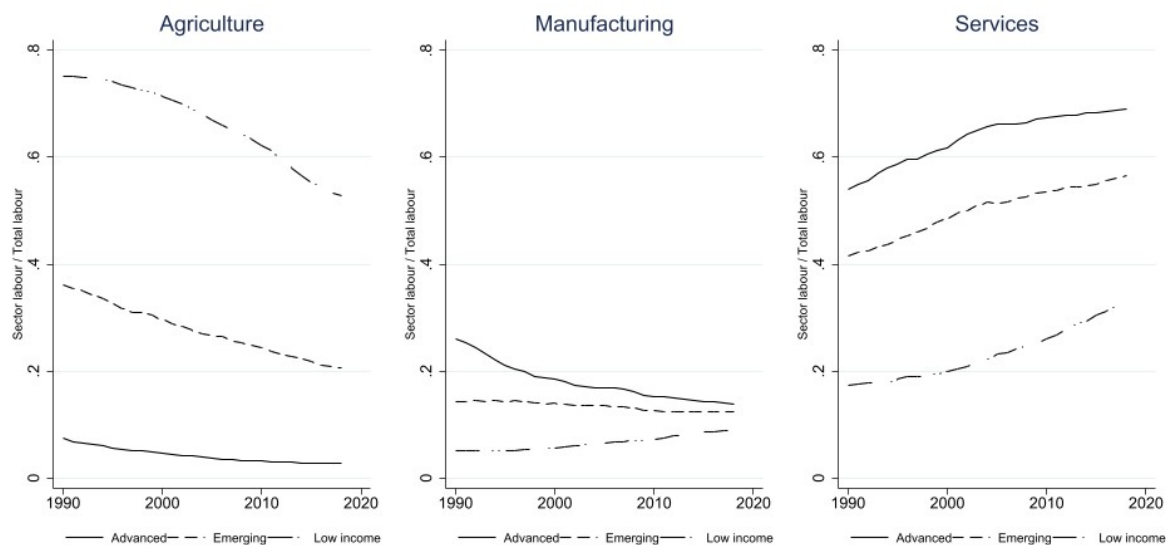


Figure 1.2: Sectoral employment shares in GGDC/UNU-WETD sample of countries (1990 - 2018)

Sample data consists of 22 emerging economies and 15 low-income countries.

Source: Economic Transformation Database, calculations, authors' own

terns in developing countries. Gollin et al. (2016) show a positive correlation between natural resource exports and urbanisation, leading to 'consumption cities' dominated by non-tradable services. Unlike high-income countries, where industrialisation has driven urbanisation, in developing economies, rapid urbanisation and growth in non-tradable services occur without industrial modernisation. This often results in a service sector concentration, with limited labour productivity gains in agriculture and manufacturing, leading to modest improvements in overall labour productivity. In Latin America, challenges such as commodity dependence, overvalued exchange rates, and deindustrialisation following market liberalisation have hindered labour productivity gains (McMillan et al., 2014). Similarly, while some labour productivity gains have enabled structural change in sub-Saharan Africa, labour reallocation has been limited, with notable growth in services and small-scale, informal manufacturing (Rodrik et al., 2019).

Dorin et al. (2013) highlight challenges in scaling up agricultural activity, noting that strategies like intensification through modern inputs and mechanisation, increasing land per worker, or migration to free land face significant obstacles. In Africa and Asia, demographic pressures and geopolitical tensions limit migration options, while scarce, low-quality land complicates reallocation efforts. Additionally, fossil fuel-based mechanisation raises environmental concerns, reducing long-term yields and increasing climate change vulnerability. These issues suggest the need for alternative agricultural models. However, addressing the impact of extreme weather and environmental factors on agriculture is crucial before developing new models for structural transformation, with agriculture as a key component.

Temperature rise is a well-documented driver of erratic rainfall changes, increasing the risk of frequent

and intense floods, droughts, and heatwaves (IPCC, 2007). More intense droughts are occurring in the Mediterranean, West Africa, Central Asia, and Central America, while precipitation is rising in high-latitude areas, leading to more significant risks of flash floods and urban flooding (IPCC, 2021; Meehl et al., 2005). Figure 1.3 shows climate anomalies from 1990 to 2020 by continent (Africa, Americas, Asia). The top row displays temperature anomalies, with annual averages rising slightly across all countries. The graph on extremely hot days ($T_{\max} > 35^{\circ}\text{C}$) shows a notable increase in Africa. The middle row depicts precipitation anomalies, highlighting extremely wet days in the Americas. SPI-12 and SPEI-12 indices⁴ indicate high probabilities of extremely dry conditions in Africa and wet conditions in Asia and the Americas. The bottom row details SPI-12 and SPEI-12 indices for country averages, showing persistent drought with increasing severity in African countries and more variable, wetter conditions in other regions. These trends suggest that while temperature anomalies, particularly extreme heat, are rising in Africa, the Americas are experiencing wetter conditions. Asia is seeing extreme wet events, alongside persistent drought in Africa. This evidence indicates a strong link between extreme weather events and delays in structural transformation, especially in low-income and emerging economies where agriculture remains a major sector.

The agricultural sector in low-income countries is highly vulnerable to meteorological conditions. The lack of green revolution technologies adoption has led to a stagnant sector with low labour productivity, limited adaptive capacity, poor infrastructure, minimal research and development, and reliance on primary commodity exports. Agriculture is disproportionately affected by extreme weather events like floods, droughts, heatwaves, and cold snaps, as well as soil issues, which are expected to decrease staple crop yields by up to 24% by 2030 (Jägermeyr et al., 2021). High temperatures reduce worker productivity, limit working hours, and decrease performance (Shayegh et al., 2021). Rising temperatures can also impair health, education, and cognitive function, worsening agriculture's challenges (Deschenes et al., 2009b). Changes in agricultural output influence demand for non-agricultural goods, potentially slowing labour migration from agriculture (Schultz, 1953; Johnston and Mellor, 1961; Timmer, 1988; Liu et al., 2020; Emerick, 2018). While food imports can offset yield declines, long-term agricultural distortions can lower labour productivity and economic growth (Gollin et al., 2016). Extreme weather can accelerate labour movement out of agriculture and prompt rural-urban migration (Barrios et al., 2006). However, migration is often limited by liquidity and relocation costs and is more likely among those with credit access and near urban centres (Wesselbaum, 2019; Henderson et al., 2017). Extreme weather also impacts financial markets and investment, influencing returns on moving capital from agriculture to other sectors (Bansal et al., 2016; Krueger et al., 2020), especially in low-income countries with limited adaptive capabilities (Addoum et al., 2020). Damage to infrastructure and key

⁴Positive SPI values indicate wet conditions, while negative values indicate drought likelihood. SPEI incorporates temperature and potential evapotranspiration. See Section 1.4.2 for details.

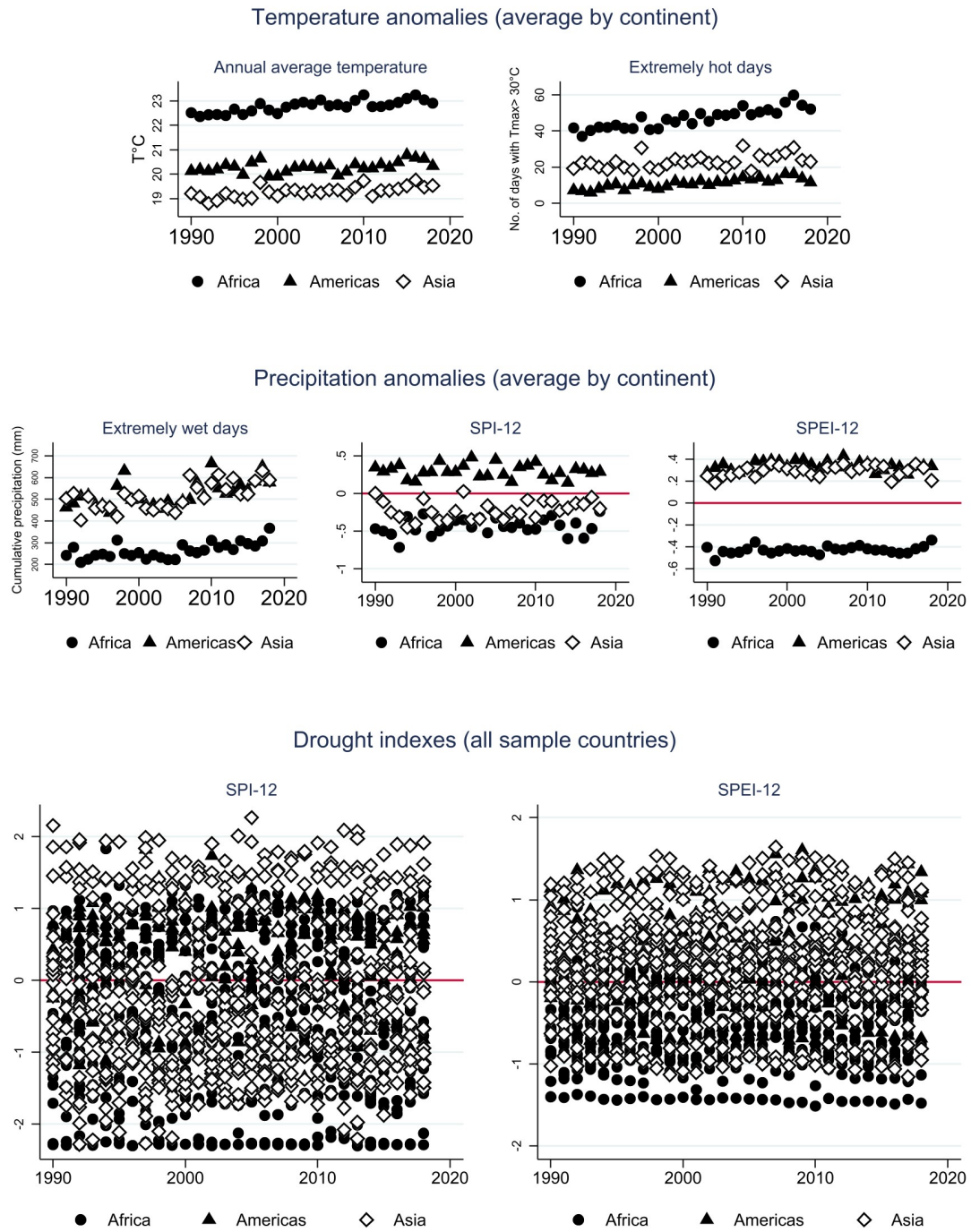


Figure 1.3: Extreme weather events in GGDC/UNU-WETD sample of countries (1990 - 2018)

Source: Climatic Research Unit, calculations, authors' own

systems can disrupt trade and supply chains (Adams et al., 2021).

Research has mainly focused on the direct effects of natural disasters like droughts and floods on GDP growth or sectoral labour productivity (i.e., 'within sector' productivity changes) (Dell et al., 2012; Deryunga and Hsiang, 2014; Burke et al., 2015). While the impact of temperature changes due to cli-

mate change is well-documented, the effects of precipitation remain unclear, with studies showing mixed results. Recent research (Berlemann and Wenzel, 2016; Boubacar, 2015; Felbermayr and Gröschl, 2014; Berlemann and Wenzel, 2018) uses advanced drought indexes like SPI and SPEI to explore the non-linear effects of dry and wet periods.⁵ However, to our knowledge, no studies have simultaneously examined how weather-related disasters affect changes in agricultural employment shares and labour productivity.

1.3 Theoretical assumptions and econometric specifications

Theoretical frameworks suggest that structural transformation begins with improvements in agricultural labour productivity, addressing the 'food problem' as noted by Schultz (1953) and Timmer (1988). Higher agricultural productivity enables labour to shift from agriculture to non-agricultural sectors. Once staple food production surpasses subsistence levels, food prices fall, crop production diversifies, and commercial farming expands. This diversification fosters backward and forward linkages with non-agricultural sectors, boosting demand for non-agricultural goods and services and providing raw materials for non-agricultural production (Johnston and Mellor, 1961). As savings and access to finance increase, farms substitute capital for labour, prompting workers to move to non-agricultural wage employment. Structural transformation in agriculture thus involves two interrelated processes: '*within-sector productivity growth*' through capital accumulation or technological change, and global labour productivity change via '*intersectoral labour reallocation*' (McMillan et al., 2014; Rodrik et al., 2019). While previous research focused mainly on total agricultural labour and changes over time, we examine shifts in agricultural employment shares relative to labour productivity changes, offering key insights. Agricultural employment share measures the proportion of the workforce in agriculture relative to other sectors, providing a clearer view of structural transformation and labour shifts to more productive sectors. This metric separates labour productivity effects from population growth effects. For example, while the number of agricultural workers may rise with population growth, a declining employment share indicates labour productivity gains and sectoral shifts. Analysing employment share enables better comparison across countries and regions with varying demographic profiles.

⁵Other studies use disaster risk and vulnerability data, such as EMDAT, to estimate climate disaster impacts on GDP and sectoral labour productivity, considering factors like injuries, missing persons, and infrastructure damage from meteorological, geological, and human-induced disasters (Noy and Nualsri, 2007; Loayza et al., 2012; Skidmore and Toya, 2002).

1.3.1 Agriculture labour productivity

The first component of structural transformation is agricultural labour productivity, or value added per worker in the agriculture sector, denoted y_{at} , which can be expressed as follows:

$$y_{at} = \frac{Y_{at}}{L_{at}} = \frac{A_{at} L_{at}^{\alpha} K_{at}^{\beta} H_{at}^{\gamma} T_{at}^{(1-\alpha-\beta-\gamma)}}{L_{at}} = A_{at} L_{at}^{\alpha-1} K_{at}^{\beta} H_{at}^{\gamma} T_{at}^{(1-\alpha-\beta-\gamma)} \quad (1.1)$$

where A_{at} represents the total factor productivity (TFP) in the agricultural sector; the term $L_{at}^{\alpha} K_{at}^{\beta} H_{at}^{\gamma} T_{at}^{(1-\alpha-\beta-\gamma)}$ represents the Cobb-Douglas production function with constant returns to scale, where α , β , and γ denote the elasticities of labour L_{at} , physical capital K_{at} , and human capital H_{at} , respectively, utilised in the agricultural sector; T_{at} represents land available for agriculture. Taking the logarithm of both sides to linearise, we have:

$$\log(y_{at}) = \log(A_{at}) + (\alpha - 1) \log(L_{at}) + \beta \log(K_{at}) + \gamma \log(H_{at}) + (1 - \alpha - \beta - \gamma) \log(T_{at}) \quad (1.2)$$

Total factor productivity (A_{at}) measures the efficiency of resource use in agriculture, influenced by factors such as local climate, soil conditions, extreme weather events (e.g., floods, droughts, heatwaves), and institutional and policy environments.

Decomposing labour productivity further reveals the interaction between land availability and land productivity, expressed as $y_{at} = \frac{Y_{at}}{T_{at}} * \frac{T_{at}}{L_{at}}$. Figure 1.4, adapted from Dorin et al. (2013), shows how labour productivity is driven by land productivity through better practices and technologies (*Intensification*) and by increased land availability through mechanisation and expanded arable land (*Extensification (Motorisation)*). Adverse weather, indicated by red arrows and shaded areas, negatively impacts both land productivity and availability, thus reducing labour productivity. Extreme weather events can lower land productivity (Y/T) by damaging crops, reducing soil fertility, and disrupting agricultural cycles. Floods and heavy rains can water-log fields, while droughts and high temperatures can stress plants, reducing yields. Adverse conditions can also degrade soil and reduce arable land, limiting land per worker (T/L) and the potential for extensification. Persistent droughts can cause desertification, shrinking cultivable land. Mechanisation, intended to boost labour productivity, can become counterproductive as environmental degradation reduces land quality and availability, creating a cycle where increased mechanisation initially raises labour productivity but also heightens vulnerability through land degradation. As shown in Figure 1.4, our variables of interest—extreme weather events—can be viewed as shocks to total factor productivity. These events impact land availability per worker, hinder the ability to achieve economies of scale through mechanisation (especially fossil fuel-based), and limit the potential for further agricultural intensification through input modernisation.

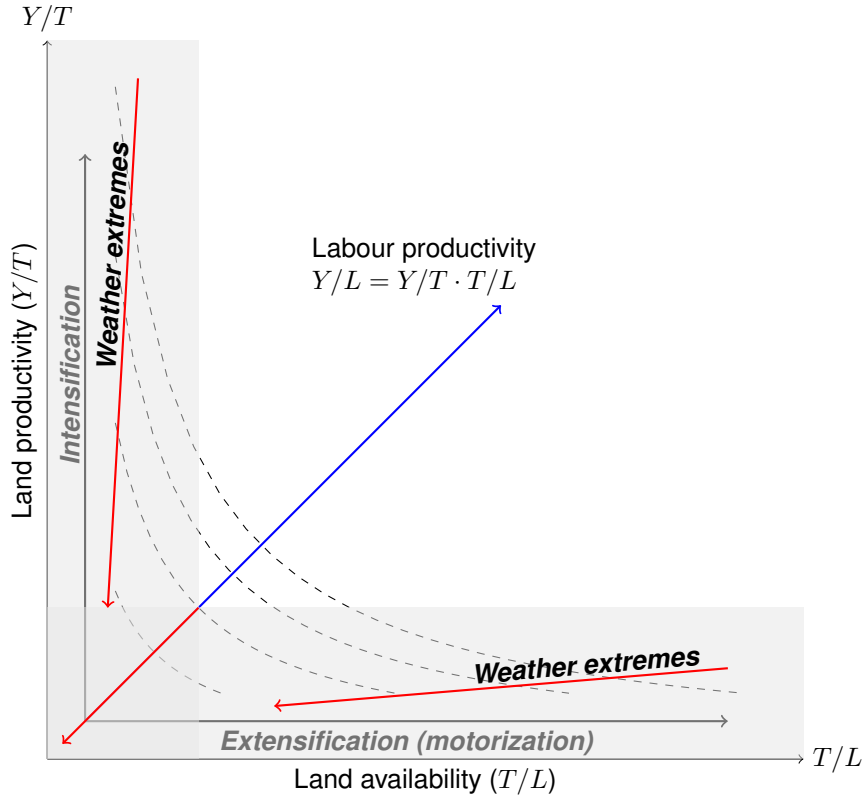


Figure 1.4: Labour productivity as a function of land productivity and availability with weather extremes
Adaptation from Dorin et al. (2013)

In addition to weather conditions, we model TFP (A_{at}) as a function of several factors influencing productivity, including institutional quality, foreign direct investment (FDI), mineral resources, population growth, and trade openness. Mineral resource discoveries and commodity price booms can lower agricultural labour productivity by causing distortions in the non-agricultural sector and reducing agricultural inputs and investments, particularly in sub-Saharan Africa (Gollin et al., 2016; Dorinet et al., 2021). FDI is crucial in low-income countries, where it can provide market access and technology, boosting agricultural output (Edeh et al., 2020). Population growth affects economic output by increasing demand for goods and services, spurring technological innovation, and enhancing labour productivity through land use intensification and adoption of new technologies (Romer, 1990; Rostow, 1982). Economies of scale arise from larger markets, attracting investment in R&D and driving agricultural advancements. Trade openness promotes efficient resource allocation via comparative advantage, facilitates technology diffusion, and fosters innovation and growth. It also significantly impacts structural transformation through differential labour productivity growth rates across sectors (Matsuyama, 1992).

We thus model the total factor productivity (A_{at}) as a function of following factors:

$$\log(A_{at}) = \delta_0 + \delta_1 WE_t + \delta_2 MR_t + \delta_3 FDI_t + \delta_4 PGR_t + \delta_5 \delta_6 Open_t + \delta_7 INS_t + \epsilon_{at} \quad (1.3)$$

with WE_t for weather extreme events, MR_t - mineral resources endowment, FDI_t - foreign direct investment, PGR_t - population growth rate, $Open$ for trade openness, and INS_t for institutional quality.

Substituting this into the log-transformed labour productivity equation, we have:

$$\begin{aligned}
\log(y_{at}) = & \delta_0 + \delta_1 WE_t + \delta_2 MR_t + \delta_3 FDI_t \\
& + \delta_4 PGR_t + \delta_5 Open_t + \delta_6 INS_t \\
& + (\alpha - 1) \log(L_{at}) + \beta \log(K_{at}) + \gamma \log(H_{at}) \\
& + (1 - \alpha - \beta - \gamma) \log(T_{at}) + \epsilon_{at}
\end{aligned} \tag{1.4}$$

In the final empirical specification of our model for agricultural labour productivity, we must carefully consider the inclusion of our variables of interest, WE . In particular, there are several reasons for excluding L (labour) and T (land) from our linear model. First, agricultural labour (L_{at}) and labour productivity (y_{at}) are interdependent; including labour could introduce simultaneity bias, as changes in labour productivity might influence labour allocation (see Section 1.3.2). Moreover, including L_{at} in the labour productivity equation risks partial identity issues due to mechanical relationships, leading to spurious correlations. Since y_{at} is Y_{at}/L_{at} , using L_{at} would affect y_{at} directly by construction rather than through genuine economic relationships. Second, labour productivity can be expressed as the product of land productivity (Y_{at}/T_{at}) and land availability per worker (T_{at}/L_{at}). Weather conditions significantly influence both. Including T_{at} could obscure the effects of weather extremes by capturing this interaction, absorbing variability caused by weather and making it difficult to isolate the specific effects. As an alternative, crop yields (particularly cereal yields) can serve as a proxy to capture modernisation and intensification effects. Crop yields measure agricultural output per land unit, reflecting land use efficiency, improvements in practices, and technological advancements, which correlate with GDP and agricultural growth (McArthur and McCord, 2017). This approach enhances international comparability and avoids mechanical relationship issues with L_{at} and T_{at} . Furthermore, cereal yields can serve as an instrumental variable to address potential endogeneity in our agricultural labour productivity equation, particularly in a system involving agricultural employment share. Using cereal yields ensures relative exogeneity since they are less influenced by labour availability but more by agricultural practices and technology, which are typically exogenous to short-term economic fluctuations. This helps identify the causal impact of land productivity and weather conditions on labour productivity without confounding effects from L_{at} and T_{at} .

Given these arguments, the final empirical model for agricultural labour productivity ($\log(y_{at})$) can be

specified as:

$$\begin{aligned}\log(y_{at}) = & \delta_0 + \delta_1 WE_t + \delta_2 MR_t + \delta_3 FDI_t \\ & + \delta_4 PGR_t + \delta_5 Open_t + \delta_6 INS_t + \delta_7 CY_t \\ & + \delta_8 \log(K_{at}) + \delta_9 \log(H_{at}) + \epsilon_{at}\end{aligned}\tag{1.5}$$

with CY_t for cereal yields.

1.3.2 Agricultural employment share

The second component of structural transformation is the reallocation of labour from agriculture to non-agricultural sectors. This shift occurs when technological improvements and capital investments increase agricultural labour productivity, moving the sector from subsistence to market-oriented production (Hamory et al., 2021; Alvarez-Cuadrado et al., 2018). As self-employment and family employment decline, specialised and differentiated agricultural employment based on skills and tasks emerges. Thus, the share of agricultural employment ($\theta_{at} = L_{at}/L_t$) is primarily determined by agricultural labour productivity (y_{at}), capital investments (K_{at}), and human capital (H_{at}).

Labour supply in agriculture is also influenced by factors such as extreme weather events, natural disasters, population size, and trade openness. As discussed in the literature, weather conditions affect employment shares by altering working hours, prompting out-migration, or impacting the time dedicated to farming, as well as by influencing wage employment opportunities in non-agricultural sectors (Emerick, 2018; Liu et al., 2020). Trade openness impacts employment shares by changing sectoral composition and output due to global competition and fostering new industries through technology transfer and innovation. Additionally, domestic demand composition, including consumption and production patterns, is critical in driving structural transformation in the context of trade globalisation (Matsuyama, 2019). Therefore, the employment share in the agricultural sector at time t can be expressed as:

$$\theta_{at} = \kappa_0 + \kappa_1 y_{at} + \kappa_2 K_{at} + \kappa_3 H_{at} + \kappa_4 WE_t + \kappa_5 POP_t + \kappa_6 DEP_t + \kappa_7 Open_t + \epsilon_{at}\tag{1.6}$$

Where y_{at} denotes agricultural labour productivity, K_{at} and H_{at} represent physical and human capital in agriculture, respectively, WE_t reflects weather extreme events, POP_t stands for population size, DEP_t denotes the age dependency ratio in the economy⁶, and $Open_t$ represents trade openness.

⁶The youth dependency ratio, which is a measure of the proportion of the working-age population in relation to the number of young individuals who are not yet of working age, serves as an indicator of the size of the available labour force.

Regressing the agricultural employment share ($\theta_{at} = L_{at}/L_t$) on labour productivity ($y_{at} = Y_{at}/L_{at}$) might suggest partial identity, but this is not the case. Although these variables are analytically related, they represent different aspects of economic dynamics. The agricultural employment share indicates how labour is structurally allocated, while agricultural labour productivity measures how effectively that labour produces output. The structural transformation literature suggests a direct link between labour productivity and labour allocation. Including both variables in a regression helps us understand the interaction between labour distribution and productivity in agriculture, providing a comprehensive analysis of the sector's economic dynamics without conflating these distinct concepts.

1.3.3 Interlinked dynamics: agricultural employment, labour productivity, and extreme weather events – a simultaneous equations approach

The relationship between agricultural dynamics required for structural transformation and extreme weather events, which is the focus of this chapter, can therefore be described in a simultaneous equation model. Combining equations 1.6 and 1.5, we arrive at the following recursive system of two equations:

$$\left\{ \begin{array}{l} \theta_{at} = \kappa_0 + \kappa_1 \log(y_{at}) + \kappa_2 WE_t + \kappa_3 \log(K_{at}) + \kappa_4 \log(H_{at}) + \kappa_5 POP_t \\ \quad + \kappa_6 DEP_t + \kappa_7 Open_t + \epsilon_{\theta_{at}} \\ \log(y_{at}) = \delta_0 + \delta_1 WE_t + \delta_2 MR_t + \delta_3 FDI_t + \delta_4 PGR_t + \delta_5 Open_t \\ \quad + \delta_6 INS_t + \delta_7 CY_t + \delta_8 \log(K_{at}) + \delta_9 \log(H_{at}) + \epsilon_{y_{at}} \end{array} \right. \quad (1.7)$$

where $\epsilon_{\theta_{at}}$ and $\epsilon_{y_{at}}$ represent error terms capturing unobserved factors and interact with each other (in a recursive model, these errors are correlated).

Two endogenous variables, θ_{at} and y_{at} , are identified, which are jointly determined in our system by using eleven explanatory variables (physical capital, K_{at} ; human capital, H_{at} ; trade openness, $Open_t$; weather extreme events, WE_t ; population size, POP_t ; foreign direct investment, FDI_t ; mineral resources endowment, MR_t ; population growth rate, PGR_t ; and institutional quality, INS_t ; as well as two exclusion variables: cereal yield, CY_t , and age dependency ratio, DEP_t). Our system, illustrated by Figure 1.5 is over-identified and may be estimated.

The use of CY_t (cereal yields) and DEP_t (youth dependency ratio) as instrumental variables in this context is motivated by the following reasons. In the first equation, our aim is to estimate the impact of labour productivity (y_{at}) and other variables on the agricultural employment share (θ_{at}). However, y_{at} might be endogenous due to the potential simultaneity with θ_{at} or the variables omitted. To address this

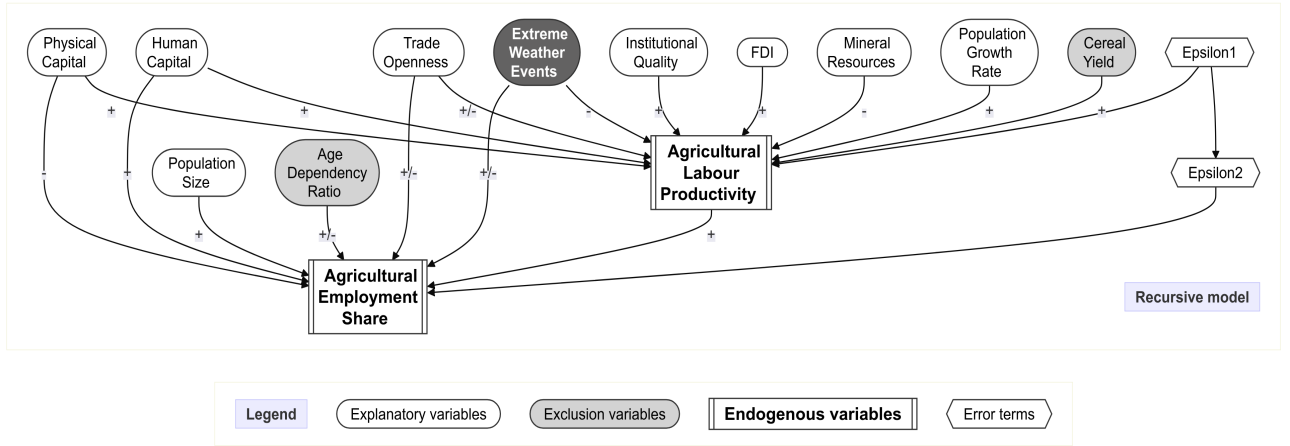


Figure 1.5: Path model linking agricultural employment shares and labour productivity to extreme weather events. The sign of expected effects is specified on arrows. ϵ represent error terms of system equations, which are estimated simultaneously using the two-step GMM technique.

issue, we thus use CY_t as an instrument for y_{at} , because it directly affects labour productivity through agricultural output improvements. Higher cereal yields increase agricultural labour productivity, which enhances overall labour productivity. However, CY_t should not directly affect the agricultural employment share (γ_{at}), except through its effect on y_{at} . This means CY_t meets the relevance condition of an instrumental variable, being correlated with y_{at} , and the exclusion restriction, being exogenous to the error term in the first equation. Essentially, variations in cereal yields provide exogenous shocks to labour productivity, helping to isolate the causal effect of y_{at} on θ_{at} . Similarly, DEP_t is used as an instrument for θ_{at} . A higher age dependency ratio indicates a larger proportion of non-working dependants, which affects the labour supply available for agricultural employment. Consequently, changes in DEP_t impact the agricultural employment share (γ_{at}) through shifts in labour supply. However, DEP_t would affect labour productivity (y_{at}) only indirectly, via its influence on the composition and size of the labour force. This indirect impact ensures that DEP_t is correlated with θ_{at} , satisfying the relevance condition, while remaining exogenous to the error term in the second equation, thus meeting the exclusion restriction.

1.4 Empirical strategy and data

1.4.1 Estimation technique

The theoretical framework posits a dual relationship between weather extremes and agricultural dynamics. The first aspect of this relationship is the direct influence of extreme weather events on agricultural employment share. The second aspect involves an indirect effect, where weather extremes impact employment shares by altering agricultural labour productivity. This dual relationship is depicted in Figure 1.5. Given the interdependence between agricultural labour productivity and employment shares, us-

ing a simplistic regression model could result in biased estimates. This potential bias stems from the intrinsic correlation between the variables in the model and the error terms.

To address the issue of potential endogeneity bias and handle important modelling concerns, a two-step GMM (generalised method of moments) was used to estimate our model on panel data. GMM estimators can handle fixed effects, endogeneity of regressors, and avoid dynamic panel bias (Nickell, 1981). Moreover, GMM allows for the assumption of conditional heteroskedasticity of residuals when jointly estimating equations. If the model is correctly specified and over-identified, and with the potential presence of arbitrary heteroskedasticity and intra-cluster correlation, GMM is more efficient than the three-stage least squares estimator (Wooldridge, 2013).⁷

1.4.2 Data sources and variables

For our dependent variables—*agricultural labour productivity* and *agricultural employment share*—we use the GGDC/UNU-WIDER Economic Transformation Database (ETD), which provides comprehensive, long-term, and internationally comparable sectoral data on employment and labour productivity in Africa, Asia, and Latin America from 1990 to 2018. The database covers 18 countries in sub-Saharan Africa, 20 in Asia, 4 in the Middle East and North Africa, and 9 in Latin America, using a harmonised sector classification (12 sectors) for consistency and comparability. Agricultural labour productivity is calculated by dividing gross value added in agriculture by the number of persons engaged in this sector, and agricultural employment shares are calculated by dividing the number of persons engaged in agriculture by the total number of persons engaged in all sectors.

To capture the impact of extreme weather events, we use the following explanatory variables:

- ***Drought_spi***: We use the Standardised Precipitation Index (SPI-12), which measures 12-month precipitation accumulations. Endorsed by the World Meteorological Organisation and developed by McKee et al. (1993), the SPI-12 compares observed precipitation to long-term historical records by using the following categories: SPI greater than -1 indicates normal to wet conditions; SPI between -2 and -1 denotes moderate to severe drought; and SPI less than or equal to -2 signifies extreme drought. For our analysis, we focus on SPI values below -1 which measure drought conditions. Values above -1 are assigned a "0". To improve readability and address non-linearities, we square negative SPI-12 values.
- ***Drought_spei***: The Standardised Precipitation Evapotranspiration Index (SPEI) extends the SPI

⁷To verify the endogeneity of regressors in our system equation model, the Durbin-Wu-Hausman test is conducted. This test examines whether agricultural employment share and agricultural labour productivity are truly endogenous. Additionally, the Hansen J test of over-identifying restrictions is reported for each estimation. Under the null hypothesis that the over-identifying restrictions are valid, the test statistic is asymptotically distributed as a chi-square variable with $m-k$, where m is the number of instruments and k is the number of endogenous variables. This helps to assess the validity of the model and ensure that the estimates are reliable.

by incorporating temperature and potential evapotranspiration. It assesses drought onset, duration, and intensity, and allows for comparison across different regions and times. Like the SPI, SPEI includes both positive and negative values for wet and dry conditions. However, its reliance on continuous temperature and precipitation data can limit its applicability, and its monthly resolution may miss rapidly developing droughts. We use SPEI to validate the robustness of our primary SPI-based estimates.

- **ExtWetDays:** One of the 40 indices developed by the ETCCDI, it measures precipitation during the 1% wettest days over the data period. Research by Zolina et al. (2010) and Fall et al. (2021) demonstrates that excessive precipitation significantly impacts the hydrologic cycle, including flooding and yields.
- **MaxHotDays:** This index measures the average number of days with temperatures exceeding 35 °C, a threshold selected by IPCC due to its critical impact on maize pollination and human health (Lobell and Gourdji, 2012; Petitti et al., 2015). It is also an ETCCDI climate change detection index.

Turning to the remaining explanatory variables, we use gross capital formation, representing additions to fixed assets, sourced from the IMF capital stock database and log-transformed. For human capital, we use years of schooling data from the Barro-Lee Educational Attainment Data, also log-transformed. For economic globalisation, we employ the KOF Globalisation Index by Axel Dreher and the KOF Swiss Economic Institute, which measures economic, social, and political integration. Our analysis includes the aggregate KOF index (*Globalisation*), the KOF Political Index (*GlobalPol*), the KOF Trade sub-index (*GlobalTrade*, a component of KOF Economic Index that includes data on foreign investment), and an explicit measure of Foreign Direct Investment (*FDI*) from the World Bank database. Additional variables sourced from the World Bank include: *MineralRent* (mineral production value as a percentage of GDP), *CerealYield* (kg per hectare of harvested land, log-transformed), *FDI* (net FDI inflows as a percentage of GDP), *ContrCorrup* (perceived corruption control index), *AgeDepend* (age dependency ratio), *PopTot* (total population, log-transformed), and *PopGR* (annual population growth rate). A time trend variable captures effects of unmeasured time-evolving variables, such as adaptation to climate change.

Variables, sources, and statistical summaries used in this chapter are detailed in Tables A.1 and A.2 in Appendix A.1. The regression analysis employs a balanced panel of 37 emerging and developing countries (Table A.3), covering the period from 1996 to 2017.

1.5 Estimation results and analysis

1.5.1 Short-run direct and indirect effects of extreme weather events

Comprehensive empirical findings derived from variant estimations of our two-equation system, excluding *WE* variables but incorporating alternative metrics for specific explanatory variables such as capital stock and Globalisation, are presented in Models (1)-(3) of Table A.4 in Appendix A.2. Empirical findings align with the theoretical expectations, confirming the assumptions underlying our analysis.

Direct effects of control variables on agricultural employment shares: In line with our expectations, variables such as agricultural labour productivity (*logAgrProd*), total (private and public) physical capital (*logKstockTot*), and human capital (*logEduc*) directly contribute to a decrease in agricultural employment shares. In contrast, changes in demographic factors, specifically increases in population size (*logPOP*) and a higher age dependency ratio (*AgeDepend*), report statistically significant positive coefficients. This suggests that demographic trends, particularly population growth and a larger proportion of dependants, contribute to an elevation in agricultural employment shares, thus slowing down the process of structural transformation. Additionally, the positive effect of the *Trend* variable indicates that over time, independent of other factors, there is a natural tendency towards an increase in agricultural employment shares, potentially reflecting broader time-related socioeconomic changes. Interestingly, our results show no statistically significant effect of Globalisation, indicating that its impact on agricultural employment shares might not be as pronounced or direct as other demographic and temporal factors in the context of the countries studied.

Direct effects of control variables on agricultural labour productivity: Our results show that high agricultural yields (*logCerealYield*), Globalisation, and institutional quality (*CorrupContr*) have a significant positive effect on agricultural labour productivity. Additionally, our decomposition of the Globalisation (KOF) index reveals that it is not trade openness (*GlobalTrade*), but openness to FDI and political integration (*GlobalPol*), that boosts agricultural labour productivity. The negative coefficient for mineral resources (*Mineral Rent*) aligns with previous studies (Dorinet et al., 2021), indicating that natural resource discoveries may detrimentally affect agricultural labour productivity. Human capital (*logEduc*) and population growth (*PopGr*) do not exhibit (highly) statistically significant effects. Furthermore, the lack of significance in the direct effect of overall physical capital investment (*logKstockTot*) contrasts with its positive effect for private investments (*logKstockPriv*) and negative for public investment stock (*logKstockGov*). The negative impact of public capital investment could suggest several scenarios, such as public investments being potentially inefficient or misallocated, or being predominantly allocated to sectors other than agriculture, thereby not directly benefiting agricultural labour productivity. With a

nuanced approach to explanatory variables (Model 3), the *Trend* variable becomes significant with a positive sign, indicating ongoing advancements and increased agricultural labour productivity in agriculture over time. We thus have chosen Model 3 for subsequent estimations that incorporate the impacts of extreme weather events.

