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Trade-offs between water use and food production in Egyptian agriculture under an uncertain future

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Agriculture and Food Security

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Declaration

I declare that the thesis has been composed by myself and that the work has not been submitted for any other degree or professional qualification. I confirm that the work submitted is my own, except where work which has formed part of jointly-authored publications has been included. My contribution and those of the other authors to this work have been explicitly indicated below. I confirm that appropriate credit has been given within this thesis where reference has been made to the work of others.

The work presented in Chapter 2 was published in Sattar, A., Brown, C., Rounsevell, M., & Alexander, P. (2024). Typology analysis of Egyptian agricultural households reveals increasing income diversification and abandonment of agricultural activities. *Agricultural Systems*, 218, 104000. <https://doi.org/10.1016/j.agsy.2024.104000>. I led the research and was responsible for the conceptualisation, methodology, software, data curation, analysis, original manuscript draft, and reviewing and editing. The other co-authors contributed to the reviewing and editing, and supervision.

The work presented in Chapter 3 was published in Sattar, A., Moulds, S., Brown, C., Rounsevell, M., & Alexander, P. (2026). A coupled land use change-ecohydrological model for multi-seasonal arid agricultural systems: an Egyptian case study. *Environmental Modelling & Software*, 197, 106845. <https://doi.org/10.1016/j.envsoft.2025.106845>. I led the research and was responsible for the conceptualisation, methodology, software, data curation, analysis, original manuscript draft, and reviewing and editing. The other co-authors contributed to the methodology, conceptualisation, reviewing and editing, and supervision.

The work presented in Chapter 4 is under review in Sattar, A., Brown, C., Rounsevell, M., & Alexander, P. (under review). Climate and socioeconomic pressures expose the limits of dietary change and agricultural expansion in Egypt. I led the research and was responsible for the conceptualisation, methodology, software, data curation, analysis, original manuscript

draft, and reviewing and editing. The other co-authors contributed to the methodology, conceptualisation, reviewing and editing, and supervision.

Acknowledgement of use of AI

During the preparation of this work, I used ChatGPT by OpenAI and Perplexity AI primarily to check grammar and spelling throughout the thesis. I also used AI to draft and debug code, and as a research tool.

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Abstract

Egypt's agricultural system is facing increasing pressure from limited water resources – sourced predominantly from the Nile River – rising demand, and climate change. Higher temperatures and evapotranspiration will intensify water stress, though CO₂ fertilisation may partially offset impacts by boosting yields and reducing water use. Meanwhile, upstream damming and extreme weather further threaten water availability and crop productivity. These challenges demand adaptive, integrated land and water management to safeguard food security for a rapidly growing population.

Despite these constraints, Egypt maintains agricultural potential due to its climate suitability for year-round crop production, extensive irrigation infrastructure, and underutilised groundwater resources. Policy efforts have focused on irrigation modernisation, improved seed varieties, and large-scale agricultural expansion. Agriculture accounts for 17% of employment and 13% of the economy, while most of the farmers are smallholders. Additionally, food subsidies have been used to help maintain food security, although they have also deepened reliance on imports, increasing vulnerability to global market fluctuations.

The interconnected nature of these challenges necessitates analytical tools that are capable of integrating biophysical and socioeconomic dimensions. Existing biophysical models effectively simulate climate impacts but treat farmer decision-making as static, whilst agent-based models capture human responses but simplify biophysical dynamics. This thesis addresses these limitations by analysing current characteristics and recent trends in farming households, and then developing a coupled agent-based land-use change and ecohydrological model that integrates farmer decision-making with biophysical processes to evaluate climate change and socioeconomic impacts on agricultural production and resources.

The research begins with a typology analysis of nationally representative labour market surveys from 2012 and 2018, revealing four distinct agricultural household clusters: specialised farming households focused on intensive production; village households reliant on subsistence agriculture; diversified income households combining agricultural and non-farm activities; and landlord households with minimal direct involvement. The analysis

demonstrates trends towards income diversification away from agricultural income as well as agricultural abandonment.

Building on these findings, this study develops a coupled modelling framework that integrates the agent-based land-use change model CRAFTY (Competition for Resources between Agent Functional Types) with the ecohydrological model SWAT+ (Soil and Water Assessment Tool). Both models operate on the same 900 m resolution grid: SWAT+ simulates daily crop growth and irrigation demand, while CRAFTY allocates land use annually by modelling competition between 56 agent functional types based on socioeconomic resources and agent characteristics.

Agents represent distinct cropping strategies and production systems, broadly classified as either commercial or subsistence types. Commercial agents reflect capital-intensive farmers who use deficit irrigation and depend on higher levels of financial and manufactured resources. In contrast, subsistence agents represent smallholders who rely on traditional flood irrigation and are more likely to persist under lower profitability conditions. These categories capture key differences in access to resources, irrigation practices, and labour dynamics, enabling the model to simulate transitions between farming systems across a range of future scenarios.

To evaluate future outcomes, the model applies a set of integrated socioeconomic and climate scenarios combining assumptions about diets, trade, and farmer behaviour, based on the Shared Socioeconomic Pathways (SSPs) and Representative Concentration Pathways (RCPs). Under high-emission scenarios, yields for key crops increase by up to 25%, with water use efficiency improving by 69%, while low-emission scenarios show modest gains (4%). Production shortfalls vary widely: the inequality pathway results in the smallest gap (22%), while the sustainability scenario still leaves a 52% shortfall despite improved efficiency. No scenario fully meets demand for domestic production, with shortfalls shaped by population growth, dietary patterns, and trade dynamics. Notably, the regional rivalry scenario, which targets agricultural self-sufficiency but also drives high exports, faces the largest gap, with unmet demand for domestic production reaching 78%.

This research shows that neither agricultural expansion nor dietary change alone can close the food production gap under Egypt's limited water and land resources. The coupled model

highlights the trade-offs that emerge when policies focus on single objectives, underscoring the need for integrated strategies that account for socioeconomic diversity, spatial variability, and environmental constraints. By capturing how different farming households respond to change, the model supports more adaptive and targeted planning, emphasising the combined role of population trends, dietary shifts, trade policy, strategic agricultural expansion, and irrigation efficiency in ensuring future food security.

Lay summary

Egypt's agriculture is under growing pressure from limited water supplies, a rising population, and the effects of climate change. With most of its water coming from the Nile River, Egypt is vulnerable to higher temperatures, changing weather patterns, and upstream dams. These factors make it harder to produce enough food for a population that is growing rapidly.

Despite these challenges, Egypt has some important advantages: a climate that allows crops to be grown all year, a long history of irrigation, and access to groundwater. The government has invested in improving irrigation systems, seeds, and expanding farmland. However, many farmers are smallholders who face economic difficulties, and the country still relies heavily on food imports, making it vulnerable to global price changes.

This thesis explores how Egypt's agriculture could change in the future under different conditions, such as changes in climate, diets, population, trade policies, and farming practices. It uses a new type of computer model that combines two tools: one that simulates water and crop growth, and another that represents how different types of farmers respond to climate and societal changes. Together, these models help show how different farming systems might respond to future pressures.

The research begins by analysing national survey data, which reveals four main types of farming households, from commercial and subsistence farmers to part-time and landlord farmers. It then uses the model to test a range of possible future scenarios. The results show that climate change might increase crop yields under some conditions, but even the best-case scenarios leave a gap between how much food is produced and how much is needed. For example, under one scenario with high population growth and limited international cooperation, Egypt may face a shortfall of up to 78% in meeting its food demand from domestic production.

The study concludes that no single solution – such as healthier diets or expanding farmland – is enough on its own. Instead, a mix of strategies is needed, tailored to different types of farmers and local conditions. The model developed in this thesis can help guide better policies to support food security in Egypt's uncertain future.

To my father, whose wisdom and values have profoundly shaped the person I have become. Although you are not here to witness this achievement, your influence has guided every stage of this journey.

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الله يرحمك ويجعل مثواك الجنة

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Abbreviations

ABM	Agent-Based Model
AFT	Agent Functional Type
ARC	Agricultural Research Centre
CAAES	Central Administration for Agricultural Extension Services
CAPMAS	Central Agency for Public Mobilization and Statistics
CMIP6	Coupled Model Intercomparison Project Phase 6
CO ₂	Carbon Dioxide
CRAFTY	Competition for Resources between Agent Functional Types
DRC	Desert Research Centre
EPIC	Erosion Productivity Impact Calculator
ESA	European Space Agency
ET	Evapotranspiration
FAMD	Factor Analysis of Mixed Data
FAO	Food and Agriculture Organization of the United Nations
GDP	Gross Domestic Product
GERD	Grand Ethiopian Renaissance Dam
ha	Hectare
HCPC	Hierarchical Clustering on Principal Components
HRU	Hydrological Response Unit
IPCC	Intergovernmental Panel on Climate Change
LHS	Latin Hypercube Sampling
LUC-EH	Land Use Change-Ecohydrological

m a.s.l.	Meters above sea level
MENA	Middle East and North Africa
Mt	Million tonnes
NRMSE	Nominal Root Mean Square Error
NSAS	Nubian Sandstone Aquifer System
PCA	Principal Component Analysis
RCP	Representative Concentration Pathway
RUE	Radiation Use Efficiency
SMS	Subject Matter Specialists
SSP	Shared Socioeconomic Pathway
SWAT+	Soil and Water Assessment Tool Plus
VEW	Village Extension Workers
WUE	Water Use Efficiency

1 Introduction

Climate change presents growing risks to environmental and socioeconomic systems, particularly in arid and semi-arid regions where land and water resources are already under strain (El-Beltagy & Madkour, 2012; Malhi et al., 2021). These regions are experiencing rising temperatures, more frequent and prolonged droughts, and intensifying pressures on freshwater supplies (Zittis et al., 2022). Agriculture, which depends heavily on irrigation in these contexts, is especially vulnerable. As climate impacts deepen, proactive adaptation is essential to safeguard productivity, manage competing demands, and support long-term resilience (Ortiz-Bobea et al., 2021).

Egypt, located within the arid and semi-arid Middle East and North Africa (MENA) region, exemplifies many of these challenges. The country's society and development have long been shaped by its dependence on the Nile River, with 95% of its population concentrated in just 4% of its 1 million km² land area along its river and delta regions (Abutaleb et al., 2018; Arab Republic of Egypt, 2023; Gado & El-Agha, 2021). The country's population increased from 20.4 million to 100.4 million between 1950 and 2019 and is expected to reach anything from 142.8 million to 179.1 million by 2050 (UN, 2019). While the population has boomed and Gross Domestic Product (GDP) has increased at an average rate of 4.4% between 1989 and 2018, water availability has remained constant (Nikiel & Eltahir, 2021). This has resulted in the total annual renewable water resource declining to 590 m³/capita in 2019 (Tutwiler, 2021), well below the 1000 m³/capita defined as the absolute water scarcity level (Falkenmark et al., 1989).

Egypt depends on the Nile River for 98.26% of its annual renewable water resource (Heggy et al., 2021). The agricultural sector accounts for 80% of total water use (Fuglie et al., 2020). Due to limited rainfall, rainfed agriculture is responsible for only 2% of production, and is limited to the coastal areas by the Mediterranean (Kassim et al., 2018). As water demand has grown, Egypt has increased water availability through the use of unconventional water resources, including groundwater and irrigation water reuse (Nikiel & Eltahir, 2021). Additionally, there has been a long history of horizontal expansion through desert reclamation to increase cultivated land (Barnes, 2012). However, this has resulted in further straining the limited water resource and has not kept up with the increasing demand for land. Current water

stresses are likely to be exacerbated by climate change in a number of ways. Rising sea levels may result in flooding of highly productive land in the Nile Delta, and increased saltwater intrusion in shallow reservoirs could lead to the salination of groundwater resources in coastal areas in the Nile Delta (Gado & El-Agha, 2021). Additionally, temperature increases are expected to result in increased evapotranspiration, reduced crop water productivity, reduced yields, and increased irrigation water requirements (Omar et al., 2021).

Egypt has undergone a number of policy transitions, but has always prioritised the agricultural sector and increasing water availability, cultivated land, and yields (Verhoeven, 2015). Major policy goals include prioritising land reclamation of the desert to increase cultivated area, installation of drainage systems to improve agricultural water re-use, mandating drip irrigation use in newly reclaimed areas to improve crop water productivity, the use of high yield seed varieties, and subsidising the cost of agricultural inputs, to name but a few (Bush, 2007; Fuglie et al., 2020). As a result, Egypt has a highly productive agricultural system, with some of the highest yields in the world (Nikiel & Eltahir, 2021). However, these efforts have not been able to meet its growing demand for agricultural products. Consequently, Egypt has become dependent on 'virtual water' through food imports (Nikiel & Eltahir, 2021). Nikiel and Eltahir (2021) estimate that annual virtual water usage will increase from 40 km³ in the 2010s to 65 km³ in the 2020s. However, this dependence on imports has left Egypt vulnerable to global food price shocks, which some credit with being partially responsible for the political crises of the 2011 Arab Spring uprising (Soffiantini, 2020).

Modelling has the potential to improve the understanding of future consequences and interactions of this range of drivers impacting agricultural systems in locations such as Egypt's, and help identify beneficial policies and land manager actions. However, the agricultural system is a complex socioecological system, comprised of interconnected social, economic, and biophysical sub-systems, which reduces the usefulness of conventional disciplinary models (Lippe et al., 2019). There has been an increased interest in coupled models to represent the aforementioned complex system, as these are more apt at representing linked dynamics between the sub-systems (Du et al., 2020). Process-based models are effective at accounting for constituent processes and do not presume system-level outcomes. Process-based ecohydrological models are used to simulate water and vegetation dynamics, enabling the explicit modelling of underlying processes, which can be invaluable in managing limited

and stressed water resources in agricultural systems (Han et al., 2021). Agent-based models represent heterogeneous behaviour and decision-making processes in the agricultural system and can be applied to create more representative ex-ante policy analyses by modelling interactions at the individual levels and allowing emergent properties of the system to be represented (Kremmydas et al., 2018).

While the coupling of ecohydrological and agent-based models enables more realistic analysis of spatiotemporal human–environment interactions, such integrated frameworks remain rare, especially at the national scale and in data-scarce contexts. Where coupled models do exist, they primarily focus on short-term irrigation scheduling or technology adoption, overlooking land use and cropping decisions that are critical for long-term adaptation in arid and semi-arid systems (Du et al., 2020; Harms et al., 2023; O'Keeffe et al., 2018). To date, no model has captured the full complexity of Egypt's agricultural system, spanning water constraints, land use change, and diverse land manager behaviours. This research addresses that gap by developing a coupled agent-based land-use change-ecohydrological model for Egypt, capable of simulating adaptive decision-making and biophysical feedbacks across scales, to generate policy-relevant insights under future climate and socioeconomic scenarios.

The following sections provide an overview of key literature on Egypt's agricultural and water context, including policy developments, resource availability, and growing demands. This is followed by a summary of modelling approaches commonly used to represent agricultural systems more broadly, along with an overview of how such approaches have been applied in the Egyptian context. The chapter concludes by identifying key gaps in the literature and outlining the aims and objectives of this research.

1.1 Literature Review

1.1.1 Egyptian context

1.1.1.1 *Policy history and effects*

Egyptian agricultural policy in the modern era (since the 1952 revolution) has undergone several major transitions in both focus and direction. The revolution was, in part, a reaction to declining standards of living in rural areas (Verhoeven, 2015). Throughout Egypt's long history, the summer months were marked by the annual inundation of the Nile, when

agricultural land was submerged and farming was not possible. During this period, Egypt's rulers often conscripted peasants, for little or no pay, to work on large state engineering projects. Until the mid-1880s, corvée labour was used to extend and maintain irrigation channels and dyke systems (Brown, 1994).

In the early 19th century, under the leadership of Mohammed Ali Pasha, the Ottoman Viceroy, Egypt underwent an agricultural revolution, aimed at modernising the sector and creating a modern state, with cotton cultivation for European markets as a central priority (Cuno, 1992). This transformation included expanding the irrigation network to increase year-round agriculture, the Viceroy assuming personal ownership of large areas of land, centralising the land tax system, controlling cropping patterns, and creating monopolies for the export of agricultural produce (Brown, 1994). By consolidating control, Mohammed Ali Pasha was able to weaken competing political forces and use the newly acquired lands to empower a new ruling class and local patrons who could reinforce his political power.

These structural reforms enabled Egypt and the ruling class to benefit from the dramatic increase in cotton prices during the American Civil War in the late 19th century (Verhoeven, 2015). During the late 19th Century and the first half of the 20th Century, when Egypt was under the influence of the British Empire, the descendants of Mohammed Ali Pasha – who had modified their status from Ottoman Viceroys to Kings of Egypt – expanded the reforms started in the 18th Century and dammed the river Nile to further increase perennial crop cultivation.

Raḍwān (1977) develops estimates for the changes in land ownership within the first half of the 20th century and demonstrates the extent of increasing inequality. The wealthiest landowners – with holdings above 50 feddan¹ – reduced from 1.5% to 0.4% of land owners. The poorest land owners – with holdings below 5 feddan – saw a reduction of average holdings from 1.54 feddan to 0.8 feddan. The number of landless rural families, often tenant farmers, also increased dramatically from 39% of the rural population in 1929 to 61% in 1950.

In response to the context before 1952, the new post-revolution socialist rulers enacted a series of agrarian laws in the 1950s and 1960s. Among the main objectives of these reforms

¹ Feddan is the standard unit of agricultural area utilised in Egypt. 1 feddan = 1.038 acres = 4,200 m²

was the redistribution of land from large-scale land owners to small farms and tenant households. The reforms achieved a redistribution of 12% of the total cultivated area, secured tenancies for tenant farmers with the possibility of inheritance of tenancies in perpetuity, and limited land rental prices to seven times the land tax (Bush, 2007). These reforms also included the abolition of large estates, starting in 1952 with a ceiling of 200 feddan and, by 1969, of 50 feddan (Richards, 1980). Although there is evidence that these distributions of land resulted in a reduction in the number of the largest land holdings, it had no impact on landless peasants as they were not eligible for redistributed land (Raḍwān, 1977). Additionally, many policies of the previous regime had been maintained or strengthened, including the expansion of state command-and-control of cropping patterns, and the expansion of state ownership of land and agricultural activities. Supervised cooperatives were introduced as part of the Land Reform laws with the aim of trying to benefit from economies of scale by organising input supply, sharing access to mechanisation, marketing, and ensuring that production complied with cropping rules (Richards, 1980).

Another key priority of the post-1952 state was the horizontal expansion of agricultural land through a process of bringing desert land into production (Adriansen, 2009). Land reclamation is the process of turning non-productive, uninhabited land into production (Voll, 1980). During the first half of the 20th century, the total cultivated area increased through land reclamation and perennial cultivation by approximately 20% (5 to 5.981 million feddan) (Raḍwān, 1977). These efforts provided diminishing returns as the land most suitable for reclamation had already been cultivated, and further expansion became progressively more difficult (Voll, 1980). Land reclamation efforts in the era immediately after the revolution (1952-61) were supported by the United States of America, and were characterised by the testing of different models of land tenure, private land distribution, and cooperative ownership (Springborg, 1979; Voll, 1980; Wolff, 1993). However, these efforts had limited success on the ground and were dogged by competing agendas among factions within the revolutionary government (Springborg, 1979). Between 1961 and 1967, Egypt pivoted towards the Soviet Union, utilising its financing and expertise. This led to the adoption of the Soviet farming model, characterised by state ownership and the use of wage-earning farm employees, rather than tenant farmers or private landowners, as the primary labour force in reclamation projects (Adriansen, 2009).

The completion of the High Aswan Dam (HAD) in 1971 allowed Egypt to implement larger-scale land reclamation activities and to crop areas already under cultivation multiple times each year (Smith, 1986). This was coupled with a transition from greater state command-and-control policies towards liberalisation of the agricultural system, allowing more private and international investment, especially from Gulf States and large investors (Adriansen, 2009). Land reclamation efforts have continued from the 20th century into the 21st, with a number of mega projects being announced, many of which did not meet their targets (Sims & Mitchell, 2015). Nour (2020) summarises that the narratives adopted under the socialist era (1952 – 1970) were dominated by state command-and-control and redistribution of land. However, under the liberalisation era (1970 to present), international investment flows, meeting the growing food demand, and increasing production of high-value export crops were prioritised. What is also very evident is the prominence of horizontal expansion as an essential policy tool under all administrations and ideological phases of the post-1952 era. A total of 3.15 million feddan is estimated to have been reclaimed by 2017 (CAPMAS, 2025). Table 1.1 summarises major land reclamation projects undertaken since 1952, while Figure 1.1 illustrates the spatial expansion of reclamation efforts in the Nile Delta since 1930, including the associated water sources. These projects, with a few exceptions, have been characterised by grand announcements and relatively limited success on the ground, with most being abandoned and resurrected at politically opportune times (Bush, 2007; Sims & Mitchell, 2015).

Table 1.1: Summary of some key land reclamation projects since 1952. (Nour, 2020; Presidency of the Arab Republic of Egypt, 2022; Sims & Mitchell, 2015)

Project	Date of initiation	Location	Water source	Description
West Delta	1954	West of the Nile Delta	Nile water	This includes a number of projects dating back to 1954. The first of these was the Tahrir project, which, after some delays, achieved its objective of reclaiming 600,000 feddan. Additional projects were less successful, but succeeded in reclaiming 300,000 feddan. Water is

Project	Date of initiation	Location	Water source	Description
				provided through a number of extensions to the irrigation network, most notably, the Al-Hammam canal and the Nasr Canal.
East Delta	1960s	East of Nile Delta	Nile water	This includes various projects in the area between the Delta to the Suez Canal. Drip irrigation and pivot irrigation systems are planned for these areas, utilising Nile water from the irrigation network.
New Valley	1958	Western Desert	Groundwater	Reclamation of land utilising groundwater wells, from Aswan in the south, connecting oases in the Western Desert. The project has only managed to reclaim 120,000 feddan to date.
Al-Salam	1960s	Sinai	1:1 mix of irrigation drainage water and Nile water	Mixing water from the Damietta canal and agricultural drainage water to reclaim land on either side of the Suez Canal. A total of 125,000 feddan had been reclaimed in North Sinai of the 620,000 feddan planned.
Toshka	1997	West of Aswan	Nile water	10% of Nile water diverted from behind the HAD to Toshka depression. Land was sold to national and Gulf investors. There have been a number of controversies relating to the lack of progress in this area.

Project	Date of initiation	Location	Water source	Description
East 'Uwaynat	1997	South of Western Desert	Groundwater from Nubian Sandstone Aquifer System	Successful reclamation of 115,000 of 250,000 feddan, but mostly automated central pivot irrigation system with limited employment opportunities and no community creation.
New Delta	2020	West of Nile Delta	Shallow groundwater, treated waste water and agricultural drainage water	Launched in 2021 to reclaim 2.2 million feddan west of the Nile Delta. Approximately 350,000 feddan cultivated to date. Focus on wheat, maize, and vegetables. Includes major infrastructure investments such as logistics hubs. Aims to create over 5 million jobs, though employment is currently limited due to mechanised operations and gradual development.
Wad' Yad	Continuous	Fringes of Nile Valley and Delta	Nile water and groundwater from the Nile valley aquifer	Informal land reclamation of public lands by private citizens. This is considered illegal, but is tolerated, and there is a route to ownership if the person reclaiming the land can prove possession for 15 years. Due to its dubious legal status, the state does not officially account for these areas. Estimates range from 1 to 2 million feddan of area reclaimed in this way since the 1980s, when it started to accelerate.

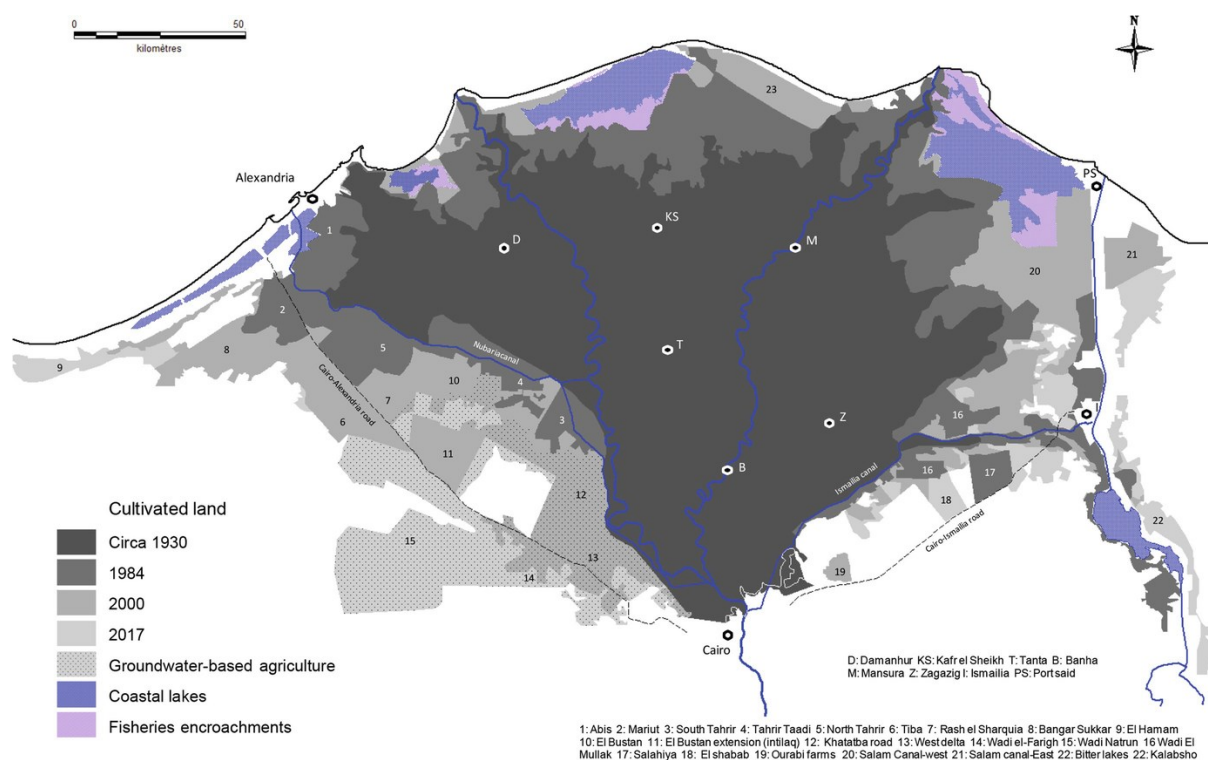


Figure 1.1: Nile Delta land reclamation since 1930, showing the reclaimed areas, groundwater agriculture, and the loss of land to expanding lakes for fisheries. Adopted from (Molle, 2019)

Following Egypt's defeat in the Six-Day War of 1967, the country's leadership began to reassess its domestic and foreign policies. Greater economic freedoms began in 1968 under the 30 March Programme, although the agricultural sector remained under the old command-and-control policy paradigm until the 1970s (Bush, 2007). This reorientation was characterised by a gradual reduction of command-and-control policies, greater freedom in cropping patterns, prioritising higher value agricultural outputs for export, reduced input subsidies, greater space for private capital, and greater freedoms for land-owners (Adriansen, 2009; Bush, 2007; Nour, 2020; Voll, 1980). The most impactful reform was Law 96 of 1992, which reversed protections for tenants introduced during the socialist reforms and enabled landowners to end tenancies and set new, uncapped rents. This allowed rents to increase more than threefold between the 1960s and 2001 (Fuglie et al., 2020). This policy led to many tenants losing the land, which had been previously protected. Many of these tenants were placated through access to newly reclaimed land where possible (Barnes, 2012).

Since the early 21st century, Egypt has developed a number of policies to prioritise the sustainability of its agricultural and water systems. These include the Sustainable Agricultural Development Strategy: Egypt's Vision 2030, National Water Strategy 2017, and National Water Resource Strategy 2017 – 2037 (Arab Republic of Egypt, 2009; Kassim, 2018). The key objectives of these policies include:

- Improving water use efficiency through the reduction of conveyance losses, reducing the areas planted with rice and cotton, and the use of efficient in-field irrigation systems;
- Increasing cropped area through sustainable land reclamation;
- Increasing water harvesting to increase the returns from the limited rainfall;
- Reducing losses of agricultural land by improving drainage and limiting losses to urban encroachment;
- Improving crop productivity through the use of biotechnology development;
- Increased national and international competitiveness of agricultural products;
- Increasing self-sufficiency of strategic products, achieving self-sufficiency of 81% for wheat, 92% for maize, 93% for sugar, 93% for red meat, and 97% for fish, by 2030;
- Reducing pre- and post-harvest losses;
- Improving standards of living for rural communities by expanding support for rural industries.

Another defining policy of the post-1952 period is the establishment of a food subsidy system, aimed at ensuring access to basic food staples for the population (Hosni & Ramadan, 2018). This system consists of two components: the provision of subsidised local 'baladi' wheat bread at a fixed affordable and below cost price; a ration card system that provides other key staples, including oil, sugar, and rice at subsidised prices (Kassim, 2018). While the subsidy system has played a crucial role in maintaining food security and social stability, it has also imposed a substantial burden on public finances. Due to Egypt's high dependence on wheat imports, the food subsidy system is a major strain on public finances, costing the state 4% of government expenditure between 2016-2020 (Breisinger et al., 2024). It has also exposed Egypt to international food price fluctuations, which some cite as being responsible for a number of protests over the years, most recently the 2011 Arab Spring demonstrations (Soffiantini, 2020).

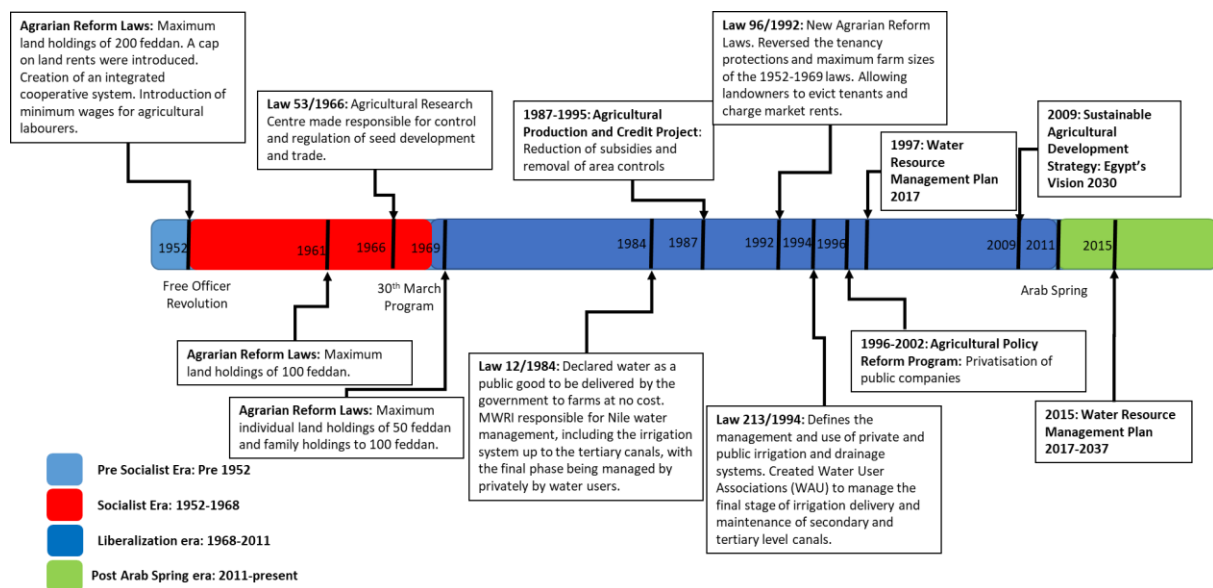


Figure 1.2: Timeline of key agricultural laws and policies since 1952. (Bush, 2007; Kassim et al., 2018)

1.1.1.2 Pressures on the agricultural system

The current agricultural area comprises 3% of Egypt's 1 million km² area (El-Ramady et al., 2013). Access to year-round irrigation has enabled Egypt to have three growing seasons: winter (November to May), summer (March to August), and Nili (July to November) (Kassim, 2018). The main crops produced in summer are cotton, rice, maize, peanuts, sesame, and soybeans. During the winter, the main crops are wheat, flax, lentils, onion, barley, and berseem (Xu et al., 2017). There has been a growing trend of increased fruit and vegetable cultivation for export markets (Bush, 2007). This has resulted in the total cropped area being greater than the cultivated area, with a 2021/2022 cultivated area estimate of 9.65 million feddan and a cropped area of 16.59 million feddan (CAPMAS, 2025).

Climate change is likely to increase pressure on Egypt's agricultural system (Abutaleb et al., 2018). Rising sea levels may result in flooding in highly productive land in the Nile Delta, and increased saltwater intrusion in shallow aquifers could lead to the salination of highly utilised groundwater resources in coastal areas in the Nile Delta (Gado & El-Agha, 2021). Additionally, temperature increases are expected to result in increased evapotranspiration, reduced crop water productivity, reduced yields, and increased irrigation water requirements (Omar et al., 2021). Omar et al. (2021) analyse the effect of cropping patterns on mitigating the effects of climate change and salinity and the resulting impact on food security and Egypt's socioeconomic system. Alobid et al. (2021) adopt a linear model of 13 crops to determine the

best allocation to reduce the food gap between 2000 and 2018. Both studies demonstrate that cropping patterns can increase the productivity of land in Egypt and mitigate some of the challenges it faces. However, it is noted that water is still the dominant constraint, and it would still not be possible to meet demands without increasing freshwater resources.

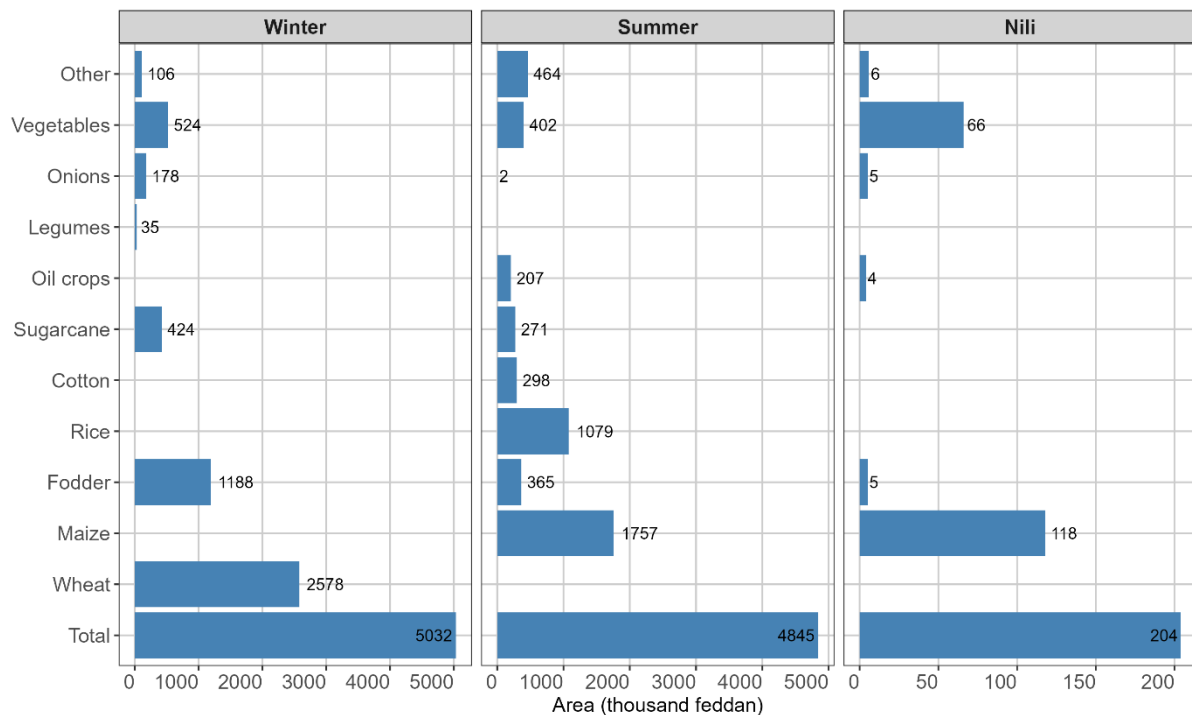


Figure 1.3: Cultivated area (in thousand feddan) of major crop types in Egypt across winter, summer, and Nili seasons in 2022 (CAPMAS, 2025)

There have been a number of studies investigating urban encroachment on agricultural land (e.g. Abd-Elmabod et al., 2019). Given the scarcity of agricultural land, legislation restricting urban construction on farmland has been in place since the 1960s (Salem et al., 2020). However, Abd-Elmabod et al. (2019) apply satellite image analysis techniques to estimate a 5-fold increase in urban area in the Nile Delta between 1972 and 2017 (from 452 km² to 2,600 km²). In addition, soil salination due to year-round irrigation and irrigation water reuse is resulting in reduced productivity in some heavily farmed areas (Abd-Elmabod et al., 2019). This conclusion is supported by Gohar et al. (2021), who conduct a quantitative analysis to consider the water-land allocation alternatives and find that improved agricultural production is possible but that complete self-sufficiency is not.

1.1.1.3 *Farming households*

The Egyptian agricultural system is shaped not only by environmental and policy constraints, but also by the diverse characteristics of its farming households. These households differ in land ownership, resource access, income sources, and education levels, factors that strongly influence decisions around cropping, irrigation practices, labour allocation, and adaptation strategies (Alary et al., 2014; Nin-Pratt et al., 2018). Understanding this heterogeneity is essential for designing relevant and effective interventions that support adaptation.

A growing body of research has used typology analysis to explore diversity among smallholder farmers, especially in relation to resource use, technology adoption, and livelihood strategies (e.g. Guarín et al., 2020; Shukla et al., 2019; Sinha et al., 2022). In Egypt, most typology studies have been conducted at local or regional scales. Alary et al. (2014) and Aboul-Naga et al. (2022), for example, applied cluster analysis to identify household types based on livestock holdings, cropping patterns, and access to markets, revealing strong differences in productivity and risk exposure. Similarly, Martin et al. (2020) found that education levels and income diversification played a key role in shaping resilience among smallholder dairy farmers in Middle Egypt. However, these studies often focus on specific production systems or communities, limiting their relevance for national-scale agricultural policy.

More recent efforts have used national-level panel datasets such as the Egypt Labour Market Panel Survey (ELMPS) (Economic Research Forum & Central Agency For Public Mobilization and Statistics (CAPMAS), 2013, 2019) to classify farming households across broader spatial and temporal scales. Nin-Pratt et al. (2018) used the 2012 round of ELMPS to group households based on land, labour, and capital resources, showing that climate impacts vary across typologies. Helmy (2020) extended this analysis using all four ELMPS waves (1998–2018) to trace shifts in livelihood strategies, highlighting a trend toward increased off-farm income among rural households. Although Helmy (2020)’s study includes all livelihoods and is not specific to farming households. Additionally, these national studies have typically focused on economic dimensions and lack integration of key social indicators such as education, housing conditions, and tenure security, factors that also influence adaptive capacity. Together, these studies reflect the considerable diversity of Egypt’s agricultural population and underscore the need for more comprehensive and dynamic household characterisations in agricultural modelling and policy analysis.

1.1.1.4 Agricultural extension system

Agricultural extension services are intended to transfer state-of-the-art practices from research institutions to farmers with the aim of improving productivity and adapting to challenges (Kassem et al., 2019). These services are often framed as an innovation-diffusion model, in which innovations stem, almost exclusively, from the research community and are delivered to farmers through public and private extension structures (Fleischer et al., 2002). Extension services are a key component of the Agricultural Knowledge and Innovation System (AKIS), which encompasses the development, dissemination, and utilisation of agricultural development (Zahran et al., 2020).

In Egypt, public agricultural research is carried out by the Agricultural Research Centre (ARC) and the Desert Research Centre (DRC). The Central Administration for Agricultural Extension Services (CAAES), the structure responsible for extension services, works to promote the adoption of this research to farmers through Subject Matter Specialists (SMSs) and Village Extension Workers (VEWs). VEWs simplify and disseminate information from SMSs to farmers and work to resolve challenges faced by farmers or relay those beyond their expertise to SMSs, who work to develop solutions (Diab et al., 2020).

A number of researchers have assessed the relationship between extension services and key topics, including adaptation to climate change (Kassem et al., 2019) and the adoption of organic and sustainable agricultural practices (Shalaby et al., 2011). These analyses highlight key challenges facing the public extension services, such as corruption, inadequate supervision of village-level activities, and misalignments between centralised objectives and local priorities (Fleischer et al., 2002). Measures have been introduced to encourage private extension services, typically provided by agritech companies and agricultural input suppliers. However, these can create barriers, especially where these services are paid (Fleischer et al., 2002). Additionally, private extension services are often focused on the delivery of a single or small number of products, which may not always represent the best interests of the farmer.

1.1.1.5 Water resources and uses

1.1.1.5.1 National context

Egypt is classified as being below the water scarcity level, with a total annual renewable water resource, in 2019, of 590 m³/capita (Tutwiler, 2021). This is well below the 1000 m³/capita defined as the absolute water scarcity level, which is required to meet total water demand

(Falkenmark et al., 1989). The country depends on 98.26% of its annual renewable water resource on a single source, the Nile River, with the remainder coming from renewable groundwater resources and rainfall (Heggy et al., 2021). The agricultural sector accounts for 80% of water use (Fuglie et al., 2020). Total agricultural water use in 2010 was estimated to be 67 km³, with shallow groundwater, deep groundwater, rainfall, and drainage water reuse accounting for 4.85 km³, 2 km³, 1.3 km³ and 16 km³, respectively; the remaining 42.85 km³ is from the Nile (Abdelkader et al., 2018).

The irrigation network, as represented in Figure 1.4, is managed by the Ministry of Water Resources and Irrigation. There is an ongoing process in place to hand over responsibility of secondary and tertiary level canals to local Water User Associations to manage, maintain, and recover costs (Luzi, 2010). The network is comprised of main irrigation channels that are supplied with water from the Nile at barrages. Primary channels are diverted to secondary and tertiary channels, which supply irrigation water to fields. Irrigation water is free of charge for farmers (Fuglie et al., 2020). Access to year-round irrigation permanently increased the water table level, leading to waterlogging and increased salination (Molle, 2019). This, in turn, resulted in reduced yields. Drainage systems, comprised of a mixture of surface and subsurface drainage channels, have been installed to channel runoff water from irrigation to allow for the reuse of 16 km³ of drainage water and reduce waterlogging and soil salination (Abdelkader et al., 2018; Sallam, 2017). This has allowed irrigation efficiency to reach an average of 68% between 2010 and 2017 (Nikiel & Eltahir, 2021). Additional reuse would be undesirable due to the increased salinity of drainage water (Barnes, 2014).

The High Aswan Dam (HAD) was constructed between 1964 and 1971 to provide multi-year water storage, additional summer water to allow for expansion of perennial agriculture, reduce the risk of flooding, and provide hydroelectric power (Smith, 1986). The dam allowed for the significant expansion of the irrigation network into new lands. However, the dam substantially reduces the quantity of silt carried in the water, as much of it is deposited upstream of the dam and in the reservoir. This precipitated a number of additional effects, including increased erosion in the coastal region, increased soil salinity, and salination of coastal inland lakes and shallow groundwater (Biswas & Tortajada, 2012).

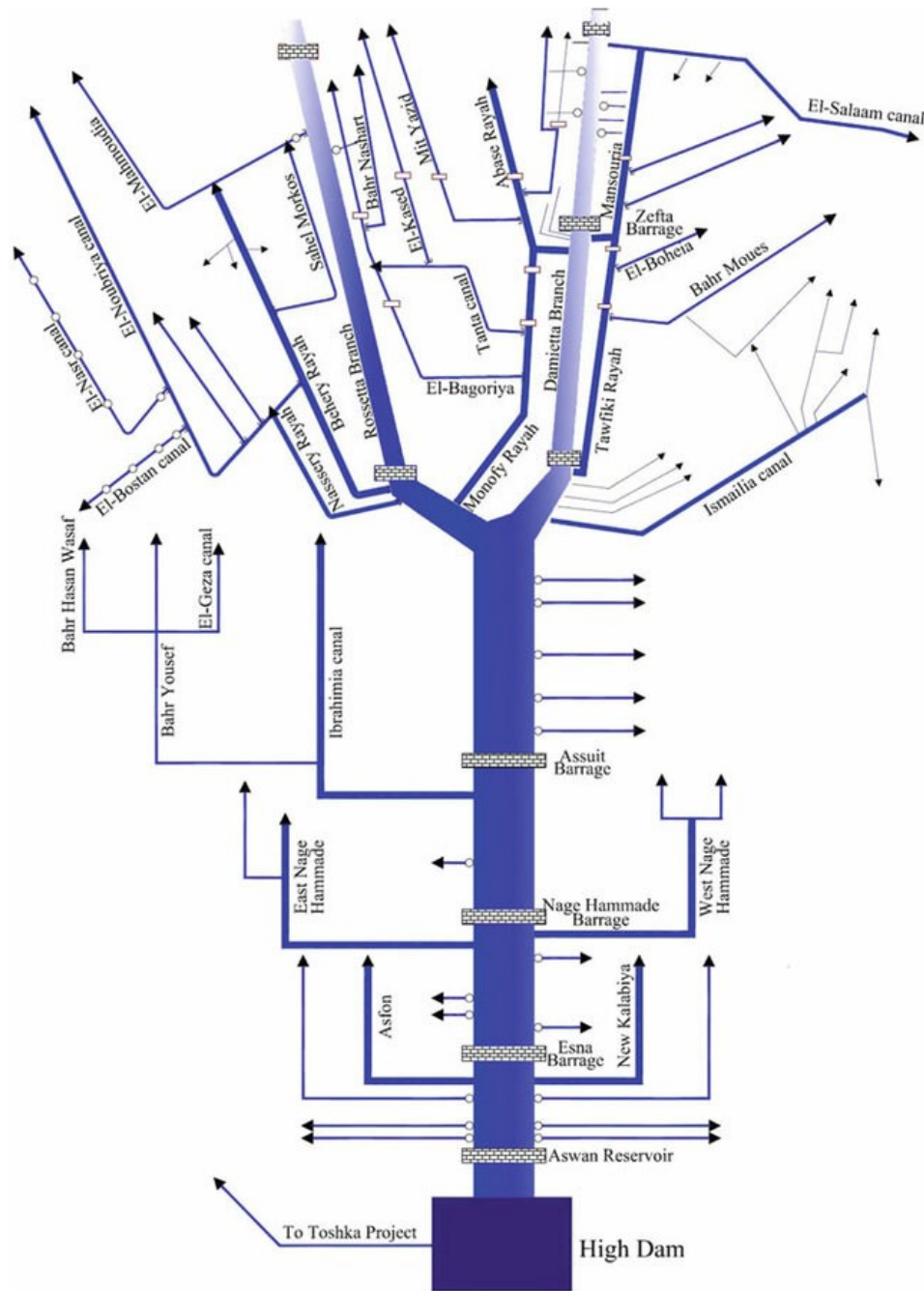


Figure 1.4: Schematic of Egypt's irrigation network showing the flow of the Nile from the High Aswan Dam (HAD) to the Mediterranean Sea. Major barrages and primary irrigation canals are illustrated, with line thickness used to indicate relative canal size (not to scale by flow volume). Adopted from El Gamal and Zaki (2017)

Groundwater resources in Egypt can be divided into shallow groundwater, which exhibit relatively quick recharge rates, and deep groundwater resources (fossil aquifers). Shallow groundwater resources are often recharged quickly through percolation of rain, Nile water, and irrigation water. This is widely used in agriculture. The Nubian Sandstone Aquifer System (NSAS), which spans Egypt, eastern Libya, northern Chad, and northern Sudan, is the main

deep groundwater resource in Egypt with an exploitable volume of 10,217 km³ (Mazzoni et al., 2018). Current fossil aquifer water use in Egypt is estimated to be around 2 km³ annually. Recharge rates of the NSAS depend on the level of the lake at HAD, ranging from a current estimate of between 0.7 km³ to 8.5 km³ per year, when Lake Nasser is at 170 m a.s.l. and 178 m a.s.l., respectively (Heggy et al., 2021). Mazzoni et al. (2018) estimate that the NSAS could be depleted within roughly 300 (± 80) years if groundwater abstraction were scaled up to meet projected water deficits arising from agricultural expansion and population growth.

Climate change is an additional threat to Egypt's already stressed water resources. A number of studies have been conducted to evaluate the impact of climate change on water availability in Egypt and the Nile River Basin more widely (e.g. Barnes, 2017; Beyene et al., 2009; Di Baldassarre et al., 2011; S. Mostafa et al., 2021; Omar et al., 2021). These models used several Global Climate Models and Regional Climate Models to predict precipitation, evapotranspiration, and resulting streamflow over the Nile Basin in the coming decades. The modelling results were inconsistent, with some models predicting an increase in average precipitation, whilst others predicted a reduction (Barnes, 2017). For example, Beyene et al. (2009), who conducted a multi-model analysis for A2 and B1 global emission scenarios from the 2007 Intergovernmental Panel on Climate Change (IPCC) report, predicted streamflow changes between a 23% reduction and a 36% increase at HAD in the 2010-2039 period. Most of the models predicted an increase in the period to 2040 and a reduction in the period between 2070 and 2100.

1.1.1.5.2 International context

The Nile River basin is shared between 11 countries in Eastern Africa: Egypt, Sudan, South Sudan, Ethiopia, Eritrea, Kenya, Uganda, Burundi, Rwanda, Tanzania and the Democratic Republic of Congo. The river's main tributaries originate in the Central African Region and the Ethiopian Highlands, with most of the water originating in the Ethiopian Highlands (Heggy et al., 2021). Senay et al. (2014) analyse the sources and sinks of the Nile River Basin between 2000 and 2012. This research concludes that there are significant losses to evapotranspiration along the basin. The research noted that 4 of the upstream riparian countries exhibit a positive water balance – greater precipitation than evapotranspiration – while Egypt, Sudan and South Sudan exhibited a negative water balance. The analysis also concludes that inflows into the HAD have been historically underestimated, and Sudan has already utilised its Nile

water allocation by the time the water arrives at the HAD, under the 1959 Nile Water Agreement, potentially enabling Egypt to increase its utilisation to 74 km³.

Cooperation between riparian countries within a river basin has been difficult in many contexts. As the two dominant powers on the Nile River basin in 1959, Egypt and Sudan signed a Nile Water Agreement for the full utilisation of Nile waters based on the average flow at the HAD. The agreement allocated Egypt 55.5 km³/year and Sudan 18.5 km³/year (Gohar & Ward, 2011). As Egypt's regional influence diminished and upstream countries, most notably Ethiopia, increased in economic and military power, there has been pressure to negotiate a new treaty. Ethiopia took a unilateral decision in 2011 to start construction of the Grand Ethiopian Renaissance Dam (GERD) (Wheeler et al., 2016). In 2015, Ethiopia, Egypt and Sudan signed a Declaration of Principles as a first step towards a new treaty. The declaration included a commitment for greater cooperation between the 3 countries, the sharing of information, cooperation on dam safety and an acknowledgement that the GERD would be primarily for energy generation, therefore not affecting water allocation in downstream countries (Barnes, 2017).

The GERD is an Ethiopian project designed to increase Ethiopia's utilisation of Blue Nile water that runs through Ethiopia and flows into the Nile in Sudan, reduce the risk of hydrological drought, and produce hydroelectric power (Heggy et al., 2021). The project has been in development for several decades and has been a source of tension between Ethiopia and the downstream riparian countries – Sudan and Egypt. Construction began in April 2011 and was completed in July 2020 (Ahmed et al., 2024). Once fully operational, it will become the largest hydroelectric project in Africa. Ethiopia asserts that during operation, the project will not affect downstream countries, with power generation being its main priority (Heggy et al., 2021). However, concerns persist about the speed and consequences of the reservoir's filling phase. Ahmed et al. (2024) analyse satellite imagery of downstream reservoirs since filling began in July 2020 to assess any impacts. Their analysis shows a slight increase in the area of Egyptian reservoirs (Toshka and Nasser), though this is attributed to a 6%–10% increase in rainfall. Nonetheless, if the current rate of filling continues over the remaining four years and coincides with a drought period, the impacts on Egyptian water security could be severe – potentially reducing water availability at Lake Nasser by 35.47% and leading to the loss of up to 33.13% of agricultural land (Ahmed et al., 2024).

1.1.2 Modelling

Understanding the dynamics of complex socioecological systems is important for anticipating how they may evolve over time and for designing policies that can effectively respond to current and emerging challenges. These systems are shaped by interactions between environmental, economic, social, and political components, and their future trajectories are highly uncertain (Rounsevell et al., 2021). Modelling provides a means to explore these interactions and to assess the potential impacts of different policy choices or external drivers under a range of plausible future conditions. However, projecting future developments is inherently uncertain, particularly when it involves long-term socioeconomic and climatic change (Rounsevell & Metzger, 2010). To address this, several widely used scenario frameworks have been developed to structure assumptions about future trajectories and to provide shared narratives that enable comparison across different modelling efforts.

Among these, the Shared Socioeconomic Pathways (SSPs) (O'Neill et al., 2017), often used in combination with Representative Concentration Pathways (RCPs) (van Vuuren et al., 2011), have become the dominant framework in climate impact and adaptation research. The SSPs present five distinct global narratives, each reflecting different levels of challenge to climate change mitigation and adaptation. Together, they capture a wide spectrum of possible futures, from sustainable development to regional rivalry and fossil-fuelled growth. These narratives are quantitative and qualitative, offering internally consistent projections of population, economic growth, urbanisation, and other key variables relevant to climate impact modelling. Before the development of the SSPs, other scenario frameworks were in use, such as those developed for the Millennium Ecosystem Assessment (Millennium Ecosystem Assessment, 2001) or the IPCC Special Report on Emissions Scenarios (SRES) (Nakicenovic, 2000). More recently, alternative scenario frameworks have been proposed to complement the SSPs, especially those that centre on biodiversity and ecosystem values, such as the Nature Futures Framework (NFF) (Kim et al., 2023). These aim to address the relative lack of ecological considerations in mainstream socioeconomic scenarios.

Nevertheless, in the context of Egypt, a country with highly constrained water resources and relatively low overlap between agricultural development zones and areas of high biodiversity, the SSPs remain a useful tool. Their focus on socioeconomic development pathways, combined with the ability to integrate RCP-based climate projections, provides a practical and

policy-relevant framework for exploring future agricultural, land-use, and water management challenges.

1.1.2.1 Econometric modelling

Econometric models are a widely used tool in empirical agricultural impact analysis. Typically relying on historical yield and climate data, these models apply regression-based techniques to identify statistical relationships between crop performance and climate variables such as temperature, rainfall, and CO₂ concentrations (Feng et al., 2023; Su & Chen, 2022). These models are well-suited for large-scale analysis and scenario forecasting under the assumption that past behavioural and environmental relationships will persist into the future. Some econometric approaches incorporate adaptive responses, such as crop switching or changes in input use, under rational utility or profit-maximising frameworks (Su & Chen, 2022).

Econometric models have been applied to the Egyptian agricultural system. For example, Nasr Ahmed et al. (2021) developed a multi-market model to assess the broader impact of climate change on the Egyptian agricultural system. They consider multiple scenarios and show that under a high stress scenario of lower yields and higher water demand, agricultural production drops by 10-18% while total value-added declines by 29%. At the farm level, Eid et al. (2007) apply a Ricardian approach to analyse the effect of climate on net farm revenue using data from 900 households across 20 governorates. Their standard model suggests that higher temperatures significantly reduce farm revenue. However, when irrigation (hydrology) is included as an explanatory variable, the impact of temperature becomes positive, highlighting the role of irrigation as a key adaptation strategy.

Econometric models offer accessible and policy-relevant tools for estimating the impact of climate variables on agricultural outcomes. However, their reliance on historical data limits their ability to predict outcomes under non-stationary climate conditions, such as novel combinations of temperature and rainfall not previously observed (Lobell & Burke, 2010). Moreover, they often struggle to capture spatial heterogeneity, non-linear thresholds, and biophysical constraints on productivity, which are increasingly important under climate extremes and long-term change.

1.1.2.2 *Biophysical modelling*

Biophysical models are mathematical models which approximate natural processes, including crop growth, soil moisture dynamics, evapotranspiration, runoff, and water extraction (Bellocchi et al., 2011; Plantinga, 2015). Biophysical models relevant to agriculture and water management are commonly categorised as crop models, hydrological models, and ecohydrological models, reflecting different levels of integration between biophysical processes and feedback.

1.1.2.2.1 Crop models

Crop models are process-based biophysical models that simulate crop growth, development, and yield in response to environmental conditions, such as temperature, solar radiation, CO₂ concentration, soil moisture, and management practices (Dlamini et al., 2023; You et al., 2024). These models are grounded in physiological processes such as photosynthesis, transpiration, and biomass partitioning, offering detailed representations of how crops respond to environmental and management changes over time (Roberts et al., 2017). Widely used models include Environmental Policy Integrated Climate Model (EPIC) (Williams et al., 1984), Decision Support System for Agrotechnology Transfer (DSSAT) (Jones et al., 2003), Agricultural Production System Simulator (APSIM) (Holzworth et al., 2014), and AquaCrop (Steduto et al., 2009), each with varying degrees of complexity, input requirements, and crop-specific calibration. These tools are commonly applied to assess the impacts of climate change on yield and water demand, evaluate irrigation strategies, and test adaptation options such as altering planting dates, selecting drought-tolerant cultivars, or modifying fertiliser use.

Several studies have applied crop models to explore climate change impacts on Egyptian agriculture, often focusing on specific regions or crops. Gabr (2023a) use a crop model (CROPWAT) to assess water requirements and yield changes in Upper Egypt, projecting 10-27% yield reductions under the highest climate change scenario by 2100. Elsadek et al. (2024) applied the AquaCrop-GIS model to the Nile Delta and found moderate yield gains until 2050, followed by 23-34% losses under a similarly high climate change scenario by the 2090s. Similarly, S. M. Mostafa et al. (2021) simulated wheat yield changes under climate scenarios using a crop model, reporting 11-25% yield declines. In contrast, Gamal et al. (2021) reported modest yield gains (+5%) under 1.5–2 °C warming scenarios, reflecting possible differences in regional conditions and assumptions.

One key factor shaping future yield projections is the CO₂ fertilisation effect, whereby elevated atmospheric CO₂ concentrations enhance photosynthesis and reduce stomatal conductance, particularly in C3 crops such as wheat, rice, and many vegetables (Ainsworth & Long, 2021; Mokhtar et al., 2025). This leads to increases in biomass production and water use efficiency, especially under non-water-stressed conditions. For example, Elsadek et al. (2024) projected that rice yields in the Nile Delta will increase under elevated CO₂, with the largest gains occurring mid-century, after which yield growth slows considerably due to rising temperatures, particularly under high-emission scenarios. Similarly, Kheir et al. (2019) reported yield gains of 5-25% for wheat under elevated CO₂ (400-700 ppm), offsetting some temperature-related losses. In contrast, C4 crops such as maize exhibit limited photosynthetic response to rising CO₂ unless under drought stress, resulting in smaller or even negative yield changes at high CO₂ levels (Rezaei et al., 2023). Collectively, these findings emphasise the importance of accounting for CO₂ dynamics in crop models, particularly for arid and semi-arid regions such as Egypt, where water-saving and yield-enhancing processes are especially important under climate change.

Collectively, these applications confirm that crop models are effective tools for projecting climate-driven changes in productivity and water use, though their outputs vary depending on regional calibration, model assumptions, and climate forcing data. One common limitation of many crop models is their simplified treatment of water supply, which typically assumes irrigation demands are fully met. While such assumptions allow for greater focus on physiological crop responses, they may limit the model's ability to reflect interactions between water availability and crop performance in water-scarce regions (Alam et al., 2022; McDermid et al., 2023). Their widespread use in Egypt highlights the value of such tools; however, the absence of a national model and the simplification of the hydrological system present an area of potential development.