Table 1.1 below focuses specifically on the results pertaining to extreme weather events.⁸ Holding other factors constant, our analysis indicates that extreme wet days contribute to a reduction in agricultural labour productivity and concurrently lead to an increase in the share of agricultural employment. On the other hand, heatwaves and droughts appear to cause a decrease in agricultural employment shares, though their impact on agricultural labour productivity is not significantly discernible, except in model (4) where varying levels of drought severity are considered. To be more precise, our empirical results show that an additional millimetre of precipitation during extreme wet days is associated with an increase of 2.62 percentage points of agricultural employment shares. In the case of droughts, it is observed that while moderate and severe droughts tend to keep people within the agricultural sector, extreme drought episodes drive people away from this sector. In developing countries extreme events often lead farmers to intensify the use of labour and land resources, including expanding their cropland areas (Zaveri et al., 2020). It is crucial to recognise that structural transformation is generally driven by the release of labour from agriculture coupled with increased agricultural labour productivity. However, our findings suggest that extreme weather events do not imply such a dynamic. On the contrary, weather extremes, and particularly extreme wet days and severe droughts, exacerbate the challenges in agricultural labour productivity, further hindering the process of structural transformation.

The overall effect on agricultural employment shares is calculated by summing the direct impact of each exogenous variable on agricultural employment shares with its indirect effect through agricultural labour productivity. The indirect effect of an exogenous variable on agricultural employment shares is determined by multiplying its direct effect on agricultural labour productivity by the coefficient representing the influence of agricultural labour productivity on agricultural employment shares. For example, to calculate the total effect of a unit increase in extreme precipitation on agricultural employment shares, we add its direct effect to the indirect effect channelled via changes in agricultural labour productivity. As per Model (2) in Table 1.1, the direct effect of a one-unit increase in precipitation intensity is 0.0262, while the exclusive indirect effect through logAgrProd is $(-0.3135) \times (-0.0798) = 0.0250$. Hence, the aggregate effect amounts to $0.0262 + 0.0250 = 0.051$. This means a one-millimetre increase in precipitation during extreme wet days leads to a total increase of 5 percentage points in employment shares within the agricultural sector. In a similar vein, moderate and severe droughts yield a combined effect on agricultural employment shares of $0.088 + (-1.0308) \times (-0.0479) = 0.137$ (or 13.7 percentage points

⁸For a detailed view of the outcomes for all variables involved in the study, please refer to the comprehensive tables provided in the Appendix A.2.

Table 1.1: Direct and indirect effects of extreme weather events on structural transformation

	(1)	(2)	(3)	(4)	(5)	(6)
AgrEmplShare						
logAgrProd	-0.0676*** (0.0128)	-0.0798*** (0.0140)	-0.0696*** (0.0133)	-0.0479*** (0.0136)	-0.0731*** (0.0126)	-0.0729*** (0.0136)
MaxHotDays	-0.0006*** (0.0002)					
ExtWetDays		0.0262** (0.0117)				
Drought_spi			-0.0140** (0.0064)		0.1243** (0.0554)	
Drought_spi: Normal				3.2803* (1.7225)		
Drought_spi: Moderate & Severe				0.0881** (0.0413)		
Drought_spi: Extreme				-0.0711** (0.0340)		
SEMP					0.0023** (0.0009)	0.0046*** (0.0016)
Drought_spi * SEMP					-0.0022** (0.0009)	
Drought_spei						0.2275** (0.0930)
Drought_spei * SEMP						-0.0052** (0.0021)
Constant	-0.6016 (1.6921)	0.5050 (1.7508)	-0.0008 (1.6311)	1.3008 (1.7198)	4.0923** (1.7517)	3.9929 (2.6213)
logAgrProd						
MaxHotDays	0.0026 (0.0021)					
ExtWetDays		-0.3135* (0.1644)				
Drought_spi			-0.0316 (0.0588)		-1.9601*** (0.6501)	
Drought_spi: Normal				21.7463 (17.1080)		
Drought_spi: Moderate & Severe				-1.0308*** (0.3559)		
Drought_spi: Extreme				0.4582 (0.4085)		
SEMP					-0.0487*** (0.0101)	-0.0963*** (0.0366)
Drought_spi * SEMP					0.0308*** (0.0116)	
Drought_spei						-5.5456** (2.4898)
Drought_spei * SEMP						0.1188* (0.0610)
<i>N</i>	810	810	810	810	514	514

Standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

increase). These results corroborate our theoretical expectation that extreme weather events hinder structural transformation by reducing agricultural labour productivity, while also preventing labour from transitioning out of the agricultural sector.

Next, we examine the impacts of weather extremes on agricultural labour productivity and employment share, conditional to self-employment. Indeed, agricultural employment in developing countries is often characterised by a high degree of informality, where self-employment plays a significant role. Traditional

knowledge and ancestral practices of adaptation can influence how self-employed individuals respond to weather extremes. Droughts for example could have different implications for self-employed farmers compared to wage workers. While the former might directly face the impacts on their income and livelihood by diversifying crops or investing in irrigation, wage workers might experience job loss or reduced working hours as employers cut back on labour costs in response to declining yields. Moreover, the capacity for adaptation among self-employed farmers could be influenced by access to resources, information, and technology. Those with better access to these resources may be more resilient to weather extremes. In contrast, wage workers often have less control over their employment conditions and may be more vulnerable to economic shocks caused by adverse weather conditions.

As we can see in Model (5) of Table 1.1, the impact of drought on agricultural labour productivity is not only negative but also coincides with a positive effect on employment in the agricultural sector, indicating a delay in structural transformation and thus validating our previous results. This phenomenon is particularly pronounced in countries with lower levels of self-employment. One intuition behind this observation could be that in economies where a larger proportion of the workforce is employed by others (rather than self-employed), the negative productivity shocks from droughts might compel employers to hire more labour to sustain or increase production levels, in an attempt to compensate for the reduced labour productivity. Alternatively, in countries with higher self-employment, individuals might have more flexibility to adapt or shift resources in response to drought, potentially mitigating the impact on employment. This dynamic underscores the complex interplay between environmental factors and economic structures in shaping the trajectory of structural transformation.

Furthermore, in Model (6), we replace the SPI index with the SPEI to more comprehensively encompass the climatic complexities that link together precipitation, temperature, and evapotranspiration. The outcomes of this model align with those from Model (5), yet the effects of droughts are notably more pronounced. This finding underscores the critical role of temperature conditions in modulating the impacts of droughts. The heightened magnitude of drought effects in the SPEI-based analysis suggests that the interaction between reduced rainfall and elevated temperatures - leading to increased evapotranspiration - intensifies the detrimental impacts of drought conditions. This more pronounced impact is likely due to the synergistic effects of higher temperatures exacerbating moisture deficits caused by reduced rainfall. This can result in more severe soil and vegetation moisture loss, increased irrigation demands, and heightened stress on crops. By capturing the combined effects of both lower precipitation and higher temperatures through the SPEI, the model reveals the complex and often compounding influence of various climatic factors on agricultural labour productivity and labour dynamics. This approach provides a deeper insight into the multifaceted challenges climate change presents to the agricultural sector in developing and emerging countries.

1.5.2 Long-run effect of weather extremes on agricultural employment shares

For the long-term effects investigation, we have specified a generalised GMM (difference GMM) for panel data.⁹ We proceed to examine the following specification for agricultural employment share in country i during time period t , with the aim of estimating long-term coefficients:

$$AgrEmplShare_{i,t} = \gamma AgrEmplShare_{i,t-1} + \beta_1 \log AgrProd_{i,t} + \beta_2 WE_{i,t} + X_{i,t} + Z_{i,t} + \varepsilon_{i,t} \quad (1.8)$$

where $AgrEmplShare_{i,t-1}$ represents the lagged value of the agricultural employment share, an endogenous variable. The variable $\log AgrProd_{i,t}$ denotes the logarithm of agricultural labour productivity. The set $WE_{i,t}$ sequentially encompasses proxy variables for drought, extremely wet conditions, and heatwaves. The term $X_{i,t}$ includes the control variables previously specified for estimating agricultural employment share, with the coefficients detailed in Table A.5 in the Appendix. Additionally, $Z_{i,t}$ refers to the set of exclusion variables for $\log AgrProd_{i,t}$, which comprise foreign direct investment ($\log FDI$), mineral resources endowment ($MineralRent$), population growth rate ($PopGr$), cereal yield ($\log CerealYield$), and institutional quality ($ContrCorrup$). $\varepsilon_{i,t}$ is the error term.

Empirical results from the dynamic panel estimations are reported, with a focus on the extreme weather variables, in Table B.2. The results, derived from a series of models, highlight several key findings. Model (2) serves as our foundational analysis, examining the long-term effects of weather extremes variables without considering their interactions.¹⁰ Here, we find that the coefficient for the lagged agricultural employment share ($L.AgrEmplShare$) is positive and highly significant¹¹, indicating a strong persistence in agricultural employment over time. The log of agricultural labour productivity ($\log AgrProd$) shows a negative impact on agricultural employment shares, suggesting that as productivity increases, reliance on agricultural labour decreases.

The negative relationship between heat intensity, as measured by maximum hot days, and agricultural employment shares is consistent with recent studies demonstrating that heat stress affects both labour supply and productivity, with long-lasting effects. This implies that workers in industries with high exposure to heat, including farming, fishing, construction, and mining, may be less available due to heat stress. Moreover, since adaptation to such extremes is limited, increasing heat stress may lead to premature migration out of the agriculture sector (Shayegh et al., 2021). However, when we introduce inter-

⁹This method, implemented using the `xtabond2` command in Stata, offers several advantages. Generalized Method of Moments (GMM) is effective in handling endogeneity in panel data by using lagged variables as instruments for potentially endogenous variables. It addresses fixed effects and dynamic panel bias, making it suitable for long-term analysis. Arellano-Bond tests (AR tests) check for autocorrelation in the residuals, with AR(1) detecting first-order and AR(2) second-order autocorrelation. The absence of significant AR(2) indicates no second-order autocorrelation, validating the GMM estimators. However, with around 300 instruments, the Hansen J test's reliability can be compromised. To address this, we conduct the Hansen J test using a static model with 5 excluded (external) instruments, reducing potential distortion. The Hansen J test's p-value in this context validates the robustness of our model, confirming that our instruments are appropriately uncorrelated with the error term and relevant to the included variables. Detailed results and further technical insights are available in Table A.5 in the Appendix A.2. These tests validate the robustness and reliability of our model.

¹⁰Model (1) reports estimations for the short-term effect model.

¹¹The fact that $\gamma < 1$ implies that the influence of the past value on the current value is strong but not complete. It shows a gradual adjustment where the current value is (here highly) dependent on the previous value but also influenced by other factors or shocks.

actions in Model (3), the context in which *MaxHotDays* affects agricultural employment becomes more complex. At the same time, we observe that both the drought indicator (*Drought_spi*) and extreme wet days (*ExtWetDays*) are positive and statistically significant only in models including interaction terms. The interactions between the drought indicator and extreme wet days (*Drought_spi * ExtWetDays*), as well as between the drought indicator and maximum hot days (*Drought_spi * MaxHotDays*), are also statistically significant. These results suggest that the long-term impact of droughts on agricultural employment shares is dependent on the presence of other extreme weather conditions. For instance, the combined occurrence of drought and extreme wet days, resulting in a negative joint effect that moderates the positive effect of drought alone, presents an intriguing dynamic in agricultural contexts. Drought conditions typically lead to water scarcity, affecting crop growth and potentially increasing the reliance on agricultural labour for irrigation and other intensive cultivation practices. This might explain the initial positive effect of drought on agricultural employment. However, when extreme wet days occur in conjunction with droughts, they can counterbalance or even negate the effects of the drought. The excess moisture from extreme wet days may alleviate water scarcity issues temporarily, reducing the immediate need for additional labour that drought conditions might necessitate. Also, while droughts and extreme wet days individually pose challenges to agriculture, their interplay can create a highly unpredictable and unstable environment for farming. For instance, a sudden transition from a drought to a period of heavy rainfall can cause significant damage to crops that are already stressed from prolonged dryness. Thus, managing agricultural resources in the face of alternating extreme weather conditions requires careful planning and rapid adaptation strategies. The combined stressors of drought, heavy rainfall and/or extreme heatwaves might force farmers to continually adjust their practices, which could include changing labour patterns in response to fluctuating conditions. The co-occurrence of these extreme conditions can have economic and psychological impacts on farmers, influencing their decision-making processes. The uncertainty and potential financial losses associated with erratic weather might lead to more conservative approaches to labour employment, moderating the overall increase in employment that might be expected during isolated, specific weather extreme events.

In Model (4), we exclude 'control of corruption' from the list of 'external' instruments, enabling us to broaden the dataset by extending both the time period analysed and the range of countries included¹². The outcomes of this model align closely with those observed in Model (3), which serves to affirm the robustness of our findings. The continued significance of lagged agricultural employment shares, alongside the persistent effects of weather extreme variables and their interactions, mirrors the patterns seen in the earlier model. This consistent alignment of results, achieved despite the expanded dataset and modified instrument set, adds substantial weight to the validity of our conclusions.

¹²Model (4) encompasses the years 1990-2018 and includes three additional countries: Egypt, Laos, and Viet Nam.

Table 1.2: Long-run effects of extreme weather events

	(1)	(2)	(3)	(4)
	AgrEmplShare	AgrEmplShare	AgrEmplShare	AgrEmplShare
<i>L.AgrEmplShare</i>		0.9486*** (0.0078)	0.9424*** (0.0071)	0.9698*** (0.0100)
logAgrProd	-0.0860*** (0.0323)	-0.0032** (0.0014)	-0.0039** (0.0015)	-0.0029** (0.0014)
Drought_spi	-0.0084 (0.0069)	-0.0008 (0.0006)	0.0637*** (0.0218)	0.0385** (0.0150)
ExtWetDays	0.0087 (0.0122)	0.0010 (0.0011)	0.0036* (0.0020)	0.0045*** (0.0015)
MaxHotDays	-0.0004 (0.0003)	-0.0001** (0.0000)	-0.0001 (0.0006)	0.0001 (0.0003)
Drought_spi * ExtWetDays			-0.0100*** (0.0035)	-0.0061** (0.0025)
Drought_spi * MaxHotDays			-0.0003* (0.0001)	-0.0003*** (0.0001)
ExtWetDays * MaxHotDays			0.0000 (0.0001)	-0.0000 (0.0001)
Drought_spi * ExtWetDays * MaxHotDays			0.0000 (0.0000)	0.0000** (0.0000)
Constant	0.1707 (0.5727)	0.0056 (0.0307)	0.0114 (0.0318)	0.0385* (0.0212)
Number of obs	810	810	810	1108

Standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Regarding the long-run effects and their computation, we use the coefficients of the lagged dependent variable and the relevant beta coefficients. The formula for the long-term effect of an independent variable in a dynamic panel data model is:

$$\text{Long-Term Effect} = \frac{\text{Coefficient of Variable}}{1 - \text{Coefficient of Lagged Dependent Variable}}$$

Applying this formula to the significant variables in Model (3), we can calculate their long-term effects on agricultural employment shares. For instance, the long-term effect of drought on agricultural employment shares is calculated as follows :

$$\text{Coefficient for drought (Direct effect of drought)} = 0.0637$$

$$\text{Coefficient of lagged agricultural employment share} = 0.9424$$

$$\text{Long-term effect of drought} = \frac{0.0637}{1 - 0.9424} = 1.106$$

As calculated, the long-term effect of drought is approximately 1.106, reflecting the cumulative impact over time and accounting for the persistence in agricultural employment shares. In contrast, the short-term effect of 0.0637 indicates a moderate immediate increase in agricultural employment shares due to

drought conditions. This comparison highlights that while drought has a noticeable immediate impact on agricultural employment, its influence becomes significantly more pronounced in the long run. Moreover, it is evident that weather extremes have a long-lasting effect on agricultural employment shares, which is significantly higher than the impact of agricultural labour productivity on labour allocation. This exacerbates the challenges toward agricultural modernisation and overall economic performance.

1.5.3 The impact of weather extremes on economy-wide labour productivity through agricultural sector dynamics

Following the decomposition of labour productivity as outlined by McMillan et al. (2014), we now analyze the decomposition of economy-wide labour productivity growth into within-sector and between-sector (structural) changes, induced by weather extremes (WE) through the dynamics of the agricultural sector.¹³ The economy-wide labour productivity y_t is defined as follows:

$$y_t = \theta_a^t y_a^t + \theta_{na}^t y_{na}^t \quad (1.9)$$

where:

- θ_a^t is the share of employment in the agricultural sector at time t ,
- $\theta_{na}^t = 1 - \theta_a^t$ is the share of employment in the non-agricultural sector at time t ,
- y_a^t is the labour productivity in the agricultural sector at time t ,
- y_{na}^t is the labour productivity in the non-agricultural sector at time t .

In the Appendix A.3, we detail the analytical modeling process that decomposes the change in economy-wide labour productivity (Δy_t), from time $t - 1$ to t , into within-sector and between-sector (structural) changes, with respect to changes in weather extremes (ΔWE). The resulting equation is:

$$\begin{aligned} \Delta y_t \Big|_{\Delta WE} = & \underbrace{\theta_a^{t-1} f'(WE) y_a^t \Delta WE}_{\text{Within-sector change (agriculture)}} \\ & + \underbrace{(y_a^t - y_{na}^t) g'(WE) \Delta WE}_{\text{Direct structural change}} \\ & + \underbrace{(y_a^t - y_{na}^t) g'(\log y_a^t) f'(WE) \Delta WE}_{\text{Indirect structural change}} \end{aligned} \quad (1.10)$$

where:

- $f'(WE)$ is the partial derivative of $\log(y_a)$ with respect to WE ($\log(y_a) = f(WE)$), representing the direct impact of weather

¹³Our analysis does not capture changes induced in non-agricultural sectors, implying that the effects outlined here are likely undervalued and represent the minimum impacts detectable. Nonetheless, omitting non-agricultural sectors should not significantly alter our conclusions, as the primary effects of weather extremes on economic output typically operate through natural capital and ecosystems, and thus through agriculture.

extremes on the logarithm of agricultural labour productivity,

- $g'(WE)$ is the partial derivative of θ_a with respect to WE ($\theta_a = g(\log y_a, WE)$), representing the direct impact of weather extremes on the employment share in agriculture,

- $g'(\log y_a^t)$ is the partial derivative of θ_a with respect to $\log(y_a)$, with $g'(\log y_a^t)f'(WE)$ representing the indirect impact of weather extremes on the employment share through agricultural labour productivity.

This equation expresses the total effect of weather extremes on the change in economy-wide labour productivity through agricultural dynamics, decomposed into within-sector changes (with a focus on agriculture) and structural changes, with the structural changes further broken down into direct and indirect effects.

We apply our empirical results from Table 1.1 to this theoretical framework to offer a comprehensive understanding of how weather extremes influence agricultural labour productivity and structural transformation across different regions and countries (see Appendix A.3). As shown in Table A.6, extreme wet and dry conditions have notable marginal effects on agricultural labour productivity ($dy_a/dExtWetDays = -1139.475$ and $dy_a/dDrought_spi = -3746.721$, respectively) and agricultural employment share ($d\theta_a/dExtWetDays = 0.051$ and $d\theta_a/dDrought_spi = 0.138$, respectively). These effects are evident in both structural changes and within-sector labour productivity declines. The negative productivity impact suggests that these extremes disrupt agricultural activities, leading to productivity losses and increased reliance on labour in agriculture.

Among all the factors influencing agricultural labour productivity, droughts have the most substantial negative marginal effect, comparable to the influence of institutional quality, land productivity, or education. Similarly, droughts have the most notable positive marginal impact on agricultural employment shares. In addition to the indirect impact through labour productivity, droughts have a significant direct effect on agricultural labour allocation, likely due to the increased labour required to manage and mitigate the impacts of drought on agricultural activities (e.g., securing water access, diversifying activities, extending land use). This direct marginal effect is equivalent but opposite to the effect of agricultural labour productivity on labour allocation in this sector, suggesting that severe drought conditions offset and delay efforts towards structural transformation.

We further present in the Table A.7 the economy-wide labour productivity changes (Δy) in our sample of countries across three periods (1997-2007, 2007-2017, and 1997-2017) and decompose these changes into the contributions of extreme wet days, droughts (measured by SPI), and maximum hot days. Economy-wide labour productivity changes are further broken down into within-agriculture sector changes, direct structural changes, and indirect structural changes through effects on agricultural labour productivity.

We depict a consistent upward trend in economy-wide labour productivity throughout the entire period, with significant increases observed in each sub-period. These outcomes were sensitive to weather extremes, with positive contributions in some periods and negative in others. Notably, extreme precipitations have increasingly exhibited negative effects on productivity, whereas the evolution of drought conditions has generally been beneficial. However, it is essential to consider whether these average results are representative for all countries (as analyzed below, based on the results in Table A.8). More precisely, we find that while changes in droughts had a positive impact on economy-wide labour productivity over all periods, extreme wet days had a small positive effect on productivity from 1997 to 2007 but a significant negative effect from 2007 to 2017 and overall from 1997 to 2017. Hot days had a very modest effect on economy-wide labour productivity. This indicates that it is not so much the high temperatures themselves that disrupt economic activities, but rather the associated climatic effects. Unlike temperature, which is relatively global, these weather extreme effects are more localized, potentially causing highly disproportionate impacts on structural transformations across different regions of the world.

Furthermore, we observe that climatic extremes affect overall labour productivity primarily through structural changes, particularly via direct impacts on agricultural employment. While the 'within' effect and the indirect structural effect mediated through agricultural labour productivity are also significant, the direct impact on employment allocation is especially pronounced. This finding suggests the importance of considering not only land productivity and the resilience of agricultural products to these extremes but also the working conditions and the adaptation of infrastructure. In the context of extreme weather events, improving the resilience of agricultural systems involves developing crop varieties that can withstand droughts and floods, enhancing irrigation systems, and adopting sustainable farming practices. However, it is equally crucial to focus on the human dimension of agriculture. This includes ensuring safe and favorable working conditions, providing training and resources for farmers to adapt to changing climates, and investing in infrastructure that supports agricultural activities. Adaptation of infrastructure could involve constructing flood defenses, improving drainage systems, and ensuring reliable access to water. It also means investing in transportation and storage facilities to prevent post-harvest losses, which are often exacerbated by extreme weather. Moreover, promoting diversification of income sources for rural populations can reduce the vulnerability of households dependent solely on agriculture. Policy-makers should also consider the broader socio-economic factors, such as access to education, health-care, and social safety nets, which can empower agricultural workers to better cope with and adapt to climatic extremes.

These initial results would suggest that climatic conditions (in particular droughts) have improved, leading to productivity gains in the studied countries. However, bearing in mind that the aforementioned re-

sults reflect an "average" situation across all countries in our sample, several realities may be obscured, especially since climatic extremes are highly localized. We extend our analysis by examining whether these initial conclusions hold true across continents and selected countries.¹⁴ Table A.8 presents various metrics across regions (Africa, Americas, Asia) and selected countries (Senegal (SEN), Tunisia (TUN), Bangladesh (BGD), India (IND), and Mexico (MEX)) for 1997-2027 period.

First, we see that countries in Latin and Central America (Americas) exhibited the highest average economy-wide labour productivity, followed by Asian and African countries, with Mexico within the Americas displaying even higher values. Agricultural labour productivity followed a similar pattern, with the Americas leading, followed by Asia and Africa. Tunisia within Africa reported a notably higher value compared to the continental average. The agricultural employment share was highest in Africa (0.50) and lowest in the Americas (0.20). Bangladesh and India in Asia had high values, exceeding even the African average, reflecting a larger proportion of agricultural employment in these countries.

Second, we observe that countries in the Americas and Asia are characterized by the highest number of extreme wet days, whereas African countries have experienced the most severe hot and dry conditions. In terms of changes in weather extremes from 1997 to 2017, Asia saw the highest increase in extreme wet days. Bangladesh, already one of the most affected Asian countries by extreme wet conditions, had the highest increase of these extremes within Asia. Africa experienced an increase in drought severity, while Asia and the Americas saw a decrease in such events. Within Africa, Senegal is generally exposed to higher drought intensity, but Tunisia experienced a more significant increase in such extreme events over the last two decades. Africa also had a larger increase in maximum hot days compared to Asia and the Americas, with Senegal experiencing the most notable increase within Africa. Additionally, while India is characterized by high levels of extreme wet days, it recorded the highest change in the number of extremely hot days, accompanied by a significant increase in drought episodes.

Finally, based on our empirical results in Section 1.5.1, we compute the contribution of weather effects to variations in agricultural labour productivity and employment shares, as well as in the economy-wide labour productivity changes (Equation 1.10) in 2017 compared to 1997. The Americas showed the most substantial increases in agricultural labour productivity, with positive contributions from declines in drought severity offsetting the negative impacts of increasing extreme wet days. The overall improved weather conditions contributed to a release of labour from the agricultural sector, accounting for a third of the observed structural change in these countries (i.e., a decline of 9 percentage points in the Americas' average agricultural employment share, of which 3 percentage points were due to the decline in severe drought events). Mexico illustrates these patterns with significant productivity gains and weather-induced reductions in agricultural employment share ($\Delta\theta_a|_{\Delta Drought_spi} = -22\%$). Given

¹⁴The countries selected for this illustrative and comparative analysis were chosen based on having either the highest levels or the most significant changes in weather extremes within their respective continents.

that the total decline in agricultural employment share was -5%, this indicates that other factors must have contributed positively (+27%) to offset the substantial negative impact of reduced drought severity. This suggests that without the positive impact of reduced drought severity, the structural transformation in Mexico would have faced stronger negative forces, thus delaying the overall progress.

Asia experienced a similar evolution but with moderate productivity gains and mixed contributions from climatic extremes. For instance, Bangladesh saw negative impacts from extreme wet days but positive contributions from reduced drought severity, while India had labour productivity losses from both extreme wet and dry conditions. Hence, while both countries recorded quite similar overall dynamics in the evolution of agricultural employment shares (a reduction of about 20% over the 1997-2017 period), changes in weather extremes contributed by enforcing structural change in Bangladesh but impeding it in India.

As regards Africa, it had a moderate increase in agricultural labour productivity, with negative contributions from both extreme wet days and drought severity. While Tunisia had the most notable increase in agricultural labour productivity (four times the average increase in African countries) in 2017 compared to 1997, we highlight that this increase would have been at least twice as high if the country had not experienced one of the most notable increases in droughts. These changes in weather conditions appear to be harmful to the ongoing structural transformation that has led the country to record high productivity levels and a low employment share in the agricultural sector. Although the agricultural employment share averaged 13% between 1997 and 2017, changes in recent dry conditions alone would have contributed to an increase of 22 percentage points in labour allocated to this sector in Tunisia. In addition to severe droughts, some African countries seem to combine vulnerabilities, with Senegal, for example, being increasingly exposed to extreme wet days (floods), in addition to droughts, which reduces its potential productivity gains and hinders structural transformation.

Economy-wide labour productivity was affected differently by various weather events across different regions. If drought conditions had remained at their 1990s levels, some Asian countries would have seen a significant decline in economy-wide labour productivity (e.g., Bangladesh, which would have experienced a decrease of 116% compared to the recorded increase of 253%), while others, particularly in Africa, could have maintained or even improved their performance (e.g., Senegal, which recorded an economy-wide labour productivity gain of +75% in 2017 compared to 1997; this gain would have been of +80% if drought conditions had not worsened). This observation is even more pronounced for Tunisia, where the labour productivity gain could have been nearly +82% compared to the actual +49% recorded. Furthermore, even within the same geographical region, disparities are evident: while Bangladesh benefits from a decrease in severe droughts, the opposite trend in these events deprived India of approximately 40% of its overall labour productivity increase in 2017 compared to 1997.

These observations prompt us to question the conventional development model and redefine the target for structural transformation. While classical factors—innovation, technological progress, human development, financial, and institutional growth—may have similar effects globally, diverse soil qualities and climatic conditions challenge the "one-size-fits-all" model of structural transformation, often aiming towards a world with minimal agriculture or farmers (Timmer, 1988, 2009; Dorin et al., 2013). It is essential to reconsider the agroecological model, which could attract labour from low value-added sectors and offer resilience to climate hazards while ensuring sustainable resource use. The current 'without farmers' model, which has shown its limits and potential for exhaustion, exacerbates climatic and environmental challenges. Thus, reevaluating development strategies to address local specificities and climatic challenges is crucial for a sustainable and equitable structural transformation.

1.6 Conclusion

In this chapter, we have undertaken a thorough investigation to estimate both the short and long-term effects of extreme weather events—namely heatwaves, droughts, and extreme wet conditions—on structural transformation, which refers to the process by which an economy shifts away from agriculture and other primary activities towards more productive sectors, typically manufacturing and services, leading to overall economic growth and development. The focus was on assessing simultaneously the direct impact of weather extreme events on agricultural employment and indirect effects through changes in agricultural labour productivity. By establishing a framework for a system of simultaneous equations and using GMM techniques for panel data analysis, we have gleaned several crucial insights.

Our results show that both drought intensity and extreme wet conditions (which can be proxies for floods) have detrimental effects on structural transformation in agriculture. These extreme events lead to declines in agricultural labour productivity and increases in agricultural employment, suggesting a shift towards more labour-intensive practices in response to yield decreases. This could result in the expansion of cropland into marginal areas, thereby escalating natural resource degradation. We also show that high heat intensity, captured by the maximum number of hot days, directly reduces agricultural employment shares, raising significant concerns about the limited capacity to adapt to extreme heat stress. This is likely to have important implications for human health, productivity, and potentially migration. However, the effects of weather extremes seem to be less pronounced in countries with high self-employment rates. These findings call for further investigation of the adaptive capacities of various social organizations within agricultural activities.

Furthermore, our empirical investigation highlights the notable difference between short- and long-term effects. While the short-term effect indicates a moderate immediate increase in agricultural employ-

ment share, the long-term effect is substantially larger, demonstrating the pronounced influence of (in particular) droughts over time. We show that co-occurrence of extreme temperature, drought and/or extreme wet days presents a complex scenario in agriculture. The presence of such combined effects suggests that models that treat weather variables in isolation may not fully capture the nuanced dynamics at play. This underscores the importance of formulating agricultural practices and policies that are versatile and adaptable to a broad spectrum of climatic conditions, acknowledging immediate and long-term impacts.

We demonstrate that extreme weather events significantly delay the structural transformation of economies most exposed and vulnerable to such disasters. By decomposing the effects into 'within and between sector' changes, we show how economy-wide labour productivity was differently affected by weather events across regions. For instance, in Asia, countries like Bangladesh would have experienced significant declines in productivity in 2017 compared to 1997 if drought conditions had remained at 1990s levels. Conversely, in Africa, countries like Senegal and Tunisia could have seen improved performance. This disparity is evident even within regions: while Bangladesh benefited from decreased droughts, worsening dry conditions hindered productivity gains in India.

In summary, structural transformation is essential for boosting incomes, reducing poverty, and enhancing living standards. This research provides critical insights for developing resilient agricultural systems and shaping policies to support structural transformation amid climate change. Our findings stress the need to integrate climate vulnerability into economic development strategies. The limitations of conventional structural transformation models in addressing social progress, alongside rapid climate change and environmental disasters, highlight the need for alternative approaches. Agroecological models offer a promising path, involving an initial labour shift within the agricultural sector to different productivity levels. These models advocate for smaller, labour-intensive farms that adapt to local conditions, improving efficiency and resilience. Emphasizing agroecology can enhance agricultural adaptability to climate extremes, thereby contributing to economic resilience and social advancement.

Chapter 2

Biodiversity, ecosystems, and agricultural total factor productivity: investigating the influence of extreme weather events

2.1 Introduction

The agriculture sector is highly dependent on nature, including biodiversity and ecosystems, which provide goods and services such as soil retention, water provision and pollination, which are critical for productive agriculture (Vanbergen et al., 2020). However, global food production historically increased due to the success of the green revolution, which resulted in a dramatic increase in the application of fertilisers, pesticides (Foley et al., 2005), and the extensive conversion of natural habitats into cropland. This has increased greenhouse gas emissions responsible for climate change and biodiversity loss, homogenisation of agricultural landscapes and the loss of natural habitats (Dudley and Alexander, 2017; Tilman et al., 2002). Flows of critical ecosystem services have declined significantly due to the loss of the stock of natural capital providing these benefits (Kremen and Miles, 2012; Reid et al., 2005). Therefore, agriculture production, particularly capital and input-intensive production, has occurred at the expense of natural capital, with negative consequences that may ultimately undermine agriculture production and future sustainability.

Despite rapid growth in the past, global agricultural total factor productivity (TFP) growth has slowed down since the 2010s, particularly in developing countries (Morgan et al., 2022). Declines in agricultural TFP growth may be due to several factors, including the increasing frequency and intensity of climate-related weather shocks, the emergence of new crop diseases and pests and natural resource degradation. This is exacerbated by fewer technological breakthroughs in agriculture and the slow diffusion of improved agricultural technologies in low-income countries due to market access barriers in international trade, which limit the acquisition of new technologies and improved inputs (Fuglie and Rada, 2013; Fuglie, 2018). Further, global food demand is projected to increase significantly by 2050 (van Dijk et al., 2021), particularly in low-income countries. In this context, sustainably increasing agricultural production to meet growing food demand without destabilising and degrading the natural capital on which the sector depends becomes even more crucial. Furthermore, findings in Chapter 1 indicated that the agricultural sector in low-income and emerging economies is particularly vulnerable to the effects of weather extremes, negatively impacting growth and hindering structural transformation. This situation necessitates a rethinking of agricultural production to enhance adaptability against such extremes.

However, although biodiversity and ecosystems have been found beneficial for sustaining agricultural production in the face of weather extremes (Reid et al., 2005), research has mainly focused on how factors such as technology and innovation (Hayami and Kawagoe, 1985), human capital (Avila and Evenson, 2010), and climate change (Ortiz-Bobea et al., 2021) impact agricultural TFP growth. As a result, although there is a strong theoretical link between the ecosystem goods and services provided by

nature and biodiversity, (van Ittersum and Rabbinge, 1997), their influence's exact nature and magnitude remain unclear. Chapter 2 therefore evaluates the effect of biodiversity and ecosystems on enhancing agricultural TFP growth. Further, we also test the hypothesis that biodiversity and ecosystem goods and services mediate the effects of weather extremes on agricultural TFP growth. To our knowledge, this is the first attempt to estimate the direct and mediating effects of biodiversity to agricultural TFP growth.

Following the introductory overview, section 2.2 presents stylised facts on agricultural TFP growth, weather extremes, biodiversity, and ecosystems, offering relevant background information. Section 2.3 outlines the theoretical assumptions that form the basis of the empirical analysis. Section 2.4 presents the estimation results, and Section 2.5 draws conclusions based on the empirical findings.

2.2 Agricultural TFP, ecosystem services and resilience against climate induced weather extremes: stylised facts and literature review

As elaborated upon in Chapter 1, agricultural total factor productivity (TFP) measures the efficiency of input use through technological advancements and management practices, leading to higher outputs with lower input consumption (Jorgenson et al., 2005). When expressed as a change over time, TFP growth reflects technological progress and efficiency in production at the farm, regional, or national level. Unlike traditional yield measures, which consider outputs per hectare, TFP encompasses a broader array of inputs involved in production. Hence, TFP growth can enable increased food production while utilising fewer resources.

Global agricultural TFP growth has slowed since the 2010s, despite rapid growth in previous years (Morgan et al., 2022). While estimates vary based on the methodology used (Coelli and Rao, 2005; Evenson and Fuglie, 2010; Fuglie, 2015), it is widely agreed that global annual TFP growth was minimal in the 1960s, grew significantly between 1980 and 2000, and has been declining in low-income and emerging countries, as shown in Figure 2.1.

Furthermore, climate change has slowed agricultural TFP growth over the past 50 years, especially in mid and low latitudes (IPCC, 2021; Corbeels et al., 2020). As Figure 2.2 show, rising temperatures are well-documented phenomena and have led to more frequent extreme weather events such as droughts, wildfires, heatwaves, and floods (IPCC, 2021). Climate change significantly impacts agricultural TFP by directly affecting outputs, input use, and farmers' adaptive behaviours, such as changing planting dates, crop varieties, and increasing irrigation. The effects of temperature and precipitation changes on

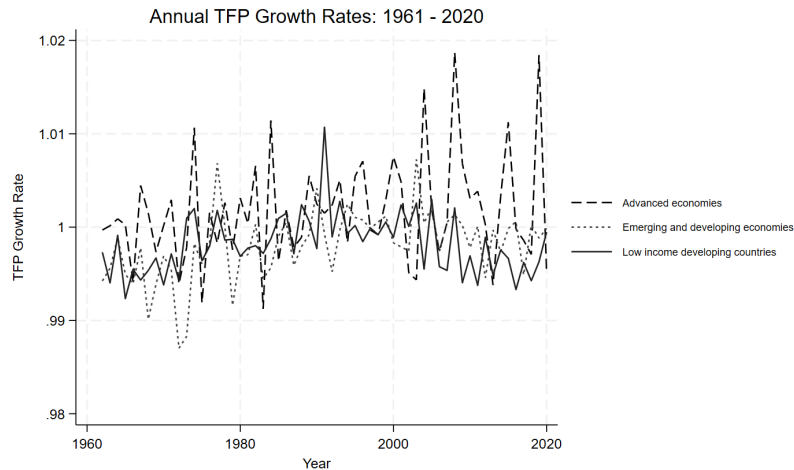


Figure 2.1: TFP change in sample of countries (1960 - 2020)
Data in the sample includes 30 advanced economies, 33 emerging economies and 19 low income countries.
Source: USDA ERA data. Author's own calculations of Malmquist Index of agricultural TFP growth

agricultural TFP are becoming more severe over time (Ortiz-Bobea et al., 2021).

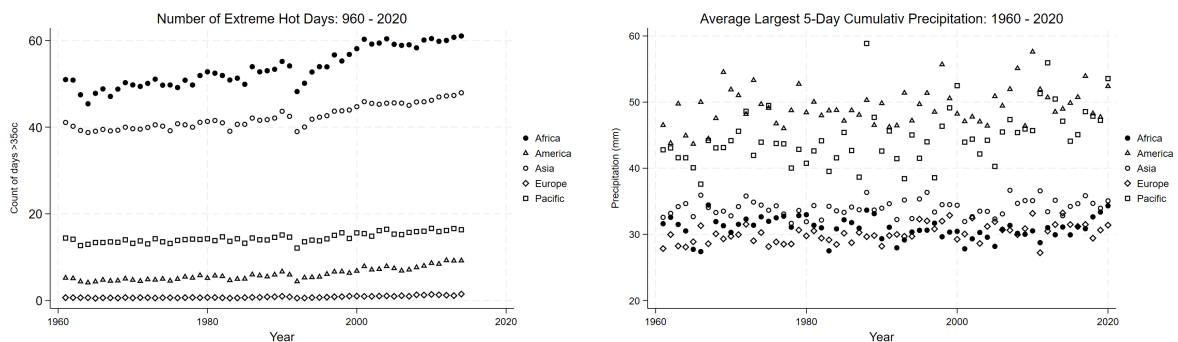


Figure 2.2: Precipitation and temperature anomalies in sample countries (1960 - 2022)
Source: European Reanalysis of the Global Climate System / ERA5) Data

Based on current trends, raising crop yields will likely continue to rely on input intensification and cropland expansion, ultimately limited by existing technology and diminishing returns. Yet, cropland expansion has been the primary cause of deforestation and natural land loss, threatening ecosystem functioning and causing species extinction through habitat loss and fragmentation (Potapov et al., 2022). Species diversity has been steadily declining, and as Figure 2.3 ¹ shows, extinction risk is higher in low-income and emerging economies, where rapid expansion of agricultural production occurred in the recent past.

The decline in biodiversity, along with climate change, has led to increased interest in understanding the role of biodiversity and ecosystems in agricultural TFP growth and enhancing resistance to weather extremes. Current assessments of agricultural TFP growth often overlook changes in natural capital, such

¹The Red List Index is based on the IUCN red list of endangered species, which is the world's most comprehensive information source on the global conservation status of animal, fungi and plant species. The Red List Index is one of the post-2020 UNCBD (UNCBD) framework indicators that track the global extent and quality of ecosystems, as well as extinction risks and conservation status of animal, plant, and fungi species.

as land, water and biodiversity, despite their social value and impacts on agricultural TFP growth. Since natural capital provides critical inputs to agriculture, their decline could negatively impact agricultural TFP growth (Duru et al., 2015; van Ittersum and Rabbinge, 1997).

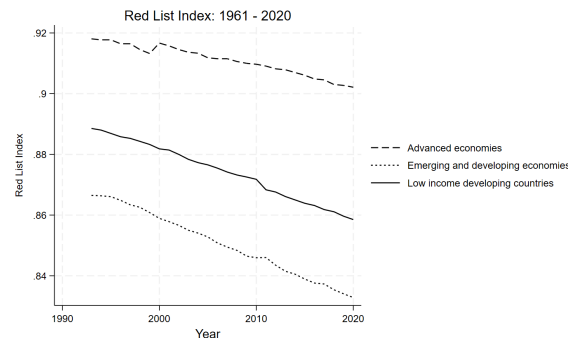


Figure 2.3: Red List Index in sample of countries (1990 - 2020).

A Red List value of 1.0 equates to all species qualifying as Least Concern (i.e., not expected to become extinct in the near future), while a value of 0 equates to all species having gone extinct. Source: IUCN Red List.

Flows of natural capital, known as ecosystem services, are benefits that ecosystems and their biodiversity provide to humanity (Reid et al., 2005), and include provisioning services, regulating services, and supporting services. However, these benefits are complex and are challenging to quantify (Council et al., 2005; Dale and Beyeler, 2001), leading to their exclusion from economic and policy decisions and resulting in the destruction of natural ecosystems for agriculture and other human activities (Barbier, 2007). Yet, while a substantial body of work focuses on the impact of agriculture on biodiversity and ecosystems, there is a dearth of studies examining their contribution to agricultural TFP growth. As a result, the role of biodiversity and ecosystems on TFP growth and resilience is poorly understood.

Theoretically, under the assumptions of weak sustainability, natural capital may be substituted with manufactured natural capital without a reduction in welfare. However, under strong sustainability, this assumption does not hold due to environmental characteristics such as irreversibility, uncertainty and the existence of 'critical' components of natural capital (Turner and Pearce, 1993). More frequent and intense weather extremes, natural resource depletion and a growing body of work on tipping points, where human activities push components of the earth system past critical states into qualitatively different modes of operation, with large-scale impacts on human and ecological systems (Lenton et al., 2008), suggest that natural capital may not be entirely substitutable with other forms of capital, and thus need to be preserved to maintain human welfare.

Hence, more research is needed on the effect of biodiversity and ecosystems on agricultural TFP, particularly when coupled with technological stagnation and erratic weather due to climate change Fuglie et al. (2019), and are critical in the context of increasing food production to meet future demand. Therefore, the objective of this study is to evaluate the direct effect of biodiversity on agricultural TFP growth and, the extent to which they amplify or diminish the impact of weather extremes on agricultural TFP

growth. In this way, this study will provide insights on the role that biodiversity play in raising agriculture TFP, and weather extremes.

This study contributes to the literature by using the Red List Index as a proxy for biodiversity and ecosystem services provision. The Red List, often called the "barometer of life," measures the extinction risk of key species, reflecting biodiversity and ecosystem health changes over time. We also use drought and climate change indices from ERA5 ERGCS reanalysis data and the Climatic Research Unit Time series (CRU-TS) data for precise precipitation and temperature extremes measurements. Additionally, we utilize the USDA ERS-IAP, which offers internationally comparable estimates of agricultural inputs and outputs, allowing us to analyze the relationship between agricultural TFP growth, biodiversity, and resilience to climate-induced variability.

2.3 Theoretical assumptions and econometric specification

As outlined in section 1.3 of chapter 1, total factor productivity represents the efficiency of resource utilisation in agriculture, and is influenced by factors such as local climatic and soil conditions, extreme weather events, as well as institutional and policy factors that shape the enabling environment for agriculture and food production in a country. Building on this analysis, this chapter explores how biodiversity impacts agricultural TFP growth. Additionally, we explore how biodiversity impacts the effect of weather extremes on agricultural TFP growth. To further motivate our analysis, we make the following assumptions based on our review of the literature and stylised facts:

- Agriculture fundamentally depends on natural capital stocks and flows, which can be substitutable or non-substitutable inputs (van Ittersum and Rabbinge, 1997). The ratio between agricultural input use and output is influenced by ecosystem flows such as biological control, soil fertility, and water provision. Variations in quality and quantity may necessitate adjustments in the input mix to substitute or complement these services, thereby affecting agricultural TFP growth.
- Agricultural TFP growth relies on the efficient use of labour, land, capital, and intermediate inputs, driven by technological advancements, management practices, and human capital. Weather extremes can affect TFP growth by altering the utilisation of these inputs and yields, potentially impacting the efficiency of the input-output relationship.
- Biodiversity and ecosystems are vulnerable to weather extremes, which may reduce the natural capital stock and affect the quantity of substitutable and non-substitutable inputs essential to agriculture, requiring adjustments to the input-output mix and therefore impacting agricultural TFP growth.

- Changes in biodiversity and natural capital stock due to weather extremes may impact the flows essential to agricultural production. This may require modifications in the input mix, further impacting the efficiency of the input-output relationship and, thus, TFP growth. Hence biodiversity may moderate the impact of weather extremes, by diminishing or amplifying their effect on agricultural TFP growth.

2.3.1 Agricultural TFP growth

Agricultural TFP is a measure of the overall efficiency of agricultural market inputs transformed into outputs. It is computed as a ratio of agriculture outputs and inputs to estimate growth rate and understand sources of TFP growth. We use the Malmquist Productivity Index (MPI) to represent TFP growth in a country using Data Envelope Analysis (DEA) Färe et al. (1994). The MPI is calculated using a non-parametric frontier approach, making it one of the most commonly used methods to compute agricultural TFP growth (Coelli and Rao, 2005). For a detailed explanation of the MPI, please refer to Appendix B.2 for a detailed explanation.

TFP growth is the result of agricultural productivity change, which comes from three broad categories (Cusolito and Maloney, 2018): rising farm productivity due to technical and managerial efficiency, more efficient reallocation of production factors such as land and labour, and replacement of less productive farms with more productive ones, resulting in scale changes as less productive farms exit. The following factors determine TFP change:

- **Research and development:** Investments in research and technology fuel innovation and new technologies such as higher yielding crop varieties, improved fertilisers and pesticides, as well as better farm management practices, which result in incremental improvements in TFP over the long term. Hence, marginal improvements to research capacity, given a minimal level of agriculture support services and schooling existed, are associated with faster TFP growth (Evenson and Fuglie, 2010; Maloney and Valencia Caicedo, 2017).
- **Enabling environment for innovation and technology adoption:** An enabling environment on both the demand and supply side is necessary to stimulate investments in innovation and adoption of new technology and practices. This includes policies that encourage investment in research, development and dissemination, agriculture extension services, financial services, security of tenure, as well as trade policies and regulations to facilitate access to stable and well-regulated markets and reduce uncertainty, hence encouraging investment and adoption of more efficient technology (Alston et al., 2009; Goyal and Nash, 2017; Rada and Schimmelpfennig, 2015).
- **Capital investment:** Public investments, especially in rural infrastructure, reduce the cost of in-

puts, facilitating technology adoption by stimulating complementary on-farm investment and input use needed to enhance agricultural TFP growth (Evenson and Fuglie, 2010; Tombe, 2015). Flows of foreign direct investment also play an increasingly important role in low-income and emerging countries, going towards investments in irrigation infrastructure as well as direct food and commodity production (Benin and Yu, 2012; Fuglie, 2016), boosting TFP growth through technology and skill transfer.

- **Accumulation of knowledge capital:** The successful diffusion and adoption of new technology and practices require minimal education to enhance agricultural TFP growth (Evenson and Fuglie, 2010). Farmers with higher education levels are likelier to adopt new technologies and management practices (Foster and Rosenzweig, 2010). They are better equipped to cope with the increasing complexity of agricultural production and marketing systems (Gollin et al., 2005). Additionally, higher levels of education facilitate the exit of workers into the non-agriculture sector (Basu and Guariglia, 2008), therefore raising labour productivity and facilitating capital deepening within the sector. Adoption of innovation, technology and new practices is consequently facilitated by institutions that train human capital and generate or collect new ideas, as well as agriculture research and extension services that train farmers on new practices and diffuse technology Kawagoe et al. (1985).
- **Trade openness:** Trade openness can raise agricultural TFP by enabling farmers to specialise in commodities they have comparative advantage and higher value commodities, therefore improving efficiency. Trade openness, particularly in countries with small domestic markets, has also been found to increase the scope for specialisation and economies of scale, boosting agricultural TFP (Limão and Xu, 2021). Smaller countries benefit more from trade openness due to less scope for specialisation (Gisselquist et al., 2002). Agricultural trade also generates significant technology spillover effects (Aldieri et al., 2021), and the elimination of burdensome regulatory frameworks can significantly boost technology transfer. However, some research (Yuan et al., 2022) shows that the effects of trade openness on agricultural TFP growth vary over time.
- **Non-farm employment growth:** The withdrawal of labour from agriculture is a fundamental part of the growth process. As countries grow, the shares of GDP and employment in agriculture fall as workers relocate to the non-agriculture sector (Lewis, 1954). However, in low-income countries, population growth and weak growth in the non-agriculture sector hamper the ability of labour to move out of agriculture into sectors with higher labour productivity (Caselli, 2005; Restuccia et al., 2008). Hence, the reallocation of workers out of agriculture into other activities would increase agricultural TFP, while farm consolidation would allow for greater economies of scale.
- **Input use:** TFP growth arises because of technical change and efficiency improvements. Many

of these changes, such as improved plant varieties, also require the intensification of inputs such as fertiliser and pesticides (Ruttan, 2002). In low-income countries, however, barriers to using modern intermediate inputs in agricultural production contribute to low levels of agricultural TFP growth. As an indirect effect, these low levels of productivity further prevent the reallocation of labour out of the sector, resulting in low levels of TFP growth (Restuccia et al., 2008; Schultz, 1953).

- **Weather extremes:** Countries experiencing extreme climatic conditions due to climate change, such as prolonged droughts, are anticipated to face sustained declines in agricultural land productivity, extending beyond immediate production losses (IPCC, 2021). Extreme weather events such as floods, droughts and heatwaves impact agriculture TFP through yield changes, land quality and quantity, and agricultural labour. Weather extremes also change the agroecological system, affecting agriculture TFP (Walthall et al., 2013). Climate change, weather extremes and technological advancements jointly influence agricultural TFP growth in global agricultural production since they impact agricultural TFP both directly through yield effects and indirectly by influencing farmers' adaptive behaviours in response to current and anticipated changes (Chen and Gong, 2021).

In the short run, farmers adapt by altering inputs, such as adjusting labour, land use, and inputs. Consequently, the negative effect of extreme events on TFP change may be either exacerbated or attenuated, depending on the nature of the input response (Ortiz-Bobea, 2021). These adaptations may result in short-term profitability, particularly in countries with capital-intensive agricultural sectors and flexible labour markets (Chen and Gong, 2021; Deschênes and Greenstone, 2007).

- **Biodiversity and ecosystems:** Ecosystems offer provisioning, regulating, and cultural services. Biodiversity within ecosystems plays a particularly pivotal role by supplying services such as nutrient cycling, pest regulation, and pollination, which have the potential to improve agricultural land productivity and diminish the reliance on external inputs (Estrada-Carmona et al., 2022). Furthermore, increased biodiversity fortifies resilience against shocks and stresses (Reid et al., 2005).

Agricultural TFP growth in country i , time period t can thus be written as a function of:

$$AGR_TFP_{i,t} = f(BE_{i,t}, INPUTS_{i,t}, H_{i,t}, WE_{i,t}, INS_{i,t}, K_{i,t}, NONFARMEMP_{i,t}, OPEN_{i,t}, DVPT_{i,t}) \quad (2.1)$$

with $BE_{i,t}$ for biodiversity and ecosystems, $INPUTS_{i,t}$ for agriculture input use, $H_{i,t}$ for human capital, $K_{i,t}$ for capital investments, $WE_{i,t}$ for climate induced weather extremes, $INS_{i,t}$ for institutional quality as well as enabling environment for investment and innovation, $NONFARMEMP_{i,t}$ for change in non-farm employment, and $OPEN_{i,t}$ for trade openness. We also include dummy variable $DVPT_{i,t}$, to

account for omitted differences related to level of economic development that may influence differences in TFP between countries.

We are particularly interested in the role of biodiversity in enhancing agricultural TFP growth. While agriculture fundamentally relies on natural capital, many of the factors that increase agricultural TFP growth are harmful to the long-term health of biodiversity, undermining the provision of ecosystem services that the agricultural sector depends on (Watson et al., 2019; Zhang et al., 2015). Hence, the Millennium Ecosystem Assessment (Reid et al., 2005) identifies several drivers of ecosystem change, including nutrient run-off, which alters the structure and function of ecosystems (Zhang et al., 2015). Climate change and weather extremes exacerbate ecosystem degradation (Watson et al., 2019), while human-induced stressors such as defaunation, invasive species, and habitat destruction—further increase ecosystems' vulnerability to climate change (Hjältén et al., 2016). (Baron and Kenny, 1986). Agricultural land expansion, driven by demographic and economic growth drives land conversion and intensification of agricultural inputs. Despite these pressures, ecosystems play a crucial role in human adaptation to climate change through their contributions to the carbon and water cycles, as well as other biogeochemical processes (Malhi et al., 2020).

Environmental policies aimed at safeguarding biodiversity, such as the establishment of protected areas, the implementation of forest certification schemes, and payment for ecosystem services programmes, have been introduced to promote conservation across both public and private lands (Miralles-Wilhelm, 2021). However, the effectiveness of these initiatives remains uncertain. Geographic factors such as latitude, altitude, sunlight, and precipitation further shape biodiversity, with species richness generally increasing from polar to tropical regions (Willig et al., 2003).

Hence, many of the factors influencing biodiversity also affect agricultural TFP growth, creating the risk of confounding collinearities in a single-equation model. Such collinearity would likely result in an incorrect estimation of biodiversity's contribution to TFP growth. Additionally, we seek to understand how weather extremes influence the role of biodiversity in agricultural TFP growth - in our model, biodiversity is expected to play an intermediary role by modulating the impact of weather extremes on agricultural TFP growth. Instead of using instrumental variables, we specify a separate equation that treats biodiversity as an endogenous variable. While instrumental variables could be employed, we instead choose to specify a separate equation that explicitly treats biodiversity as an endogenous variable, which not only allows us to isolate the direct effect of biodiversity on agricultural TFP growth but also to identify its effect as a mediator of weather extremes.

Therefore, biodiversity in country i , time period t can thus be written as a function of:

$$BE_{i,t} = f(URBANPOP_{i,t}, POPDENSITY_{i,t}, INPUTS_{i,t}, CERTIFIEDFOREST_{i,t}, WE_{i,t}, LAT_i, DVPT_{i,t}) \quad (2.2)$$

with $POPDENSITY_{i,t}$ for demographic factors and $URBANPOP_{i,t}$ for demographics related land-use change, $INPUTS_{i,t}$ agriculture input use intensification, $WE_{i,t}$ as an indicator for weather extremes, and the proportion of certified forests, $CERTIFIEDFOREST_{i,t}$, as a proxy for environmental protection policy. We also include dummy variables to account for changes in ecosystems due to different levels of economic development, $DVPT_{i,t}$ and latitude as an indicator of geographic conditions, LAT_i , which captures geographically determined conditions for which no data is readily available.

2.3.2 Analysing the role of biodiversity by endogenising it into Agricultural TFP growth

The relationship between agricultural TFP, biodiversity, ecosystems, and weather extremes can thus be represented using a system of simultaneous equations, explicitly endogenising biodiversity. By doing so, we can estimate both the direct and mediating effects of biodiversity on agricultural TFP growth while addressing the issue of confounding collinearities, as discussed in the previous section. Specifically, we employ a recursive model structure, where the biodiversity equation (2.2) does not depend on agricultural TFP, but the TFP equation (2.1) includes biodiversity as a key determinant. This structure allows us to isolate the direct contribution of biodiversity to agricultural TFP growth, while also capturing its role as a mediator of the effects of weather extremes. The relation between agricultural TFP, biodiversity and weather extremes can be therefore be described in a simultaneous equation model based on the combination of equations 2.1 and 2.2 as follows:

$$\begin{cases} BE_{i,t} = f(URBANPOP_{i,t}, POPDENSITY_{i,t}, INPUTS_{i,t}, CERTIFIED_FOREST_{i,t}, \mathbf{WE}_{i,t}, LAT_i, DVPT_{i,t}) \\ AGR_TFP_{i,t} = f(\mathbf{BE}_{i,t}, INPUTS_{i,t}, H_{i,t}, \mathbf{WE}_{i,t}, INS_{i,t}, K_{i,t}, NON_FARM_EMP_{i,t}, OPEN_{i,t}, DVPT_{i,t}) \end{cases} \quad (2.3)$$

As illustrated in Figure 2.4, two endogenous variables, $AGR_TFP_{i,t}$ and $BE_{i,t}$, are identified, which are jointly determined in our system by using ten explanatory variables (agriculture input use, $INPUTS_{i,t}$, climate related extreme events, $WE_{i,t}$, capital investment, $K_{i,t}$, trade openness, $OPEN_{i,t}$ human capital, $H_{i,t}$, changes in non-farm employment, $NONFARMEMP_{i,t}$, share of population living in urban areas, $URBANPOP_{i,t}$, $POPDENSITY_{i,t}$, population, institutional quality, $INS_{i,t}$, trade openness, $OPEN_{i,t}$, latitude, LAT_i , dummy variables to distinguish between levels of economic development,

$DVPT$, and account for omitted variables linked to economic development levels, as well as two exclusion variables: latitude, LAT_i , and proportion of certified forests as a proxy for environmental policy $CERTIFIEDFOREST_{i,t}$.

We include two exclusion variables, latitude LAT_i and proportion of certified forest, $CERTIFIEDFOREST_{i,t}$ in our biodiversity equation to enhance the identification of the model and address endogeneity. The proportion of certified forest primarily affects biodiversity and ecosystems, but does not directly agricultural TFP. Certified forest areas are specifically managed to preserve biodiversity and protect ecosystems, with the intention of reducing/ managing human interference in natural habitats to protect biodiversity, hence reducing extinction risk of species. However, forest certification does not directly influence agricultural TFP growth because it is primarily intended for conservation, rather than improving agricultural production. While healthy ecosystems can provide benefits to agriculture (such as pollination and water regulation), these effects are generally diffuse, making the direct impact of certified forest areas on agricultural TFP growth minimal. Therefore, the certified forest proportion is expected to impact biodiversity directly, justifying its role as an instrument affecting the Red List Index but not TFP change directly. Similarly, latitude is an important determinant of biodiversity due to its influence on climate and sunlight, and hence species richness, which varies predictably from polar to tropical regions. This directly affects biodiversity but is unlikely to influence agricultural TFP growth except through its effect on ecosystems.

Our system of simultaneous equations, illustrated in Figure 2.4 meets the rank condition, is overidentified, and can thus be estimated.

2.3.3 Model specification and estimation

This chapter examines the role of biodiversity in enhancing agricultural TFP growth and evaluates how biodiversity mediate the effect of weather extremes on Agricultural TFP growth. Since many factors that drive agricultural TFP growth also affect biodiversity, there is a risk of omitted variable bias in OLS regression, leading to biased estimates. To address endogeneity, we use a two-step GMM (generalised method of moments) on panel data, which handles fixed effects, simultaneity, and dynamic panel bias (Nickell, 1981). GMM also provides consistent results in the presence of different sources of endogeneity, which is useful in this context (Wintoki et al., 2012). It also is more efficient than three-stage least squares when accounting for heteroskedasticity and intra-cluster correlation. To verify instrument validity, the Hansen J test of over-identifying restrictions is reported for each estimation.

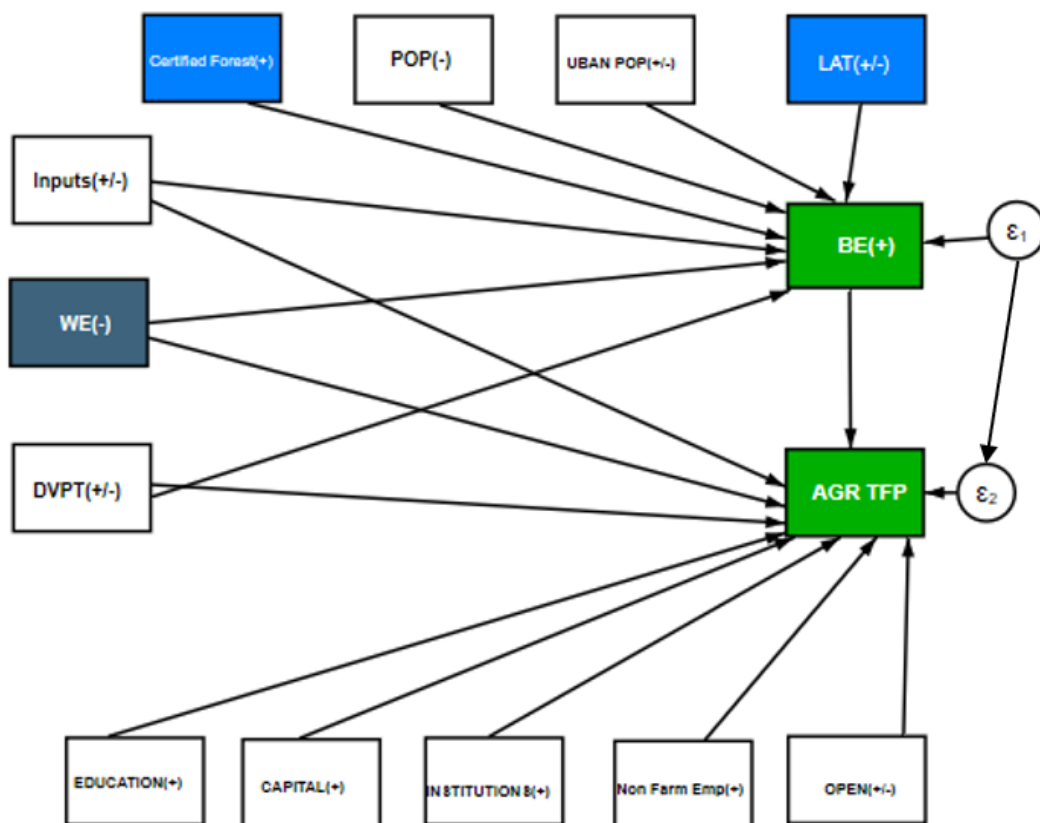


Figure 2.4: Path model linking ecosystem services, climate induced weather extremes, and agricultural TFP growth. The sign of expected effects is specified in parentheses; green boxes indicate endogenous variables; blue boxes indicate exclusion variables and white boxes indicate explanatory variables. ϵ represents error terms of system equations, which are estimated simultaneously using the two-step GMM technique.

2.3.4 Data sources and variables

While data on some variables is available from as early as 1960 for some countries, our dataset is limited to 82 countries from 2000 - 2010 to ensure a balanced panel. (See appendix B.1 for countries included.) Our model specifies two endogenous variables - Agriculture TFP growth and biodiversity. Data to estimate agricultural TFP growth was taken from the USDA International Agricultural Productivity database. The TFP index was calculated using the quantity of total crop output (USD 2015 constant prices) and the following: quantity of total cropland (hectares), quantity of total agricultural fertilisers (metric tonnes), quantity of total agricultural machinery (metric horsepower), quantity of persons economically active in agriculture and quantity of total agricultural capital stock (USD 2015 constant prices). TFP growth was calculated using the Malmquist DEA method, outlined in appendix B.2.

The Red List Index, based on global extinction risk estimates by the International Union for Conservation of Nature (IUCN), was chosen as an indicator of biodiversity and ecosystem health. It measures the extinction risk for species within a country or region on a scale of 0 to 1, with 1 indicating all species are classified as Least Concern and 0 indicating all species have gone extinct (Bland et al., 2017). The

risk of extinction for a species is influenced by the size of its geographic range and the extent to which human activities, including climate change, are reducing its natural habitat, making it a useful proxy for understanding human influence on biodiversity and ecosystem health at aggregate scale. Furthermore, ecosystem functioning and services is often directly dependent on biodiversity loss, and therefore species extinction creates an ecosystem service debt - where a gradual loss of biodiversity-dependent benefits that people obtain from remaining fragments of natural ecosystems (Isbell et al., 2015). Red List Index data, available from 1993 to 2022, meets the criteria for tracking progress toward the United Nations Convention on Biological Diversity (UNCBD) post-2020 goals (Bland et al., 2017; Nicholson et al., 2021).² In analysing the effect of weather extremes on agricultural TFP, we are especially interested in the impact of precipitation and temperature extremes. Similar to chapter 1, we use the following variables:

- **Standardized Precipitation Drought index (SPI Drought):** Our study uses the SPI-12, which represents a 12-month accumulation of precipitation compared to long-term historical averages. It is a widely recognised tool for identifying droughts, used by the World Meteorological Organization (McKee et al., 1993). As in Chapter 1, SPI-12 values below -1 indicate drought conditions, while values above 1 signal surplus rainfall. The original negative SPI-12 values are squared for better interpretability. Categories consist of normal/wet ($SPI > 1$), moderate to severe droughts ($-2 > SPI \geq -1$), and extreme drought ($SPI \leq -2$).
- **Standardized Evapotranspiration Index (SPEI Drought):** The Standardized Precipitation Evapotranspiration Index (SPEI) builds upon the SPI index by incorporating additional factors such as temperature and potential evapotranspiration to detect the onset, duration, and intensity of droughts. We use this to test for robustness.
- **Average Largest 5-Day Cumulative Precipitation (Ext Wet Days):** The average highest precipitation amount over a consecutive 5-day period during each month in the data period is used as an indicator of extreme precipitation. It is one of the 40 climate change detection indices developed by the Expert Team on Climate Change Detection and Indices (ETCCDI).
- **Number of Extreme Temperature Days (Ext Hot Days):** The count of days with maximum temperatures exceeding 35°C serves as an indicator of extreme temperature events. The 35°C threshold was selected globally by the IPCC due to its significance for maize pollination and production, and its considerable health risks to humans (Lobell and Gourdji, 2012; Petitti et al., 2015). Additionally, it is an ETCCDI climate change detection index.

²The Red List Index is also meets the UNCBD (UNCBD), criteria of availability and suitability for use at global and national scale; scientific robustness, with indicator methodologies and data published, peer reviewed and thus replicatable; geographic coverage of data for all regions of the world and; easily understandable in presentation and interpretation (Nicholson et al., 2021) for use as an indicator of progress towards meeting the UNCBD post 2020 goals.

- **Number of floods (*Nb flood*)** We construct a simple flood indicator, which is the sum of the number of reported floods per country per year using the number of floods as reported in the Emergency Events Database (EM-DAT) database by the Centre for Research on the Epidemiology of Disasters (CRED). We use reported data on the occurrence of floods, which are defined to include riverine flooding, coastal flooding as well as flash floods due to excessive rainfall. We use this to test for robustness.

We use data from the CRU TS (Climatic Research Unit Timeseries) to calculate the SPI and SPEI indexes, and ERA-5 reanalysis data from the European Centre for Medium-Range Weather Forecasts (ECMWF) is used to obtain extreme wet days and extreme hot days.

We include several explanatory variables based on the literature on agricultural TFP growth. Fertiliser use per hectare, using data from the USDA International Agriculture Productivity database, and converting it to log is used as indicator of agriculture input use. For capital, we use general government investment (gross capital fixed formation), which is a measure of the addition to the fixed assets of an economy, was obtained from the IMF capital stock database from 1960 - 2019 and was transformed into natural log. For our human capital development indicator, we use the number of years of schooling obtained from the Barro-Lee Educational Attainment Data covering the period from 1950 to 2010, transformed into natural log. Our indicator of off-farm employment change was calculated as annual change in the number of people employed in industry using data on the number of workers in industry from 1991 - 2020 from the UNIDO INDSTAT2 database. We also used the KOF globalisation index, widely used to measure the economic, social and political dimensions of globalisation, and covers the period 1970 - 2020.

Data on the proportion of people living in urban areas and population density, which is the number of people per kilometre squared, were obtained from the WDI database, for the period 1960 - 2020, as a proxy for demographic changes and landuse change. The Government Effectiveness: Estimate from the World Governance Indicators data-set was used as a proxy for institutional quality. It captures perceptions of the quality of public services, civil service, policy formulation and implementation, and the credibility of the government's commitment to such policies. Thus, it denotes the ability of a government to provide public goods and services necessary for agriculture, as well as sound macroeconomic policy that create an enabling environment for investment in agriculture. Estimates give the country's score on the aggregate indicator, in units of a standard normal distribution, ranging from approximately -2.5 to 2.5. Data from the WGI is from 1996 - 2022.

We also used the proportion of forest area under independently verified forest management schemes of total forest area as an indicator of environmental policy. Data on forest area and verified forest area are obtained from the FAOSTAT database for the period 2000 -2022. We include latitude coordinates from

the CEPII GeoDist database, as a proxy indicator for geographical conditions that determine the natural state of ecosystems. We also include dummy variables to capture omitted variables related to economic development, based on IMF country classification, which categorises 30 countries as advanced economies, 33 as emerging market and middle-income economies, and 19 as low-income developing countries. For a list of countries in each category in our panel, please see Appendix B.1. A time trend variable was also used to capture the effect of relevant variables that change over time but are not directly measurable. The variables used in our study and their statistical summaries in Appendix B.1.

2.3.5 Study limitations

This paper aims to assess the effect of biodiversity on agricultural TFP growth in the context of extreme weather events. However, a key challenge is the lack of high-quality, aggregate-level data on ecosystem services. Many ecosystem services are difficult to quantify directly, necessitating proxy indicators, which can introduce limitations in accuracy and scope (de Bello et al., 2010). Additionally, available data on ecosystem services is limited, relying on a small number of indicators. Secondary indicators, such as agricultural land and forest cover, often represent aggregated measures of land-use change rather than direct measures of ecosystem service quality, leading to potential oversights in understanding the full scope of ecosystem function (Bostian and Lundgren, 2022). Hence, to date, few indicators of ecosystem quality in low-income countries are freely available annually at the aggregate level. However, multinational institutional programs have been initiated to address this data gap.

This study utilises the Red List Index as an indicator of biodiversity trends, reflecting changes in species' extinction risk categories. However, the Red List Index has its limitations, such as that most countries (74%) report data for fewer than three of the five taxonomic groups tracked by the index. Additionally, the Red List Index is designed to show national contributions to global extinction risk trends, which may lead to an underestimation of actual national species changes (Raimondo et al., 2023). Furthermore, the level of reporting effort varies among countries. As a result, the Red List Indicator, with a relatively narrow range with little variation over time, is susceptible to measurement errors or biases.

Despite these challenges, the Red List Index remains valuable because it is based on a single, comprehensive global dataset (the IUCN Red List) and is available for all countries across the same taxonomic groups. This consistency allows for meaningful comparisons between nations' contributions to global species conservation, offering a useful proxy for biodiversity. As such, the Red List Index provides important insights into the health of ecosystems and their role in sustaining agricultural TFP growth.

Lastly, although agricultural R&D is a key driver of agricultural TFP growth, incorporating it into the model poses challenges due to inconsistencies in data across countries and time periods. Variations

in how R&D is defined and measured can introduce biases, making it difficult to include in a consistent analytical framework. Therefore, this model focuses on factors with more reliable data to ensure robust analysis. Hence, the results presented in this study are provisional, and although based on available data and best efforts at the time of writing, may be subject to future revision due to limitations discussed above.

2.4 Estimation Results

2.4.1 Effect of biodiversity and weather extremes on agricultural TFP growth

Empirical findings derived from the estimation of our system of simultaneous equations are summarised in Table 2.1. Model (1) shows empirical findings derived from the estimation of our system of simultaneous equations excluding weather extreme variables, while Model (2) - (6) present findings with extreme temperature, precipitation and drought indicators. These findings align with the theoretical expectations, confirming the assumptions underlying our analysis as elaborated below:

Biodiversity, ecosystems and agriculture TFP growth: Across all model specifications, the coefficient for BE is consistently positive and highly significant at the 1% level. This indicates a robust and positive relationship between biodiversity and agricultural TFP growth. Specifically, a one-unit increase in the Red List Index (*BE*) is associated with an increase in agriculture TFP growth by approximately 0.23 to 0.30 percentage points, depending on the specification. This aligns with ecological theories positing that biodiversity rich ecosystems contribute to enhanced crop productivity in agricultural systems.

Direct effect of control variables on agricultural TFP growth: In line with expectations, agriculture inputs (*Log(Inputs)*) and institutional quality (*INST (GE EST)*) are positive and statistically significant, indicating that they directly contribute to a positive change in agricultural TFP growth. TFP growth is calculated based on the best-performing countries, suggesting that effective institutions and increasing input use in the least-performing countries bring them closer to the efficient production frontier. On the other hand, our openness variable, *Globalisation*, is negative, indicating that trade openness has a negative effect on agricultural TFP growth. This suggests that the relationship between global economic integration and agricultural TFP growth is potentially detrimental in some contexts. The low-income country dummy, *IMF LIC dummy*, shows a negative trend, indicating that these experience lower levels of agricultural TFP growth than emerging and advanced economies.³ The time trend variable is positive and significant, suggesting that agricultural TFP growth is positive over time, excluding other

³We use the International Monetary Fund country classification, which categorises countries into three major groups: advanced economies, emerging market and middle-income economies (EME), and low-income developing countries (LIC). A list of countries according to their classification is included in Appendix B.1.