1.1.2.2.2 Hydrological models

Hydrological models are essential for understanding and managing water resources, especially in regions where supply is limited and competing demands exist. These models simulate the movement, distribution, and storage of water across landscapes, helping to assess the impacts of climate change, land use, and infrastructure on water availability for agriculture and other uses. Ideally, these models represent all water balance components and

fluxes, including areas of storage (e.g. lakes, snow, soil-water content, groundwater reservoirs) and flows (e.g. evapotranspiration (ET), rainfall, runoff, recharge into aquifers, extraction) (P. K. Paul et al., 2021). Hydrological models apply empirical and governing equations at different complexities: lumped, semi-distributed and fully distributed (Moges et al., 2020). Distributed models create a representation of the hydrological system, which is discretised into hydrological response units based on common soil, land use, and slope properties.

Although most models will consider all aspects of the hydrological system, they will simplify one or more components, resulting in them being best suited for specific applications (P. K. Paul et al., 2021). This has led to a growing trend of coupled surface water-groundwater models, which can better represent the full hydrological system. Models can be either tightly coupled or loosely coupled. Tightly coupled surface water-groundwater models are most effective at simulating the integrated system (Tian et al., 2015). However, tightly coupled models have greater input demands. This may create challenges, especially where there is limited field data for the parameterisation (Wang & Chen, 2021). Loosely coupled models communicate one-way information between submodels and have lower data requirements and simpler operations (Haque et al., 2021).

Hydrological modelling of Egypt has taken place, but is limited to small geographical areas, usually sub-basin catchment scales, and is often focused on groundwater modelling and extreme precipitation events. For example, Tügel et al. (2020) consider flash flooding in Wadi Billi. They use a 2D shallow water model and the STORM hydrological model of the catchment to evaluate different rainfall and flood mitigation method scenarios in Gouna city. They propose the use of flood retention basins to capture flash floodwater from heavy rainfall events, thereby reducing flood impacts and storing water for future use. Coppola et al. (2019) analysed a terraced wadi basin in Egypt using a combined runoff model (KINEROS2) and an agro-hydrological model (FLOWS-HAGES), calibrated with distributed water storage and outlet discharge data. Their results showed that terraces could retain up to 50,000 m³ of rainfall, providing a valuable water source capable of sustaining crops through the spring-summer period. At the aquifer scale, Switzman et al. (2015) applied a groundwater flow model (MODFLOW) to Wadi El Natrun, where rapid agricultural reclamation since the 1960s has driven intensive groundwater abstraction. To overcome severe data limitations, they

developed Novel Spatiotemporal Infilling Models (STIMs) that combined sparse field and literature estimates with remote sensing data to generate pumping and recharge inputs. This enabled the construction of an ensemble of groundwater model scenarios, validated against monitoring records, which revealed a cumulative deficit of approximately 24 km³ between 1957 and 2011, with declining water levels directly attributed to abstraction.

Hydrological models provide valuable tools for analysing the movement and availability of surface and groundwater, as well as their interactions. In the Egyptian context, their application has been largely localised, often limited to sub-basin or wadi-scale studies focused on specific issues such as flash flooding or groundwater depletion. While these models offer important insights into water dynamics, they often simplify or exclude key processes such as crop growth, land management, and water use in agriculture. This limits their usefulness in evaluating agricultural adaptation strategies or the full impacts of climate change on water-land-crop systems. To address these limitations, recent research has shifted towards ecohydrological models, which explicitly couple water and vegetation processes and allow for the assessment of interactions between hydrology, crop growth, and land management.

1.1.2.2.3 Ecohydrological models

Ecohydrological models extend traditional hydrological approaches by integrating vegetation dynamics, crop growth, and land management processes, offering a more comprehensive representation of interactions between water, land, and climate systems. These models typically combine hydrological modules with land-surface energy balance, biogeochemical cycling, and ecological process models (Maxwell et al., 2014). Their applications range from assessing water quality and land use change to evaluating the impacts of climate change and human activity on ecological systems (Haque et al., 2021; Jose et al., 2021; Wang & Chen, 2021).

A range of ecohydrological models has been developed to simulate interactions between hydrology, vegetation, land use, and management processes at various spatial and temporal scales. One example is MIKE SHE, a fully distributed, physically-based ecohydrological model widely used for simulating coupled surface-subsurface water dynamics and vegetation-water interactions, though its implementation often requires significant data, expertise, and calibration effort (Ma et al., 2016). Another, the Regional Hydro-Ecologic Simulation System (RHESSys), provides a modular framework for simulating coupled water, carbon, and nutrient

cycles, with applications largely focused on forested and mountainous ecosystems (Tague & Band, 2004). The AgroEcoSystem-Watershed (AgES-W) model is a modular, spatially distributed ecohydrological model developed to simulate hydrological and water quality processes – such as streamflow, nitrogen, and sediment transport – at the watershed scale, integrating components from established models and demonstrating strong performance even with minimal calibration (C. Ascough II et al., 2015). Similarly, ecohydrological extensions to MODFLOW (a widely used groundwater model), such as the One-Water Hydrologic Flow Model (MF-OWHM), enable simulation of irrigation demands and crop water use within groundwater-dominated systems (Hanson et al., 2014). Other large-scale models, such as Hydrological Predictions for the Environment (HYPE), include simplified representations of crop and nutrient cycling, with wide applications across Europe, Africa, and Asia (Arheimer et al., 2020).

Among these tools, the Soil and Water Assessment Tool (SWAT) has gained particular prominence for agricultural and watershed-scale applications. It was originally developed as a semi-distributed ecohydrological model to simulate the long-term impacts of land management on water, sediment, and agricultural productivity (Arnold et al., 1998). Building on this foundation, SWAT+ represents a major redevelopment that introduces a more flexible spatial framework and enhanced configurability of landscape and management processes (Bieger et al., 2017). While retaining the core integration of hydrology and crop growth through the EPIC model (Williams et al., 1984), SWAT+ supports both traditional semi-distributed structures using hydrological response units (HRUs) and more spatially explicit gridded configurations via SWATgrid, which allows routing between cells (Pignotti et al., 2017). A key strength of SWAT+ lies in its ability to simulate a wide range of biophysical processes under different climate scenarios, including crop yields, irrigation water use, nutrient cycling, sediment and pesticide transport, and water resource allocation. Its decision table system enables flexible and automated management, allowing operations such as planting, irrigation, and fertilisation to be triggered by either fixed dates or environmental thresholds (Arnold et al., 2018). Combined with a large crop library and default parameters, SWAT+ is particularly well-suited for applications in data-scarce regions, such as Egypt.

In summary, biophysical models provide valuable tools for understanding crop growth, water use and availability, and land–climate interactions. While crop and hydrological models offer

detailed process simulations, their limited integration can restrict system-wide assessments. Ecohydrological models, such as SWAT+, address this by combining land, water, and management processes within a unified framework. However, these models typically treat human decision-making in a simplified or static way, highlighting the need for complementary approaches that explicitly represent behavioural dynamics and adaptive responses.

1.1.2.3 Agent-based modelling

Agent-based models (ABMs) are a type of model which represents the interactions and the trade-offs between heterogeneous, autonomous stakeholders in complex socioecological systems (Berger & Troost, 2014). ABMs enable a bottom-up approach to the representation of these complex systems (Huber et al., 2018). They differ from neo-classical economic models by relaxing overarching rules for equilibrium and instead modelling the dynamics between individual agents and allowing emergent properties to manifest in the model (Lippe et al., 2019). In neo-classical economic models, the decision maker is characterised through a definition of their objectives, available resources and constraints, and complete access to information (Parker et al., 2008). Agents may be used to represent human, group, or institutional actors.

There have been many reviews of ABMs, which have covered topics including: governance in socioecological system models (Bourceret et al., 2021); climate change adaptation in agriculture (Berger & Troost, 2014); agricultural policies in Europe (Kremmydas et al., 2018); decision making in Earth system models (Müller-Hansen et al., 2017); theoretical foundations for decision making (Groeneveld et al., 2017); decision making in European agriculture (Huber et al., 2018). These reviews have differed in their focus, but demonstrate the bottom-up approach inherent in model design. ABMs allow for the inclusion of environmental and geospatial variables, local and global interactions between agents, the transmission of information, and the influence of varying levels of policy actors (Kremmydas et al., 2018).

Behavioural patterns of agents have traditionally been modelled using rational choice models. These models assume complete information and use utility maximisation goals to define agent behaviour, based on resource constraints (Müller-Hansen et al., 2017). Bounded rationality models decision-making in a context of imperfect information. Additionally, the decision may not be optimised for maximum utility but seeks a satisfactory outcome. Some models have implemented geospatial rules that define behaviour based on proximity to

environmental factors or other agents (An, 2012). Other methods include heuristics that define a range of potential responses and assign a probabilistic distribution to each agent's response (Huber et al., 2018). Learning theory can also be used to define the decision-making process of an agent. This would involve utilising historical behaviours to inform current decisions. For example, a decision is more likely to be repeated if the outcome is deemed positive by the agent (Müller-Hansen et al., 2017). Additionally, models may utilise a number of more complex theoretical foundations from psychological, innovation or social theories to define decision making (Bourceret et al., 2021). Groeneveld et al. (2017) conducted a review of 134 articles to explore the state of behavioural modelling in land use change ABMs and found the majority (83 of 134) were not explicitly based on a theory but used ad hoc representations of behaviour. Where theories were used, Expected Utility Theory was the most commonly used. The need to represent agent behaviour realistically can be met through the coupling of various theoretical models, which can pose issues of intractability and difficulty in replication and validation (Jager, 2021; Schwarz et al., 2020). Schlüter et al. (2017) developed the Modelling Human Behaviour (MoHuB) framework to support modellers in understanding the diversity of behavioural theories and encourage their explicit use in socioecological system modelling.

ABMs have been mostly applied to specific contexts or small spatial extents (Brown et al., 2017; Lippe et al., 2019). As with many simulation techniques, there is a need to define model boundary conditions. However, Lippe et al. (2019) highlight the limitations in the extrapolation of any conclusions from the focus on small scales. Many social and environmental dynamics manifest differently at different scales (Huber et al., 2018). There are also interactions between the scales that, when excluded, are likely to reduce the accuracy of the predictions of any model. Lippe et al. (2019) outline the need to incorporate the multi-scale dynamics of human agents, including social norms and culture, economic structures and processes, governance, ecosystem dynamics and technology to ensure adequate modelling of cross-scale socioecological systems. Where large-scale models have been implemented, assumptions are made to simplify human decision-making, often utilising macroeconomic drivers to explain the decision-making process, to enable modelling to take place without an excessive computational demand (Brown et al., 2019). Murray-Rust et al. (2014), who developed the Competition for Resources between Agent Function Types

(CRAFTY) modelling framework, overcame this challenge somewhat by utilising Agent Functional Types (AFTs) as the basis of modelling diverse agent behaviour. They group agents based on characteristics, including behavioural rules, but enable a diversity in action by drawing individual behaviour from a probability distribution which describes each agent's possible behaviours.

Agent-based modelling has been utilised for both ex-ante and ex-post policy analysis (Huber et al., 2018). However, models often parametrise policy as an exogenous variable or boundary condition, which eliminates the dynamic nature of policy development and the endogenous nature of the policy maker in the system (Holzhauer et al., 2019; Lippe et al., 2019). The inclusion of institutional agents endogenously and assigning them behavioural rules was demonstrated by Holzhauer et al. (2019). They created a land use ABM, with both global and regional institutional agents and land managers, to determine the impact of different policies and institutional dynamics on ecosystem services. Holzhauer et al. (2019) observed that the institution's tendency to react, the degree of intervention, the level of coordination between the levels of institutional agents, and the revision of a decision all showed non-linearity. These results demonstrate the need to include institutional agents endogenously in policy analysis ABMs.

In summation, agent-based modelling is a useful tool to represent complex socioecological systems utilising a bottom-up approach that allows for heterogeneity in agent type and decision-making to be explicitly represented. The majority of models either do not explicitly consider behavioural theory or adopt economic theories of utility maximisation (Brown et al., 2017; Groeneveld et al., 2017). The importance of adequately representing complex decision-making while maintaining its clarity and model transparency is well documented (Schlüter et al., 2017). Additionally, there is a need to ensure the inclusion of multi-scale interactions of decision makers at individual and institutional levels (Holzhauer et al., 2019). Furthermore, this review demonstrates that there are few examples of ABMs being applied in the developing world, and none applied to Egypt.

1.1.2.4 Coupling biophysical-agent-based models

Effective agricultural resource management requires not only a strong understanding of physical systems, but also an appreciation of how stakeholders respond to environmental and policy changes (Hu et al., 2017). In response, researchers have increasingly explored the

coupling of ABMs with biophysical models – most commonly hydrological models – to better represent the feedback between human decisions and water systems. However, the majority of these efforts have focused on either groundwater (e.g. Hu et al., 2017; Hyun et al., 2019; Noël & Cai, 2017; Zolfagharipoor & Ahmadi, 2021) or surface water models (e.g. Abebe et al., 2019; Hyun et al., 2019; Khan et al., 2017; Yuan et al., 2017; Zia et al., 2016), with fewer examples fully integrating ecohydrological models that also simulate crop growth and land use dynamics.

Several case studies highlight the diversity of methods used. Zolfagharipoor and Ahmadi (2021) couple a groundwater model (FlowLogo) with an economic module and an ABM to simulate groundwater trading between farms and industrial agents in central Iran, using behavioural parameters informed by field interviews. Hu et al. (2017) integrate a MODFLOW groundwater model with an ABM in the Republican River Basin to assess how agent pumping behaviour, shaped by machine learning and expert knowledge, affects the aquifer. For surface water models, Zia et al. (2016) link climate scenarios, land-use decisions, and a hydro-ecological model (RHESSys) to simulate nutrient flows and lake water quality under different behavioural and policy scenarios. Meanwhile, Yuan et al. (2017) develop an ABM of household land-use behaviour linked to a non-point source pollution model, using survey data and decision trees to simulate changes in water quality.

Other examples focus on urban water management or the food-water-energy-environment (FWEE) nexus. Abebe et al. (2019) couple an ABM with MIKEFLOOD to model institutional responses to flood events in Sint Maarten, while Khan et al. (2017) integrate SWAT with an ABM across the Mekong and Niger basins, modelling annual water allocation decisions by administrative agents across agriculture, hydropower, and ecosystem services. Du et al. (2020) go further by tightly coupling GSFLOW with an ABM at the source code level to simulate daily water use and policy compliance in the Heihe River Basin. However, despite its process-rich structure, this model focuses exclusively on corn and does not simulate crop selection or adaptive management.

In conclusion, recent advances in coupled ABM-(eco)hydrological models have improved the realism of water policy analysis, flood modelling, and land-water interactions. These models span a range of scales and integrate diverse decision-making frameworks. Yet, most remain focused on short-term irrigation or extraction decisions, often with fixed crop types and

simplified institutional representation. Rarely do they simulate strategic land-use change or capture complex interactions between water availability, crop choice, and policy over time. As a result, their capacity to assess long-term adaptation pathways under climate and socioeconomic change, particularly in water-scarce agricultural regions, remains limited.

1.1.2.5 Model uncertainty

Understanding and quantifying uncertainty is a critical aspect of modelling. In ecohydrological models, uncertainty arises from three main sources: input and calibration data, model structure, and parameterisation (Moges et al., 2020; Wang & Chen, 2021). While data and parameter uncertainty are frequently analysed, structural uncertainty remains less commonly addressed. Model intercomparison studies provide a useful approach for assessing structural uncertainty, and increased field measurements can help reduce parametric uncertainty, particularly in data-scarce regions (Almuhaylan et al., 2020).

The primary driver of uncertainty across all sources is often the lack of high-quality data at appropriate spatial and temporal resolutions (Moges et al., 2020). This includes incomplete or inaccurate datasets and poorly constrained parameters due to limited monitoring networks – an issue especially pronounced in developing countries (P. K. Paul et al., 2021). Open-access satellite datasets offer opportunities to reduce these gaps and improve model calibration (Dembélé et al., 2020; M. Paul et al., 2021). Nevertheless, Krysanova and Hattermann (2017), in a climate change intercomparison study across 12 major river basins, found that the greatest source of uncertainty stemmed from the climate models themselves, rather than from the hydrological models or emission scenarios.

In agent-based models, uncertainty is often addressed through sensitivity analysis, particularly where agent behaviour is based on assumed rather than empirical rules (Ligmann-Zielinska et al., 2020). Design of Experiments (DOE) is commonly used to explore how variations in input variables influence model outcomes and to evaluate the robustness of decision logic (Kleijnen et al., 2005). Ligmann-Zielinska et al. (2020) differentiate between local and global sensitivity techniques, with the choice depending on the model's purpose. Approaches such as one-at-a-time variation and regression-based methods remain prevalent in ABM literature.

1.2 Research gap

Egypt's agricultural system is under intensifying strain from the intersecting pressures of water scarcity, limited arable land, rapid population growth, shifting dietary preferences, and growing dependence on food imports. These pressures are further complicated by climate change and socioeconomic uncertainties, raising urgent questions about the future viability of agricultural production, national food security, and the livelihoods of farming households. Government strategies have historically centred on land expansion and irrigation improvements, yet the scope for such interventions is increasingly constrained by physical, institutional, and behavioural limits. Addressing these challenges requires a perspective that not only considers food demand and supply but also examines how farmers interact with the agricultural system, how the system in turn shapes farmer decisions, and what these feedbacks mean for production, food security, and rural livelihoods.

Despite widespread recognition of these pressures, many studies focus either on agricultural productivity or irrigation demand, but rarely on how they interact through land-use and management decisions. There is limited understanding of how water-related decisions, such as crop choice or irrigation intensity, might evolve under different climate and policy futures. In particular, few models capture how farmers may adapt their practices in response to changes in socioeconomic, climate, or policy context. Most analyses of climate impacts on agriculture continue to assume fixed cropping systems and full irrigation, without accounting for spatial or seasonal variability or behavioural adaptation. This limits our ability to evaluate how Egypt's agricultural landscape might change, and under what conditions it could become more efficient, or to what extent it can meet increasing demand.

Compounding this is a lack of attention to behavioural diversity and social dynamics. Egyptian farmers are not a homogeneous group. Smallholders, who constitute the vast majority of agricultural households, vary widely in landholding size, income diversification, and adaptive capacity. Yet national-scale models and scenarios often rely on stylised or top-down representations of agricultural behaviour, overlooking how different types of farmers might respond to environmental and economic stress. Without understanding who is likely to adapt, how, and at what cost, scenario analysis risks reinforcing existing inequalities or missing key opportunities for change.

Addressing these challenges calls for a more holistic and dynamic representation of the agricultural system, one that recognises the co-evolution of biophysical processes and human behaviour. There is growing recognition of the need to link social and environmental dynamics in models of land and water systems. In particular, coupling agent-based approaches with biophysical models offers a way to represent feedback between farmer decision-making and environmental constraints. While such integrated models have gained traction in high-income contexts, their application in data-scarce, water-stressed countries remains limited. Most coupled approaches focus on irrigation scheduling or basin-scale water allocation, often with simplified or static land use assumptions. Few explicitly address land use change as a behavioural process shaped by heterogeneity, adaptation, and institutional context.

This thesis seeks to address these gaps by developing a spatially explicit, coupled agent-based land-use change and ecohydrological model for Egypt. The model captures interactions between farmer behaviour, land management, and water use under multiple future scenarios. Methodologically, it advances the integration of behavioural heterogeneity with biophysical constraints, enabling exploration of how micro-level decisions can generate macro-scale outcomes, and vice versa. By embedding feedback between water use, crop production, land-use change, and farmer characteristics, the model provides a tool to evaluate the feasibility, trade-offs, and distributional consequences of different policy and development pathways.

Although the research focus is Egypt, the modelling approach has wider relevance for low- and middle-income countries facing similar pressures. Many arid and semi-arid regions contend with the challenge of increasing food production within strict environmental limits, while also addressing rural poverty. The need for integrated, empirically informed models is particularly acute in such contexts, where conventional planning tools often prove insufficient. By contributing to this emerging body of work, the thesis aims to offer both context-specific insights and a methodological contribution that can inform more inclusive and adaptive agricultural transitions in water-scarce regions.

1.3 Aims and research questions

This research investigates how land and water management in Egyptian agriculture may evolve under future climate, socioeconomic, and policy trajectories. It focuses on the interactions between resource constraints, biophysical processes, and the adaptive decisions of diverse farming households. The overarching aim is to understand how Egypt can enhance agricultural resource-use efficiency and food security in the face of mounting environmental and socioeconomic pressures. To this end, the study aims to address the following research questions:

- What are the key dimensions of diversity among Egypt's agricultural households, how can they be meaningfully grouped into household types, and what do recent trends reveal about changes in their composition and characteristics over time?
- What are the potential impacts of climate change on crop production efficiency, including changes in yields and water use efficiency?
- What plausible future development pathways could shape Egypt's agricultural sector, given uncertainties in demographic growth, dietary change, agricultural expansion, and water or trade policy objectives?
- How do different land managers respond to future climate and socioeconomic scenarios, and how do their decisions influence land-use patterns, water use efficiency, and agricultural production?

These objectives are addressed through a novel, spatially explicit modelling approach which couples agent-based land-use change and ecohydrological components. This coupled model enables the simulation of interactions between land manager characteristics, crop performance, and resource pressures over time. While developed in the context of Egypt, the approach offers broader relevance for assessing agricultural transitions in other water-scarce, low- to middle-income settings where behavioural diversity and policy decisions are critical to maximising output from limited resources.

1.4 Thesis methodological overview

This thesis brings together biophysical and socioeconomic processes in order to explore how Egyptian agriculture may change under future climate and socioeconomic pathways. The modelling is scenario-based and spatially explicit, and it is designed to address the research questions set out in Section 1.3. The aim is not only to quantify potential changes in yields and irrigation water use efficiency, but also to understand how different types of land

managers might respond to future pressures, and how these responses shape national production and agricultural resource use efficiency. Figure 1.5 provides a visual summary of the workflow and the temporal and spatial scales at which the individual components operate.

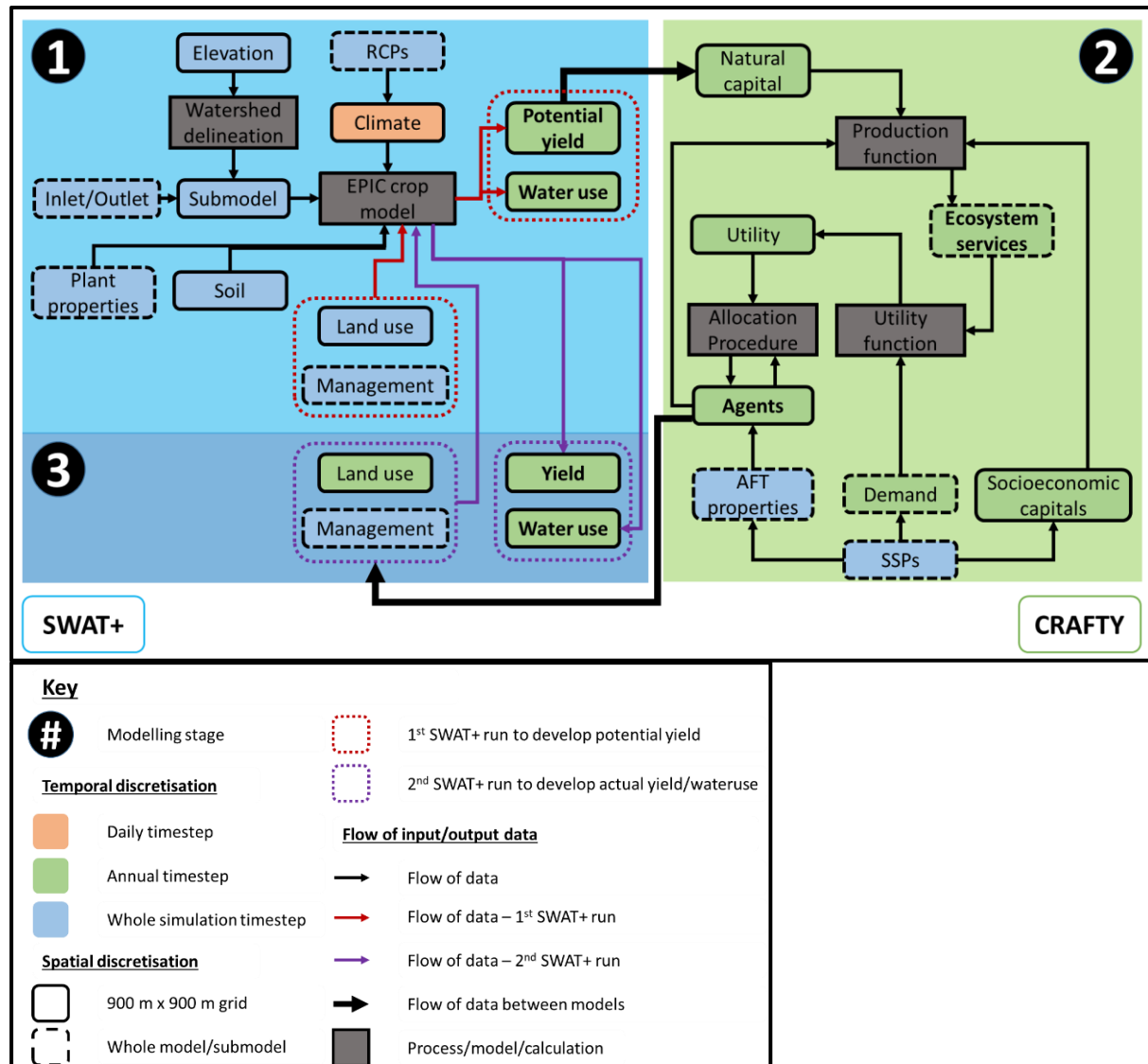


Figure 1.5: Thesis methodology schematic. Overview of the coupled model developed and applied in this thesis. The diagram illustrates the key inputs, processes, and outputs, and shows how data move between the SWAT+ and CRAFTY models. It also indicates the spatial resolution and the temporal scales of each component. The key outputs are highlighted in bold.

Although the model ultimately focuses on forward-looking scenario analysis, it begins from the recognition that land managers in Egypt are highly diverse. Chapter 2 develops a typology of agricultural households using national survey data. The analysis identifies the major structural, socioeconomic, and production factors that differentiate farming households. Additionally, it shows how the distribution of these households has changed in recent

decades. The typology does not provide direct numerical inputs to the coupled model, but it helps frame how different households are understood within the overall modelling design. In particular, it clarifies the broader behavioural and resource differences that motivate the separation between commercial and subsistence land managers used later in the scenarios. This provides essential context for interpreting why different agents respond in distinct ways under future pressures, and it supports the discussion of model results rather than driving the model parameterisation itself.

Building on this foundation, Chapter 3 presents the coupled model that develops national SWAT+ and CRAFTY models for Egypt and couples them. Only a specific subset of SWAT+ functionality is used. The focus is on crop growth and water use rather than hydrology, and the model is configured accordingly. Elevation data is used to delineate the watersheds and establish the six regional submodels covering the Mediterranean, and Nile Valley and Delta regions. Daily, bias-corrected climate data from the RCP scenarios provide the meteorological forcing. These inputs are combined with static, 900 m resolution soil maps, calibrated plant parameters, land-use maps, and fixed management schedules. The latter specifies planting and harvesting dates, and fertiliser and irrigation application. Hydrological processes such as groundwater flow, canal routing, and reservoir operation are not modelled due to the absence of available data; irrigation is, therefore, applied according to the selected management setting rather than water availability.

The first stage of the modelling process is the development of potential yields. For each RCP scenario, SWAT+ is run once for the entire simulation period using optimal fertiliser and a full-irrigation (flood) regime that aims to produce unconstrained crop growth. This produces a complete time series of potential yield and irrigation requirement for every crop, scenario, and 900 m grid cell from 2020 to 2099. These outputs represent the maximum attainable performance of each crop under ideal water and nutrient conditions for each grid cell. The potential yields are then normalised to construct the natural capital layer that is used by CRAFTY.

The second stage of the workflow applies CRAFTY for the full simulation period. The model is driven by annual socioeconomic capitals defined at 900 m resolution, together with the natural capital layer generated from the SWAT+ potential-yield simulations. Each scenario also includes an annual national demand trajectory, which is applied uniformly across the

landscape, and a set of AFT properties that vary by scenario but remain constant across years within each scenario. Before the dynamic simulation begins, an initial spatial distribution of agents is established using ten alternative land-use maps for 2020. These maps are constructed from governorate-level crop area statistics and then disaggregated to the 900 m grid, allowing the model to represent uncertainty in field-level land-use patterns. Using these inputs, CRAFTY simulates land-use change through competition between subsistence and commercial agents, who assess their ability to supply ecosystem services based on their capital endowments, crops grown, and behavioural sensitivities. Land is allocated to the agent that achieves the highest utility, generating spatially explicit changes in cropping patterns and irrigation strategies over time. The model produces annual maps of agents and their associated land-use choices for each scenario, including crop type by season and irrigation strategy, and also generates annual national estimates of non-crop ecosystem services such as employment, animal-product, and water use efficiency.

The third stage of the modelling process is the second SWAT+ run. In this stage, the annual land-use and management maps produced by CRAFTY are read back into SWAT+, replacing the static land-use layer used during the potential-yield run. SWAT+ then operates year by year at a daily timestep on the same 900 m grid, using identical planting dates, harvesting dates, and fertiliser schedules to those applied in the first run. This configuration ensures that any differences between the two SWAT+ runs arise solely from the land-use and irrigation decisions generated by CRAFTY. The outputs of this stage provide the final estimates of production and water use efficiency for each year and scenario.

Chapter 4 applies this coupled model to the scenario analysis. The chapter assesses the influence of climate change on agricultural production and irrigation water use efficiency, the responses of land managers to changing pressures, and the resulting shifts in the spatial distribution of crops. The scenario design is based on a set of Egyptian SSP narratives that reinterpret the global SSP framework for the national context. These narratives draw on expert judgement, informed by the author's understanding of Egyptian agriculture and by insights from existing scenario studies on various aspects of Egyptian agriculture (e.g. Abdelkader et al., 2018; Kheir et al., 2019; Mazzoni et al., 2018; Nikiel & Eltahir, 2021). The draft narratives were reviewed and refined through iterative discussion with supervisors. They were then translated into quantitative model inputs by specifying annual national

demand trajectories, constructing spatially explicit socioeconomic capital layers on the 900 m grid, and defining the behavioural properties of the agent types for each scenario. Population growth, dietary change, agricultural expansion, and policy assumptions were integrated consistently across all elements. By combining these scenario drivers with the biophysical impacts derived from the RCP climate projections, Chapter 4 analyses climate impacts, adaptive behaviour, and the plausibility of alternative development pathways for Egypt's agricultural sector.

Finally, Chapter 5 synthesises the results from the typology analysis, the development of the coupled model, and the scenario simulations. It discusses the implications for food security, water use efficiency, and agricultural planning. The five chapters, therefore, form a logical progression: beginning with the diversity of land managers, moving through the development of the modelling system, applying the system to future scenarios, and concluding with an integrated interpretation. This progression supports the overarching aim of identifying how Egypt can improve agricultural resource-use efficiency and food security under increasing environmental and socioeconomic pressures.

2 Typology analysis of Egyptian agricultural households reveals increasing income diversification and abandonment of agricultural activities

Authors: Aimen Sattar, Calum Brown, Mark Rounsevell, Peter Alexander

2.1 Chapter introduction

Following the introduction's discussion of Egypt's agricultural challenges, ranging from water scarcity and population growth to climate change and policy constraints, this chapter begins the empirical analysis by examining the diversity of farming households across the country. Understanding this heterogeneity is crucial for designing effective responses to future pressures, particularly given that most Egyptian farms are smallholder-operated and exhibit variation in their socioeconomic contexts, resource access, and livelihood strategies.

Using nationally representative household survey data from 2012 and 2018, this chapter develops a typology of agricultural households based on their structural, socioeconomic, and production characteristics. Through multivariate statistical analysis, the study identifies distinct household types and examines how these have evolved over the six-year period. This analysis highlights the structural and socioeconomic dimensions of heterogeneity within Egypt's farming population and how these have changed over time.

2.2 Abstract

2.2.1 Context

Egyptian agriculture is challenged by increasing demands from a rapidly expanding population, and insufficient water and arable land resources, exacerbated by the expected impact of climate change further reducing these resources. Recent government policy has focused on large projects to meet increasing demand, with a reduced focus on the livelihoods and economic sustainability of low-income farmers. Insights into variations and changes within the farming population are needed to improve the effectiveness of policies to meet these challenges.

2.2.2 Objective

This research aims to understand the heterogeneity within farming households in Egypt, to determine the characteristics which best describe these variations, and to trace developments within the sector over recent years and their dependencies on contextual factors.

2.2.3 Methods

We performed a typology analysis based on the 2012 and 2018 Egyptian labour market panel surveys, identifying and using 12 categorical and 31 continuous variables to describe farming households. Highly skewed continuous variables were transformed, and highly correlated variables were removed. Subsequently, a factor analysis was carried out to determine which variables contribute the most to variation within the dataset. Hierarchical clustering was used to identify the number of clusters and a cluster analysis was carried out to define the clusters. The evolution of the clusters was determined by tracking the households present in both surveys and determining how their type changed between the two surveys.

2.2.4 Results and conclusions

The variables which contributed the most to the variation within the household population were the degree of income diversification, cropping intensity, and water use per unit area. The clustering analysis resulted in four clusters being identified, which were specialised farming, village farming, diversified income, and landlord households. High levels of abandonment of farming were identified, with 45% of households abandoning agricultural activity in 2018 having participated in agriculture in 2012. There was a clear trend towards

greater income diversification with 59% of households new to farming in 2018 being part of the diversified income household cluster. The analysis demonstrates a clear trend away from dependence on agricultural income, presenting risks to the sustainability of small-holder farming.

2.2.5 Significance

Using the characteristics of the household types, this research presents policymakers with the opportunity to simulate responses to policies targeting greater water use efficiency, and increased income for the lowest-income households, and investigate how to meet increasing demand most efficiently. Additionally, it reinforces the global trend towards reduced participation in agricultural activities due to environmental and socioeconomic challenges.

2.3 Introduction

Agriculture is an important sector within the Egyptian economy, accounting for an average of 13.7% of the gross domestic product (GDP) between 2010 and 2014 (e.g. Bertini & Zouache, 2021). Additionally, it provided employment to more than 17% of the population in 2018 (Assaad et al., 2020). Meanwhile, Egyptian agriculture faces challenges that have been developing over decades. Rapid population growth coupled with limited water availability has reduced Egypt's renewable water from 1,750 m³.capita⁻¹.year⁻¹ in 1970 to 590 m³.capita⁻¹.year⁻¹ in 2019 (Tutwiler, 2021), well below the 1000 m³.capita⁻¹.year⁻¹ threshold of water scarcity (Falkenmark et al., 1989). Additionally, urban encroachment on agricultural land and desertification threaten the limited arable land (Abd-Elmabod et al., 2019). Climate change will exacerbate the already constrained water and land resources in the coastal region through salination of groundwater resources and loss of agricultural land due to sea-level rise, increased crop water demand due to increasing temperatures, and more severe and more frequent extreme weather events, to name but a few (Abutaleb et al., 2018).

Egypt has been increasingly dependent on imports of key staples to meet growing demand and compensate for stagnant domestic production. Egypt imports over half of all of the wheat it consumes, the staple which constitutes a third of total calorific intake and nearly half of all protein (Veninga & Ihle, 2018). This makes Egypt very vulnerable to global food price shocks. The years preceding the significant political instability of 2011 were characterised by low domestic yields due to extreme weather, followed by global food price rises (Soffiantini, 2020).

Most Egyptian farming households are categorised as smallholders, with more than 80% of households holding less than 2 hectares (Abdalla et al., 2022). Because of a warm winter climate and access to year-round Nile River waters, farmers can grow a variety of field crops, fruit and vegetables over three seasons (Abdalla et al., 2022; Abdelaal & Thilmany, 2019). Although Egyptian farmers enjoy some of the highest yields globally (Nikiel & Eltahir, 2021), the dominance of smallholder farming, downward pressure on prices and upward pressure on costs, has resulted in farming households becoming dependent on mixed livestock-crop farming systems and secondary incomes (Abdelaal & Thilmany, 2019; El Nour, 2015).

Policy has played a major role in farming choices in Egypt. For decades, strong top-down governance has characterised agricultural policy (Bush, 2007). Since the 1980s, market liberalisation attempted to reduce state spending while maintaining cheap inputs for key staple crops, limiting the production of ‘thirsty’ crops such as rice and cotton, and, at times, restricting exports of key staples in order to increase self-sufficiency and improve water use efficiency (Fuglie et al., 2020). These governmental policies have been inconsistent, however, with rapidly changing agricultural policy priorities creating instability for farmers and limiting policy impact (Abdalla et al., 2022). One policy priority of the 1990s was the liberalisation of land rental laws, which allowed landlords to set land rents (previously constrained to no more than 7-times the land tax rate) based on free market prices. Furthermore, liberalisation removed the ‘tenancy in perpetuity’ provided under previous laws. These changes resulted in more than 900,000 tenants losing tenancy (El Nour, 2015). Large headline-grabbing projects have dominated agricultural policy at the expense of investment in low-income farming households (Bush, 2022). The 1.5 Million Feddan Project, a project to reclaim 1.5 million feddan² of desert land in the Western Desert and bring it under cultivation, is typical in focusing on large private or state investments. Additionally, it is predominantly operated by either large state or commercial enterprises. The main aim of the 1.5 Million Feddan Project is to reduce Egypt’s dependence on imports for key grains, with a minor focus on providing land and income to the low-income, landless, and underemployed section of the population (Bush, 2022; Nour, 2020).

The Egyptian context presents a number of complex social, environmental, and policy challenges. Farm and farmer typology analyses are widely used to support policy design for such challenges through the identification of important socio-environmental, farmer, and farm structural characteristics (Huber et al., 2024). Typologies reveal commonalities within farmer populations, summarise large groups into representative types (Hammond et al., 2020; Shukla et al., 2019), and help in the development and ex-ante analysis of policy options (Nyambo et al., 2019; Rega et al., 2022). They can also focus on relatively neglected aspects

² Feddan is the standard unit of agricultural area utilised in Egypt. 1 feddan = 1.038 acres = 4,200 m² = 0.42 hectares.

such as roles, desires, and goals (Blanco et al., 2015) alongside environmental and structural resources (Huber et al., 2024).

Typology analysis has been widely used to understand and summarise the diversity within smallholder farmers in various contexts (Guarín et al., 2020; Nin-Pratt et al., 2018; Shukla et al., 2019; Sinha et al., 2022), and is a common tool in the assessment of technology adoption (Nin-Pratt et al., 2018; Rega et al., 2022; Sarker et al., 2021; Shukla et al., 2019). Farm household typology analysis would enable a greater understanding of the key characteristics and needs within Egyptian farming households while developing common archetypes, which can be used to define and assess the impact of policy, maximise the benefit derived from positive characteristics of the system, and respond to challenges of climate change.

Several farmer typologies have been developed for the Egyptian context. Most examples in Egypt are limited to small spatial areas (e.g. Aboul-Naga et al., 2022; Alary et al., 2014; Alary et al., 2020) or address a single socioeconomic level (e.g. Martin et al., 2020). These studies usually develop and implement local surveys to delineate typologies, but national-level market panel surveys have been used to produce national typologies (Helmy, 2020; Nin-Pratt et al., 2018). For example, Nin-Pratt et al. (2018) conducted a farming household typology analysis based on 2012 labour market panel survey data. This analysis utilised continuous variables to develop typologies based on resource and environmental characteristics and used these typologies to analyse the impact of different climate change scenarios on agricultural production. Helmy (2020) used the complete labour market panel survey series (1996, 2006, 2012, 2018) to analyse the evolution of livelihood diversification in Egypt. Farming, salaried agricultural labour, and livestock activities were included within diverse livelihood strategies, but the diversity and characteristics of the farmer and farm structures were not specifically investigated. Together, these past studies provide an overview of agriculture's role in Egypt, but do not trace developments within the sector over recent years or their dependencies on contextual factors. In particular, a typology analysis including household economic and social characteristics, for example levels of education, dwelling type and ownership status, is so far lacking.

This study identifies farming household types utilising structural and functional characteristics and determines how these types evolve over time. The study is not intended to find a preferred farmer type that could improve farmer welfare and efficiency, but rather to

understand the characteristics of farmer typologies and how they have changed in order to enable the development of targeted interventions with relevant policies. This is achieved by addressing the following research questions: 1. What are the key structural and functional characteristics that explain variability in Egyptian agricultural households? 2. Using a multivariate analysis, how can agricultural households be classified? 3. How have these farming typologies evolved through time? 4. What are the possible causes of such changes?

2.4 Data

The most recent Egypt Labour Market Panel Surveys (ELMPS), carried out in 2012 and 2018 (Krafft et al., 2021), were used to determine the farming household typology. The ELMPS started in 1998 and was conducted in 2006, 2012, and 2018. It was designed to be representative of the labour market (Assaad & Krafft, 2013; Krafft et al., 2021). The surveys were conducted via individual and household interviews over a number of months, and included details on demography, employment, and income, among others. Sampling was carried out using primary sampling units based on enumeration areas of the government statistical master sample. Each new survey recruited the original households, new households that emerged due to splits in the original households, as well as refresher samples. At each round of the panel survey, the number of primary sampling units was increased. Results were compared to labour force surveys and censuses to ensure the representativeness of the ELMPS to the labour market (Assaad & Krafft, 2013; Krafft et al., 2021).

The 2012 survey was the first year in which detailed enquiries into the specifics of farming households were included. The ELMPS data were reinforced with data from annual governmental statistical reports (CAPMAS, 2025). These reports included annual, governorate-level agricultural area and production bulletins and water use reports per crop type, and national crop and livestock incomes. These reports were used to calculate values for regional water use per unit area for each crop, crop-specific yields for each governorate, and national income per tonne of crop produced.

The 2012 and 2018 ELMPS included both individual and household questions relating to the socioeconomic conditions of the survey participants. The individual questionnaire included questions on demographic details, such as employment and education. Additionally, a household questionnaire included details of household income and capital, such as off-farm

and farm enterprises, remittance, and other household income (Economic Research Forum & Central Agency For Public Mobilization and Statistics (CAPMAS), 2013, 2019).

A summary of the total and farming individuals and households of ELMPS 2012 and 2018 surveys are included in Table 2.1.

Table 2.1: Summary of 2012 and 2018 Egypt Labour Market Panel Survey details.

Property	ELMPS 2012 (% of total)	ELMPS 2018 (% of total)
Total number of individuals	49,186	61,231
Total households	12,060	15,746
Farming individuals	9,210 (18.72%)	8,197 (13.39%)
Farming households	1,821 (15.10%)	1,772 (11.25%)

2.5 Methodology

The first stage of the analysis was data preparation. This included utilising 2012 and 2018 ELMPS and complementary data from various national statistical reports to estimate missing responses and standardise units where necessary, summarising individual responses across each household, and rebasing 2018 monetary values to 2012. Data preparation details are provided in Appendix A.1. Variables were chosen from those available to capture functional and structural characteristics of the households, and for consistency with similar typology analyses (e.g. Huber et al., 2024; Nin-Pratt et al., 2018; Sarker et al., 2021; Shukla et al., 2019). Analyses of key variables of farming households demonstrate that important descriptors of variability include characteristics of the head of household – such as age and level of education - and characteristics of the household - including size, education levels of members, and dwelling type. Additionally, farming household income, capital, and off-farm income have been widely used to produce typologies for the development of policies to improve farm income and increase production (Huber et al., 2024). These variables are then used to complete an initial exploratory analysis followed by statistical and clustering analyses. Although some statistical and clustering analyses transform mixed data either into categorical or continuous forms, statistical methods using survey data in their original forms retain all information in the original data within the analysis and do not diminish its variability (Shukla et al., 2019).

Subsequently, outliers were identified by defining rational limits on certain variables, to account for missing and incorrect data – see Appendix A.1 for more details – reducing the original 3593 cases to 3526. Histograms, given in Appendix A.1, were used to visualise the distributions of the continuous variables. The skewness of all continuous variables was calculated, with skewness greater than 1 and below -1 considered highly skewed and transformed to satisfy normality assumptions in subsequent methods. Box-Cox transformations were carried out using the ‘MASS’ R package (Venables & Ripley, 2002). Due to the nature of the agricultural system in Egypt, many variables are highly positively skewed, representing the dominance of subsistence farming.

Correlated variables were identified using the ‘hetcor’ function of the ‘polycor’ R package (Fox, 2022), which provides Pearson product-moment correlation coefficients between continuous variables, polyserial correlations between continuous and categorical variables, and polychoric correlations between categorical variables. Correlations greater than an absolute value of 0.7 were deemed high and the variables were removed. Variable reduction was then carried out using the Factor Analysis on Mixed Data (FAMD) technique using the ‘FAMD’ function of the ‘clustMixType’ R package (Szepannek, 2018). FAMD is a combination of Principal Component Analysis and Multi Correspondence Analysis that reduces the number of variables in a mixed dataset whilst maintaining key variability (Nyambo et al., 2019).

To determine the number of clusters, hierarchical clustering on principal components was used. The defined number of clusters was used in the ‘kproto’ function of the ‘clustMixType’ R package (Shukla et al., 2019). K-Prototypes is an unsupervised clustering on mixed data that partitions the data into k clusters, where each data point belongs to the cluster with the nearest centroid (van de Velden et al., 2018). K-prototypes uses a combination of the Euclidean distance for numerical features and the dissimilarity measure for categorical features (Foss et al., 2018).

2.6 Results

A total of 43 variables were included in the analysis: 10 nominal variables, 2 ordinal variables, and 31 continuous variables. Table 2.2 gives the mean and standard deviation of the continuous variables and the frequency and percentage of each response for the categorical variables. Figure A.1 in Appendix A.1 shows the distribution of each continuous variable and

the count of each response for categorical variables. Skewness is detailed in Table A.5 in Appendix A.1. Most continuous variables were highly skewed ($-1 > \text{skewness} > 1$), indicating unequal distribution of resources between households. The most highly skewed variables were the total agricultural area, with a skewness of 59, and total off-farm capital, with a skewness of 50. This high positive skewness is an indication of many very low values for both variables and a small number of very high values. There were two negatively skewed variables – cropping intensity and ratio of owned to rented land – which had a skewness of -0.27 and -0.79, respectively. These results indicate a prevalence of multiple harvests per year and a high degree of land ownership, respectively. Categorical variables are in line with expectations for farming households in Egypt, with 87% being male-headed households, higher rates of illiteracy among the heads of households than in the household, and 88% of households being rural.

Table 2.2: Data summary of typology analysis dataset. This includes the description, variable code, and data type for each variable. Additionally, the means and standard deviation for continuous variables, and count and percentage of each response for categorical variables, are included. Details of advanced, intermediate, and basic agricultural equipment are included in Appendix A.1.

Variable (unit)	Data Type	Response ⁺	Mean (Standard Deviation)* / Count (%) ⁺
Characteristics of head of household			
Age of head of HH (yr)	Continuous		51.07 (13.85)
Sex of head of HH	Categorical (nominal)	1 (male) 2 (female)	3073 (87.15) 453 (12.85)
Level of education of head of HH	Categorical (ordinal)	0 (none) 1 (primary) 2 (preparatory) 3 (general secondary) 4 (technical secondary -3 years)	1957 (55.50) 542 (15.37) 175 (4.96) 45 (1.28) 531 (15.06)

Variable (unit)	Data Type	Response ⁺	Mean (Standard Deviation)* / Count (%) ⁺
		5 (technical secondary - 5 years)	23 (0.65)
		6 (middle institute)	36 (1.02)
		7 (higher institute)	18 (0.51)
		8 (university)	184 (5.22)
		9 (postgraduate)	15 (0.43)
HH characteristics			
Size of HH	Continuous		4.84 (2.30)
HH region	Categorical (nominal)	Lower Egypt	1669 (47.33)
		Middle Egypt	863 (24.48)
		Upper Egypt	994 (28.19)
Urban/rural	Categorical (nominal)	1 (urban)	413 (11.71)
		2 (rural)	3113 (88.29)
Housing type	Categorical (nominal)	1 (apartment)	1682 (47.70)
		2 (more than one apartment)	46 (1.30)
		3 (villa/house)	542 (15.37)
		4 (village house)	1063 (30.15)
		5 (one room or more in same unit)	140 (3.97)
		6 (one independent room or more)	49 (1.39)
		7 (cottage/tent)	2 (0.06)
		8 (cemetery)	1 (0.03)
		9 (other/basement)	1 (0.03)

Variable (unit)	Data Type	Response ⁺	Mean (Standard Deviation)* / Count (%) ⁺
Housing ownership or rental type	Categorical (nominal)	1 (owned) 2 (condominium) 3 (rent, unfurnished) 4 (rent, furnished) 5 (rent, new law) 6 (fringe benefit/grant)	2868 (81.34) 148 (4.20) 33 (0.94) 6 (0.17) 20 (0.57) 451 (12.79)
Highest level of education within HH	Categorical (ordinal)	0 (none) 1 (primary) 2 (preparatory) 3 (general secondary) 4 (technical secondary -3 years) 5 (technical secondary - 5 years) 6 (middle institute) 7 (higher institute) 8 (university) 9 (postgraduate)	1369 (38.83) 455 (12.90) 256 (7.26) 71 (2.01) 820 (23.26) 30 (0.85) 64 (1.82) 32 (0.91) 399 (11.32) 30 (0.85)
Type of internet access	Categorical (nominal)	1 (dsl) 2 (usb modem) 3 (dial-up) 4 (through neighbours) 5 (none) 6 (other)	177 (5.02) 30 (0.85) 107 (3.03) 59 (1.67) 3147 (89.25) 6 (0.17)

Variable (unit)	Data Type	Response⁺	Mean (Standard Deviation)* / Count (%)⁺
Total HH income per capita (2012 EGP**)	Continuous		11695 (29964)
Agricultural details			
Agricultural capital			
Area of agricultural land (feddan)	Continuous		3.15 (106.11)
Advanced agricultural equipment	Categorical (nominal)	1 (yes) 2 (no)	642 (18.21) 2884 (81.79)
Intermediate agricultural equipment	Categorical (nominal)	1 (yes) 2 (no)	876 (24.84) 2650 (75.16)
Basic agricultural equipment	Categorical (nominal)	1 (yes) 2 (no)	562 (15.94) 2964 (84.06)
Number of cattle	Continuous		0.91 (1.29)
Number of sheep and goat	Continuous		0.77 (3.47)
Total livestock capital (2012 EGP**)	Continuous		16430 (20583)
Agricultural income and expenses			
Total income from crops (2012 EGP**)	Continuous		17138 (41848)
Income from animal products e.g. poultry, honey, dairy (2012 EGP**)	Continuous		130.75 (1347)
Income from rent of land (2012 EGP**)	Continuous		734.02 (3784)
Cost of land rental (2012 EGP**)	Continuous		1101 (5995)

Variable (unit)	Data Type	Response⁺	Mean (Standard Deviation)* / Count (%)⁺
Total agricultural income (2012 EGP**)	Continuous		18032 (41870)
Agricultural resource use			
Cropped area (feddan)	Continuous		1.53 (2.75)
Total agricultural water use (m ³)	Continuous		5189 (10147)
Number of HH agricultural workers	Continuous		1.76 (1.27)
Number of hired agricultural workers	Continuous		0.59 (3.21)
Agricultural efficiency			
Cropping intensity (copped area/land area)	Continuous		1.31 (0.82)
Ratio of crop earnings to crop income	Continuous		0.32 (0.34)
Cropping income per unit area (2012 EGP/feddan)	Continuous		9743 (11115)
Ratio of high-value to field crop	Continuous		0.06 (0.20)
Ratio of crop production sold at market	Continuous		0.30 (0.32)
Ratio of owned to rented land	Continuous		0.68 (0.45)
Water use per unit area (m ³ /feddan)	Continuous		2666 (1974)
Livestock capital per unit area (2012 EGP/feddan**)	Continuous		26951 (51420)
Ratio of hired agricultural workers to household workers	Continuous		0.09 (0.24)

Variable (unit)	Data Type	Response ⁺	Mean (Standard Deviation) [*] / Count (%) ⁺
Ratio of agricultural to total income	Continuous		0.49 (0.37)
Non-agricultural income and capital			
Total HH income from off-farm employment (2012 EGP**)	Continuous		7000 (22004)
Income from remittance (2012 EGP**)	Continuous		936.41 (6527)
Other income (2012 EGP**)	Continuous		12339 (56589)
Total non-agricultural income (2012 EGP)	Continuous		18032 (41870)
Total non-agricultural capital (2012 EGP)	Continuous		2362 (41180)
Survey year	Categorical (nominal)	12 18	1806 (51.22) 1720 (48.78)

^{*} Mean and standard deviation for continuous variables.

⁺ Response, count and percentage for categorical variable

^{**} All monetary values are presented in 2012 Egyptian pounds (EGP). This exchange rate in 2012 was 6.06 EGP to 1 USD

(<https://data.worldbank.org/indicator/PA.NUS.FCRF?locations=EG>).

2.6.1 Multivariate analysis

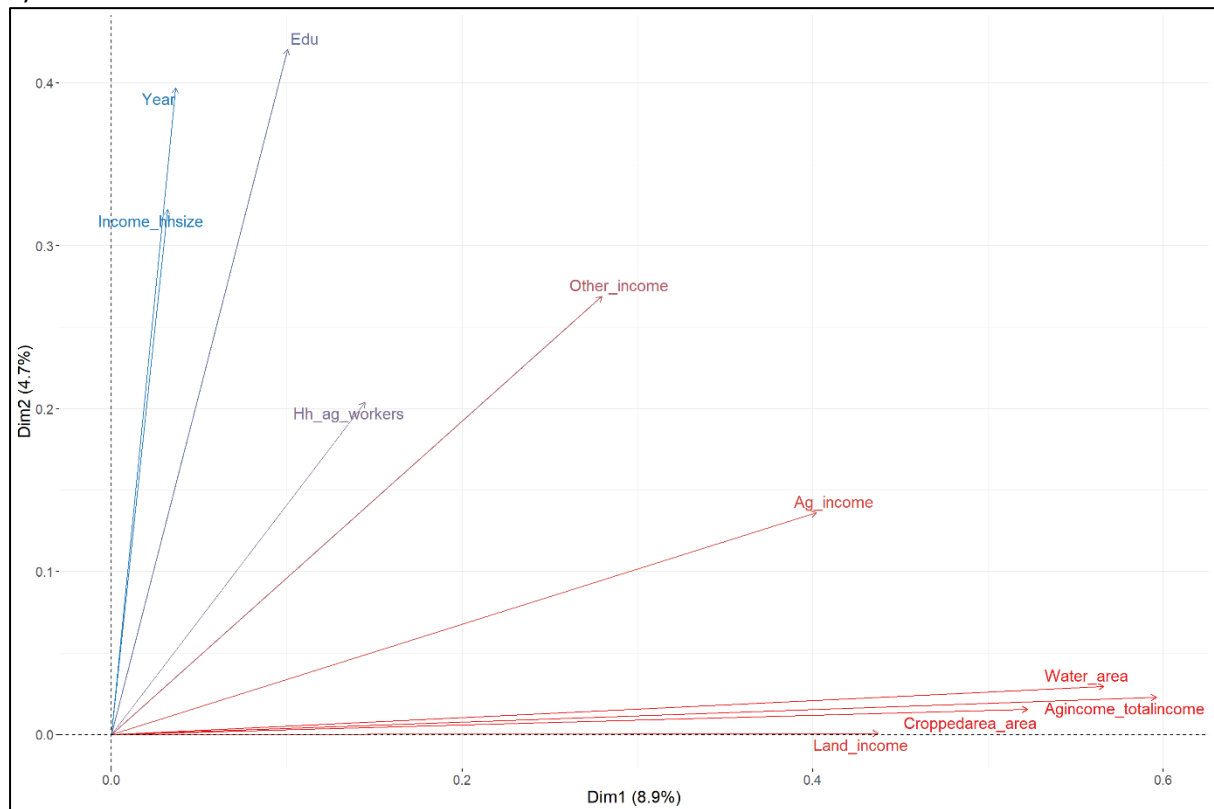
After the transformation of the highly skewed continuous variables, a correlation analysis was carried out on the transformed variables. Figure A.3 in Appendix A.1 shows the correlation plot for all variables. Eight variables had a correlation greater than 0.9, a further eleven variables had a correlation between 0.7 and 0.9. Four variables had large negative correlations. For each highly correlated pair of variables, a single variable was removed. Table A.6 in Appendix A.1 includes details of the highly correlated variables, the details of the

degree of correlation, and the 10 variables which were removed from further stages of the analysis.

The factor analysis was carried out on the reduced set of transformed variables, and returned eigenvalues detailed in Table A.7 of Appendix A.2. As per the Kaiser criterion, dimensions with eigenvalues above 1 were retained. Therefore, 22 dimensions were retained, explaining a cumulative variance of 59%. Table A.8, in Appendix A.2, gives the contribution that each variable makes to the dimension of the FAMD. Figure 2.1 shows the eigenvectors for dimension 1 and 2, and 1 and 3 of the factor analysis, indicating the relative contributions of each variable to each of the dimensions. The total variance explained by dimensions 1 and 2 is 13.6%. Cropping intensity, water use per unit area, and the ratio of agricultural to total income have the highest loading for dimension 1, whilst year of survey, the highest level of education in the household, and total household income per capita were the largest contributors to dimension 2.