Table 2.1: Effects of ecosystem services and climate induced weather extremes on agricultural TFP growth

	(1)	(2)	(3)	(4)	(5)	(6)
TFPCH						
BE	0.233*** (0.053)	0.299*** (0.057)	0.282*** (0.051)	0.296*** (0.047)	0.280*** (0.048)	0.277*** (0.050)
Log(Inputs)	0.013*** (0.004)	0.014*** (0.004)	0.011** (0.004)	0.015*** (0.004)	0.016*** (0.004)	0.015*** (0.004)
Log(KStockGov)	0.000 (0.002)	0.002 (0.002)	0.001 (0.002)	0.002 (0.002)	0.002 (0.002)	0.001 (0.002)
Log(Education)	0.007 (0.013)	0.007 (0.015)	0.009 (0.014)	-0.014 (0.017)	0.004 (0.013)	-0.006 (0.015)
Industry Emp Change(%)	0.019 (0.028)	0.014 (0.028)	0.009 (0.027)	0.018 (0.027)	0.019 (0.025)	0.016 (0.027)
Globalisation	-0.004*** (0.001)	-0.005*** (0.001)	-0.004*** (0.001)	-0.005*** (0.001)	-0.005*** (0.001)	-0.004*** (0.001)
INS(GE EST)	0.027*** (0.010)	0.025** (0.011)	0.029*** (0.011)	0.032*** (0.011)	0.030*** (0.010)	0.028*** (0.011)
Ext Hot Days		-0.001*** (0.000)				
Ext Wet Days			0.011 (0.007)			
SPI:Drought				-0.013*** (0.004)		
SPI:Moderate & Severe					-0.027** (0.011)	
SPI: Extreme						-0.040*** (0.012)
Trend	0.021*** (0.002)	0.020*** (0.002)	0.019*** (0.002)	0.022*** (0.003)	0.020*** (0.002)	0.021*** (0.002)
IMF LIC Dummy	-0.042** (0.021)	-0.051** (0.024)	-0.036* (0.020)	-0.040* (0.023)	-0.039* (0.020)	-0.035 (0.022)
IMF EME Dummy	-0.001 (0.014)	-0.000 (0.016)	0.006 (0.013)	0.002 (0.015)	0.004 (0.014)	0.002 (0.014)
Cons	0.800*** (0.245)	0.862*** (0.234)	0.840*** (0.234)	0.880*** (0.235)	0.874*** (0.225)	0.856*** (0.241)
BE						
Log(Inputs)	-0.029*** (0.007)	-0.032*** (0.007)	-0.027*** (0.007)	-0.029*** (0.007)	-0.029*** (0.007)	-0.031*** (0.007)
Certified Forest(%)	-0.000 (0.003)	0.002 (0.003)	-0.002 (0.003)	-0.000 (0.003)	-0.001 (0.002)	-0.002 (0.003)
Latitude	0.001*** (0.000)	0.001*** (0.000)	0.001*** (0.000)	0.001*** (0.000)	0.002*** (0.000)	0.001*** (0.000)
Urban Pop(%)	0.001 (0.001)	0.001 (0.001)	0.001 (0.001)	0.001 (0.001)	0.001 (0.001)	0.001 (0.001)
POP Density	-0.016** (0.007)	-0.014* (0.007)	-0.014* (0.008)	-0.013* (0.007)	-0.015** (0.007)	-0.013* (0.007)
Ext Hot Days		-0.001*** (0.000)				
Ext Wet Days			-0.019 (0.020)			
SPI:Drought				-0.004 (0.007)		
SPI:Moderate & Severe					-0.037*** (0.013)	
SPI: Extreme						0.016 (0.020)
Trend	0.007 (0.006)	0.005 (0.005)	0.005 (0.005)	0.005 (0.005)	0.005 (0.005)	0.006 (0.006)
IMF LIC Dummy	-0.046 (0.033)	-0.029 (0.033)	-0.033 (0.032)	-0.043 (0.034)	-0.024 (0.033)	-0.051 (0.033)
IMF EME Dummy	-0.072*** (0.020)	-0.057*** (0.021)	-0.070*** (0.020)	-0.071*** (0.020)	-0.058*** (0.020)	-0.076*** (0.020)
N	735	735	711	735	735	735
Hansen J Statistic	17.2493	12.6648	16.5196	14.0692	15.1051	14.968
Hansen p-value	0.0159	0.0807	0.0208	0.0500	0.0347	0.0364

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

factors. The human capital *Log(Education)*, non-farm employment change *Non Farm Emp Change* and government investment *Log(KstockGov)* variables are not significant.

Direct effect of control variables on biodiversity and ecosystems: Our results show that an increase in input use (*Log(Inputs)*) and demographic factors (*Log(PopDensity)*) have a negative effect on biodiversity and ecosystems. These findings align with scientific literature, showing that increasing input use, particularly inorganic fertiliser, have a detrimental impact on species biodiversity and ecosystem health. Moreover, the larger magnitude of the negative effect suggests that the indirect impact of fertiliser use on agricultural TFP through biodiversity is greater than its direct contribution to agricultural TFP growth. Likewise, demographic pressure is a significant driver of ecosystem degradation and biodiversity loss.

The IMF EME dummy is negative and statistically significant, suggesting that emerging economies contribute more to global species extinction risk than other regions. This may be due to biodiversity loss driven by the intensification of commodity crops in emerging economies such as Brazil (Fearnside, 2005; Nepstad et al., 2006), Indonesia and Malaysia (Curran et al., 2004). Indeed, species extinction risk accelerated the fastest in Central and Southern Asia, Eastern and South-Eastern Asia, and Oceania between 1993 and 2022 (Economic and Council, 2023).

Latitude, our proxy for natural factors contributing to ecosystem services, is positive and statistically significant. Although species diversity is highest at the equator and lowest at the poles, (Willig et al., 2003), this suggests that lower latitudes are linked to species extinction risk, aligning with previous research on the impact of agricultural land expansion in tropical regions (Economic and Council, 2023).

Direct effect of weather extreme variables on agricultural TFP growth: Models (2) - (6) summarise estimation results with weather extreme variables. Holding other factors constant, our analysis indicates that extremely hot days (*Ext Hot Days*), as shown in Model(2), have a negative effect on agricultural TFP growth. In contrast, extremely wet days (*Ext Wet Days*), as shown in Model (3), are not statistically significant. However, droughts exhibit a clear negative impact on agricultural TFP growth. Model (4)-(6) shows that droughts, regardless of intensity, have a negative effect on agricultural TFP growth, with coefficients ranging from -0.027 to -0.040 for moderate & severe and extreme droughts. These findings suggest that drought conditions consistently hinder agricultural TFP growth regardless of severity.

Direct effect of weather extremes on ecosystem services: Holding all other factors constant, we find that moderate to severe droughts and extreme hot days have a negative effect on ecosystem services. This suggests that moderate to severe drought conditions directly impair ecosystem services, diminishing their positive contributions to agricultural TFP growth. Indicators for excessive precipitation (*Ext Wet Days*), undifferentiated drought (*SPI:Drought*) and extreme drought (*SPI:Extreme*) are not

significant.

Indirect and total effects of climate extremes on agricultural TFP growth: To obtain the total effect of weather extremes on agricultural TFP growth, we sum the direct impact of each exogenous variable on agricultural TFP growth with its indirect effect through our biodiversity indicator. The indirect effect of an exogenous variable on agricultural TFP growth is determined by multiplying its direct effect on biodiversity change by the coefficient representing the influence of biodiversity on agricultural TFP growth. Therefore, Model (2) shows that the direct effect of temperature on agricultural TFP growth is -0.001, and the indirect effect through biodiversity is $(-0.001) \times (0.299) = -0.003$. When mediated by biodiversity, the total effect of an additional extremely hot day on agricultural TFP growth is $(-0.001 + -0.003) = -0.004$. Considering the varying levels of drought, Model (2) shows that the effect of drought, undifferentiated by intensity, is -0.013, while Model (6) shows that the impact of extreme drought is -0.040. Model (5) shows that the direct effect of moderate & severe drought is -0.027, while the indirect impact through biodiversity is $(-0.037) \times (0.280) = -0.010$. Therefore, the total effect of moderate to severe droughts on agricultural TFP growth is -0.41.

These results confirm our expectation that biodiversity mediates the relationship between weather extremes and agricultural TFP growth. Hence, while biodiversity directly enhances agricultural TFP, weather extremes disrupt this effect. Specifically, extreme heat and drought negatively affect biodiversity, causing diebacks and altering ecosystem structure, which in turn diminishes biodiversity's contribution to TFP growth (Clark et al., 2016). However, excessive precipitation (Ext Wet Days) does not show a significant impact in our model. This may be due to the varied effects of precipitation across different ecosystems and geographic regions (Thakur et al., 2022), as well as the lack of an agreed definition of "flooding", which likely explains the lack of statistical significance for our Ext Wet days variable.

2.4.2 Effects of weather extremes on agricultural TFP growth when moderated by biodiversity

We have observed that weather extremes, and in particular, drought, have direct effects on agricultural TFP growth and indirect effects through biodiversity. However, we might intuit biodiversity may also affect the strength or direction of the relationship between weather extremes and agricultural TFP growth, hence play a moderating role. We therefore refine our analysis by intersecting our biodiversity indicator with our weather extreme variables, as presented in Table 2.3.

Regarding the results, as shown in Model (1) of Table 2.3, the interaction term between biodiversity and extreme hot days is negative but not statistically significant, suggesting that while the interaction might be negative, it is not strong enough to be statistically conclusive based on our panel of data. As shown

Table 2.2: Effect of weather extremes on agricultural TFP growth when moderated by biodiversity

	(1)	(2)	(3)	(4)
TFPCH				
BE	0.326*** (0.072)	1.520** (0.608)	0.394*** (0.075)	0.425*** (0.101)
Log(Inputs)	0.008 (0.006)	-0.008 (0.010)	0.015*** (0.005)	0.014*** (0.004)
Log(KStockGov)	0.002 (0.003)	-0.000 (0.002)	-0.002 (0.003)	-0.001 (0.003)
Log(Education)	-0.030 (0.030)	0.021 (0.015)	0.006 (0.013)	-0.041 (0.033)
Industry Emp Change(%)	-0.000 (0.033)	-0.011 (0.021)	-0.013 (0.029)	0.010 (0.029)
Globalisation	-0.005*** (0.001)	0.003 (0.004)	-0.004*** (0.001)	-0.004*** (0.001)
INS(GE EST)	0.038** (0.017)	-0.025 (0.033)	0.019 (0.012)	0.035*** (0.013)
Ext Hot Days	0.042 (0.036)			
BE*Ext Hot Days	-0.050 (0.041)			
Ext Wet Days		0.412** (0.188)		
BE*Ext Wet Days		-0.482** (0.227)		
SPI: Moderate & Severe			0.870* (0.525)	
BE*SPI: Moderate & Severe			-1.052* (0.622)	
Trend	0.024*** (0.004)	-0.012 (0.015)	0.018*** (0.003)	0.023*** (0.003)
IMF LIC Dummy	-0.055* (0.031)	0.021 (0.033)	-0.042* (0.023)	-0.049* (0.029)
IMF EME Dummy	0.008 (0.018)	-0.020 (0.018)	0.011 (0.015)	0.016 (0.017)
b0				
Constant	0.814*** (0.236)	0.767*** (0.243)	0.872*** (0.224)	0.838*** (0.239)
BE				
Log(Inputs)	-0.026*** (0.007)	-0.024*** (0.007)	-0.024*** (0.008)	-0.027*** (0.008)
Certified Forest(%)	0.002 (0.003)	-0.002 (0.003)	-0.000 (0.003)	-0.001 (0.003)
Latitude	0.001*** (0.000)	0.001*** (0.000)	0.001*** (0.000)	0.001*** (0.000)
Urban Pop(%)	0.001 (0.001)	0.000 (0.001)	0.001 (0.001)	0.001 (0.001)
POP Density	-0.013* (0.007)	-0.019** (0.009)	-0.018** (0.007)	-0.015** (0.007)
Ext Hot Days	-0.001** (0.000)			
Ext Wet Days		-0.008 (0.020)		
SPI: Moderate & Severe			-0.038*** (0.013)	
Trend	0.005 (0.005)	0.009 (0.006)	0.005 (0.005)	0.006 (0.005)
IMF LIC Dummy	-0.030 (0.033)	-0.039 (0.032)	-0.016 (0.034)	-0.046 (0.033)
IMF EME Dummy	-0.062*** (0.021)	-0.069*** (0.021)	-0.056*** (0.021)	-0.073*** (0.020)
N	735	711	735	735
Hansen J Statistic	8.6465	8.57531	10.142	10.0935
Hansen p-value	0.1945	0.1989	0.1188	0.1208

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

in Model (2), the interaction term between biodiversity and extreme wet days is negative and significant, suggesting that the positive marginal effects of biodiversity on agricultural TFP growth are diminished in the presence of extreme wet days. Turning to our indicators of drought, the interaction term in Model (3) is negative and significant, indicating that drought can stress biodiversity enough to reduce their efficacy in supporting agricultural TFP growth. This highlights the vulnerability of ecosystems to severe water scarcity, which can drastically reduce their efficacy in supporting agricultural TFP growth. As drought severity increases, the marginal benefits provided by ecosystem services on agricultural TFP growth decline further. These findings confirm the complex relationship between drought and biodiversity (Chen et al., 2022).

Lastly, as shown in Models (2)-(3), our weather extreme indicators turn positive when interacted with biodiversity. While counter-intuitive, this can be interpreted as short-term changes farmers make in response to weather extremes. Farmers may adjust labour, land, and inputs, or increase irrigation and deploy available technology to stabilise production. In the short term, these responses may buffer yield losses, and depending on the ratio between inputs and outputs, may yield positive or negative effects on agricultural TFP change (Ortiz-Bobea, 2021). However, as extreme weather events intensify and further degrade ecosystem services, these adjustments must also intensify to compensate for both the effects of extreme events, and resulting declines in ecosystem services.

Overall, findings suggest that extreme weather events reduce the positive impact of biodiversity on agricultural TFP growth. They are also susceptible to extreme weather conditions, which diminish their contribution to agricultural TFP growth. One possible explanation for this finding is that our dependent variable, agricultural TFP growth, is derived from the best-performing countries, which tend to prioritise yield maximisation through intensive reliance on inputs such as fertilisers and machinery, predominantly within large-scale monoculture farming systems. As a result, these monocultural systems may appear more resilient in the short term due to their reliance on tailored inputs and technologies. However, their dependence on a small number of crop varieties increases their long-term vulnerability to extreme weather events. Furthermore, these systems, which prioritise conventional agriculture and/or Green Revolution technologies, often overlook the potential of agricultural practices that leverage synergies and ecosystem services to improve their ability to withstand weather extremes. Consequently, ecosystems and biodiversity are not viewed as valuable assets that could enhance their capacity to cope with climate variability, leading to increased vulnerability in the face of such challenges.

2.4.3 Sensitivity analysis

The regression results show a significant positive relationship is observed between biodiversity, ecosystems and agricultural TFP growth, with consistent significance across all model specifications. The

inclusion of control variables influencing this relationship, such as input use, globalisation, and institutional quality, also show consistent significance and expected directional relationships, suggesting a robust model specification.

However, there are some notable concerns regarding the models. For instance, the coefficient on *Log(KStockGov)* is consistently insignificant, suggesting that the model may not fully capture the role of total capital stock in driving agricultural TFP growth. Additionally, the significance of weather extremes variables such as extreme hot days and drought indicators varies across specifications, indicating potential sensitivity to model specification. Hence, to enhance the robustness of the model, several sensitivity tests are performed, and results are presented in Table 2.3 below.

In Model (1), we use government capital stock (*Log(KStockGov)*) as an indicator of physical capital, which is our baseline model. At the same time, in Model (2), we incorporate private physical capital stock (*Log(KPrivStock)*), while in Model(3), we used an indicator of total investments (*Log(KTotStock)*). Results show that only private investments have a positive and statistically significant effect on agriculture TFP growth.

Turning to our weather extreme indicators, we replace the SPI drought indicators with the SPEI, which encompasses both temperature and evapotranspiration in capturing drought conditions, as shown in Model (3) and Model (4). Results closely align with our main findings, with the effects of drought slightly amplified. Lastly, in Model (5), we use an alternative indicator of floods, namely the number of flooding events in the EMDAT database, which demonstrates a direct negative effect on agricultural TFP growth and an indirect negative effect through biodiversity. This suggests that while the impact of extreme precipitation is difficult to quantify, floods severe enough to be registered on the EMDAT database are highly destructive to biodiversity and ecosystems. The severity and impact of flooding is often site-specific, highlighting the complexity of evaluating extreme precipitation effects, which complicates capturing its impact on agricultural TFP growth (Wen et al., 2023).

Overall, the sensitivity analysis demonstrates robustness in our original findings. The consistently positive and significant impact of biodiversity on agriculture TFP growth across different model specifications validates the original results. The inclusion of alternative measures of weather extremes (drought, severe drought, flooding) confirms that extreme weather conditions negatively affect agricultural TFP, reinforcing our original conclusions. Furthermore, while the choice of capital measure has minor effects, the overall conclusions remain stable, affirming the validity of our principal findings.

Table 2.3: Sensitivity analysis

	(1)	(2)	(3)	(4)	(5)
TFPCH					
BE	0.233*** (0.053)	0.223*** (0.049)	0.288*** (0.058)	0.277*** (0.053)	0.223*** (0.052)
Log(Inputs)	0.013*** (0.004)	0.011*** (0.004)	0.011*** (0.004)	0.012*** (0.004)	0.012*** (0.004)
Log(KStockGov)	0.000 (0.002)				
Log(Education)	0.007 (0.013)	0.009 (0.014)	0.001 (0.016)	-0.000 (0.015)	0.008 (0.014)
Industry Emp Change(%)	0.019 (0.028)	0.013 (0.028)	0.011 (0.030)	0.006 (0.029)	0.018 (0.027)
Globalisation	-0.004*** (0.001)	-0.005*** (0.001)	-0.005*** (0.001)	-0.005*** (0.001)	-0.005*** (0.001)
INS(GE EST)	0.027*** (0.010)	0.033*** (0.010)	0.036*** (0.011)	0.030*** (0.011)	0.032*** (0.011)
Log(KStockPriv)		0.003* (0.002)			
Log(KStockTot)			0.003 (0.002)	0.003 (0.002)	0.005** (0.002)
SPEI: Drought			-0.015** (0.006)		
SPEI: Severe Drought				-0.040*** (0.015)	
NB.Flood					-0.002** (0.001)
Trend	0.021*** (0.002)	0.021*** (0.002)	0.022*** (0.003)	0.022*** (0.003)	0.021*** (0.002)
IMF LIC Dummy	-0.042** (0.021)	-0.041* (0.021)	-0.053** (0.027)	-0.056** (0.026)	-0.040* (0.021)
IMF EME Dummy	-0.001 (0.014)	-0.003 (0.014)	0.001 (0.016)	-0.004 (0.016)	-0.001 (0.014)
Constant	0.800*** (0.245)	0.728*** (0.243)	0.772*** (0.225)	0.787*** (0.241)	0.752*** (0.225)
BE					
Log(Inputs)	-0.029*** (0.007)	-0.028*** (0.007)	-0.028*** (0.007)	-0.030*** (0.007)	-0.025*** (0.008)
Certified Forest(%)	-0.000 (0.003)	-0.000 (0.003)	0.001 (0.003)	0.004 (0.003)	0.000 (0.003)
Latitude	0.001*** (0.000)	0.001*** (0.000)	0.001*** (0.000)	0.002*** (0.000)	0.001*** (0.000)
Urban Pop	0.001 (0.001)	0.000 (0.001)	0.001 (0.001)	0.001 (0.001)	0.000 (0.001)
Log(POP Density)	-0.016** (0.007)	-0.017** (0.007)	-0.014** (0.007)	-0.015** (0.007)	-0.017** (0.007)
SPEI: Drought			-0.005 (0.013)		
SPEI: Severe Drought				-0.068*** (0.026)	
NB.Flood					-0.004* (0.002)
Trend	0.007 (0.006)	0.009 (0.006)	0.007 (0.005)	0.007 (0.005)	0.008 (0.005)
IMF LIC Dummy	-0.046 (0.033)	-0.051 (0.033)	-0.038 (0.033)	-0.034 (0.033)	-0.053* (0.032)
IMF EME Dummy	-0.072*** (0.020)	-0.071*** (0.020)	-0.066*** (0.021)	-0.057*** (0.021)	-0.064*** (0.020)
N	735	735	735	733	735
Hansen J Statistic	17.2493	16.2511	12.7377	10.8531	15.3471
Hansen p-value	0.0159	0.0229	0.0788	0.1452	0.0318

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

2.5 Conclusion

In this chapter, we employed a system of simultaneous equations to evaluate the direct effects of biodiversity on agricultural TFP growth, as well as its indirect role in mediating the impact of weather extremes on agricultural TFP growth.

- **Biodiversity enhances agricultural TFP growth:** Biodiversity consistently shows a positive effect on agricultural TFP growth, as demonstrated using the IUCN Red List Index. This direct impact likely arises from biodiversity's role in improving soil health, supporting pollination, and promoting ecological balance, all of which boost agricultural efficiency and hence TFP growth.
- **Weather extremes hamper agricultural TFP growth:** Drought, extreme heat and severe flooding have a direct and negative effect on agricultural TFP growth, confirming previous studies. Hence, more frequent and intense weather extremes will reduce agricultural TFP growth.
- **Weather extremes diminish the contribution of biodiversity to agricultural TFP growth:** Biodiversity directly enhances agricultural TFP growth and mediates the impact of weather extremes. However, rather than mitigating their effects, extreme weather harms biodiversity, reducing its ability to support agricultural TFP growth. As a result, in countries with abundant biodiversity, agricultural TFP growth is more negatively affected by weather extremes. The increasing intensity of these events further diminishes biodiversity's benefits, limiting its contribution to TFP growth.

These findings challenge the assumptions of weak sustainability, which suggests that natural capital can be replaced by human and physical capital without reducing well-being. Our results indicate that natural capital remains essential for maintaining or improving agricultural TFP growth. Thus, sustainably boosting agricultural TFP depends on protecting and preserving biodiversity, which face growing threats from both human activities and weather extremes. This calls for more systemic approaches to strengthening agricultural systems. Accordingly, the following policy implications arise from our findings:

Investment in research to support technology and innovation for short-term responses to extreme weather events: Ecosystems and biodiversity are vulnerable to weather extremes, and as these intensify and become more frequent, their contribution to enhancing agricultural efficiency will continue to decline, threatening agriculture. It is thus critical to improve investment in agricultural research & development to develop technological and management practices to maintain agricultural TFP growth in the short-term. This includes drought and pest-resistant crop varieties and technologies that enhance water harvesting and use efficiency. Although technological responses cannot fully replace the contribution of biodiversity, they remain a critical element to enhancing agricultural TFP growth, especially in vulnerable countries with more frequent and intense droughts and heatwaves.

Promote integrated approaches to enhance ecosystem resilience and food production: Our results indicate that while inputs have a direct, positive effect on agricultural TFP growth, they also exert a larger, negative impact via biodiversity, ultimately reducing agricultural TFP growth. However, more complex and diversified landscapes are vital for strengthening biodiversity and ecosystem health, which are key to enhancing ecosystem resilience and crop productivity (Estrada-Carmona et al., 2022). Approaches such as agroecology, ecological intensification, and other biodiversity-enhancing practices can sustain yields by harnessing natural processes and promoting positive interactions within agroecosystems. These practices aim to reduce reliance on synthetic inputs and utilize ecosystem services to develop sustainable agricultural systems (Gliessman, 2018; Wezel et al., 2020). Beyond farm-level production, they integrate landscape approaches and consider the broader social and economic contexts of food systems, adapting flexibly to local socio-cultural and institutional factors (Diaz et al., 2015).

Investment in biodiversity protection and ecosystem restoration: Given that biodiversity and ecosystems are vulnerable to extreme weather and agricultural activity, investing in their conservation, protection, and restoration is crucial. While there is a conflict between the immediate needs of farmers and the long-term benefits of biodiversity and ecosystem protection, offering incentives such as Payments for Ecosystem Services to provide stable, long-term incomes for ecosystem service providers could support the transition to more sustainable agroecological food production systems that maintain or enhance biodiversity and ecosystems. When coupled with more integrated agroecological food production, biodiversity and ecosystem protection can build resilience over time, making ecosystems better able to withstand and recover from weather extremes.

While this chapter used an aggregate indicator to explore the relationship between agricultural TFP growth, weather extremes, and ecosystems, future research should employ indicators to identify thresholds where biodiversity loses its capacity to enhance agricultural TFP growth under increasing weather extremes. Additionally, a more granular analysis at the farm level is necessary, as our results are driven by high-performing, input-intensive, likely monoculture farms that do not leverage biodiversity or ecological practices to enhance resistance to weather extremes. This reliance on country-level data limits our ability to differentiate between conventional and ecological practices. Further research should therefore focus on small-scale farming, which accounts for only 12% of global agricultural land but produces 36% of the world's food (Lowder et al., 2019). These small farms are of particular interest, since they often practice polyculture, achieving 20-60% higher yields than conventional farms by reducing losses from weeds, pests, and diseases, while making more efficient use of resources (Altieri, 2009). Hence, their ability to sustain yields with lower environmental impact, even in the face of weather extremes, makes them crucial for understanding how ecological principles can enhance agricultural TFP growth.

Chapter 3

Effectiveness of sustainable farming practices in combating land degradation and weather extremes: insights from Senegal's agriculture census^{*}

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3.1 Introduction

In many low-income countries, particularly in sub-Saharan Africa and parts of Asia, a large majority of the population resides in rural areas and depends on agriculture for their livelihoods. In these regions, agriculture provides employment for as much as 60% of the economically active population and contributes a substantial portion of value added to the economy, and accounts for a significant share of exports. Despite its importance, agriculture output per capita in these countries remains low and has continued to lag behind global trends, due to adverse resource endowments, weak institutions, and insufficient capital accumulation (Binswanger and Townsend, 2000; Fuglie, 2011). Small-scale farmers, who dominate the sector, are especially vulnerable to climate change and weather extremes, exacerbated by their geographic location in the tropics and limited adaptive capacity due to socioeconomic and policy constraints (Morton, 2007).

As discussed in chapter one, raising agricultural labour productivity in low-income countries is critical for food security and a necessary condition for countries to begin the growth process and structural transformation. However, the historic growth process that led to industrialisation is increasingly out of reach for developing countries due to land constraints, limited growth in domestic manufacturing, as well as changes in global manufacturing and supply chains, resulting in a lower capacity to absorb labour (Rodrik, 2016). Conventional agricultural practices, reliant on intensive inputs like pesticides and fertilisers, have led to diminishing returns and potential "intensification traps" where high input use reduces yields due to biodiversity loss (Dainese et al., 2019). These unsustainable models contribute to pollution, groundwater depletion, habitat destruction, biodiversity decline, and greenhouse gas emissions, exacerbating climate change (Dudley and Alexander, 2017). Additionally, as chapter 2 illustrated, conventional agriculture relies on biodiversity but is increasingly vulnerable to weather extremes, which directly and indirectly harm biodiversity, further weakening its contribution to agriculture. These challenges highlight the need for sustainable farming methods that boost agricultural yields, withstand climate change, and create quality rural employment (Dorin et al., 2013).

While several studies have explored the causes of low agricultural land productivity in low-income countries, few have examined how agricultural production techniques impact structural transformation in Africa. Using data from Senegal, a country vulnerable to multiple weather extremes such as floods, droughts and extreme temperatures, with a large share of employment in small-scale agriculture, this chapter analyses the effects of sustainable agriculture practices on land productivity. Senegal's emerging policy and institutional framework to support the adoption of agroecology and availability of data, thanks to the FAO-supported 2020-2021 agriculture survey provide a valuable basis for assessing these practices. The specific objectives of this chapter are, therefore, to identify all sustainable agriculture

practices (as defined in the census) that farmers have put in place to enhance land productivity, analyse their effects on agricultural land productivity as well as their interaction with production challenges such as land degradation and extreme weather events ¹.

Following the introductory overview, section 1 briefly discusses the concept of sustainable agriculture in relation to structural transformation; section 2 describes the theoretical assumptions and methods; section 3 presents the empirical findings; and section 4 concludes.

3.1.1 Sustainable agriculture and structural transformation in low income countries

As discussed extensively in chapter 1, the process of structural transformation is characterised by agriculture's declining share in national income and employment, accompanied by a rise in overall labour productivity as labour moves out of the agriculture sector to higher productivity non-agriculture sectors (Lewis, 1954). Historically, labour productivity in agriculture increases due to higher land productivity or higher land availability per farmer, as well as mechanisation and the replacement of human and animal labour with fossil fuel energy. An exit of labour from the agriculture sector facilitates higher land availability per farmer, allowing for mechanisation and economies of scale, translating into higher labour productivity.

On the other hand, raising land productivity is facilitated by the intensive use of inputs such as fertilisers and synthetic pesticides, as well as investments in irrigation infrastructure, improved crop varieties and other practices associated with the "green revolution". While this was highly successful in closing the yield gap and increasing food production in developing countries, such intensification undermines the long-term survival of natural capital and ecosystems that agriculture fundamentally depends on (Burian et al., 2024). Furthermore, climate change will likely increase crop water demand, particularly in areas where groundwater depletion is already resulting in significant reductions in yields, cultivated areas and production (Bhattarai et al., 2021, 2023). Maintaining agricultural production will thus require sustainable agriculture production models with potentially higher levels of labour, ecologically enhanced land productivity, and more equitable outcomes in the context of declining land availability.

Dorin et al. (2013) propose an alternative 'farmer developing' model that supports increasing total agricultural production and farmers' income without downsizing their numbers or jeopardising natural resources. This model focuses on reducing reliance on industrial inputs to lower environmental and production costs, fostering biological synergies to enhance production and increase resilience, and offering

¹ In addition to the selection criteria, I had the opportunity to conduct fieldwork in Senegal with funding from the French Institute for Research and Development (IRD). This allowed me to carry out qualitative interviews, providing insights into the adoption of sustainable agriculture practices and challenges. Although not directly used in the analysis, these interviews helped me understand the barriers and drivers of sustainable agriculture adoption and improved my ability to contextualise and analyse secondary data used and presented in this chapter.

higher prices to farmers to encourage the provision of diversified, nutritious foods and goods.

Although agricultural production today follows the logic of intensification, a wide range of sustainable agriculture practices and concepts exist. Therefore, this chapter focuses on practices that either increase the efficiency of conventional practices to reduce the use and consumption of costly or environmentally damaging inputs or substitute alternative practices for synthetic inputs to maximise food production while minimising environmental impacts without fundamentally altering the governance of food systems (Francis, 2016; FAO, 2011). This includes agronomic measures to improve soil cover, organic matter, soil fertility, and pest and weed management; vegetative measures, such as planting agroforestry trees and shrubs; and structural measures, such as constructing bunds and water storage structures (Liniger and Critchley, 2007). These strategies aim to prevent land degradation, restore ecosystem services, improve crop resilience, enhance water use efficiency, and increase farm productivity.

By reducing land degradation and restoring ecosystem services, these practices alter output and the use of other factors of production, including labour and land, and, therefore, structural transformation. Considering changes to labour, Montt and Luu (2020) found that conservation agriculture in eastern and southern Africa increases farms' labour input requirements, although this demand is usually met by household labour rather than paid work. Similarly, Laske and Michel (2022) found no overall increase in labour allocation but an increase in the number of working hours for women within households implementing agroecological practices in Senegal. On the other hand, Fontes (2020) found that adopting soil and water conservation practices in Ethiopia increased working days for adults and children. The impacts on child labour are higher for households with fewer adults. Evidence remains mixed, depending on the local context and specific practice implemented. Furthermore, the effect of these changes in labour use depends on output changes, which determine changes in overall labour productivity.

Evidence for higher land productivity due to various sustainable agriculture packages, such as conservation agriculture, also varies, with outcomes differing depending on context-specific practices and environmental and climatic conditions. For example, Pittelkow et al. (2015) find that no-till practices reduce yields unless combined with principles of residue retention and crop rotation, particularly in dry climates, suggesting that it may become an important climate-change adaptation strategy. Additionally, the successful implementation of conservation agriculture is often challenging in resource-poor and vulnerable smallholder farming systems, thereby increasing the likelihood of yield losses rather than gains. Likewise, Castle et al. (2021) find that agroforestry systems positively impact yields in fields with severe soil fertility issues. In contrast, in other cases, incorporating trees into the production system reduces crop productivity by taking land out of production for conservation benefits, necessitating incentive provision schemes to economically offset yield reductions.

Smallholder crop farmers remain vulnerable to the effects of climate change, including altered rainfall patterns, rising temperatures, and extreme weather events, which can disrupt food production and lower yields, particularly in developing countries. Overall, socio-economic context and local conditions influence the effectiveness of sustainable agriculture practices. Many subsistence farmers lack the financial resources to invest in inputs such as organic fertiliser and drought-tolerant crop varieties. Additionally, they may not have access to the necessary information, support, or training to fully implement these practices, limiting their efficacy. Institutional barriers to small-scale agriculture, such as limited access to agriculture extension services, technical support, and market opportunities for organic products, would also need to be addressed to fully realise the potential benefits of sustainable agriculture practices (Zenda and Rudolph, 2024).

However, research shows that smallholder farms employing polyculture, agroforestry, and other traditional techniques are biologically diverse, enhancing their resilience to climate change, pests, and diseases. These farms often outperform conventional ones by minimising losses and using resources more efficiently (Altieri, 2009). The success of these farms across millions of hectares highlights the effectiveness of indigenous practices, which thrive without agrochemicals, sustain year-round yields, and promote biodiversity. Consequently, the adoption of such sustainable agriculture strategies has gained renewed attention as a promising approach to enhance the resilience and adaptive capacity of smallholder farmers in the face of climate change (Odusola, 2021; Nicholls and Altieri, 2018).

3.2 Theoretical assumptions

As elaborated in Chapter 1, the combined effect of land productivity through better agricultural practices and technologies, i.e., Intensification, and through higher land availability through mechanisation, i.e. Extensification, drives overall labour productivity. In this chapter, we turn to intensification, focusing on the dynamics between land productivity, sustainable agriculture practices and production challenges due to land degradation and extreme weather events. As chapter 2 illustrates, country level data is not sufficient to differentiate between agricultural practices, necessitating an analysis at the micro-level. Therefore, we examine the types of sustainable agriculture practices farmers in Senegal implement, their effect on agricultural land productivity, and whether these practices enhance resilience against said production challenges.

Agriculture output per hectare is determined by labour, human and physical capital and is influenced by total factor productivity (TFP) in the agricultural sector. The adoption of agricultural practices also depends on labour availability, and households may use their own labour or may hire permanent, temporary or daily workers for production. As discussed in chapter 2, TFP reflects resource use efficiency

in agriculture, shaped by local conditions such as climate, soil quality, extreme weather events, and land availability. Institutional and policy frameworks also play a significant role in shaping the agricultural environment, as do other factors, such as social capital, networks and access to information (Alobo Loison, 2016). In this context, sustainable agriculture practices may be considered a determinant of TFP, as they are implemented to improve the way that labour is used to improve land quality and quantity, by preventing the loss of agricultural land due to environmental degradation, as well as using knowledge to improving it by harnessing ecological processes to improve land quality and enhance resistance to environmental stressors. Sustainable agriculture practices may also reduce the need for expensive inputs and may also reduce losses from weather-related shocks (Liniger and Critchley, 2007). Hence, agriculture yield per hectare is thus a function of:

$$y_{at} = f(L_{at}K_{at}H_{at}X_{at}SAP_{at}PC_{at}SE_{at}) \quad (3.1)$$

where, L_{at} denotes household agricultural labour, K_{at} denotes physical household assets, H_{at} represents household human capital factors, namely education, age, and gender, X_{at} represents purchased agriculture inputs, SAP_{at} represents sustainable agriculture practices, PC_{at} represents production challenges, namely environmental degradation and weather extremes, and SE_{at} represents other socio-economic factors that influence TFP, namely access to information, support services and social networks.

In this model, therefore, households operating in a constrained environment may cope with a negative production shock in the following ways:

- An increase in the use of non-tradeable resources, mainly additional family labour, to increase overall production and compensate for declining yields.
- Farmers may also invest in land-enhancing infrastructure such as irrigation and physical infrastructure to conserve soil and water, thereby reducing losses from weather shocks.
- Households may invest in enhancing total factor productivity through changing management practices, such as soil and water conservation and other sustainable practices, or the use of improved inputs, such as drought and heat-resistant crop varieties.

3.3 Approaches and methods to explore the role of sustainable agriculture practices in land productivity and resistance to shocks

3.3.1 Overview of small-scale agriculture in Senegal

In Senegal, 54% of the population live in rural areas, and agriculture remains the primary source of income and employment for more than 52% of Senegalese (ANSD, 2016). The country is divided into six agroecological zones based on biophysical and socio-economic characteristics, namely- The River Valley (*Vallée du fleuve Sénégal*) which specialises in the production of irrigated rice and vegetables; Niayes, which specialises in market garden production; The Groundnut Basin (*Bassin arachidier*), where groundnuts and millet are the main crops; Ferlo (*Zone sylvo-pastorale*), where livestock keeping is predominant; Eastern Senegal (*Sénégal oriental*) and Casamance, where rainfed rice is produced.

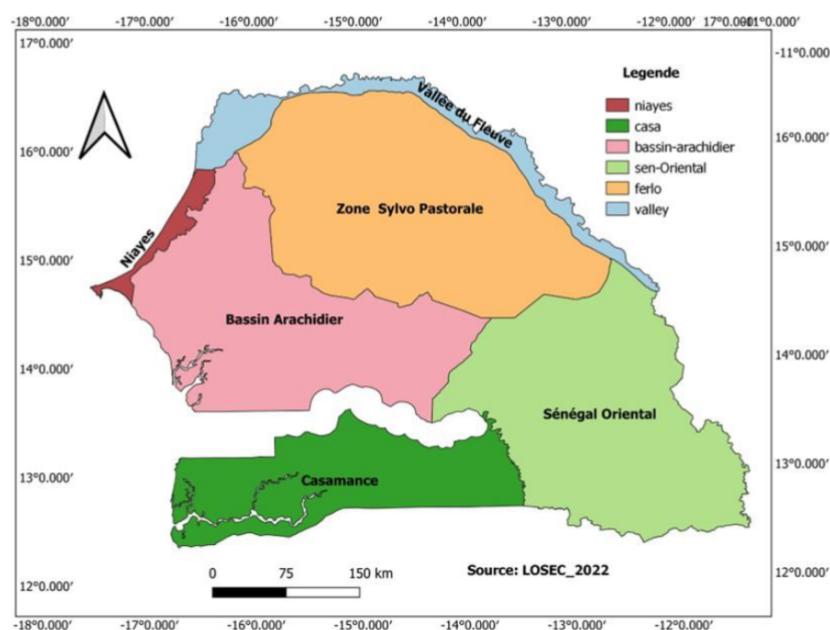


Figure 3.1: Agroecological zones in Senegal
Source: (MASAE, 2023)

Mean annual temperatures range from 25°C to 30°C with lower values closer to the coast and higher values further inland. Annual precipitation sums range from 250 mm in northern Senegal, which has an arid desert climate, to 1 450 mm in the southwestern part of the country, which is characterised by a more tropical climate. Senegal has a single rainy season, which varies along a latitudinal gradient (north-south), from June/July to September/October, with decreasing length and precipitation amounts towards the north (WorldBank, 2024).

According to the 2020-2021 agriculture census (DAPSA, 2021), more than half of agricultural house-

holds practice mixed crop and livestock farming, with 18% practising rain-fed agriculture, 15.6% livestock farming, and less than 10% practising market gardening (*maraîchage*) and fruit cultivation using irrigation. Rain-fed agriculture depends on the seasonal calendar, while market gardening occurs year-round, except during the June/July-September/October rainy season due to flooding and pest risks (Fall et al., 2000).

The average farm size is 4 hectares, varying regionally from 0.6 hectares in areas of intensive agriculture along the eastern coast to 7.5 hectares in eastern agro-pastoral areas. Agricultural households average 9.6 members, with most labour provided by family members. Farmers practising rainfed agriculture dedicate more time to farming, with an average of Rainfed farms having 5.6 family members working full-time, compared to 0.5 in market gardens. Rainfed farming also involves 88 days of work per season versus 66 in market gardening. Agriculture labour is mostly manual, with 80% of parcel managers being male and over 75% under the age of 55. About 70% have no formal education, and only 7% have received agricultural training. Agriculture is mainly informal, with less than 10% of households keeping formal records, and only 6.7% accessed credit in the previous season. Input use is low, with 7.6% using irrigation, 38.5% using mineral fertilisers, and 28% using pesticides, herbicides, and fungicides. Most households, except groundnut and rice cultivators, do not use certified or improved seeds.

Agriculture in Senegal is vulnerable to climate-induced weather extremes. Mean annual temperature has increased by 1.6 °C since 1950, with a stronger observed increase in the north of Senegal averaging +3 °C (WorldBank, 2024). Additionally, there has been a 30% decline in rainfall between 1950 and 2000 (Aguiar, 2008), with a reduction in the duration of the rainy season, with high interannual variability. Flooding, dry spells, and hot days are frequent, and about 25.7% of agricultural households in the census reported experiencing extreme events or environmental shocks in 2020-2021. While there is uncertainty in climate models for projections on precipitation, similar trends are expected to continue with higher but fewer rainfall events overall, leading to dry spells. Additionally, the annual number of very hot days (daily maximum temperature above 35 °C) is projected to rise substantially and with high certainty, particularly over western and southern Senegal (WorldBank, 2024).

Farmers seeking to maximise yields have invested in a wide range of practices, including high-quality certified seeds and short-cycle varieties adapted to shorter growing seasons, crop diversification, renewable energy and low-cost irrigation technologies (Dugué et al., 2017). There is also some evidence of farmers using sustainable agriculture practices, mainly through exposure to government, development and NGO programs (Laske and Michel, 2022; Ariom et al., 2022; Niang et al., 2022). Based on data from the Senegalese agriculture census (DAPSA, 2021), a modest number of farmers implement the following sustainable agriculture practices:

- **Structural measures to reduce soil erosion:** a small number of farmers reported using soil

protection and conservation measures such as the installation of plots with dykes and bunds (10%) as well as windbreaks and hedges (3%). Other types of installations, such as gabions, drainage channels and stone barriers, are also used marginally.

- **Conservation agriculture:** such practices are more frequently used, with 64% of households using rotational grazing and 28% leaving a portion of their land fallow in Senegal overall. Vegetative strips and terracing are not frequently used. About 28% of households report using soil cover practices such as the use of crop residues.
- **Soil fertility management:** The use of organic matter is widespread, with 56% of households using manure, while organic fertiliser use (0.7%), compost and mulching are extremely limited.
- **Agroforestry:** About 16% of households reported planting agroforestry trees, although the percentage varies greatly, ranging from 0.6% in the north to 53% of households in the south.
- **Climate adapted agriculture:** To cope with the impacts of extreme events, the most common adaptation practices cited by households include crop diversification, the use of traditional knowledge and the use of adapted crop varieties and animal species.

To perform our empirical analysis, we use a three-step approach, beginning with a hierarchical clustering on principal components (HCPC) to develop a typology of farmers in Senegal based on the set of farming practices reported in the 2020 -2021 Senegalese agriculture survey. The objective is to distinguish farms according to their incorporation of sustainable agriculture practices, identify typologies and compare land productivity and use of labour. Secondly, we use a binary logistic regression model to explore the determinants of the adoption of sustainable agriculture practices since our hierarchical clustering on principal components does not yield well-defined clusters of farmers exclusively using sustainable agriculture practices. Lastly, we perform a regression analysis to evaluate the effect of sustainable agriculture practices identified on agricultural land productivity and resilience against self-reported weather extremes and environmental production challenges.

3.3.2 Hierarchical clustering on principal components

The adoption of agricultural practices is determined by socio-demographic characteristics, resource endowments, access to information, and social capital (Arslan et al., 2022). Using our survey data, we construct several variables capturing these factors to understand household characteristics and adoption of sustainable agriculture practices. Hierarchical clustering on principal components (HCPC) was used to generate farm typologies.

In the first step, Principal Component Analysis (PCA) is applied to reduce the multivariate dataset of

variables to non-correlated principal components (PCs). Hierarchical agglomerative cluster analysis according to Ward's method is used to group the farms into homogeneous types based on the variable loadings of retained PCs from the PCA (Ward Jr, 1963). The Ward method initially treats each observation as a separate cluster and merges the two most similar ones in a stepwise process. This procedure continues until all the observations are merged into one cluster (Kuivanen et al., 2016). The interpretation of distinct farming types is based on the graphical results from the PCA and cluster analysis and statistical calculations of the mean differences between each cluster and the rest (Alvarez et al., 2014). Results are presented in section 3.4.

3.3.3 Empirical strategy for regression models

Logistic regression to identify determinants of sustainable agriculture practice adoption

In addition to the HCPC analysis, we use a binary logistic regression model to assess the factors influencing the adoption of sustainable agriculture practices (SAP). As explained in subsection 3.3.2, the adoption of SAPs is shaped by socio-demographic characteristics, resource endowments, access to information, and social capital. Therefore, we employ the following model to evaluate the determinants of SAP adoption:

$$SAP_i = \beta_0 + \beta_1 F_i + \beta_2 H_i + \beta_3 SE_i + \beta_4 PC_i + \beta rd + \epsilon_i \quad (3.2)$$

where SAP_i represents the adoption of sustainable agriculture practices, a dummy variable that takes on 1 if household i has implemented at least one practice in each of the following categories: structural measures to reduce soil erosion, conservation agriculture, and climate-adapted agriculture. F , H , SE , and PC represent human capital, socio-economic characteristics, and production challenges, respectively. ϵ_i is the error term, and we include administrative regional dummies (rd) to account for institutional differences that may influence the adoption of SAPs.

Given that SAP adoption is rare in our dataset, with less than 5% of households adopting SAPs, we also employ a penalised logistic regression model to validate the robustness of our findings. This penalised model addresses potential biases caused by the imbalance in the dependent variable, preventing overfitting and providing more reliable estimates of the factors influencing SAP adoption. The penalised regression confirms the validity of our initial results, enhancing confidence in the model's findings.

Evaluating the impact of adoption of sustainable agriculture practices on agricultural land productivity and resistance to shocks

To evaluate the impact of adoption of sustainable agriculture practices, we use total crop yields (output per hectare) as our explained variable, which are assumed to be a linear function of observed household and plot characteristics, along with sustainable agriculture practices, and production challenges related to environmental degradation and weather extremes. We specify our agricultural land production function for household i as follows:

$$\ln y_i = \beta X_i + \alpha_1 SAP_i + \alpha_2 PC_i + \alpha_3 SAP_i * PC_i + \alpha_a z + \varepsilon_{it} \quad (3.3)$$

where $\ln y_i$ represents the estimated logarithm of household i land productivity and; β and α denote the estimated coefficients for i . X_i denotes our vector of socio-economic characteristics, resource endowments, purchased input and human capital variables that determine agricultural land productivity. Socio-economic characteristics are distance to market, membership in an agricultural association, use of agriculture support services, and household size; purchased inputs consist of fertiliser use; human capital variables consist of household head age, gender and education; resource endowments include irrigation use, access to credit and number of working days dedicated to crop production per hectare; SAP_i is a dummy variable with 1 if household has adopted at least one practice in each category-structural measures to reduce soil erosion, conservation agriculture, and climate adapted agriculture practice and 0 if not and; PC_{it} is an indicator of production challenges, namely perceived extreme weather events or environmental challenge as reported in the agriculture census. We also include the interaction term $SAP_{it} * PC_{it}$ to study the effect of sustainable agriculture practices when conditioned on production challenges. We also add $\alpha_a z$ as dummies for agroecological zone to control for differences between agroecological zones such as altitude and soil quality that affect land productivity and; ε_{it} is the error term. Given that our data is cross-sectional, the OLS model was used for estimation.

3.3.4 Data

We use data from the 2020-2021 "Enquête Agricole Annuelle (EAA)". The EAA is a nationally representative panel with comprehensive, self-reported information on 6 971 rural households classified according to Senegal's agroecological zones and subnational levels². It is the primary nationwide sample survey for household agricultural production in Senegal, administered with technical assistance from the Food and Agriculture Organisation (FAO). The 2020 -2021 survey is unique because it is the only

²Regions: Dakar, Diourbel, Fatick, Kafrine, Kaolack, Kedougou, Kolda, Louga, Matam, Saint-Louis, Sedhiou, Tambacounda, Thies, Ziguinchor

available survey that integrated a module on "Production methods and environment", collecting detailed information on agricultural practices, environmental issues and climate change adaptation strategies for farmers in the census. It contains information on agricultural production, including parcel size, inputs, crop yields and agricultural practices for rain-fed agriculture, livestock, arboriculture and market gardening at plot and household levels. Additionally, it contains information on household socio-demographic characteristics, including family size, education levels, and age. The census classifies crop production as either arboriculture ³, market gardening⁴ or rain-fed production ⁵. Quantities are reported in kilograms or local measuring units without a corresponding monetary value.

We eliminate households with missing observations and those that reported output in non-metric values. Since most farmers harvest multiple types of crops per year, we used a set of producer prices for Senegal provided by FAOSTAT to convert output for each household into FCFA. However, the FAOSTAT producer prices cover a limited set of crops, which restricts our analysis to the following crops: potatoes, onions, green eggplant (*diakhathou*), okra and tomatoes, maize, rice, sorghum, millet and groundnut. Our database consists of 665 households, of which 340 are market garden producers. While the EAA is a comprehensive source of household agricultural activity, it lacks geospatial coordinates and information on household wealth or non-agriculture activities.

We construct the following variables for our OLS regression analysis:

Dependent variables: We use total agriculture yields, namely - LogTotYield as our dependent variable, which is total crop output in FCFA divided by total area under cultivation, converted to log. As summary statistics in Appendix C.1 show, data on yields reveal extremely high variability, reflecting differences in farm management practices, crop types, environmental conditions and socio-cultural factors across the observations.

Sustainable agriculture practices: We use the 2020/2021 module on production methods and the environment to construct dummy variables capturing the use of agronomic, vegetative and structural measures designed to reduce land degradation and restore ecosystem services, as well as climate adaptation measures as follows:

1. **Non-toxic pest management:** households that report any of the following: manual weed removal, biological control of pests, use of bio-pesticides, changing crop planting dates, spacing and rotation to manage pests.
2. **Natural soil fertility management:** households practising at least one of the following soil amend-

³Bananas, lemons, guavas, mandarins, mangoes, oranges, papaya, *anacadre*

⁴Potatoes, onions, aubergines, carrots, tomatoes, sweet potatoes, green eggplant(*diakhathou*), okra, chilli, cabbage, courgettes, melons, cucumbers, radishes, peppers, hibiscus)

⁵Ground-nut, *beref*, cotton, *fonio*, manioc, maize, millet, *niebe*, rice, sorghum, sesame

ment practices: enhance soil fertility with organic material, compost, and manure, use legumes, cover crops and other green manures as a means to enhance soil health and fertility.

3. **Structural measures to prevent soil erosion:** households that have constructed gabions, stone bunds, drainage canals, windbreaks or other installations to prevent soil erosion.
4. **Conservation agriculture:** households that practice any combination of three practices: reduced soil disturbance, crop rotation, leaving land fallow, rotational pasture, and continuous soil cover.
5. **Agroforestry:** households that report planting trees for soil fertilisation, nutrition, micro-climate, fencing, medicine, firewood, or nutrition.
6. **Climate adapted practices:** households that report using improved seeds, adapted plant varieties, crop diversification, traditional knowledge, insurance, machinery and other practices as a climate change adaptation strategy.
7. **Sustainable agriculture information:** households that report having access to information on sustainable agriculture techniques.

Hence, we construct a dummy variable, sustainable agriculture practices (SAP), capturing any household that has adopted at least one practice from the following categories of practices: structural measures to prevent soil erosion (3), conservation agriculture (4) and climate-adapted agriculture (6)⁶.

Other explanatory variables: Our explanatory variables include household characteristics, agricultural practices, input use, labour and production constraints as documented in the agriculture census. We use household size, age of household head, and dummy variables capturing household head gender and literacy to capture household characteristics. As shown in Appendix C.1, household heads are overwhelmingly male, middle-aged and with low levels of literacy. To capture other socio-economic factors that may influence production, we also include dummy variables indicating membership in an agriculture association, use of agriculture support services (number of visits from an agriculture extension officer) and distance to market, with the average time to travel to the nearest market as reported by each household. As the summary statistics show, membership in agriculture associations is generally low, and there is great variability in the use of agriculture support services. To account for input use, we constructed a categorical indicator for fertiliser use per hectare, given that there is very high variability in synthetic fertiliser use and a very large number of households that do not use any fertiliser at all. The categorical variable was calculated based on percentiles. We also included a dummy variable indicating the use of synthetic pesticides, as well as the proportion of irrigated land. We also included a dummy

⁶The SAP dummy variable is constructed for practical reasons. It is not necessarily an indicator of households practising sustainable agriculture overall but rather of implementing multiple sustainable agriculture practices. Since most households do not adopt any practices, and those that do typically adopt very few, this dummy helps to capture the small proportion of households engaging in multiple practices. For the same reason, we restrict our SAP variable to only these three kinds of practices.

indicator for households that reported having access to credit from both formal and informal institutions as well as family and friends.

Labour: Our indicator for labour use $-\text{Log}(\text{Totdays})$ is the total number days spent working on crop farming per household divided by total cultivated area⁷.

Production constraints: We used the number of plots per household that reported experiencing the following production challenges: erratic rainfall, soil siltation, flooding, water erosion, pests, and salinisation, as well as a dummy variable for households that reported extreme temperature as a production challenge.

Lastly, we include regional dummies based on agroecological zones to account for differences that might arise due to geography, soil types and climatic differences that may influence agriculture production.

3.3.5 Methodological limitations

This analysis used data from the EAA agriculture survey, which has several limitations due to reliance on farmer recall and lack of geolocalisation. Inconsistent reporting and entries recorded in non-metric units also mean that a large number of observations were excluded, which may have contributed to significant variability within the sample in key indicators such as yield. Although data was transformed before analysis, this was not sufficient to fully address these issues. A lack of anonymised geospatial coordinates also meant that more accurate weather extreme indicators could not be integrated into the analysis, likely underestimating their effect. Reliance on self-reported data, particularly on the implementation of sustainable agriculture practices, extreme weather events, and land degradation, introduces potential bias, as farmers may inaccurately report their activities and challenges.

The cross-sectional nature of the data also limits the ability to draw causal inferences, as it only captures a snapshot in time rather than changes over time. Additionally, the final step in HCPC and the creation of typologies is validation with local stakeholders and experts. At the time of submission, this step has not yet been undertaken. However, it would contribute to strengthening the findings presented⁸. Lastly, the dataset is from 2020/2021, a period marked by the COVID-19 pandemic, which may have influenced the outcomes. To address this, we utilized survey data where farmers reported whether they were affected by the pandemic. Robustness tests incorporating a dummy variable for these farmers were conducted (see C.11, but the results were not statistically significant, indicating that the pandemic likely had a limited impact on our findings).

⁷ Although data on the use of temporary and hired labour is recorded in the survey, less than 10% of households in our dataset use paid labour, so we combine both paid and family labour for our labour use variable.

⁸ Work with Senegalese colleagues to prepare for validation and additional data collection is in the early stages, but will not be part of this dissertation due to time constraints

3.4 Uptake of sustainable agriculture practices: findings from hierarchical clustering on principal components

After several tests, 38 variables were selected as sufficient to convey the necessary information. They consist of categorical and continuous variables on the use of chemical inputs, organic matter, physical structures to reduce soil erosion, conservation agriculture practices, irrigation, climate change adaptation measures, knowledge of sustainable agriculture as well as the use of irrigation. To better understand their economic and social contexts (Alvarez et al., 2014), we also include variables capturing size and number of cultivated parcels, the use of draft animals, access to formal and informal credit, household size, gender, access to agriculture information, number of days spent working on the farm, annual yields, membership in farm organisations and use of agriculture support services. The dataset thus captures farm output, input use, land and labour, as well as sustainable agriculture practices as shown in Appendix C.2.

Overall, the data shows high variability for variables such as yields, fertiliser use, irrigation and labour use. Additionally, the means of several agricultural practices are very low, indicating that these practices are not widely adopted among the households surveyed. Hence, yield, labour and land variables variables were transformed into log, while other variables with extreme right skewness were transformed using standardisation, square root transformation or converted into categorical variables. Extreme outliers were retained as they were deemed sufficiently grouped together to form a farm-type (Alvarez et al., 2014).

Thirteen principal components (PCs) were derived from the PC analysis, explaining 59% of the variability in the dataset as shown in Table 3.1. The first PC explained the greatest variance of about 10% of the variability of farms, and has the highest eigenvalue of 3.65, indicating it explains the most variance. The first three components cumulatively explain 25% of the variance. The proportion of variance explained by each subsequent component decreases, with Component 4 through Component 13 each contributing around 3% to 5% individually.

Table 3.1: Retained principal components

Component	Eigenvalue	Difference	Proportion(%)	Cumulative Variance (%)
Comp1	3.65	0.56	0.10	0.10
Comp2	3.09	0.43	0.08	0.18
Comp3	2.67	0.90	0.07	0.25
Comp4	1.77	0.20	0.05	0.29
Comp5	1.57	0.21	0.04	0.34
Comp6	1.36	0.02	0.04	0.37
Comp7	1.34	0.05	0.04	0.41
Comp8	1.29	0.06	0.03	0.44
Comp9	1.23	0.06	0.03	0.47
Comp10	1.17	0.06	0.03	0.50
Comp11	1.10	0.07	0.03	0.53
Comp12	1.03	0.01	0.03	0.56
Comp13	1.02	0.04	0.03	0.59

Nb. Observations:665; Rho:0.59

For the full PC loadings, please see Appendix C.2.

Based on variable loadings of the thirteen retained PCs, we use hierarchical agglomerative cluster analysis using Ward's method to group farms into homogeneous types as shown below:

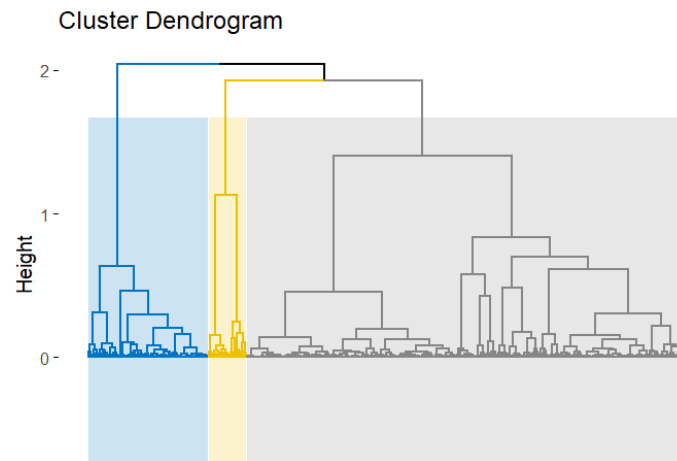


Figure 3.2: Cluster dendrogram illustrating range of cluster solutions using Ward's method of cluster analysis. Clusters are delineated using blue, yellow and gray.

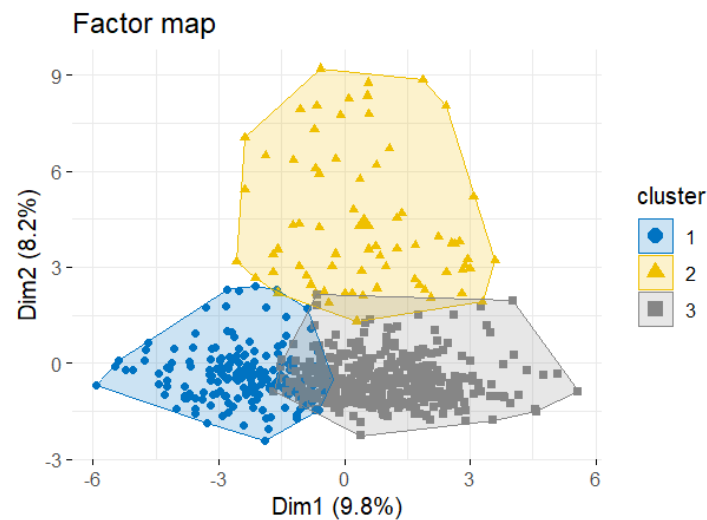


Figure 3.3: Factor map of observations based on Dimension 1 and Dimension 2.

The hierarchical clustering procedure results suggest a three-cluster cut-off point as illustrated in figure 3.2. The dendrogram displays the hierarchical clustering of data points, where the vertical axis represents the height or dissimilarity at which clusters are merged. Cluster 1 (blue) and Cluster 2 (yellow) are more compact and merge at a relatively low dissimilarity level, indicating that the elements within them are more similar to each other compared to those in Cluster 3 (grey), which merges at a higher dissimilarity, suggesting greater diversity within this group.

As figure 3.3 shows, Cluster 1 is spread across lower Dimension 1 and Dimension 2 values, indicating that this group is distinct from the other clusters in these dimensions. Cluster 2 is positioned in the upper range of Dimension 2, showing a distinct separation from the other clusters, particularly in the positive values of Dimension 2. Cluster 3 is more centrally located but spreads across positive values of Dimension 1 and lower Dimension 2 values, indicating that it shares some characteristics with the other clusters but still maintains its distinctiveness.

Table 3.2 summarises cluster characteristics based on different variables' mean and standard deviation (in parentheses). Clusters are compared using the Kruskal-Wallis tests on all variables in Table 3.2. The Dunn test is used to identify statistically significant differences between clusters and results are indicated. Cluster 3 has the largest number of observations (426), followed by cluster 1, with 169 observations, and Cluster 2, with 70 observations.

Based on the cluster analysis, we therefore categorise farm households into three broad farm types as detailed below:

- **Cluster 1: Intensive, high-input agriculture:** Cluster 1 comprises 25.4% of the total sample and is distinguished by the highest yields per hectare. Farmers in this cluster show limited adoption of climate-adapted practices, structural measures to prevent soil erosion and conservation agriculture practices. However, specific practices, such as using windbreaks and canals, are significantly higher than those in other clusters. This cluster also shows relatively high use of synthetic pesticides, fossil fuel energy, synthetic fertiliser and irrigation compared to other clusters. Cluster 1 is also characterised by smaller cultivated land areas (4.134 ha), fewer parcels than average, a high number of workers per hectare (4.423), a higher share of hired workers (0.110), and the highest number of days worked per hectare, suggesting intensive input, land and labour use. As a result, this cluster has the highest yields per hectare (12.722) and per day (5.786). Households in Cluster 1 also show the highest rates of membership in agriculture associations (0.479), agriculture support services (0.048), and smaller household sizes. As shown in figure 3.4, Cluster 1 households are concentrated in the Senegal River Valley and the Niayes agroecological zones.
- **Cluster 2: Climate-adapted agriculture:** Cluster 2 is the smallest, representing 10.5% of the

Table 3.2: Household characteristics by cluster

	cluster						
N	1	2	3	Total	ChiSquared	PValue	Dunn Test
	169 (25.4%)	70 (10.5%)	426 (64.1%)	665 (100.0%)			
Agricultural practices							
<i>Climate adaptation practices</i>							
Crop diversification	0.036 (0.186)	0.729 (0.448)	0.073 (0.260)	0.132 (0.339)	243.3286	0.00***	1-2***; 2-3***
Crop varieties	0.012 (0.108)	0.500 (0.504)	0.012 (0.108)	0.063 (0.243)	251.9441	0.00***	1-2***; 2-3***
Adapted seeds	0.024 (0.152)	0.514 (0.503)	0.019 (0.136)	0.072 (0.259)	228.034	0.00***	1-2***; 2-3***
Shift cultivation	0.012 (0.108)	0.200 (0.403)	0.009 (0.097)	0.030 (0.171)	77.34911	0.00***	1-2***; 2-3***
Information	0.018 (0.132)	0.114 (0.320)	0.005 (0.068)	0.020 (0.139)	37.65422	0.00***	1-2***; 2-3***
Indigenous knowledge	0.024 (0.152)	0.400 (0.493)	0.021 (0.144)	0.062 (0.241)	154.5908	0.00***	1-2***; 2-3***
Adapted techniques	0.000 (0.000)	0.129 (0.337)	0.012 (0.108)	0.021 (0.144)	44.62554	0.00***	1-2***; 2-3***
Mechanisation	0.000 (0.000)	0.114 (0.320)	0.000 (0.000)	0.012 (0.109)	68.72451	0.00***	1-2***; 2-3***
<i>Conservation agriculture practices</i>							
Other CA	-0.128 (0.519)	1.492 (2.321)	-0.190 (0.436)	0.003 (1.006)	152.1891	0.00***	1-2***; 2-3***
Fallow	-0.062 (0.638)	-0.069 (0.672)	0.029 (1.152)	-0.004 (1.001)	4.866175	0.09	1-3*
Rotational pasture	-0.120 (0.409)	-0.019 (0.581)	0.046 (1.192)	-0.003 (0.996)	2.236631	0.33	
Vegetative bands	-0.182 (0.630)	-0.186 (0.623)	0.091 (1.130)	-0.008 (0.988)	11.82224	0.00**	1-3***; 2-3**
<i>Sustainable land management practices</i>							
Gabions	-0.136 (0.782)	1.237 (2.244)	-0.151 (0.476)	-0.001 (1.002)	142.8934	0.00***	1-2***; 2-3***
Canals	0.549 (1.830)	-0.137 (0.542)	-0.202 (0.000)	-0.004 (0.992)	74.81196	0.00***	1-2***; 1-3***;
Dykes	-0.075 (0.481)	-0.171 (0.741)	0.058 (1.171)	-0.000 (1.000)	15.04306	0.00***	1-2***; 1-3***
Stone bunds	-0.098 (0.462)	-0.134 (0.000)	0.063 (1.219)	0.002 (1.006)	4.68542	0.10	
Windbreaks	0.201 (1.340)	-0.100 (0.766)	-0.091 (0.786)	-0.018 (0.963)	11.76213	0.00**	1-2***; 1-3**
<i>Other sustainable practices</i>							
Non-toxic pest management	0.320 (0.468)	0.629 (0.487)	0.439 (0.497)	0.429 (0.495)	19.79713	0.00***	1-2***; 1-3***; 2-3***
Natural soil fertility management	0.408 (0.493)	0.671 (0.473)	0.754 (0.431)	0.657 (0.475)	63.98354	0.00***	1-2***; 1-3***
Agroforestry	0.148 (0.356)	0.529 (0.503)	0.282 (0.450)	0.274 (0.446)	36.40566	0.00***	1-2***; 1-3***; 2-3***
<i>Agriculture inputs</i>							
Synthetic pesticides	0.751 (0.433)	0.586 (0.496)	0.650 (0.477)	0.669 (0.471)	8.051926	0.02*	1-2***; 1-3**
Renewable energy	0.030 (0.170)	0.114 (0.320)	0.085 (0.278)	0.074 (0.261)	7.225848	0.03*	1-2***; 1-3**
Fossil fuel energy	0.544 (0.500)	0.143 (0.352)	0.075 (0.264)	0.202 (0.401)	167.018	0.00***	1-2***; 1-3***
Synthetic fertiliser(kg/ha)	1.036 (1.336)	1.257 (1.431)	1.697 (1.454)	1.483 (1.450)	30.21473	0.00***	1-3***; 2-3**
Draft animals (nb)	-0.346 (0.855)	0.050 (0.833)	0.183 (0.957)	0.035 (0.946)	69.36379	0.00***	1-2***; 1-3***
Irrigated land(%)	0.676 (0.722)	0.075 (0.229)	0.028 (0.106)	0.198 (0.472)	232.6275	0.00***	1-2***; 1-3***
Access to credit	0.799 (0.402)	0.543 (0.502)	0.878 (0.328)	0.823 (0.382)	47.05166	0.00***	1-2***; 1-3***; 2-3***
<i>Labour and land</i>							
Cultivated land(ha)	4.134 (1.230)	5.248 (1.175)	5.869 (1.048)	5.363 (1.334)	193.7299	0.00***	1-2***; 1-3***; 2-3***
Cultivated parcels(nb)	-0.743 (0.416)	-0.002 (0.861)	0.299 (1.033)	0.002 (1.001)	193.351	0.00***	1-2***; 1-3***; 2-3***
Total workers(Nb/Ha)	4.423 (2.153)	4.745 (2.267)	3.064 (1.819)	3.586 (2.078)	102.3643	0.00***	1-3***; 2-3***
Days worked(Nb/Ha)	0.281 (0.939)	0.020 (0.616)	-0.192 (0.269)	-0.050 (0.592)	134.5729	0.00***	1-3***; 2-3***
Hired workers(%)	0.110 (1.121)	-0.137 (0.488)	-0.062 (0.847)	-0.026 (0.900)	7.228675	0.03*	1-2***; 1-3**
<i>Household characteristics</i>							
Agriculture support services	0.048 (1.554)	-0.012 (0.306)	-0.047 (0.453)	-0.019 (0.868)	15.84688	0.00***	1-2***; 1-3***
Household head literate	0.083 (0.276)	0.057 (0.234)	0.153 (0.360)	0.125 (0.331)	8.654384	0.01*	1-3***; 2-3**
AGR Association membership	0.479 (0.501)	0.257 (0.440)	0.204 (0.404)	0.280 (0.449)	45.56949	0.00***	1-2***; 1-3***
Household size(Nb)	-0.146 (0.954)	0.237 (1.072)	0.019 (0.999)	0.000 (1.000)	10.63473	0.00**	1-2***; 1-3***; 2-3*
Sustainable AGR information	0.343 (0.476)	0.857 (0.352)	0.620 (0.486)	0.574 (0.495)	63.33009	0.00***	1-2***; 1-3***; 2-3***
<i>Land and Labour productivity</i>							
Yields (FCFA/Ha)	12.722 (1.721)	10.615 (1.739)	9.645 (1.538)	10.529 (2.075)	258.1295	0.00***	1-2***; 1-3***; 2-3***
Yields(FCFA/Days)	5.786 (1.893)	5.491 (1.181)	4.402 (1.364)	4.868 (1.624)	134.5729	0.00***	1-2***; 1-3***; 2-3

total sample, and is characterised by the highest adoption rates of climate adaptation practices.

This cluster has significantly higher scores in the use of crop diversification (0.729), crop varieties (0.500), and adapted seeds (0.514). This suggests that farmers in this cluster are the most proactive in adopting climate adaptation strategies. Farmers in this cluster also report using "Other" conservation agriculture strategies⁹, while structural measures to prevent soil erosion are limited to the installation of gabions, which are commonly used to prevent soil erosion due to the unrestricted flow of water. Households in Cluster 2 also have the highest score in the use of non-toxic pest management techniques, including practices such as manual weed removal and the biological control of pests. Households in Cluster 2 also have the highest scores in renewable energy use (0.114) and modest use of synthetic fertilisers and pesticides. Land use is average compared to the other clusters. Cluster 2 has the highest number of workers per hectare (4.745), but lower use of hired labour and significantly fewer days worked per hectare (0.020) than cluster 1.

Yields per hectare (10.615) and per day (5.491) are moderate, indicating that land productivity

⁹"Other" practices listed in the agriculture census report include terracing and soil liming, although not counted as separate in census data.

is lower than in Cluster 1 but higher than in Cluster 3. Household sizes in Cluster 2 are significantly larger than in other clusters, with lower literacy levels and membership in agriculture associations. However, they have the highest engagement in accessing sustainable agriculture information (0.857). As shown in figure 3.4, the most significant proportion of Cluster 2 households are found in the Casamance agroecological zone.

- **Traditional agriculture with mixed sustainable practices:** Cluster 3 is the largest, encompassing 64.1% of the total sample. Households in this cluster show low rates of adoption of climate adaptation practices but high engagement with structural measures to prevent soil erosion, such as the use of stone bunds (0.063) and dykes, as well as conservation agriculture practices such as leaving land fallow (0.029) and rotational pasture (0.046). Additionally, they have the highest scores in natural soil fertility management (0.657), which includes practices such as using organic material, compost and cover crops to enhance soil fertility. However, synthetic fertiliser use (1.697) is the highest among all clusters, which might indicate the use of synthetic and non-synthetic inputs in a complimentary manner.

Households in Cluster 3 have the highest scores in total cultivated land (5.869) and number of cultivated parcels, which may explain the higher use of conservation agriculture techniques such as fallowing, which consists of leaving parcels of land without sowing for a period to allow the restoration of soil organic matter. Cluster 3 has the lowest labour intensity, with the fewest workers per hectare (3.064) and the fewest days per hectare. Productivity in Cluster 3 is low, with yields per hectare (9.645) and per day (4.402) being the lowest among the clusters.

Cluster 3 has the highest proportion of literate household heads (0.153) and slightly higher household size (0.019) than the other clusters. However, the involvement in agriculture associations (0.204) is the lowest among the clusters, and engagement with sustainable agriculture information is moderate (0.620). As shown in figure 3.4, households in cluster 1 make up the majority of households in the Groundnut Basin, Casamance, Ferlo and Eastern Senegal.

Households across all clusters have adopted various sustainable agriculture practices at modest but varying rates, as shown in figure 3.5. Cluster 1 achieves high land productivity through intensive labour, synthetic inputs, and some structural measures to prevent soil erosion. Cluster 2 shows high engagement in climate adaptation practices and moderate land productivity. Cluster 3, the largest, has moderate adoption of conservation agriculture and natural soil fertility management but the lowest yields. Overall, as shown in figure 3.6, the adoption of sustainable agriculture practices is moderate to low, with the exception of natural soil fertility management and non-toxic pest management, which are relatively easy to implement and do not require significant investment. Households in all clusters use both artificial inputs and sustainable practices.