Based on the factor analysis, variables contributing less than 10% to the first 22 dimensions of the factor analysis were removed. A total of 13 variables were removed, leaving 20 variables for the cluster analysis. The remaining variables are those highlighted in yellow in Table A.8 of Appendix A.2.

a)



b)

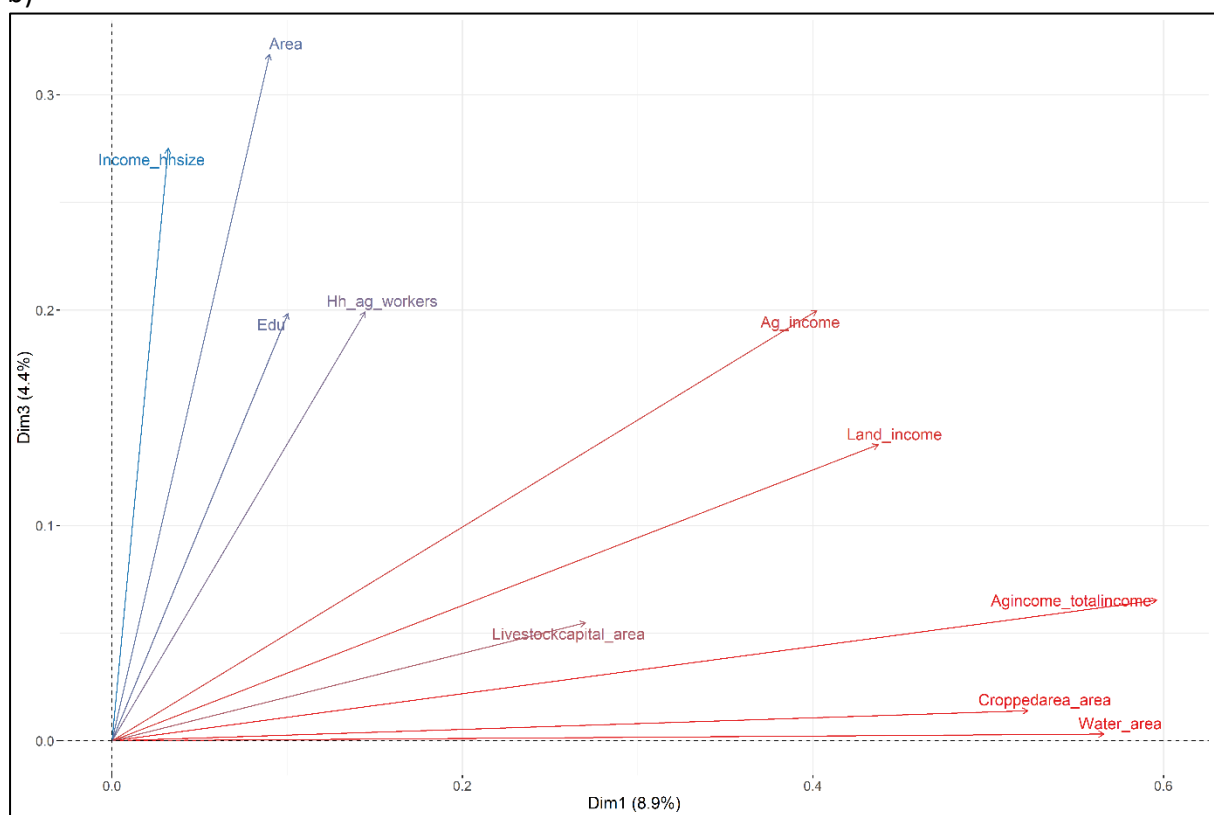
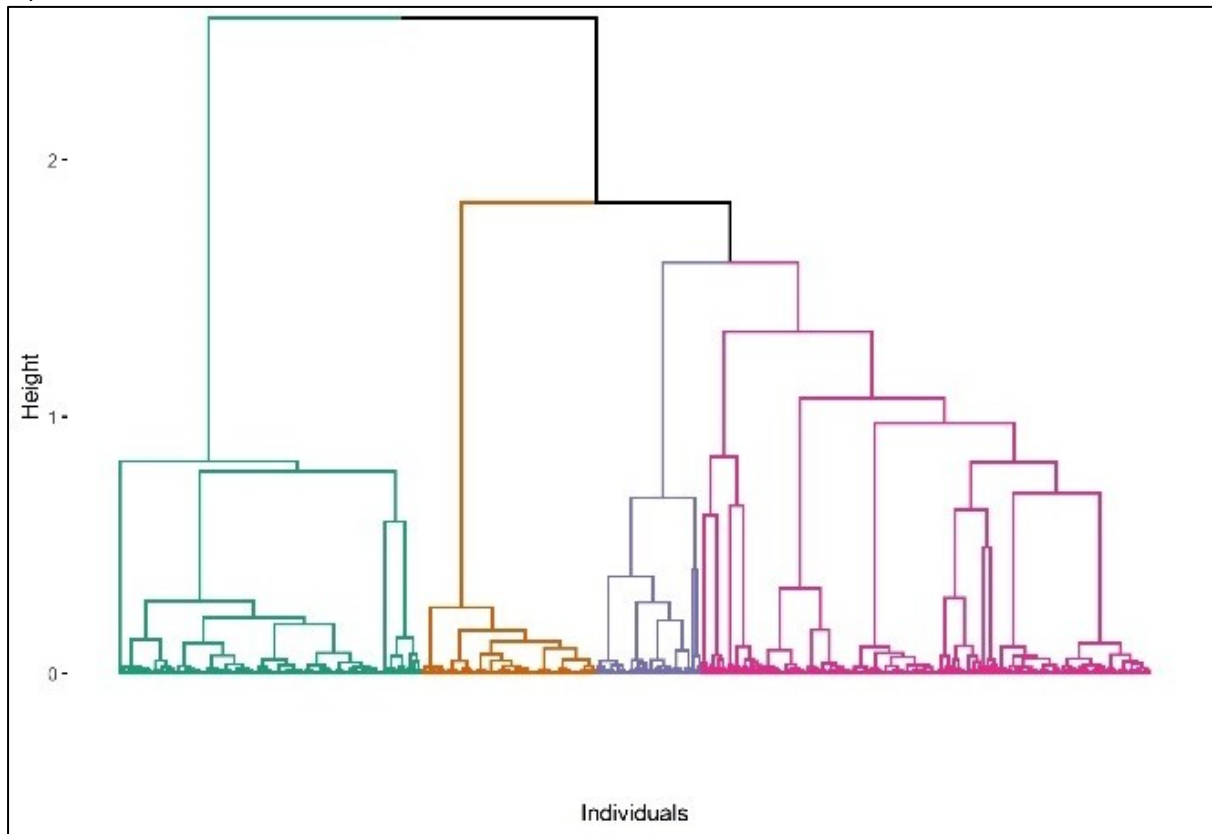


Figure 2.1: Results from the Factor Analysis on Mixed Data: The ten variables which contribute the most to a) dimensions 1 and 2, b) dimensions 1 and 3. The length of the arrow shows the eigenvector, a degree of contribution. The colour of the arrow demonstrates the extent to which it contributes more to the dimension 1 (red) or the y-axis dimension (dimension 2 or 3) (blue).

a)



b)

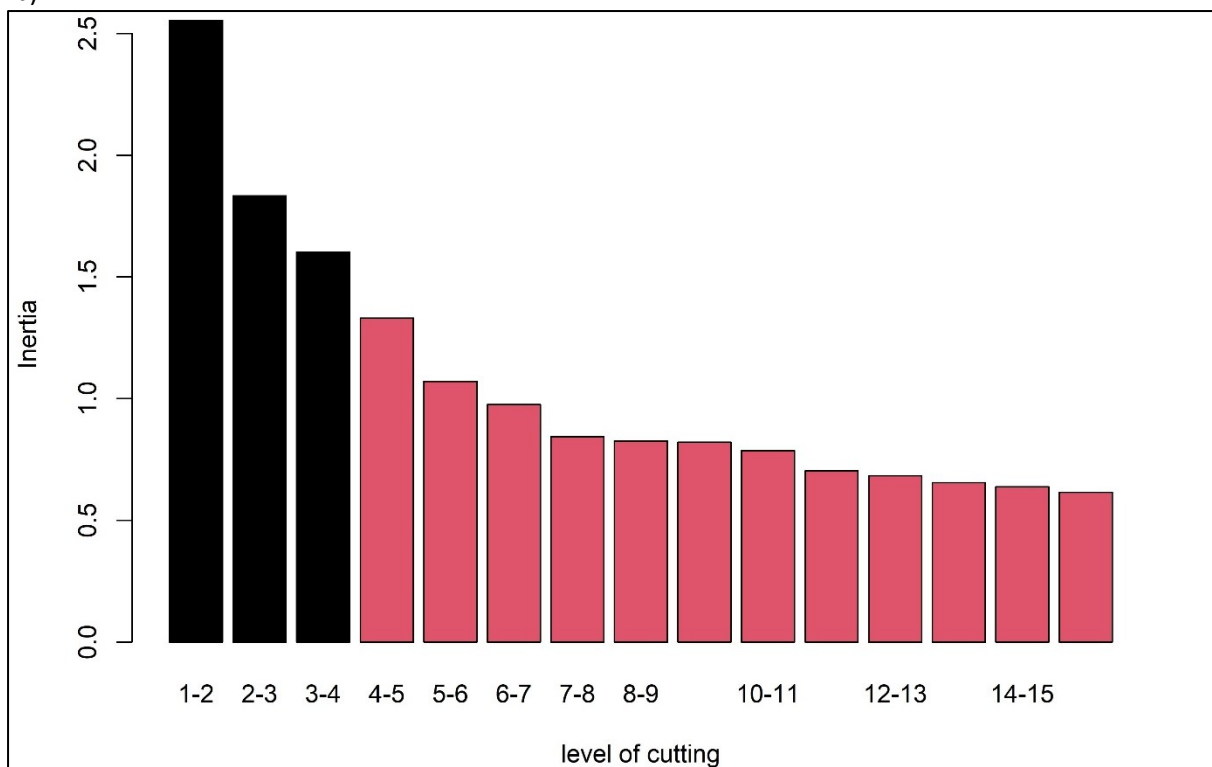


Figure 2.2: Hierarchical Clustering on Principal Components results: a) Cluster dendrogram derived from the Hierarchical Clustering on Principal Components (HCPC) of survey individuals. This is derived by conducting a Principal Component Analysis of continuous variables and binary coded categorical variables, identified in the FAMD, using Ward's criterion. Four different clusters are highlighted in different colours. b) The inter-cluster inertia gain, showing the drop in inertia between each pair of cluster number. For example, the first bar shows the difference in inertia between having a single cluster and having two clusters. The difference in colour highlights the relative drop in inertia of 4 clusters.

The subsequent stage of the analysis entailed the completion of hierarchical clustering on principal components (HCPC) to determine the appropriate number of clusters for the cluster analysis. To make this possible, categorical variables were converted to binary coding, with each response becoming a new variable and zero or one used to identify which observation is included in this response. A principal component analysis (PCA) was carried out on the converted data. Figure 2.2 shows the cluster dendrogram and inter-cluster inertia gain plot for the HCPC. A review of both diagrams in Figure 2.2 shows that there are between 2 and 5 appropriate clusters. Only utilising two clusters was deemed too coarse to allow for the sufficient description of the variability within the sample population. The relative difference in inter-cluster inertia for 3, 4 and 5 clusters is similar, with 4 being slightly greater than 5 and 3. The “NbClust” R package was used to assess the appropriate number of clusters using 23 different indices (Charrad et al., 2014). Most indices returned 4 as the most appropriate number of clusters. Appendix A.5 includes details of results for 3 and 5 clusters as a comparison to the results presented below.

The final stage of the analysis entailed the use of k-prototype clustering on the dataset post-FAMD to determine the final clusters. There is a need to stipulate the number of clusters for this methodology. As per the result of the HCPC, 4 clusters were used. Table 2.3 includes the number and percentage of households in each cluster. Figure 2.3 includes the percentage of each response for each cluster for categorical variables. Additionally, Figure 2.4 includes the constituent components and total value of agricultural and off-farm income for each cluster. Finally, Figure 2.5 is a radar chart of key efficiency indicators for each cluster. The efficiency indicators were scaled based on the range of each variable and the mean was calculated for all cases. The results are summarised in detail in the emergent clusters section below. The emergent cluster names were assigned based on their key differentiating attributes.

Table 2.3: Number of households in each cluster and percentage each cluster represents from the whole sample.

Cluster	Number of households	Percentage of households
1 - Specialised	650	18
2 - Village	1085	31
3 - Diversified	1130	32
4 - Landlord	661	19

2.6.2 Emergent clusters

2.6.2.1 Cluster 1: Specialised farming household

The specialised farming household type is highly specialised, generating 62% of their income from agricultural activity, compared to an overall mean of 49%. It exhibits the greatest profitability – 51% earnings to income - and has the highest average cropped area (2.37 feddan). This household type also has the highest ratio of high-value to field crops, with 15% of crops produced being high-value, (the mean across all households is 6%). Additionally, specialised farming households sell 49% of produced crops and use the remainder for household consumption. This household type also uses the most water per unit area at 5,406 m³/feddan. Specialisation is focused on crop production, with livestock capital per feddan being the lowest of the three household types focused on agricultural activity (17,888 EGP). However, this household type generates the most income from the sale of animal products, with a mean annual income of 187 EGP.

The off-farm income of this household type is dominated by off-farm employment (6,335 EGP) and governmental support (5,874 EGP). The specialised farming household receives the second highest income from remittances (1,182 EGP), 26% higher than the overall mean of 936 EGP. However, the specialised farming household has lower levels of education, with 71% having no one with a secondary education, second only to the village farming household. Additionally, the household type has high rates of living in apartments (64%; compared to an average of 48%). This household type is also less likely to live in a village house (21% compared to the 30% average). The dwelling type may be due to a high geographical skew; 74% of specialised farming households reside in Lower Egypt which is more densely populated. Finally, the specialised farming household type is highly skewed to 2012, with 69% of this type being from 2012 households.

2.6.2.2 Cluster 2: Village farming household

This cluster is characterised by a very high rate of village-dwelling, with 60% living in village houses, compared to a mean of 30%. Agricultural income contributes 70% to the total household income, well above the survey average of 49%. However, the mean total agricultural income is 18,115 EGP, the second lowest of the four household types. The village farming household has the highest level of livestock capital (21,437 EGP). Although this household type has the highest cropping intensity (1.64), it has the lowest income per unit

area (10,999 EGP per feddan). This can be explained, in part, due to the village farming household being less likely to grow high-value crops – 6% of crops grown are high-value on average – and the lowest water use per unit area between farming types that grow crops (2,454 m³/feddan). This household type employs the most external workers compared to the number of household members who work on the household's farm (0.16).

The village farming household type has the lowest level of education, with 78% of heads of households not having completed primary education and 93% not having completed secondary education. For the household, levels of education are also the lowest amongst the household types, with 90% of households having no one who has completed a secondary education. The village farming household type has the lowest access to internet – 96% of households are without any internet access. This household type, with an average of 5.54 people, also has the largest average household size. In terms of off-farm income, off-farm employment, and support and benefits from the government and other organisations contribute 4,291 EGP and 2,490 EGP annually to the total off-farm household income of 9,643 EGP. The lower income and high dependence on agricultural income contribute to this household type having the lowest household income per capita (5,987 EGP). The village farming household type was far more common in 2012 than 2018, with 84% of households in this household type coming from 2012. Geographically, the village farming household cluster is skewed towards Middle Egypt – 63% compared to an overall percentage of 24%.

2.6.2.3 Cluster 3: Diversified income household:

This household type has the most diversified income, with 46% of income from agricultural activities and the remainder from off-farm income. The 23,098 EGP annual agricultural income is mostly generated from crop production (22,778 EGP). The diversified income household type spends the most on land rental (1,341 EGP). Of the 3 household types which participate in crop production, this household type sells the least at market; only 32% of produced crops. However, the crop income per feddan is the highest of any household (13,343 EGP/feddan). The diversified income household type is most dependent on household labour and least on hired labour for farming activities, with 2.47 household farm workers and 0.26 hired workers per household. Additionally, this household type has more sheep and goats than cattle, with a mean of 0.78 head of cattle per household and 0.96 head

of sheep or goats per household; a pattern that is unique among crop-producing household types.

The diversified income household type has the highest level of education, with 50% of households having at least one person who has completed a 3-year technical secondary education and 13% with university undergraduate or postgraduate education. Additionally, this household type has the lowest level of illiteracy among heads of household as only 37% have not completed primary education. Regarding off-farm income, the diversified income household type generates a total of 25,439 EGP per year. This is made up primarily from off-farm employment (8,280 EGP) and governmental support (8,062 EGP). This household type is much more common in 2018, with 88% coming from the 2018 survey.

The results, in Figure 2.4 and Figure 2.5, show that the diversified income household type is similar to the village farming household type in terms of income, and agricultural efficiency. However, the difference in degree of dependence on agricultural income, dwelling type, location, education level, and year of survey, are important differences which warrant maintaining two household types for these households.

2.6.2.4 Cluster 4: Landlord household

This household type has a mean income per member of household of 21,118 EGP, the highest of any household. Additionally, the typical household generates 3,273 EGP per year from land rental, ten times that of any other household type. This is further highlighted by the absence of any cropped area and, therefore, no income from crop production and no crop water use. The 7% of income derived from agricultural activities comes from land rental and the sale of animal products. Additionally, this household type has low agricultural capital, with the lowest mean livestock capital of (5,266 EGP) and the lowest access to basic, intermediate, and advanced agricultural equipment – with 3.5%, 5.8%, and 2.9% having access to each of those levels of equipment, respectively. The landlord household is mostly dependent on government support, deriving 42,174 EGP of a total of 68,399 EGP of off-farm income from pensions and other governmental support. Additionally, this household type earns the most from household off-farm employment, with a mean income of 9,914 EGP.

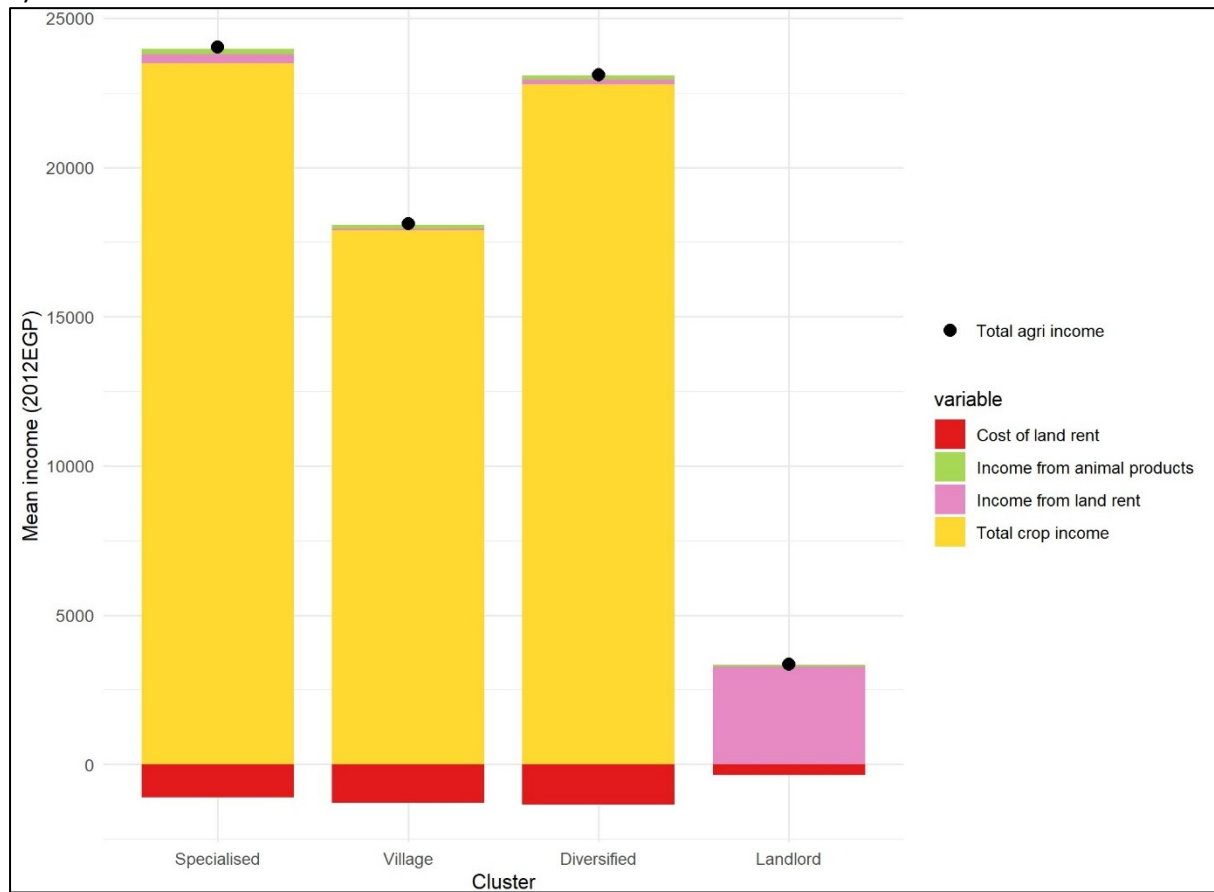
The landlord household type is more likely than others to have a female head – 24% are female-headed compared to an overall survey percentage of 13%. Although this household

type has the highest level of higher education – 14% of household heads have a university or postgraduate education and 22% of households have at least one person who has a university or postgraduate education – 50% of households have no one who has completed a secondary education. This appears high, but is the second-lowest among the household types. Furthermore, 61% of this household type live in apartments, compared to 48% of the overall surveyed households. The landlord household type has the highest access to the internet (23%). Additionally, this household type is the most likely to be from an urban area, with 18% coming from urban areas compared to an overall percentage of 11%. The geographic distribution of the households in this household type is similar to the overall sample, and the temporal distribution is almost equal with 48% of households from 2012.



Figure 2.3: A summary of categorical variables for each cluster: The charts show the percentage of each response. Key: HH=household, agri=agricultural, equip=equipment.

a)



b)

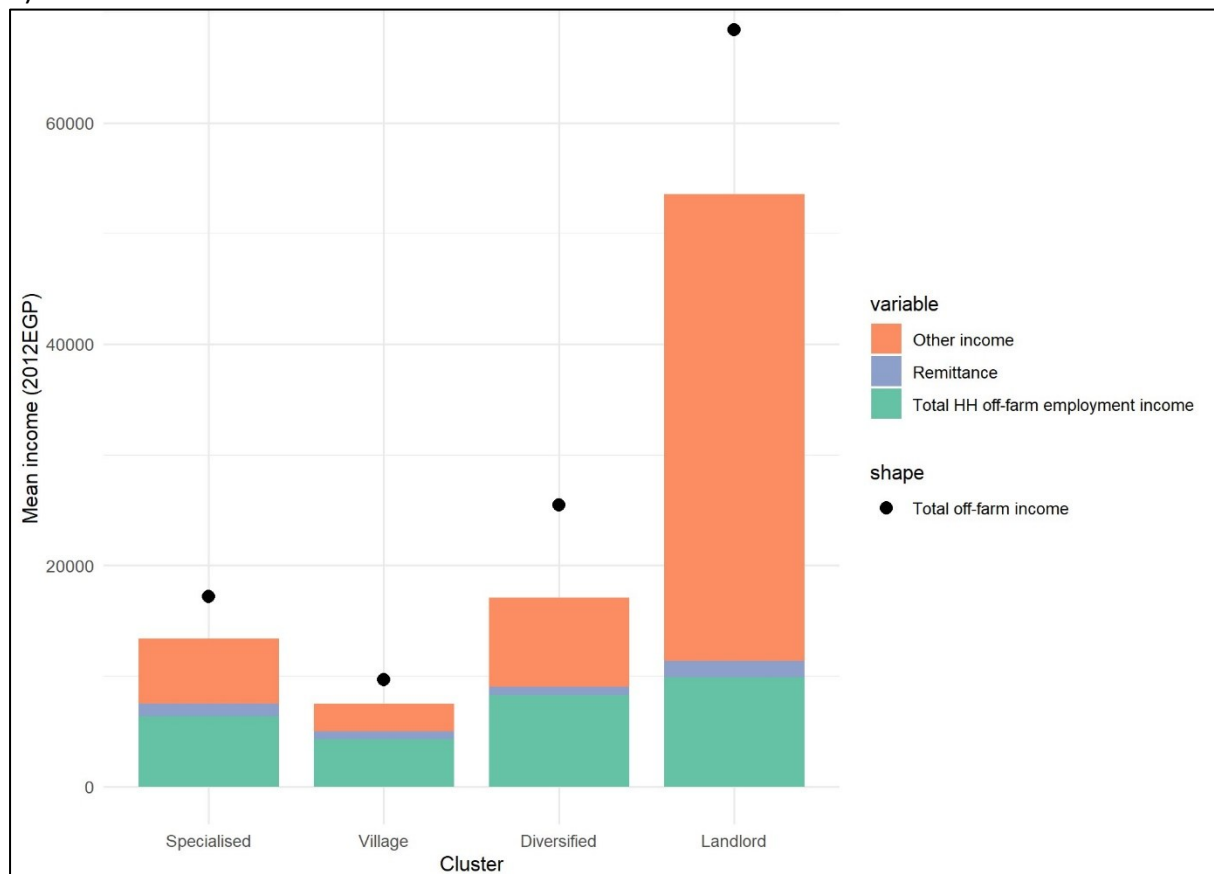


Figure 2.4: Breakdown of agricultural and off-farm income for each cluster: a) The mean income per household type for agricultural income, including constituent parts and the overall mean. b) The mean income per household type for off-farm income, including constituent parts and the overall mean. Key: agri=agricultural, HH=household

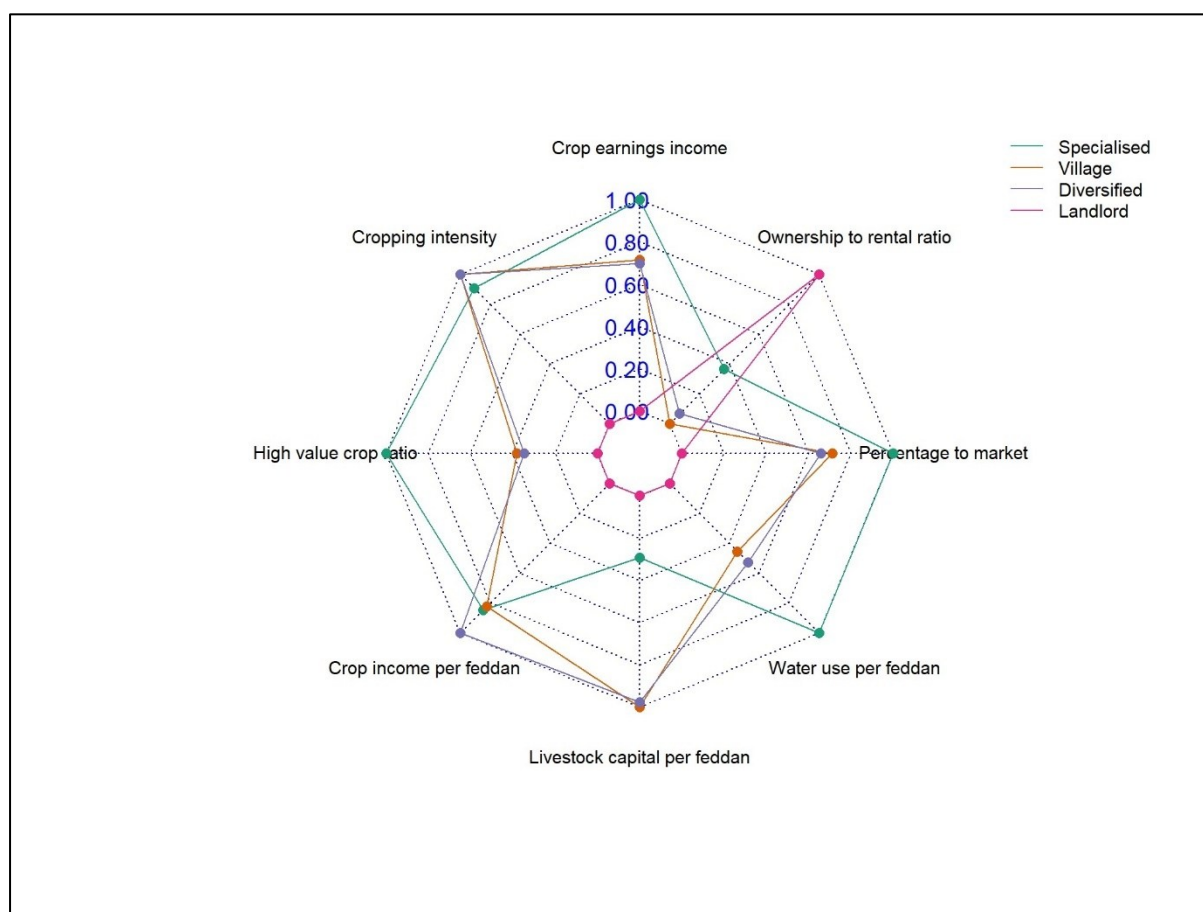


Figure 2.5: Radar chart of agricultural efficiency: The ratio of crop earnings to crop income, the cropping intensity, ratio of high value to field crops, the crop income per unit area, livestock capital per unit area, water use per unit area, percentage of crop sold at market, ratio of ownership to rental of land. All variables have been standardised by range and the cluster mean for each variable is included in the chart.

2.6.3 Cluster evolution

Utilising the 2018 ELMPs, it was possible to identify the previous household IDs and determine how households transitioned between types. Figure 2.6 shows the Sankey diagram from this analysis. A total of 163 (4.7%) farming households exited the panel survey after the 2012 survey, while 417 (12%) were new survey entrants to the survey series in 2018. A further 481 were new to agricultural activities in 2018. Abandonment of agricultural activities was high, with 45% (1,554) of households from 2018 abandoning agricultural activity having come from households that participated in them in 2012.

In terms of household type evolution, 59% (530) of all new landowners (both new entrants to the survey and those households which are new farming households) were part of the

diversified income household type in 2018. Additionally, there was a marked reduction in the number of households in the village farming household type as this household type reduced from 50% of 2012 households to 10% of 2018 households. There was also a reduction in the specialised farming household type. This household type reduced from 25% of 2012 farming households to 12% of 2018 farming households.

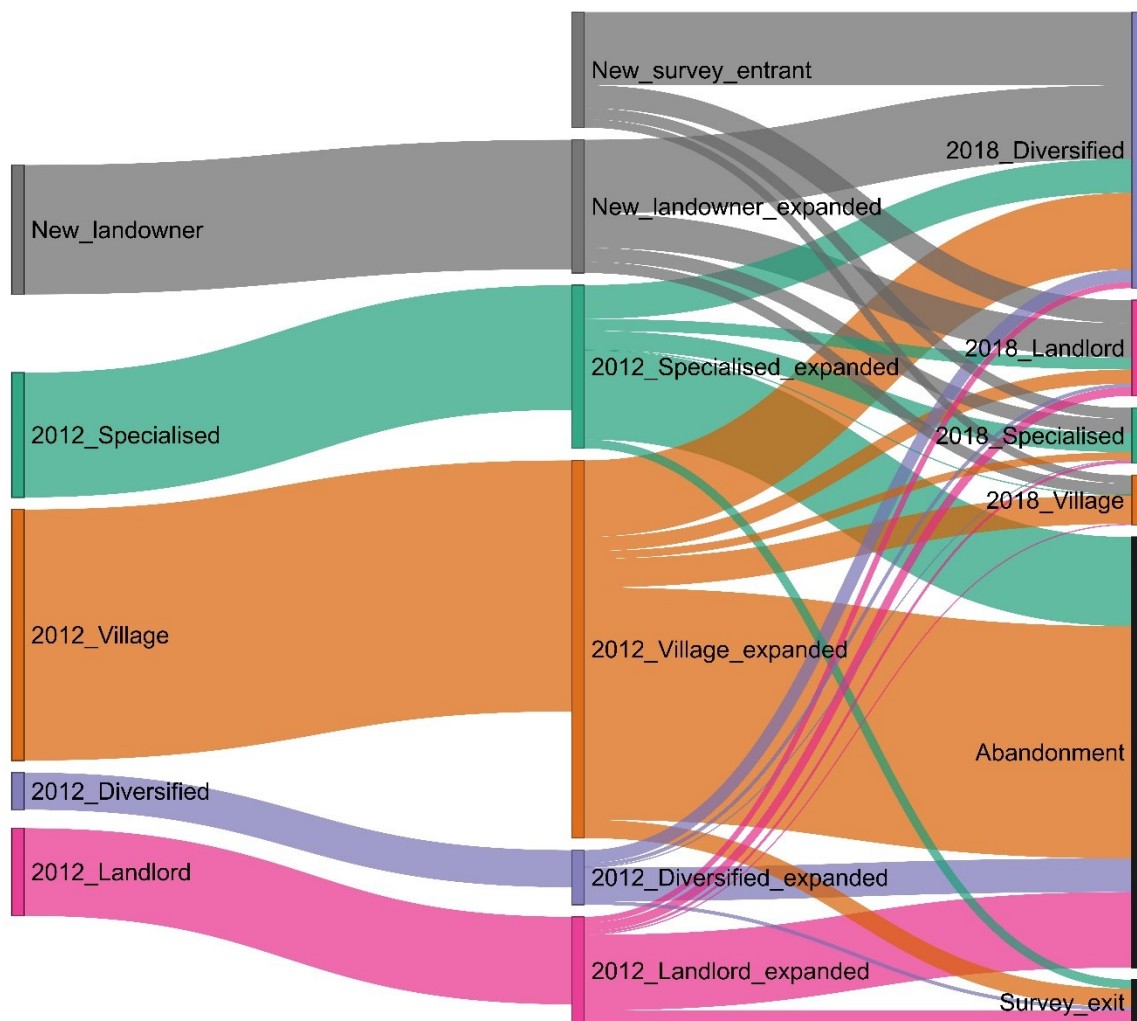


Figure 2.6: Sankey plot of the transition between household types: The transition of household clusters from 2012 (left) through the expansion of the 2012 households due to household members establishing secondary households between 2012 and 2018 (middle) and the 2018 household types (right). “New_landowner” are participants in the 2012 ELMPs that only became farming households in the 2018 ELMPs. “Survey_exit” refers to households which exited the survey after 2012. “Abandonment” are households which were farming households in 2012, remain in the ELMPs but are no longer farming. “Specialised” refers to Specialised farming household, “Village” refers to Village farming household, “Diversified” refers to Diversified income household, and “Landlord” refers to Landlord household.

Figure 2.6 details the expansion of households. It shows the number of households in each household type in 2012 and 2018. For example, the 906 households in the village farming household type in 2012 became 1363 households in 2018 due to household splitting as members of the household began independent households – shown here as the central,

“expanded” section of Figure 6. The village farming household and the diversified income household types exhibited the greatest rate of household expansion at 50% and 47%, respectively. The original and secondary households either continued as the same household type, transitioned to another household type, or abandoned agriculture altogether. The splitting of households explains, to some extent, the high level of household abandonment of agricultural activity. The total number of unique 2012 households which had a subsidiary household in 2018 which abandoned agricultural activity is 1098. Of these 1098 unique households, 858 had no secondary households in 2018 which carry out agricultural activities.

An analysis of the 2012 households which abandoned agricultural activities and those that continued is summarised in Table A.11 of Appendix A.4. These results show that households with higher livestock capital, income from crop production, and cropped area remained within agricultural activities. There were also differences between the types most dependent on farming for their income (specialised farming and village farming households) and those with greater off-farm income (diversified income and landlord households). Those most dependent on agricultural income abandoned agriculture if their off-farm income or income from governmental support was higher, whilst those who were less dependent on agricultural income remained if their off-farm income was higher.

2.7 Discussion

This analysis has identified four farming household types with distinct properties. Two household types are more dependent on agricultural income (specialised and village households) whilst two household types derive most of their income from other sources (diversified income and landlord households). The analysis of the evolution of agricultural households demonstrates a large transition of households away from agricultural activities. Although this is in part due to the expansion of households, there are 45% of households which no longer participate in agricultural activities in 2018 having been part of agricultural households in 2012.

2.7.1 Abandonment of agricultural activities

The abandonment of farming as a means of livelihood has been widely studied in developed countries but is relatively unstudied in developing country contexts (Ahmad et al., 2020). Examples where it has been studied for low-income, smallholder contexts (e.g. Helmy, 2020;

Shukla et al., 2019; Valbuena et al., 2014) highlight lower resources and income as being a key driver for exiting farming. In Egypt, Helmy (2020) demonstrated that farming households were abandoning farming activity at a high rate: 40% of households included some farming activity in 2006 but only 14% in 2019. Although Helmy (2020) includes all farming activities and employment within the agricultural sector, and this analysis only includes households which own or rent land, the trend is generally reflected in the work presented here, with a rate of abandonment of agricultural activities of 45% in the observations overall. An analysis of farming household typologies in the Himalayas identified different climate change adaptation strategies (Shukla et al., 2019) and a clear trend that the least diversified and lowest-resourced household types were the most likely to abandon agricultural activities. This is represented in this analysis by households which abandoned agricultural activities, in all household types, having a lower mean livestock capital and cropped area.

Subedi et al. (2022) conducted a systematic literature review of global land abandonment and identified biophysical, economic, regulatory, and socio-political characteristics to be key causes of abandonment. The most common causes discussed in the literature were accessibility of farm, migration and depopulation, farm income, and off-farm employment. A review of land abandonment in the Mediterranean region identified similar causes for abandonment (Quintas-Soriano et al., 2022). The lowest income household type – village household – exhibited the highest rate of household abandonment of agricultural activities, suggesting that low farm income is a contributor to the abandonment of agricultural activities. However, it is not clear from this analysis what was the extent of land abandonment, but it is clear that a large proportion of households no longer depended on agricultural activities for their livelihoods.

The two surveys used here were conducted in the context of the post-Arab Spring era. There is evidence that this period of instability saw a rapid rise in urbanisation, potentially explaining the extent of the household abandonment of agricultural activities in the results. An analysis of the satellite data for Lower Egypt showed an average rate of urban expansion between 2012 to 2017 of 60 km²/year, with a loss of cropland between 2010 and 2011 – the period of the Arab Spring – of 1.63% (502.21 km²) (Badreldin et al., 2019). This is mirrored in the review of land abandonment, which highlights political instability and collapse of political systems as a cause of abandonment of agricultural activities (Subedi et al., 2022).

2.7.2 Explanatory variables

Resource use efficiency, such as water use per unit area, cropping intensity, and the percentage of total income derived from agricultural activity, were the main variables contributing to the principal dimension of the FAMD. Additionally, household properties such as household education level, dwelling type, and total household income per capita are key to explaining the variability within the farming households. Resource endowment is commonly a key dimension in farming household typologies (Falconnier et al., 2015; Sarker et al., 2021; Shukla et al., 2019), with higher resource endowment resulting in greater efficiency and productivity. However, in this analysis, the village farming household, which has the greatest livestock capital, land area, and cropping intensity, has the lowest income per unit area.

Characteristics of the head of household, most notably their level of education, are key descriptors of variation between household types in this analysis. The education level of the head of household varies between the different household types in this analysis – household types which are less dependent on agricultural income have heads of households with higher levels of education. This is similar to the results of the typology analysis in Beni Suef (a governorate in Middle Egypt) by Martin et al. (2020), which identified heads of households with a higher level of education as a key indicator of increased income diversification. However, unlike Shukla et al. (2019), for example, who demonstrate that household types with high resource endowment have older heads of household, this analysis does not identify age as a key descriptor of the differences between household types. Although this relationship is not common in all analyses; for example, a farming typology analysis in Bangladesh showed that age did not improve the adoption of technology (Sarker et al., 2021).

The degree of livelihood diversification is a key differentiator between the different household types. Martin et al. (2020), who undertook a typology analysis of smallholder dairy farmers in Beni Suef, identified the greatest income diversification among poor farming households, with the very poor and the rich diversifying less. This is similar to the results here, where the village farming household and landlord household – the lowest and highest income household types, respectively – were highly dependent on farm and off-farm income, respectively. Martin et al. (2020) propose that low educational or material resources limit the ability for income diversification. This is similar to the results of the clusters identified in this

analysis, where the village farming household type has the lowest level of education and is the most dependent on agricultural income. However, the household type with the lowest land resource – diversified income household – has the lowest dependence on agricultural income of the three household types which produce crops. The increase in the diversified income household in 2018 compared to 2012 would suggest that fewer households depend on agricultural income, with more utilising off-farm income, such as income from off-farm employment, to meet household needs.

2.7.3 Gender

This research considered gender by including the sex of the head of the household amongst the analysis variables. Female-headed households are not common in Egypt, as shown in the results. The landlord household type, which has 24% female-headed households, compared to around 10% in other household types, was less likely to participate in crop production and was more dependent on income from land rental. This may be in part due to social norms about physical labour and single women participating in male-only spaces. An investigation of female participation in irrigation activities in Egypt showed that women from lower-income female-headed households were likely to participate in irrigation activities out of necessity due to lack of alternative income and the absence of means or the support for someone else to do it (El Garhi et al., 2019). The higher representation of female-headed households in the landlord household type is notable because these households have a greater average income per capita. Most studies of female-headed households in Egypt suggest that the majority of female-headed households are less well-off than male-headed households, often with higher rates and deeper levels of poverty (AbdelLatif et al., 2019). This analysis suggests that this is not the case, at least amongst farming households.

2.7.4 Limitations

This analysis utilised a large, national labour market panel survey dataset. However, several typology analyses include more detailed questions on attitudes, views, and perceptions (Hien et al., 2014; Sarker et al., 2021). This can be particularly useful when trying to understand technology adoption or climate change adaptation strategies. Additionally, a long-term longitudinal survey enables the identification of clear trends in the evolution of household types (Falconnier et al., 2015). This analysis would benefit from being repeated using a longer time series and more survey responses relating to attitudes to and perceptions of technology

adoption and climate change adaptation. Another limitation of this study is that the survey is designed to be nationally representative of the labour market and demographic characteristics (Krafft et al., 2021; Nin-Pratt et al., 2018) and not necessarily of farming characteristics, such as the crops grown, and access to agricultural equipment. Due to the dataset size, it may be representative of the agricultural sector in Egypt, however, a dedicated survey that specifically attempts to represent the agricultural sector may provide more representative results. What is not specifically clear from these results is to what extent the abandonment of agricultural activities directly relates to abandonment of land. A survey designed to be representative of the agricultural sector could include questions to determine the degree of land abandonment and compare this to household abandonment of agricultural activities.

2.8 Conclusion

Egyptian agriculture faces several resource constraints which are exacerbated by climate change and continued population growth. Farm and farmer typology analyses are useful tools to identify key characteristics and describe the heterogeneity within a diverse population whilst maintaining a manageable number of archetypes. This work utilises labour market panel survey data for 2012 and 2018 to carry out a typology analysis. Measures of agricultural efficiency - such as the cropping intensity and water use per unit area, household characteristics, and the survey year were important for describing the variability within the survey population. The analysis identifies four household types: specialised farming households, village farming households, diverse income households, and landlord households. The analysis demonstrates a trend towards greater income diversification and reduced dependence on agricultural income. This is mirrored by high rates of abandonment of agricultural activities, and a strong move away from the agriculture-dependent village farming household type, in 2012, to more diverse incomes, in 2018. This analysis provides the basis for targeted policy strategies and development interventions by identifying farm typologies, the key variables which describe the variation between them, and the evolution of the typologies. Targeted interventions could improve the profitability of households dependent on diverse incomes, enabling them to achieve higher incomes for the limited time available to conduct farming activities. Additionally, less profitable farming households that are more dependent on agricultural income, could be targeted to either improve livelihoods

through diversification of income or finding alternative incomes in rural settings. Further analysis of the relationship between households who abandon agricultural activities, identified here, and land abandonment is needed to ensure that productive land is not left unused, especially in the context of the large shortfall in domestic production. Additionally, policies are needed to empower smallholder farmers to become profitable enough to continue agricultural activities, whilst increasing resource use efficiency.

2.9 Chapter Conclusion

The typology analysis reveals four distinct farming household clusters that reflect differences in household characteristics, livelihood orientation, and agricultural engagement in Egypt: specialised producers focused on crop cultivation, village-based subsistence farmers who are highly dependent on agricultural income, diversified-income households balancing farm and off-farm activities, and largely disengaged landlord households relying primarily on land rental and off-farm income. Importantly, the results highlight marked trends towards income diversification and abandonment of agricultural activities between 2012 and 2018, raising concerns about long-term agricultural resilience and food security.

These findings contribute to the development of a coupled model presented in the next chapter. The identified household types provide insights into the diversity of farmer characteristics that inform the design of agent functional types in the land-use change model. However, the model extends beyond direct representation of these household types to address additional research objectives, including the implementation of different irrigation strategies and the deliberate amplification of differences in resource endowment between agent types to better reflect the spectrum of land- and water-use strategies under climate stress. The observed trends toward abandonment also highlight the importance of incorporating agricultural expansion and abandonment dynamics in response to changing environmental and socioeconomic conditions across Egypt's agricultural system.

3 A coupled land use change-ecohydrological model for multi-seasonal arid agricultural systems: an Egyptian case study

Authors: Aimen Sattar, Simon Moulds, Calum Brown, Mark Rounsevell, Peter Alexander

3.1 Chapter introduction

The preceding chapter established the range of agricultural households across Egypt and their evolving patterns of income diversification and abandonment of agricultural activities. While this analysis provides crucial insights into farmer heterogeneity, it represents only one dimension of the complex interactions between climate, water resources, crop production, and farming household characteristics that shape Egypt's agricultural future. To understand how these systems might respond to a changing climate, a more integrated approach is needed, one that can capture the dynamic feedback between biophysical processes and adaptive human behaviour across space and time.

This chapter presents the development of a novel coupled model that integrates agent-based land-use change dynamics with ecohydrological processes. The model combines SWAT+, a spatially explicit ecohydrological model that simulates crop growth and irrigation water use, with CRAFTY, an agent-based framework representing land-use decisions through competing agent functional types. The coupled model demonstrates how climate-driven changes in crop yields and water use efficiency drive spatial and temporal shifts in cropping patterns, with important implications for agricultural productivity and water resource management in this water-scarce region.

3.2 Abstract

Modelling interactions between climate, water, crops, and human decision-making requires coupling of biophysical and socioeconomic processes to model outcomes and explore potential futures. This study presents a novel coupled model of land-use change and ecohydrological processes in arid agricultural systems. The model links SWAT+, which simulates ecohydrological processes, including crop growth and irrigation water use, with CRAFTY, an agent-based framework that allocates land according to agent characteristics and resource conditions. Egypt is used as a case study where climate and socioeconomic stressors constrain agricultural production. The coupling captures how shifts in potential yields, driven by elevated CO₂ and warming, shape land-use change. Crop yields vary by crop and scenario, with the largest gains – and declines – under high-emission futures, while water use efficiency consistently improves, especially at higher CO₂ concentrations. Relying on open global datasets, the model provides a transferable approach for exploring climate adaptation in data-scarce, water-limited regions.

3.3 Introduction

Climate change poses significant risks to environmental and socioeconomic systems, particularly for land use and freshwater management (Z. Cao et al., 2022). The agricultural sector, as the largest global user of both land and freshwater, is especially vulnerable (Malhi et al., 2021). These vulnerabilities include more frequent and extreme weather events, shrinking arable land area, declining soil quality, and rising crop water demand; trends which are already occurring rapidly in arid and semi-arid agricultural systems (El-Beltagy & Madkour, 2012). Climate change has already reduced global agricultural productivity by an estimated 21% since 1961 compared to a no-climate-change baseline, with higher losses in some of the most climate-exposed regions, including Sub-Saharan Africa (34%), and the Middle East and North Africa (30%) (Ortiz-Bobea et al., 2021). However, the net impact remains uncertain due to the potential counteracting effect of elevated CO₂, which may enhance photosynthesis and water use efficiency for some crops under certain conditions (Ainsworth & Long, 2021; Jägermeyr et al., 2021). As the rate and severity of climate change are likely to increase over the coming decades (Zittis et al., 2022), proactive adaptation remains essential to manage risks, sustain agricultural productivity and capitalise on the benefits to some crops (Grigorieva et al., 2023).

The responses of governments and farmers to constrained freshwater resources and the impacts of climate change on water and land systems are crucial for both farmer welfare and food and water security (Grigorieva et al., 2023). Agricultural activity in arid and semi-arid regions has long been defined by its ability to meet these challenges (El-Beltagy & Madkour, 2012). Whether or not it continues to do so is likely to be determined by the interaction of hydrological and land-use systems, and the extent to which they can be influenced by agricultural management decisions at various spatial scales. It is therefore essential to understand the dynamics of these complex systems, predict how they may change in the future, and assess the efficacy of policies for natural resource management, food and water security, and rural development (Alam et al., 2022).

A wide range of modelling approaches have been used to assess agricultural responses to climate and socioeconomic change, each with distinct strengths and limitations. Econometric models capture statistical relationships between climate variables and yields, often assuming profit-maximising behaviour, but they lack spatial and behavioural detail (Feng et al., 2023;

Su & Chen, 2022). More sophisticated economic models, such as computable general equilibrium (CGE) models, can capture economy-wide impacts of agricultural change but struggle to represent physical constraints and heterogeneity in farmer behaviour (Huber et al., 2018). Physical models, including crop and hydrological models, simulate biophysical processes such as photosynthesis, transpiration, and runoff generation with high resolution and are useful for analysing yield and water impacts under climate change (Dlamini et al., 2023; You et al., 2024). However, they typically represent cropping decisions and water management as static or uniform, limiting their ability to account for local adaptation (Alam et al., 2022; McDermid et al., 2023). Addressing these limitations, agent-based models (ABMs) simulate heterogeneous decision-making in response to changing environmental and socioeconomic conditions, and are particularly useful in arid regions where farm-level decisions shape water use outcomes (Alam et al., 2022; Schrieks et al., 2021). However, their effectiveness depends on their ability to be adequately calibrated and on the availability of spatially and behaviourally rich data, which can be challenging in data-scarce contexts (Brown et al., 2023; Kimpton et al., 2024).

Recent advances in agricultural systems modelling reflect a growing recognition of the need to capture feedback between climate, water, crop growth, and human decision-making. Increasingly, models are coupling biophysical processes and socioeconomic behaviour to improve the realism and relevance of climate impact assessments (e.g. Canales et al., 2024; Mijic et al., 2023; Streefkerk et al., 2023). These integrated models are particularly relevant to arid and semi-arid contexts, where agricultural outcomes are tightly constrained by both environmental stressors and adaptive management strategies (El Fartassi et al., 2025; Harms et al., 2023). Coupled models allow for the simultaneous analysis of yields, water demand and behavioural responses, dimensions which are often addressed separately in standalone crop, hydrological, or agent-based models (El Fartassi et al., 2025; O'Keeffe et al., 2018).

However, most existing coupled models focus primarily on short-term farm management decisions, particularly irrigation scheduling and technology adoption (Du et al., 2020; Harms et al., 2023; O'Keeffe et al., 2018). This limits their capacity to explore long-term adaptation pathways in arid and semi-arid systems, where shifting cropping patterns represent a crucial response to sustained climate and resource pressures. Ecohydrological models such as the Soil and Water Assessment Tool (SWAT), Agricultural Production Systems Simulator (APSIM),

and AquaCrop provide detailed simulations of crop growth, hydrology, and irrigation demand, but often assume static land use and uniform management practices (Bieger et al., 2017; Holzworth et al., 2014; Steduto et al., 2009). Conversely, agent-based models, such as Competition for Resources between Agent Functional Types (CRAFTY) or mathematical programming-based multi-agent systems (MP-MAS), capture heterogeneity in decision making and resource endowments (Berger et al., 2007; Murray-Rust et al., 2014), but typically rely on externally prescribed productivity and water availability inputs, limiting their capacity to reflect feedback from environmental processes (Alam et al., 2022).

To address these limitations, we develop a novel coupled model linking biophysical and agent-based components to simulate land-use and irrigation dynamics in large, intensively managed agricultural systems. The coupled model combines SWAT+, a spatially explicit ecohydrological model (EHM) that simulates crop growth and water use, with CRAFTY, an agent-based model representing land-use decisions through agent functional types. SWAT+ supports applications in data-scarce regions and has proven effective in capturing yield and water use in managed systems such as Egypt's Nile Valley and Delta (Bieger et al., 2017; Chawanda et al., 2024). CRAFTY complements this by modelling farmers' adaptive land-use responses to changes in resource access, climate, and policy drivers (Murray-Rust et al., 2014). The coupled model captures both irrigation decisions and transitions in cropping patterns and land use.

This research presents the development and application of the coupled model. We describe the model components, coupling strategy, and input datasets. Egypt serves as a case study due to its reliance on irrigation and a multi-seasonal cropping system. The model is applied to estimate potential yield and water use trajectories under climate change to 2099, providing insight into how future conditions may affect agricultural productivity and water use efficiency in arid systems. We go on to apply the coupled model using static socioeconomic conditions to demonstrate the benefit of the coupling over a standalone ecohydrological model.

3.4 Model description

We present a novel model that implements a coupling process between biophysical and agent-based components (Figure 3.1). The biophysical model (SWAT+) calculates potential crop yields under optimal management for different climate change scenarios, generating

annual natural capital inputs that represent grid-cell productivity ceilings. These outputs inform the agent-based model (CRAFTY), where agricultural producers, competing through capital-weighted utility functions, determine land use patterns and management practices. Socioeconomic capitals (infrastructure access, financial resources, access to mechanisation, human resources, social cohesion, access to water resources) drive agent competition. This coupled model prioritises provisioning services such as crop production while incorporating policy objectives such as water use efficiency. Finally, the annual gridded agents derived from the competition in CRAFTY are passed onto the SWAT+ model, where the land use and management practices are used to determine gridded production and water use. The coupling propagates spatial heterogeneity in water use efficiency through agent-specific irrigation strategies, with commercial agents adopting modern techniques and subsistence agents persisting with traditional practices.

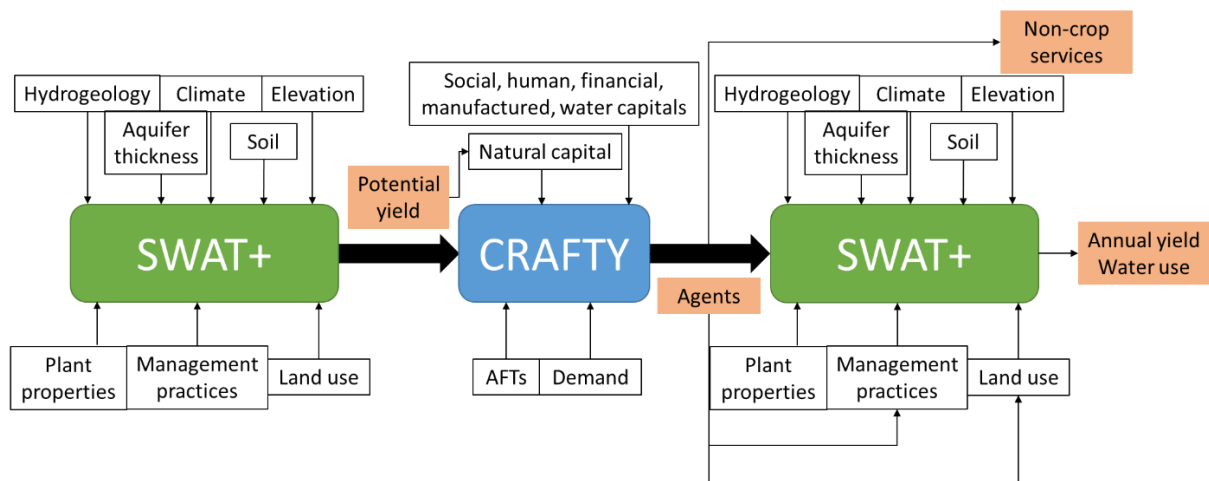


Figure 3.1: Diagram of the coupled Land Use Change-Ecohydrological (LUC-EH) model: Model coupling process showing input data for each model, the transfer of data between models, and the outputs.

3.4.1 SWAT+ biophysical model

We use the SWAT+ model, a semi-distributed watershed ecohydrological model (Arnold et al., 1998), to simulate biophysical processes. The SWAT+ model simulates hydrology and crop production at a regional scale. SWAT+ builds on the original SWAT model, offering enhanced flexibility in model component configuration and spatial discretisation (Bieger et al., 2017). It simulates hydrology and crop growth processes across large regions by linking subbasins, defined by topography, with hydrological response units (HRUs). HRUs represent homogeneous areas defined based on land use, soil type, and slope. Although these semi-distributed HRUs are computationally efficient, they do not include connectivity and

interactions between HRUs. SWATgrid was developed to enable gridded, location-specific HRUs, which also represent watersheds, allowing for the linking of grids and routing flow between them (Pignotti et al., 2017).

Crop growth in SWAT+ is simulated using the Erosion Productivity Impact Calculator (EPIC) crop growth model (Williams et al., 1984), which provides a process-based representation of photosynthesis, transpiration, and biomass accumulation. Management practices are implemented using decision tables that define actions such as planting, harvesting, irrigation, reservoir management, fertiliser application, ploughing, and pesticide application (Arnold et al., 2018). These management activities can be scheduled by date or triggered by thresholds, such as soil water content, plant water stress, or accumulated plant heat units. The decision table structure allows simulation of diverse crop and irrigation practices, including the automation of irrigation based on crop water requirements and the availability of water from surface or groundwater sources. The flexibility of the decision table structure also supports seasonal and perennial systems, as well as fixed calendars and rules tied to environmental triggers. Combined with its comprehensive library of plant types and default agronomic parameters, SWAT+ remains accessible for applications in data-scarce regions. Full details of the decision tables as they are applied in SWAT+ are included in Arnold et al. (2018).

To estimate potential yields, we implement the biophysical model under optimal management assumptions. Irrigation is triggered automatically when soil moisture falls below field capacity, applying sufficient water to prevent crop water stress and maintain optimal growth. Fertiliser is also applied based on nutrient stress to ensure non-limiting growth conditions. This approach prioritises yield maximisation, which is the required input for the CRAFTY natural capital layer, and represents common practices in low-income irrigated systems, simplifying operation variations such as Egypt's dominant flood irrigation (Abdelhafez et al., 2020). Additionally, tree crops (fruit/date) are assumed to be at full maturity. Other multi-year perennial crops, such as sugarcane, are simplified and harvested and replanted on an annual basis to facilitate annual land-use change.

Elevated atmospheric CO₂ concentrations under future climate scenarios are also an important aspect of crop modelling. Elevated CO₂ levels can enhance crop growth through the carbon fertilisation effect, which increases photosynthetic and water use efficiencies (Wang et al., 2017). SWAT+ incorporates this effect through adjustments in the EPIC crop

model, where crop transpiration and biomass accumulation respond dynamically to prescribed CO₂ concentrations, typically aligned to Representative Concentration Pathways (RCPs) (Meinshausen et al., 2020; Zhang et al., 2022). The model uses a radiation use efficiency (RUE) approach to simulate crop growth, with RUE specified at both ambient and elevated CO₂ levels. Default parameters are available for many crops within SWAT+'s plant database (plants.plt), facilitating implementation in data-scarce regions where crop-specific trial data may not be available. These built-in features support consistent incorporation of CO₂ fertilisation effects across diverse crop and climate scenarios (USDA Agricultural Research Service, 2020).

3.4.2 CRAFTY agent-based model

The agent-based component of the coupled model is implemented using the Competition for Resources between Agent Functional Types (CRAFTY) framework (Murray-Rust et al., 2014). The CRAFTY framework has been applied to various contexts, including Sweden (Blanco et al., 2017), Europe (Brown et al., 2019), Britain (Brown et al., 2022), and Brazil (Millington et al., 2021). CRAFTY models the production of ecosystem services by agents utilising spatially explicit resources (capitals) (Murray-Rust et al., 2014). Competition between Agent Functional Types (AFTs) reflects how land use and management practices evolve. Their competitiveness is determined by a utility function that incorporates unmet demand and a Cobb–Douglas production function. AFTs are defined based on the distribution of “give in” and “give up” thresholds and their capital sensitivities. The “give in” threshold represents the agent’s willingness to yield to competition, while the “give up” threshold represents the agent’s likelihood to relinquish land if they are not profitable (Murray-Rust et al., 2014). The capital sensitivities describe how sensitive an AFT is to a resource in the production of an ecosystem service.

3.4.3 Model coupling of SWAT+ and CRAFTY

In the coupled model, information flows sequentially between SWAT+ and CRAFTY. Initially, SWAT+ is employed to simulate crop growth and water use for each crop type across all agricultural grid cells within the six regional models under optimal management conditions. This process determines potential yields without irrigation or fertiliser resource constraints. The maximum yield for each cell and crop is then established as the potential yield, which is subsequently normalised for each crop type. These normalised values serve as the natural

capital inputs for the CRAFTY model. Following this, the CRAFTY model simulates inter-agent competition, generating annual gridded AFTs. These AFTs can be translated into land use and management practices within SWAT+, which in turn simulate crop growth and provide annual crop production and water use results under different socioeconomic and climate change scenarios. Non-crop ecosystem services, such as employment and water use efficiency, are defined in CRAFTY.

3.5 Egypt case study

3.5.1 SWAT+ model implementation for Egypt

To demonstrate the application of this coupled model, we implement SWAT+ for Egypt, a highly irrigated agricultural system characterised by multi-seasonal cropping and high dependence on Nile River flows for irrigation. The model uses a daily timestep and 900 m x 900 m grid resolution to model yield and water use for winter and summer crops. Model input data is summarised in Table 3.4. The model is structured into six separate submodels representing the Nile Delta, Nile Valley, and Mediterranean regions, collectively covering 28% of Egypt's land area and 92% of its cultivated land (Figure 3.2 and Table B.4). Due to SWAT+'s data handling limitations for gridded models, each model is constrained to fewer than 90,000 grid cells. This segmentation ensures efficient processing while maintaining comprehensive coverage of the entire region.