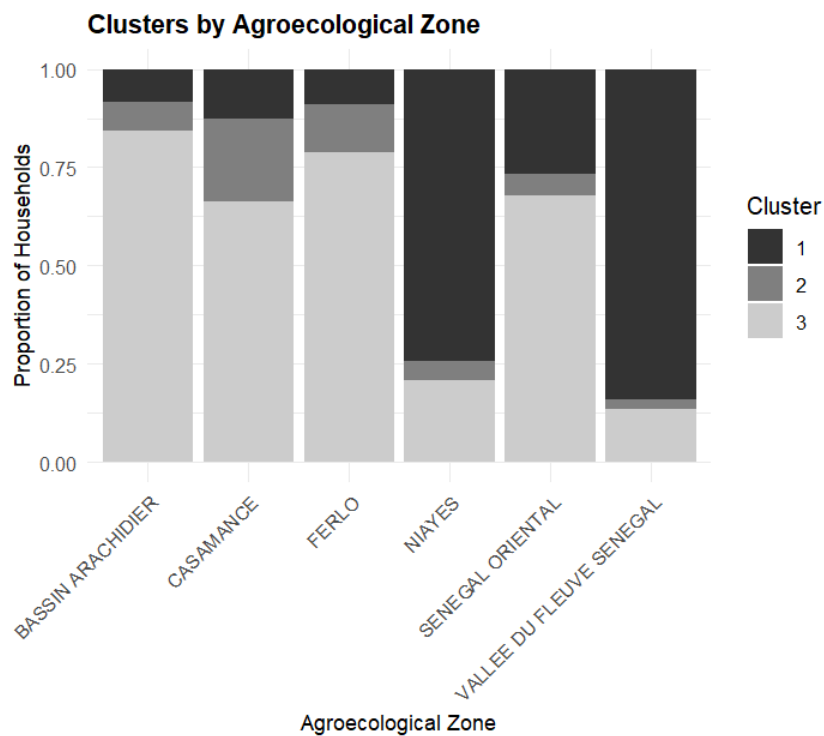


Figure 3.4: Clusters by agroecological zone
Source: DAPSA, 2020-2021. Author's own calculations

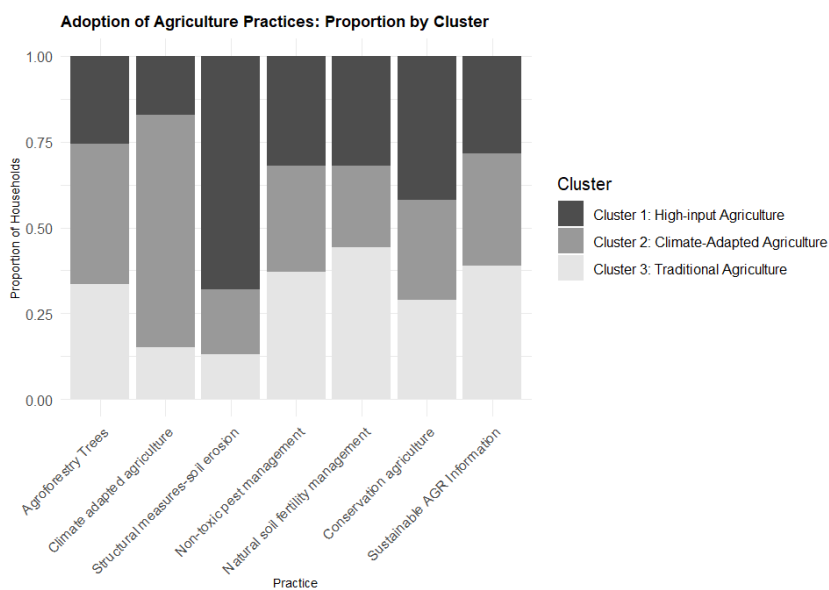


Figure 3.5: Proportion of households within each cluster that have adopted selected practices
Source: DAPSA, 2020-2021. Author's own calculations

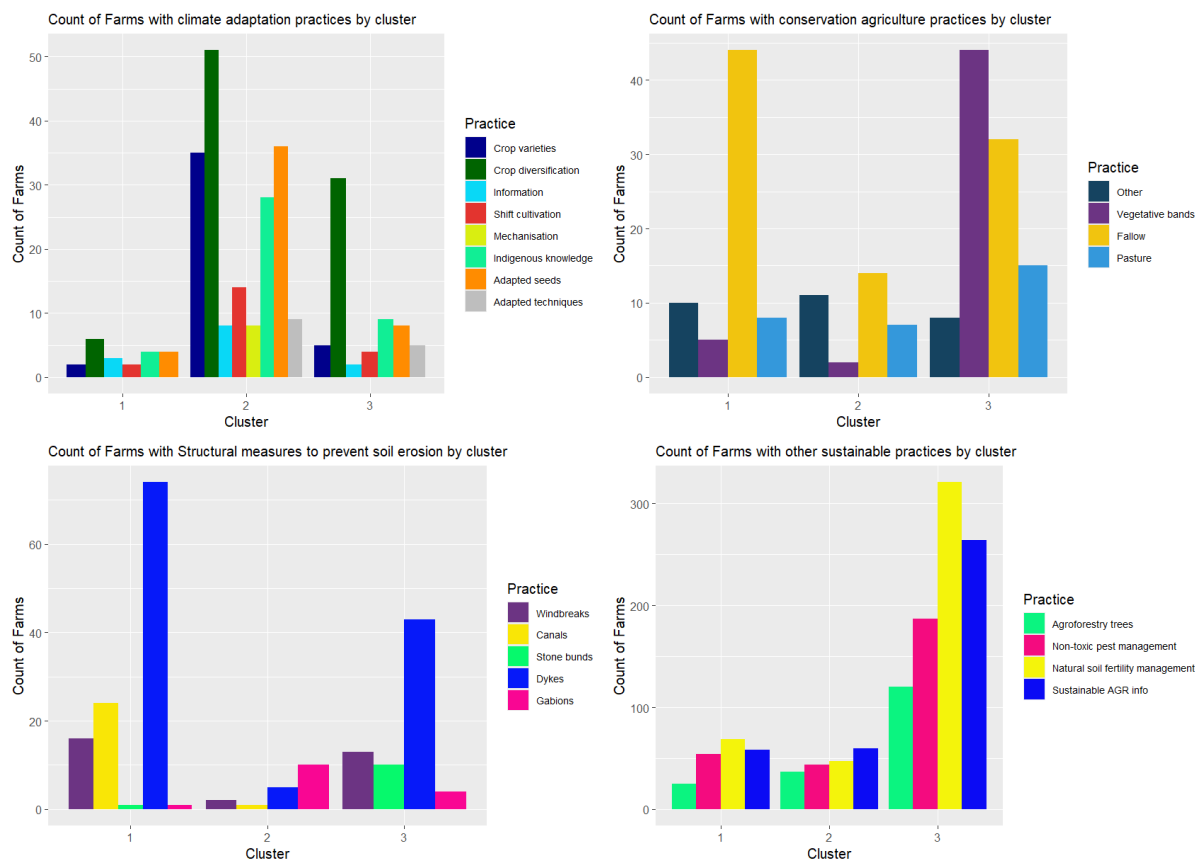


Figure 3.6: Selected sustainable agriculture practices by cluster
DAPSA, 2020-2021. Author's own calculations

3.5 Estimation Results

3.5.1 Determinants of adoption of sustainable agriculture practices

The HCPC analysis conducted in this chapter has provided significant insights while not identifying distinct groups characterised by strong dimensions of sustainable agriculture practices. Instead, the clusters revealed variations primarily in farm size, labour intensity, and land productivity. Given the absence of clusters with a strong sustainable agriculture focus, we employ a logistic regression model to examine the determinants of adoption of sustainable agriculture practices (SAPs). Table 3.3 presents the results of three models estimated, with Model (1) without fixed effects, Model (2) with agroecological zone fixed effects, and Model (3) with regional fixed effects.

Across all three models, several variables consistently emerge as significant determinants of SAP adoption. Concerning demographic characteristics, we find that literacy of the household head is a strong predictor positively associated with SAP adoption in all models, with coefficients ranging from 1.78 to 3.66. However, other characteristics, such as the gender of the household head, are insignificant across all models. The household head's age is only significant in Model (1) and Model (2) but becomes insignificant once regional fixed effects are introduced in Model (3), suggesting that the variable may have been capturing some of the variation explained by the fixed effects.

Considering socio-economic characteristics, access to agricultural support is another important factor, with positive and significant coefficients in all models, highlighting the importance of external assistance in promoting sustainable practices. Households with legal title over their agricultural land (Title Deed) are likelier to adopt SAPs across all models. Interestingly, membership in an agriculture association is negatively associated with adopting SAPs across all models. While some previous research has found a positive association between agriculture association membership and the adoption of sustainable agriculture practices, this may be explained by the fact that in our sample, agriculture association membership is linked to Cluster 1, which also has the lowest adoption of SAP. Hence, it may be possible that agriculture associations in our sample are related to production and commercialisation rather than to sustainable agriculture practices. Distance to market is significant in Model (1) and Model (2) but becomes insignificant in Model (3) when regional fixed effects are introduced. Access to sustainable agriculture information, credit, and cultivated land size is insignificant across all models.

Biophysical characteristics, namely, production constraints and extreme weather, also play a notable role. Extreme temperatures are positively linked to SAP adoption in all three models, sug-

gesting that rising temperatures may drive households to adopt more sustainable practices. Pest infestations are another important factor, with significant and positive effects in all models, implying that households dealing with pest problems may be more inclined to adopt SAPs. Erratic rainfall is significant in Model (1) and Model (2), but not in Model (3), suggesting that the effect of erratic rainfall on sustainable agriculture practices (SAP) adoption may vary across regions. Although flooding is insignificant in Model(1) and Model(2), it becomes significant in Model(3) once unobserved heterogeneities are controlled, suggesting that in specific regions, floods may intensify the need for resilient farming practices. Revenue loss due to natural disasters was also a highly significant predictor across all models, showing that severe production constraints caused by weather extremes push farmers towards adopting more sustainable and resilient agricultural practices.

Model (2), which includes agroecological zone fixed effects, shows an improved fit over Model (1), with a lower log likelihood (-49.93 vs -54.34), as well as a higher pseudo-R-square (0.6136), suggesting that accounting for variations across agroecological zones provides additional explanatory power for the adoption of sustainable agriculture practices. Model (3), which incorporates administrative region fixed effects, shows the best overall fit, with the highest pseudo R-squared of 0.6806 and the lowest log likelihood of -36.44, indicating that the inclusion of region-specific characteristics play a crucial role in explaining adoption behaviour. Overall, however, critical determinants to SAP adoption across models include the household head's literacy, access to agriculture support, production challenges and weather extremes, and revenue loss due to extreme weather.

Lastly, we explore determinants of adopting specific sustainable agriculture practices, summarising results in Appendix C.7. We use dummy variables for any households that have adopted at least one practice categorised as Climate Adapted Agriculture practices in Model (1), Structural Measures to Reduce Soil Erosion in Model (2), Conservation Agriculture in Model (3), Agroforestry in Model (4), Natural Soil Fertility Management in Model (5), and Sustainable Pest Management in Model (6).

Key findings show that agricultural support and pests are consistently significant across several practices, with agricultural support positively influencing climate-adapted practices, conservation agriculture, agroforestry, and natural pest management. Revenue loss from extreme weather and extreme temperatures strongly predict the adoption of climate-adapted practice adoption but are less influential for the other practices. In contrast, household size plays a significant role in climate-adapted practices and natural soil fertility management, while literacy of the household head is particularly important for soil erosion measures and agroforestry adoption. Credit access, land ownership and membership in an agriculture association significantly influence the adoption of soil erosion measures but have less impact on other practices. Access to sustainable agri-

Table 3.3: Determinants of adoption of sustainable agriculture practices

SAP	(1)	(2)	(3)
Household size	0.002 (0.050)	-0.006 (0.055)	0.005 (0.075)
Household Head(Male)	0.755 (1.083)	1.075 (1.140)	0.076 (1.246)
Household Head(Literate)	1.780** (0.813)	2.174** (0.912)	3.660*** (1.383)
Household Head(Age)	0.042** (0.019)	0.038* (0.021)	0.029 (0.027)
Log(Cultivated Land)	-0.283 (0.238)	-0.098 (0.316)	-0.248 (0.405)
Title Deed	2.448*** (0.929)	2.507** (0.991)	2.409* (1.235)
Credit	1.447 (0.942)	1.270 (0.999)	1.619 (1.313)
AGR Support	2.004** (0.847)	2.201** (0.885)	2.744*** (1.024)
AGR Association	-2.273*** (0.876)	-2.385** (0.946)	-2.711** (1.121)
Distance to Market	0.590** (0.293)	0.663* (0.339)	0.506 (0.468)
Sustainable AGR Info	0.507 (0.614)	0.346 (0.662)	1.299 (0.826)
Siltation	0.211 (0.259)	0.358 (0.254)	0.446 (0.345)
Extreme Temp	1.883* (1.105)	2.014* (1.130)	3.644** (1.503)
Erratic rain	0.838** (0.406)	0.843* (0.449)	0.897 (0.677)
Pests	2.016*** (0.639)	2.096*** (0.721)	1.933** (0.931)
Floods	1.331 (1.025)	1.509 (1.103)	4.084** (1.862)
Revenue Loss(ND)	5.170*** (0.956)	5.148*** (0.998)	6.597*** (1.577)
Cons	-11.614*** (2.236)	-13.367*** (2.682)	-12.034*** (2.917)
Agroecological zone fixed effects	No	Yes (.)	No
Region fixed effects	No	No	Yes
N	673	626	402
Log likelihood	-54.3401	-49.9318	-36.4418
P-value	0.000	0.000	0.000
Pseudo R2	0.5873	0.6136	0.6806

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

culture information positively influences the adoption of climate-adapted agriculture, conservation agriculture, and sustainable pest management.

The differences highlight the validity of practice-specific models in uncovering unique determinants that might be masked in aggregate models. For instance, access to sustainable agriculture information appears to significantly influence the adoption climate-adapted practices and natural pest management but was not as strongly indicated in the general model. Moreover, variables like extreme temperature and distance to market also show differential effects depending on the practice, indicating that extreme weather and market factors may influence certain practices more

acutely.

In terms of model fit, all the models are statistically significant, with some models, such as those for climate adapted agriculture (CAA) and structural measures to reduce soil erosion (SME) showing the strongest fit, with pseudo-R square values of 0.5187 and 0.3721. Other models, such as agroforestry and sustainable pest management exhibit weaker fits, with pseudo R-squared values below 0.22. Specific determinants also appear more prominently depending on the practice, supporting the need for targeted interventions to promote different sustainable agricultural practices.

However, the selected sustainable agriculture practice indicators used are notably weaker than our original model since our dummy variables are set to 1 for any household practising at least one sustainable agriculture practice in each category. In contrast, our principal SAP variable is a more robust indicator because it requires households to implement multiple sustainable agriculture practices. This distinction makes the original model more robust, reflecting a more comprehensive commitment to sustainable practices rather than single-practice adoption.

Lastly, since our SAP variable takes a value of 1 in only 5% of cases, indicating a rare event, we complement this approach by using a penalised logistic regression model to test the robustness of our results. The penalised model adjusts for the potential bias introduced by the imbalanced outcome variable, helping to ensure the validity of our findings. The results of the penalised model, presented in Table 3.3, are consistent with those of the initial logistic regression, affirming the significance of key determinants such as household literacy, agricultural support, and title deed ownership in influencing SAP adoption. This suggests that our initial findings are robust, even in the context of a low-prevalence dependent variable.

3.5.2 Sustainable agriculture practices, land productivity and resistance to shocks

Declining soil fertility and soil erosion are increasingly threatening the sustainability of small-scale farming systems throughout Africa, and affordable external nutrient inputs are seldom available to farmers (Cooper et al., 1996; Heerink, 2005). Weather extremes such as droughts, floods and heatwaves directly impact yields and also exacerbate existing challenges such as soil erosion and soil salinisation, resulting in land degradation and lower levels of land productivity (IPBES, 2019; Allan et al., 2023). Consequently, practices such as the construction of structures to reduce soil erosion, conservation agriculture, various soil management practices, and agroforestry are promoted to enhance soil fertility, prevent soil erosion, and increase land productivity, while climate-adapted agriculture practices are promoted to reduce vulnerability to the impacts of climate change.

Therefore, we interact our sustainable agriculture practices dummy variable with production challenges. Although the SAP variable was insignificant when considered in isolation, its impact may only become evident in the presence of environmental or weather-related challenges. We limit ourselves to the most commonly reported constraints, which are pest infestations, soil siltation, soil salinisation and water erosion, as well as weather extremes, namely - extreme temperatures and erratic rainfall ¹⁰, as shown in figure 3.7.

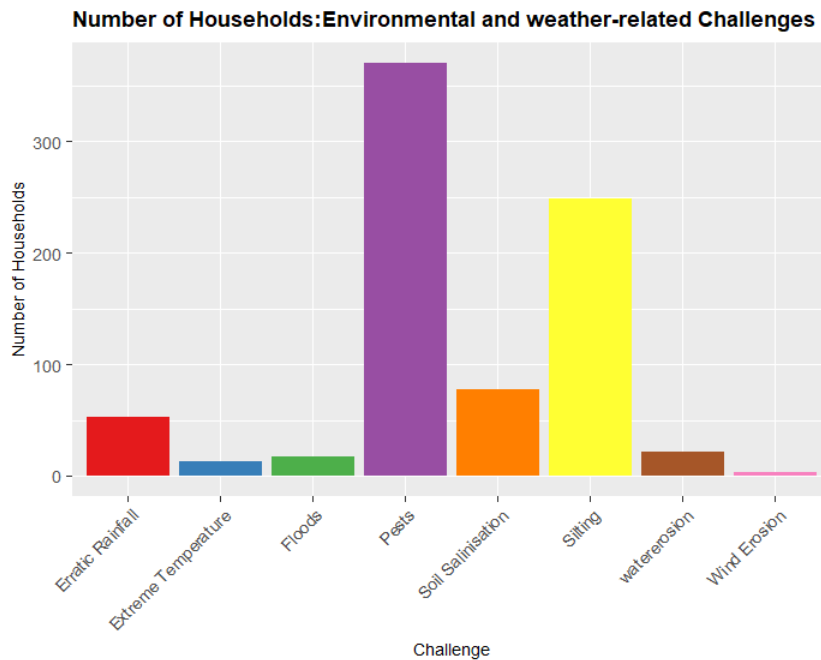


Figure 3.7: Number of households and environmental challenges in the Senegal Agriculture Census (2020-2021)
Source: DAPSA, 2020-2021. Author's own calculations.

¹⁰While the census contains information on other extremes, namely drought, wind-erosion, fires, and storms, less than 0.5% of households in our sample reported experiencing these challenges, hence we exclude them from our analysis.

The regression results presented in Table 3.4 examine the effect of sustainable agriculture practices (SAP) on total agriculture yields, along with household characteristics and agricultural inputs, as shown in Model (1). We also interact weather extremes and environment-related challenges reported in the census, as shown in Model (2) to Model (8), to examine whether sustainable agriculture practices enhance resilience against these production challenges. Agroecological zone fixed effects are included to control for geographical heterogeneity.

Results show that household size consistently has a negative and statistically significant impact on land productivity across all specifications. This suggests that larger households may face labour inefficiencies or resource allocation issues, reducing land productivity. This finding aligns with prior research that suggests household labour dynamics can influence agricultural output. On the other hand, male-headed households are associated with lower land productivity compared to female-headed households in most models. This suggests that there may be gender differences in agricultural production efficiency. Indeed, previous findings have shown that women's land productivity may be higher in certain circumstances, which may be related to the fact that women often intensively cultivate plots that are much smaller compared to men, while previous research in Senegal has shown that plots managed by women tend to have higher land productivity for rain-fed crops, while plots managed by men tend to have higher land productivity for cash crops such as groundnuts (Kane and Aidara, 2022).

Regarding agricultural inputs, fertiliser use is a highly significant positive driver of land productivity across all models. This underscores the critical role of fertiliser in enhancing yields, consistent with the broader literature on input-driven agricultural land productivity. Access to irrigation is another critical factor positively associated with land productivity. Both results highlight the importance of adequate inputs and water access in improving agricultural yields. Additionally, agriculture support (agriculture extension services) is found to have a positive and statistically significant effect. However, access to credit and membership in an agriculture association is not found to be significant.

The primary variable of interest, sustainable agriculture practices (SAP), is not statistically significant across any of the specifications. Regarding weather and environment-related production challenges, the results indicate that extreme weather events, namely erratic rainfall, extreme temperature, siltation and water erosion, have a significant negative effect on agricultural land productivity. Erratic rain is associated with yield reductions of approximately 1.11 units, while extreme temperatures are associated with an even more substantial decline of 1.22 units. Siltation is associated with a yield decline of 0.19, and water erosion with a decline of 0.78. On the other hand, only the interaction term between SAP and extreme temperature is positive and significant, sug-

gesting that SAPs are associated with a reduction in the negative effect of extreme temperatures.

Table 3.4: Effects of environmental degradation and sustainable agriculture practices on agricultural land productivity

Log(TotYield)	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Household size	-0.039*** (0.012)	-0.037*** (0.012)	-0.039*** (0.012)	-0.037*** (0.012)	-0.041*** (0.012)	-0.039*** (0.013)	-0.039*** (0.012)	-0.036*** (0.012)
Household Head(Male)	-0.413* (0.233)	-0.408* (0.231)	-0.425* (0.233)	-0.420* (0.232)	-0.379 (0.232)	-0.417* (0.233)	-0.399* (0.235)	-0.410* (0.231)
Household Head(Literate)	0.024 (0.201)	0.023 (0.200)	0.025 (0.201)	-0.018 (0.201)	-0.029 (0.201)	0.025 (0.201)	0.033 (0.201)	0.015 (0.200)
Household Head(Age)	-0.004 (0.005)	-0.003 (0.005)	-0.004 (0.005)	-0.004 (0.005)	-0.004 (0.005)	-0.004 (0.005)	-0.004 (0.005)	-0.004 (0.005)
Fertiliser	0.426*** (0.100)	0.399*** (0.100)	0.436*** (0.100)	0.428*** (0.099)	0.420*** (0.099)	0.429*** (0.101)	0.420*** (0.101)	0.423*** (0.100)
Credit	0.245 (0.173)	0.249 (0.173)	0.243 (0.173)	0.216 (0.173)	0.239 (0.173)	0.268 (0.176)	0.243 (0.174)	0.264 (0.172)
AGR Support	0.066** (0.031)	0.064** (0.031)	0.065** (0.031)	0.062** (0.031)	0.073** (0.031)	0.067** (0.032)	0.065** (0.031)	0.072** (0.031)
AGR Association	0.082 (0.154)	0.106 (0.154)	0.089 (0.155)	0.088 (0.153)	0.077 (0.153)	0.072 (0.155)	0.083 (0.154)	0.059 (0.153)
Irrigation(%)	0.148*** (0.034)	0.141*** (0.034)	0.147*** (0.034)	0.147*** (0.034)	0.154*** (0.034)	0.150*** (0.034)	0.148*** (0.034)	0.148*** (0.034)
Log(Totdays)	0.663*** (0.052)	0.680*** (0.052)	0.664*** (0.052)	0.661*** (0.052)	0.637*** (0.052)	0.656*** (0.052)	0.667*** (0.052)	0.654*** (0.051)
SAP	0.400 (0.308)	0.333 (0.329)	0.279 (0.320)	0.318 (0.316)	0.368 (0.325)	0.256 (0.462)	0.381 (0.321)	0.474 (0.319)
Erratic Rain		-1.114*** (0.356)						
SAP*Erratic Rain		1.209 (0.814)						
Floods			-0.321 (0.426)					
SAP*Floods			1.576 (1.065)					
Extreme Temp				-1.221** (0.492)				
SAP*Extreme Temp				2.176* (1.283)				
Siltation					-0.192*** (0.064)			
SAP*Siltation					0.065 (0.296)			
Pests						0.112 (0.174)		
SAP*Pests						0.192 (0.622)		
Salinisation							0.153 (0.294)	
SAP*Salinisation							0.238 (1.031)	
Water Erosion								-0.781*** (0.274)
SAP*Water Erosion								-0.135 (1.020)
Cons	7.627*** (0.483)	7.506*** (0.482)	7.640*** (0.484)	7.689*** (0.482)	7.793*** (0.483)	7.622*** (0.484)	7.609*** (0.489)	7.650*** (0.480)
Agroecological zone fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	649	649	649	649	649	649	649	649
R2	649	649	649	649	649	649	649	649
R2 Adj.	649	649	649	649	649	649	649	649

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

These findings suggest that adopting SAP alone may not yield immediate land productivity benefits. This may be because SAP may require more time to deliver measurable benefits, particularly regarding soil health and resilience to environmental stress. Second, partial or incomplete adoption of SAP techniques may limit their effectiveness. Additionally, given that our SAP variable is an aggregate of all sustainable agriculture practices adopted, differential impacts between techniques may be masked.

Lastly, SAP is represented as a dummy variable, with only 4.5% of observations indicating adop-

tion. Since this is below the commonly accepted threshold of 10% for robust statistical analysis, relying solely on this variable would limit the reliability and validity of our findings. To address this, we drop this restrictive variable, and, to assess differences amongst various sustainable agriculture practices, we interact erratic rainfall, extreme temperature, siltation and water erosion with the following agriculture practices - Structural Measures to Reduce Soil Erosion(SME), Climate Adapted Agriculture(CAA) and Conservation Agriculture (CA) as shown in Appendix C.8.

Model(1) and Model(4) show positive interactions between our structural measures to reduce soil erosion variable and extreme weather and erratic rainfall. This suggests that SME practices, such as the construction of canals and dykes can significantly buffer against the effects of extreme temperature and erratic rain, potentially by improving soil retention and water management. However, when interacting with water erosion, SME exhibits a negative coefficient, indicating a detrimental effect in environments prone to severe water erosion. This may reflect the use of inappropriate SME measures or limitations of these measures in controlling soil loss due to increasingly severe flooding.

Regarding Climate Adapted Agriculture (CAA), Model (2) shows that the interaction term between CAA and extreme temperature is insignificant. Model(5) shows that the interaction term between CAA and erratic rainfall is positive and significant, while Model (8) shows that the interaction term between CAA and water erosion is not significant. While a variety of climate-adapted practices have been proven to be effective against extreme heat, households in our sample mainly use crop diversification, traditional knowledge and adapted crop varieties and animal species, which may explain why CAA practices appear to be ineffective in reducing the effect of extreme temperature and water erosion.

Model (3), Model (6), and Model (9) show that Conservation Agriculture (CA) displays a positive and significant interaction with extreme temperature but not with erratic rainfall or water erosion. Practices such as mulching, cover cropping, and minimal soil disturbance are likely to help conserve soil moisture and reduce crops' vulnerability to temperature extremes.

We also interact the same weather and production challenges with other sustainable agriculture practices, namely agroforestry, natural soil fertility management (NSFM) and sustainable pest management (SPM) as shown in Appendix C.9. Agroforestry demonstrates a positive interaction with erratic rainfall, suggesting its potential to mitigate rainfall variability. However, its interaction with water erosion is negative and significant, indicating limitations in controlling soil erosion under heavy water flow. NSFM's interactions with extreme temperature and erratic rain were largely insignificant, suggesting that low-cost soil fertility measures like compost may not be sufficient to mitigate extreme weather impacts.

These mixed outcomes could also be due to low adoption rates of sustainable practices in the sample, as well as measurement error in self-reported SAP adoption and production and weather challenges, which could also contribute to the lack of significance. Additionally, the minimal effects might reflect the relatively small scale of these interventions in practice, making them less impactful in the face of significant production constraints.¹¹ Therefore, while sustainable practices hold promise, their measured benefits in this chapter are limited, calling into question the robustness of some of the results given the reliance on self-reported measures and the low rates of practice adoption in the observed sample.

Lastly, we examine whether households in the clusters identified using HCPC respond differently to weather extremes and environmental production challenges. However, as shown in Appendix C.10, although households in Cluster 2 and Cluster 3 are more negatively affected by some challenges, the interaction terms between clusters and weather extremes are generally insignificant. The lack of significant interaction effects may imply that other factors, such as access to resources or pre-existing agricultural practices, could be more influential than adopting sustainable practices alone in determining household resilience to climate-related challenges. The lack of interaction may also be due to overall low adoption rates of sustainable agriculture practices, suggesting that clusters may not differ enough in their responses to weather shocks and production challenges. Hence, their resilience or vulnerability might be similar regardless of the cluster. Additionally, the impact of weather extremes on agricultural yield may not be immediate and could require extended observation periods to capture their long-term effects.

Overall, these findings should be understood in the context of the relatively low adoption of these practices in our sample and potential measurement errors in the survey. Hence, the findings of this chapter could be significantly improved through the use of panel data, which would allow for more precise tracking of the long-term effects of sustainable agriculture practices, erratic weather patterns, and agricultural yields. Panel data would enable us to observe changes within the same households or farms over time, reducing the risk of biases caused by unobserved heterogeneity. Additionally, it would help account for variations in adoption rates of sustainable practices and provide better insights into how various practices perform across different climate conditions and seasons. This would lead to more reliable and dynamic estimates, as the longitudinal nature of panel data captures the delayed or cumulative effects of both interventions and environmental stressors on land productivity.

¹¹For example, less than 1% of households in our sample report planting agroforestry trees on their agricultural land, limiting interpretation of these results.

3.6 Conclusion

In this chapter, we used hierarchical clustering on principal components and a binary logistic regression model to explore the determinants of the adoption of sustainable agriculture practices, as well as OLS regression to assess the relationship between agricultural land productivity, sustainable agriculture practices, environmental degradation and weather extremes using agriculture census data from Senegal covering the year 2020-2021. Using factor analysis, we identified three farm typologies: farms practising intensive, high-input agriculture, farms implementing climate-adapted agriculture, and farms practising traditional agriculture integrated with elements of sustainable agriculture practices. A comparison of land productivity indicators revealed that the highest total land productivity is found in the input-intensive farms, with moderate levels of land productivity found in the climate-adapted cluster. The log-likelihood model revealed that the household head's literacy, access to agriculture support and land tenure were significant determinants of adopting sustainable agriculture practices. Additionally, households that have experienced revenue losses due to extreme weather and constraints such as extreme temperature, pest infestations, and erratic rainfall are more likely to adopt sustainable agriculture practices.

Using OLS regression, we then evaluated the effect of sustainable agriculture practices on total agricultural land productivity and the effect of self-reported constraints in the production environment due to extreme weather and environmental degradation. Overall, we found that households implementing multiple sustainable agriculture practices simultaneously are less likely to experience negative impacts from extreme temperatures. Additionally, specific practices, such as conservation agriculture and structural measures to reduce soil erosion, are correlated with less severe impacts of erratic rainfall. However, we found no evidence that other practices, such as natural soil fertility management and sustainable pest management, reduce the effects of specific production challenges. Policy implications arising from our findings highlight the following:

Enhancing access to information on sustainable agriculture practices and climate change adaptation measures: The promotion of context-specific sustainable practices enhances land productivity and is associated with less severe losses due to environmental degradation and extreme weather. However, the use of such measures is minimal among farming households with low knowledge, low membership in agriculture organisations and little contact with agriculture support services. Enhancing land productivity in challenging environments can be achieved by increasing access to information and knowledge on appropriate sustainable agriculture practices. Additionally, relatively few households in the sample reported implementing measures for climate change adaptation and hence may benefit from more context-specific information. Enhancing ac-

cess to information may be supported by increasing agriculture support services and peer-to-peer exchanges through farmer organisations.

Investment in research & development: Adoption rates of sustainable practices were very low overall, hence there may be a need for more research and investment in encouraging farmers to adopt full suites of these practices. While this may include research into technology and practices that are more suited to the local context, as well as drought and heat resistant seeds more suited to adverse production conditions, it is also crucial to further investigate barriers to the adoption of said practices. Further, while many of these practices aim to maximize land productivity and enhance ecosystem services, the increasing frequency and severity of extreme weather events driven by climate change will require long-term structural changes to agricultural production systems. Research highlights the importance of integrating holistic approaches such as the integration of agroecological practices such as the diversification of agroecosystems, organic soil management, water conservation and harvesting and the enhancement of agrobiodiversity, that enhance ecological interactions, synergy, and integration, enhancing resilience, protecting the environment, and promoting social inclusion for more equitable outcomes (Altieri et al., 2015).

Creating an enabling environment for small-scale farmers: Lastly, results show that agriculture support services are correlated with higher agricultural land productivity, highlighting the need for more substantial technical and institutional support for farmers to fully realise the potential benefits of present and future sustainable agriculture practices. Likewise, removing financial and institutional barriers that limit farmer adaptation capacity is necessary to support the uptake of sustainable agriculture practices.

While this chapter presented an exploratory analysis of the implementation of sustainable agriculture practices among small-scale farmers, future research should focus on collecting more precise and longitudinal data to improve the understanding of sustainable agricultural practices and their impact on land productivity. Moreover, there is a need for more robust indicators to measure agrobiodiversity and ecosystem health, which are critical for assessing both the sustainability of agricultural systems and the effectiveness of sustainable agriculture practices.

Chapter 4

General conclusion

The three chapters of this thesis contribute to the literature on the determinants of structural transformation and alternative pathways in low-income countries. They build on existing literature by first examining the impacts of weather extremes on structural transformation in low-income and emerging economies, focusing on agricultural labour productivity and employment shares. Secondly, they evaluate the role of biodiversity in agricultural total factor productivity and, by extension, structural transformation in the context of sustainable development. Lastly, they explore the potential of sustainable agricultural practices in increasing land productivity and resistance to weather extremes using data from Senegal.

The first chapter demonstrates that extreme weather events, including droughts, floods, and heatwaves, hinder structural transformation by reducing agricultural labour productivity and increasing dependence on agricultural employment. Using a system of simultaneous equations and a dynamic panel model, we find that while some countries in regions such as Latin America and Asia benefit from favourable weather trends, worsening conditions in some African countries have slowed development. This highlights the need for localised, climate-adapted strategies. The second chapter extends this analysis, demonstrating that while biodiversity enhances agricultural TFP growth, extreme weather events, particularly droughts, undermine their contribution, further lowering TFP growth. These findings emphasise the importance of natural capital in sustaining agricultural TFP growth, which relies on protecting biodiversity increasingly threatened by human activity and climate change. This calls for more systemic approaches to bolstering agricultural TFP growth in the face of weather extremes. The third chapter focuses on the adoption of sustainable agriculture practices in Senegal, using data from the 2020-2021 agriculture census to explore the implications of sustainable agriculture practices on the process of structural transformation. Three farm typologies are identified using hierarchical clustering on principal components: high-input intensive, climate-adapted, and traditional farms with sustainable practices. Input-intensive

farms achieve the highest land productivity, while climate-adapted farms demonstrate moderate results. Adoption of sustainable practices is influenced by household literacy, agricultural support, and extreme weather events, with some practices like conservation agriculture associated with less severe effects due to weather extremes and environmental degradation. Findings from this thesis provide insights that can inform decision-makers and other actors concerned with employment, labour and land productivity, resilience and biodiversity protection and conservation in the following ways:

Climate-induced weather extremes significantly distort the process of structural transformation and therefore require the development of alternative pathways to development: Our empirical investigation demonstrates that weather extremes have both short-run and long-run impacts on economic development. Long-run effects result in substantial delays in structural transformation, mainly through declines in agricultural labour productivity and increases in agriculture employment, significantly delaying the growth of the non-agriculture sector and overall economic growth. Hence, our findings highlight the importance of addressing climate vulnerabilities as part of broader economic development strategies. Furthermore, it increasingly distances us from a "one-size-fits-all" model of structural transformation (typically, an evolution towards a world "without agriculture" or rather "without farmers" (Timmer, 1988, 2009; Dorin et al., 2013)). This model, which depends on the intensive use of fossil fuels, is a source of climatic and environmental disasters and shows signs of weaknesses in facing these challenges. Therefore, reevaluating development strategies is imperative, considering local specificities and climatic challenges to ensure sustainable and equitable structural transformation.

Biodiversity and ecosystems are crucial for agricultural total factor productivity, but are also vulnerable to weather extremes: In chapter 2, we demonstrate that biodiversity is essential for agricultural total factor productivity growth, but they are increasingly vulnerable to extreme weather events. As these events intensify, the benefits that biodiversity provide to agriculture diminish. This calls into question the concept of weak sustainability, where natural capital can be easily replaced by human and physical capital. Our findings suggest that natural capital is crucial for maintaining agricultural TFP growth, yet is vulnerable from intensive agricultural input use and climate change. Hence, investments in biodiversity protection and ecosystem restoration are necessary to ensure their survival. This should be accompanied by more integrated agroecological food production practices, which aim to enhance agricultural production by minimising synthetic inputs, leveraging natural processes and enhancing synergies among agroecosystem components, in order to maintain agricultural TFP growth in the face of more extreme and unpredictable weather events.

Support for comprehensive implementation of sustainable agriculture practices is essential: Promoting context-specific sustainable practices improves land productivity and mitigates losses from environmental degradation and extreme weather. Chapter 3 shows that adoption of these practices

remains limited in low-income countries due to low knowledge, weak organisational membership, and limited access to agricultural support services. However, partial adoption is insufficient to address weather extremes and degradation. Therefore, greater technical and institutional support, along with reducing financial barriers, is needed to enable full adoption and realisation of the benefits of sustainable practices. Additionally, research on locally suited technologies, nature-based practices, and heat- and drought-resistant inputs is necessary.

Overall, these findings suggest that climate-induced weather extremes and biodiversity decline are significant barriers to countries embarking on the "Lewis Path" to transformation. Furthermore, while there are ongoing efforts to support farmers in adopting sustainable agriculture practices to enhance land productivity and resistance to weather extremes in Sub-Saharan Africa, they fall short of expected improvements. Additionally, other factors, namely, limitations on land availability, foreclose the extent to which farmers in non-OECD countries can invest in machinery and inputs to maximise economies of scale in order to replicate industrial agricultural models. Moreover, the intensive use of synthetic inputs, combined with the accelerating effects of climate change, would result in more biodiversity destruction, eventually undermining the natural capital that agriculture fundamentally depends on. Lastly, rapid demographic growth, particularly in Africa, creates disincentives for further exclusion of the working population through mechanisation and automation. These factors suggest that alternative development pathways are necessary.

While development policy has favoured the support of competitive, export-oriented monoculture agricultural sector, the growing number of economic, social, and ecological impacts and risks discussed in this thesis point to the necessity of supporting alternative agriculture development strategies. One alternative pathway is agroecological agriculture, which is based on the application of ecological concepts and principles to the design and management of sustainable agricultural ecosystems (Altieri, 2009). Practices such as the diversification of agroecosystems, organic soil management, water conservation and harvesting and agroforestry can, therefore, be used at the farm and landscape level to create diversified agroecological systems that are more resilient against weather extremes and protect the environment (Francis, 2016). Agroecological practices are also more labour-intensive compared to conventional agriculture. In low-income countries, where the working-age population is expected to rapidly increase, small-scale, agroecological farms thus have the potential to absorb labour, as long as they are economically and socially attractive.

However, this dissertation has several limitations, primarily inadequate data on biodiversity indicators and insufficient data on sustainable agriculture practices. Hence, while Chapter 2 utilised the Red List Index to proximate biodiversity, this indicator has considerable limitations, mainly that most countries report insufficient data on species diversity, and as an indicator designed to show contribution to global

extinction risk trends, can only be interpreted as a proximate indicator of agrobiodiversity. Hence, the development, tracking and monitoring of agrobiodiversity indicators would significantly contribute to more accurate analyses of the actual contribution of biodiversity to agriculture in low-income countries at the aggregate scale. Likewise, chapter 3 utilised agriculture census data to explore the role of sustainable agriculture practices in the process of structural transformation. While the census contained valuable information on production methods in Senegal, inconsistent reporting, reliance on self-reported data, and a lack of anonymised geospatial coordinates mean that more accurate weather extreme indicators could not be integrated into the analysis. Therefore, it is likely that both the effects of weather extremes and sustainable agriculture production methods were underestimated. Hence, more accurate, longitudinal data on sustainable production methods is required for a more precise analysis of the effect of sustainable agriculture practices on agricultural land productivity, particularly in sub-Saharan African countries.

Lastly, this dissertation focused on the impact of weather extremes on the process of structural transformation. While the broad patterns of structural transformation are expected to continue, other long-term trends—such as demographic shifts, technological advancements, urbanisation, and globalisation—create vastly different conditions for low-income countries today. One critical area that remains under-researched is the rapid expansion of mostly informal food processing, transformation, and distribution sectors, which will significantly impact agricultural production and food security (Reardon et al., 2021). These sectors primarily employ women and young adults, making age and gender differences in downstream food production increasingly important in low-income countries and deserving of deeper integration into the literature on structural transformation. For example, while these changes would be expected to result in higher yields and labour productivity, emerging evidence suggests that yields are declining, particularly in agricultural areas near urban and peri-urban areas, primarily driven by a decline in hours spent on farm-work as non-farm employment opportunities and profitability rise (Udry, 2024). Further research is also needed on the social, economic, and institutional factors that support agroecology adoption. Economic and institutional aspects include the impact of trade and globalisation, particularly how international regulations can promote agrobiodiversity and protect ecosystem services. Globalisation and interconnected food markets also affect small-scale farm incomes, raising questions about whether sustainable, diversified production can drive inclusive growth and poverty reduction. Social factors, such as gender-specific drivers of sustainable practices, require deeper understanding, along with more evidence on the land productivity potential of agroecological systems.

Declaration of Generative AI and AI-assisted Technologies in the Writing Process: During the preparation of this work, the author partially used ChatGPT for language translation and editing. After using this tool, the author reviewed and edited the content as needed and takes full responsibility for the content of the publication.

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Appendix A

Appendix to chapter 1: Weather extremes and agricultural labour productivity: impacts on structural transformation in low-income and emerging economies

A.1 Data description

Table A.1: Summary statistics

	count	mean	sd	min	max
AgrEmplShare	810	.4142673	.2233168	.0518967	.9339408
AgrProd	810	3634.782	6990.146	177.5639	61523.43
logAgrProd	810	7.386262	1.194456	5.17933	11.02717
AgeDepend	810	59.63714	20.17907	23.66923	106.8938
CerealYield	810	2593.369	1402.822	152.6	9453.7
logCerealYield	810	7.675401	.6799251	5.02782	9.154161
ContrCorrup	810	-.3632618	.5269269	-1.67334	1.216737
Educ	810	6.638885	2.142495	.9591233	11.59177
logEduc	810	1.82366	.4112106	-.0417356	2.450295
ExtWetDays	810	5.919211	.5274262	3.991389	7.536225
FDI	810	8.28e+09	2.82e+10	-4.55e+09	2.91e+11
logFDI	810	22.72296	1.101621	0	26.41186
Globalisation	810	54.61278	10.54293	25.63181	81.39252
GlobalPol	810	69.20365	15.47106	27.14446	92.49353
GlobalTrade	810	45.80676	13.47224	17.30428	83.6423
KstockTot	810	1687.465	4731.808	6	54542
logKstockTot	810	5.497663	2.042025	1.791759	10.90673
KstockGov	810	665.0198	2525.744	3	26396
logKstockGov	810	4.28165	1.954141	1.098612	10.18097
KstockPriv	810	998.9988	2381.742	1	27994
logKstockPriv	810	5.048874	2.121178	0	10.23975
MaxHotDays	810	28.609	38.17788	0	212.69
MineralRent	810	.7168779	1.717682	0	14.994
PopGr	810	1.731987	.8803601	-.6163564	8.117947
PopTot	810	1.11e+08	2.77e+08	1133996	1.39e+09
logPopTot	810	17.15501	1.566665	13.94126	21.04997
SPEI_12	810	-.1871775	1.047677	-3.072733	2.717108
Drought_spei	810	.6022325	1.293897	0	9.441688
SPI_12	810	-.0474186	1.007182	-2.301613	2.089457
Drought_spi	810	.4891109	1.119975	0	5.297422

Table A.2: Data definition and sources

Variable	Definition (Source)
AgrEmplShare	Employment in agriculture (% of total employment) (GGDC/UNU-WIDER ETD)
AgrProd	Agriculture VA / Agriculture employment (USD altern. conv. factor) (GGDC/UNU-WIDER ETD)
<i>logAgrProd</i>	<i>log(AgrProd)</i>
AgeDepend	Age dependency ratio, young (% of working-age population) (WB)
CerealYield	Cereal yield (kg per hectare) (WB)
<i>logCerealYield</i>	<i>log(CerealYield)</i>
ContrCorrup	Corruption control, WB Worldwide Governance Indicators (WGI)
Educ	Years of education (Barro-Lee)
<i>logEduc</i>	<i>log(Educ)</i>
ExtWetDays	Accumulated precipitation during 1% of wettest days (ETCCDI)
FDI	Direct investment equity flows in the reporting economy (WB)
<i>logFDI</i>	<i>log(FDI + abs(FDI_{min} + 1))</i>
Globalisation	KOF Index of Globalization (Dreher, 2006)
GlobalPol	KOF Political Globalisation Index
GlobalTrade	KOF Trade Globalisation Index
KstockTot	Total capital stock (gov+priv+ppp) (IMF)
<i>logKstockTot</i>	<i>log(KstockTot)</i>
KstockGov	General government capital stock (IMF)
<i>logKstockGov</i>	<i>log(KstockGov)</i>
KstockPriv	Private capital stock (IMF)
<i>logKstockPriv</i>	<i>log(KstockPriv)</i>
SEMP	Self-employment (% of total employment) (WB)
LandProd	Agriculture VA / Total agriculture land (USD per ha) (GGDC/UNU-WIDER ETD)
MaxHotDays	Average count of days when the maximum temperature surpassed 30 °C (ETCCDI)
MineralRent	Mineral rents (% of GDP) (WB)
PopGr	Population, growth (WB)
PopTot	Population, total (WB)
<i>logPopTot</i>	<i>log(PopTot)</i>
SPEI_12	Standardized Precipitation-Evapotranspiration Index (12 month) (CRU)
Drought_spei	$(SPEI_{12})^2$
SPI_12	Standardized Precipitation Index (12 month) (CRU)
Drought_spi	$(SPI_{12})^2$

Table A.3: List of countries

Africa	Americas	Asia
Botswana	Argentina	Bangladesh
Cameroon	Bolivia	Cambodia
Ghana	Brazil	China
Kenya	Colombia	India
Lesotho	Costa Rica	Indonesia
Malawi	Ecuador	Malaysia
Mauritius	Mexico	Myanmar
Mozambique	Peru	Nepal
Namibia		Pakistan
Rwanda		Philippines
Senegal		Sri Lanka
South Africa		Thailand
Tanzania		Turkey
Tunisia		
Uganda		
Zambia		
16	8	13

Note: 22 observations for each country (1996-2017) excepting Myanmar, with 18 observations for the same period.

A.2 Detailed estimation results

Table A.4: Direct and indirect effects of extreme weather events on agricultural employment share, detailed estimation results

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
AgrEmplShare									
<i>logAgrProd</i>	-0.0511*** (0.0163)	-0.0532*** (0.0148)	-0.0737*** (0.0128)	-0.0696*** (0.0133)	-0.0798*** (0.0140)	-0.0676*** (0.0128)	-0.0479*** (0.0136)	-0.0731*** (0.0126)	-0.0729*** (0.0136)
logKstockTot	-0.0583*** (0.0115)	-0.0580*** (0.0109)	-0.0680*** (0.0107)	-0.0665*** (0.0103)	-0.0586*** (0.0106)	-0.0623*** (0.0097)	-0.0638*** (0.0113)	-0.0745*** (0.0092)	-0.0679*** (0.0097)
logEduc	-0.0550* (0.0329)	-0.0562* (0.0323)	-0.0448 (0.0310)	-0.0586* (0.0305)	-0.0545* (0.0311)	-0.0713** (0.0297)	-0.1778*** (0.0664)	-0.1321*** (0.0369)	-0.0733** (0.0337)
logPopTot	0.0737*** (0.0070)	0.0741*** (0.0071)	0.0780*** (0.0072)	0.0794*** (0.0069)	0.0678*** (0.0076)	0.0761*** (0.0065)	0.0596*** (0.0102)	0.0778*** (0.0086)	0.0629*** (0.0097)
AgeDepend	0.0018*** (0.0006)	0.0018*** (0.0006)	0.0017** (0.0007)	0.0016** (0.0006)	0.0020*** (0.0006)	0.0021*** (0.0006)	0.0029*** (0.0009)	-0.0000 (0.0007)	0.0008 (0.0007)
Globalisation	-0.0040** (0.0019)	-0.0038** (0.0017)	-0.0017 (0.0016)	-0.0023 (0.0016)	-0.0016 (0.0016)	-0.0020 (0.0016)	0.0041 (0.0028)	0.0020 (0.0018)	0.0015 (0.0020)
Trend	0.0034*** (0.0009)	0.0033*** (0.0008)	0.0033*** (0.0007)	0.0035*** (0.0007)	0.0033*** (0.0007)	0.0039*** (0.0007)	-0.0002 (0.0018)	0.0026*** (0.0008)	0.0016 (0.0011)
Drought_spi				-0.0140** (0.0064)				0.1243** (0.0554)	
ExtWetDays					0.0262** (0.0117)				
MaxHotDays						-0.0006*** (0.0002)			
Drought_spi: Normal							3.2803*		

Continued on next page

Table A.4: (continued)

Table A.4 – continued from previous page									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
							(1.7225)		
Drought_spi: Moderate & Severe							0.0881**		
							(0.0413)		
Drought_spi: Extreme							-0.0711**		
							(0.0340)		
SEMP								0.0023**	0.0046***
								(0.0009)	(0.0016)
Drought_spi * SEMP								-0.0022**	
								(0.0009)	
Drought_spei									0.2275**
									(0.0930)
Drought_spei * SEMP									-0.0052**
									(0.0021)
Constant	1.0217	1.3378	-0.6104	-0.0008	0.5050	-0.6016	1.3008	4.0923**	3.9929
	(1.1981)	(1.1810)	(1.7304)	(1.6311)	(1.7508)	(1.6921)	(1.7198)	(1.7517)	(2.6213)
logAgrProd									
logKstockTot	-0.0148								
	(0.0550)								
logKstockPriv		0.2180**	0.1900	0.2268*	0.2364*	0.1553	0.2741**	0.2853**	-0.1373
		(0.1034)	(0.1302)	(0.1282)	(0.1431)	(0.1419)	(0.1298)	(0.1311)	(0.4100)
logKstockGov		-0.2495**	-0.2582*	-0.2930**	-0.2934*	-0.2140	-0.0104	-0.4763***	0.1205
		(0.1064)	(0.1417)	(0.1373)	(0.1591)	(0.1512)	(0.1599)	(0.1626)	(0.4106)
logEduc	0.2313	0.1683	0.3962	0.3223	0.4032	0.5052*	0.6926*	0.3369	0.1698
	(0.1844)	(0.1841)	(0.2426)	(0.2307)	(0.2621)	(0.2870)	(0.3937)	(0.4683)	(0.8900)

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Table A.4: (continued)

Table A.4 – continued from previous page									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
PopGr	-0.0759 (0.0671)	-0.0884 (0.0736)	-0.1718* (0.0963)	-0.1852* (0.1048)	-0.1532* (0.0908)	-0.1545 (0.1025)	-0.1683 (0.1236)	-0.0709 (0.1553)	0.0865 (0.1856)
logCerealYield	0.3082* (0.1637)	0.2489 (0.1583)	0.3829* (0.1989)	0.3565* (0.1948)	0.5362*** (0.1911)	0.4144** (0.2040)	0.5329*** (0.2044)	0.2452* (0.1355)	0.4415** (0.1828)
MineralRent	-0.0808*** (0.0199)	-0.0899*** (0.0192)	-0.0697** (0.0294)	-0.0712** (0.0285)	-0.0736** (0.0297)	-0.0650** (0.0290)	-0.0628** (0.0312)	-0.0402 (0.0360)	-0.0128 (0.0822)
Globalisation	0.0735*** (0.0127)	0.0759*** (0.0110)							
GlobalTrade			0.0092 (0.0060)	0.0079 (0.0064)	0.0106 (0.0068)	0.0111 (0.0069)	0.0001 (0.0090)	-0.0051 (0.0059)	-0.0020 (0.0116)
logFDI			0.1220*** (0.0414)	0.1106*** (0.0366)	0.1055*** (0.0356)	0.1022** (0.0399)	0.0492** (0.0223)	0.0682** (0.0348)	0.0773 (0.0733)
GlobalPol			0.0221** (0.0087)	0.0223** (0.0097)	0.0172* (0.0092)	0.0192* (0.0098)	-0.0217 (0.0136)	0.0323*** (0.0116)	0.0307 (0.0227)
ContrCorrup	0.4202*** (0.1425)	0.4059*** (0.1228)	0.7727*** (0.1069)	0.7783*** (0.1080)	0.7787*** (0.1024)	0.7827*** (0.1091)	0.3856* (0.2064)	-0.1093 (0.2128)	-0.0955 (0.3898)
Trend	0.0019 (0.0100)	0.0028 (0.0085)	0.0219*** (0.0080)	0.0243*** (0.0078)	0.0268*** (0.0087)	0.0207** (0.0085)	0.0271*** (0.0098)	0.0352*** (0.0085)	0.0469 (0.0288)
Drought_spi				-0.0316 (0.0588)				-1.9601*** (0.6501)	
ExtWetDays					-0.3135* (0.1644)				
MaxHotDays						0.0026 (0.0021)			

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Table A.4: (continued)

Table A.4 – continued from previous page									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Drought_spi: Normal							21.7463 (17.1080)		
Drought_spi: Moderate & Severe							-1.0308*** (0.3559)		
Drought_spi: Extreme							0.4582 (0.4085)		
SEMP								-0.0487*** (0.0101)	-0.0963*** (0.0366)
Drought_spi * SEMP								0.0308*** (0.0116)	
Drought_spei									-5.5456** (2.4898)
Drought_spei * SEMP									0.1188* (0.0610)
Number of obs	810	810	810	810	810	810	810	514	514
Hansen J statistic	14.4794	13.7671	24.3786	24.5753	24.5861	23.3349	15.2239	15.8441	14.4849
Hansen J p-value	0.0247	0.1309	0.0278	0.0262	0.0261	0.0378	0.1725	0.1471	0.2073

Standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.5: Long-term effects of extreme weather events on agricultural employment share

	(1)	(2)	(3)	(4)
L.AgrEmplShare		0.9486*** (0.0078)	0.9424*** (0.0071)	0.9698*** (0.0100)
logAgrProd	-0.0860*** (0.0323)	-0.0032** (0.0014)	-0.0039** (0.0015)	-0.0029** (0.0014)
logKstockTot	-0.0549** (0.0248)	-0.0021 (0.0015)	-0.0018 (0.0015)	0.0018 (0.0013)
logEduc	-0.1022** (0.0410)	-0.0056*** (0.0020)	-0.0091*** (0.0032)	-0.0073*** (0.0023)
logPopTot	0.0685* (0.0280)	0.0026 (0.0017)	0.0016 (0.0018)	-0.0025* (0.0014)
AgeDepend	0.0018* (0.0008)	0.0001*** (0.0000)	0.0002*** (0.0000)	0.0002*** (0.0000)
Globalisation	-0.0002 (0.0020)	-0.0000 (0.0001)	0.0000 (0.0001)	-0.0001 (0.0001)
Trend	0.0033*** (0.0012)	0.0001 (0.0001)	0.0001 (0.0001)	0.0001 (0.0001)
Drought_spi	-0.0084 (0.0069)	-0.0008 (0.0006)	0.0637*** (0.0218)	0.0385** (0.0150)
ExtWetDays	0.0087 (0.0122)	0.0010 (0.0011)	0.0036* (0.0020)	0.0045*** (0.0015)
MaxHotDays	-0.0004 (0.0003)	-0.0001** (0.0000)	-0.0001 (0.0006)	0.0001 (0.0003)
Drought_spi * ExtWetDay			-0.0100*** (0.0035)	-0.0061** (0.0025)
Drought_spi * MaxHotDays			-0.0003* (0.0001)	-0.0003*** (0.0001)
ExtWetDays * MaxHotDays			0.0000 (0.0001)	-0.0000 (0.0001)
Drought_spi * ExtWetDays * MaxHotDays			0.0000 (0.0000)	0.0001** (0.0000)
Constant	0.1707 (0.5727)	0.0056 (0.0307)	0.0114 (0.0318)	0.0385* (0.0212)
Number of obs	810	810	810	1108
Models 1 to 3: Instruments for first differences equation: D.(Drought_spi ExtWetDays MaxHotDays logPopTot) AgeDepend logKstockTot logEduc PopGr logCerealYield MineralRent GlobalTrade logFDI GlobalPol ContrCorrup Trend)				
Instruments for levels equation: Drought_spi ExtWetDays MaxHotDays logPopTot AgeDepend logKstockTot logEduc PopGr logCerealYield MineralRent GlobalTrade logFDI GlobalPol ContrCorrup Trend Constant				
Model 4: same instruments as used in Models 1 to 3, with the exception of D.ContrCorrup and ContrCorrup				
Hansen J statistic	3.6604	24.5193	20.8313	20.5800
Hansen J p-value	0.5993	1.0000	1.0000	1.0000
AR(1) statistic		-3.0886	-3.3042	-3.3663
AR(1) p-value		0.0020	0.0010	0.0008
AR(2) statistic		0.7884	0.4831	0.9580
AR(2) p-value		0.4305	0.6291	0.3381

Standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

A.3 Decomposition of economy-wide labour productivity growth considering the impact of weather extremes on agricultural dynamics

Considering only two sectors, denoted as the agricultural sector (a) and the non-agricultural sector (na), we can write the economy-wide labour productivity y_t as:

$$y_t = \theta_a^t y_a^t + \theta_{na}^t y_{na}^t \quad (\text{A.1})$$

Where:

- θ_a^t and θ_{na}^t are the shares of employment in the agricultural and non-agricultural sectors at time t , respectively.
- y_a^t and y_{na}^t are the labor productivities in the agricultural and non-agricultural sectors at time t , respectively.

By definition, the sum of the employment shares must equal 1. Therefore, we can express θ_{na}^t as:

$$\theta_{na}^t = 1 - \theta_a^t \quad (\text{A.2})$$

Now, let's note the change in y_t from time $t-1$ to t :

$$\Delta y_t = y_t - y_{t-1} \quad (\text{A.3})$$

Substituting the definitions, we get:

$$\Delta y_t = (\theta_a^t y_a^t + (1 - \theta_a^t) y_{na}^t) - (\theta_a^{t-1} y_a^{t-1} + (1 - \theta_a^{t-1}) y_{na}^{t-1}) \quad (\text{A.4})$$

Expanding, simplifying, and rearranging terms, we consider the contributions from the changes in sectoral labour productivity and employment shares:

$$\Delta y_t = \theta_a^t (y_a^t - y_{na}^t) - \theta_a^{t-1} (y_a^{t-1} - y_{na}^{t-1}) + (y_{na}^t - y_{na}^{t-1}) \quad (\text{A.5})$$

We can decompose the change into within-sector changes and between-sector (structural) changes as follows:

$$\Delta y_t = \underbrace{(y_a^t - y_{na}^t) \Delta \theta_a^t}_{\text{Structural change}} + \underbrace{\theta_a^{t-1} \Delta y_a^t + (1 - \theta_a^{t-1}) \Delta y_{na}^t}_{\text{Within-sector change}} \quad (\text{A.6})$$

Where:

- $\Delta \theta_a^t = \theta_a^t - \theta_a^{t-1}$ is the change in the share of employment in the agricultural sector.

- $\Delta y_a^t = y_a^t - y_a^{t-1}$ is the change in labour productivity in the agricultural sector.
- $\Delta y_{na}^t = y_{na}^t - y_{na}^{t-1}$ is the change in labor productivity in the non-agricultural sector.

Next, let's consider the impact of weather extremes (WE) on θ_a and y_a in logarithmic form, as in our regressions. Assume that weather extremes affect both the agricultural labour productivity and the share of employment in the agricultural sector directly and indirectly. We can express these dependencies as:

$$\begin{aligned}\log y_a^t &= f(WE) \\ \theta_a^t &= g(\log(y_a^t), WE)\end{aligned}\tag{A.7}$$

Using these relationships, we calculate the partial derivatives of y_a and θ_a with respect to WE :¹

$$\begin{aligned}\frac{\partial y_a^t}{\partial WE} &= f'(WE)y_a^t \\ \frac{\partial \theta_a^t}{\partial WE} &= g'(WE) + g'(\log(y_a^t))f'(WE)\end{aligned}\tag{A.8}$$

Using these derivatives, we can express the changes in y_a and θ_a due to weather extremes:

$$\begin{aligned}\Delta y_a^t &= f'(WE)y_a^t \Delta WE \\ \Delta \theta_a^t &= (g'(WE) + g'(\log(y_a^t))f'(WE)) \Delta WE\end{aligned}\tag{A.9}$$

Substituting these expressions into our equation for Δy_t , and focusing on the conditional effect of ΔWE , we get:

$$\Delta y_t \Big|_{\Delta WE} = (y_a^t - y_{na}^t) (g'(WE) + g'(\log(y_a^t))f'(WE)) \Delta WE + \theta_a^{t-1} f'(WE)y_a^t \Delta WE\tag{A.10}$$

Further decomposing, the structural change can be split into:

$$(y_a^t - y_{na}^t) \Delta \theta_a^t = \underbrace{(y_a^t - y_{na}^t) g'(WE) \Delta WE}_{\text{Direct structural change}} + \underbrace{(y_a^t - y_{na}^t) g'(\log(y_a^t)) f'(WE) \Delta WE}_{\text{Indirect structural change}}\tag{A.11}$$

The total change in economy-wide labor productivity due to weather extremes, decomposed into structural and within-sector changes, is:

$$\begin{aligned}\Delta y_t \Big|_{\Delta WE} &= \underbrace{\theta_a^{t-1} f'(WE)y_a^t \Delta WE}_{\text{Within-sector change (agriculture)}} \\ &\quad + \underbrace{(y_a^t - y_{na}^t) g'(WE) \Delta WE}_{\text{Direct structural change}} \\ &\quad + \underbrace{(y_a^t - y_{na}^t) g'(\log(y_a^t)) f'(WE) \Delta WE}_{\text{Indirect structural change}}\end{aligned}\tag{A.12}$$

¹We differentiate the logarithmic form of the agricultural labour productivity function. Given that $\log(y_a) = f(WE)$, the derivative of $\log(y_a)$ with respect to WE is $f'(WE)$. When we exponentiate $f(WE)$ to obtain y_a , the chain rule gives us the derivative:

$$\frac{dy_a}{dWE} = \frac{d}{dWE} \left(e^{f(WE)} \right) = e^{f(WE)} f'(WE) = y_a f'(WE)$$

This ensures that both the direct impact of weather extremes on agricultural labour productivity and the exponential nature of the relationship are appropriately captured.

Table A.6: Partial marginal effects on agricultural labour productivity and agricultural employment share

Variable	$d \log(y_a)/dX$	dy_a/dX	$d\theta_a/dX(\text{dir})$	$d\theta_a/dX(\text{indir})$	$d\theta_a/dX(\text{tot})$
logAgrProd			-.080		-.080
ExtWetDays	-.313	-1139.475	.026	.025	.051
Drought_spi	-1.031	-3746.721	.088	.049	.138
MaxHotDays	0	0	-.001	0	-.001
logKstockTot	0	0	-.059	0	-.059
logKstockPriv	.236	859.374	0	-.019	-.019
logKstockGov	-.293	-1066.62	0	.023	.023
logEduc	.403	1465.468	-.054	-.032	-.087
logPopTot	0	0	.068	0	.068
PopGr	-.153	-556.684	0	.012	.012
AgeDepend	0	0	.002	0	.002
logCerealYield	.536	1948.978	0	-.043	-.043
MineralRent	-.074	-267.462	0	.006	.006
Globalisation	0	0	-.002	0	-.002
GlobalTrade	.011	38.496	0	-.001	-.001
logFDI	.105	383.296	0	-.008	-.008
GlobalPol	.017	62.424	0	-.001	-.001
ContrCorrup	.779	2830.523	0	-.062	-.062

Table A.7: Economy-wide labor productivity changes across different periods: influence of weather extremes

	1997-2007	2007-2017	1997-2017
Δy (\$/pp)	2354.08	2894.24	5267.71
$\Delta y _{\Delta \text{ExtWetDays}}$	7.69	-136.34	-166.33
<i>Within-agr.sector change</i>	-10.52	-34.60	-56.60
<i>Direct structural change</i>	9.32	-52.08	-56.17
<i>Indirect structural change</i>	8.89	-49.67	-53.56
$\Delta y _{\Delta \text{Drought_spi}}$	189.33	130.93	277.31
<i>Within-agr.sector change</i>	144.61	-35.93	73.98
<i>Direct structural change</i>	28.66	106.94	130.32
<i>Indirect structural change</i>	16.06	59.92	73.01
$\Delta y _{\Delta \text{MaxHotDays}}$	17.42	-0.04	15.69
<i>Within-agr.sector change</i>	0.00	0.00	0.00
<i>Direct structural change</i>	17.42	-0.04	15.69
<i>Indirect structural change</i>	0.00	0.00	0.00

Table A.8: economy-wide labor productivity changes across various regions and countries (1997-2017)

	Africa	Americas	Asia	SEN	TUN	BGD	IND	MEX
avg_y	5745.76	14424.99	6253.95	2830.90	10872.02	1896.39	2434.38	20187.98
avg_y _a	2056.36	8418.07	2789.20	1029.20	7868.98	705.49	960.54	4834.44
avg_θ _a	0.50	0.20	0.44	0.48	0.13	0.52	0.52	0.15
avg_ExtWetDays	5.58	6.23	6.16	5.23	4.79	6.56	6.11	5.72
avg_Drought_spi	0.46	0.07	0.83	5.13	0.37	2.54	1.59	0.55
avg_MaxHotDays	34.94	13.53	30.81	188.99	65.54	19.82	79.19	35.64
ΔExtWetDays	0.01	0.23	0.40	0.31	-0.00	0.52	0.08	0.08
ΔDrought_spi	0.11	-0.20	-0.56	0.10	1.63	-3.80	0.33	-1.60
ΔMaxHotDays	8.52	4.19	5.82	15.13	10.68	7.76	22.65	3.92
Δy _a	1530.22	7313.08	2596.07	1724.23	6180.69	898.47	1709.43	2042.82
Δy _a ΔExtWetDays	-114.91	-268.04	-378.88	-96.69	2.63	-113.68	-23.21	-113.28
Δy _a ΔDrought_spi	-806.65	981.82	517.70	-103.47	-12972.69	2708.23	-321.45	7854.53
Δθ _a	-0.15	-0.09	-0.16	-0.38	-0.09	-0.25	-0.22	-0.05
Δθ _a ΔExtWetDays	0.00	0.01	0.02	0.02	-0.00	0.03	0.00	0.00
Δθ _a ΔDrought_spi	0.02	-0.03	-0.08	0.01	0.22	-0.52	0.05	-0.22
Δθ _a ΔMaxHotDays	-0.00	-0.00	-0.00	-0.01	-0.01	-0.00	-0.01	-0.00
Δy	3463.21	7786.51	5994.53	1415.82	3669.37	2687.37	3945.20	6830.47
Δy ΔExtWetDays	-75.42	-247.45	-233.47	-81.07	0.49	-185.09	-33.07	-87.89
Δy ΔDrought_spi	-195.15	653.80	656.28	-82.68	-2402.49	3927.30	-410.24	5230.42
Δy ΔMaxHotDays	16.51	14.54	15.38	11.35	1.36	17.99	59.24	38.55
%y	108.88	100.40	258.25	75.88	49.47	253.24	404.39	48.49
%y if ΔExtWetDays=0	107.65	104.00	266.84	80.23	49.46	270.69	407.78	49.11
%y if ΔDrought_spi=0	110.89	95.75	198.16	80.31	81.86	-116.84	446.44	11.36
%y if ΔMaxHotDays=0	108.21	100.16	257.28	75.27	49.45	251.55	398.31	48.21

Appendix B

Appendix to chapter 2: Biodiversity, ecosystems, and agricultural total factor productivity: investigating the influence of extreme weather events

B.1 Data description

Table B.1: Summary statistics

Variable	Obs	Mean	Std. dev.	Min	Max
TFPCH	735	1.00089	0.01424	0.91243	1.08079
BE	735	0.86592	0.10249	0.47000	0.99000
SPI 12	735	-1.05441	0.86592	-2.67224	0.96077
SPI: Drought	735	0.39092	1.06757	0.00000	5.29742
SPI: Moderate & Severe	735	0.06259	0.24238	0.00000	1.00000
SPI: Severe & Extreme	735	0.12925	0.33571	0.00000	1.00000
SPEI 12	733	0.02081	0.87672	-1.86446	2.41100
SPEI: Drought	735	0.25623	0.74440	0.00000	3.47620
SPEI: Severe	733	0.04775	0.21338	0.00000	1.00000
Ext Hot Days	735	2.46687	9.51278	0.00000	73.07000
Ext Wet Days	735	36.96627	21.47457	0.00000	127.49000
Log(Ext Wet Days)	711	3.50905	0.61901	1.17248	4.85585
NB. Flood	735	1.44218	2.27152	0.00000	20.00000
Inputs(ha)	735	167.77890	239.94750	1.44941	2265.83100
Log(Inputs	735	6.88142	1.32804	2.82016	10.17470
KStockTot	735	2,141.95	5,089.17	5.00	40,353.00
Log(KStockTot)	735	5.95080	2.01023	1.60944	10.60542
KGovTot	735	648.51	1,918.65	1.00	16,415.00
Log(KGovTot)	735	4.58752	1.95568	0.00000	9.70595
KPrivTot	735	1493.43400	3491.22900	1.00000	29208.00000
Log(KPrivTot)	735	5.59	2.08	0	10.28
Education	735	8.53793	2.88362	1.08036	13.18264
Log(Education)	735	5.06393	0.44788	3.07730	5.57890
Industry Emp	735	2,369,831	8,061,573	1,206	83,900,000
Industry Emp Change (%)	735	0.00096	0.10057	-0.98898	0.48401
Globalisation	735	63.94972	15.67812	23.42047	89.36237
INS (GE EST)	735	0.36277	0.97708	-1.74186	2.34636
Certified Forest(%)	735	1.73219	3.48548	0.00000	24.98960
Latitude	735	22.43334	29.95028	-44.28333	64.15000
Urban Pop(%)	735	58.38586	23.51204	8.24600	97.65100
Pop Density	735	133.98360	175.90420	1.54318	1133.71300
Log(Pop Density)	735	4.61126	1.41720	0.93384	7.53325
IMF AE Dummy	735	0.36463	0.48165	0.00000	1.00000
IMF EME Dummy	735	0.41088	0.49233	0.00000	1.00000
IMF LIC Dummy	735	0.22449	0.41753	0.00000	1.00000
Trend	735	45	3	40	50

Table B.2: Variable definitions and sources

Variable	Definition	Source	Years
TFPCH	Malmquist Index of Agriculture TFP change	USDA-IAP	1961 - 2020
BE	IUCN Red List Index: global estimates of species extinction risk	IUCN	1990 - 2022
INPUTS	Total quantity of agricultural fertilisers in metric tonnes per hectare.	USDA-IAP	1961-2020
<i>Log(INPUTS)</i>	<i>Log(INPUTS)</i>	USDA-IAP	1961-2021
Education	Total number of years of school	Barro-Lee	1950 - 2010
<i>Log(Education)</i>	<i>Log(Education)</i>	Barro-Lee	1950 - 2010
KStockTot	Total gross capital formation(government, private, PPP)	IMF	1960 - 2020
<i>Log(KStockTot)</i>	<i>Log(KStockTot)</i>	IMF	1960 - 2020
KStockkGov	Government government capital stock	IMF	1960 - 2020
<i>Log(KStockGov)</i>	<i>Log(KStockGov)</i>	IMF	1960 - 2020
KStockPriv	Private capital stock	IMF	1960 - 2020
<i>Log(KStockPriv)</i>	<i>Log(KStockPriv)</i>	IMF	1960 - 2020
SPI 12	Standardized Precipitation Drought Index	CRU TS	1901 -2020
<i>Drought SPI</i>	<i>(SPI 12)2</i>	CRU TS	1901 -2020
SPEI 12	Standardized Evapotranspiration Index	CRU TS	1901 -2020
<i>Drought SPEI</i>	<i>(SPEI 12)2</i>	CRU TS	1901 -2020
EXT Hot Days	average number of days with a maximum temperature over 35oC	ETCCDI	1960 - 2020
EXT Wet Days	Average Largest 5-day Cumulative Precipitation	ETCCDI	1960 - 2020
NB. Floods	Count of the number of floods reported in the Emergency Events Database	EM-DAT(CRED)	1900 -2023
INST(GE EST)	Institutional quality: Government Effectiveness: Estimate	WGI	1960 - 2022
Non Farm Emp	Number of workers in each country's industrial sector	UNIDO INDSTAT 2	1991 - 2020
<i>Non Farm Emp change</i>	<i>Annual change in number of workers in each country's industrial sector</i>	UNIDO INDSTAT 3	1991 - 2020
Globalisation	KOF Index of globalisation	Axel Dreher	1970 - 2020
IMF Dummies	Income levels based on the IMF country classification	IMF	
Pop Density	Midyear population divided by land area in square kilometres	WDI	1961 - 2021
<i>Log(PopDensity)</i>	<i>Log(PopDensity)</i>	WDI	1961 -2021
UrbanPop	Proportion of population living in urban areas	WDI	1960 -2020
<i>Certified Forest (%)</i>	<i>Proportion of forest area under independently verified forest management schemes of total forest area</i>	FAOSTAT	2000 - 2022
Latitude	Coordinates	CEPII GeoDist	

Advanced Economies	Emerging market and middle-income economies	Low-income developing countries
Australia	Algeria	Bangladesh
Austria	Argentina	Burma
Belgium and Luxembourg	Botswana	Burundi
Canada	Brazil	Cambodia
Cyprus	Bulgaria	Cameroon
Czech Republic	Chile	Ghana
Denmark	China	Kenya
Estonia	Colombia	Lesotho
Finland	Croatia	Malawi
France	Ecuador	Mozambique
Germany	Guatemala	Nepal
Hungary	India	Niger
Iceland	Indonesia	Rwanda
Ireland	Iran	Senegal
Israel	Iraq	Tanzania, United Rep. of
Italy	Kazakhstan	Viet Nam
Japan	Malaysia	Yemen
Korea	Mauritius	Zambia
Latvia	Mexico	Zimbabwe
Lithuania	Mongolia	
Netherlands	Panama	
New Zealand	Peru	
Norway	Philippines	
Poland	Russian Federation	
Portugal	Saudi Arabia	
Slovakia	South Africa	
Slovenia	Spain	
Sweden	Sri Lanka	
United Kingdom	Swaziland	
United States of America	Tunisia	
	Turkey	
	Ukraine	
	Uruguay	

Years: 2000 - 2010

B.2 Malmquist Productivity Index using DEA frontier

The MPI calculates the relative performance of a DMU at different periods of time using the technology of a base period, measuring productivity changes and variations, which are decomposed into efficiency, technology and scale change as expressed below:

$$TFP = TC + TEC + SC \quad (B.1)$$

Therefore agricultural TFP growth is a measure of technical change (TC), which can be understood as improvement stemming from innovation and the diffusion of new knowledge and technologies; technical efficiency (TEC), which can be understood as the efficient allocation of resources and therefore the extent to which actual production practices move closer to the production frontier and; scale change (SC) which can be understood as the extent to which actual production practices move along the frontier toward a technically optimal scale. This study will use the MPI method to calculate TFP change to evaluate the relation between ecosystem services, temperature and precipitation extremes and TFP change in the short and long run.

The MPI can be expressed in terms of distance function(E) as equation B.2 and equation B.3 using the observations at time t and t+1.

$$MPI_I^t = \frac{E_I^t(x^{t+1}, y^{t+1})}{E_I^t(x^t, y^t)} \quad (B.2)$$

$$MPI_I^{t+1} = \frac{E_I^{t+1}(x^{t+1}, y^{t+1})}{E_I^{t+1}(x^t, y^t)} \quad (B.3)$$

where I denotes the orientation of MPI model. The geometric mean of equation B.2 and B.3 gives equation B.4:

$$MPI_I^G = (MPI_I^t MPI_I^{t+1})^{1/2} = \left[\left(\frac{E_I^t(x^{t+1}, y^{t+1})}{E_I^t(x^t, y^t)} \right) \cdot \left(\frac{E_I^{t+1}(x^{t+1}, y^{t+1})}{E_I^{t+1}(x^t, y^t)} \right) \right]^{1/2} \quad (B.4)$$

The input oriented geometric mean of MPI can be decomposed using the concept of input oriented technical change(TECHCH) and input oriented efficiency change(EFFCH) as given in equation B.5:

$$MPI_I^G = (MPI_I^t MPI_I^{t+1})^{1/2} = \left[\left(\frac{E_I^t(x^{t+1}, y^{t+1})}{E_I^t(x^t, y^t)} \right) \cdot \left(\frac{E_I^{t+1}(x^{t+1}, y^{t+1})}{E_I^{t+1}(x^t, y^t)} \right) \right]^{1/2} \quad (B.5)$$

The first and second terms represent the efficiency change and the technology change. By utilizing both constant returns to scale (CRS) and VRS DEA frontiers to estimate the distance functions in equation

B.5, the technical efficiency can be decomposed into scale efficiency and pure technical efficiency components. A scale efficiency change(SECH) is given in equation B.6:

$$SECH = \left[\frac{E_{vrs}^{t+1}(x^{t+1}, y^{t+1}) / E_{crs}^{t+1}(x^{t+1}, y^{t+1})}{E_{vrs}^{t+1}(x^t, y^t) / E_{crs}^{t+1}(x^t, y^t)} \cdot \frac{E_{vrs}^t(x^{t+1}, y^{t+1}) / E_{crs}^t(x^{t+1}, y^{t+1})}{E_{vrs}^t(x^t, y^t) / E_{crs}^t(x^t, y^t)} \right]^{1/2} \quad (B.6)$$

The pure technical efficiency component is given in equation B.7:

$$PECH = \frac{E_{vrs}^{t+1}(x^{t+1}, y^{t+1})}{E_{crs}^t(x^t, y^t)} \quad (B.7)$$

For this analysis, the author calculated the input-oriented MPI using STATA, with the user generated command malmq2. The TFP index was calculated using the quantity of total crop output (in USD 2015 constant prices) and the following agriculture inputs: quantity of total cropland (hectares), quantity of total agricultural fertilisers (in metric tonnes), quantity of total agricultural machinery stock(metric horsepower), quantity of persons economically active in agriculture and quantity of total agricultural capital stock (in USD 2015 constant prices).