We utilise statistical reports of annual land use (CAPMAS, 2025) to generate land use maps using the European Space Agency (ESA) land cover dataset (Copernicus Climate Change Service, 2019) as the underlying land cover distribution. Appendix B.1 includes details of the process used to develop the land use map in 2020. We use the total area grown for each crop in each governorate as the basis for this. As the model attempts to efficiently simulate the cropping rotations within the agricultural system, it is necessary to simplify the rotations. There are limited rules for crop rotations, although there are some relatively common practices, such as Egyptian clover (berseem), a leguminous nitrogen-fixing crop, and maize. But this is not consistent; therefore, using 2010 statistical reports of cropped areas for seasonal and perennial crops (CAPMAS, 2025), a series of cropping patterns is developed to minimise the number of unique cropping patterns.

The SWAT+ model inputs include crop-specific decision tables for planting, harvesting, and irrigation (summarised in Table 3.1 and Table 3.2). Cropping calendars are based on regional planting and harvesting dates and heat unit thresholds. For modelling potential yields, irrigation is triggered automatically when soil moisture falls below field capacity, ensuring optimal water supply to maximise crop productivity. In preparation for actual yield and water use modelling, additional irrigation settings are developed to reflect deficit irrigation strategies. These are applied during the final stage of the workflow, when land use from CRAFTY is used to drive SWAT+. In this case, irrigation is triggered by either soil moisture thresholds or plant water stress, and the volume of water applied is either sufficient to prevent stress or specified quantities. These settings are derived through a sensitivity analysis, detailed in Section 3.6.1.

Multi-cut crops such as alfalfa and berseem clover are typically harvested multiple times annually under real-world conditions. Berseem and alfalfa achieve 3-7 cuts per year in Egypt (FAO, 2014), while sugarcane's perennial growth allows annual harvesting up to 5 times (Mehareb et al., 2021). Berseem and alfalfa crops are harvested based on reaching 90% of the plant-heat units to maturity, up to four times per season, followed by a final harvest and termination. To facilitate annual land-use change modelling, sugarcane is simplified to a single-year growth and harvest cycle. Perennial crops are assumed to align with winter cropping calendars, with termination occurring 10 days before replanting. Fruit and date trees, modelled at full maturity, follow fixed annual harvests on 15th September to reflect simplified regional practices.

While a detailed analysis of fertiliser impacts is beyond this study's scope, calibration requires fertilisation to be defined. The Food and Agriculture Organization of the United Nations (FAO) report on crop-specific fertiliser use in Egypt (Food and Agriculture Organization of the United Nations, 2005) provides estimates of fertiliser use for each crop in Egypt. This is used in the initial phase of the modelling to allow for calibration of the model. Fertiliser application is defined using the same decision table structure, with automatic application triggered by nutrient stress. The default crop-specific fertiliser setting is included in Table B.3.

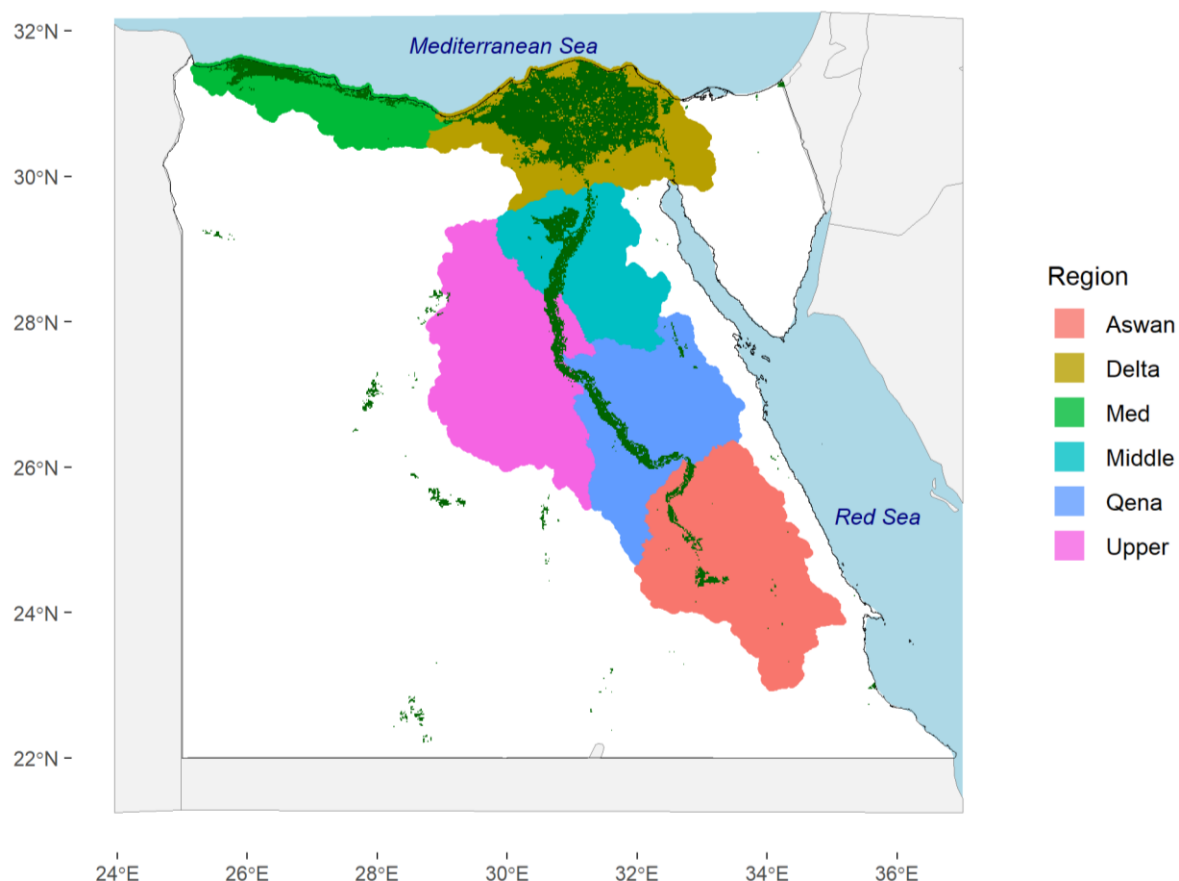


Figure 3.2: Model regions and cropped area in Egypt: SWAT+ submodel areas and national cropped area in 2020. The cropped area is in dark green.

Table 3.1: Planting and harvesting decision table details for winter, summer, perennial, and tree crops.

Season	Decision	Planting	Harvesting
Winter	Date	6 th November	30 th April
	Heat Units	-	1.15
Summer	Date	15 th May	27 th October
	Heat Units	-	1.15
Perennial	Date	6 th November	27 th October
	Heat units	-	0.9
Trees	Date	-	15 th September

To maintain hydrological continuity across the modelled domain, a cascading configuration is implemented for the Nile Valley and Delta submodels. In this setup, the outlet of each upstream region serves as the inlet for the downstream model, thereby replicating the natural

flow progression of the Nile River and enabling a coherent simulation of water movement across regions. While the model does not calibrate streamflow explicitly – owing to the simplified representation of Egypt’s irrigation system, in which irrigation water is applied from an abstract, unlimited source – streamflow values are based on historical records (Hou et al., 2024). Streamflow projections are estimated by averaging values across the historical period and extending them uniformly to 2100. The Mediterranean submodel is excluded from the cascading configuration due to the absence of major upstream inflows.

Table 3.2: Irrigation decision table details for commercial and Subsistence farmers.

Modelling stage/ Management	Method	Threshold method	Threshold quantity	Water per application
Potential yield modelling	Furrow	Soil moisture	100%	Based on demand
Deficit irrigation	Defined per crop and region	Soil moisture/ plant water stress	Defined per crop and region	Defined per crop and region

3.5.2 CRAFTY model implementation for Egypt

We apply the CRAFTY framework to Egypt to model the process of land-use change through competition between AFTs. CRAFTY-Egypt uses a 900 m x 900 m resolution grid and is developed to simulate land use change between 2020 and 2100. The model is comprised of capitals, which represent the spatially explicit resources. These include socioeconomic capitals – manufactured, human, social and financial. Table 3.5 contains details of the indicators used for each of these capitals. Each distributed indicator is sampled to the base grid of the model, so for every model grid cell, there is a value for each year. The indicators are scaled between 0 and 1 and summed for each grid to develop the capitals. The indicators use a range of spatial resolutions. The education and health indices (Smits & Permanyer, 2019), farm machinery prevalence, and per capita membership of agricultural cooperatives (CAPMAS, 2025) are governorate-level datasets. GDP per capita is calculated using 1 km² resolution gridded GDP and population datasets (Wang & Sun, 2022; Wang et al., 2022). The population and GDP gridded values are scaled to account for updated projections (Koch & Leimbach, 2023). These datasets are then resampled at 900 m x 900 m resolution to match the model resolution. We define human capital by summing the health and education indices

and scaling the values by gridded population data. Gridded GDP per capita is used to represent the financial capital. Social capital is represented by the combination of per capita membership in agricultural cooperatives (CAPMAS, 2025) and the Gini index (OAMDI, 2023). Finally, manufactured capital is derived from gridded road infrastructure data (Meijer et al., 2018) and governorate-level agricultural machinery per unit agricultural area (CAPMAS, 2025).

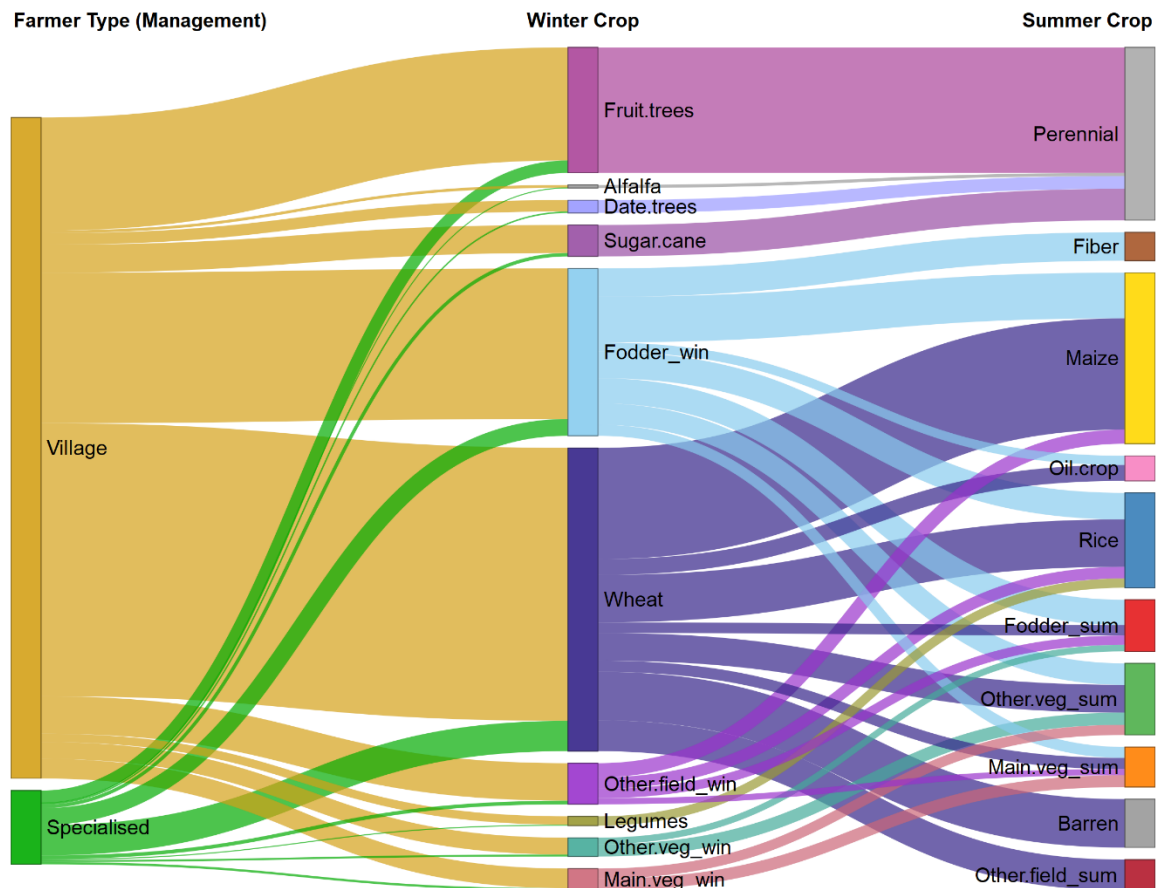


Figure 3.3: Management practice, and winter and summer cropping patterns in 2020: The width represents the percentage area of each. The very left shows the division between commercial and subsistence farmers, the middle shows the crops grown in winter, and the right shows the crops grown in summer. For crops grown in both winter and summer, “_win” denotes the area in winter and “_sum” the area in summer.

The representation of water availability in the model necessitated the explicit inclusion of a water capital variable. While Egypt is classified as a highly water-stressed nation due to its limited renewable freshwater resources (Gado & El-Agha, 2021), this scarcity primarily reflects current technological and infrastructural constraints rather than absolute physical limits. Non-renewable water sources – including fossil groundwater reserves, wastewater

reuse, and desalination – hold the potential to expand freshwater access significantly under future technological advancements. As the model is designed for scenario analysis, water capital is conceptualised not as a fixed physical quantity but as a dynamic measure of access to water, contingent on technological capacity and infrastructure development. This capital is integrated in the model using three spatially explicit components: (1) rainfall patterns derived from climate projections (Lange & Büchner, 2021), (2) proximity to surface water infrastructure, mapped via open-source geospatial datasets (Humanitarian OpenStreetMap Team (HOT), 2024; Messenger et al., 2016), and (3) the hydraulic head of confined groundwater aquifers, which governs extraction feasibility (Verkaik et al., 2024). By integrating these factors, the model captures both natural hydrological constraints and human-mediated water accessibility, enabling robust exploration of future scenarios where technological innovations reduce costs or enhance efficiency in non-renewable water exploitation.

In addition to capitals, the CRAFTY framework includes AFTs, which represent land managers. Our application of the framework has 56 AFTs, which characterise different cropping patterns and management practices. Although not direct representations of the farming household types described in Sattar et al. (2024), our model draws loosely on their typology to define two broad agent categories: Commercial (inspired by specialised households) and Subsistence (based on village households), in line with the model’s objectives. All cropping patterns are represented by both agent types to reflect variation in management strategies.

The cropping patterns in Egypt are not fixed. Some crops are only grown in a specific season – Winter: legumes, wheat; Summer: maize, fibre, rice, oil crops – whilst others can be grown in both seasons. The final cropping patterns are estimated based on annual production and area reports (CAPMAS, 2025). As the seasonal data is not available for 2020, the 2010 seasonal areas are used. Crops are grouped based on the groupings used by the Government of Egypt in its annual production and area reports, with the most important crops for each group being used as the representative plant. Table B.1 includes details of the plant used to represent each crop grouping. Figure 3.3 illustrates the relative size of different cropping patterns. It includes, on the left, the relative size (by area) of the subsistence and commercial farmers in 2020. As the diagram shows, we estimate that 10% of the cropped areas are commercial and 90% are subsistence. The middle section of the diagram shows the relative

areas of winter crops, and finally, the right section of the diagram shows the relative areas of summer crops.

The model differentiates agricultural agents based on management practices, encoded through distinct behavioural parameters. Subsistence agents represent smallholder farmers who rely on flood irrigation and are characterised by lower income levels, limited access to technology, and strong dependence on social capital such as community networks. These agents exhibit a greater propensity to persist with agricultural production even under economically non-competitive conditions, prioritising subsistence needs over market-driven optimisation. In contrast, commercial agents adopt market-oriented farming practices, including the use of deficit irrigation, alongside external labour, advanced technologies, and greater adaptability to production risks. These behavioural distinctions are systematically embedded within the model's sensitivity matrices and AFT parameters, which govern the competition (land-use change) processes. The details of how the sensitivity matrices and AFT parameters are developed for a business-as-usual scenario are included in Tables B.10 and B.11.

The AFTs compete to produce ecosystem services. The Egyptian implementation of the CRAFTY framework quantifies ecosystem services across four dimensions critical to agricultural systems: crop production, water use efficiency, livestock products, and employment generation. Service provision varies according to AFT, reflecting differences in crop selection and management strategies. Crop production is universal across all agricultural agents, with each cultivating either one or two crops depending on their AFT. Water use efficiency varies between AFTs, with commercial agents achieving greater efficiency through deficit irrigation methods, whereas subsistence agents rely on traditional flood irrigation practices. Additionally, AFTs cultivating water-intensive crops (i.e. rice and fibre) exhibit reduced efficiency compared to those focusing on less water-intensive crop types.

Livestock products, including meat and milk, are generated indirectly through two pathways: by agents specialising in fodder crops (i.e. alfalfa and seasonal fodder), and via crop residues from cereal cultivation. Employment generation occurs universally but varies in magnitude, with commercial agents creating more opportunities due to the labour-intensive nature of advanced practices and larger operational scales, whilst subsistence farmers are likely to depend more on household labour.

In Egypt, agricultural expansion through land reclamation, the process of converting desert or other non-cultivated land into farmland, has been a common practice to increase agricultural production (Adriansen, 2009). Government-sponsored projects, such as those in the New Valley, prioritise desert land conversion through centralised irrigation infrastructure. Simultaneously, smallholder farmers along the Nile Valley and Delta fringes engage in informal reclamation, leveraging shallow groundwater from Nile-dependent aquifers (Nour, 2020). As the New Valley Governorate is outside the boundaries of our model, large state-sponsored projects are not included. However, to reflect the process of informal reclamation within the model, an Unmanaged Land (UL) agent is introduced. This agent is assigned to all grid cells that are neither cultivated nor masked as urban or wetland areas. Additionally, due to agents' sensitivity to socioeconomic capitals, grid cells with zero socioeconomic capitals are also excluded. The UL agent represents state ownership of uncultivated land and remains in place unless displaced by a competing agricultural agent. The UL agent does not produce any ecosystem services, does not 'give-up' land, and has a 0 'give-in' threshold, thus relinquishing land to any other agent regardless of their competitiveness.

3.5.2.1 Demand

CRAFTY does not simulate international trade and, as such, does not represent actual demand. Instead, demand for domestic production of food, fibre, and animal products is used as a proxy for demand (included in Table B.9). In this application of the coupled model, we applied static demand values to demonstrate model functionality. These 2020 baseline values for food and fibre ecosystem services are derived from national statistical and dietary reports (CAPMAS, 2025). We used a different approach for non-food and non-fibre ecosystem services, namely employment and water use efficiency. We estimated employment demand by multiplying the total population by the proportion employed in agriculture. Water use efficiency is treated as an index, with a baseline value of 100 in 2020.

3.6 Sensitivity analysis and calibration

3.6.1 Sensitivity analysis and calibration of SWAT+

Calibration and validation are critical steps in ecohydrological modelling, ensuring model outputs align with observed data while understanding model uncertainty (Zou et al., 2023). For this study, the SWAT+ calibration focused on two primary outputs: crop yield and

irrigation water use. The process addressed data limitations through a hierarchical calibration methodology using Latin Hypercube Sampling (LHS) and targeted parameter adjustments.

The six regional submodels (encompassing the Nile Delta, Nile Valley, and Mediterranean regions) were calibrated separately to ensure model parameters are developed specifically for each region (Čerkasova et al., 2023). Due to the size of the models, it was not possible to use them directly for calibration. Smaller models were developed using a subbasin within each submodel for the calibration process. All land uses were distributed randomly and evenly across the representative regional model in cropped areas only.

Fertiliser parameters were excluded from calibration, as Egypt's agricultural practices maintain near-optimal application rates (Food and Agriculture Organization of the United Nations, 2005). Instead, fertiliser settings were adjusted during sensitivity analysis to determine maximum potential yield. Additionally, irrigation parameters were not included in the calibration. Optimal irrigation was implemented for the calibration process as this is representative of the dominant flood irrigation methods used in Egypt (Abdelhafez et al., 2020).

The calibration prioritised parameters directly influencing crop yield and water use per unit area, as detailed in Table 3.3. Yield calibration focused on the optimal and base temperatures (tmp_opt and tmp_base), biomass energy conversion rate (bm_e), harvest index (harv_idx), potential leaf area index (lai_pot), and plant heat units to maturity (phu_mat). Irrigation calibration targeted parameters governing soil water dynamics, including the soil conservation service curve number (cn2), soil evaporation compensation factor (esco), percolation coefficient (perco), available soil capacity of the soil layer (awc), surface runoff lag coefficient (surlag), and aquifer delay.

We calibrate simulated average annual yield and irrigation water use per unit area against observed data, similar to the "soft calibration" method applied by Čerkasova et al. (2023), using a modified version of the RSWAT package (Nguyen et al., 2022). Observed yield and irrigation data were obtained from annual governorate-level statistical data (CAPMAS, 2025), providing regionally aggregated statistics for crops used. As crop models simulate dry matter yield, while observed yield data typically includes moisture content, we applied a range of crop-specific moisture percentages (detailed in Table B.5). During calibration, we identified

whether the minimum, average, or maximum moisture content yielded the lowest error for each crop. To enable unconstrained land use transitions, all crops were included in every region's calibration. For crops not currently grown in a region, we used the average observed yield across all governorates as a proxy.

Unlike Čerkasova et al. (2023), however, who apply plant uptake compensation factor (EPCO) – a measure of the compensation of water uptake from lower soil layers – adjustments on a HRU level, our approach requires a uniform EPCO value for each model, as the crop in each HRU will be modified in further modelling. This ensures EPCO values are suitable for all crops used in the model. Table 3.3 summarises the calibrated parameters, their adjustment methods (absolute change, replace or percentage change), allowable ranges, and scope (model-wide or crop-specific). A step-by-step summary of the calibration and sensitivity analysis is outlined below.

Table 3.3: Yield and irrigation application parameters, method of change, minimum and maximum value range and whether the variable is model-wide or crop-specific. Change: abschnng=absolute change of value, percent=percentage change, replace=replace value. Parameters: bm_e.plt=biomass-energy ratio, tmp_pot.plt=optimal temperature for plant growth, tmp_base.plt=minimum temperature for plant growth, harv_idx.plt=harvest index for optimal growth conditions, lai_pot.plt=maximum potential leaf area index, phu_mat.plt=plant heat units to maturity, esco.hru=soil evaporation compensation factor, cn2.hru=Condition II curve number, perco.hru=percolation coefficient, awc.sol=available water capacity of the soil layer, surlag.bsn=surface runoff lag coefficient, aquifer_delay.hru=delay time for groundwater flow to stream.

Observed data	Parameter	Change	Min	Max	Details
Yield	bm_e.plt	abschnng	-5	5	Crop specific
Yield	tmp_opt.plt	abschnng	-3	3	Crop specific
Yield	tmp_base.plt	abschnng	-1	1	Crop specific
Yield	harv_idx.plt	percent	-70	70	Crop specific
Yield	lai_pot.plt	percent	-70	70	Crop specific
Yield	phu_mat.plt	percent	-70	70	Crop specific
Irrigation	esco.hru	replace	0	1	Model
Irrigation	cn2.hru	percent	-70	70	Model
Irrigation	perco.hru	replace	0.01	1	Model
Irrigation	awc.sol	percent	-70	70	Model
Irrigation	surlag.bsn	replace	0.05	24	Model
Irrigation	aquifer_delay.hru	replace	0	1000	Model

Step 1: Yield parameter calibration

We use a Latin Hypercube Sampling (LHS) ensemble of 10,000 parameter sets per region to calibrate crop-specific growth parameters. After filtering parameter sets for those within 25% of the lowest normalised root mean square error (NRMSE) value, we evaluated model performance using a weighted scoring metric prioritising error reduction (50% NRMSE, 25% PBIAS) while retaining explanatory power (25% R^2). To reduce the changes to the default values, we also add a penalty for the parameters, with lower deviation from default values being preferred. The optimal parameter combination for each crop in each region was selected based on this composite score.

Step 2: Irrigation water use calibration

A subsequent LHS ensemble of 10,000 parameter sets was used to optimise irrigation variables, with water use per unit area in Egypt's simplified irrigation zones (Upper, Middle, and Lower regions) serving as the observed dataset. In the initial filtering step, we retained only those runs whose yield NRMSE was within 25% of the best-performing run, ensuring that irrigation calibration did not come at the cost of yield accuracy. The remaining runs were then ranked using a multi-criterion scoring system weighted 75% towards NRMSE and 25% towards R^2 , allowing us to balance calibration accuracy against the model's stylised representation of irrigation.

Step 3: Fertiliser sensitivity for maximum yield

Fertiliser application rates and stress thresholds were systematically adjusted to identify configurations maximising simulated yields. This aligned with Egypt's high-input farming norms, where nitrogen application typically ranges 200–300 kg/ha (Food and Agriculture Organization of the United Nations, 2005). The resulting parameters defined potential yields under idealised nutrient conditions.

Step 4: Deficit irrigation analysis

A similar sensitivity analysis identified irrigation strategies that reduced water use per unit area relative to yield penalties $\leq 10\%$. We iteratively adjusted parameters governing irrigation triggers (soil water deficit and plant water stress thresholds) and application volumes and frequencies to map trade-offs between water conservation and productivity.

3.6.2 Sensitivity Analysis of CRAFTY

Within CRAFTY, the natural capital layers, as defined by potential yields, have the greatest influence on ecosystem service supply. To a lesser extent, ecosystem services are also influenced by the socioeconomic capitals. At model initialisation, the CRAFTY model automatically scales demand to match the modelled supply, therefore preserving the supply provided from the biophysical model, removing the need for further calibration. Model evaluation is primarily carried out via analysis of the sensitivity of the model output to parameter values, in line with previous applications of the model (e.g. Blanco et al., 2017; Brown et al., 2022), while evaluation of the model framework itself ensures appropriate functioning (Brown et al., 2023).

The sensitivity analysis entails modifying the AFT parameters ('giving-in' and 'giving-up') and production sensitivity tables for socioeconomic capitals to determine their impact on the supply of ecosystem services. This is completed for a single scenario representing the business-as-usual case. The socioeconomic capitals are held constant at 2020 levels during the analysis, while natural capitals reflect potential yields under the same scenario. To further assess the influence of sensitivities, an additional run was conducted where all socioeconomic capital sensitivity values or all AFT parameters were set to zero. Due to the model size and time required for each run, a one-at-a-time sensitivity analysis is adopted (Pianosi et al., 2016).

The initial distribution of land use was based on a random allocation of crops, informed by land cover satellite data and governorate-level statistics on cropped areas for each crop. While this ensures accuracy at the administrative level, it does not necessarily reflect field-level patterns. To account for the potential influence of initial conditions, the model was run ten times with different initial land-use distributions, and results were aggregated across these runs for reporting.

3.6.3 Coupled model implementation

After completing the CRAFTY sensitivity analysis, we ran the CRAFTY model using static demand, business-as-usual AFT parameters and production sensitivities, and fixed socioeconomic capitals and demand based on 2020 conditions. Natural capital, however, was dynamically derived from the biophysical model simulations under RCP2.6, RCP4.5, RCP6.0, RCP7.0, and RCP8.5 climate scenarios. To account for the influence of initial conditions, the

CRAFTY model was run ten times using different randomised initial land-use maps, as explained above. The model simulated land-use change and shifts in management practices, specifically irrigation, under each scenario through competition between AFTs. Outputs from these simulations were then used to drive SWAT+, which provides a more detailed and process-based representation of crop growth and water use under varying land use configurations. This stylised implementation of the coupled model serves to demonstrate the value of integration, with results presented in Section 3.8.5 below. The coupled model is summarised in Figure 3.4.

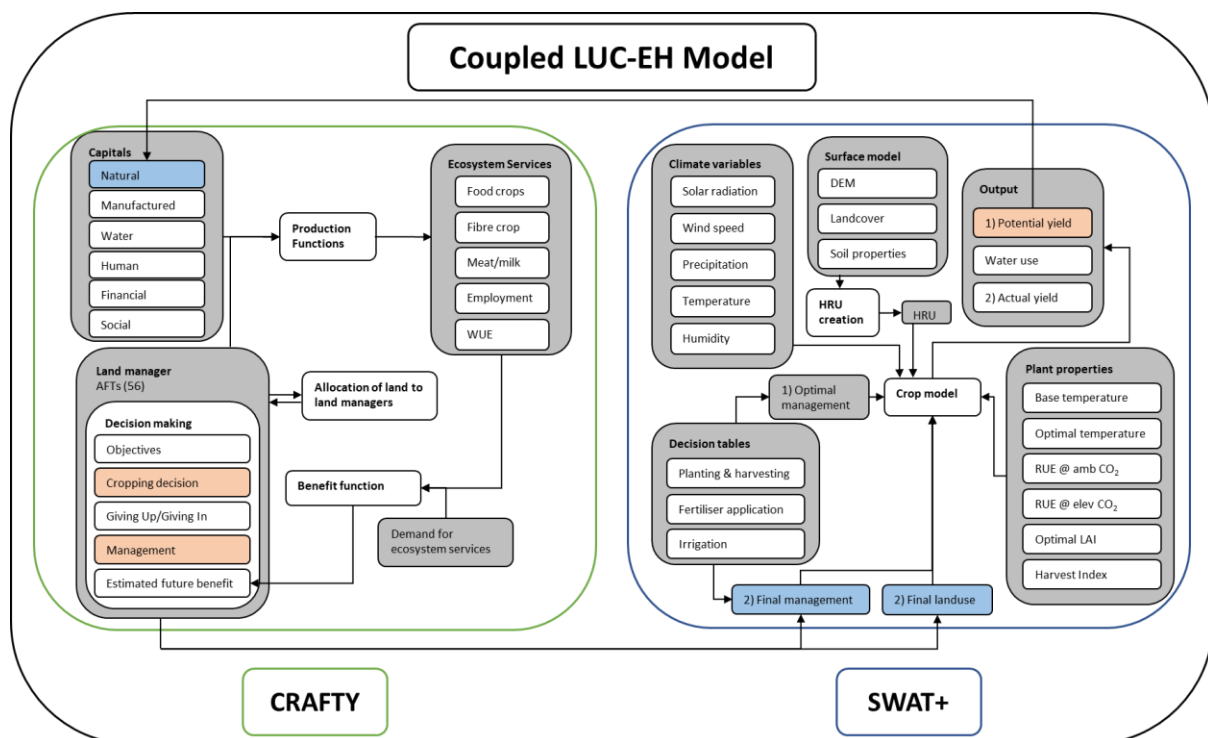


Figure 3.4: Coupled LUC-EH model schematic for Egypt: The diagram shows information exchange between CRAFTY (left) and SWAT+ (right). Orange boxes represent model outputs passed as inputs (blue) to the other model. In SWAT+, Step 1 refers to the initial run simulating potential yield, and Step 2 uses land use and management from CRAFTY to simulate actual yield and water use. The schematic has been simplified to include the most relevant aspects of each model (especially SWAT+) to the coupled model and does not include, for example, many hydrological features of the SWAT+ model.

3.7 Data

Developing ecohydrological models requires a large, diverse dataset to characterise the physical characteristics of the model area. The absence of good-quality, open-source, national GIS datasets necessitated the use of global datasets. National data was used for cropped areas and yields. Table 3.4 includes details of the data used to drive and parameterise the SWAT+ model of Egypt. Table 3.5 includes details of the data used to create the CRAFTY model of

Egypt. Global datasets, which can be utilised for different regional applications of the coupled model, are separated from national and modelled data that are specific to the model application for Egypt.

Table 3.4: Input data used to develop the SWAT+ model.

Submodel	Data	Spatial resolution	Temporal resolution	References
Global datasets				
Surface water	MERIT DEM	90m	-	(Yamazaki et al., 2017)
	ESA Landcover	300m	Annual (2020)	(Copernicus Climate Change Service, 2019)
	DSOLMap	250m	-	(Hengl et al., 2017; López-Ballesteros et al., 2023)
	Lake shapefile		-	(Messenger et al., 2016)
	Streamflow			(Hou et al., 2024)
	CO ₂ concentration		2020-2100	(Meinshausen et al., 2020)
Groundwater	Soil grid depth to bedrock	250m	-	(Hengl et al., 2017)
	GLHYMPS			(Gleeson, 2018; Huscroft et al., 2018)
Climate data	Climate data bias corrected and downscaled for MRI-ESM2-0	0.25° (25km at the equator)	Daily	(Lange & Büchner, 2021; Yukimoto et al., 2019)

Submodel	Data	Spatial resolution	Temporal resolution	References
	climate model: rainfall, min/max temperature, relative humidity, solar radiation, wind speed			
National datasets				
Cropping pattern	2010 cropped areas	Governorate	Annual (2010-2019)	(CAPMAS, 2025)
Calibration	Yield data	Governorate		(CAPMAS, 2025)
	Water use data	Governorate		(CAPMAS, 2025)

Table 3.5: Input data used to develop the capital layers for the CRAFTY model.

Capital	Indicator	Details	References
Global datasets			
Human	Education index	Subnational Human Development Index indicator	(Smits & Permanyer, 2019)
	Health index	Subnational Human Development Index indicator	(Smits & Permanyer, 2019)
	Population downscaling	1 km ² gridded population datasets resampled to 0.81 km ² resolution. These are rescaled based on updated national population values and used to downscale human capital.	(Koch & Leimbach, 2023; Wang et al., 2022)

Capital	Indicator	Details	References
Manufactured	Road infrastructure inventory	Developed based on 2015 data.	(Meijer et al., 2018)
Financial	GDP per capita	1 km ² gridded GDP and population datasets resampled to 0.81 km ² resolution. These are rescaled based on updated national GDP and population values.	(Koch & Leimbach, 2023; Wang & Sun, 2022; Wang et al., 2022)
Water Capital	Rainfall	0.25° resolution gridded daily rainfall data summed per year from data bias corrected and downscaled for MRI-ESM2-0 climate model.	(Lange & Büchner, 2021; Yukimoto et al., 2019)
	Distance to surface water infrastructure	Distance to lakes and canals calculated using surface water layer from Opens Street Map for canals and rivers.	(Humanitarian OpenStreetMap Team (HOT), 2024) (Messenger et al., 2016)
	Groundwater head of confined aquifer layer		(Verkaik et al., 2024)
National datasets			
Social	Coop membership per capita	Governorate-level dataset	(CAPMAS, 2025)
	Gini index	Calculated from the Household Expenditure, Income, and Consumption	Calculated from (OAMDI, 2023)

Capital	Indicator	Details	References
		Survey expenditure statistics.	
Manufactured	Tractors per feddan	Governorate-level statistics of tractors per feddan	(CAPMAS, 2025)
Modelled datasets			
Natural capital	Potential yield	Calculated from the SWAT+ model at 900m resolution.	

3.8 Results

3.8.1 SWAT+ calibration analysis



Figure 3.5: Yield calibration and validation plots for key crops for the Delta region: Observed dry yield in blue and modelled dry yield in red. The calibration period (2013-2017) and the validation period (2018-2022) are represented by a circle and a triangle, respectively.

Calibration performance varied by crop and region. In the Delta region (Figure 3.5), wheat and oil crops both achieved strong agreement with observed yields, each with an R^2 of 0.67 and NRMSE values of 24% and 29%, respectively. Maize also produced relatively accurate yield magnitudes, with an NRMSE of 33%, but its low R^2 of 0.30 indicates limited ability to capture interannual variability. Performance declined slightly during validation. On average, R^2 dropped from 0.52 in calibration to 0.25 in validation, while NRMSE increased from 44% to 108% (Table 3.6). However, although absolute PBIAS increases from 1.79% to 12.65% in calibration and validation stages, it remains below 15% showing that systematic bias is acceptable during the validation stage.

Performance also varied by region. The Mediterranean region recorded the lowest calibration error ($R^2 = 0.59$, NRMSE = 34.52%), while the Upper region achieved the strongest model fit ($R^2 = 0.66$, NRMSE = 35.55%). Qena exhibited the weakest performance, particularly during calibration ($R^2 = 0.47$, NRMSE = 72.01%). These patterns persisted into the validation phase, where regions that calibrated well tended to validate more reliably. Full calibration and validation plots for all crops and regions are provided in the Appendix B.2.

Table 3.6: Average yield calibration and validation NRMSE, R^2 , and PBIAS for each region.

Region	Calibration			Validation		
	R^2	NRMSE (%)	PBIAS (%)	R^2	NRMSE (%)	PBIAS (%)
Aswan	0.51	44.14	2.77	0.12	91.24	18.80
Delta	0.46	32.79	0.38	0.18	98.08	10.56
Med	0.59	34.52	2.46	0.34	97.22	13.64
Middle	0.44	44.90	1.83	0.14	101.37	8.48
Qena	0.47	72.01	2.23	0.31	114.86	10.43
Upper	0.66	35.55	1.10	0.43	145.56	14.02
Average	0.52	43.98	1.79	0.25	108.19	12.65

3.8.2 Sensitivity analyses

3.8.2.1 *Fertiliser sensitivity analysis*

The fertiliser sensitivity analysis revealed that for many crops and regions, the default nutrient application settings were already optimal for yield. This was particularly evident for crops such as alfalfa, seasonal fodder, legumes, oil crops, and fibre, where no improvements in average yield were observed through further fertiliser adjustments. However, for other crops – particularly sugarcane, rice, other vegetables, and wheat – adjusting fertiliser inputs improved performance, with sugarcane consistently showing the highest yields under high nitrogen and phosphorus input scenarios. Notably, maize and rice responded strongly to reduced nitrogen stress, but excessive phosphorus application often showed diminishing returns.

3.8.2.2 *Irrigation sensitivity analysis*

The irrigation sensitivity analysis aimed to identify deficit irrigation configurations that achieved water savings while maintaining yield losses within an acceptable 10% threshold. On average across all regions and crops, water use per unit area was reduced by approximately 51%, while yield declined by only 6.7%, confirming the effectiveness of the selected settings. Some systems showed particularly efficient trade-offs: for instance, legumes and winter other vegetables (winter potatoes) achieved water savings of 76% and 72%, respectively, with yield reductions of 4.01% and 5.49%, respectively. Conversely, sugarcane and date trees experienced lower irrigation reductions (25% and 26%), with yield reductions of 5.00% and 7.47%, respectively. The highest yield reduction was exhibited by winter seasonal fodder (9.15%), which resulted in an irrigation reduction of 54%.

3.8.2.3 *CRAFTY sensitivity analysis*

The analysis of the CRAFTY model's sensitivity to changes in socioeconomic capital sensitivities showed a moderate response (detailed results included in Appendix B.8). Higher capital sensitivities led to lower production of most crop-related ecosystem services, while animal products, employment, and water use efficiency were less affected. This pattern was consistent with the sensitivity analysis of AFT parameters. Regarding abandonment and agricultural expansion, differences between sensitivity runs were relatively limited. The minimum abandoned area was 41,472 ha, compared to a maximum of 58,806 ha. Abandonment was higher when AFT parameters were at their lowest. However, when the

‘give-up’ probability or the sensitivity to capitals was set to zero, abandonment was lowest. Reclamation of unmanaged land, which varied across runs from 247,698 ha to 382,644 ha, followed a similar pattern: the smallest reclaimed area occurred when AFT parameters were at their lowest, while the highest reclamation occurred when the ‘give-up’ probability or sensitivity to capitals was set to zero.

3.8.3 Potential yields under different climate scenarios



Figure 3.6: Projected yield trajectories for key crops under different climate scenarios (2020–2099): Yield values are based on modelled outputs for currently cultivated lands only, illustrating changes over time for each crop and scenario.

Model outputs show varying yield responses across crops and climate scenarios (Figure 3.6). Fodder crops, including seasonal fodder and alfalfa, demonstrate the largest percentage increases between 2020 and 2099, with gains of 119% and 117%, respectively. Wheat also shows a marked increase under RCP8.5, with average yields in currently cultivated areas rising by over 43%. This represents a 36% increase in 5-year average yield (2095-2099 vs. 2020-2024), reaching approximately 9 t/ha by the end of the century.

Main vegetables and sugarcane also exhibit strong yield gains of 25% and 34% between 2020 and 2099, respectively. In contrast, maize, fibre crops, and rice display non-linear trends under RCP8.5, with yields peaking between 2060 and 2080 before declining towards 2099. Fruit tree yields remain relatively stable, with modest increases between 4% and 13% across scenarios based on the 5-year average comparison. The greatest reduction in yield was observed for other vegetables, which reduces by 31% between 2020 and 2099, under the RCP8.5 scenario. Overall, RCP8.5 leads to the greatest gains, with a 25% increase in yield across all crops. By comparison, under RCP2.6, yields remain relatively stable, with an average increase of just 4% over the century.

Yield responses also vary spatially. Under all climate scenarios, maize yields decline across much of Egypt by the late 21st century, with reductions of up to 25% in some areas, particularly in the southern region (Figure 3.7b). In contrast, wheat yields increase in all scenarios and across all regions (Figure 3.7a), with the most pronounced gains in currently uncultivated areas of the Western Desert (Upper Egypt SWAT+ submodel), where increases of up to 75% are projected.

A noticeable spatial distinction emerges between currently irrigated areas in the Nile Valley and Delta and newly cultivated zones. For both wheat and maize, currently irrigated areas maintain higher yields across all scenarios, except in the case of wheat under RCP8.5, where new expansion areas also experience marked gains.

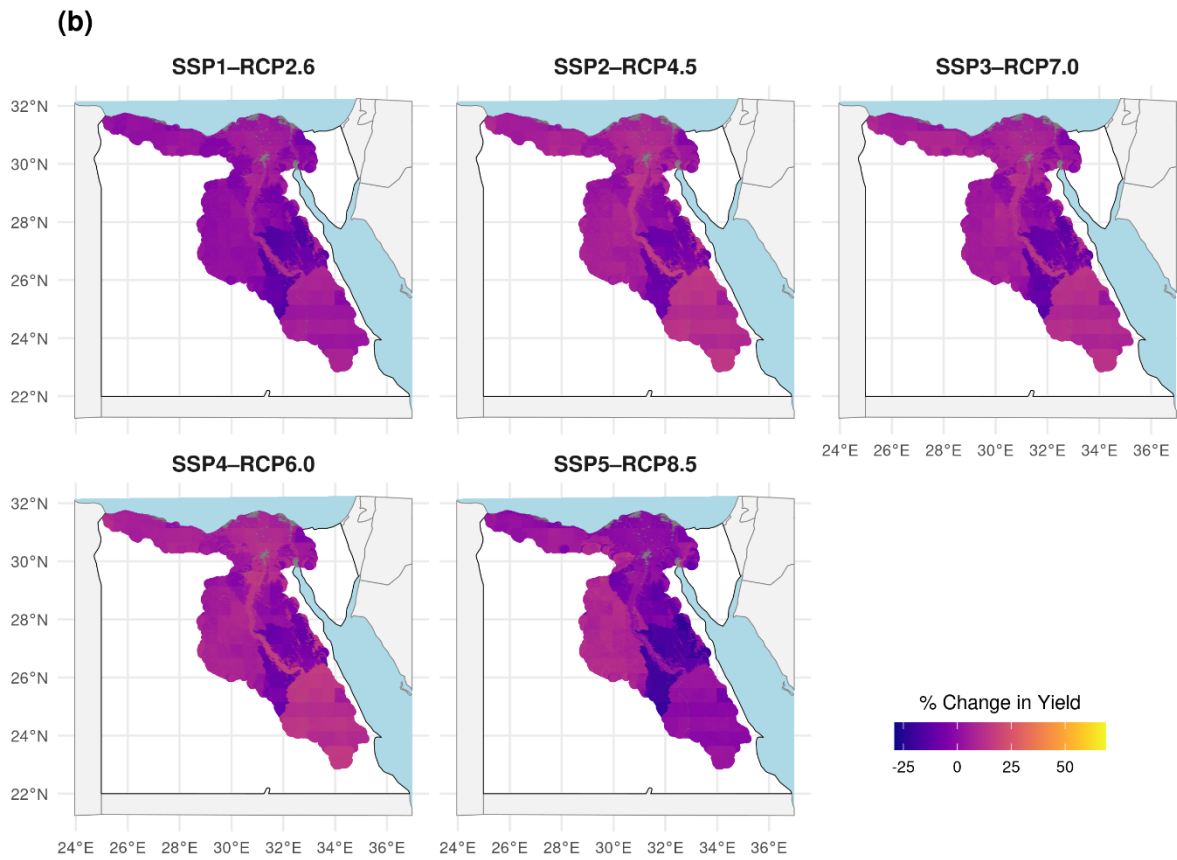
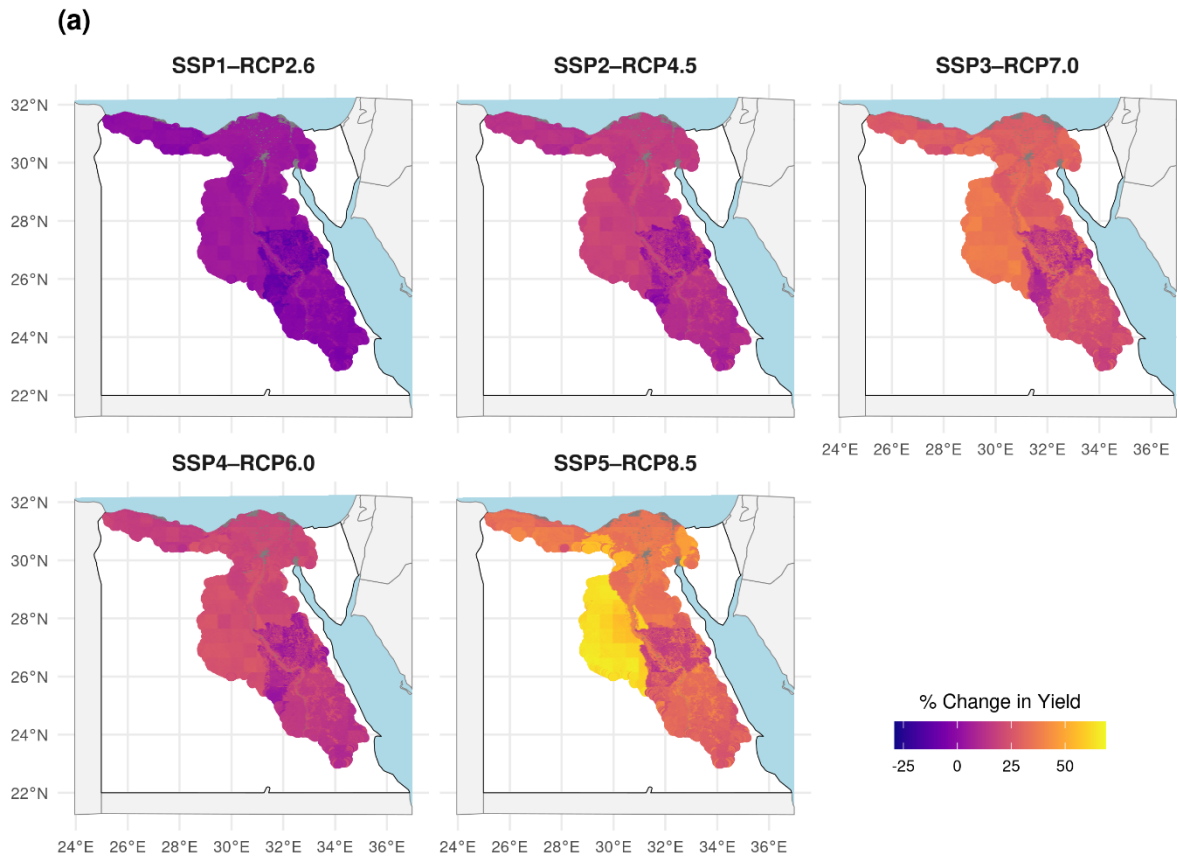


Figure 3.7: Spatial change in crop yield under different climate scenarios: Percentage change in yield for (a) wheat and (b) maize between 2020 and 2099. Five-year average yields are used to smooth interannual variability (2020-2024 and 2095-2099)

3.8.4 Water use efficiency

Water use efficiency (WUE) in old lands (Figure 3.8) shows considerable variation across climate scenarios under assumptions of ideal irrigation and optimal fertiliser application. The most substantial improvements are observed under RCP8.5, which leads to an average 69% reduction in water use per tonne of yield across all crops. Alfalfa and seasonal fodder exhibit the greatest improvements, reducing water use per tonne of yield by 88% and 85%, respectively. Sugarcane and wheat also benefit, with water use per tonne of yield reductions of 79% and 75% between 2020 and 2099.

In contrast, RCP2.6 shows minimal gains, with an average WUE improvement of just 4% over the same period. For other vegetables, WUE remains relatively stable across most scenarios, with a slight increase in water use per tonne of 0.6% under RCP2.6 and a modest decrease of 2.1% under RCP7.0. However, RCP8.5 again stands out, reducing water use per tonne for this crop group by 47%.

Most crops follow a consistent trend of improvement, with the magnitude of gains increasing along the scenario severity gradient: RCP2.6 (-4%), RCP4.5 (-16%), RCP6.0 (-21%), RCP7.0 (-32%), and RCP8.5 showing the greatest improvement in WUE.

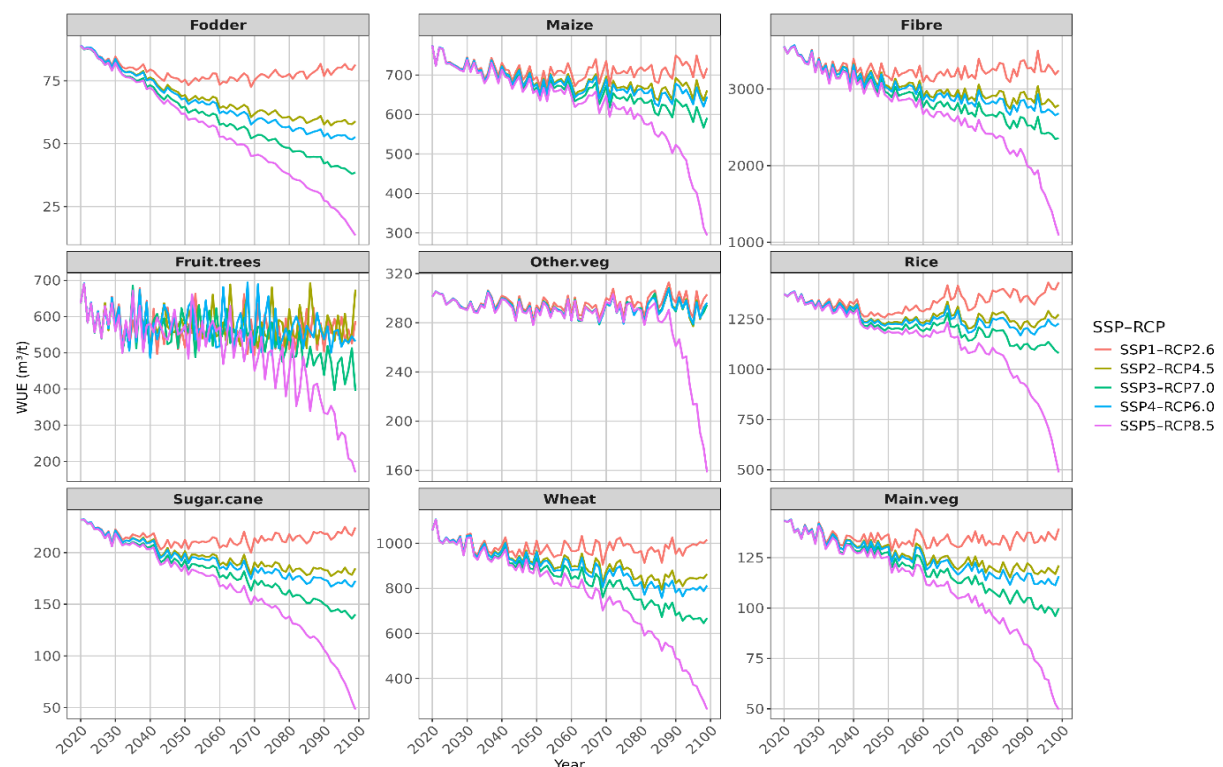


Figure 3.8: Trajectories of water use efficiency (WUE) under future climate scenarios: Projected WUE for major crops from 2020 to 2099.

3.8.5 Land use change

The implementation of the coupled model reveals notable variations in crop areas and production levels across scenarios (Figure 3.9). Seasonal fodder, wheat, sugarcane, and main vegetables all show increased production under RCP4.5, RCP7.0, RCP6.0, and RCP8.5. Among these, seasonal fodder experiences the most substantial rise, increasing from 130 Mt in 2020 to 255 Mt in 2100 under RCP8.5. In contrast, RCP2.6 results in either stable or slightly declining production levels for these crops. Despite rising production, cropped areas for seasonal fodder, wheat, and main vegetables show gradual declines across all scenarios.

Fibre crops, rice, and maize exhibit non-linear trends under RCP8.5, peaking around 2070 before declining towards the end of the century. Other vegetables initially decline to 7.44 Mt before increasing again to reach 10.0 Mt by 2100. The area under other vegetables also expands markedly between 2080 and 2099, from 568,851 ha to 817,493 ha.

Patterns in abandoned land (Appendix B.4) are consistent across all scenarios except RCP8.5, which shows a sharp decline in abandonment after 2080, reaching 21,708 ha by 2099. In other scenarios, abandonment increases gradually, ranging from 43,092 ha (RCP7.0) to 49,896 ha (RCP4.5).

The conversion of unmanaged land (Appendix B.4) follows a similar trajectory across scenarios. Total unmanaged land declines sharply from 939,600 ha in 2020 to between 650,000 and 700,000 ha by 2025. This reduced level remains relatively stable through to 2100, ending between 649,296 ha and 668,979 ha, depending on the scenario.

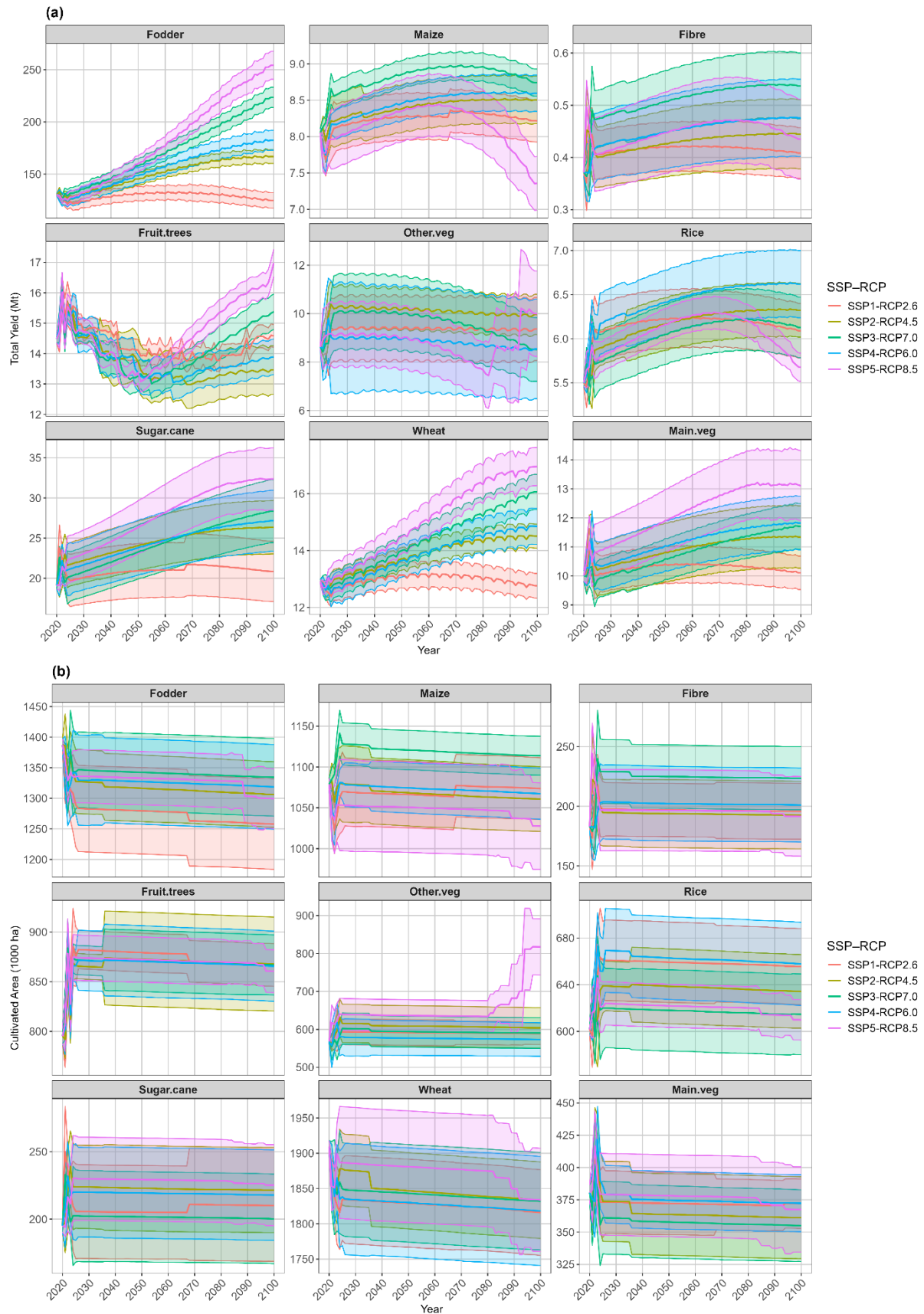


Figure 3.9: Projected crop production and cultivated area under future scenarios: (a) Total crop production and (b) total cultivated area for key crops across all scenarios. Solid lines represent the median across 10 initial land use map runs, while shaded ribbons indicate the inter-run standard deviation.

3.9 Discussion

This study develops a coupled land-use change-ecohydrological model to assess climate and socioeconomic impacts on agricultural production and water use in multi-seasonal arid and semi-arid agricultural systems. The approach integrates the SWAT+ ecohydrological model, which generates spatially distributed potential crop yields (serving as a natural capital layer), with CRAFTY, an ABM simulating land-use change and management decisions. Within the ABM, agricultural agents, representing cropping patterns and management practices, compete based on natural and socioeconomic capitals and agent characteristics. Calibrated and validated against observed annual yield and irrigation data, the ecohydrological model demonstrates acceptable performance given data limitations. We conduct a climate change scenario analysis, which project potential yield increases under scenarios with elevated atmospheric CO₂ levels for wheat, main vegetables, sugarcane, fodder crops, while declines were observed for maize, rice, and other vegetables, suggesting that any declines due to increasing temperatures are counteracted by CO₂ fertilisation effects for some crops but not for others. We also show that irrigation water use efficiency improved at the highest rate for scenarios with the highest CO₂ levels, demonstrating the impact of elevated CO₂ on crop water requirements. Finally, we establish the benefit of the coupled model by running the model using potential crop yields under different climate scenarios, static socioeconomic capitals and demand, and business-as-usual agent properties. This demonstrates that even in light of the static socioeconomic capitals and demand, the coupled model results in some adaptation in response to dynamic potential yields.

3.9.1 Climate change impact on crop yields

Our results indicate that C3 crops, such as wheat, and fodder crops experience increased yields under elevated CO₂ concentrations. This finding aligns with previous studies (Ahmed et al., 2019; Ainsworth & Long, 2021; Elsadek et al., 2024; Rezaei et al., 2023), which consistently report enhanced productivity in C3 crops due to increased photosynthetic efficiency under elevated CO₂. In contrast, C4 crops, such as maize, show no benefit of elevated CO₂ concentrations, except under drought-stressed conditions (Rezaei et al., 2023). This is consistent with our results, where maize yields increase modestly across most climate scenarios, with slight reductions occurring under scenarios with the highest atmospheric CO₂ concentrations. Since we model potential yields under non-water-stressed conditions, the

reduction observed for maize further supports expectations based on physiological crop responses.

A study of the Mediterranean region using the Lund-Potsdam-Jena managed Land (LPJmL) ecohydrological and agro-ecosystem model found yield increases for multiple crops under global warming scenarios ranging from 2 °C to 5 °C (Fader et al., 2016). For sugarcane, yields increased by 30% and 120% when comparing 2000–2009 to 2080–2090 under 2 °C and 5 °C scenarios, respectively, using dynamic CO₂ concentrations. Notably, under elevated CO₂, all crops experienced some level of yield gain across all scenarios. In contrast, under constant CO₂ levels, most crops showed yield reductions, typically within 20%, although some crops, including sugarcane, maintained their yield increases. Broadly, our findings align with these results. However, while Fader et al. (2016) report continuous increases in rice yield across all scenarios, our results show an initial increase followed by a decline, especially under high-emissions scenarios. This discrepancy may stem from differences in climate and CO₂ input data; their scenarios reach a maximum of 720 ppm CO₂ under 5 °C warming, whereas our RCP8.5 scenario reaches 1,135 ppm by 2100.

Previous studies assessing climate change impacts on Egyptian agriculture report mixed findings (Elsadek et al., 2024; Gamal et al., 2021; Kheir et al., 2019; Moghazy & Kaluarachchi, 2021; S. M. Mostafa et al., 2021). For instance, Moghazy and Kaluarachchi (2021) used linear regression with climate projections to estimate yield impacts in the Siwa region (Western Desert), projecting reductions of 10.4-27.4% by 2100 under RCP8.5. However, their model did not include elevated CO₂ effects. In contrast, Elsadek et al. (2024), applying the AquaCrop-GIS model for rice in the Nile Delta, found yield gains under both RCP4.5 and RCP8.5 with elevated CO₂. Their projections show rice yields increasing from 14.5% in the 2030s to 16.9% in the 2090s under RCP4.5, while RCP8.5 shows a peak gain of 16.9% in the 2050s followed by a smaller increase of 1.6% by the 2090s. Our model also shows an initial yield increase for rice under RCP4.5, peaking around 2070, followed by a decline, resulting in a net gain of just 1.8% between 2020 and 2099. Moreover, under RCP8.5, rice yields decline by 5.1% over the modelling period. These differences may reflect the broader geographic scope of our model, which includes southern Egypt, where higher warming is expected. In these areas, the positive effects of CO₂ fertilisation may be outweighed by heat stress more than in the cooler Delta region.

Our results show increases in wheat yield under all scenarios, with the largest gain (36%) under RCP8.5. Kheir et al. (2019) investigated the effects of sea-level rise, increased temperature, and elevated CO₂ on two wheat cultivars in a Kafr-El-Sheikh, a Nile Delta governorate, using two DSSAT wheat models. Their results showed that a 4 °C temperature increase could reduce yields by up to 18%, while elevated CO₂ concentrations (400-700 ppm) increased yields by 5-25%. Although our model does not simulate these specific cultivars and assumes ideal growing conditions with combined climate effects, the general trends are consistent, demonstrating that elevated CO₂ can offset some of the negative impacts of warming on wheat yield.

Overall, these studies highlight the complex and uncertain nature of climate change impacts on crop yields. Rising temperatures are generally expected to reduce yields, while elevated CO₂ concentrations may offset some of these losses, particularly for C3 crops. Our findings are broadly consistent with this pattern, though rice shows some divergence, likely due to differences in climate sensitivity and spatial variation across Egypt.

3.9.2 Water use under future climate scenarios

Our modelling results show improvements in water use efficiency across all scenarios and crops. This trend is generally consistent with other studies that account for both increased temperatures and elevated CO₂ concentrations (Tian et al., 2023; Toreti et al., 2020), where reductions in crop transpiration are primarily attributed to decreased stomatal conductance under elevated CO₂. For example, Fader et al. (2016) analysed irrigation water use for multiple crops across the Mediterranean region and found a net reduction in irrigation water requirement for most crops included in our simulations, such as temperate cereals (e.g. wheat), potatoes (included under other vegetables), and pulses (included under legumes). In contrast to our results, however, their results showed increased irrigation for sugarcane, citrus, and rice. These differences may reflect the relatively higher dependence on irrigation in our study area compared to the broader Mediterranean average.

Mokhtar et al. (2025) conducted a meta-analysis of WUE responses to elevated CO₂ across various crops and field experiments. They found that C3 crops such as wheat and tomatoes (main vegetables) exhibited consistent improvements in WUE, with increases of up to 40–50% in some cases. C4 crops, including maize and sugarcane, also showed improvements, albeit to a lesser extent. Similar patterns are observed in Q. Cao et al. (2022), who reported

WUE increases of 27.8% for wheat and 49.7% for maize under 800 ppm CO₂ in non-drought conditions.

Several studies have explored the impacts of climate change on water use in Egypt, though most focus solely on temperature effects (Gabr, 2023a; S. Mostafa et al., 2021). These studies consistently project increases in irrigation demand, such as S. Mostafa et al. (2021), who estimate increases ranging from 6.1% to 7.3% for winter crops and 11.7% to 13.2% for summer crops due to higher evapotranspiration under warming scenarios.

Overall, our results are in agreement with studies that incorporate both temperature rise and CO₂ fertilisation effects, showing net improvements in water use efficiency under future climate scenarios. However, such integrated modelling studies remain limited for Egypt, highlighting a gap in the regional literature.

3.9.3 Model evaluation

We use our coupled model implementation to demonstrate the value of coupling a biophysical model with an agent-based land-use change model, under a simplified scenario framework. This example assumes dynamic potential yields driven by climate change, but holds socioeconomic capitals, demand, and AFT parameters constant and uniform across scenarios. Despite these simplified assumptions, the model produces notable land-use dynamics, including land abandonment, reclamation, and shifts in crop areas in response to changing yield potentials. For instance, the greatest decline in potential yield is observed for other vegetables under RCP8.5. This yield reduction leads to an expansion in cultivated area for that crop after 2080, accompanied by the re-cultivation of previously abandoned land.

Previous models that couple biophysical and agent-based components (e.g. Du et al., 2020; Harms et al., 2023; O'Keeffe et al., 2018) have primarily focused on irrigation decision-making while limiting endogenous land-use change, despite its central role in adaptation to climate change (e.g. Adly et al., 2018; Boazar et al., 2020; Chouchane et al., 2020). Unlike optimisation-based approaches (e.g. Fikry et al., 2021; Sardo et al., 2024), the coupled LUC-EH model enables land-use change to emerge endogenously by defining initial conditions and allowing land allocation to evolve without imposing prescriptive decision rules.

3.10 Limitations

Although the model presents some key developments, limited access to high-resolution gauging data and evapotranspiration (ET) measurements constrained the accuracy of model calibration. Such limitations are common in data-scarce regions, where ecohydrological models must often rely on sparse and fragmented monitoring networks (Chawanda et al., 2024). While SWAT+ benefits from open-source datasets, global satellite products, and climate model integrations, making it suitable for applications in data-poor regions, the absence of detailed records on irrigation return flows and groundwater abstraction complicates the calibration of key hydrological parameters (Akoko et al., 2021).

Egypt's hydrological system is highly complex, involving interactions between surface irrigation infrastructure, subsurface tile drainage, and the widespread reuse of agricultural drainage water (Barnes, 2014). Although SWAT+ supports the conceptual separation of surface and groundwater irrigation sources, the current implementation does not explicitly assign or quantify these sources. Furthermore, groundwater withdrawals are not directly modelled, limiting the ability to assess their contribution to aquifer depletion or the risk of saltwater intrusion in coastal regions. This is largely due to the absence of openly accessible, regularly updated spatial and temporal datasets describing the structure, operation, and management of irrigation infrastructure, including pumping stations, return flows, and conveyance systems. Incorporating these processes into future model development would significantly improve assessments of groundwater sustainability and irrigation system resilience.

3.11 Conclusion

This study demonstrates the value of coupling behavioural and biophysical models to simulate agricultural responses to climate change in arid, multi-seasonal agricultural systems. By linking CRAFTY and SWAT+, we move beyond static impact modelling to explore how cropping patterns and irrigation decisions might shift in response to changing environmental conditions. While this application uses a stylised version of the model with static socioeconomic conditions and demand, it shows that even under stagnant assumptions, land-use change processes can enhance the interpretation of biophysical responses, highlighting how even with fixed socioeconomic conditions, dynamic land-use shifts can redistribute cropping patterns in ways that partially offset or amplify climate-driven yield changes.

The results also underscore the potential significance of rising atmospheric CO₂ concentrations, which improve water use efficiency and may benefit the yields of some crops, particularly C3 species such as wheat and fodder crops. However, these gains are not uniform and may be offset by increased heat stress, pointing to the need for cautious interpretation. More broadly, the coupled model offers a transferable and open-access tool for scenario analysis in regions facing similar constraints. Applying the model to fully developed climate–socioeconomic scenarios would allow for more robust exploration of adaptation pathways and the complex interplay between natural and human systems.

3.12 Chapter conclusion

This chapter developed and applied a coupled land-use change-ecohydrological model for Egypt, linking CRAFTY and SWAT+ to capture interactions between climate-driven biophysical changes and heterogeneous farmer decision-making. The model illustrated how variations in yields, water use efficiency, and land allocation emerge from these interactions, highlighting both the potential benefits of strategies such as deficit irrigation and the spatially varied impacts of climate change on crop production and land use.

While the implementation here used simplified socioeconomic assumptions, it provides the technical foundation for integrating more detailed and dynamic future conditions. The next chapter builds directly on this coupled model, combining it with downscaled climate and socioeconomic scenarios to explore how Egypt's agricultural system could evolve under alternative development pathways.

4 Climate and socioeconomic pressures expose the limits of dietary change and agricultural expansion in Egypt

Authors: Aimen Sattar, Calum Brown, Mark Rounsevell, Peter Alexander

4.1 Chapter introduction

The previous chapter developed and applied a coupled land-use change-ecohydrological model for Egypt, combining CRAFTY and SWAT+ to capture interactions between crop yields, water use efficiency, and heterogeneous farmer decision-making under changing climate conditions. While this implementation provided valuable insights into how biophysical and behavioural processes interact, it was based on fixed socioeconomic assumptions, meaning it could not reflect how shifts in population, dietary patterns, resource availability, or changes in agent characteristics might alter agricultural outcomes.

This chapter applies the coupled model to nationally downscaled SSP-RCP scenarios. By linking scenario-specific socioeconomic and climate conditions with AFT parameterisations, we explore how Egypt's agricultural system may evolve under contrasting futures. The results illustrate how differences in demographic trends, economic development, and climate severity shape land use, production, and water use efficiency, providing the basis for assessing trade-offs and potential adaptation strategies.

4.2 Abstract

Egypt's agricultural system faces pressures from rapid population growth, increasing water scarcity, and heavy reliance on food imports. The impacts of these pressures depend on heterogeneous farmers' land-use decisions and biophysical constraints, but there have been no spatially explicit analyses linking these for different future scenarios that would contribute to a better understanding of these complex, interacting pressures. To address this gap, this study explores how Egypt's agriculture could respond to future climate and socioeconomic challenges by applying a coupled land-use change-ecohydrological model. This approach downscales integrated socioeconomic and climate scenarios, incorporating farmer decision-making processes, agricultural expansion and abandonment dynamics, and adaptation to resource constraints. Results show none of the scenarios considered fully satisfy the demand for domestic production, highlighting persistent vulnerabilities in Egypt's food system. The inequality scenario (SSP4-RCP6.0) produces the smallest food shortfall due to lower population growth and moderate calorific intake, whereas the regional rivalry scenario (SSP3-RCP7.0) performs worst, underscoring the limits of self-sufficiency. A high-development pathway (SSP5-RCP8.5) achieves large production gains but falls short of demand due, in part, to substantial export commitments. All scenarios reveal trade-offs between boosting crop yields and improving water use efficiency, alongside extensive agricultural expansion and farmland abandonment. The findings highlight population growth as a major pressure on Egypt's agricultural system and underscore the need for dietary shifts, sufficient resource provision, and the importance of trade to improve food security.

4.3 Introduction

Climate change presents major challenges to agricultural production, affecting both farmers' livelihoods and food security. Arid and semi-arid agricultural systems, such as Egypt's, are already experiencing increasingly hotter and longer summers, leading to higher crop water demand, increased intra- and interannual variability, and declining rainfall (S. Mostafa et al., 2021; Singh & Chudasama, 2021). The Middle East and North African (MENA) region is warming at a faster rate than global averages, with observed warming of 1.68 °C by 2020 relative to pre-industrial levels, compared with the global average increase of 1.15 °C (Malik et al., 2024; Mostafa et al., 2019). Projections for Egypt from a multi-model ensemble indicate that with global warming of 1.5 °C and 2 °C, extreme precipitation events along Egypt's northern coast may increase by 14%, while the length of the longest dry spells across much of the country could rise by as much as 160% during 2081–2100 relative to 1971–2014 (Nashwan & Shahid, 2022). Some modelling and experimental studies suggest that elevated CO₂ concentrations may partially offset climate stress by improving yields and water use efficiency, though these benefits remain uncertain and may be constrained by rising temperatures or extreme weather events (Ainsworth & Long, 2021; Ainsworth et al., 2025).

Responses to these challenges are not predictable, and to support the development of policies to enable adaptation to and mitigation of climate change, it is important to consider different potential human development paths (Bohl et al., 2018; El Chami et al., 2022). The Shared Socioeconomic Pathways (SSPs) provide a globally standardised framework for evaluating alternative human development trajectories under varying challenges to climate change mitigation and adaptation (O'Neill et al., 2020). These five narratives – ranging from sustainability-focused (SSP1) to fossil-fuelled growth (SSP5) – are often paired with Representative Concentration Pathways (RCPs) to explore interactions between socioeconomic drivers and greenhouse gas emissions. Common SSP-RCP pairings include SSP1-RCP2.6 (sustainability), SSP2-RCP4.5 (middle of the road), SSP3-RCP7.0 (regional rivalries), SSP4-RCP6.0 (inequality), and SSP5-RCP8.5 (fossil fuelled development), forming the basis for integrated assessments of climate impacts and policy responses (Riahi et al., 2017). Recent studies have focused on downscaling global SSP-RCP scenarios to regional and sectoral contexts (e.g. Brown et al., 2022; Chen et al., 2022; Mitter et al., 2020; Wang et al.,

2024). These studies underscore the value of SSP-RCP scenarios in linking global projections with local planning, allowing for the exploration of a wide range of plausible future conditions.

Egypt's agricultural system is characterised by multiple growing seasons, year-round cultivation, and near-total reliance on irrigation from the Nile River, which provides 95% of the country's water resources (Arab Republic of Egypt, 2023). Approximately 80% of total available water is used for agriculture under the country's arid and semi-arid climate conditions (Fuglie et al., 2020). The Nile Valley and Delta regions achieve globally competitive yields for staple crops, attributed to intensive irrigation practices and multi-cropping systems enabled by regulated water allocations (55.5 km³/year) from the High Aswan Dam (HAD) (Fuglie et al., 2020; Nikiel & Eltahir, 2021). However, rapid population growth, which is projected to continue to increase annually by between 0.5% and 1.5% to the end of the century (Koch & Leimbach, 2023), has driven per capita water availability to 590 m³/year, far below the 1,000 m³/year scarcity threshold (Falkenmark et al., 1989; Tutwiler, 2021), while import dependence often exceeds 50% for critical cereals such as wheat and maize (Abdelkader et al., 2018). Although Egypt's Nile water quota is fixed, climate change is increasing crop water demand. In particular, changes in rainfall patterns and the construction or operation of dams upstream have the potential to alter the timing and reliability of Nile flows, posing additional risks to Egypt's long-term water and food security and underscoring the need for adaptive agricultural strategies (Ahmed et al., 2024; Elsadek et al., 2024).

To address these challenges, Egypt has pursued irrigation modernisation and agricultural expansion into desert land through land reclamation. Improved seed varieties and fertiliser access have enhanced crop productivity, while subsurface drainage systems, spanning 2.7 million hectares, reclaim 7.2 km³/year of irrigation drainage water, mitigating soil salinisation and augmenting water availability by 13% of Nile allocations (Elbialy et al., 2025; Esraa et al., 2023; Ritzema et al., 2023). Simultaneously, the "1.5 Million Feddan" initiative plans to exploit some of the 150,000 km³ of the Nubian Sandstone Aquifer System (NSAS) to irrigate 630,000 ha in the Western Desert (Gabr, 2023b). Ensuring the long-term viability of these projects will require not only infrastructure development and sustainable groundwater extraction, but also the establishment of well-served communities with the capacity to endure over time (Barnes, 2012; Elsharkawy et al., 2022).

Scenario analyses project significant challenges for Egypt's agricultural sector under climate change, with irrigation demands and yield gaps intensifying across multiple pathways. Ayyad and Khalifa (2021) modelled Eastern Nile Basin scenarios to 2050, demonstrating that intensive strategies – halving water footprints while boosting yields – could close production gaps but require 30% more irrigation water, contrasting with extensification's unsustainable land conversion. S. Mostafa et al. (2021) quantified rising irrigation demands using CROPWAT 8, projecting winter crop water use increases of 6.1–7.3% by 2050 and 11.7–13.2% by 2100 under RCP scenarios, with summer crops facing 5–10% higher demands. Regional analyses, such as the Gabr (2023a) study of Upper Egypt, corroborate these trends, showing elevated net irrigation requirements for staples such as wheat and maize due to temperature-driven evapotranspiration. While optimisation models such as Adly et al. (2018) suggest that yield gains through heat-tolerant cultivars could double agricultural revenues by 2030. Additionally, Smith et al. (2013) warn of 10% yield declines by 2050 without adaptation, underscoring the urgency of integrating socioecological feedback into resilience planning. Although these modelling efforts are limited in only considering the impact of rising temperatures on yield and do not account for the effect of elevated CO₂ concentrations, which is expected to result in yield increases in at least some crops (Ahmed et al., 2019).

Existing scenario analyses of Egypt's agricultural system predominantly rely on static optimisation models or projections focused on specific regions or crop types, which prescribe fixed cropping patterns and neglect dynamic socioecological feedback, which could lead to less realistic or robust outcomes. While studies such as Ayyad and Khalifa (2021) utilise statistical methods to close yield gaps, their reliance on historical correlations fails to capture emergent behaviours under shifting demographics or climate extremes. Similarly, irrigation demand projections (e.g. S. Mostafa et al., 2021) often isolate ecohydrological processes from farmer decision-making, overlooking adaptive responses to socioeconomic and climate futures. Crucially, no prior study integrates spatially explicit, behaviourally relevant land-use dynamics with ecohydrological processes across Egypt's agricultural system.

This study develops and simulates socioeconomic scenarios for Egypt's agricultural system, addressing gaps in previous analyses by integrating dynamic farmer adaptation with biophysical constraints. The research aims to understand how Egyptian farmers will adapt to rapidly developing socioeconomic and climate pressures, and what opportunities exist to

enhance agricultural systems and output. This includes understanding what the most plausible socioeconomic futures for Egypt's agricultural system are, and how they might influence priorities around food, agriculture, and rural development. We also address the following research questions: to what extent can Egypt balance agricultural production and water use efficiency under different combinations of socioeconomic development and climate change? How do farmer characteristics and biophysical constraints interact to shape land-use outcomes across future scenarios?

4.4 Methodology

This study builds on the global SSPs (O'Neill et al., 2017), adapting them to Egypt's context by developing downscaled scenario narratives. We develop these narratives through a structured expert-based process. An initial set of assumptions is drafted by the lead author using knowledge of Egypt's agricultural, food, water, and rural development systems, together with insights from existing national and sector-specific scenario studies (e.g. Abdelkader et al., 2018; Adly et al., 2018; Ayyad & Khalifa, 2021; Elsayed et al., 2025; Kheir et al., 2019; Mazzoni et al., 2018; Nikiel & Eltahir, 2021; Yahaya et al., 2024). These drafts are then reviewed by the co-authors, who provide feedback on their coherence, realism, and internal consistency. For each scenario, key drivers are assigned qualitative trajectories that remain consistent with the global SSP framework while reflecting Egyptian conditions. The narratives outline the evolving socioeconomic and policy environment expected between 2020 and 2100, focusing on key features of Egypt's broader agricultural, food, and rural development context that influence production, employment, and water resource use. We apply these scenarios using an integrated model that couples biophysical and agent-based components to simulate how Egypt's agricultural system might evolve under different climate and socioeconomic futures. The full downscaled scenarios are outlined in Section 4.5. The development of spatially explicit input data, along with the structure and operation of the coupled model, is described in the following section.

We summarise the main scenario themes using a 7-point Likert-style scale that indicates both the direction and the approximate strength of change. We interpret each scenario to determine whether a theme is likely to increase, decrease, or remain broadly stable over the century, and to assess how strong that change should be. This judgement is based on the narrative descriptions, including the language used to describe the pace or scale of change,

together with the wider evidence on Egypt's agricultural, food, and water systems. An initial assessment is made by the lead author and then reviewed by the co-authors to ensure that the assigned direction and magnitude are coherent and consistent with the underlying storyline. These qualitative assessments form the basis of the entries in Table 4.3, which summarises the expected direction and approximate strength of change for each theme.

4.4.1 Coupled model

We use a coupled land use change-ecohydrological (LUC-EH) model to simulate how Egypt's agricultural system may evolve under different climate and socioeconomic futures (Sattar et al., 2026). This model integrates an ecohydrological model (Soil and Water Assessment Tool plus – SWAT+) with an agent-based land-use change model (Competition for Resources between Agent Functional Types – CRAFTY) across a shared 900 m x 900 m spatial grid (summarised in Figure 4.1). By linking scenario-driven changes in climate, resource availability, and societal priorities to farmer decision-making, the model captures dynamic shifts in land use and irrigation practices over time.

The SWAT+ model (Bieger et al., 2017) simulates crop growth and hydrology across regional watersheds using gridded Hydrological Response Units (HRUs) defined by land use, soil type, and slope. It uses the Erosion-Productivity Impact Calculator (EPIC) crop model (Williams et al., 1984) to simulate key biophysical processes, including photosynthesis, transpiration, and biomass accumulation. We define crop management practices – such as irrigation, fertilisation, and harvesting – using flexible decision tables that respond to environmental triggers, complemented by cropping calendars to specify date-based activities such as planting (Arnold et al., 2018). To estimate potential yields, we assumed optimal management: automatic irrigation when soil moisture drops below field capacity; optimal fertiliser application in response to nutrient stress, to maximise yields; and perennial tree crops at full maturity. SWAT+ also accounts for rising atmospheric CO₂ concentrations by adjusting crop radiation use efficiency based on scenario-specific CO₂ levels (Meinshausen et al., 2020; Zhang et al., 2022). Details of the data used for the SWAT+ model are included in Table 4.1.

We normalised potential yields for each crop and grid cell and passed these to CRAFTY as natural capital inputs. The CRAFTY model (Murray-Rust et al., 2014) simulates land-use change through competition between agent functional types (AFTs). AFTs represent distinct farmer types that vary in their sensitivity to spatially distributed resources (capitals), their

behavioural thresholds for competition – the willingness to yield land to more competitive agents ('give-in' threshold), and the likelihood of abandoning land when profitability is too low ('give-up' threshold) – and the ecosystem services they provide through specific cropping patterns and irrigation practices.

In our application, we defined two broad AFT categories, drawing loosely on the typology of Egyptian farmers developed by Sattar et al. (2024): commercial agents, inspired by specialised households, and subsistence agents, based on village households. Subsistence agents are smallholders who rely on traditional flood irrigation, have lower access to capital and mechanisation, and depend heavily on social networks. They are more likely to persist under marginal economic conditions. In contrast, commercial agents adopt market-oriented practices, including deficit irrigation, external labour, and greater use of technology, and are more responsive to profitability and resource availability. All cropping patterns, both seasonal and perennial, are represented by both agent types to capture variation in land management strategies (Sattar et al., 2026). At model initialisation, 10% of cultivated land is allocated to commercial agents and 90% to subsistence agents, reflecting the dominance of smallholder farming in Egypt.

To reflect land that is not actively managed by agricultural agents, we also included an Unmanaged Land (UL) agent. This agent is assigned to all grid cells that are neither cultivated nor masked. Masked cells include those classified as urban, wetland, or those that have zero socioeconomic capital across all years. The UL agent represents state-held or marginal land that remains inactive unless claimed by a more competitive agricultural agent. It does not produce any ecosystem services, does not abandon land, and always relinquishes land when challenged. This setup captures informal land reclamation processes occurring along the fringes of the Nile Valley and Delta, where smallholders gradually convert previously uncultivated land using shallow groundwater resources (Nour, 2020). Although not the dominant form of land reclamation, this process represents a significant and underreported dynamic in Egypt's agricultural system and serves as a partial proxy for large-scale government-led projects, such as those in the New Valley Governorate, that fall outside the model's spatial scope (Sims & Mitchell, 2015).

We represented spatially explicit socioeconomic capitals, including financial, human, manufactured, and social, using gridded indicators derived from scenario-aligned datasets,

including gross domestic product, population, infrastructure, education, healthcare, access to agricultural machinery, and agricultural cooperative membership rates (CAPMAS, 2025; Koch & Leimbach, 2023; Smits & Permanyer, 2019; Wang & Sun, 2022; Wang et al., 2022). To represent water capital, we incorporated rainfall data, proximity to surface water infrastructure, and groundwater accessibility based on the hydraulic head of confined aquifers (Humanitarian OpenStreetMap Team (HOT), 2024; Lange & Büchner, 2021; Verkaik et al., 2024). Full details on the development of the capital indicators are provided in Sattar et al. (2026), and the input datasets used to construct the CRAFTY model are included in Table 4.2.

The direction and extent of change for each indicator are derived directly from the scenario narratives. For each scenario, we interpret the narrative text to decide whether an indicator should increase, decrease, or remain broadly stable, and to judge whether the overall change should be weak, moderate, or strong. This assessment is carried out by the lead author, drawing on knowledge of Egypt's agricultural, food, water, and rural development systems, as well as on findings from national and sector-specific scenario studies (e.g. Abdelkader et al., 2018; Adly et al., 2018; Ayyad & Khalifa, 2021; Elsayed et al., 2025; Kheir et al., 2019; Mazzoni et al., 2018; Nikiel & Eltahir, 2021; Yahaya et al., 2024). Based on this interpretation, we first define values for each decade from 2020 to 2100. These decadal values are chosen to reflect the strength and timing of the changes described in the narratives. Some indicators show steady movement across the century, others rise quickly and then level off, and some increase to a mid-century peak before declining. Once the decadal values are set, annual data are produced by linearly interpolating between each pair of decadal points. The draft trajectories are reviewed by the co-authors to ensure that the resulting numerical values remain coherent, plausible, and consistent with the scenario storylines. The full set of decadal values is provided in Appendix C.3.

We initialised the distribution of AFTs using governorate-level crop area statistics from CAPMAS (2025), which define the proportional area allocated to each crop within each governorate, and gridded European Space Agency (ESA) landcover data (Copernicus Climate Change Service, 2019). However, due to the lack of spatially explicit field-level data, the precise geographic distribution of these crops is uncertain. To address this, we generated 10 alternative initial AFT maps that preserve the crop area proportions at the governorate level

while randomly assigning them to grid cells within each governorate. We ran the model using all 10 initial configurations to capture the influence of initial conditions on model outcomes and to ensure that results reflect systemic dynamics rather than artefacts of spatial uncertainty.

CRAFTY simulates changes in land use and management practices as AFTs respond to shifting demand for ecosystem services, including food, fibre, employment, and water use efficiency (outlined in detail in Section 4.4.1.1). As agents adjust their land use and irrigation practices, the model produces annual gridded maps of AFTs. We re-imported these maps into SWAT+ to simulate actual production and irrigation water use, this time under constrained management conditions that reflect different agent strategies. For example, subsistence AFTs use traditional flood irrigation, while commercial AFTs adopt deficit irrigation strategies. Flood irrigation represents the baseline irrigation parameters used to define potential yield, whereas deficit irrigation strategies were identified through a structured sensitivity analysis designed to explore trade-offs between yield and water savings (Sattar et al., 2026). This coupled model allows us to track how land use, water use, and agricultural production evolve under integrated climate and socioeconomic scenarios. A full description of the model architecture, coupling logic, and indicator development is included in Sattar et al. (2026).

4.4.1.1 Demand projections

CRAFTY does not simulate international trade directly, and as such, it does not represent actual demand. Therefore, demand for domestic production is used as a proxy for demand. To estimate food demand, we calculate the total available food supply per crop type and year ($AF_{c,y}$) using Equation 1:

$$AF_{c,y} = \frac{C_{c,y}F_cP_y}{100-(NF_c-L_{c,y})} \quad (1)$$

$$D_{c,y} = \frac{AF_{c,y}(100-I_{c,y})}{100-E_{c,y}} \quad (2)$$

where $C_{c,y}$ is the per capita calorific intake for each food type and year, F_c is the conversion from calories to the weight of food in 2020, P_y is the population for a given year, NF_c is the percentage of non-food uses for each food type in 2020, and $L_{c,y}$ is the percentage of food losses per food type and year. Equation 2 is used to calculate the demand for domestic production for each food type and year ($D_{c,y}$). We use imports for each food type and year

($I_{c,y}$) and exports for each food type and year ($E_{c,y}$) to calculate demand for domestic production. For the fibre ecosystem service (cotton), demand for domestic production was calculated based on total national consumption and does not include losses or other uses. Appendix C.4 includes details of the values used to calculate the demand for domestic production in 2020 and 2100 for food and fibre ecosystem services.

For non-food and non-fibre ecosystem services, namely employment and water use efficiency, a distinct approach was used to calculate demand. We calculated demand for employment by multiplying the total population by the percentage of the population employed in agriculture. Water use efficiency is an index, set at 100 in 2020, and the projection was defined based on scenario projections.

The projection of the individual components used to calculate food, fibre, and non-food ecosystem service demand follows the same approach applied to the socioeconomic indicators. For each scenario, we use the narratives to guide how the relevant components, such as calorific intake, imports, exports, food losses, non-food uses, agricultural employment, and water use efficiency, are expected to change over time. Draft decadal trajectories for each component are developed by the lead author using the scenario logic, the broader understanding of Egypt's agricultural and food systems, and evidence from previous scenario studies (e.g. Breisinger et al., 2024; Maire et al., 2022; Sardo et al., 2024). These draft values are then reviewed by the co-authors to confirm that the resulting trends are plausible and consistent with the narratives and with the wider indicator assumptions described earlier. Annual values are produced by interpolating between the decadal points. The full set of component trajectories used to construct the demand estimates is provided in Appendix C.4.5.

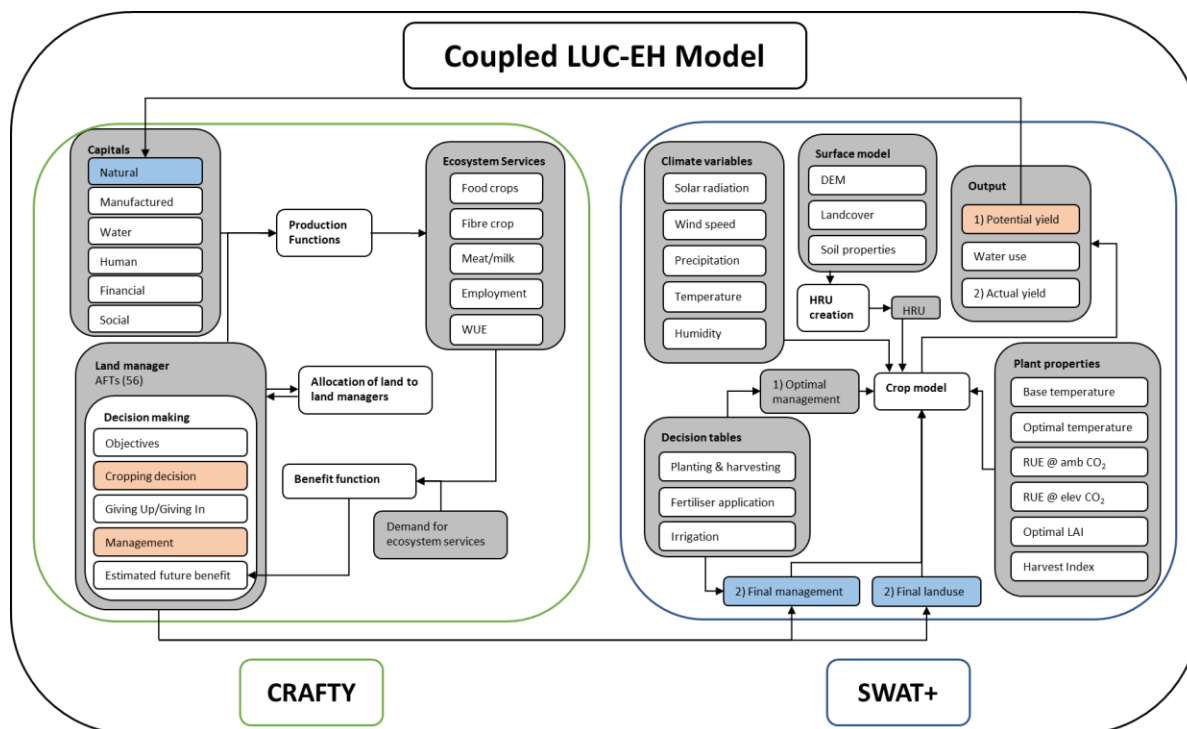


Figure 4.1: Schematic of the coupled LUC-EH model for Egypt, adopted from Sattar et al. (2026). The diagram illustrates information exchange between the agent-based land-use change model CRAFTY (left) and the ecohydrological model SWAT+ (right). Orange boxes represent model outputs passed as inputs (blue) to the other model. In SWAT+, Step 1 simulates potential yield under optimal conditions, and Step 2 uses land use and management from CRAFTY to estimate actual yield and water use. The schematic is simplified to show only components most relevant to this model application, excluding features such as detailed hydrological processes in SWAT+.

4.4.2 Data

Table 4.1 and Table 4.2 summarise the input datasets used to develop and parameterise the SWAT+ and CRAFTY model components of the coupled model, respectively. Each table includes details on spatial resolution, data sources, and any pre-processing or adaptations required for model integration.

Table 4.1: Input data used to develop and parameterise the SWAT+ model of the coupled LUC-EHM.

Submodel	Data	Spatial resolution	Temporal resolution	References
Surface water	MERIT DEM	90m	-	(Yamazaki et al., 2017)
	ESA Landcover	300m	Annual (2020)	(Copernicus Climate Change Service, 2019)

Submodel	Data	Spatial resolution	Temporal resolution	References
	DSOLMap	250m	-	(Hengl et al., 2017; López-Ballesteros et al., 2023)
	Lake shapefile		-	(Messenger et al., 2016)
	Streamflow			(Hou et al., 2024)
	CO ₂ concentration		2020-2100	(Meinshausen et al., 2020)
Groundwater	Soil grid depth to bedrock	250m	-	(Hengl et al., 2017)
	GLHYMPS			(Gleeson, 2018; Huscroft et al., 2018)
Climate data	Climate data bias corrected and downscaled for MRI-ESM2-0 climate model: rainfall, min/max temperature, relative humidity, solar radiation, wind speed	0.25° (25km at the equator)	Daily	(Lange & Büchner, 2021; Yukimoto et al., 2019)
Cropping pattern	2010 cropped areas	governorate	Annual (2010-2019)	(CAPMAS, 2025)
Calibration	Yield data	Governorate		(CAPMAS, 2025)
	Water use data	Governorate		(CAPMAS, 2025)

Table 4.2: Input data used to construct the capital layers for the CRAFTY model of the coupled LUC-EHM.

Capital	Indicator	Details	References
Human	Education index	Subnational Human Development Index indicator	(Smits & Permanyer, 2019)
	Health index	Subnational Human Development Index indicator	(Smits & Permanyer, 2019)
	Population downscaling	1 km ² gridded population datasets resampled to 0.81 km ² resolution. These are rescaled based on updated national population values and used to downscale human capital.	(Koch & Leimbach, 2023; Wang et al., 2022)
Social	Coop membership per capita	Governorate-level dataset	(CAPMAS, 2025)
	Gini index	Calculated from the Household Expenditure, Income, and Consumption Survey expenditure statistics.	Calculated from (OAMDI, 2023)
Manufactured	Road infrastructure inventory	Developed based on 2015 data.	(Meijer et al., 2018)
	Tractors per feddan	Governorate-level statistics of tractors per feddan	(CAPMAS, 2025)
Financial	GDP per capita	1 km ² gridded GDP and population datasets resampled to 0.81 km ² resolution. These are rescaled based on updated	(Koch & Leimbach, 2023; Wang & Sun, 2022; Wang et al., 2022)

Capital	Indicator	Details	References
		national GDP and population values.	
Water Capital	Rainfall	0.25° resolution gridded daily rainfall data summed per year from data bias corrected and downscaled for MRI-ESM2-0 climate model.	(Lange & Büchner, 2021; Yukimoto et al., 2019)
	Distance to surface water infrastructure	Distance to lakes and canals calculated using surface water layer from Opens Street Map for canals and rivers.	(Humanitarian OpenStreetMap Team (HOT), 2024) (Messenger et al., 2016)
	Groundwater head of confined aquifer layer		(Verkaik et al., 2024)
Natural capital	Potential yield	Calculated from the SWAT+ model at 900m resolution.	

4.5 Scenarios

The following section, which summarises the scenario narratives for Egyptian food, agriculture, water, and rural development, is adapted from the globalSSPs (O'Neill et al., 2017). To ensure relevance to Egypt, we develop these narratives using expert judgement, drawing on national and sector-specific scenario studies (e.g. Abdelkader et al., 2018; Adly et al., 2018; Ayyad & Khalifa, 2021; Elsayed et al., 2025; Kheir et al., 2019; Mazzoni et al., 2018; Nikiel & Eltahir, 2021; Yahaya et al., 2024) and refining the assumptions through co-author review. This process allows the global SSP logic to be translated into qualitative trajectories that reflect Egypt's institutional, demographic, and environmental conditions.

4.5.1 SSP1: Sustainability

In the context of global cooperation towards achieving a fair and sustainable future, the Egyptian government prioritises enhancing the efficiency of its food and agricultural systems. This involves substantial investments in water-efficient irrigation technologies and the

continued integration of subsurface farm-level tile drainage to optimise irrigation water reuse. Additionally, efforts are directed towards developing drought-resistant crops, which are crucial for adapting to climate challenges. The government also allocates significant resources to improve education, particularly in rural areas, thereby increasing human capital and facilitating the adoption of advanced technological solutions.

Healthy diets are integrated into the education system, promoting a balanced diet high in fruits and vegetables, whilst reducing calorific intake from staple crops. Diets in 2100 are aligned with the EAT-Lancet recommended diet (Willett et al., 2019). Although global cooperation leads to reduced tariffs and more efficient trade systems, the Government of Egypt aims for greater self-sufficiency to ensure the affordability of healthy diets. However, water-intensive crops such as rice and cotton are being phased out, with their cultivation areas gradually reduced to enhance crop water efficiency. Improved transport infrastructure, packaging, and localised processing capacity all contribute to minimising waste of fresh produce.

Reducing inequality is a central policy objective, achieved partly through investments in health and education, particularly in rural areas, and a progressive taxation system. This strategy enhances societal cohesion, leading to increased membership in agricultural cooperatives and higher rates of technology adoption, including improved cultivars and water-efficient irrigation technologies. These investments contribute to rural community development, creating local jobs in expanded food production and processing. They also involve greater use of local labour for farm activities alongside improved access to machinery. Fair pricing for agricultural products and increased value-added through food processing enhance job quality in the agricultural sector. Consequently, the rapid urbanisation trend observed in Egypt since the mid-20th century begins to slow and eventually reverse, with rural communities experiencing growth towards the latter half of the 21st century.

Land reclamation in the desert remains a key government objective, but it is conducted with strict sustainability measures. Aquifer use is constrained to ensure consumption matches inflow in shallow aquifers, whilst deep aquifer use is limited to higher recharge rates, which, although challenging to maintain consistently, ensures a very slow depletion rate. Only areas with high-quality soil are utilised. Infrastructure development is integrated with agricultural land development in reclamation projects to ensure long-term sustainability. Research

focuses on improving yields and water efficiency in these areas. Reclaimed land is primarily allocated to lower-income households, rather than being limited to large private enterprises and government agencies.

Newly reclaimed areas are developed with 100% renewable energy infrastructure. In line with Egypt's current Nationally Determined Contribution (NDC) target of achieving 42% of electricity generation from renewables by 2030 (Arab Republic of Egypt, 2023), the government implements various financial tools to encourage rapid technology adoption at the household, business, and national levels. This enables Egypt to achieve 42% of its energy mix through renewables by 2030 and reach net zero by 2040. This shift reduces dependence on hydropower generation from the HAD, allowing its management to prioritise agricultural water use over energy production. This is complemented by regional cooperation and co-management of Nile waters through clear treaties and cooperation during droughts or periods of sustained heavy rainfall.

4.5.2 SSP2: Middle of the road

In the SSP2 scenario, the global context is characterised by a continuation of current trends, marked by slow and inconsistent progress towards sustainability. Egypt continues to develop drought-resistant crops and improve water-efficient irrigation technologies, albeit with a fragmented policy and investment approach that yields mixed results.

Investments in health and education persist, but are unevenly distributed, resulting in slower development in rural areas. Coupled with low agricultural commodity prices, limited investment in rural infrastructure, and negligible investment in food processing facilities in rural communities, these factors contribute to the ongoing trend of urbanisation, leading to dwindling rural populations. However, this trend results in fewer, large-scale farmers, which can improve production efficiency.

As urbanisation continues, the total agricultural area expands at a slow pace, driven by low-productivity land reclamation projects undertaken by both the government and private sector corporations. These efforts aim to compensate for lost land in traditional agricultural areas and enhance greening around the Delta, but the growth is not dramatic. Infrastructure projects improve the road network, although they are neither executed efficiently nor adequately maintained. Nonetheless, improvements in road infrastructure and limited

growth in food processing capabilities lead to a small reduction in food waste for perishable items.

Groundwater use persists at a higher rate, with limited concern for sustainability. Subsidies for staple crops remain in place, prioritising wheat and maize production, while fruits and vegetables for export also receive significant attention. Most desert greening projects focus on meeting domestic demand for staples and the production of fruits and vegetables for export. There are few attempts to improve diets, and efforts to reform subsidies are met with protests and quickly reversed. Although total calorific intake remains relatively stable, there is slow progress towards healthier diets aimed at addressing the growing health burden of non-communicable diseases.

As the cost of renewable energy decreases, its adoption rate increases, supported by government policies promoting its uptake. However, these policies are insufficient, and the objective of achieving 42% of the energy mix from renewables by 2030 is not met. Consequently, the HAD remains crucial for energy generation, necessitating the maintenance of water levels for energy production. Regional tensions with Nile Basin countries persist but do not escalate into conflict. Diplomatic efforts ensure that annual releases from the HAD remain at 55.5 km³, maintaining downstream water availability.

4.5.3 SSP3: Regional rivalries

In the SSP3 scenario, regional and global tensions and conflicts dominate, shaping Egypt's policies and development priorities. Heightened tensions with riparian and neighbouring countries in North and East Africa, as well as the Middle East, drive the government to prioritise self-sufficiency. This shift is partly a response to high trade barriers, embargoes, and difficulties in importing agricultural products. Consequently, the government sets ambitious zero-import targets for all agricultural products. High-value crops such as fruits, vegetables, and cotton are prioritised for export to generate foreign currency needed to support Egypt's efforts in regional conflicts.

The focus on self-sufficiency is accompanied by reduced investments in education, resulting in limited development of human capital. Scientific research is narrowly directed towards gaining an edge over regional rivals, which restricts progress in developing improved crop cultivars and water-efficient irrigation technologies. This stagnation extends to rural areas,

where limited technological advancement and infrastructure development hinder growth. A return to a top-down approach in agricultural production ensures that priority crops, including staples for domestic consumption, and fruit and vegetables for export, are promoted widely under state intervention.

Rising external tensions foster greater social cohesion within Egypt, reflected in increased membership in agricultural cooperatives. However, this internal unity comes at the cost of reduced living standards across both urban and rural areas. Inequality narrows largely due to a widespread reduction in quality of life rather than as a result of targeted social reforms. Rural communities experience reduced access to subsidies for agricultural inputs, although cooperatives help disseminate available technologies.

Urbanisation trends slow significantly as declining standards of living in cities make rural areas relatively more attractive. However, rural development remains sluggish due to limited investment in infrastructure and services. The transport network sees continued investment, particularly in road infrastructure, which initially reduces food losses by improving the efficiency of moving perishable goods. However, poor maintenance over time leads to worsening conditions in the latter decades of the 21st century. This deterioration results in higher rates of food waste, undermining earlier gains in food production efficiency.

Water resource management becomes a critical point of contention with riparian countries due to poor cooperation and a lack of agreements on Nile water governance. Reduced inflows into the HAD occur periodically, leading to reduced outflows at times. These tensions risk escalating into regional conflict. Despite these challenges, international trade with partners in the global North and Gulf countries continues to be prioritised to secure foreign currency for supporting Egypt's military and economic efforts.

Groundwater use increases dramatically as fossil water resources from the NSAS are exploited with little regard for sustainability. Desert greening projects are dominated by state intervention, focusing on staple crops for domestic consumption and fruit and vegetables for export.

In response to trade challenges and fluctuating HAD inflows, Egypt leverages its high solar radiation levels to expand renewable energy production, particularly solar power. However,

renewable energy adoption occurs alongside continued reliance on domestic fossil fuel resources, reflecting a dual approach, driven by energy security rather than sustainability.

4.5.4 SSP4: Inequality

The inequality scenario is characterised by a large disparity within countries, including Egypt, where a small, internationally mobile elite enjoys high income and access to resources, while the majority of the population, comprising low-income working and middle classes, faces increasing economic hardship. This disparity manifests in underinvestment in the agricultural sector, leading to stagnation in technological development and rural progress. As a result, urbanisation accelerates, productivity remains stagnant, and agricultural water use efficiency is deprioritised. Wealth becomes increasingly concentrated among a small number of families who control privatised resources that were previously state-owned.

The standard of living for low-income communities, particularly in rural areas, declines steadily over time. Education levels improve very slowly due to limited investment in public education. This contributes to reduced social cohesion and heightened instability. The adoption of water-efficient irrigation technologies slows dramatically as a result of these systemic inequalities.

Dietary improvements are not a priority. Efforts to reduce subsidies on staple crops frequently lead to unrest and are only partially successful. However, lower incomes and reduced subsidies result in a slight reduction in consumption of staples and an increase in healthier foods, with the majority of calorific intake still derived from subsidised starchy staples, such as wheat.

Poorly maintained road infrastructure, combined with limited investment in rural food processing and packaging facilities, results in only marginal reductions in food losses for perishable produce. Most smallholder farmers rely on local trade networks for their produce, which helps reduce food losses at a local level but does little to address broader inefficiencies. Urbanisation continues at a rapid pace as industrialisation becomes a key focus for the elite ruling class. However, this industrial growth creates predominantly low-quality, poorly paid jobs in urban centres. Wealthy landowners accumulate more land, leading to a resurgence of tenant farming systems that further marginalise rural communities. Declining social cohesion and increasing urbanisation result in lower membership rates in agricultural cooperatives.

Regional tensions ease somewhat under this scenario, allowing for stable inflows into the HAD. Water management ensures an annual discharge of 55.5 km³ from the HAD. However, renewable energy projects progress only at rates comparable to current development levels. Energy production from the HAD remains an essential part of Egypt's energy mix, necessitating higher water levels behind the dam to sustain hydropower generation.

Groundwater resources from the NSAS are heavily exploited by private investors for desert greening projects with minimal oversight or sustainability constraints. These projects primarily focus on export crops but also allocate significant areas to staple crop production to meet domestic demand for cheap wheat.

4.5.5 SSP5: Fossil fuelled development

This scenario is characterised by a fossil-fuel-driven future where rapid growth shapes the policy sphere. In Egypt, this manifests as a strong focus on export-oriented agriculture, with significant expansion in the production of fruits and vegetables. Large-scale desert greening projects dominate agricultural development, driven by state and private investors. These projects rely heavily on groundwater extraction from the NSAS, leading to unsustainable exploitation of fossil water resources. Export crops remain the primary priority of these initiatives, while staple crops for domestic consumption are deprioritised.

Agricultural production becomes increasingly centralised, with large projects managed to a lesser extent by state entities and predominantly by private corporations. The widespread exploitation of oil and gas resources enables affordable access to fuel for farm machinery, improving production efficiency and expanding cultivated areas. This mechanisation supports large-scale farming operations but leaves smallholder farmers struggling to compete.

Climate conditions under RCP 8.5 bring increased rainfall in upstream riparian countries, resulting in higher inflows into the HAD. Power generation becomes a key priority, leading to higher water levels behind the dam to sustain hydropower production. This emphasis on energy generation often comes at the expense of water availability for crop irrigation, further disadvantaging smallholder farmers reliant on traditional irrigation systems.

Investment in technology development sees significant improvement in water use efficiency and access to drought-resistant crop varieties, which helps mitigate some impacts of unsustainable practices. However, these advancements are primarily accessible to wealthier

farmers and large-scale agricultural enterprises, exacerbating inequality within the agricultural sector.

Education, health, and infrastructure investments increase dramatically under this scenario. Improved education enhances human capital and strengthens the labour force. Infrastructure development focuses on expanding transport networks and market access, which reduces food waste by improving supply chain efficiency for perishable goods. However, these benefits are unevenly distributed; rural areas lag behind urban centres in accessing these improvements.

Diets follow global trends influenced by shifts in consumer preferences and economic growth. Meat and sugar consumption increases, while consumption of staple crops declines. This results in a more balanced diet overall, but total calorific intake remains slightly higher than recommended levels, resulting in reduced but continued prevalence non-communicable diseases.

Urbanisation accelerates rapidly as industrialisation becomes a cornerstone of economic policy, drawing labour away from rural areas. Rural communities experience further decline as land ownership consolidates among wealthy investors who take advantage of scaled operations to improve efficiency. Membership in agricultural cooperatives diminishes due to reduced social cohesion, growing inequality, and the reduced number of smallholder farmers.

Table 4.3: Summary of scenario narratives describing the direction and relative magnitude of change in key variables between 2020 and 2100, using a 7-point Likert-style scale. The number of arrows indicates the relative strength of anticipated change, while arrow direction and colour represent the expected trend: green upward arrows for increases, red downward arrows for decreases, and a dash (–) for no expected change.

	SSP1- RCP2.6	SSP2- RCP4.5	SSP3- RCP7.0	SSP4- RCP6.0	SSP5- RCP8.5
Population	↑↑	↑↑	↑↑↑	↑	↑↑
Economic growth	↑↑	↑↑	↑	↑	↑↑↑
Education	↑↑↑	↑↑	↑	↑↑	↑↑↑
Health	↑↑↑	↑↑	↓	↑	↑↑↑
Social cohesion	↑↑↑	↑	↑↑	↓↓↓	↓
Water use efficiency	↑↑	↑	↑	↓	↓↓↓
Export focused	—	↑	↓	↑	↑↑
Non-hydro renewable energy	↑↑	↑	↓↓↓	↓	↑
Regional cohesion	↑↑	—	↓↓↓	↑	↑

4.6 Results

4.6.1 Dietary shifts and service demand projections

Per capita calorific intake changes markedly across scenarios between 2020 and 2100 (Figure 4.2a). Under SSP2, total intake remains relatively stable, increasing slightly from 3,741 to 3,850 kcal/capita/day. In contrast, all other scenarios show declines; the daily per capita intake in 2100 ranges from 3,026 kcal under SSP3 and SSP4 to a low of 2,471 kcal/capita/day for SSP1. Staple crop consumption falls in every pathway, dropping from 2,697 kcal/capita/day in 2020 to between 811 (SSP1) and 2,315 (SSP2) by 2100. Animal product intake increases under all scenarios except SSP1, which sees a minor decline from 253 to 245 kcal/capita/day. The highest animal product consumption is observed in SSP2 (542 kcal/capita/day) and SSP5 (500 kcal/capita/day). Intake of legumes, sugarcane, and main vegetables increases consistently across all pathways, while trends for oil crops and other vegetables remain mixed, with some scenarios showing gains and others declines.

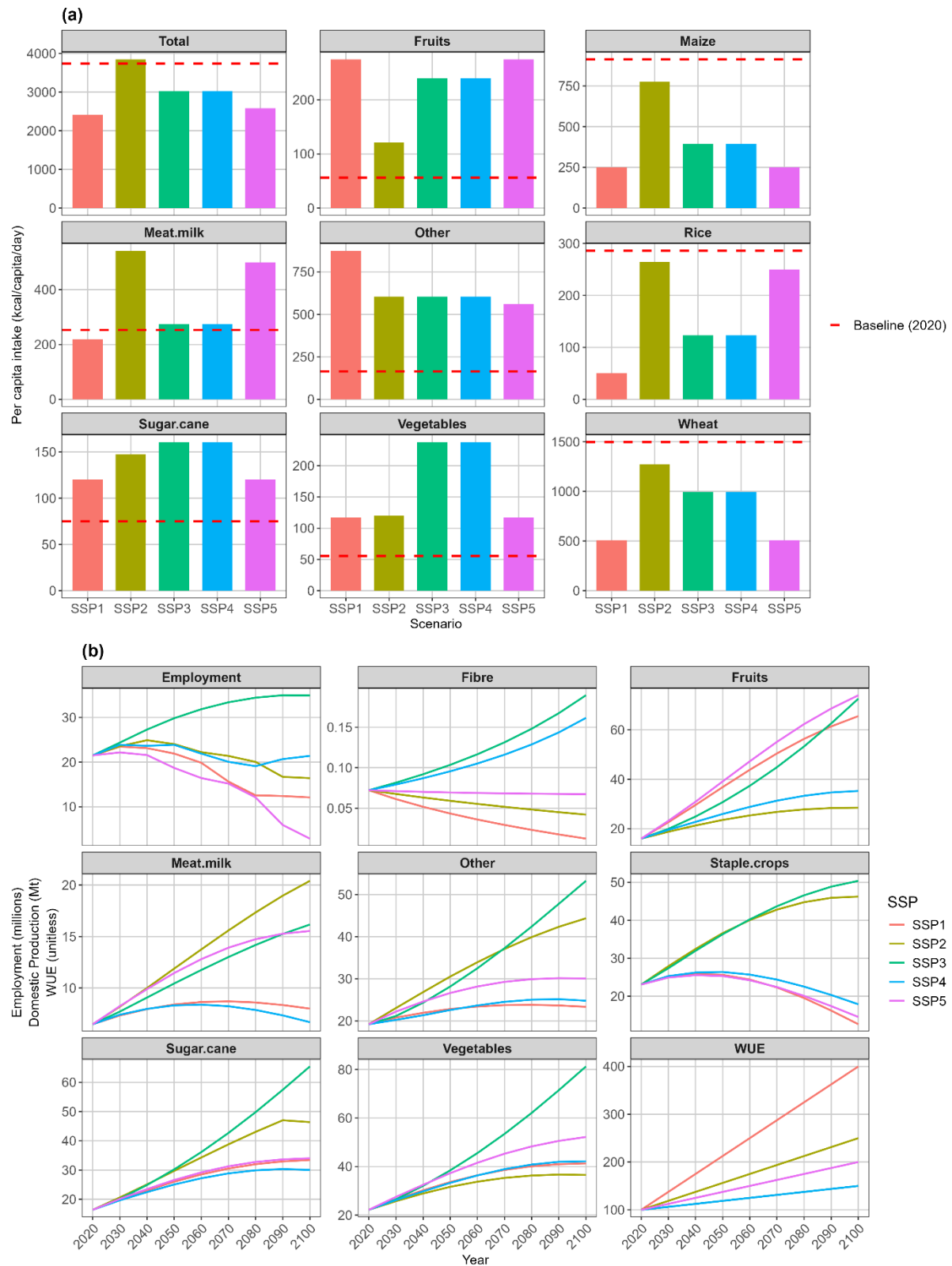


Figure 4.2: Demand projections: a) Projected per capita calorific intake (kcal/capita/day) in 2020 and 2100, aggregated by food group and SSP. b) Projections of demand for domestic production (modelled demand) across ecosystem services, including employment and water use efficiency (WUE). Employment refers to the size of the agricultural workforce. WUE is expressed as an index set to 100 in 2020. Table of crop groupings is included in Appendix C.7.

These shifts in dietary patterns are reflected in demand for domestic production (i.e. modelled demand), which diverges between scenarios (Figure 4.2b). SSP3 generates the

highest production requirements for dates, sugarcane, oil crops, fibre, other vegetables, wheat, and agricultural employment. By contrast, SSP1 sees the greatest reductions in demand for domestic production for ecosystem services, including dates, fibre, maize, other field crops, other vegetables, rice, and legumes. While demand for most ecosystem services increases across scenarios by 2100, staple crops stand out as an exception, with production falling below 2020 levels in several pathways. The demand for domestic production is calculated by defining the required supply to the scenario-specific population, and accounts for imports, exports, agricultural losses, and other uses (included in Appendix C.4). This ranges from 278 Mt for SSP4 to 597 Mt for SSP3.

4.6.2 Ecosystem service supply-demand dynamics under future scenarios

The coupled model integrates scenario-specific demand for domestic production alongside spatial capitals and agent behaviours to generate varied supply outcomes (Figure 4.3a). Staple crop (wheat, maize, and rice) production declines by 42% under SSP1-RCP2.6 and 39% under SSP5-RCP8.5 by the end of the century. Although there is a decline in demand for domestic production, a production shortfall of 1.15 Mt (9.7%) for SSP1-RCP2.6 and 2.18 Mt (17%) for SSP5-RCP8.5 (Figure 4.3b) remains in 2100. SSP4-RCP6.0 represents the only scenario where staple crop production exceeds domestic production objectives, generating a surplus of 0.220 Mt (1.2%). In contrast, both SSP2-RCP4.5 and SSP3-RCP7.0 experience substantial production increases of 27% and 51%, respectively. However, these same scenarios show the highest shortfalls, with supply deficits of 16.9 Mt (37%) in SSP2-RCP4.5 and 15.5 Mt (31%) in SSP3-RCP7.0 relative to their demand for domestic production.

Although substantial supply increases are observed for fruits under SSP5-RCP8.5 (286%) and SSP1-RCP2.6 (238%) between 2020 and 2100, production shortfalls of 38% and 42% of demand for domestic production persist, respectively. SSP2-RCP4.5 represents the only scenario where fruit supply decreases slightly (8%) in 2100 relative to 2020. These results contrast sharply with fibre supply-demand dynamics, where most scenarios result in supply reductions, except SSP4-RCP6.0, which exhibits a substantial increase of 236% between 2020 and 2100. Fibre supply declines across all other scenarios, ranging from 2.1% (SSP3-RCP7.0) to 93% (SSP1-RCP2.6).