Appendix C

Appendix to chapter 3: Effectiveness of sustainable farming practices in combating land Degradation and weather extremes: insights from Senegal's agriculture census

C.1 Data description

Table C.1: Summary statistics of variables used in regression analysis

Variable	Obs	Mean	Std. dev.	Min	Max
Yields(FCFA/ha)	665	375,026.00	1,538,600.00	110.50	19,900,000.00
Log Totyield(FCFA/ha)	665	10.53	2.07	4.71	16.81
Total days worked (nb/ha)	665	409.26	945.66	0	13,161.85
Log (TotDays)	665	4.87	1.62	0	9.49
Household head(Male)	665	0.91	0.29	0	1.00
Household head(Age)	665	54.38	12.83	24	80.00
Household head(Literate)	665	0.12	0.33	0	1.00
Household size	665	9.88	5.31	1.00	37.00
Household size(std)	665	0.00	1.00	-1.67	5.10
Title Deed	665	0.09	0.28	0	1
AGR Association membership	665	0.28	0.45	0	1.00
AGR support	665	1.88	3.85	0	60.00
Climate adapted AGR(CAA)	665	0.17	0.38	0	1.00
Conservation AGR (CA)	665	0.38	0.49	0	1.00
Structural measures to reduce soil erosion(SME)	665	0.40	0.49	0.00	1.00
Non-toxic pest management	665	0.43	0.50	0.00	1.00
Natural soil fertility management	665	0.66	0.48	0.00	1.00
Agroforestry(%)	665	0.06	0.91	0	21.03
SAP(dummy)	665	0.05	0.22	0	1.00
Synthetic fertiliser(kg/ha)	665	51.85	222.89	0	4,000.00
Synthetic fertiliser (categorical)	665	0.40	0.74	0	3.00
Irrigation(%)	665	0.26	1.01	0	10.73
Irrigation(std)	665	0.20	0.47	0	3.28
Credit	665	0.82	0.38	0	1.00
Soil siltation (Nb parcels/hh)	665	0.36	1.03	0	10.00
Water Erosion (Nb parcels/hh)	665	0.03	0.24	0	3
Erratic rain(Nb parcels/hh)	665	0.08	0.41	0	4.00
Floods(Nb parcels/hh)	665	0.25	0.16	0	2
Salinisation (Nb parcels/hh)	665	0.12	0.60	0	9.00
Pests(Nb parcels/hh)	665	0.55	1.20	0	8.00
Extreme temp	665	0.02	0.14	0	1.00
Revenue Loss(ND)	665	0.20	0.40	0	1.00
AGR zone 1: Groundnut basin	255	1	0	1	1
AGR zone 2: Casamance	190	2	0	2	2
AGR zone 3: Ferlo	33	3	0	3	3
AGR zone 4: Niayes	43	4	0	4	4
AGR zone 5: Eastern Senegal	56	5	0	5	5
AGR zone 6: Senegal River Valley	88	6	0	6	6
Region 1: Dakar	649	0.01	0.08	0	1
Region 2: Diourbel	649	0.09	0.29	0	1
Region 3: Fatick	649	0.05	0.21	0	1
Region 4: Kafrine	649	0.07	0.26	0	1
Region 5: Kaolack	649	0.13	0.34	0	1
Region 6: Kedougu	649	0.06	0.24	0	1
Region 7: Kolda	649	0.03	0.16	0	1
Region 8: Louga	649	0.08	0.27	0	1
Region 9: Matam	649	0.04	0.21	0	1
Region 10: Saint-Louis	649	0.11	0.31	0	1
Region 11: Sedhiou	649	0.09	0.29	0	1
Region 12: Tambacounda	649	0.02	0.12	0	1
Region 13: Thies	649	0.05	0.23	0	1
Region 14: Ziguinchor	649	0.17	0.38	0	1

Table C.2: HCPC data summary statistics

Variable	Obs	Mean	Std. dev.	Min	Max
Yields					
Yields(FCFA/ha)	665	375,026.00	1,538,600.00	110.50	19,900,000.00
Log yields(FCFA/ha)	665	10.53	2.07	4.71	16.81
Land and labour					
Cultivated land(ha)	665	2.89	3.39	0.01	25.32
Log Cultivated land(ha)	665	5.36	1.33	0.75	8.23
Cultivated parcels(nb)	665	2.59	1.77	1.00	12.00
Cultivated parcels(std)	665	0.00	1.00	-0.90	5.31
Total workers(nb/ha)	665	3.32	10.01	0	197.23
Log Total workers(nb/ha)	665	3.59	2.08	0	9.28
Total days worked (nb/ha)	665	409.26	945.66	0	13,161.85
Log total days	665	4.87	1.62	0	9.49
Hired workers(%)	665	0.02	0.07	0	0.60
Hired workers(std)	665	-0.03	0.90	-0.23	7.18
Household characteristics					
Household head(Male)	665	0.91	0.29	0	1.00
Household head(Age)	665	54.38	12.83	24	80.00
Household head(Literate)	665	0.12	0.33	0	1.00
Household size	665	9.88	5.31	1.00	37.00
Household size(std)	665	0.00	1.00	-1.67	5.10
AGR Association membership	665	0.28	0.45	0.00	1.00
Sustainable AGR information	665	0.57	0.49	0.00	1.00
AGR Support	665	1.88	3.86	0.00	60.00
AGR Support (std)	665	-0.02	0.87	-0.44	13.07
Agricultural practices					
Climate adaptation practices					
Crop diversification	665	0.13	0.34	0	1.00
Crop varieties	665	0.06	0.24	0	1.00
Adapted seeds	665	0.07	0.26	0	1.00
Shift cultivation	665	0.03	0.17	0	1.00
Information	665	0.02	0.14	0	1.00
Indigenous knowledge	665	0.06	0.24	0	1.00
Adapted techniques	665	0.02	0.14	0	1.00
Mechanisation	665	0.01	0.11	0	1.00
Conservation agriculture practices					
Other CA	665	0.14	0.54	0	5.00
Other CA(std)	665	0.00	1.01	-0.26	9.03
Fallow	665	0.47	1.09	0.00	10.00
Fallow(std)	665	-0.00	1.00	-0.44	8.76
Rotational pasture	665	0.11	0.52	0.00	6.00
Rotational pasture(std)	665	-0.00	1.00	-0.21	11.32
Vegetative bands	665	0.08	0.27	0.00	1.00
Vegetative bands(std)	665	-0.01	0.99	-0.29	3.42
Structural measures to reduce soil erosion					
Gabions	665	0.08	0.41	0.00	4.00
Gabions(std)	665	-0.00	1.00	-0.21	9.67
Canals	665	0.04	0.22	0.00	2.00
Canals(std)	665	-0.00	0.99	-0.20	8.87
Dykes	665	0.05	0.21	0.00	1.00
Dykes(std)	665	-0.02	0.96	-0.23	4.33
Other sustainable practices					
Non-toxic pest management	665	0.43	0.50	0.00	1.00
Natural soil fertility management	665	0.66	0.48	0.00	1.00
Agroforestry (dummy)	665	0.27	0.45	0.00	1.00
Agroforestry(%)	665	0.06	0.91	0.00	21.03
Inputs					
Synthetic pesticides	665	0.67	0.47	0.00	1.00
Synthetic fertiliser (categorical)	665	0.40	0.74	0.00	3.00
Synthetic fertiliser(kg/ha)	665	51.85	222.89	0.00	4,000.00
Renewable energy	665	0.07	0.26	0.00	1.00
Fossil fuel energy	665	0.20	0.40	0.00	1.00
Draft animals (nb)	665	1.23	1.90	0.00	20.00
Draft animals(std)	665	0.03	0.95	-0.58	9.39
Irrigation(%)	665	0.26	1.01	0.00	10.73
Irrigation(std)	665	0.20	0.47	0.00	3.28
Credit	665	0.82	0.38	0.00	1.00

C.2 Principle Component Analysis

Following (Arslan et al., 2022), variables that determine the adaptive capacity of households were used for the principal component analysis, as well as our indicators of agroecological practices. Before performing PCA, variables were transformed as follows: yield variables (FCFA/Ha & FCFA/days) and Total workers (Nb/Ha) were converted to log, while square root transformation was applied to Irrigated land (%) (proportion of irrigated land). All variables describing climate adaptation practices, conservation agriculture practices, sustainable land management practices were standardized using the z score. Draft animals, AGR support and household size were also standardized using the z score. Dummy variables were used to indicate all variables categorised as "Other sustainable practices", as well as access to credit, synthetic pesticides, renewable energy, fossil fuel energy, synthetic fertiliser, Household head(Literate), AGR Association and Sustainable AGR info.

As shown in table C.3, only variables with loadings above 0.3 were retained for the interpretation of each principal component, so as to capture only the most significant factors which contribute meaningfully to each component. Component 1 is mainly associated with variables related to land size, including cultivated land and number of cultivated parcels indicating its focus on the scale of agricultural operations. Component 2 is strongly linked with climate adapted agriculture practices, while Component 3 is most heavily associated with synthetic pesticides and yields, reflecting a focus on intensive agricultural practices and agricultural land productivity. The remaining components have mixed loadings, often involving negative associations, indicating their roles in explaining more specialized or residual variance not captured by the first three components.

Table C.3: Principal component loadings

Variable	Comp1	Comp2	Comp3	Comp4	Comp5	Comp6	Comp7	Comp8	Comp9	Comp10	Comp11	Comp12	Comp13	Unexplained
Agriculture practices														
Climate adaptation practices														
Crop diversification		0.3616												0.4143
Crop varieties		0.3289												0.5194
Adapted seeds		0.3094												0.4954
Shift cultivation														0.6178
Information														0.4143
Indigenous knowledge												0.3676		0.4671
Adapted techniques										- 0.4378				0.3910
Mechanisation													- 0.4516	0.3956
Conservation agriculture practices														
Other CA		0.3560												0.3322
Fallow							- 0.3428							0.3663
Rotational pasture									0.3481					0.6022
Vegetative bands							0.4808		0.3113					0.4070
Structural measures to prevent soil erosion														
Gabions		0.3389												0.3853
Canals											- 0.3670			0.4390
Dykes					0.3151			0.3136			- 0.3194	0.3714		0.1752
Stone bunds					- 0.3428									0.5158
Windbreaks														0.5586
Other sustainable practices														
Non-toxic pest management														0.4531
Natural soil fertility management														0.5717
Agroforestry								0.3610						0.4183
Agriculture inputs														
Synthetic pesticides			0.3706											0.4384
Renewable energy					- 0.4693									0.3798
Fossil fuel energy														0.4979
Synthetic fertiliser							- 0.3162							0.4048
Draft animals(Nb)														0.5293
Irrigated land (%)	- 0.3226													0.3844
Access to credit								0.3938						0.4611
Labour and land														
Cultivated land (ha)	0.3772													0.2451
Cultivated parcels(ha)	0.3521													0.2161
Total workers(Nb/Ha)														0.3886
Total days worked(Nb/ha)				-0.3553										
Hired workers(%)										- 0.3776		0.3551		0.3936
Household characteristics														
AGR Support (Nb visits)										0.3223	0.4841			0.3665
Household head(Literate)					- 0.4292									0.4612
AGR Association							0.3133							0.3576
Sustainable AGR info										0.3123				0.4439
Household size														0.4738
Labour and land productivity														
Yields(FCFA/Ha)	- 0.3599													0.1334
Yields(FCFA/Days)			0.4359			- 0.3028								0.1959

Table C.4 shows the component loadings, which represent the correlation between component 1 and the original variable. Components with loadings that are above .3. are retained.

Table C.4: Component rotation

Variable	Comp1	Comp2	Comp3	Comp4	Comp5	Comp6	Comp7	Comp8	Comp9	Comp10	Comp11	Comp12	Comp13	Unexplained
Crop diversification														0.4143
Crop varieties														0.5194
Adapted seeds					0.3594									0.4954
Shift cultivation														0.6178
Information								0.5724						0.4143
Indigenous knowledge														0.4671
Adapted techniques					0.6378									0.391
Mechanisation								0.6428						0.3956
Other CA		0.4973												0.3322
Fallow							0.6077							0.3663
Rotational pasture									0.4526					0.6022
Vegetative bands									0.6305					0.407
Gabions		0.4984												0.3853
Canals												-0.3129	-0.3773	0.439
Dykes											0.7936			0.1752
Stone bunds														0.5158
Windbreaks							0.4053							0.5586
Non-toxic pest management														0.4531
Natural soil fertility management														0.5717
Agroforestry										-0.4299				0.4183
AGR Support (Nb visits)												0.7032		0.3665
Synthetic pesticides										0.3421				0.4384
Renewable energy				0.5868										0.3798
Fossil fuel energy														0.4979
Synthetic fertiliser										0.5028				0.4048
Draft animals (Nb)	0.3373													0.5293
Irrigated land (%)														0.3844
Credit		-0.3698								-0.3293				0.4611
Household head(Literate)				0.5231										0.4612
AGR Association					0.5988									0.3576
Sustainable AGR Info											-0.3142			0.4439
Cultivated land(ha)	0.3792													0.2451
Cultivated parcels(ha)	0.3758										0.3831			0.2161
Total workers(Nb/ha)					0.306									0.3886
Total days worked (Nb/ha)	0.5636												0.3936	
Hired workers (%)													0.7056	0.3936
Yields(FCFA/Ha)			0.5321											0.1334
Yields(FCFA/Days)			0.5808											0.1959
Household size	0.3724				0.3036									0.4738
Component rotation matrix														
	Comp1	Comp2	Comp3	Comp4	Comp5	Comp6	Comp7	Comp8	Comp9	Comp10	Comp11	Comp12	Comp13	
Comp1	0.779	0.0785	-0.4405	0.222	-0.2728	0.1835	0.0287	0.0626	0.1253	-0.0008	0.0563	0.1015	-0.0414	
Comp2	0.0116	0.8141	0.1302	-0.0656	0.1896	0.3143	-0.2339	0.2992	0.017	-0.0335	-0.1427	-0.1202	0.024	
Comp3	0.3637	-0.125	0.7077	0.2411	0.2569	0.0871	0.3309	0.0422	0.2336	0.0398	-0.1115	0.1055	0.169	
Comp4	0.0035	-0.4563	0.0002	0.0032	0.1424	0.4143	-0.3717	0.4481	-0.2147	0.3982	-0.173	0.0924	-0.1331	
Comp5	0.258	-0.0753	0.0661	-0.7976	0.1215	-0.0552	0.1295	0.2776	0.0351	-0.084	0.4052	0.0508	-0.0221	
Comp6	-0.1684	0.0323	-0.3652	0.2496	0.5182	-0.0601	0.3439	0.2187	0.3242	0.2978	0.2936	-0.2043	-0.1222	
Comp7	-0.0583	-0.2244	-0.0061	0.0358	-0.1224	-0.1449	-0.4123	0.299	0.6377	-0.3213	-0.0636	-0.2715	0.2489	
Comp8	-0.0084	-0.0969	-0.0134	0.3109	0.3583	0.1448	-0.1926	0.0378	-0.2697	-0.6448	0.4096	0.2198	-0.0352	
Comp9	-0.2575	0.0374	0.1302	-0.0382	-0.2463	0.4925	-0.0571	-0.2627	0.4766	0.0946	0.3349	0.3345	-0.2798	
Comp10	0.1628	0.1353	0.1307	0.0679	0.1612	-0.5936	-0.4107	-0.0189	0.1236	0.1847	0.0068	0.3573	-0.4572	
Comp11	-0.0978	0.0153	-0.3272	-0.1799	0.2952	0.0197	0.0565	-0.0694	0.1845	-0.0536	-0.3775	0.642	0.4045	
Comp12	-0.1352	0.1427	0.0951	0.2164	-0.3289	-0.1952	-0.031	0.3365	-0.1456	0.2944	0.4403	0.2838	0.5126	
Comp13	0.2043	-0.0205	-0.0081	-0.0811	0.3077	0.0791	-0.4226	-0.5485	-0.003	0.3023	0.2516	-0.2386	0.399	

Table C.5 reports the Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy. The KMO measure takes values between 0 and 1, with small values indicating that overall the variables have little in common to warrant a principal components analysis and values above 0.5 are considered satisfactory for a principal components analysis. The variables used in the factor analysis and construction of PC indicators have an overall score of 0.59, which is therefore satisfactory. While some indicators score below 0.5, they are nonetheless retained due to their theoretical importance (as is the case for yield indicators and land size). Additionally, the exploratory nature of this study further justifies retaining agriculture practice indicators (such as dykes) with a low score, in order to much information as possible and identify any unexpected patterns or hypotheses for future research.

Table C.5: Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy

Variable	kmo
Crop diversification	0.762
Crop varieties	0.774
Adapted seeds	0.777
Shift cultivation	0.805
Information	0.577
Indigenous knowledge	0.750
Adapted techniques	0.671
Mechanisation	0.700
Other CA	0.691
Fallow	0.601
Rotational pasture	0.413
Vegetative bands	0.574
Gabions	0.706
Canals	0.678
Dykes	0.297
Stone bunds	0.507
Windbreaks	0.620
Non-toxic pest management	0.728
Natural soil fertility management	0.742
Agroforestry	0.722
AGR Support (Nb visits)	0.642
Synthetic pesticides	0.750
Renewable energy	0.593
Fossil fuel energy	0.747
Synthetic fertiliser	0.643
Draft animals (Nb)	0.888
Irrigated land (%)	0.858
Credit	0.720
Household head(Literate)	0.652
AGR Association	0.666
Sustainable AGR Info	0.770
Cultivated land(ha)	0.419
Cultivated parcels(ha)	0.591
Total workers(Nb/ha)	0.750
Total days worked(Nb/ha)	0.6936
Hired workers (%)	0.548
Yields(FCFA/Ha)	0.439
Yields(FCFA/Days)	0.333
Household size	0.778
Overall	0.598

Table C.6: Determinants of adoption of sustainable agriculture practices

SAP	(1)	(2)	(3)
Household size	0.003 (0.046)	-0.001 (0.049)	0.001 (0.053)
Household Head(Male)	0.497 (0.946)	0.762 (0.981)	0.137 (1.078)
Household Head(Literate)	1.648** (0.739)	1.897** (0.801)	2.355** (0.988)
Household Head(Age)	0.036** (0.018)	0.031* (0.018)	0.025 (0.022)
Log(Cultivated Land)	-0.248 (0.216)	-0.106 (0.275)	-0.162 (0.321)
Title Deed	2.131*** (0.810)	2.059** (0.822)	1.615* (0.906)
Credit	1.341 (0.838)	1.133 (0.863)	1.160 (1.068)
AGR Support	1.613** (0.746)	1.732** (0.756)	1.948** (0.817)
AGR Association	-1.881** (0.782)	-1.868** (0.808)	-1.942** (0.898)
Distance to Market	0.531** (0.268)	0.565* (0.302)	0.411 (0.381)
Sustainable AGR Info	0.408 (0.558)	0.235 (0.583)	0.852 (0.668)
Siltation	0.222 (0.234)	0.326 (0.217)	0.348 (0.289)
Extreme Temp	1.705* (0.980)	1.734* (0.968)	2.450** (1.233)
Erratic rain	0.766** (0.350)	0.742** (0.367)	0.809* (0.481)
Pests	1.715*** (0.571)	1.714*** (0.618)	1.356* (0.718)
Flooding	1.243 (0.830)	1.360 (0.857)	2.171** (1.044)
Revenue Loss(ND)	4.264*** (0.772)	4.027*** (0.755)	4.204*** (0.985)
Agroecological zone fixed effects	No	Yes	No
Region fixed effects	No	No (.)	Yes
Cons	-9.631*** (1.875)	-10.567*** (2.179)	-4.240* (2.342)
N	673	673	673
Penalized log likelihood	-36.8876	-33.32269	-28.67963
Wald chi2	47.66	48.52	42.73
P-value	0.0001	0.0009	0.0618

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table C.7: Determinants of adoption of selected sustainable agriculture practices

	(CAA)	(SME)	(CA)	(AF)	(NSFM)	(SPM)
Household Size	0.057* (0.031)	-0.004 (0.023)	0.018 (0.019)	0.020 (0.020)	0.046** (0.022)	0.023 (0.019)
Household Head(Gender)	-0.297 (0.567)	-0.253 (0.385)	-0.272 (0.317)	0.285 (0.344)	-0.261 (0.321)	-0.384 (0.335)
Household Head(Literate)	0.440 (0.506)	1.281*** (0.346)	-0.185 (0.290)	0.604** (0.288)	-0.088 (0.342)	-0.121 (0.291)
Household Head(Age)	0.007 (0.013)	0.011 (0.009)	0.006 (0.007)	-0.000 (0.008)	-0.000 (0.008)	-0.007 (0.008)
Log(Cultivated Land)	0.147 (0.164)	-0.039 (0.096)	-0.024 (0.086)	-0.101 (0.092)	0.136 (0.089)	-0.042 (0.086)
Title Deed	0.331 (0.595)	1.139*** (0.434)	0.150 (0.323)	-0.239 (0.369)	-0.519 (0.399)	-0.603* (0.362)
Credit	0.743 (0.511)	1.462*** (0.376)	-0.051 (0.296)	-0.117 (0.312)	-0.237 (0.369)	0.472 (0.304)
AGR Support	1.614*** (0.460)	0.243 (0.253)	0.616*** (0.229)	0.748*** (0.246)	0.261 (0.234)	0.606*** (0.234)
AGR Association	-0.208 (0.406)	-0.595** (0.292)	-0.235 (0.229)	-0.190 (0.244)	-0.313 (0.255)	0.048 (0.238)
Distance to Market	-0.033 (0.201)	0.374*** (0.133)	0.490*** (0.112)	-0.171 (0.118)	0.030 (0.121)	0.247** (0.111)
Sustainable AGR Info	1.373*** (0.400)	-0.287 (0.239)	0.589*** (0.212)	0.154 (0.220)	-0.063 (0.229)	1.079*** (0.213)
Siltation	0.089 (0.151)	0.115 (0.097)	0.044 (0.092)	0.051 (0.099)	-0.271*** (0.101)	0.278** (0.108)
Extreme Temp	4.399*** (0.902)	-0.160 (0.815)	-0.323 (0.690)	-0.034 (0.702)	-0.409 (0.831)	1.449** (0.721)
Erratic Rain	-0.352 (0.439)	0.445* (0.246)	0.445* (0.235)	-0.013 (0.250)	0.230 (0.281)	0.060 (0.233)
Pests	1.390*** (0.412)	-0.270 (0.282)	0.619*** (0.240)	0.620** (0.253)	0.626** (0.255)	0.468* (0.252)
Flooding	1.137 (0.831)	0.569 (0.659)	-0.639 (0.569)	0.158 (0.573)	0.002 (0.628)	0.401 (0.558)
Revenue Loss(ND)	4.558*** (0.402)	0.402 (0.271)	0.493** (0.227)	0.341 (0.239)	0.358 (0.268)	-0.338 (0.236)
Region fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
N	667	667	673	667	673	667
Log likelihood	-149.8028	-283.3786	-380.3832	-347.9532	-308.0437	-359.3686
P-value	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Pseudo R2	0.5187	0.3721	0.1544	0.1745	0.2851	0.2139

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table C.8: Effect of selected sustainable agriculture practices, environment and weather related production challenges on agricultural land productivity

Log(TotYield)	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Household Size	-0.039*** (0.013)	-0.040*** (0.013)	-0.037*** (0.012)	-0.038*** (0.013)	-0.037*** (0.012)	-0.036*** (0.012)	-0.037*** (0.013)	-0.036*** (0.013)	-0.036*** (0.012)
Household Head(Male)	-0.415* (0.231)	-0.399* (0.232)	-0.417* (0.231)	-0.390* (0.230)	-0.383* (0.230)	-0.371 (0.231)	-0.379 (0.231)	-0.389* (0.231)	-0.390* (0.231)
Household Head(Literate)	0.007 (0.200)	0.039 (0.201)	-0.006 (0.200)	0.098 (0.199)	0.060 (0.199)	0.041 (0.200)	0.011 (0.200)	0.029 (0.200)	0.027 (0.200)
Household Head(Age)	-0.003 (0.005)	-0.004 (0.005)	-0.004 (0.005)	-0.001 (0.005)	-0.002 (0.005)	-0.002 (0.005)	-0.003 (0.005)	-0.003 (0.005)	-0.003 (0.005)
Fertiliser	0.419*** (0.100)	0.414*** (0.100)	0.435*** (0.100)	0.417*** (0.100)	0.398*** (0.099)	0.385*** (0.100)	0.423*** (0.100)	0.420*** (0.100)	0.421*** (0.100)
Credit	0.154 (0.168)	0.182 (0.170)	0.137 (0.171)	0.130 (0.168)	0.206 (0.171)	0.160 (0.171)	0.200 (0.168)	0.211 (0.170)	0.193 (0.171)
AGR Support	0.069** (0.031)	0.069** (0.031)	0.068** (0.031)	0.074** (0.031)	0.069** (0.031)	0.071** (0.031)	0.072** (0.031)	0.077** (0.031)	0.079** (0.031)
AGR Association	0.076 (0.154)	0.074 (0.154)	0.088 (0.153)	0.118 (0.154)	0.093 (0.153)	0.079 (0.154)	0.064 (0.154)	0.048 (0.154)	0.049 (0.153)
Irrigation(%)	0.151*** (0.035)	0.146*** (0.034)	0.149*** (0.034)	0.145*** (0.035)	0.140*** (0.034)	0.141*** (0.034)	0.146*** (0.035)	0.148*** (0.034)	0.149*** (0.034)
Log(TotDays)	0.670*** (0.051)	0.676*** (0.052)	0.668*** (0.051)	0.674*** (0.051)	0.680*** (0.051)	0.679*** (0.051)	0.662*** (0.051)	0.660*** (0.051)	0.661*** (0.051)
SME	-0.158 (0.158)			-0.125 (0.158)			0.027 (0.160)		
Extreme Temp	-1.514*** (0.518)	-0.270 (0.945)	-1.549*** (0.548)						
SME*Extreme Temp	2.755** (1.076)								
CAA		0.139 (0.176)			-0.036 (0.171)			0.028 (0.171)	
CAA*Extreme Temp		-0.870 (1.097)							
CA*Extreme Temp			-0.089 (0.138)			-0.028 (0.139)			-0.056 (0.138)
CA*Extreme Temp			2.195** (0.986)						
Erratic Rain				-0.993*** (0.242)	-0.643*** (0.166)	-0.788*** (0.297)			
SME*Erratic Rain				0.851*** (0.308)					
CAA*Erratic Rain					0.935** (0.386)				
CA*Erratic Rain						0.430 (0.350)			
Water Erosion							0.172 (0.579)	-0.782*** (0.275)	-0.791*** (0.283)
SME*Water Erosion							-1.175* (0.647)		
CAA*Water Erosion								0.249 (0.994)	
CA*Water Erosion									0.176 (0.789)
Cons	7.667*** (0.481)	7.635*** (0.483)	7.748*** (0.486)	7.501*** (0.479)	7.444*** (0.480)	7.488*** (0.484)	7.576*** (0.480)	7.611*** (0.482)	7.639*** (0.484)
Agroecological zone fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	649	649	649	649	649	649	649	649	649
R2	0.4661	0.4611	0.4645	0.4720	0.4705	0.4668	0.4671	0.4644	0.4645
Adj. R2	0.4509	0.4457	0.4492	0.4569	0.4553	0.4515	0.4519	0.4491	0.4492

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table C.9: Effect of selected sustainable agriculture practices, environment and weather related production challenges on agricultural land productivity

Log(TotYield)	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Household Size	-0.038*** (0.012)	-0.034*** (0.012)	-0.037*** (0.012)	-0.037*** (0.012)	-0.034*** (0.012)	-0.034*** (0.012)	-0.038*** (0.012)	-0.037*** (0.012)	-0.035*** (0.012)
Household Head(Male)	-0.386* (0.232)	-0.353 (0.229)	-0.378 (0.230)	-0.408* (0.232)	-0.390* (0.230)	-0.399* (0.231)	-0.411* (0.232)	-0.369 (0.231)	-0.391* (0.231)
Household Head(Literate)	0.052 (0.201)	0.115 (0.199)	0.004 (0.201)	0.027 (0.200)	0.040 (0.199)	0.031 (0.199)	0.035 (0.200)	0.078 (0.199)	0.034 (0.200)
Household Head(Age)	-0.004 (0.005)	-0.002 (0.005)	-0.003 (0.005)	-0.004 (0.005)	-0.002 (0.005)	-0.003 (0.005)	-0.004 (0.005)	-0.002 (0.005)	-0.003 (0.005)
Fertiliser	0.446*** (0.101)	0.418*** (0.100)	0.440*** (0.100)	0.438*** (0.100)	0.400*** (0.100)	0.435*** (0.100)	0.419*** (0.100)	0.407*** (0.100)	0.418*** (0.099)
Credit	0.181 (0.169)	0.164 (0.167)	0.216 (0.167)	0.169 (0.168)	0.166 (0.169)	0.206 (0.168)	0.165 (0.168)	0.115 (0.168)	0.200 (0.168)
AGR Support	0.067** (0.031)	0.069** (0.031)	0.070** (0.031)	0.070** (0.031)	0.071** (0.031)	0.079** (0.031)	0.070** (0.031)	0.077** (0.031)	0.081** (0.031)
AGR Association	0.073 (0.154)	0.104 (0.152)	0.068 (0.153)	0.059 (0.154)	0.064 (0.154)	0.033 (0.153)	0.088 (0.154)	0.095 (0.153)	0.054 (0.153)
Irrigation(%)	0.143*** (0.034)	0.135*** (0.034)	0.145*** (0.034)	0.150*** (0.034)	0.145*** (0.034)	0.152*** (0.034)	0.146*** (0.034)	0.142*** (0.034)	0.148*** (0.034)
Log(TotDays)	0.683*** (0.052)	0.690*** (0.052)	0.670*** (0.052)	0.668*** (0.051)	0.676*** (0.051)	0.657*** (0.051)	0.677*** (0.052)	0.678*** (0.051)	0.661*** (0.051)
Agroforestry	-0.211 (0.142)	-0.275* (0.142)	-0.129 (0.142)						
Extreme Temp	-0.949 (0.579)			-1.090 (0.817)			0.048 (0.814)		
Agroforestry*Extreme Temp	0.259 (0.940)								
Erratic Rain		-0.849*** (0.194)			-0.819*** (0.296)			-0.210 (0.213)	
Agroforestry*Erratic Rain		0.946*** (0.303)							
Water Erosion			0.279 (0.581)			-0.357 (1.156)			-0.468 (0.395)
Agroforestry*Water Erosion			-1.265* (0.649)						
NSFM				-0.260 (0.161)	-0.256 (0.160)	-0.247 (0.160)			
NSFM*Extreme Temp				0.337 (0.983)					
NSFM*Erratic Rain					0.484 (0.346)				
NSFM*Water Erosion						-0.429 (1.187)			
NPM							-0.051 (0.139)	-0.052 (0.139)	-0.070 (0.139)
NPM*Extreme Heat							-1.295 (0.986)		
NPM*Erratic Rain								-0.527* (0.300)	
NPM*Water Erosion									-0.527 (0.525)
Cons	7.654*** (0.483)	7.462*** (0.477)	7.579*** (0.479)	7.911*** (0.508)	7.723*** (0.506)	7.864*** (0.505)	7.697*** (0.490)	7.536*** (0.488)	7.632*** (0.489)
Agroecological zone fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	649	649	649	649	649	649	649	649	649
R2	0.4621	0.4752	0.4687	0.4625	0.488	0.4666	0.4619	0.4684	0.4655
Adj. R2	0.4467	0.4602	0.4535	0.4471	0.4537	0.4513	0.4465	0.4532	0.4503

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table C.10: Determinants of adoption of selected sustainable agriculture practices

Log(TotYield)	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Household Size	-0.010 (0.012)	-0.013 (0.012)	-0.012 (0.012)	-0.012 (0.012)	-0.011 (0.012)	-0.011 (0.012)	-0.009 (0.012)
Household Head(Male)	-0.201 (0.211)	-0.199 (0.213)	-0.211 (0.211)	-0.180 (0.211)	-0.180 (0.212)	-0.170 (0.216)	-0.194 (0.211)
Household Head(Literate)	0.075 (0.185)	0.079 (0.186)	0.062 (0.186)	0.044 (0.185)	0.063 (0.185)	0.095 (0.186)	0.074 (0.184)
Household Head(Age)	-0.004 (0.005)	-0.004 (0.005)	-0.005 (0.005)	-0.004 (0.005)	-0.004 (0.005)	-0.004 (0.005)	-0.004 (0.005)
Fertiliser	0.320*** (0.089)	0.332*** (0.090)	0.330*** (0.089)	0.315*** (0.089)	0.291*** (0.091)	0.326*** (0.090)	0.321*** (0.089)
Credit	-0.022 (0.162)	-0.021 (0.162)	-0.052 (0.161)	-0.065 (0.161)	0.000 (0.164)	-0.047 (0.162)	-0.028 (0.160)
AGR Support	0.048* (0.029)	0.050* (0.029)	0.046 (0.029)	0.057** (0.029)	0.054* (0.029)	0.050* (0.029)	0.056* (0.029)
AGR Association	-0.198 (0.144)	-0.239 (0.145)	-0.231 (0.144)	-0.213 (0.143)	-0.210 (0.145)	-0.231 (0.144)	-0.243* (0.143)
Irrigation(%)	0.266*** (0.065)	0.276*** (0.065)	0.275*** (0.064)	0.275*** (0.065)	0.277*** (0.065)	0.274*** (0.065)	0.277*** (0.064)
Log(TotDays)	0.336*** (0.040)	0.327*** (0.040)	0.323*** (0.040)	0.327*** (0.040)	0.340*** (0.050)	0.327*** (0.040)	0.319*** (0.040)
Cluster 1	0.000 (.)	0.000 (.)	0.000 (.)	0.000 (.)	0.000 (.)	0.000 (.)	0.000 (.)
Cluster 2	-1.589*** (0.243)	-1.570*** (0.238)	-1.407*** (0.243)	-1.655*** (0.248)	-1.215*** (0.316)	-1.569*** (0.242)	-1.566*** (0.235)
Cluster 3	-2.091*** (0.188)	-2.104*** (0.186)	-2.091*** (0.185)	-2.020*** (0.190)	-1.948*** (0.207)	-2.123*** (0.188)	-2.090*** (0.183)
Erratic Rain	-0.591 (0.554)						
Cluster 1c:Erratic Rain	0.000 (.)						
Cluster 2c:Erratic Rain	0.669 (0.819)						
Cluster 3c:Erratic Rain	-0.352 (0.796)						
Flooding		-0.102 (0.691)					
Cluster 1c:Flooding		0.000 (.)					
Cluster 2c:Flooding		0.911 (1.288)					
Cluster 3c:Flooding		0.301 (0.832)					
Extreme Temp			0.013 (1.075)				
Cluster 1'Extreme Temp			0.000 (.)				
Cluster 2'Extreme Temp			-1.265 (1.217)				
Cluster 3'Extreme Temp			-0.830 (1.390)				
Siltation				0.006 (0.276)			
Cluster 1'Siltation				0.000 (.)			
Cluster 2'Siltation				0.309 (0.360)			
Cluster 3'Siltation				-0.177 (0.284)			
Pests					0.383 (0.258)		
Cluster 1'Pests					0.000 (.)		
Cluster 2'Pests					-0.765* (0.455)		
Cluster 3'Pests					-0.430 (0.345)		
Salinisation						-0.074 (0.775)	
Cluster 1'Salinisation						0.000 (.)	
Cluster 2'Salinisation						0.274 (1.196)	
Cluster 3'Salinisation						0.349 (0.821)	
Water Erosion							-0.715*** (0.249)
Cluster 1'Water Erosion							0.000 (.)
Cluster 3'Water Erosion							0.619 (1.540)
Cluster 3'Water Erosion							0.000 (.)
Cons	10.520*** (0.511)	10.589*** (0.514)	10.685*** (0.513)	10.623*** (0.513)	10.314*** (0.534)	10.577*** (0.519)	10.599*** (0.510)
N	642	642	642	642	642	642	642
R2	0.4828	0.4787	0.4829	0.4861	0.4808	0.4790	0.4849
Adj. R2	0.4704	0.4663	0.4705	0.4738	0.4684	0.4665	0.4734

Standard errors in parentheses
* p < 0.10, ** p < 0.05, *** p < 0.01

Table C.11: Robustness test: Effect of COVID-19 on agriculture land productivity

Log(TotYield)	(1)
Household Size	-0.037*** (0.013)
Household Head(Male)	-0.410* (0.232)
Household Head(Literate)	0.022 (0.201)
Household Head(Age)	-0.004 (0.005)
Fertiliser	0.430*** (0.100)
Credit	0.291* (0.176)
AGR Support	0.065** (0.031)
AGR Association	0.081 (0.154)
Irrigation (%)	0.148*** (0.034)
Log(TotDays)	0.664*** (0.052)
SAP	0.325 (0.312)
COVID 19 Dummy	0.189 (0.135)
Agroecological zone fixed effects	Y
N	649
R2	0.3770
Adj. R2	0.3652

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