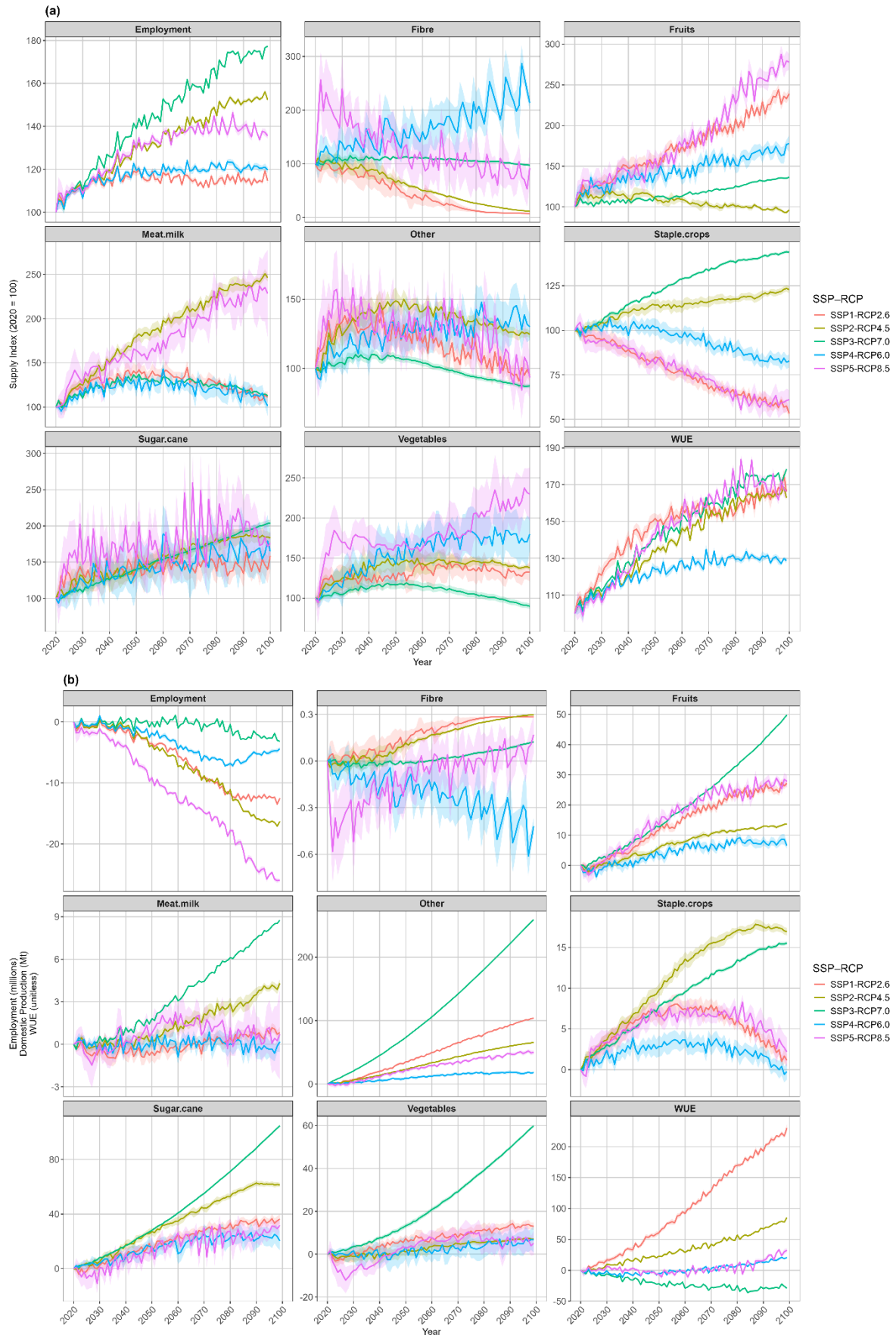


Figure 4.3: Supply-demand dynamics under different SSP-RCP scenarios. (a) Supply index for ecosystem services, normalised to 2020 (baseline = 100); (b) Change in unmet demand for domestic production (defined as modelled scenario-specific)

domestic production - supply) for ecosystem services over time. Solid lines represent the median across the 10 initial land cover configurations, while shaded ribbons indicate the standard deviation.

Vegetable supply increases in 2100 compared to 2020 across all scenarios except SSP3-RCP7.0, where a modest reduction of 1.73 Mt (9.2%) occurs. SSP3-RCP7.0 also demonstrates the largest production shortfall relative to demand for domestic production for vegetables at 59.9 Mt, which is 4.5 to 11.6 times greater than shortfalls observed in other scenarios. Animal product supply similarly rises under SSP3-RCP7.0, peaking at 2050 with a 37% increase before declining to 7.3 Mt (13%) by 2100. Despite strong supply growth under SSP3-RCP7.0, this scenario consistently exhibits the highest production shortfalls across nearly all crop ecosystem services. Other crops (legumes, other field crops, oil crops), for this scenario, demonstrate the largest absolute production shortfall of 259 Mt (90%) relative to demand for domestic production.

For non-crop ecosystem services, the trends diverge. Agricultural employment increases under all scenarios, from a 14% increase (3.2 million) in SSP1-RCP2.6 to 77% (17 million) in SSP3-RCP7.0. This leads to oversupply in all cases, with SSP5-RCP8.5 generating the largest surplus of 26 million. In contrast, water use efficiency, represented as a scenario-aligned index, shows the largest shortfall under SSP1-RCP2.6. Most other pathways perform similarly in terms of delivering water use efficiency outcomes (approximately a 70% increase in 2100 relative to 2020), indicating limited scenario differentiation for this indicator.

4.6.3 Land abandonment and reclamation dynamics

In response to the production shortfall, the coupled model allows agricultural agents to reclaim desert land (unmanaged land) and abandon marginal areas. Reclamation occurs fastest under SSP5-RCP8.5, with 91% of all land available for reclamation converted to productive land by 2027, a total of 856,859 ha. This rapid expansion is visible in the Delta region map (Figure 4.4c), where the area available for reclamation (shown in green) nearly disappears by 2030. In contrast, under SSP1-RCP2.6, 235,629 ha (25%) of the original national reclaimable area of 939,600 ha remain available in 2030. All scenarios eventually reclaim almost all available land by 2100, but the rate and timing of conversion differ (Figure 4.4b).

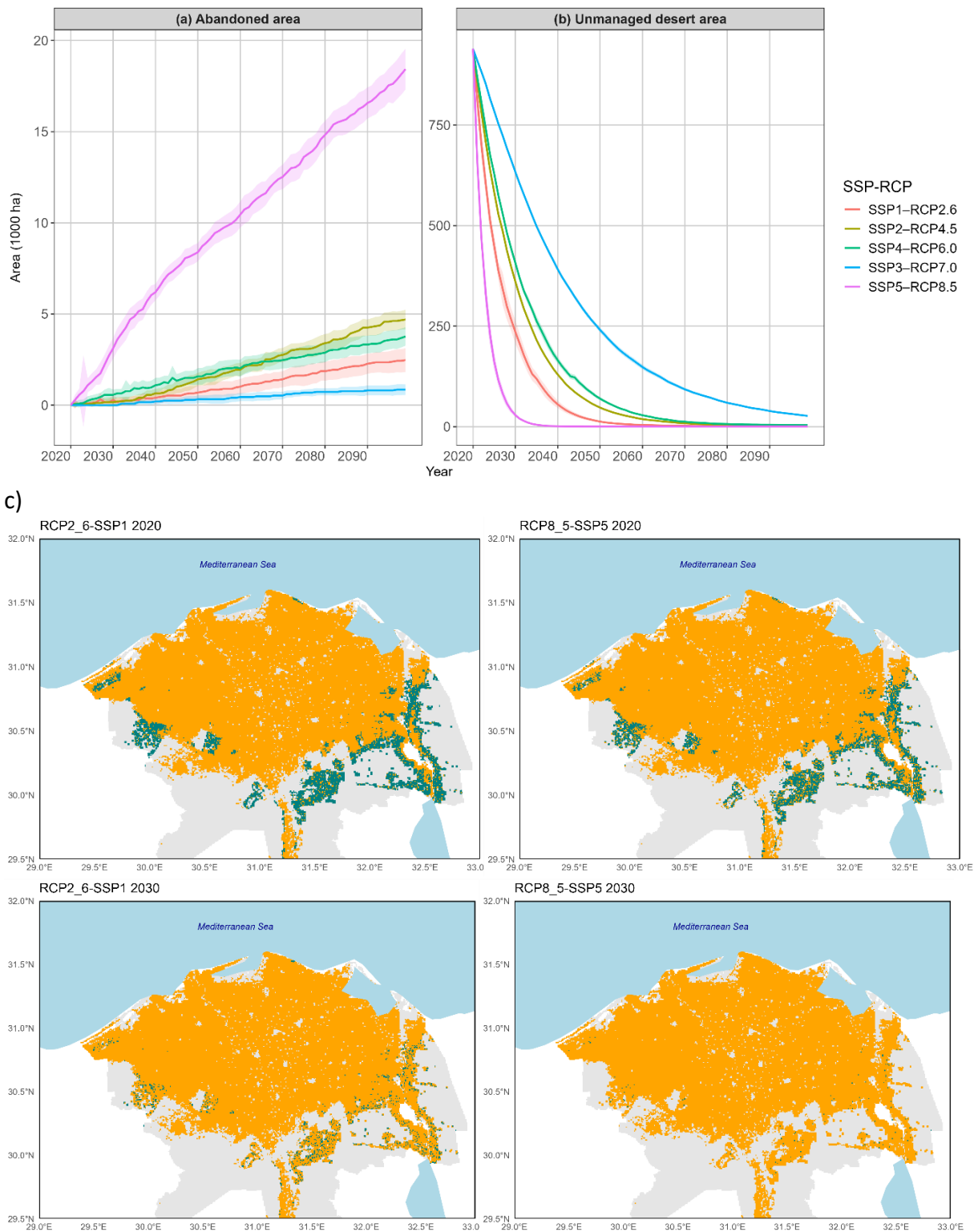


Figure 4.4: Land abandonment and reclamation dynamics under future scenarios. (a) Area of abandoned land under different climate and socioeconomic pathways. (b) Area of unmanaged desert land remaining over time across scenarios. (c) Agricultural expansion in the Nile Delta for SSP1–RCP2.6 and SSP5–RCP8.5, showing conversion of unmanaged land (green) to cropped land (orange) between 2020 and 2030. Grey areas represent masked cells (urban, wetland, or barren land). In panels a and b, the solid line represents the median across the 10 initial land use configurations, while the ribbon indicates the standard deviation.

SSP3-RCP7.0 exhibits the slowest rate of reclamation, with 26,933 ha remaining unreclaimed in 2100. The pace of conversion under this scenario is steady, starting at 28,998 ha/year in 2020 and gradually falling to 1,094 ha/year by 2100. SSP2-RCP4.5 begins with a higher rate of 79,502 ha/year in 2020, but drops below 1,000 ha/year by 2062. SSP1-RCP2.6 is the second fastest overall, reaching this threshold by 2053. By 2100, only 243 ha of unmanaged land remain under SSP5-RCP8.5.

Abandonment patterns also vary by scenario (Figure 4.4a). SSP3-RCP7.0 shows the lowest and slowest abandonment, with just 851 ha abandoned by 2100, an average of 10 ha/year. In contrast, SSP5-RCP8.5 sees the highest levels, with 18,428 ha abandoned by 2100 (230 ha/year on average). SSP2-RCP4.5 has the second-highest abandonment, but still at a rate nearly four times lower than SSP5-RCP8.5, reaching 4,698 ha by the end of the century. SSP4-RCP6.0 also follows a slow trajectory, averaging 47 ha/year and reaching 3,767 ha by 2100.

4.6.4 Evolution of management practices and water use efficiency

The percentage area managed by commercial agents, which use deficit irrigation practices, decreases across all scenarios (Figure 4.5a). In 2020, commercial agents occupy 10% of the total area. By the end of the century, this share falls below 1% in all scenarios except SSP1-RCP2.6, which retains a higher proportion at 3.9%. Under SSP1-RCP2.6, the area under commercial management initially declines, reaching a low of 1.9% (153,243 ha) in 2079, before recovering to 351,681 ha by 2100 (Figure 4.5b). In all other scenarios, the commercial agent manages between 72,349 ha (0.84%) in SSP5-RCP8.5 and 88,339 ha (0.96%) in SSP3-RCP7.0 by the end of the century. In terms of the rate of decline, SSP5-RCP8.5 shows the most rapid reduction, with commercial management falling below 1% of the total area by 2030. SSP2-RCP4.5 follows, reaching this threshold by 2060, marking the second-fastest decline in the commercial management type.

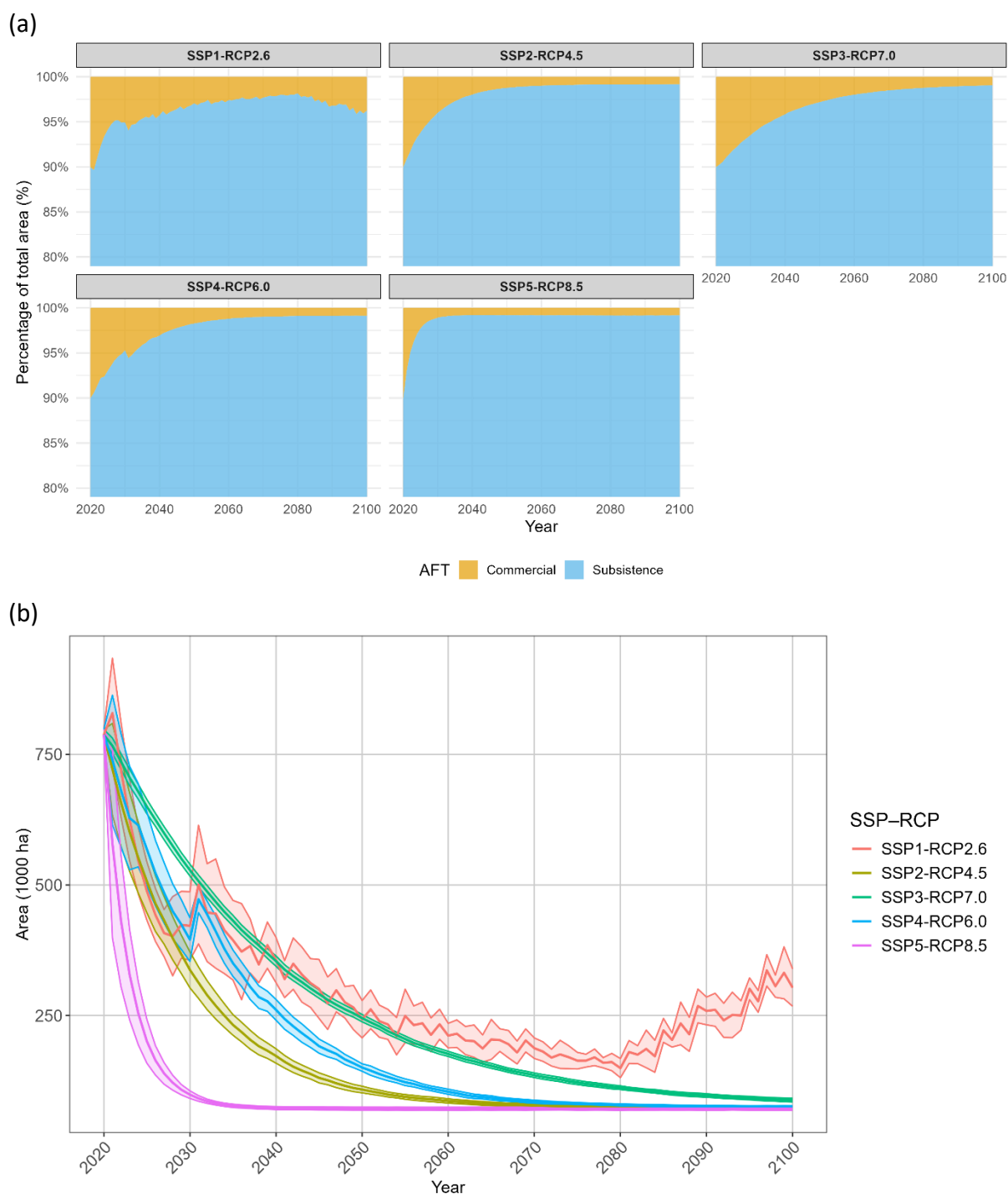


Figure 4.5: (a) Percentage of area managed by commercial and subsistence agents under different scenarios. (b) Total area (in hectares) managed by commercial agents over time across scenarios. In panel b, the solid line represents the median across the 10 initial land use configurations, while the ribbon indicates the standard deviation.

Although all scenarios show a decline in commercial AFTs, which use deficit irrigation methods, water use efficiency (WUE) improves across the board (Figure 4.6). Under SSP1-RCP2.6, the trend is relatively flat. For commercial AFTs in winter, WUE improves slightly from 213 m³/t in 2020 to 193 m³/t in 2100, while summer WUE rises modestly from 567 m³/t to

584 m³/t (3%). Subsistence AFTs follow a similar pattern, with WUE decreasing from 518 m³/t to 417 m³/t in winter but increasing from 934 m³/t to 977 m³/t in summer for SSP1-RCP2.6. The most pronounced gains are seen under SSP5-RCP8.5, where WUE reaches 104 m³/t in winter and 239 m³/t in summer by 2100. This marks a 71% reduction in water used per tonne of crop compared to 2020, and less than half the amount used under the next best-performing scenario (SSP3-RCP7.0) by the end of the century. Commercial AFTs consistently achieve higher WUE than subsistence AFTs, especially in winter. On average, they require only 210 m³/t, compared to 521 m³/t for subsistence AFTs. In summer, the gap narrows slightly, with commercial AFTs using 568 m³/t, while subsistence AFTs use 995 m³/t.

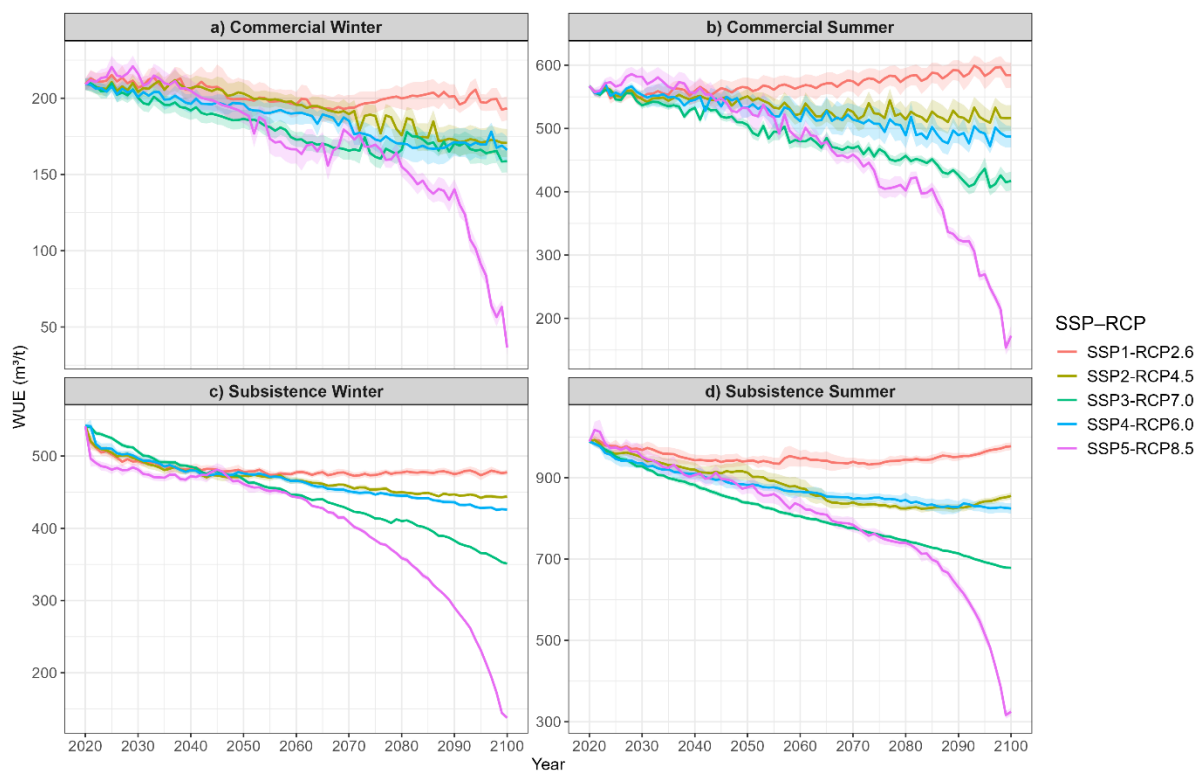


Figure 4.6: Evolution of water use efficiency (m³ per tonne) under different scenarios for each management and seasonal combination: (a) Commercial AFTs – Winter, (b) Commercial AFTs – Summer, (c) Subsistence AFTs – Winter, and (d) Subsistence AFTs – Summer. Each line shows the median WUE across 10 simulation runs, while the shaded ribbon represents the standard deviation.

4.7 Discussion

This study develops national SSP-RCP scenarios for the Egyptian agricultural system and employs a coupled agent-based land-use change-ecohydrological model to evaluate Egypt's agricultural system under these scenarios for 2020-2100. By simulating competition between heterogeneous land managers and water-use dynamics for diverse cropping patterns and

management practices, the analysis reveals divergent trajectories for food security, land-use patterns, and water use efficiency.

4.7.1 Food security

Domestic production, used as a proxy for demand in CRAFTY, is defined based on population, average daily calorific intake, food waste, other non-food uses, imports, and exports (Section 4.4.1.1). These values are developed based on the national scenario narratives. Our results show that demand for domestic production is not met under any of the scenarios. The smallest shortfall occurs under SSP4-RCP6.0, which achieves 78% of demand for domestic production by the end of the century. This is largely due to the relatively low population in 2100 (107 million). The largest shortfall is observed under SSP3-RCP7.0, where the population reaches 232 million by the end of the century, and only 26% of demand for domestic production is met.

Beyond population growth, our analysis indicates that dietary trajectories influence Egypt's ability to meet future food demand. Under SSP4-RCP6.0, daily calorific intake per capita declines by 19% by 2100 relative to current levels, helping to reduce pressure on domestic production. In contrast, SSP1-RCP2.6, which envisions a shift towards the EAT-Lancet diet by 2100 (Willett et al., 2019), still falls short of its projected domestic production by 182 Mt (52%). SSP5-RCP8.5, despite having a similarly low daily calorific intake (2,584 kcal/capita), achieves the second-highest share of demand for domestic production. These findings underscore the role of dietary patterns in shaping food security outcomes. This is consistent with the work of Sardo et al. (2024), who showed that optimising crop allocations for healthy diets could meet 95% of Egypt's 2019 food demand while reducing irrigation water use by 8%. However, these gains were calculated under static population assumptions. Population growth, which was not included in Sardo et al. (2024) analysis, can quickly erode such efficiency gains. Abdelkader et al. (2018) further contextualise these challenges through a national water-food-trade model, projecting reductions in food self-sufficiency (45-59%) and water self-sufficiency (40-50%) by 2050 across critical, balanced, and optimistic water supply scenarios.

Trade also plays a substantial role in shaping the supply–demand balance. For instance, SSP5-RCP8.5 achieves the highest production levels (208 Mt) and has the second-lowest calorific intake per capita and a relatively modest population (143 million), yet still experiences a

shortfall of 36% relative to demand for domestic production. This is partly due to high export volumes (49.7 Mt) and relatively low imports (129 Mt). Abdelkader et al. (2018) estimated average food imports of 150 Mt by 2050 across the five SSPs using a national-scale model – slightly lower than our estimates but affirming the ongoing importance of trade for Egypt’s food security. To explore trade sensitivity, we also examined a zero-import scenario under SSP3-RCP7.0. This results in the highest level of unmet demand for domestic production (78%), clearly demonstrating that self-sufficiency through zero imports is unfeasible. Notably, this scenario also exhibits the highest level of food exports (86.0 Mt), further exacerbating the shortfall.

Taken together, these findings highlight that the primary challenge lies in rising demand, driven by population growth and dietary shifts. While adjusting trade balances, by increasing imports or reducing exports, can help narrow the gap, these measures alone are unlikely to resolve the pressures on Egypt’s food system without broader changes in consumption and resource planning.

4.7.2 Land abandonment and reclamation

Land-use change in Egypt, particularly the interplay between agricultural expansion, land abandonment, and urban encroachment, has been extensively documented in recent studies. Salem et al. (2020) quantified an annual loss of 1,200 ha of agricultural land between 2010 and 2018 in Greater Cairo, attributing this to informal urban sprawl and industrialisation. Nationally, Bratley and Woodcock (2024) analysed satellite-derived land-use trends from 1987 to 2019, revealing a net agricultural expansion of 16,286 km² (1.6286 million ha) alongside losses of 2,343 km² to urban expansion and 1,731 km² to abandonment. Our scenario-based results align with these trends: under SSP5-RCP8.5 (fossil-fuelled development), 18,428 ha of agricultural land are projected for abandonment by 2100, contrasting with SSP3-RCP7.0’s low levels of abandonment (851 ha). Although urban expansion is not explicitly modelled, our highest cumulative abandonment estimate (74,561 ha from 2020 to 2100) represents only 9.4% of the abandonment reported by Bratley and Woodcock (2024), this may be, in part, due to the higher rate of land abandonment during the unstable period post the Arab Spring (Salem et al., 2020). Furthermore, the agricultural expansion projected under SSP5-RCP8.5 in our model amounts to 58% of the net expansion observed by Bratley and Woodcock (2024) between 1987 and 2019. This slower growth may

partly reflect the limited spatial extent of our model, which does not include the New Valley, an area with the greatest agricultural expansion.

Land reclamation in the model is primarily driven by changes in natural capital. On average, areas that undergo a transition from UL to crop production experience an increase in natural capital (+0.0074), suggesting reclamation occurs where potential yield is increasing. Although low in number, reclamation to commercial agents tends to coincide with increases in water capital, while transitions to subsistence AFTs occur even where water capital slightly declines. For SSP5-RCP8.5, reclamation to commercial agents is also associated with increased financial and manufactured capital, but a decline in social and water capital. This is due to commercial agents having greater sensitivity to manufactured and financial capital. In contrast, land abandonment often coincides with falling natural capital, particularly for winter crops and perennials, while abandonment of summer crops occurs despite slight natural capital gains.

Although land reclamation is widely studied in Egypt, its impacts on biodiversity are rarely addressed despite important ecological consequences. Desert reclamation disrupts habitats with generally lower species richness, whilst coastal reclamation and wetland encroachment threaten some of Egypt's most biodiverse areas through direct habitat destruction and fragmentation (Davies & Harhash, 2021; Fouad, 2017). Land reclamation, urbanisation, and industrial activities are key causes of habitat destruction, resulting in biodiversity loss, destroying critical natural habitats along with their plant and animal life (Fouad, 2017). Coastal development, intensive tourism and land reclamation for agriculture place particular pressure on key wildlife habitats in the Mediterranean, whilst drainage of water bodies for conversion into agricultural developments destroys wetland habitats and reduces their areas (Fouad, 2017). These ecological impacts merit explicit inclusion in comprehensive assessments of land reclamation and food security strategies.

4.7.3 Water use efficiency

Commercial agents, who are characterised by the use of deficit irrigation practices, decline rapidly across all scenarios, driven by their higher likelihood of abandoning unprofitable land and a lower give-in threshold (i.e. they are more likely to relinquish land to more competitive agents). The observed 90% reduction in commercial agents suggests that greater responsiveness to profitability and greater inertia of subsistence AFTs (lower likelihood to give-up) are key drivers of this trend. Moreover, commercial AFTs require greater access to

manufactured and financial capital, making them less viable under constrained resource conditions. However, under SSP1-RCP2.6, the number of commercial agents begins to increase again toward the end of the century. This is likely due to consistent improvements in capital availability, as well as rising unmet demand for WUE. This highlights the importance of investing in both WUE technologies and the necessary resources, such as machinery and financial tools, to support more efficient agricultural systems, and ensuring the pressure and support for improved irrigation practices continues.

Although commercial agents decline over time, WUE improves as a physiological consequence of elevated CO₂ levels, which enhance stomatal conductance and reduce transpiration (Q. Cao et al., 2022; Mokhtar et al., 2025). This climate-linked physiological response reduces crop water use across all scenarios, offering a potential benefit in Egypt's water-scarce context. The CO₂ fertilisation effect, where yields, particularly for C3 crops like wheat and fodder, increase under elevated CO₂, may further support this trend (Rezaei et al., 2023). However, the long-term gains from elevated CO₂ remain uncertain, as current models often inadequately capture interactions with extreme temperatures and climate variability, including the impact of heatwaves and droughts on crop physiology (Ainsworth et al., 2025). Furthermore, elevated CO₂ is associated with reductions in the nutritional quality of staple crops, including declines in grain protein content and micronutrients such as zinc and iron, potentially undermining food security even where yields increase (Ainsworth et al., 2025).

4.7.4 Limitations

Scenario analyses remain inherently uncertain, and while our SSP-RCP scenarios build upon established global narratives, the interpretation of regional pathways reflects the views of the authors. As demonstrated by Voinov et al. (2016), integrating key stakeholders, including local agricultural communities and agricultural and water management authorities, in scenario co-design processes improves the legitimacy of model assumptions, particularly regarding crop prioritisation and adaptation thresholds.

Geographically, the model excludes watersheds in the Western Desert and most of Sinai, which account for a large proportion of Egypt's current reclamation efforts (Elsharkawy et al., 2022). This omission is particularly significant given that 63% of the government's "1.5 Million Feddan" initiative targets the New Valley Governorate (Nour, 2020). While computational constraints justified this simplification, further expansion of the modelled area could provide

an opportunity to analyse the impact of government land reclamation targets. This expansion would also require the inclusion of institutional land reclamation agents to represent the dominance of government and institutional actors in land reclamation in these areas.

The model does not explicitly represent water infrastructure or differentiate between irrigation water sources. This simplification, necessitated by limited data on Egypt's complex irrigation networks and surface and groundwater withdrawal patterns, affects the assessment of agricultural expansion sustainability across scenarios. For instance, while SSP5-RCP8.5 projects extensive desert reclamation (939,519 ha by 2050), real-world constraints such as canal seepage and aquifer depletion risks remain unaccounted for. Incorporating these factors in future work could clarify how infrastructure trajectories influence the viability of large-scale reclamation initiatives under different socioeconomic pathways.

However, the combined modelling approach and national-scale scenarios offer clear advantages over static analyses by simulating feedback and emergent behaviours. For policymakers, the model provides a dynamic tool to explore development options by generating outputs such as spatially explicit land-use patterns, projected water use, and crop production trends across alternative futures. The model can be adapted to test specific policy interventions, including dietary shifts, trade adjustments, and investment in socioeconomic capital. This enables decision-makers to navigate trade-offs between short-term goals, such as increasing food self-sufficiency, and long-term sustainability objectives, such as long-term land reclamation projects, ensuring policies are informed by Egypt's specific environmental and socioeconomic context.

4.8 Conclusion

Egypt's agricultural system faces substantial challenges from rapid population growth, increasing climate extremes, and dependence on the finite resources of the Nile River. This study developed national SSP-RCP scenarios for the Egyptian agricultural system to evaluate how socioeconomic pathways and farmer adaptation influence crop production, land use, and water use through to 2100. By coupling the SWAT+ ecohydrological model with the CRAFTY agent-based land-use change model, the analysis captures dynamic interactions between biophysical and socioeconomic constraints and farmer decision-making. Scenarios with higher population and calorific intake show large shortfalls in food supply, emphasising

the need to improve diets and stabilise population growth. While agricultural expansion increases production, it does not meet rising demand, and marginal lands continue to be abandoned. The regional rivalry pathway (SSP3-RCP7.0) shows the highest unmet demand for domestic production, illustrating how self-sufficiency remains unfeasible under Egypt's resource constraints. While the model suggests that elevated CO₂ concentrations could improve WUE and yield for some key crops, these potential gains are highly uncertain due to possible declines in nutritional quality and the likely offsetting effects of more frequent extreme weather events.

4.9 Chapter conclusion

Using a coupled land-use change-ecohydrological model with nationally downscaled SSP-RCP scenarios, we link scenario-specific climate and socioeconomic conditions to AFT characteristics. Across these scenarios, yields and water use efficiency often improve, but the domestic production gap persists. The high-development pathway, for example, raises output yet increases abandonment, while the more sustainable pathway eases resource pressure but results in large shortfalls in production. Notably, the scenario targeting self-sufficiency produces the largest domestic production gap, highlighting the challenge of this policy in a resource-constrained context.

Chapter 5 synthesises the thesis findings by situating Egyptian agriculture's dual constraints – limited agricultural resources alongside rising demand – and then integrating insights from the household typology, the coupled land-use change-ecohydrological model, and the SSP-RCP scenario analysis. This discussion highlights the constraints on land and water productivity, the influence of climate change and technological improvements on future pathways, and the implications for food security, water policy, agricultural development, and future model development.

5 Discussion

Like many arid and semi-arid low- and middle-income countries, Egyptian agriculture faces a dual challenge of resource scarcity and growing demand. Only 3% of Egypt's land is arable, and renewable water resources are limited to low rainfall and a fixed Nile River water quota (Abdelkader et al., 2018; El-Ramady et al., 2013; Fuglie et al., 2020). Simultaneously, a rapidly expanding population and high reliance on subsidised staple crops continue to intensify pressure on these finite land and water resources (Nikiel & Eltahir, 2021; Terwisscha van Scheltinga et al., 2021). Climate change compounds this uncertainty, with rising temperatures already observed to reduce crop yields and increase irrigation needs (Gado & El-Agha, 2021). Although elevated atmospheric CO₂ can enhance crop yields and water use efficiency, the net impact of climate trends and extremes remains uncertain (Ainsworth et al., 2025). There are opportunities to bolster food production by raising yields, expanding agricultural area through agricultural expansion, and exploiting underutilised groundwater aquifers (Nikiel & Eltahir, 2021). However, Egypt remains highly vulnerable to global market shocks, given its dependence on food imports for key staples (Nikiel & Eltahir, 2021; Soffiantini, 2020). The country's climate permits year-round cultivation under irrigation, and extensive irrigation infrastructure allows a wide variety of crops to be cultivated. Additionally, there is scope for efficiency gains through improved cropping patterns, better irrigation conveyance, and the adoption of improved crop cultivars (Adly et al., 2018; Alobid et al., 2021). Yet, while numerous studies have examined components of these socioeconomic and environmental challenges, they are rarely addressed in an integrated manner.

This research addresses that gap by first analysing the structure of farming households in Egypt and how they have developed in the recent past. We then continue to develop a coupled land-use change-ecohydrological model that links farmer decision-making with biophysical processes, and develop and analyse potential future scenarios. By capturing the feedback between farmer characteristics, water use, crop growth, and land-use change, the model provides a means to explore potential futures in an integrated way. The sections that follow address the research questions set out in the Introduction:

- What are the key dimensions of diversity among Egypt's agricultural households, how can they be meaningfully grouped into household types, and what do recent trends reveal about changes in their composition and characteristics over time?

- What are the potential impacts of climate change on crop production efficiency, including changes in yields and water use efficiency?
- What plausible future development pathways could shape Egypt's agricultural sector, given uncertainties in demographic growth, dietary change, agricultural expansion, and water or trade policy objectives?
- How do different land managers respond to future climate and socioeconomic scenarios, and how do their decisions influence land-use patterns, water use efficiency, and agricultural production?

5.1 Diversity among farming households: typologies and trends

To understand the potential future of Egyptian agriculture, this research first explores its current structure and recent trends through a national-level typology analysis of farming households. Drawing on the 2012 and 2018 rounds of the Egypt Labour Market Panel Survey (ELMPS) (Economic Research Forum & Central Agency For Public Mobilization and Statistics (CAPMAS), 2013, 2019), the analysis identifies four distinct farming household types: specialised, village, diversified-income, and landlord households (Sattar et al., 2024). Each type is defined by a particular combination of attributes. For example, households in the specialised category tend to have larger landholdings, derive a high share of their income from crop production, and achieve the greatest profitability (51% earnings-to-income). They also devote a relatively larger portion of their land to higher-value crops (15%) compared to other household types. In terms of resource use, specialised households use more irrigation water per unit area than other groups. By contrast, village households are characterised by smaller landholdings and a high reliance on farming for subsistence needs. They obtain 70% of their income from agriculture (compared to a survey average of 49%), yet their absolute farm income is the lowest among the three agricultural producer types. These village farmers tend to practice intensive cultivation (the highest cropping intensity of 1.64) but achieve the lowest income per unit area, reflecting resource constraints. The other two types occupy intermediate positions: diversified-income households earn a substantial share of income off-farm, while landlord households own the largest average area, but most of their farming income is through renting land. Despite these socioeconomic differences, it is notable that all household types grow a broadly similar mix of crops, indicating that nearly all farmers engage in staple crop rotations to some extent. The differentiation lies more in resources, income strategies, and productivity levels than in specialisation by crop.

The longitudinal nature of the panel data allows for the analysis of household transitions over time. The results indicate a marked trend between 2012 and 2018 towards reduced reliance on agricultural income. Village and specialised households – those most dependent on farming income – decline from 50% and 25% of households in 2012 to 10% and 12% in 2018, respectively. Simultaneously, diversified income households increase from 7.4% to 58% between the two surveys, suggesting greater engagement in off-farm employment and other non-agricultural income sources. Meanwhile, the landlord group remain relatively stable at around 17% to 20% of households. Notably, 45% of households that were engaged in farming in 2012 had exited agriculture by 2018. While part of this change is due to household splits and demographic expansion (i.e., children forming new households that do not continue agricultural activities), the data also points to a broader trend of agricultural abandonment.

The results indicate that households with greater livestock holdings, higher income from crop production, and larger cropped areas were more likely to persist in agricultural activities (Table A.11, Appendix A.4). This underscores the importance of sufficient income and resources in enabling continued engagement in farming. The contrast between households most reliant on agriculture (village and specialised types) and those with more diversified income sources (diversified-income and landlord types) is particularly noteworthy. For households reliant on non-farm income, greater access to off-farm opportunities supports their persistence in agriculture, whereas the opposite holds for households whose livelihoods depend primarily on farming. This suggests that those most dependent on agriculture are also the most likely to exit when alternative opportunities emerge.

Farming in Egypt is increasingly being supplanted or supplemented by other income sources, especially for smaller-scale producers (Helmy, 2020; Martin et al., 2020). These findings highlight growing economic and demographic pressures on smallholder agriculture in Egypt. Stagnant or low farm incomes are driving many rural families to reduce their dependence on farming. The next wave of the panel survey, conducted in 2023 and published at the end of 2024 (OAMDI, 2023), offers an opportunity to evaluate whether these structural shifts have persisted or accelerated in the intervening years.

Understanding this household heterogeneity and its trajectory is crucial for any analysis of future pathways of Egyptian agriculture. For our modelling exercise, the typology informed the definition of AFTs in the ABM. We distilled the diversity into two representative farmer

types: a Commercial AFT, broadly corresponding to the specialised cluster, and a Subsistence AFT, broadly corresponding to the village cluster. These two were chosen as archetypes representing contrasting positions in terms of resource endowments and structural characteristics. The Commercial agent type represents larger, capital-intensive farmers with more land and greater access to financial and manufactured capital. However, the Subsistence AFT represents smallholder family farms with limited resources. In addition, we differentiate the AFTs by irrigation practice, with commercial AFTs defined as using deficit irrigation and subsistence farmers using traditional flood irrigation.

From a policy perspective, the typology and its recent evolution signal that support for smallholders is a pressing issue. The decline in households depending mostly on agricultural income suggests that without interventions, such as improving farm profitability, access to credit, or rural services, small-scale farmers will continue to leave the sector. This could lead to greater land consolidation under larger operators, potentially improving efficiency but raising equity concerns. Alternatively, it may signal growing rural depopulation and the socioeconomic decline of farming communities.

5.2 Impact of climate change on crop yields and water use

To address the second research question, we investigate the potential impacts of climate change on crop production efficiency, particularly changes in yields and irrigation water requirements. Gridded potential yields from SWAT+ serve as inputs to CRAFTY; we use these outputs, along with irrigation water use, to analyse the impact of climate change on yield and water use efficiency. We ran the SWAT+ model for all crop-season combinations under 5 Representative Concentration Pathways (RCP2.6, RCP4.5, RCP6.0, RCP7.0, RCP8.5), which include different climate and atmospheric CO₂ trajectories to the end of the century.

5.2.1 Yield responses to climate change scenarios

Our model projections suggest that rising atmospheric CO₂ will have a pronounced fertilisation effect on many crops in Egypt, leading to higher potential yields in the coming decades, especially under high-emission scenarios. In particular, C3 crops exhibit substantial yield gains as CO₂ levels increase. Wheat, alfalfa, and seasonal fodder crops show yield improvements, consistent with other studies (Ainsworth & Long, 2021; Rezaei et al., 2023). For example, in our RCP8.5 scenario, wheat yields increase by 36% by the end of the century,

and alfalfa and seasonal fodder more than double their yields compared to 2020 levels (Figure 3.6). By contrast, C4 crops benefit much less from elevated CO₂. Maize, a key C4 summer crop, shows only modest yield changes in our simulations, and under the most extreme scenario (RCP8.5), its yields decline slightly by the end of the century. This outcome aligns with physiological expectations that C4 crops gain little from higher CO₂ except under water stress conditions (Rezaei et al., 2023). Due to our model assuming non-water-stressed conditions, maize did not experience a CO₂-related yield increase; instead, rising temperatures eventually reduced its potential yield. These diverging responses between C3 and C4 crops highlight the importance of crop physiology in mediating climate change impacts, and underscore that benefits from CO₂ fertilisation will be crop-specific.

Some crops exhibit non-linear trends or net declines under severe warming, even with CO₂ fertilisation. In our analysis, rice, a C3 crop, initially shows a yield increase as CO₂ concentrations increase, but beyond mid-century, its gains are reversed under high-emission conditions, resulting in a net decline by 2099. This suggests that intensified heat stress towards the end of the century may offset the positive effects of CO₂ fertilisation for rice. Other temperature-sensitive crops, such as other vegetables, also appear vulnerable. In our projections, other vegetables (modelled as potatoes) experience one of the largest yield reductions (31% under RCP8.5), likely because potatoes are a cool-season crop susceptible to high-temperature stress during tuber formation. These findings reinforce that even among C3 crops, those with critical growth stages sensitive to heat (e.g. rice flowering, potato tuber development) may not sustain yield gains as climates become hotter (Rezaei et al., 2023).

Regional differences within Egypt further modulate these impacts (Figure 3.7). For instance, maize yields are projected to decline by up to 20–25% in the hottest southern governorates by 2099. In contrast, wheat sees yield increases across all regions, with the largest relative gains occurring in newly reclaimed desert lands of Upper Egypt, where baseline yields were low and CO₂ fertilisation improves yields. Overall, the climate change scenarios result in divergent impacts on yield. Under a low-emission scenario (RCP2.6), climate effects on yields are minimal, with average yields across all crops increasing by 4%, whereas under a high-emission scenario (RCP8.5), the net effect is a 25% increase in average yield. Notably, for the low emissions scenario, yields are stable across all crops, whereas for the high emissions

scenario, there are certain crops that experience large increases in yields while others experience large declines.

Our results are broadly consistent with other studies that include CO₂ fertilisation, while also pointing to some uncertainties at extreme CO₂ levels. A regional modelling study by Fader et al. (2016) found that across the Mediterranean basin, higher CO₂ offset the negative impact of warming for most crops, leading to net yield increases even under 5 °C of global warming. For example, Fader et al. (2016) projected sugarcane yields to rise by 30% under +2 °C and over 100% under +5 °C (with CO₂ concentrations up to 720 ppm), whereas nearly all crops would have seen yield declines if atmospheric CO₂ remained at current concentrations. Our simulations align with this pattern; we also observe strong CO₂-driven yield gains (e.g. for sugarcane, wheat, and vegetables). One notable discrepancy is rice; Fader et al. (2016) projected continual rice yield increases even under the most extreme warming scenarios, whereas our model shows rice yields peaking in the 2070s, then decreasing. A possible explanation is the higher CO₂ concentration in our RCP8.5 scenario (1,135 ppm by 2100, far above the levels examined by Fader et al. (2016)), combined with more intense local warming in southern Egypt. This also underscores a key uncertainty at very high CO₂ levels. As most studies of crop responses to elevated CO₂ are between 400ppm-700ppm, it is not clear how these crops would respond at higher CO₂ levels beyond this (Ainsworth & Long, 2021). Thus, while models such as ours project continued gains up to 1,135 ppm for many crops, the real-world response could plateau or even decline at such high concentrations.

When compared to studies focused specifically on Egypt, our findings help reconcile some of the mixed results in the literature. Several impact assessments which exclude the effects of elevated CO₂ have predicted yield declines in Egypt due to warming alone. For example, in the western Siwa oasis, yields in 2100 were projected to drop by 10–27% under RCP8.5 (El-Rawy et al., 2021). Such studies likely overestimate yield losses because they omit the countervailing CO₂ fertilisation effect. In contrast, experiments and models that include elevated CO₂ often foresee yield gains. For example, Elsadek et al. (2024) used an AquaCrop model for rice in the Nile Delta and found that with CO₂ enrichment, rice yields could increase by about 15%–17% by the end of the century under both RCP4.5 and RCP8.5 scenarios. Our rice results show a similar early-century increase, but by 2099, we project a 2% net rise under RCP4.5 and a decrease of 8% under RCP8.5. This difference likely stems from our inclusion of

southern Egypt, which has a warmer climate than the Delta region. This appears to erode the CO₂ benefit for rice over time, whereas Elsadek et al. (2024) Delta-focused study in a milder climate, maintained net positive gains. For wheat, our projections show yield increases under all scenarios (for example, +36% by 2099 in RCP8.5). This agrees with the general trend reported by Kheir et al. (2019), who found that elevated CO₂ could raise Egyptian wheat yields by 4%–25%, partially offsetting the 10–18% losses expected from 4°C of warming. In our optimal-management simulations, elevated CO₂ offsets warming impacts and raises wheat yields, though this assumes unrestricted irrigation and optimal fertiliser supply.

Real-world outcomes for all crops will depend on cultivar heat tolerance and on farmers' ability to sustain adequate water and nutrient inputs to take advantage of elevated CO₂. The interplay between rising CO₂ concentrations and higher temperatures means that climate change impacts on yields remain uncertain and will differ across regions and crops. Our findings highlight this complexity: while they suggest that elevated CO₂ can enhance yields even under warming, the potential for more frequent extreme weather events, which we do not capture, introduces additional uncertainty and may diminish or even reverse these gains (Ainsworth et al., 2025; Rezaei et al., 2023).

5.2.2 Impact of climate scenarios on water use efficiency

Our study also indicates that future climate conditions will affect irrigation water requirements, generally improving WUE for Egyptian agriculture. Across all scenarios, the model shows a decline in crop water use per unit yield. Higher CO₂ concentrations induce partial closure of plant stomata, which reduces transpiration rates and crop water requirements (Ainsworth & Long, 2021; Tian et al., 2023). In our RCP8.5 scenario, this translates into improvements of WUE of 69% on average by 2099 relative to 2020. C3 crops again show the most pronounced improvements. For instance, alfalfa and seasonal fodder crops achieve around an 85–88% reduction in water use per unit of yield. Wheat also sees major efficiency gains of 75%. This is also observed with C4 crops, such as sugarcane, for which WUE improves by 79%. This is consistent with meta-analyses that find CO₂-driven WUE increases in both C3 and C4 plants, but stronger effects are observed in C3 crops (Mokhtar et al., 2025). For example, a recent review article reported WUE increases on the order of 30–50% for wheat and tomato (C3 crops), and smaller yet still substantial improvements for maize and sugarcane (C4 crops) under elevated CO₂ conditions (Mokhtar et al., 2025).

Similarly, controlled experiments have shown wheat's WUE rising by 28% and maize's by 50% when grown under 800 ppm CO₂ concentration without drought stress (Q. Cao et al., 2022). Our model results align with these findings and show that elevated CO₂ enhances WUE across all crops, a potentially positive outcome in the water-scarce context of Egypt.

Fader et al. (2016) conducted a study examining climate change effects, including increased CO₂ concentrations, for the broader Mediterranean region. Despite warming, they found overall decreases in irrigation requirements for most crop types when elevated CO₂ was included, owing to reduced transpiration. However, there are some crop-specific nuances. Fader et al. (2016) noted that in their simulations, a few water-intensive crops such as sugarcane, citrus, and rice might require more irrigation under future climate scenarios. In our model, by contrast, sugarcane and rice both used less water per tonne produced by the end of the modelling period. This difference may be due to Egyptian agriculture being almost entirely irrigated already, so any CO₂-induced water savings translate directly into reduced irrigation volumes. In regions with rain-fed agriculture, certain crops might require more irrigation to maintain higher yields.

In summary, our results suggest that climate change may have predominantly positive effects on crop production efficiency in Egypt under optimal management. Elevated CO₂ is projected to raise yields of major C3 crops and some key C4 crops, while substantially improving WUE, offsetting the pressures of rising temperatures and water scarcity. These gains appear strongest under high-emission scenarios, when CO₂ fertilisation is greatest. However, the benefits are uneven across crops and may be undermined by extreme heat, particularly for sensitive crops such as rice and potatoes. Importantly, these outcomes are contingent on reliable access to irrigation water; without it, the potential benefits of elevated CO₂ could be far more limited. Thus, while our findings point to cautious optimism, they also underscore the need for adaptation, including the development of heat-tolerant cultivars, continued access to reliable irrigation, and adjustments in cropping patterns to safeguard vulnerable crops against climate stresses.

5.2.3 Improved cultivars

Crop genetic improvement has been a key driver of increased agricultural productivity in Egypt. Over the past several decades, advances in plant breeding and the release of improved cultivars, particularly heat-tolerant and high-yielding varieties of key crops, have led to

substantial yield gains (Al-Naggar et al., 2020; Ali et al., 2021; Mehana et al., 2021). These developments have helped buffer the agricultural system against rising temperatures and growing water stress, although the extent and sustainability of future gains remain uncertain.

Despite its importance, cultivar development is not currently represented in the coupled model. SWAT+ simulations rely on a fixed set of crop growth parameters, calibrated to reflect crop performance around the 2020 baseline. As a result, all future scenarios assume that crops retain the same traits over time, regardless of any improvements in breeding or seed technology. This creates a limitation, particularly in scenarios that include investment in research and development or anticipate faster diffusion of improved varieties, as potential yields may be underestimated.

Model development could improve realism by allowing crop parameters to evolve. Key variables such as optimal and base temperatures (t_{opt} and t_{base}), potential leaf area index (lai_{pot}), and biomass energy ratio (bm_e) could be adjusted to reflect plausible cultivar development. These changes could be made scenario-specific to represent different assumptions about investment levels, institutional support, and the effectiveness of seed systems across crops or regions.

However, projecting the pace of breeding progress carries considerable uncertainty. While crop yields have generally improved in recent decades, future advances are not guaranteed, particularly under climate stress, where breeding for heat and drought tolerance is especially challenging. Nonetheless, accounting for ongoing cultivar development is essential for understanding Egypt's future food system resilience. Integrating these dynamics into coupled models would enable more comprehensive evaluations of adaptation pathways under diverse future scenarios, providing a stronger foundation for long-term agricultural planning.

5.3 Future development pathways for Egyptian agriculture

To analyse the potential impact of future trajectories on the Egyptian agricultural system, we develop a range of credible socioeconomic scenarios. Using global SSP narratives (O'Neill et al., 2017) tailored to Egypt, we consider futures ranging from a sustainability-focused scenario (SSP1) to a regional rivalry scenario (SSP3), alongside intermediate cases of business-as-usual (SSP2), high inequality (SSP4), and fossil fuelled development (SSP5). Each pathway embodies distinct assumptions about demographic pressures, consumption patterns, desert land

reclamation, and policy reforms in water management and trade. These uncertainties lead to markedly different outcomes for food production and security in Egypt's agricultural system. Below, we integrate the scenario assumptions and implications, highlighting key differences.

5.3.1 Demographics and dietary change

Population trajectories are a dominant force shaping future food demand. Egypt's population in 2020 was approximately 107 million and is projected to grow at 0.5–1.5% per year over this century (Koch & Leimbach, 2023). By 2100, projections diverge sharply: under SSP3 (regional rivalry), the population is expected to reach 232 million, whereas under SSP4 (inequality), a low-fertility pathway, it is projected to stabilise at around 107 million (Koch & Leimbach, 2023). These contrasting population futures carry important implications for agricultural demand.

Likewise, dietary shifts alter per capita demand. In a health-oriented development (as in SSP1), Egypt gradually adopts healthier diets in line with EAT-Lancet guidelines – high in fruits and vegetables and reduced levels of starchy staples with total daily calorific intake of 2,471 kcal/capita/day (Willett et al., 2019). As the current Egyptian diet – 3741 kcal/capita/day – is one of the highest globally (CAPMAS, 2025; Nikiel & Eltahir, 2021), all scenarios, except SSP2, include a reduction in total calorific intake. Although SSP3 and SSP4 assume the same diet (total calorific intake of 3,026 kcal/capita/day), the large difference in population results in a marked divergence in the total demand. In contrast, the middle of the road scenario (SSP2) sees diets increase slightly to 3,850 kcal/capita/day by the end of the century. This includes continuing to depend on high levels of staple crops. The fossil fuelled development scenario (SSP5) assumes diets with higher consumption of meat and sugar. Total calorie intake declines in SSP5 to 2,584 kcal/capita/day as consumption of starchy staples falls. Therefore, it is the combination of both population growth and dietary patterns which impacts demand.

Notably, the model does not include mechanisms for how population size or dietary patterns might be influenced through policy interventions. While the scenario narratives suggest potential pathways, such as integrating healthy diets into education systems, using subsidies to promote dietary shifts, or ensuring access to affordable calories, these factors remain exogenously defined. Additionally, the model does not capture how changes in food availability might, in turn, shape population dynamics or dietary behaviour.

5.3.2 Agricultural expansion

To meet the growing demand for agricultural products within the constraints of Egypt's limited arable land, all scenarios continue the country's longstanding policy focus on land reclamation (Nour, 2020). Since the 1950s, over 3.22 million feddan (1.4 million hectares) have been reclaimed, and recent mega-projects such as the 1.5 Million Feddan and New Delta initiatives aim to add a further 3.7 million feddan (1.55 million hectares) (Nour, 2020; Presidency of the Arab Republic of Egypt, 2022). In our scenarios, the extent and sustainability of land reclamation vary considerably. While the narratives specify differences in land reclamation policy, such as the rate of expansion, sources of irrigation water, and levels of water extraction, our model operationalises reclamation indirectly by adjusting the attributes of AFTs and the gridded resource levels, allowing reclamation to emerge dynamically rather than being imposed directly. Additionally, specific irrigation water sources are not defined in the model due to data limitations. This approach reflects the fact that many of the major reclamation zones fall outside the modelled area. Moreover, these large-scale projects are typically implemented by government bodies or major investors, neither of which is currently represented in our model. Future developments could incorporate such institutional actors to better capture the dynamics of state-led or corporate land reclamation activities.

One dimension of variation between land reclamation under different scenarios is the scale and approach of expansion. In the sustainability scenario (SSP1), land reclamation proceeds in a restrained manner, emphasising long-term viability by targeting areas with relatively good soils and constraining groundwater extraction to levels nearer to natural recharge, thereby slowing depletion. In contrast, SSP3 (regional rivalries) and SSP5 (fossil fuelled development) pursue rapid reclamation, aiming to quickly green the desert through state-led or corporate mega-projects. SSP2 (middle of the road) envisions slower expansion, with both state and private actors reclaiming land at a modest pace. In the inequality scenario (SSP4), land reclamation continues but is largely driven by wealthy investors with minimal oversight or concern for sustainability.

One of the key challenges highlighted across scenarios is the need to provide adequate support services, such as infrastructure, energy, and community facilities, to ensure the long-term success of newly reclaimed areas (Bush, 2007). SSP1 treats this as a core priority, with reclaimed land developed with renewable energy, water-efficient technology, and services to

foster stable rural communities. By contrast, SSP3 and SSP5 neglect these sustainability safeguards. These scenarios exploit groundwater, especially from the NSAS, without consideration for recharge rates, leading to declining groundwater tables, salinisation, and eventual land abandonment. SSP2 includes limited infrastructure development, while in SSP4, chronic underinvestment results in low productivity and further concentration of land among elites.

5.3.2.1 Impact of agricultural expansion on biodiversity

Although land reclamation in Egypt has been widely studied, its consequences for biodiversity are rarely addressed despite important ecological implications. Egypt hosts a rich and globally significant biodiversity relative to its land area (Shaltout & El-Khalafy, 2024). Desert reclamation typically disrupts habitats with lower overall species richness, but these areas may still host highly localised biodiversity, particularly around oases, which have been cultivated and expanded over centuries (El-Sheikh et al., 2020). In contrast, coastal reclamation and wetland drainage threaten some of the most biodiverse habitats in the country, including the Nile Delta wetlands and coastal lagoons. These areas support unique flora and fauna, many of which face conservation threats (Davies & Harhash, 2021; Fouad, 2017).

The drainage of water bodies for agricultural expansion, as well as urbanisation and industrial expansion, directly destroys and fragments critical habitats, reducing the range and abundance of many species (Fouad, 2017). In the Mediterranean coastal zone, intensive tourism, coastal infrastructure development, and agricultural reclamation exert significant pressure on key wildlife habitats, leading to declines in species diversity and abundance (Davies & Harhash, 2021). Furthermore, agricultural expansion can shift ecosystem balances, for example, by increasing populations of certain insect species, including pest and disease vectors (El-Sheikh et al., 2020).

Given these threats, the ecological impact of land reclamation merits explicit consideration in national and regional planning for food security and land-use change. Within our coupled framework, the CRAFTY component can represent biodiversity as a spatially explicit resource and also account for demand for this ecosystem service. Future extensions could integrate biodiversity conservation into scenario analyses, enabling exploration of trade-offs between agricultural development and ecological sustainability.

5.3.3 Water resources and policy reforms

Egypt's fixed annual water quota of 55.5 km³ from the Nile River remains an essential component of its agricultural water supply (Nikiel & Eltahir, 2021). Continuing to secure this volume, however, is contingent on regional cooperation with upstream riparian countries. Increasing water infrastructure developments, particularly Ethiopia's GERD, alter the geopolitical dynamics of Nile Basin governance (Wheeler et al., 2020). While such projects may not directly infringe upon Egypt's formal quota, they could introduce volatility in seasonal flow regimes and reduce Egypt's control over water timing, particularly during droughts or high rainfall periods (Heggy et al., 2021). Our scenario narratives incorporate these complexities, especially the implications of cooperation versus conflict on water security.

In cooperative pathways such as SSP1 (sustainability) and, to a lesser extent, SSP4 (inequality), regional water diplomacy improves. In these futures, water policy reforms are paired with enforceable transboundary agreements and mechanisms for shared drought management. These scenarios envision adaptive governance frameworks that respond proactively to climate-induced variability in Nile flows. Crucially, SSP1 promotes co-management strategies and investments in non-conventional water sources to complement the fixed Nile supply, recognising that Egypt's quota already provides only half the annual 1,000 m³/capita threshold for water security (Falkenmark et al., 1989).

Non-conventional water sources are already central to Egypt's water balance. This includes water reuse, which is estimated to add 16 km³ to Egypt's water resources annually – approximately 5 km³ from formal drainage stations, 2 km³ from treated municipal/industrial effluent, and an estimated 9 km³ from informal, untreated reuse (Tawfik et al., 2021). Further expansion is constrained by rising pollution loads and the lack of water-quality monitoring in the drainage canal (El-Rawy et al., 2020). This water is frequently mixed with Nile water and utilised in land reclamation projects, such as the El-Salam Canal, which aims to reclaim about 251,310 ha of barren land in the Sinai Peninsula (Elbialy et al., 2025).

Another non-conventional water source is the NSAS, a non-renewable aquifer system, which is estimated to have up to 15,000 km³ reserves, although only 5,356.89 km³ is considered economically recoverable under current technology and sustainability thresholds (Bakbakh, 2006). While this fossil water can serve as a short- to medium-term buffer, it is non-renewable

with negligible recharge, making its continued exploitation unsustainable in the long term. Moreover, over-extraction risks soil salinisation, water table decline, and resource depletion.

SSP3 (Regional Rivalries) and SSP5 (Fossil-Fuelled Development) represent high-risk trajectories for water sustainability. In both, groundwater is exploited extensively and indiscriminately to support rapid land reclamation and export-oriented agriculture. Water efficiency improvements exist but are skewed towards large-scale investors, exacerbating inequality and putting pressure on remaining water resources. SSP3 also see reduced inflows to the HAD during certain periods due to regional tensions and poor cooperation, further destabilising Egypt's surface water supply.

In the absence of other sustainable alternatives to address Egypt's limited water supply, desalination emerges as a potential long-term solution. As Egypt possesses some of the highest solar radiation levels globally (Abubakr et al., 2022), expanding solar-powered desalination facilities on non-arable desert land presents an opportunity to reduce pressure on freshwater sources while decarbonising energy supply. Desalination has become an important source of fresh water for many countries in the region; however, it remains costly, energy-dependent, and geographically limited in scope, suggesting it should complement, rather than replace, broader efficiency and reuse strategies.

Enhancing WUE emerges as the most immediate and broadly applicable strategy across all scenarios. Adoption of water-efficient technologies is most strongly emphasised in SSP1, where the narratives describe government investment, financial incentives, and education programmes that facilitate widespread uptake. In contrast, SSP3 and SSP4 highlight the constraints imposed by inequitable access, limited public investment, and rural marginalisation, which slow the diffusion of such technologies. While the narratives include measures that support technology adoption, they give less attention to other possible policy approaches, such as pricing or regulatory instruments. Achieving improvements in WUE is therefore challenging, and doing so equitably is even more difficult. For example, while water tariffs could in theory encourage conservation, they may also disproportionately burden smallholders in contexts where agricultural prices are low and rural poverty is high (Saleh, 2018).

Although water dynamics are integral to each narrative, our model does not currently simulate water source allocation explicitly. Irrigation water use is modelled, but its origin – whether surface water, groundwater, drainage reuse, or desalination – is not distinguished. Incorporating SWAT+'s existing water allocation functionality would enable the simulation of reservoir operations, pumping thresholds, and aquifer storage levels, enhancing model realism (Arnold et al., 2018). However, implementing such measures would require detailed, spatially explicit, and regularly updated data on infrastructure, management, and hydrological storage, which remain limited or unavailable in the Egyptian context.

5.3.4 Trade policy and food self-sufficiency

Policy debates around food security in Egypt have long centred on the tension between self-sufficiency and strategic reliance on trade (Bush, 2007; Soffiantini, 2020; Veninga & Ihle, 2018). Egypt has long relied on imports to meet more than half of its cereal demand, particularly for wheat and maize (Abdelkader et al., 2018). To ensure affordable access to food, the government sustains one of the world's largest food subsidy programmes, centred on wheat (Hosni & Ramadan, 2018). This close link between high dependence on cereal imports and extensive wheat subsidies has become a defining feature of national food policy (Breisinger et al., 2024). The scenario narratives explore a range of possible evolutions of this balance, revealing shared constraints and divergent political and economic responses.

Egypt's existing ambition for greater self-reliance, such as policy targets of 81% for wheat, 92% for maize, 93% for sugar, and 93% for red meat by 2030 (Arab Republic of Egypt, 2009), is acknowledged, but not all scenarios treat these as achievable or even desirable targets. For instance, in more cooperative and sustainability-oriented futures, such as SSP1, the narratives envision a strategic role for imports. In this pathway, moderate diets and improvements in domestic production reduce the import burden, but global trade remains open and affordable, allowing Egypt to continue importing key staples, particularly wheat, while focusing on exporting higher-value crops such as fruits and vegetables. This strategy reflects policy interest in diversifying agricultural exports to strengthen the rural economy while safeguarding access to essential calories (Fuglie et al., 2020).

By contrast, more inward-looking pathways (SSP3) emphasise food sovereignty and national control. Faced with a fragmented world order, restricted trade, and external shocks, the state promotes domestic production of all crops and curtails exports except for critical export

commodities, such as cotton or fruits. These scenarios reflect familiar historical nationalist narratives around self-reliance (Bush, 2007). In the growth-oriented scenario (SSP5), production expands substantially, yet a large share is channelled to export markets. Rising affluence and stronger global integration drive export growth, while imports remain important to meet domestic demand amid dietary change. By contrast, in the inequality scenario (SSP4), lower population growth reduces overall demand, but trade still plays a central role.

Taken together, the narratives show that no development pathway achieves full food self-sufficiency. SSP3 is the only scenario that aims for total self-sufficiency for all agricultural products. By contrast, the other pathways pursue a more balanced approach: they strive to reduce import dependence, especially for staple crops, but acknowledge that some level of imports will remain necessary. In these scenarios, import reliance is moderated to varying degrees, while exports of higher-value crops are actively promoted. This contrast highlights that Egypt's food system is likely to remain structurally linked to international trade, but that this reliance need not be a vulnerability if managed strategically. Robust trade partnerships, diversified export portfolios, and carefully designed subsidy policies can all help to buffer shocks and strengthen long-term food security.

5.4 Land manager responses to future climate and socioeconomic scenarios

Building on these narratives, we examined how contrasting futures unfold within the coupled land-use change-ecohydrological model. This approach enables us to assess how alternative pathways for Egypt's agricultural system shape land-use patterns, water use efficiency, and food security outcomes. The results reveal marked differences across scenarios, reflecting both opportunities and constraints for Egypt's agricultural future.

5.4.1 Diverging dynamics between land managers

The trajectories of commercial and subsistence AFTs diverge markedly across scenarios, shaped by differences in efficiency, resource sensitivity, and competitive resilience within Egypt's constrained agricultural system. While commercial AFTs consistently represent more market-oriented behaviour and subsistence AFTs represent more traditional, resource-constrained practices, the degree of these characteristics varies by scenario to reflect different social, economic, and political contexts.

The model initialisation reflects Egypt's current agricultural structure, with 10% of cultivated land allocated to commercial agents and 90% to subsistence agents, consistent with the dominance of smallholder farming. Across most scenarios, the share of land managed by commercial AFTs declines sharply, averaging a 90% reduction, largely due to their higher sensitivity to profitability and resource constraints. An important exception is the sustainability pathway (SSP1-RCP2.6), where commercial AFTs decline only to 1.9% in 2080 (Figure 4.5) before recovering to 3.9% by the end of the century. This outcome reflects both the higher resource levels available under this scenario and the higher demand for WUE as an ecosystem service, which favours commercial AFTs. The speed and extent of these transitions are also influenced by CRAFTY's configuration (Appendix C.5), which determines how many competition events occur per time step and what proportion of the landscape is open to competition. More open-market scenarios (i.e. SSP5-RCP8.5) accelerate competition, while more restrictive scenarios (i.e. SSP3-RCP7.0) slow it down. This is demonstrated in SSP5-RCP8.5, where rapid turnover drives accelerated land abandonment (18,428 ha abandoned by 2100), land reclamation, and reductions in commercial agents.

In contrast, subsistence AFTs expand their share of managed land across all futures due to their relative inertia. These smallholders rely on traditional flood irrigation, have lower access to capital and mechanisation, and depend on social networks, yet their persistence is reinforced in scenarios where economic margins are thin. The behavioural differences between AFTs and under different scenarios become particularly pronounced under greater scenario stresses. For example, under the regional rivalry pathway (SSP3-RCP7.0), subsistence AFTs, which manage 99% agricultural area in 2100, maintain land use with minimal abandonment – just 851 ha by 2100, averaging only 10 ha per year. This limited land-use change reflects high demand for domestic production across all crops and scenario-specific AFT characteristics, which assume greater inertia under an unstable context dominated by regional conflict. This persistence occurs despite lower levels of resource development in SSP3-RCP7.0.

These diverging responses have implications for Egypt's agricultural policy development, particularly given the country's dependence on the sector. Modernisation strategies that assume uniform responsiveness across farmer types risk exacerbating existing inequalities and undermining system resilience. In our model, commercial agents may be better

positioned to respond to policy incentives and invest in efficiency-enhancing technologies, but they represent a smaller, more volatile, and declining component of Egypt's farming system. Their deficit irrigation practices and technological adoption can contribute to water use efficiency improvements, yet their tendency toward abandonment under stress creates gaps in production and employment that must be filled by other agents or imports. Recent research further highlights that technology adoption is highly uneven across farmer groups, shaped by behavioural inertia, risk perceptions, and institutional constraints, reinforcing the need for policies that are tailored rather than standardised interventions (Salem et al., 2024)

Subsistence agents, by contrast, require fundamentally different policy approaches that recognise both their constraints and their systemic importance. Their greater inertia and lower likelihood to give up land provide crucial stability to Egypt's agricultural system, but their productivity limitations constrain overall sectoral performance. Targeted interventions must address their specific needs – improved access to extension services, affordable credit, irrigation support, and appropriate technologies – whilst avoiding displacement through policies that inadvertently favour larger, more capital-intensive operations. The challenge lies in enhancing productivity and water use efficiency amongst subsistence farmers without undermining the social and economic foundations that enable their persistence.

Agricultural expansion patterns highlight these fundamental differences between AFTs and their implications for policy design. Land reclamation in the model occurs primarily where natural capital improves, with areas undergoing transition from unmanaged land to crop production experiencing an average increase of +0.0074 in natural capital. However, the conditions and motivations driving reclamation differ markedly between AFTs. Reclamation to commercial agents tends to coincide with increases in water capital, whilst transitions to subsistence agents occur even where water capital slightly declines.

The current coupled model operates with simplified AFTs that capture key behavioural dimensions between farming households but lack the complexity observed in real-world systems. It employs only two broad categories (commercial and subsistence AFTs), deliberately exaggerated to represent distinct archetypes, which necessarily overlooks heterogeneity within categories and gradations between these stylised extremes. While CRAFTY does allow for some variation in characteristics around the mean for each AFT (Murray-Rust et al., 2014), the model remains more limited in representing adaptive

behaviour. In particular, it lacks mechanisms for behavioural memory or learning, meaning AFTs cannot incorporate past performance into future decisions. In reality, farmers' choices are shaped by experience: repeated success tends to increase risk tolerance and competitiveness, while failures may discourage further innovation (Müller-Hansen et al., 2017).

Additionally, the model treats socioeconomic capitals as externally determined projections independent of land use history or management decisions. This approach fails to capture dynamic feedback where financial capital should vary based on cropping choices, for example, and where successful reclamation creates spillover effects in surrounding areas through infrastructure development and innovation diffusion. Currently, competition for grid cells occurs at each time step based solely on agent characteristics and pre-defined resource levels, without accounting for how historical cropping decisions modify local conditions or create momentum for further development. Incorporating behavioural memory, adaptive learning, and dynamic resource feedback would enhance realism by allowing agents to adjust based on accumulated experience and feedback, rather than responding solely to immediate conditions, ultimately providing more nuanced insights for policy analysis of agricultural development trajectories.

5.4.2 Food security: supply-demand dynamics

Across all scenarios, the model highlights a persistent and deepening challenge between crop production and demand for domestic production, reflecting Egypt's long-standing struggle with food security in a context of resource constraints and rapid population growth. This demographic pressure combines with Egypt's current import dependence, which often exceeds 50% for critical cereals such as wheat and maize (Veninga & Ihle, 2018), to create a complex food security landscape.

The scenario analysis reveals that even substantial production increases are consistently outpaced by rising demand, with demand for domestic production ranging from 278 Mt in SSP4-RCP6.0 to 597 Mt in SSP3-RCP7.0 (Figure 4.2b). In the sustainability-focused SSP1-RCP2.6, staple crop production declines by 42% by the end of the century, leaving a shortfall of 1.15 Mt (9.7%) by 2100. This reflects both reduced calorific intake of staples and higher demand for fruits and vegetables, alongside policies prioritising WUE, which highlight the tension between resource-use efficiency and immediate food security needs in a water-scarce

environment (Fuglie et al., 2020). In contrast, the more production-oriented scenarios deliver significant supply gains – 27% in SSP2-RCP4.5 and 51% in SSP3-RCP7.0 – yet still fail to keep pace with surging demand, resulting in shortfalls of 16.9 Mt (37%) and 15.5 Mt (31%), respectively. Together, these outcomes underscore that neither efficiency-focused nor production-focused strategies alone can secure Egypt's food future when demographic pressures and dietary shifts continually drive demand beyond supply.

The critical role of international trade becomes evident when examining these supply-demand imbalances within Egypt's existing policy framework. Egypt's food subsidy system, established as a defining policy of the post-1952 period, consists of two components: the provision of subsidised local 'baladi' wheat bread at a fixed affordable and below-cost price, and a ration card system that provides other key staples, including oil, sugar, and rice at subsidised prices (Kassim, 2018). Due to Egypt's high dependence on wheat imports, this food subsidy system imposes a strain on public finances, costing the state 4% of government expenditure between 2016-2020 (Breisinger et al., 2024). The system has also exposed Egypt to international food price fluctuations, which have been linked to episodes of social unrest, most notably and recently the 2011 Arab Spring demonstrations (Soffiantini, 2020).

Trade dynamics reveal the complexity of Egypt's food security challenge beyond simple production metrics. SSP5-RCP8.5 achieves the highest production levels (208 Mt) and has the second-lowest calorific intake per capita combined with a relatively modest population (143 million), yet still results in a shortfall of 36% relative to demand for domestic production. This outcome occurs partly due to high export volumes (49.7 Mt) and relatively low imports (129 Mt), illustrating how trade patterns and economic priorities can disconnect domestic production from domestic food security outcomes. The scenario highlights tensions between export-oriented agricultural development strategies and food security objectives.

The feasibility of self-sufficiency strategies is illustrated by the zero-import scenario (SSP3-RCP7.0), which results in the highest level of unmet demand for domestic production (78%), clearly demonstrating that self-sufficiency through zero imports is unfeasible under current production constraints and demographic pressures. Notably, this scenario also exhibits the highest level of food exports (86.0 Mt), further exacerbating the domestic shortfall and underscoring the trade-offs between export revenue and ensuring access to affordable food through domestic production. The production gap identified in the model represents either

increased imports, exposing Egypt to potentially high international food prices, or food insecurity.

These findings align with other assessments of Egypt's food security trajectory. Abdelkader et al. (2018) estimated average food imports of 150 Mt by 2050 across the five SSPs using their national model, affirming the ongoing critical importance of trade for Egypt's food security. In our model, only SSP4-RCP6.0 represents a scenario where staple crop production exceeds demand for domestic production, generating a modest surplus of 0.220 Mt (1.2%) by the end of the century. This outcome stems from the scenario's distinctive characteristic of a population reduction relative to 2020. However, this pathway raises equity concerns, as improved aggregate food security metrics may mask growing disparities in access to adequate nutrition among different socioeconomic groups.

Beyond questions of quantity and access, food security in Egypt must also contend with the quality of nutrition under changing environmental conditions, particularly given the country's high reliance on wheat as both a calorie and protein source (Veninga & Ihle, 2018). Current research indicates that elevated atmospheric CO₂ concentrations negatively affect the nutritional content of crops. Ainsworth et al. (2025) report consistent reductions in both macro- and micronutrients in plants grown under elevated CO₂, while Myers et al. (2014) found that levels of 25 essential micronutrients declined across 130 plant species under elevated CO₂ conditions. The protein implications are particularly concerning for Egypt's dietary landscape. Based on a synthesis of 120 controlled experiments, Taub et al. (2008) estimate an average 9.8% decline in wheat protein under elevated CO₂ conditions. Given that wheat accounts for around one-third of average calorific intake and nearly half of average protein intake in the national diet (Veninga & Ihle, 2018), such nutritional degradation could undermine food security even in scenarios where calorific needs are nominally met.

The scenario results demonstrate that Egypt's food security challenges cannot be resolved through supply-side interventions alone, despite the importance of maintaining and enhancing domestic production capacity. The persistent shortfalls across multiple scenarios and the structural limits to full self-sufficiency underscore the necessity of integrated approaches that combine production enhancement, strategic trade relationships, demand-side management, nutritional quality preservation, and social protection systems. The complexity of these challenges, embedded within Egypt's broader water scarcity and climate

change pressures, requires food security strategies that acknowledge both the possibilities and limitations of agricultural intensification whilst building resilience through diversification and adaptive management.

5.4.3 Water use efficiency

Water use represents the fundamental constraint on Egypt's agricultural system. Although the coupled model does not explicitly simulate water sourcing or allocation constraints, it overcomes this limitation through differentiated irrigation strategies and abstract demand for WUE that reflects policy and economic pressures and incentives for water conservation. The model simulates competition between different management practices through commercial and subsistence AFTs, which represent distinct approaches to irrigation. Commercial AFTs, characterised by deficit irrigation practices, initially manage only 10% of cultivated land but demonstrate different trajectories across scenarios based on demand for WUE. Under all pathways, commercial AFTs decline, dropping below 1% of managed area across all scenarios except SSP1-RCP2.6. In this sustainability-focused scenario, commercial AFTs initially decline to 1.9% but subsequently recover to 3.9% of the managed area by 2100, driven by rising demand for WUE that encourages adoption of deficit irrigation practices. This recovery reflects policy mechanisms that promote water-efficient management, such as water pricing reforms or subsidies for efficient irrigation technologies, though the model represents these as abstract demand pressures and incentives rather than specific policy interventions.

Increasing temperatures under future climate scenarios are expected to raise evapotranspiration and irrigation water requirements. Previous studies suggest winter crop water use in Egypt will rise by 6–13% by 2100, although these estimates exclude the moderating effects of elevated CO₂ (S. Mostafa et al., 2021). Elevated CO₂ reduces stomatal conductance and can substantially improve WUE, often more than irrigation technology alone (Ainsworth et al., 2025; Q. Cao et al., 2022). Our results (Figure 4.6) confirm this moderating effect, but with clear seasonal and scenario differences. The greatest efficiency gains occur under SSP5-RCP8.5, where WUE improves dramatically by the end of the century, especially in winter. By contrast, improvements are marginal under SSP1-RCP2.6, with little change from present-day levels. Commercial AFTs consistently achieve higher WUE than subsistence AFTs, using less than half as much water per tonne of crop in winter, and about 40% less in summer.

This highlights both the critical role of elevated CO₂ in offsetting climate-driven water stress and the persistent efficiency gap between production systems.

Promoting more efficient irrigation practices in Egypt is complicated by structural and behavioural constraints that limit their adoption. While government policies have prioritised the expansion of drainage systems to enhance water reuse and mandated drip irrigation in newly reclaimed areas to improve crop water productivity (Bush, 2007; Fuglie et al., 2020), uneven adoption across farmer groups has produced persistent disparities in water consumption (Salem et al., 2024). Egypt has also sought to increase overall water availability through unconventional sources, including groundwater abstraction and irrigation water reuse (Nikiel & Eltahir, 2021). The challenge, therefore, is to design water management strategies that both support the adoption of efficient practices across diverse farming systems and account for regional and seasonal variations in potential gains. This requires balancing policy incentives with technological and economic barriers, while recognising that widespread deficit irrigation adoption remains constrained. Finally, although elevated CO₂ concentrations may enhance WUE, these benefits only become significant under the extreme CO₂ levels associated with severe climate scenarios, making them at best a limited buffer rather than a solution to Egypt's water challenges.

5.5 Conclusion

This thesis has examined how Egypt's agricultural system may evolve under the combined pressures of climate change, rapid population growth, dietary shifts, and resource scarcity. By linking household diversity, land-use dynamics, and water constraints, it shows that the country's agricultural future will be defined by difficult trade-offs between food production and water use. These challenges are not unique to Egypt, with many arid, food-import-dependent countries facing similar pressures, making the insights relevant beyond the Egyptian context.

This thesis contributes methodologically by coupling an agent-based model of farmer behaviour with an ecohydrological model, capturing how decisions over land use and water interact with crop performance under uncertain futures. Unlike static or purely biophysical approaches, the framework demonstrates how adaptive choices by diverse farming households shape national outcomes, and how different policy and climate trajectories

produce distinct trade-offs between food production and water use. Because it draws largely on open-source and widely available data, the model can be adapted to other contexts where data is scarce, extending its usefulness beyond Egypt. While limited data meant that the sustainability of different water sources and long-term extraction risks could not be fully represented, the framework nonetheless provides a valuable tool for exploring plausible futures. In spite of these constraints, the findings point to critical areas where policy can make a decisive difference.

For Egypt, the results underline that demand growth remains the central driver of the production gap. Population growth, combined with diets that exceed recommended intake levels and depend heavily on subsidised staples, will intensify pressure on limited land and water resources. On the supply side, both land and water expansion remain part of the government agenda, but without adequate infrastructure and community support, large-scale reclamation projects risk becoming unsustainable and ultimately abandoned. Non-renewable water sources may provide short-term relief but cannot offer long-term security. At the same time, opportunities to improve productivity exist, including improved cultivars and more efficient technologies that can raise water use efficiency. Their impact, however, depends on the capacity and incentives of smallholders – who continue to dominate Egypt’s farming system – to adopt them. Trade will remain indispensable, both to offset staple deficits and to generate income through high-value exports. Complete self-sufficiency is neither attainable nor necessarily desirable; a balanced strategy that strengthens domestic production while supporting smallholder adaptation and engaging in strategic trade relations is more likely to deliver resilience.

Ultimately, Egypt’s agricultural resilience will depend on integrated and adaptive policy. Expansion of land and water resources must be pursued with sustainability safeguards, technological gains must be made accessible to all farmers, and planning must anticipate rather than react to crises. By prioritising inclusivity, efficiency, and long-term sustainability, Egypt can navigate the twin challenges of demand growth and resource scarcity while safeguarding the livelihoods of its rural communities.

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A Appendix A

A.1 Detailed data preparation methodology

The 2012 and 2018 Egypt Labour Market Panel Survey (ELMPS) (Krafft et al., 2019), were used to determine the farmer typologies. The 2012 and 2018 ELMPSs comprised individual and household surveys. The 2012 ELMPS fieldwork was carried out between March and June 2012 (Assaad & Krafft, 2013) and the 2018 survey was conducted between April 2018 and November 2018 (Krafft et al., 2021). The first stage of the analysis included extracting survey responses from individuals within farming households. The following stage entailed extracting individual survey responses pertinent to the farming household. This included summing the total income from employment for each household member, including basic wage, bonuses, incentives, profits, and secondary employment. Subsequently, the total number of household members working within the family farm and the total time spent working on the family farm were summed up. For the 2012 survey, to determine the number of staff employed in farming activities, we used the number of people supervised in farming activities. Although this may include those supervised on non-family farms, this response was the only indication of non-household employees. The 2018 survey, included details of farm employment within the household survey (family members working within the farm, and the number of days and average daily rate paid to external employees). The total number of worker days was divided by 204 to estimate the number of hired labourers. This value was calculated by using the average number of days worked in the last 3 months for all survey respondents employed in agricultural activity in the 2018 ELMPS. This included permanent and temporary or informal labour for all survey respondents and not just those who were part of farming households. The highest level of education within the household was also extracted from each household and included in the analysis. As the analysis considers the household as a unit, the survey results were reduced to include a single row for each household, maintaining the details of the head of the household from the results of the individual survey.

The household survey included details of crops harvested within the last year. This included details of areas, quantity produced for household consumption and for sale, and the net income from each crop. Some crop quantities were measured in traditional volumetric units (qintar, ardab) and area (kirat). Where conversions were available, these quantities were

converted into tonnes. Governorate-specific yield estimates – in tonnes per feddan – were derived from CAPMAS agricultural bulletins for the respective years (CAPMAS, 2025), and used where a conversion was not possible or where the area was used as the unit of measurement for the quantity. The total production quantity (for consumption and sale) was used for the analysis. Heml (camel load), another volumetric unit, is used to measure crop residue (straw/stalks etc.). This unit is used in the 2018 ELMPS. It was not possible to find conversion from heml to tonnes or prices for straw, therefore, this was ignored where heml was identified as the unit of the crop produced.

Annual agricultural income reports (CAPMAS, 2025), detailing the total income per crop each year (including total income from straw or stalk), were used to calculate the income per tonne for each crop. This was used to determine the income per tonne of crop by dividing the total national income by total national production for each crop type. This in turn was used to determine the income per household for each harvested crop. Sharecropping is sometimes practised in Egypt. These survey responses were included in the analysis so that actual household income from crop production could be calculated for the analysis. The survey included a question on the estimated net income for each produced crop. Furthermore, the income derived from the hiring of agricultural equipment was included in the analysis based on survey responses. This included details of equipment jointly shared with others; the percentage ownership was used to calculate the household's actual income from any hiring activities.

Water use was estimated using the governorate-specific total water use per crop derived from CAPMAS annual irrigation bulletin for the respective years (2013 was used instead of 2012 as 2012 was not available) (CAPMAS, 2025). The CAPMAS reports also include total water use from groundwater and wastewater reuse for each crop per governorate. To estimate the annual water use per unit area per crop per governorate, the flood irrigation, and groundwater and wastewater reuse were summed and divided by the total area per governorate. The mean of the water use per feddan for each governorate and each crop was calculated by region – Lower, Middle, and Upper Egypt. This was used with the crop type and area of each crop to calculate the total water use per crop.

The surveys included details of additional agricultural income from the sale of dairy products, honey, eggs, and poultry. This was also included as it is an important contributor to incomes within many farming households.

Livestock and equipment capital details were included in the survey. The value of the livestock was estimated, as described in Appendix A.1.1. It was not possible to estimate the value of agricultural equipment capital. Therefore, different equipment was divided into basic, intermediate, and advanced agricultural equipment, as described in Appendix A.1.2.

Non-farm income is an important feature of farm typologies (Nin-Pratt et al., 2018). Therefore, I included the value of non-agricultural enterprise income and capital in the analysis. The survey included details of partial ownership of enterprises. This was considered when calculating the capital and income from non-agricultural enterprises. Additionally, survey responses relating to remittances were included. Finally, the income from governmental support, such as pensions and benefits, and support from charities is included under other income.

In terms of household characteristics, the age of the household head and the size of the household have been widely used in typology analysis (e.g. Hien et al., 2014; Sarker et al., 2021; Shukla et al., 2019). These were extracted from the survey and included in the typology analysis. Additionally, several categorical variables, for the household and the head of household, were identified as potentially important for understanding the variability within the sample population. These included the highest level of education within the household, the level of education of the head of household, the type of dwelling, the ownership status of the dwelling, the region in which the household is based, and the sex of the head of household.

A.1.1 Livestock prices

Livestock prices are calculated based on the price per head of livestock derived from the CAPMAS report on agricultural income – 2011/12 and 2017/18 – and the animal production report – 2012 and 2018 – (CAPMAS, 2025). Horses and donkeys are estimated based on the price of a camel (horse=camel, donkey=camel/2). Table A.1 and

Table A.2 include these calculations and the price per head used in the multivariate analysis for 2012 and 2018, respectively.

*Table A.1: Total animals slaughtered (2012) and total value of sales of meat for each animal (2011/12) from CAPMAS reports.
Calculated price per head.*

Code	Description	Total animals slaughtered (1000s)	Total value of meat production (1000s EGP)	Price per head (EGP)
501	cows	1462	15686370	10,729
502	buffaloes	1205	13104981	10,875
503	goats	2663	2291126	860
504	sheep	2335	3133202	1,341
505	camels	35	329074	9,402
506	donkeys/mules			4,701
507	horses			9,402

*Table A.2: Total animals slaughtered (2018) and total value of sales of meat for each animal (2017/18) from CAPMAS reports.
Calculated price per head.*

Code	Description	Total animals slaughtered (1000s)	Total value of meat production (1000s EGP)	Price per head (EGP)
1	Cows	1145	33763188	29,488
2	Poultry	1163381	46813950	40
3	Goats	1473	2991889	2,031
4	Sheep	1496	4699365	3,141
5	Camels	21	502922	23,949
6	Donkeys/Mules			11,974
7	Horses			23,949
8	Buffaloes	1096	30053112	27,421
9	Other animals			

A.1.2 Capital equipment grouping

Capital equipment is grouped based on whether it is advanced, intermediate, or basic. I have included the groupings for 2012 and 2018 in Table A.3. The multivariate analysis includes a categorical variable for each level of capital equipment.

Table A.3: Capital equipment grouping into advanced, intermediate, and basic.

2012		2018	
Code	Description	Code	Description
601	large tractor (>12 horse power)	1	large tractor (>12 horse power)
602	small tractor (<12 horse power)	2	small tractor (<12 horse power)
603	machine pulled plough or harrower	3	machine pulled plough or harrower
604	animal pulled plow	4	animal pulled plow
605	mechanical water pump	5	drip irrigation system
606	manually powered water pump	6	sprinkler
607	sprinkler	7	mechanical water pump
608	motorized thresher	8	manually powered water pump
609	hand thresher	9	motorized thresher
610	rice winnower	10	hand thresher
611	machine to process livestock feed	11	machine to process livestock feed
612	motorized insecticide pump	12	motorized insecticide pump
613	hand insecticide pump	13	hand insecticide pump
614	donkey cart	14	donkey cart
615	small cart pulled by person	15	small cart pulled by person
616	poultry battery	16	poultry battery
617	beehives	17	beehives
Key		18	office furniture
	Advanced capital equipment	19	boat
	Intermediate capital equipment	97	Other equipment (specify)
	Basic capital equipment	97_other	Please specify what the other equipment is:

A.1.3 Inflation calculation

The cumulative inflation from 2012 to 2017 is used to rebase 2018 financial information to 2012 values and is included in Table A.4. The inflation rate is extracted from the consumer prices inflation World Bank database (<https://data.worldbank.org/indicator/FP.CPI.TOTL.ZG>).

Table A.4: Annual and cumulative inflation 2012-2018.

Year	Annual inflation	Cumulative inflation from 2012
2012	7.11%	107.11%
2013	9.47%	117.25%
2014	10.07%	129.06%
2015	10.37%	142.44%
2016	13.81%	162.12%
2017	29.51%	209.96%
2018	14.40%	240.19%

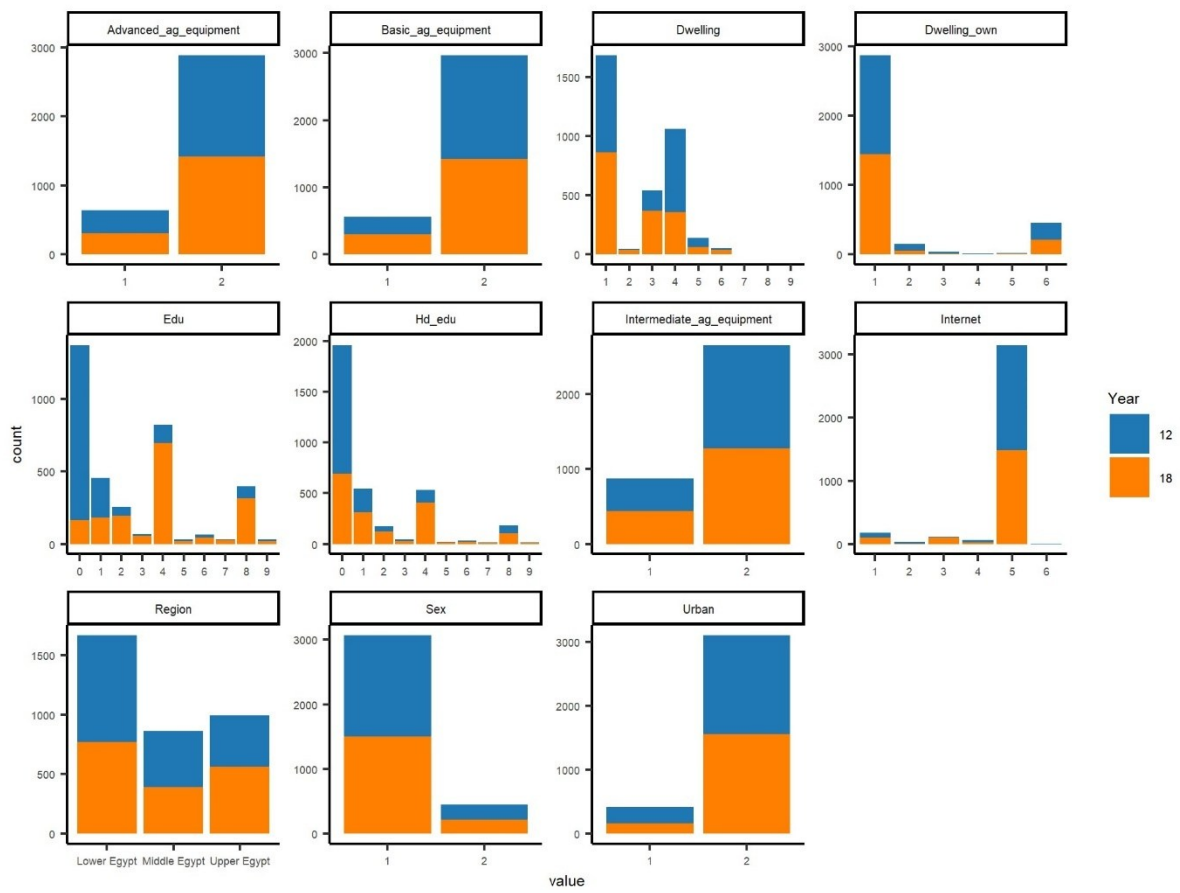
A.1.4 Outliers

Due to non-responses and missing responses, some outliers exist in the dataset. There were a number of responses that appeared to be non-responses but were not coded correctly (e.g. do not know response should be 99998, however the results included responses of 9999998, 9998 etc.). Non-responses were set to zero, where possible. Additionally, some logical outlier identification and removal rules were applied:

- Area equals zero whilst the cropped area is greater than zero.
- Cropped area is zero and crop income is greater than zero.
- Cropping intensity is greater than 3. Cropping intensity greater than 3 is possible using intercropping, however this is not common. Results significantly higher than 3 must be as a result of missing or inaccurate responses.

A.1.5 Histograms plots pre-transformation

a)



b)

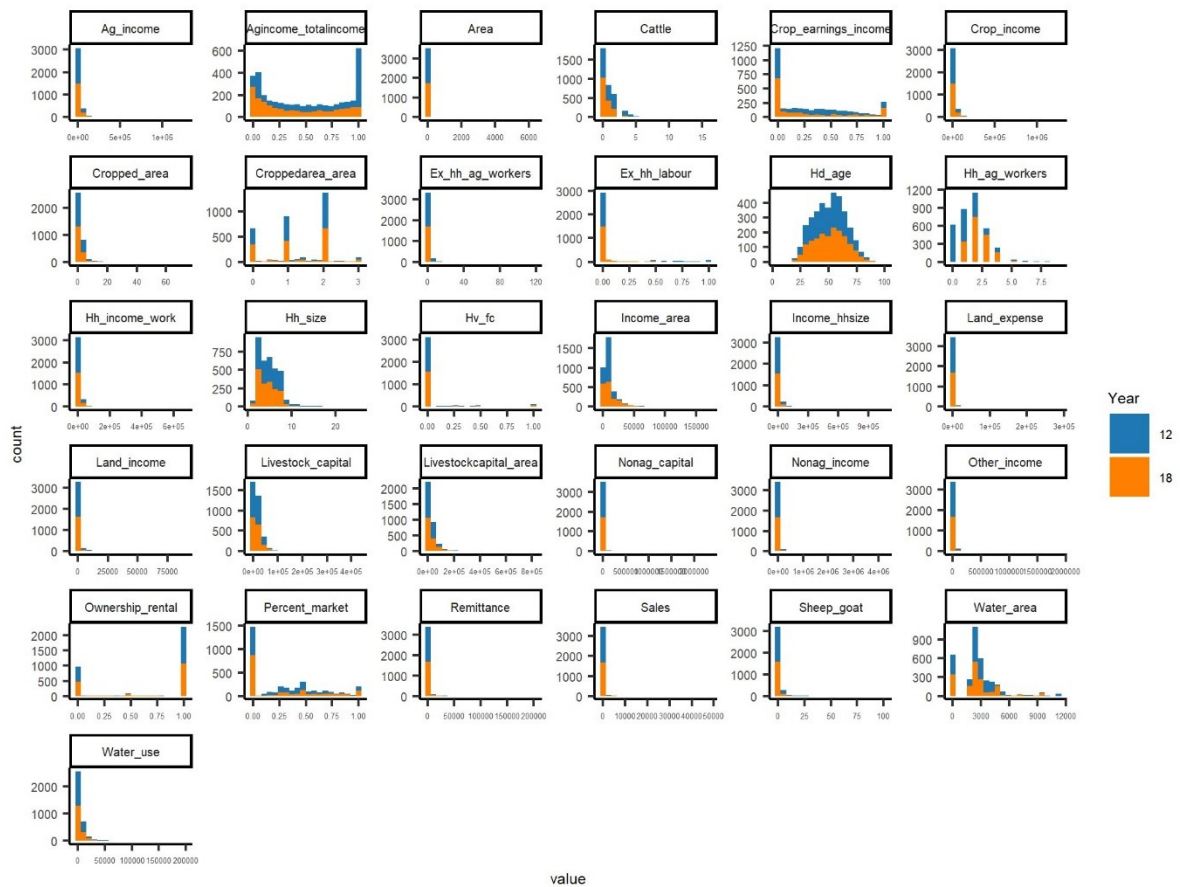


Figure A.1: Histogram of variables used in the analysis. The 2012 and 2018 survey years are represented in blue and orange, respectively. a) Histogram of categorical variables. b) Histogram of each continuous variable.

A.1.6 Box-Cox transformation

Table A.5 includes the calculated skewness of continuous variables prior to transformation, the Box-Cox lambda to normalise highly skewed variables ($-1 < \text{skewness} < 1$), and the skewness post transformation.

Table A.5: Skewness of continuous variables before and after transformation and Box-Cox lambda transformation values.

Variable	Untransformed skewness	Lambda	Transformed skewness
Hd_age	0.057657	-	0.057657
Hh_income_work	15.61488	-0.18182	0.561398
Hh_ag_workers	0.688156	-	0.688156
Ex_hh_ag_workers	23.38536	-2	2.1259
Hh_size	1.354602	0.181818	0.015189
Hv_fc	3.703981	-2	2.893507
Cropped_area	9.746562	-0.66667	0.119182
Area	59.26281	-1.07071	0.18065
Water_use	7.832535	0.222222	-0.27387
Crop_income	13.24439	0.222222	-0.22027
Sales	27.3344	-1.07071	1.761553
Cattle	2.721348	-0.86869	0.265326
Sheep_goat	16.69052	-2	1.720424
Livestock_capital	4.002754	0.141414	-0.39092
Remittance	17.16487	-1.15152	2.50982
Other_income	17.8896	0.10101	-0.26114
Nonag_income	24.73504	0.181818	-0.33131
Nonag_capital	50.34889	-2	3.788658
Land_expense	33.80066	-0.42424	1.097774
Land_income	12.15978	-0.86869	2.008607
Ag_income	13.1941	0.222222	-0.01739
Agincome_totalincome	0.093641	-	0.093641

Variable	Untransformed skewness	Lambda	Transformed skewness
Croppedarea_area	-0.26882	-	-0.26882
Income_area	4.18218	0.343434	-0.47335
Crop_earnings_income	0.722729	-1.79798	0.722729
Water_area	1.381413	0.464646	-0.77999
Livestockcapital_area	5.90046	0.10101	-0.3295
Ex_hh_labour	2.703529	-2	2.307199
Income_hhsize	17.56299	0.141414	0.205081
Percent_market	0.685254	-	0.685254
Ownership_rental	-0.78622	-	-0.78622

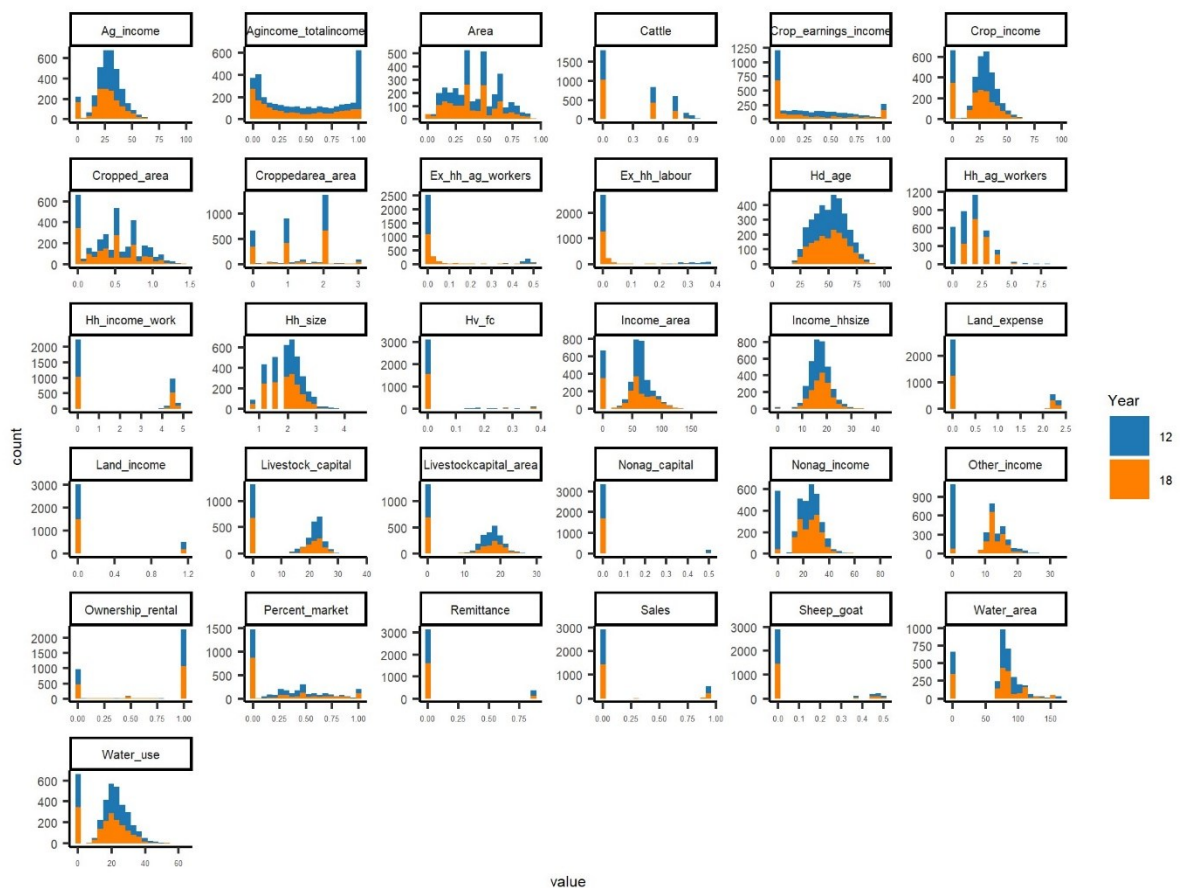


Figure A.2: Histograms of transformed continuous variables.

A.1.7 Heterogeneous correlation

Table A.6: Correlated variables, with correlation greater than 0.7 or less than -0.7.

Variable to be removed	Correlated variables	Correlation
[Water_use]	[Cropped_area]	0.95
	[Water_area]	0.83
	[Crop_income]	0.91
	[Ag_income]	0.76
[Crop_income]	[Ag_income]	0.87
	[Income_area]	0.84
	[Water_area]	0.74
	[Cropped_area]	0.88
	[Agincome_totalincome]	0.70
[Cattle]	[Livestockcapital_area]	0.74
	[Livestock_capital]	0.81
[Nonag_income]	[Agincome_totalincome]	-0.77
[Income_area]	[Water_area]	0.77
[Livestock_capital]	[Livestockcapital_area]	0.96
[Ex_hh_ag_workers]	[Ex_hh_labour],	0.99
[Hd_edu]	[Edu]	0.84
[Land_expense]	[Ownership_rental]	-0.75
[Cropped_area]	[Ag_income]	0.79

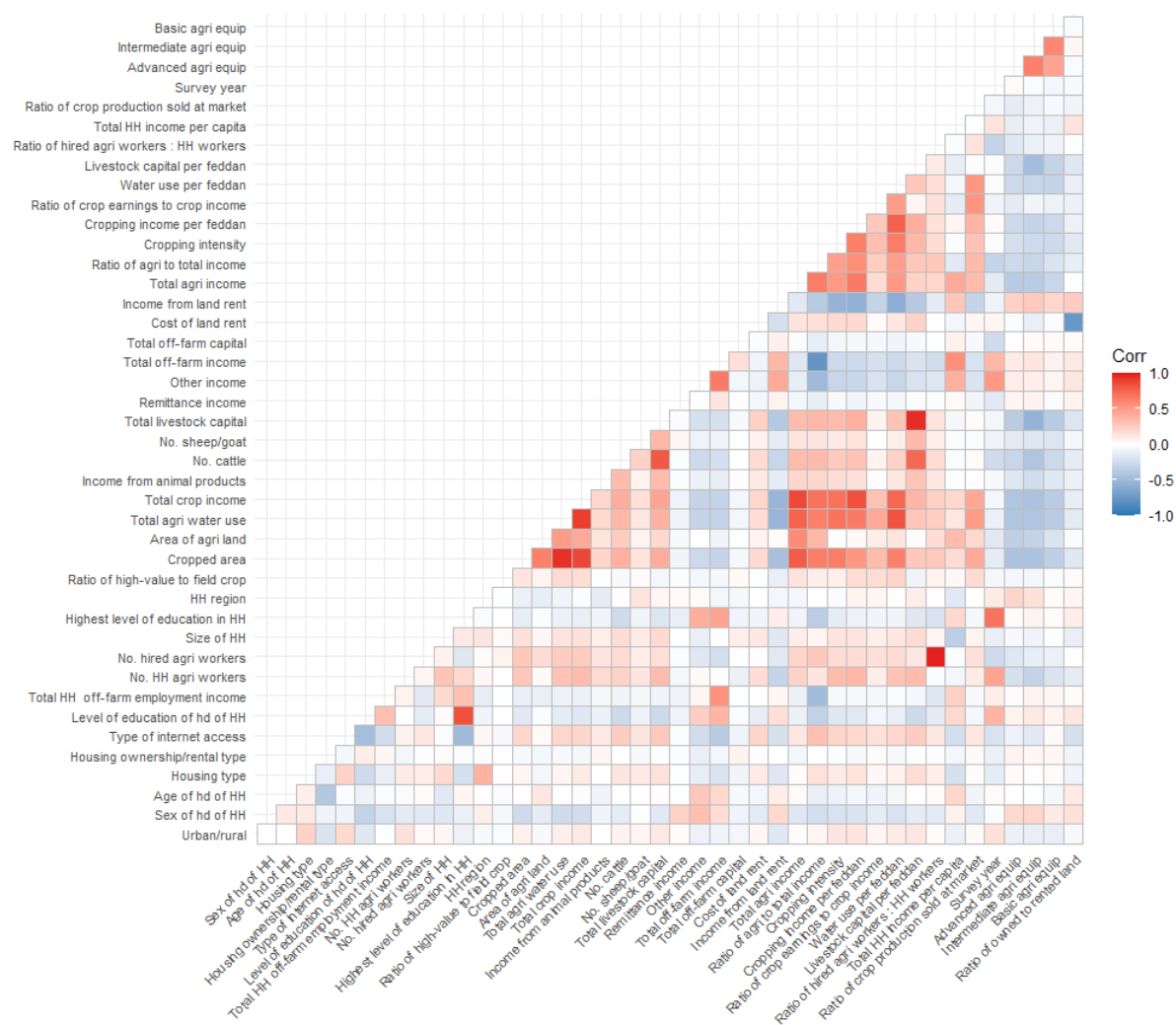


Figure A.3: **Correlation plot:** The heterogeneous correlation between all variables after the transformation of highly skewed variables. The darkness of the colour represents the degree of correlation, with darker colours representing a greater degree of correlation. Red represents a positive correlation and blue represents a negative correlation. White is a correlation of zero. Key: HH=household, hd=head, agri=agricultural, equip=equipment, No.= number of, feddan=0.42 hectares.

A.2 Factor analysis on mixed data

Table A.7: Eigenvalues, variance, and cumulative variance of each dimension in FAMD.

	Eigenvalue	Variance (%)	Cumulative variance (%)
Dim.1	5.084121	8.919511	8.919511
Dim.2	2.68393	4.70865	13.62816
Dim.3	2.500844	4.387445	18.01561
Dim.4	1.976886	3.468221	21.48383
Dim.5	1.747132	3.065143	24.54897
Dim.6	1.571333	2.756724	27.30569
Dim.7	1.359046	2.384291	29.68998
Dim.8	1.304613	2.288795	31.97878
Dim.9	1.198353	2.102374	34.08115
Dim.10	1.172255	2.056588	36.13774
Dim.11	1.149446	2.016572	38.15431
Dim.12	1.138347	1.997099	40.15141
Dim.13	1.114551	1.955352	42.10677
Dim.14	1.082599	1.899297	44.00606
Dim.15	1.072012	1.880723	45.88679
Dim.16	1.065119	1.868629	47.75542
Dim.17	1.043094	1.82999	49.58541
Dim.18	1.037525	1.82022	51.40563
Dim.19	1.032668	1.811698	53.21732
Dim.20	1.022399	1.793683	55.01101
Dim.21	1.019523	1.788637	56.79964
Dim.22	1.013242	1.777617	58.57726
Dim.23	0.996934	1.749007	60.32627
Dim.24	0.988707	1.734573	62.06084
Dim.25	0.981784	1.722427	63.78327
Dim.26	0.965909	1.694578	65.47785
Dim.27	0.959842	1.683933	67.16178

	Eigenvalue	Variance (%)	Cumulative variance (%)
Dim.28	0.944439	1.656911	68.81869
Dim.29	0.935046	1.640432	70.45912
Dim.30	0.930308	1.63212	72.09124
Dim.31	0.921078	1.615927	73.70717
Dim.32	0.892064	1.565024	75.27219
Dim.33	0.884226	1.551274	76.82347

The eigenvalues for each dimension of the factor analysis of mixed data (FAMD) is included in Table A.7. As per the Kaiser criterion, dimensions with eigenvalues above 1 are retained. Therefore, 22 dimensions are retained, explaining a cumulative variance of 58.6 %. Table A.8 is the contribution each variable makes to the dimension of the FAMD. I highlighted in green contributions above 10% and highlighted in yellow variables that contribute 10% or more to the first 22 dimensions; the other variables were removed from the clustering analysis due to their limited contribution.

Table A.8: Contribution of variables to each dimension in factor analysis on mixed data

	Dim.1	Dim.2	Dim.3	Dim.4	Dim.5	Dim.6	Dim.7	Dim.8	Dim.9	Dim.10	Dim.11	Dim.12	Dim.13	Dim.14	Dim.15	Dim.16	Dim.17	Dim.18	Dim.19	Dim.20	Dim.21	Dim.22
Edu	1.976353	15.67118	7.934134	3.931083	2.509682	10.01348	5.098026	11.31264	10.62948	11.91196	16.95149	14.59168	16.98242	26.37449	26.21187	42.56541	48.43154	32.18765	35.39957	23.38299	58.53166	7.356058
Dwelling_own	0.567421	0.778784	1.571052	1.848957	11.24117	3.411285	1.772128	18.93075	23.23302	14.50955	14.86687	17.92477	8.855041	22.85877	29.09361	11.80147	10.844	1.20078	14.6235	10.14993	2.750195	4.39725
Dwelling	1.233438	5.252084	4.40961	4.554964	14.65075	17.00486	5.020331	9.968218	16.54176	15.48284	17.29207	19.82344	20.00096	17.47307	22.14637	25.41408	15.78415	23.93592	22.48343	10.65442	21.12306	42.41221
Internet	1.824633	2.646423	1.948548	1.724795	1.707107	8.933577	4.684565	8.053117	1.085775	2.648961	17.63821	12.98857	10.1038	11.36475	6.0285	8.290892	13.51447	33.2968	16.3711	39.25987	6.158461	20.9713
Urban	0.293528	0.008221	1.143765	0.531891	0.827201	3.492111	2.753282	3.926499	12.77267	4.575959	4.509128	2.889471	1.584227	0.233053	0.471463	1.231806	1.103473	0.182721	0.090879	1.275213	0.071918	6.26E-06
Region	0.754572	1.397821	4.760787	2.227989	13.89128	8.941572	14.78378	10.31962	0.571548	0.476274	9.946198	2.037637	4.641129	2.870465	0.826269	1.854477	0.096583	0.283178	0.039503	1.017145	0.546703	0.210263
Hd_age	0.401517	1.998151	1.755639	2.62412	12.73899	0.134837	0.004726	11.11634	1.913532	0.018932	0.000332	0.103296	0.020374	0.534325	0.009468	0.070018	0.065229	0.069658	2.063664	0.108075	0.540272	0.196189
Remittance	0.163027	0.746108	0.098322	0.81292	0.849155	0.278265	10.78204	3.558992	5.258421	8.064864	2.916512	2.497508	0.367509	0.486181	0.045621	2.530689	0.513809	0.157999	1.023023	0.109561	0.129396	3.990779
Basic_ag_equipment	1.379269	2.951077	0.447691	3.644333	0.517083	0.482414	13.28167	1.92333	3.734506	1.608497	0.099817	0.119626	0.19721	0.754595	0.002356	0.20486	0.004186	0.026422	0.182807	0.653579	1.279174	0.055543
Hh_size	1.194648	0.007623	5.562196	0.129084	1.357911	22.24842	0.01279	0.006406	2.645636	0.014452	0.110624	0.037073	0.91669	3.035187	1.688701	0.008015	0.683455	0.063117	0.324592	0.099682	0.000169	0.601771
Crop_earnings_income	4.467555	0.012919	0.06068	11.86597	1.909673	0.003238	1.047252	0.047509	0.559179	0.066627	0.560619	0.915104	1.544722	0.153782	0.002041	0.185533	0.448363	1.303243	0.123673	1.963669	0.050125	0.007901
Livestockcapital_area	5.312948	0.131048	2.192943	11.57688	0.759983	0.041057	0.391492	0.1008	0.037667	2.407465	0.072486	0.361259	3.043108	0.833856	0.030369	0.225919	0.000716	0.02912	0.180685	0.137871	0.011097	0.162244
Percent_market	5.052146	0.172406	0.257068	14.05059	2.192334	0.115052	0.107366	0.139036	0.019394	0.042716	0.677649	1.201352	0.886656	0.013807	0.000422	0.009674	0.096894	1.545892	7.70E-05	1.822405	0.036428	0.509772
Income_hhsize	0.630773	12.00461	11.00194	0.017284	0.403001	0.010869	0.046238	0.005525	3.337401	5.042353	0.008699	0.635991	3.493308	0.087457	1.700954	0.241443	0.112683	0.062061	0.27323	0.14074	0.096467	0.231547
Area	1.767531	3.292638	12.74625	0.26035	0.127555	1.014312	4.533257	0.372968	1.023963	0.055866	0.131476	1.165529	0.022571	2.88777	0.389457	0.471219	1.002197	0.567048	0.145959	0.133049	0.06758	0.0326
Other_income	5.503589	10.01968	0.000468	0.685231	3.368482	0.29507	2.002145	0.272302	0.249293	0.454246	1.024628	0.693583	0.241518	0.058144	0.005296	0.002798	0.000417	0.147421	0.233945	0.949459	0.095543	0.003682
Year	0.721151	14.79343	9.289156	0.156469	0.509741	4.039487	2.765319	0.970319	0.262129	0.697865	0.002914	0.14089	0.115096	0.104517	0.015675	0.029858	0.075947	0.001851	0.055732	0.059621	0.038934	0.073397
Agincome_totalincome	11.72513	0.852738	2.611628	0.007945	0.515502	0.551098	3.921338	0.74021	0.175074	0.65925	0.598913	2.250369	0.153183	0.628461	0.681211	0.010601	0.055018	0.191862	0.363171	0.788857	0.088001	0.002731
Croppedarea_area	10.27862	0.577025	0.557589	0.920766	0.062267	0.266334	0.381467	0.540729	0.381061	3.120827	0.071529	1.756608	0.655813	0.363684	0.09901	0.047381	0.290697	0.546931	0.091657	0.127408	0.082639	0.599329
Water_area	11.13453	1.099909	0.125885	6.135504	1.129173	0.259041	2.389064	0.167904	0.012449	1.385216	0.091429	0.421438	0.081253	0.144131	0.00813	0.101338	0.045058	0.003017	0.003419	0.17835	0.042277	0.04848
Hh_income_work	0.929806	3.717559	1.388474	2.469692	5.434071	7.346395	5.380853	5.108999	1.887156	2.353998	0.716508	2.074588	1.261837	0.031768	0.882768	0.862926	0.454717	0.154684	1.170768	0.03113	0.017638	0.23906
Hh_ag_workers	2.842738	7.601417	7.965729	1.178138	0.094709	0.137541	0.631966	0.023581	0.402813	0.310406	0.126531	0.605864	0.528361	0.014983	0.049208	0.095165	0.156581	0.063654	0.006862	0.158743	0.19051	0.316126
Hv_fc	0.593898	0.065181	0.408189	4.76476	0.510386	1.361616	0.882169	1.912037	0.032339	0.513476	5.741716	2.219776	2.076696	2.394203	1.29356	0.221601	0.8813	1.086755	0.004948	0.001001	1.642392	5.307665
Sales	1.914908	0.41891	0.092005	3.806241	5.269211	0.012144	1.132411	0.017557	0.950884	0.192479	0.416363	1.606204	0.027248	0.334086	0.630239	0.955415	0.041494	0.107562	0.040521	1.407912	1.24694	2.964081
Sheep_goat	1.20657	0.007599	0.18138	8.50363	0.157135	2.028092	1.279882	1.531581	0.225184	1.672846	0.015971	0.071671	4.919857	0.278852	0.944739	1.019903	0.002952	0.014594	0.91283	0.087258	1.912632	0.001029
Nonag_capital	0.10959	0.675567	0.952032	0.002534	2.964674	3.625716	0.567207	0.035685	0.868578	1.578592	0.161085	1.596862	0.338945	2.147774	4.1872	0.128329	3.253927	2.150809	2.326513	2.611016	0.086264	5.625645
Land_income	8.601	0.024983	5.498729	0.878802	0.009279	0.424982	0.726962	0.808777	1.129158	0.065859	0.001998	0.72538	0.075973	0.91181	0.000615	0.191946	0.094378	0.192831	0.037297	0.00076	0.683188	0.274648
Ag_income	7.910992	5.077482	7.985762	0.002994	0.784963	0.542481	1.677605	0.345451	2.867401	1.665625	0.371635	0.162997	1.205683	0.740479	3.61E-06	0.251224	0.00114	0.15011	0.078542	0.554806	0.494543	0.441596
Ex_hh_labour	2.27923	0.659617	2.363686	0.112274	0.317249	0.914941	0.408526	0.172201	0.219677	3.67749	0.410274	0.49265	0.575871	0.06844	0.112432	0.00242	0.362607	0.090708	0.003058	0.138669	0.193939	0.0014
Ownership_rental	1.191782	0.209005	2.396154	7.42E-05	2.237076	0.816153	5.897879	1.507931	0.000808	3.560295	0.378482	0.587523	0.075172	1.125753	0.371443	0.689104	0.455015	0.000175	0.791367	0.707872	0.404806	2.767021
Sex	1.023618	0.28034	0.105153	1.19478	5.458993	0.985615	1.036511	5.094752	3.750439	3.384415	2.561577	2.665766	6.311222	0.544311	1.801233	0.106491	1.080442	0.164947	0.35532	0.988049	0.147719	0.161822
Advanced_ag_equipment	2.091978	2.951825	1.620065	2.753758	2.518032	0.011822	1.888261	0.353454	1.733089	5.024584	1.322141	3.175737	6.145238	0.138463	0.243821	0.038165	0.045033	0.009098	0.119238	0.229422	1.08004	0.022164
Intermediate_ag_equipment	2.921517	3.896637	0.567291	6.625199	2.976185	0.256127	2.71149	0.614782	1.488521	2.755221	0.204126	1.459791	2.551308	0.00859	0.025941	0.139832	0.001516	0.011378	0.079125	0.071461	0.159288	0.014696

A.3 Cluster results

Table A.9: Cluster means and standard deviations for continuous variables and number of responses and percentage for categorical variables based on household type.

Variable (unit) [variable code]	Response	Specialised	Village	Diversified	Landlord
Number of households		650 (18.43)	1085 (30.77)	1130 (32.05)	661 (18.75)
Characteristics of head of household					
Age of head of HH (yr) [Hd_age]		51.88 (13.41)	49.50 (13.61)	50.86 (13.33)	53.19 (15.17)
Sex of head of HH [Sex]	1 (male)	587 (90.31)	976 (89.95)	1007 (89.12)	503 (76.10)
	2 (female)	63 (9.69)	109 (10.05)	123 (10.88)	158 (23.90)
Level of education of head of HH [Hd_edu]	0 (none)	392 (60.31)	846 (77.97)	422 (37.35)	297 (44.93)
	1 (primary)	94 (14.46)	139 (12.81)	215 (19.03)	94 (14.22)
	2 (preparatory)	31 (4.77)	32 (2.95)	82 (7.26)	30 (4.54)
	3 (general secondary)	7 (1.08)	9 (0.83)	16 (1.42)	13 (1.97)
	4 (technical secondary -3 years)	73 (11.23)	42 (3.87)	308 (27.26)	108 (16.34)
	5 (technical secondary - 5 years)	3 (0.46)	2 (0.18)	9 (0.80)	9 (1.36)
	6 (middle institute)	10 (1.54)	3 (0.28)	11 (0.97)	12 (1.82)
	7 (higher institute)	3 (0.46)	0 (0.00)	8 (0.71)	7 (1.06)
	8 (university)	37 (5.69)	11 (1.01)	56 (4.96)	80 (12.10)
	9 (postgraduate)	0 (0.00)	1 (0.09)	3 (0.27)	11 (1.66)
HH characteristics					
Size of HH [Hh_size]		4.53 (1.97)	5.54 (2.64)	4.79 (2.09)	4.11 (2.01)

Variable (unit) [variable code]	Response	Specialised	Village	Diversified	Landlord
HH region [Region]	Lower Egypt	479 (73.69)	241 (22.21)	593 (52.48)	356 (53.86)
	Middle Egypt	20 (3.08)	559 (51.52)	181 (16.02)	103 (15.58)
	Upper Egypt	151 (23.23)	285 (26.27)	356 (31.50)	202 (30.56)
Urban/rural [Urban]	1 (urban)	74 (11.38)	118 (10.88)	100 (8.85)	121 (18.31)
	2 (rural)	576 (88.62)	967 (89.12)	1030 (91.15)	540 (81.69)
Housing type [Dwelling]	1 (apartment)	416 (64.00)	211 (19.45)	653 (57.79)	402 (60.82)
	2 (more than one apartment)	9 (1.38)	9 (0.83)	18 (1.59)	10 (1.51)
	3 (villa/house)	72 (11.08)	132 (12.17)	237 (20.97)	101 (15.28)
	4 (village house)	138 (21.23)	649 (59.82)	159 (14.07)	117 (17.70)
	5 (one room or more in same unit)	8 (1.23)	71 (6.54)	38 (3.36)	23 (3.48)
	6 (one independent room or more)	6 (0.92)	13 (1.20)	23 (2.04)	7 (1.06)
	7 (cottage/tent)	0 (0.00)	0 (0.00)	1 (0.09)	1 (0.15)
	8 (cemetery)	0 (0.00)	0 (0.00)	1 (0.09)	0 (0.00)
	9 (other/basement)	1 (0.15)	0 (0.00)	0 (0.00)	0 (0.00)
Housing ownership or rental type [Dwelling_own]	1 (owned)	530 (81.54)	890 (82.03)	930 (82.30)	518 (78.37)
	2 (condominium)	35 (5.38)	35 (3.23)	37 (3.27)	41 (6.20)
	3 (rent, unfurnished)	7 (1.08)	8 (0.74)	3 (0.27)	15 (2.27)
	4 (rent, furnished)	2 (0.31)	3 (0.28)	0 (0.00)	1 (0.15)
	5 (rent, new law)	2 (0.31)	0 (0.00)	5 (0.44)	13 (1.97)
	6 (fringe benefit/grant)	74 (11.38)	149 (13.73)	155 (13.72)	73 (11.04)

Variable (unit) [variable code]	Response	Specialised	Village	Diversified	Landlord
Highest level of education within HH [Edu]	0 (none)	322 (49.54)	758 (69.86)	73 (6.46)	216 (32.68)
	1 (primary)	93 (14.31)	156 (14.38)	137 (12.12)	69 (10.44)
	2 (preparatory)	47 (7.23)	58 (5.35)	108 (9.56)	43 (6.51)
	3 (general secondary)	9 (1.38)	11 (1.01)	32 (2.83)	19 (2.87)
	4 (technical secondary -3 years)	69 (10.62)	48 (4.42)	563 (49.82)	140 (21.18)
	5 (technical secondary - 5 years)	5 (0.77)	5 (0.46)	14 (1.24)	6 (0.91)
	6 (middle institute)	12 (1.85)	6 (0.55)	30 (2.65)	16 (2.42)
	7 (higher institute)	5 (0.77)	3 (0.28)	15 (1.33)	9 (1.36)
	8 (university)	83 (12.77)	36 (3.32)	151 (13.36)	129 (19.52)
	9 (postgraduate)	5 (0.77)	4 (0.37)	7 (0.62)	14 (2.12)
Type of internet access [Internet]	1 (dsl)	25 (3.85)	23 (2.12)	51 (4.51)	78 (11.80)
	2 (usb modem)	7 (1.08)	6 (0.55)	3 (0.27)	14 (2.12)
	3 (dial-up)	15 (2.31)	7 (0.65)	57 (5.04)	28 (4.24)
	4 (through neighbours)	10 (1.54)	5 (0.46)	16 (1.42)	28 (4.24)
	5 (none)	591 (90.92)	1044 (96.22)	1003 (88.76)	509 (77.00)
	6 (other)	2 (0.31)	0 (0.00)	0 (0.00)	4 (0.61)
Total HH income per capita (2012 EGP) [Income_hhsize]		11133 (16083)	5987 (10112)	11987 (20828)	21118 (59058)
Agricultural details					
Agricultural capital					
Area of agricultural land (feddan) [Area]		1.70 (2.33)	6.95 (191.24)	1.29 (3.14)	1.52 (3.76)
Advanced agricultural equipment [Advanced_ag_equipment]	1 (yes)	142 (21.85)	237 (21.84)	240 (21.24)	23 (3.48)
	2 (no)	508 (78.15)	848 (78.16)	890 (78.76)	638 (96.52)
Intermediate agricultural equipment [Intermediate_ag_equipment]	1 (yes)	185 (28.46)	311 (28.66)	342 (30.27)	38 (5.75)
	2 (no)	465 (71.54)	774 (71.34)	788 (69.73)	623 (94.25)

Variable (unit) [variable code]	Response	Specialised	Village	Diversified	Landlord
Basic agricultural equipment [Basic_ag_equipment]	1 (yes) 2 (no)	137 (21.08) 513 (78.92)	170 (15.67) 915 (84.33)	236 (20.88) 894 (79.12)	19 (2.87) 642 (97.13)
Number of cattle [Cattle]		1.01 (1.43)	1.38 (1.43)	0.78 (1.11)	0.25 (0.74)
Number of sheep and goat [Sheep_goat]		0.44 (1.59)	1.07 (2.88)	0.96 (5.16)	0.28 (1.40)
Total livestock capital (2012 EGP) [Livestock_capital]		15414 (18734)	21437 (22525)	18739 (20250)	5266 (14375)
Agricultural income and expenses					
Total income from crops (2012 EGP) [Crop_income]		23480 (37433)	17896 (32577)	22788 (58445)	0.00 (0.00)
Income from animal products e.g. poultry, honey, dairy (2012 EGP) [Sales]		186.99 (1985)	122.79 (727.93)	142.24 (1533)	68.86 (954.35)
Income from rent of land (2012 EGP) [Land_income]		304.76 (1813)	52.13 (505.01)	150.50 (1304)	3273 (7869)
Cost of land rental (2012 EGP) [Land_expense]		1107 (5510)	1295 (2799)	1341 (8843)	365.22 (3841)
Total agricultural income (2012 EGP) [Ag_income]		24021 (37672)	18115 (32691)	23098 (58499)	3346 (7939)
Agricultural resource use					
Cropped area (feddan) [Cropped_area]		2.37 (2.94)	1.72 (2.15)	1.76 (3.51)	0.00 (0.00)
Total agricultural water use (m3) [Water_use]		11730 (16054)	4362 (6181)	5258 (9778)	0.00 (0.00)
Number of HH agricultural workers [Hh_ag_workers]		1.49 (1.16)	1.83 (1.44)	2.47 (0.94)	0.72 (0.58)
Number of hired agricultural workers [Ex_hh_ag_workers]		1.16 (5.46)	0.95 (3.66)	0.26 (1.25)	0.00 (0.09)
Agricultural efficiency					

Variable (unit) [variable code]	Response	Specialised	Village	Diversified	Landlord
Cropping intensity [Croppedarea_area]		1.49 (0.56)	1.64 (0.58)	1.64 (0.60)	0.00 (0.00)
Ratio of crop earnings to crop income [Crop_earnings_income]		0.51 (0.34)	0.36 (0.30)	0.36 (0.34)	0.00 (0.00)
Cropping income per unit area (2012 EGP/feddan)[Income_area]		11295 (10456)	10999 (8274)	13343 (13628)	0.00 (0.00)
Ratio of high-value to field crop [Hv_fc]		0.15 (0.33)	0.06 (0.16)	0.05 (0.17)	0.00 (0.00)
Ratio of crop production sold at market [Percent_market]		0.49 (0.34)	0.35 (0.28)	0.32 (0.32)	0.00 (0.00)
Ratio of owned to rented land [Ownership_rental]		0.70 (0.44)	0.62 (0.47)	0.64 (0.45)	0.84 (0.36)
Water use per unit area (m3/feddan) [Water_area]		5406 (2224)	2454 (450.26)	2853 (751.46)	0.00 (0.00)
Livestock capital per feddan (2012 EGP/feddan) [Livestockcapital_area]		17888 (41082)	34692 (51004)	34101 (59195)	10931 (40880)
Ratio of hired agricultural workers to household workers [Ex_hh_labour]		0.13 (0.29)	0.16 (0.30)	0.05 (0.16)	0.00 (0.04)
Ratio of agricultural to total income [Agincome_totalincome]		0.62 (0.34)	0.70 (0.31)	0.46 (0.32)	0.07 (0.14)
Non-agricultural income and capital					
Total HH income from off-farm employment (2012 EGP) [Hh_income_work]		6335 (15714)	4291 (13950)	8280 (25602)	9914 (29640)
Income from remittance (2012 EGP) [Remittance]		1182 (10271)	685.54 (4193)	739.96 (4420)	1442 (7810)
Other income (2012 EGP) [Other_income]		5874 (14575)	2490 (9368)	8062 (25620)	42174 (120431)
Total non-agricultural income (2012 EGP) [Nonag_income]		17186 (35020)	9643 (24771)	25439 (58344)	68399 (209784)

Variable (unit) [variable code]	Response	Specialised	Village	Diversified	Landlord
Total non-agricultural capital (2012 EGP) [Nonag_capital]		2184 (19047)	1495 (10553)	1054 (11137)	6198 (91030)
Survey year [Year]	12	450 (69.23)	906 (83.50)	134 (11.86)	316 (47.81)
	18	200 (30.77)	179 (16.50)	996 (88.14)	345 (52.19)

A.4 Cluster evolution

Table A.10: Cluster transitions between 2012 and 2018

2012 cluster	No. of households in 2012	2018 cluster	No. of households in 2018
Specialised	68	Specialised	69
Specialised	1	Village	1
Specialised	117	Diversified	122
Specialised	42	Landlord	43
Specialised	241	Abandonment	322
Village	28	Specialised	28
Village	100	Village	104
Village	267	Diversified	276
Village	49	Landlord	51
Village	556	Abandonment	838
Diversified	3	Specialised	3
Diversified	46	Diversified	47
Diversified	13	Landlord	13
Diversified	84	Abandonment	121
Landlord	9	Specialised	9
Landlord	4	Village	4
Landlord	20	Diversified	21
Landlord	31	Landlord	31
Landlord	217	Abandonment	273
New_landowner	51	Specialised	51
New_landowner	40	Village	40
New_landowner	257	Diversified	266
New_landowner	122	Landlord	124
Specialised	32	Survey_Exit	32
Village	66	Survey_Exit	66
Diversified	13	Survey_Exit	13
Landlord	52	Survey_Exit	52

2012 cluster	No. of households in 2012	2018 cluster	No. of households in 2018
New_survey_entrant	0	Specialised	40
New_survey_entrant	0	Village	30
New_survey_entrant	0	Diversified	264
New_survey_entrant	0	Landlord	83

Table A.11: Cluster means and standard deviations for continuous variables and number of responses and percentage for categorical variables for 2012 households based on household type and whether the household abandoned agricultural activity or not.

Variable (unit) [variable code]	Response	Specialised		Village		Diversified		Landlord	
		Abandon	Remain	Abandon	Remain	Abandon	Remain	Abandon	Remain
Number of households		241	223	556	436	84	62	217	64
Characteristics of head of household									
Age of head of HH (yr) [Hd_age]		51.99 (13.22)	51.74 (13.23)	50.01 (13.16)	49.81 (12.63)	56.69 (10.36)	57.27 (9.14)	53.13 (14.54)	52.41 (14.16)
Sex of head of HH [Sex]	1 (male)	214 (88.80)	201 (90.13)	502 (90.29)	403 (92.43)	77 (91.67)	59 (95.16)	156 (71.89)	52 (81.25)
	2 (female)	27 (11.20)	22 (9.87)	54 (9.71)	33 (7.57)	7 (8.33)	3 (4.84)	61 (28.11)	12 (18.75)
Level of education of head of HH [Hd_edu]	None	172	152	448	340	21 (25.00)	12 (19.35)	126	45 (70.31)
	Primary	(71.37)	(68.16)	(80.58)	(77.98)	22 (26.19)	17 (27.42)	(58.06)	5 (7.81)
	Preparatory	31 (12.86)	33 (14.80)	65 (11.69)	62 (14.22)	4 (4.76)	5 (8.06)	23 (10.60)	2 (3.12)
	General second	10 (4.15)	8 (3.59)	14 (2.52)	12 (2.75)	0 (0.00)	2 (3.23)	3 (1.38)	1 (1.56)
	Technical second -3	1 (0.41)	1 (0.45)	4 (0.72)	2 (0.46)	26 (30.95)	19 (30.65)	2 (0.92)	5 (7.81)
	yr	15 (6.22)	13 (5.83)	17 (3.06)	13 (2.98)	2 (2.38)	0 (0.00)	24 (11.06)	0 (0.00)
	Technical second -5	2 (0.83)	1 (0.45)	1 (0.18)	1 (0.23)	4 (4.76)	0 (0.00)	3 (1.38)	1 (1.56)

Variable (unit) [variable code]	Response	Specialised		Village		Diversified		Landlord	
	yr	3 (1.24)	2 (0.90)	1 (0.18)	0 (0.00)	2 (2.38)	2 (3.23)	4 (1.84)	0 (0.00)
	Middle institute	0 (0.00)	1 (0.45)	0 (0.00)	0 (0.00)	2 (2.38)	5 (8.06)	1 (0.46)	4 (6.25)
	Higher institute	7 (2.90)	12 (5.38)	6 (1.08)	5 (1.15)	1 (1.19)	0 (0.00)	29 (13.36)	1 (1.56)
	University	0 (0.00)	0 (0.00)	0 (0.00)	1 (0.23)			2 (0.92)	
	Postgraduate								
HH characteristics									
Size of HH [Hh_size]		4.65 (1.92)	4.95 (2.01)	5.94 (2.89)	6.04 (2.82)	4.85 (2.29)	4.56 (1.88)	4.21 (1.90)	4.55 (1.93)
HH region [Region]				147 (26.44)	106 (24.31)				
	Lower Egypt	188 (78.01)	185 (82.96)	248 (44.60)	213 (48.85)	72 (85.71)	55 (88.71)	120 (55.30)	33 (51.56)
	Middle Egypt	7 (2.90)	4 (1.79)	161	117	1 (1.19)	1 (1.61)	29 (13.36)	9 (14.06)
	Upper Egypt	46 (19.09)	34 (15.25)	(28.96)	(26.83)	11 (13.10)	6 (9.68)	68 (31.34)	22 (34.38)
Urban/rural [Urban]		33 (13.69)	13 (5.83)	61 (10.97)	49 (11.24)			57 (26.27)	
	1 (urban)	208	210	495	387	8 (9.52)	5 (8.06)	160	6 (9.38)
	2 (rural)	(86.31)	(94.17)	(89.03)	(88.76)	76 (90.48)	57 (91.94)	(73.73)	58 (90.62)

Variable (unit) [variable code]	Response	Specialised		Village		Diversified		Landlord	
Housing type [Dwelling]	Apartment	151	144	130				134	
	One apartment+	(62.66)	(64.57)	(23.38)	77 (17.66)			(61.75)	37 (57.81)
	Villa/house	3 (1.24)	2 (0.90)	3 (0.54)	3 (0.69)	72 (85.71)	53 (85.48)	2 (0.92)	1 (1.56)
	Village house	18 (7.47)	24 (10.76)	64 (11.51)	40 (9.17)	0 (0.00)	1 (1.61)	17 (7.83)	7 (10.94)
	One room+ same unit	65 (26.97)	47 (21.08)	320	285	10 (11.90)	6 (9.68)	56 (25.81)	16 (25.00)
	One room+	3 (1.24)	2 (0.90)	(57.55)	(65.37)	2 (2.38)	1 (1.61)	7 (3.23)	2 (3.12)
	Cottage/tent	1 (0.41)	3 (1.35)	37 (6.65)	25 (5.73)	0 (0.00)	1 (1.61)	0 (0.00)	0 (0.00)
	Cemetery	0 (0.00)	0 (0.00)	2 (0.36)	6 (1.38)	0 (0.00)	0 (0.00)	0 (0.00)	0 (0.00)
	Other/basement	0 (0.00)	0 (0.00)	0 (0.00)	0 (0.00)	0 (0.00)	0 (0.00)	1 (0.46)	1 (1.56)
		0 (0.00)	1 (0.45)	0 (0.00)	0 (0.00)	0 (0.00)	0 (0.00)	0 (0.00)	0 (0.00)
Housing ownership or rental type [Dwelling_own]	Owned	203	176	456	361			155	
	Condominium	(84.23)	(78.92)	(82.01)	(82.80)	67 (79.76)	48 (77.42)	(71.43)	56 (87.50)
	Rent, unfurnished	10 (4.15)	17 (7.62)	16 (2.88)	12 (2.75)	6 (7.14)	6 (9.68)	18 (8.29)	1 (1.56)
	Rent, furnished	3 (1.24)	3 (1.35)	6 (1.08)	0 (0.00)	1 (1.19)	1 (1.61)	11 (5.07)	1 (1.56)
	Rent, new law	1 (0.41)	1 (0.45)	2 (0.36)	2 (0.46)	0 (0.00)	0 (0.00)	1 (0.46)	0 (0.00)
	Fringe benefit/grant	0 (0.00)	1 (0.45)	0 (0.00)	0 (0.00)	0 (0.00)	0 (0.00)	4 (1.84)	0 (0.00)
		24 (9.96)	25 (11.21)	76 (13.67)	61 (13.99)	10 (11.90)	7 (11.29)	28 (12.90)	6 (9.38)

Variable (unit) [variable code]	Response	Specialised		Village		Diversified		Landlord	
Highest level of education within HH [Edu]	None								
	Primary	160	145	439	324			120	
	Preparatory	(66.39)	(65.02)	(78.96)	(74.31)	11 (13.10)	8 (12.90)	(55.30)	43 (67.19)
	General secondary	37 (15.35)	39 (17.49)	71 (12.77)	73 (16.74)	30 (35.71)	19 (30.65)	27 (12.44)	6 (9.38)
	Technical second -3 yr	12 (4.98)	8 (3.59)	15 (2.70)	14 (3.21)	5 (5.95)	5 (8.06)	5 (2.30)	3 (4.69)
	Technical second -5 yr	1 (0.41)	1 (0.45)	4 (0.72)	2 (0.46)	0 (0.00)	2 (3.23)	2 (0.92)	1 (1.56)
	Technical second -5 yr	17 (7.05)	12 (5.38)	15 (2.70)	14 (3.21)	27 (32.14)	21 (33.87)	23 (10.60)	5 (7.81)
		2 (0.83)	1 (0.45)	2 (0.36)	1 (0.23)	1 (1.19)	0 (0.00)	3 (1.38)	0 (0.00)
	Middle institute	3 (1.24)	2 (0.90)	1 (0.18)	0 (0.00)	5 (5.95)	0 (0.00)	4 (1.84)	1 (1.56)
	Higher institute	0 (0.00)	0 (0.00)	0 (0.00)	0 (0.00)	2 (2.38)	2 (3.23)	2 (0.92)	0 (0.00)
	University	8 (3.32)	14 (6.28)	9 (1.62)	7 (1.61)	2 (2.38)	5 (8.06)	29 (13.36)	4 (6.25)
	Postgraduate	1 (0.41)	1 (0.45)	0 (0.00)	1 (0.23)	1 (1.19)	0 (0.00)	2 (0.92)	1 (1.56)
Type of internet access [Internet]	1 (dsl)	5 (2.07)	7 (3.14)	11 (1.98)	7 (1.61)			30 (13.82)	
	2 (usb modem)	4 (1.66)	2 (0.90)	2 (0.36)	3 (0.69)	3 (3.57)	1 (1.61)	11 (5.07)	4 (6.25)
	3 (dial-up)	0 (0.00)	0 (0.00)	0 (0.00)	1 (0.23)	0 (0.00)	2 (3.23)	1 (0.46)	2 (3.12)
	4 (through neighbours)	5 (2.07)	4 (1.79)	3 (0.54)	1 (0.23)	1 (1.19)	1 (1.61)	8 (3.69)	0 (0.00)
		226	209	540	424	3 (3.57)	1 (1.61)	163	3 (4.69)
	5 (none)	(93.78)	(93.72)	(97.12)	(97.25)	77 (91.67)	57 (91.94)	(75.12)	54 (84.38)
	6 (other)	1 (0.41)	1 (0.45)	0 (0.00)	0 (0.00)	0 (0.00)	0 (0.00)	4 (1.84)	1 (1.56)

Variable (unit) [variable code]	Response	Specialised		Village		Diversified		Landlord	
Total HH income per capita (2012 EGP)		9736	9531	5110	5359	7607	15306	22729	25343
[Income_hhsize]		(14411)	(14566)	(6246)	(6046)	(7214)	(40789)	(53870)	(38600)
Agricultural details									
Agricultural capital									
Area of agricultural land (feddan) [Area]		1.61	1.81	1.08	1.30	1.24	1.80	1.41	2.23
		(1.89)	(2.38)	(1.23)	(1.58)	(1.32)	(3.44)	(3.69)	(4.84)
Advanced agricultural equipment	1 (yes)	46 (19.09)	54 (24.22)	115 (20.68)	112 (25.69)			1 (0.46)	0 (0.00)
[Advanced_ag_equipment]	2 (no)	195 (80.91)	169 (75.78)	441 (79.32)	324 (74.31)	18 (21.43)	17 (27.42)	216 (99.54)	64 (100.00)
Intermediate agricultural equipment	1 (yes)	62 (25.73)	71 (31.84)	169 (30.40)	129 (29.59)			7 (3.23)	
[Intermediate_ag_equipmen t]	2 (no)	179 (74.27)	152 (68.16)	387 (69.60)	307 (70.41)	20 (23.81)	16 (25.81)	210 (96.77)	4 (6.25)
Basic agricultural equipment	1 (yes)	46 (19.09)	57 (25.56)	93 (16.73)	66 (15.14)			5 (2.30)	
[Basic_ag_equipment]	2 (no)	195 (80.91)	166 (74.44)	463 (83.27)	370 (84.86)	6 (7.14)	3 (4.84)	212 (97.70)	2 (3.12)
						78 (92.86)	59 (95.16)		62 (96.88)

Variable (unit) [variable code]	Response	Specialised		Village		Diversified		Landlord	
Number of cattle [Cattle]		1.16 (1.49)	1.35 (1.43)	1.44 (1.51)	1.69 (1.67)	1.25 (1.60)	1.55 (1.59)	0.22 (0.85)	0.38 (1.39)
Number of sheep and goat [Sheep_goat]		0.51 (1.84)	0.50 (1.58)	1.22 (3.02)	1.12 (2.77)	1.33 (3.71)	0.85 (3.59)	0.22 (1.00)	0.45 (2.32)
Total livestock capital (2012 EGP) [Livestock_capital]		16012 (18907)	18276 (18612)	20736 (19039)	23544 (20610)	17653 (20485)	21009 (19327)	3154 (10655)	5077 (16480)
Agricultural income and expenses									
Total income from crops (2012 EGP) [Crop_income]		19966 (26845)	25117 (38048)	16123 (20251)	19973 (23579)	15749 (17377)	18171 (23202)	0.00 (0.00)	0.00 (0.00)
Income from animal products e.g. poultry, honey, dairy (2012 EGP) [Sales]		79.89 (340.39)	168.77 (751.16)	167.49 (990.38)	137.42 (773.76)	148.15 (894.52)	219.76 (1078)	5.76 (43.32)	9.38 (46.18)
Income from rent of land (2012 EGP) [Land_income]		335.98 (2213)	186.10 (1075)	51.26 (521.24)	18.00 (224.74)	92.26 (541.61)	782.26 (3918)	3885 (6340)	6556 (11771)
Cost of land rental (2012 EGP) [Land_expense]		905.27 (2696)	1235 (3739)	1267 (2810)	1624 (3412)	1236 (3093)	800.00 (2237)	355.30 (3146)	193.91 (1087)
Total agricultural income (2012 EGP) [Ag_income]		20405 (27219)	25581 (38189)	16377 (20321)	20195 (23637)	15998 (17469)	19197 (24453)	3891 (6342)	6565 (11769)
Agricultural resource use									

Variable (unit) [variable code]	Response	Specialised		Village		Diversified		Landlord	
Cropped area (feddan) [Cropped_area]		2.22 (2.44)	2.63 (2.79)	1.72 (2.07)	2.10 (2.53)	1.91 (2.22)	2.31 (3.68)	0.00 (0.00)	0.00 (0.00)
Total agricultural water use (m3) [Water_use]		10557 (15427)	11318 (12508)	4464 (6135)	5551 (7887)	5326 (6709)	6649 (10737)	0.00 (0.00)	0.00 (0.00)
Number of HH agricultural workers [Hh_ag_workers]		1.02 (1.07)	1.17 (1.08)	1.71 (1.55)	1.86 (1.64)	1.32 (1.36)	1.65 (1.15)	0.43 (0.74)	0.55 (0.69)
Number of hired agricultural workers [Ex_hh_ag_workers]		1.22 (3.46)	1.31 (2.94)	1.18 (4.73)	1.08 (2.36)	0.69 (2.13)	0.95 (2.72)	0.01 (0.15)	0.00 (0.00)
Agricultural efficiency									
Cropping intensity [Croppedarea_area]		1.49 (0.57)	1.54 (0.54)	1.63 (0.58)	1.70 (0.57)	1.65 (0.63)	1.48 (0.56)	0.00 (0.00)	0.00 (0.00)
Ratio of crop earnings to crop income [Crop_earnings_income]		0.51 (0.31)	0.51 (0.31)	0.37 (0.30)	0.39 (0.28)	0.32 (0.29)	0.32 (0.25)	0.00 (0.00)	0.00 (0.00)
Cropping income per unit area (2012 EGP/feddan)[Income_area]		10320 (7274)	10691 (11981)	10377 (7964)	10146 (5287)	9387 (4402)	10061 (7651)	0.00 (0.00)	0.00 (0.00)
Ratio of high-value to field crop [Hv_fc]		0.14 (0.31)	0.12 (0.29)	0.07 (0.17)	0.05 (0.14)	0.05 (0.17)	0.03 (0.10)	0.00 (0.00)	0.00 (0.00)

Variable (unit) [variable code]	Response	Specialised		Village		Diversified		Landlord	
Ratio of crop production sold at market [Percent_market]		0.47 (0.32)	0.43 (0.29)	0.36 (0.28)	0.37 (0.24)	0.33 (0.25)	0.32 (0.25)	0.00 (0.00)	0.00 (0.00)
Ratio of owned to rented land [Ownership_rental]		0.65 (0.47)	0.68 (0.45)	0.61 (0.47)	0.61 (0.47)	0.67 (0.47)	0.78 (0.41)	0.92 (0.27)	0.94 (0.24)
Water use per unit area (m3/feddan) [Water_area]		5026 (2229)	4673 (1937)	2516 (435.94)	2540 (469.84)	2626 (448.92)	2664 (492.52)	0.00 (0.00)	0.00 (0.00)
Livestock capital per unit area (2012 EGP/feddan) [Livestockcapital_area]		21978 (57284)	15379 (20311)	33721 (46676)	30527 (36040)	20685 (25503)	24476 (27643)	6030 (21984)	5714 (18925)
Ratio of hired agricultural workers to household workers [Ex_hh_labour]		0.16 (0.33)	0.20 (0.35)	0.19 (0.32)	0.18 (0.32)	0.14 (0.32)	0.16 (0.32)	0.01 (0.08)	0.00 (0.00)
Ratio of agricultural to total income [Agincome_totalincome]		0.63 (0.33)	0.69 (0.31)	0.71 (0.32)	0.77 (0.29)	0.50 (0.28)	0.51 (0.26)	0.05 (0.06)	0.06 (0.06)
Non-agricultural income and capital									
Total HH income from off-farm employment (2012 EGP) [Hh_income_work]		6236 (12482)	6026 (13675)	4807 (13239)	3473 (8163)	9326 (11316)	9621 (16463)	8808 (17861)	11013 (25994)
Income from remittance (2012 EGP) [Remittance]		1488 (13350)	1675 (15401)	567.72 (2520)	910.50 (5679)	432.14 (1732)	397.26 (1575)	1195 (3951)	1086 (4432)

Variable (unit) [variable code]	Response	Specialised		Village		Diversified		Landlord	
Other income (2012 EGP) [Other_income]		5774 (15316)	4378 (14214)	2394 (11120)	1853 (11451)	4406 (8058)	14257 (49374)	63021 (166326)	79089 (142348)
Total non-agricultural income (2012 EGP) [Nonag_income]		15458 (31105)	14400 (32730)	9452 (19689)	7832 (18796)	16303 (13653)	25162 (49994)	75872 (167735)	94749 (159754)
Total non-agricultural capital (2012 EGP) [Nonag_capital]		2122 (15966)	3840 (28757)	1903 (11289)	1478 (9748)	5874 (26869)	4041 (20847)	4969 (22278)	5597 (20127)
Survey year [Year]		241 (100.00)	223 (100.00)	556 (100.00)	436 (100.00)	84 (100.00)	62 (100.00)	217 (100.00)	64 (100.00)

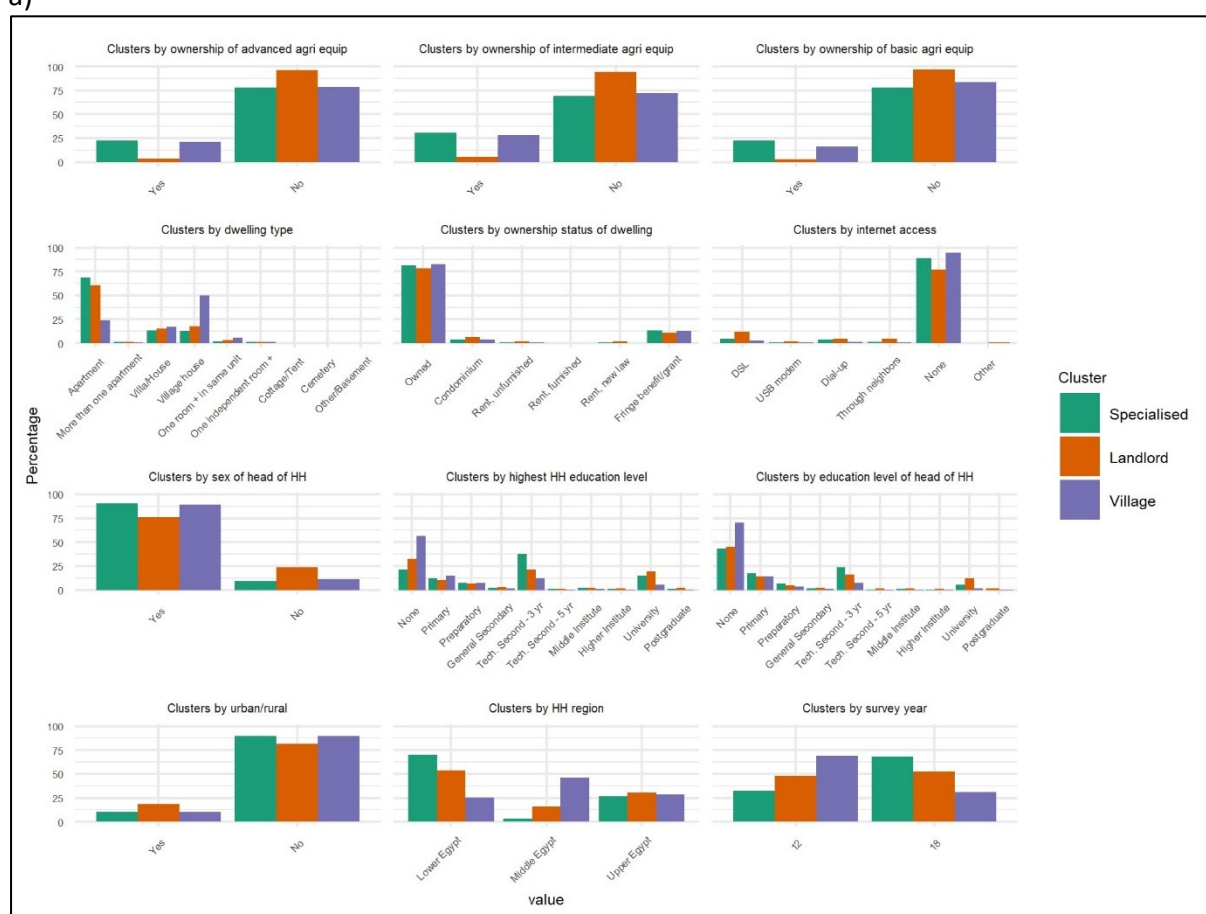
A.5 Alternative number of clusters

A.5.1 Three clusters

Table A.12: Number of households in each cluster and percentage each cluster represents from the whole sample.

Cluster	Number of households	Percentage of households
1 - Specialised	1313	37.2
2 - Landlord	661	18.7
3 - Village	1552	44.0

a)



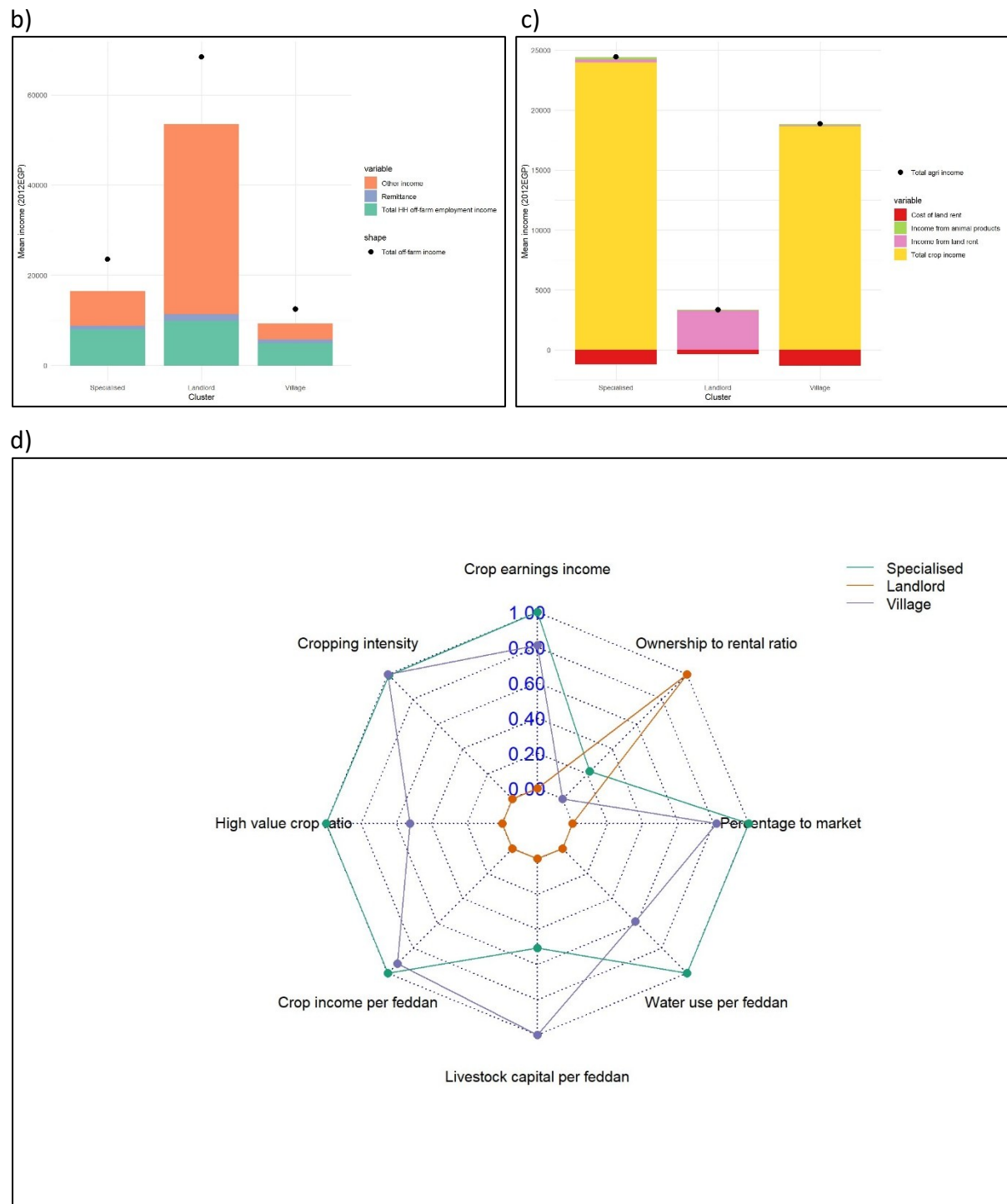


Figure A.4: Summary of results by cluster for 3 clusters, including: a) percentage each response for categorical variables; b) total mean agricultural income and mean constituent components of agricultural income; c) total mean off-farm income and mean constituent components of off-farm income; d) radar chart of mean range standardised efficiency metrics.

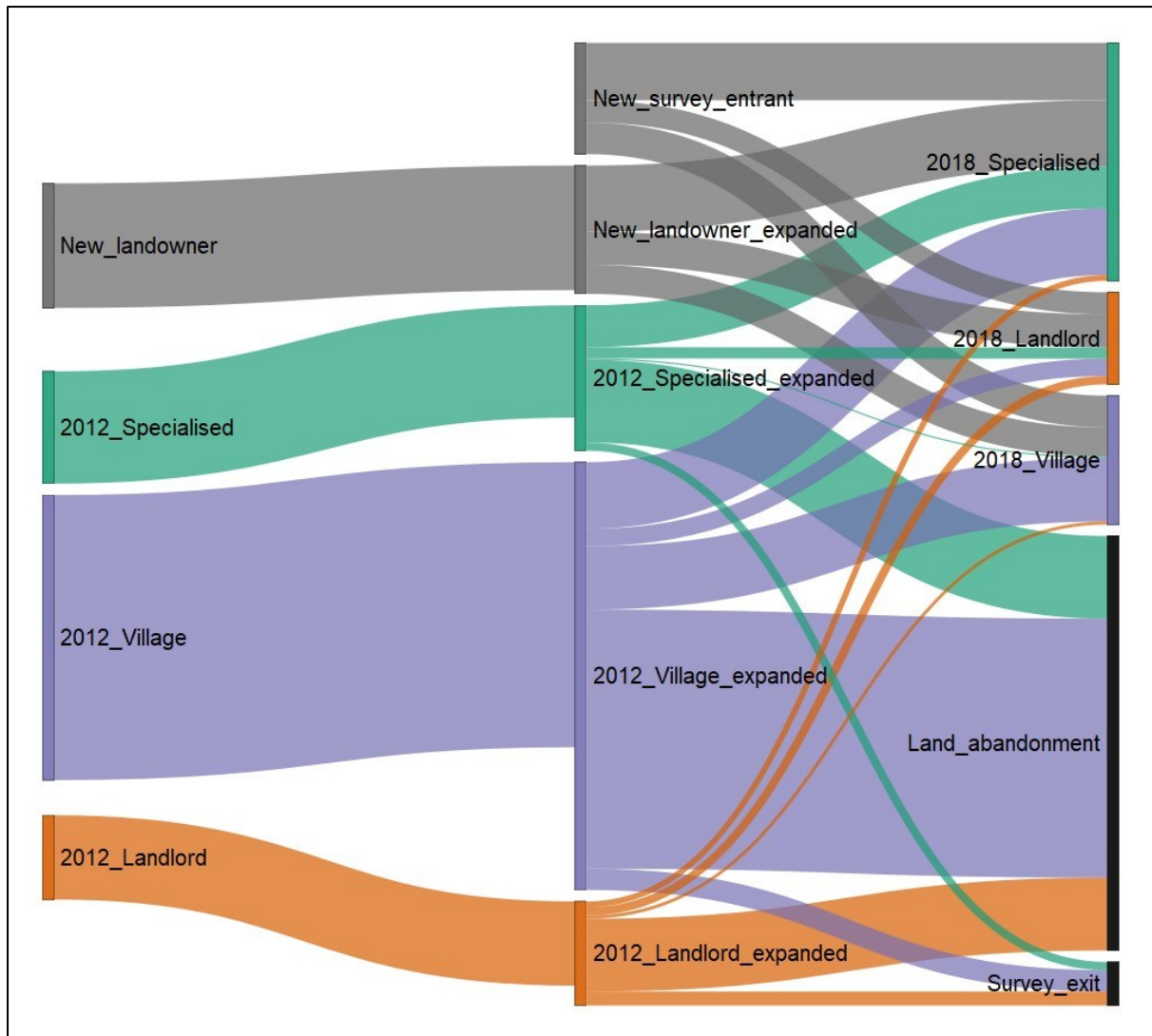


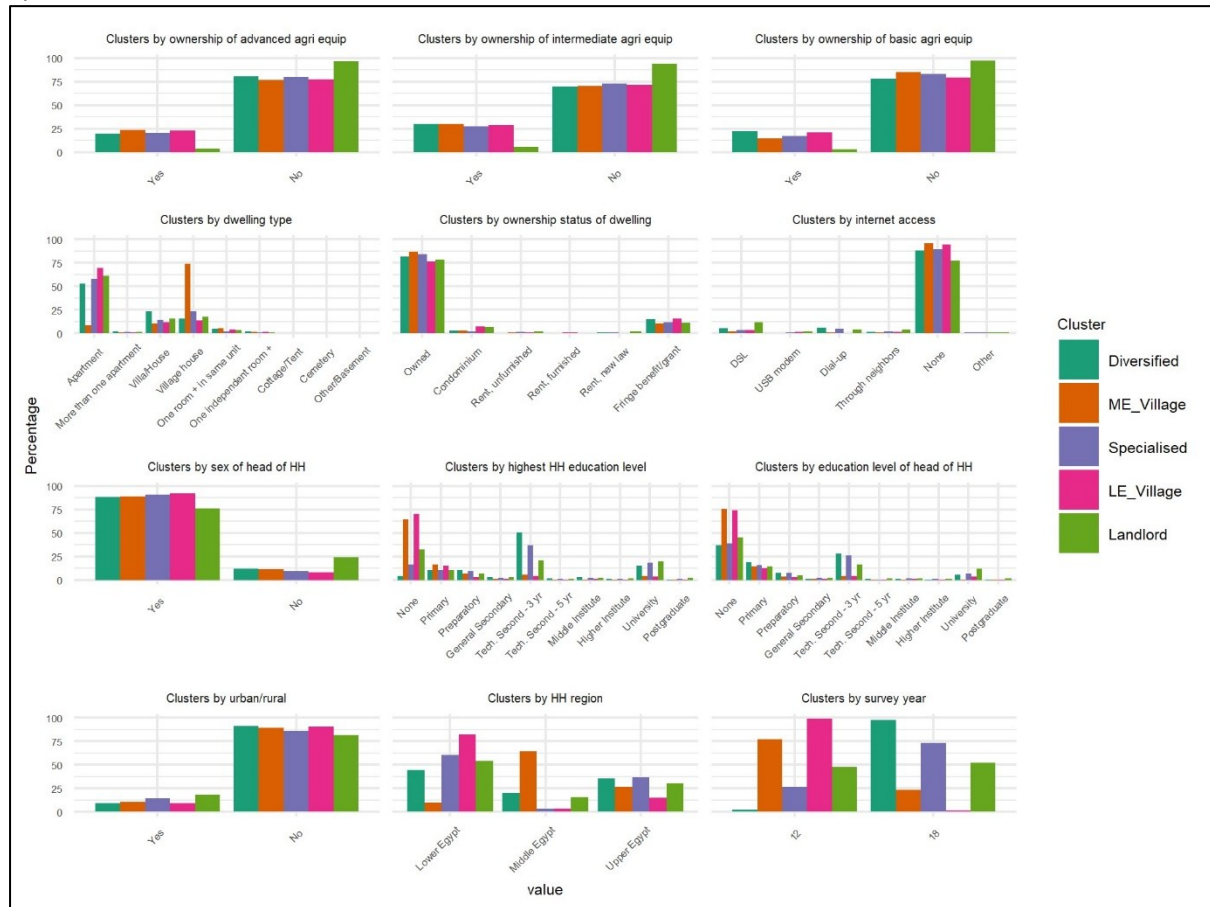
Figure A.5: Sankey plot showing the transition of household clusters, for 3 clusters, from 2012 (left) through the expansion of the 2012 household types (middle) and the 2018 household types (right).

A.5.2 Five clusters

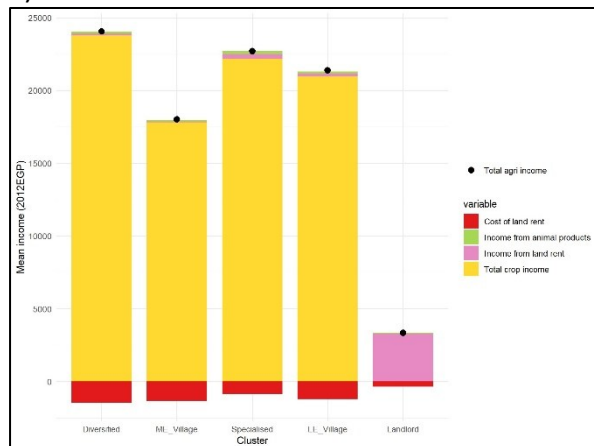
Table A.13: Number of households in each cluster and percentage each cluster represents from the whole sample.

Cluster	Number of households	Percentage of households
1 - Diversified	911	25.8
2 - ME_Village	837	23.7
3 - Specialised	386	10.9
4 - LE_Village	731	20.7
5 - Landlord	661	18.7

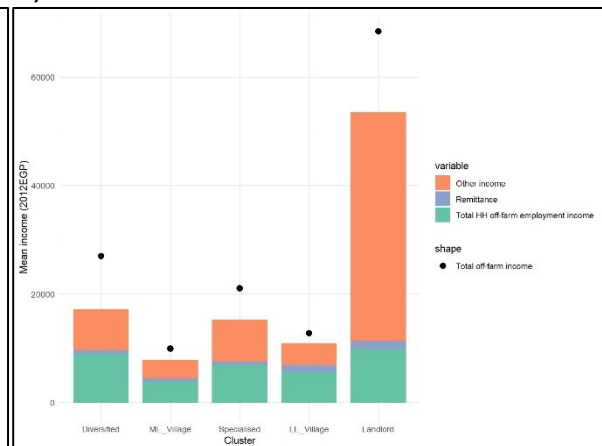
a)



b)



c)



d)

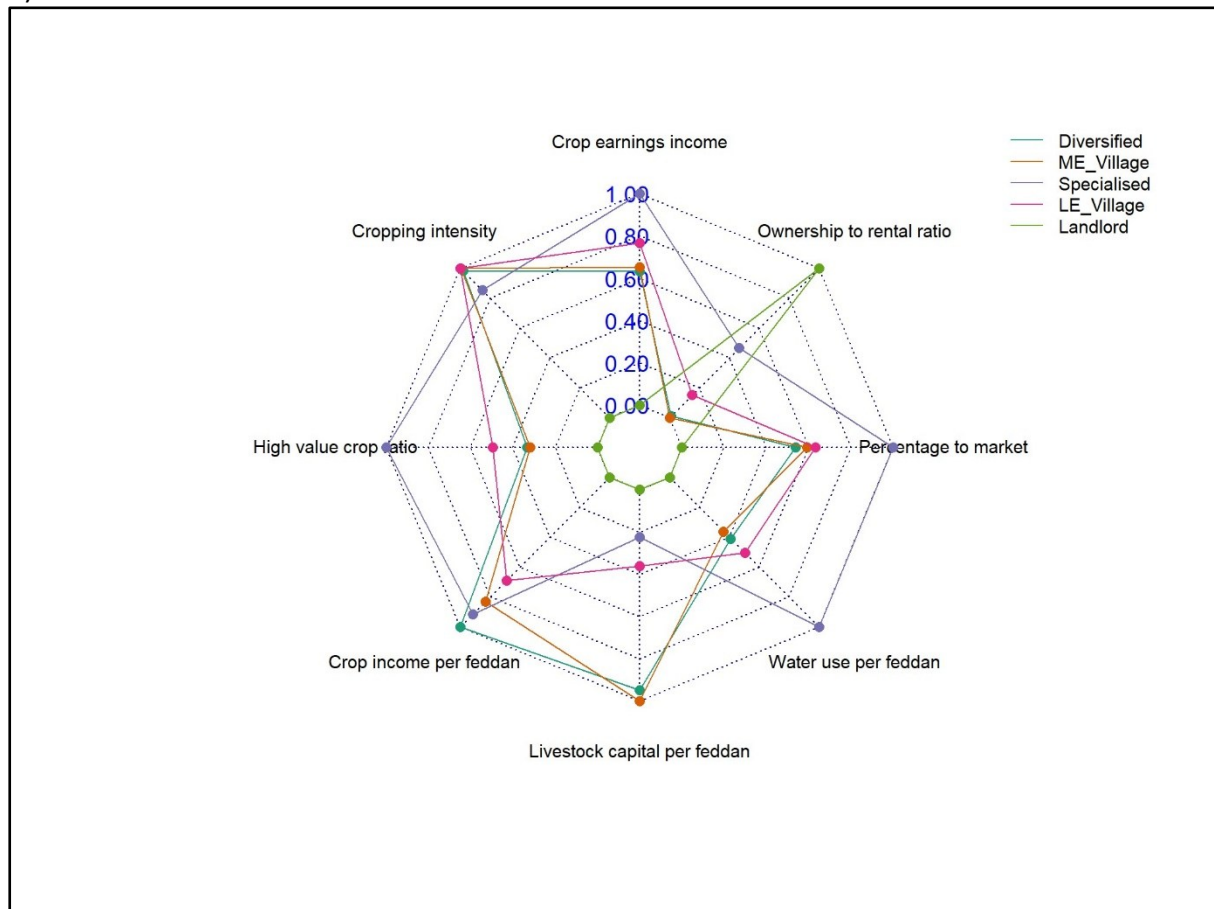


Figure A.6: Summary of results by cluster for 5 clusters, including: a) percentage each response for categorical variables; b) total mean agricultural income and mean constituent components of agricultural income; c) total mean off-farm income and mean constituent components of off-farm income; d) radar chart of mean range standardised efficiency metrics.

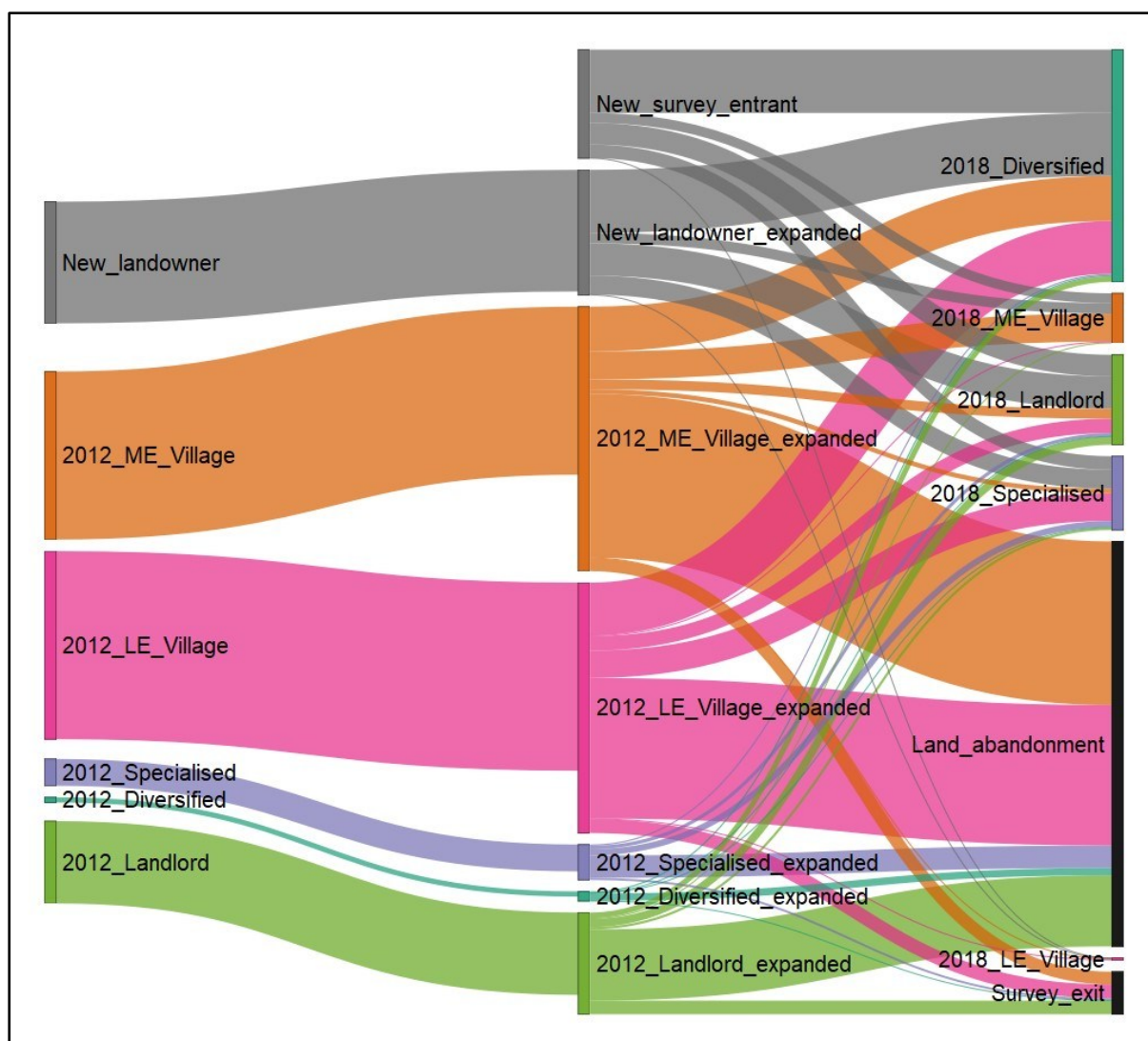


Figure A.7: Sankey plot showing the transition of household clusters, for 3 clusters, from 2012 (left) through the expansion of the 2012 household types (middle) and the 2018 household types (right).

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B Appendix B

This appendix includes:

- B.1: details of the development of the ecohydrological model.
- B.2: details of the SWAT+ calibration.
- B.3: details of cropping patterns.
- B.4: plots of unmanaged land and abandoned land areas.
- B.5: details of demand for domestic production.
- B.6: details of capital sensitivities.
- B.7: details of AFT properties.
- B.8: CRAFTY sensitivity results zip file.

B.1 Ecohydrological model development

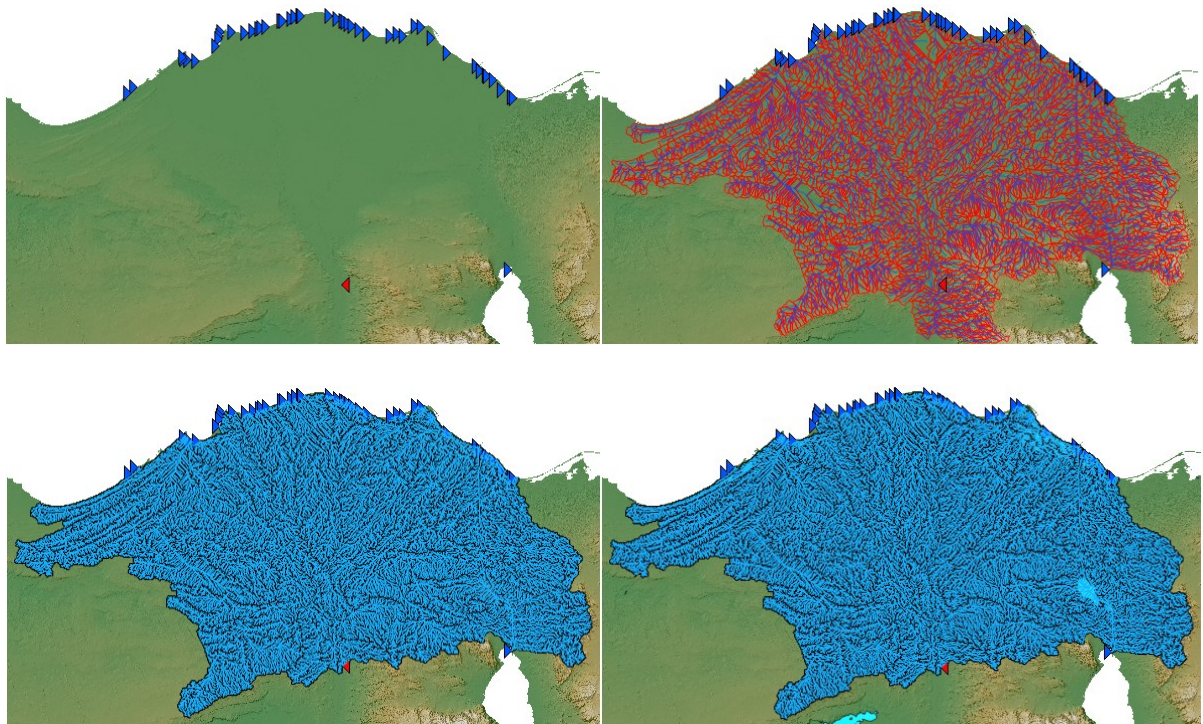


Figure B.1: Watershed delineation stages for Delta region. From top left to bottom right: a) DEM and inlet/outlets; b) Stream shape and subbasins; c) Grids and grid streams; d) Lakes.

The first stage of SWAT+ model development involves watershed delineation using a digital elevation model (DEM) with 90m x 90m resolution and an inlet/outlet shapefile. This process entails the creation of subbasins and stream networks based on the topographic information provided by the DEM and the outlets from the outlet/inlet shapefile. The stream threshold is

set to 1000 grid cells (0.81 km²). This threshold determines the minimum drainage area required to form a stream channel. The resulting delineation creates subbasins (shown in red) and stream shapes (shown in blue) as depicted in

Figure B.1b. A grid size of 10 DEM cells (900m x 900m) is defined for further analysis. This grid is used in conjunction with the inlet information to clip the watershed to the area of interest. The clipped watershed is illustrated in

Figure B.1c. The final step in this initial stage involves adding lakes to the delineated watershed. This completes the basic topographic structure of the model, providing a foundation for subsequent hydrological and land use analyses. Details of the datasets used for this stage of the modelling are included in Table 5.

The next stage in the SWAT+ model development process involves the creation of Hydrologic Response Units (HRUs). This step utilises landuse and soil raster files to define the dominant class of each of these characteristics within each grid cell. Due to the presence of NA (No Data) values along the coastal areas and the grid overlapping with these regions, it was necessary to implement a buffer for soil data. To address this issue, we employed the dominant soil and land use types found in the region, which is sandy soil. This approach ensures continuity in the model and prevents errors that might arise from data gaps. A single slope class is used across the model area, simplifying the topographic representation while still maintaining the essential hydrological characteristics of the landscape. Figure B.2 provides visual representations of the land use and soil maps used in this process. These maps illustrate the spatial distribution of different land-use categories and soil types across the study area.

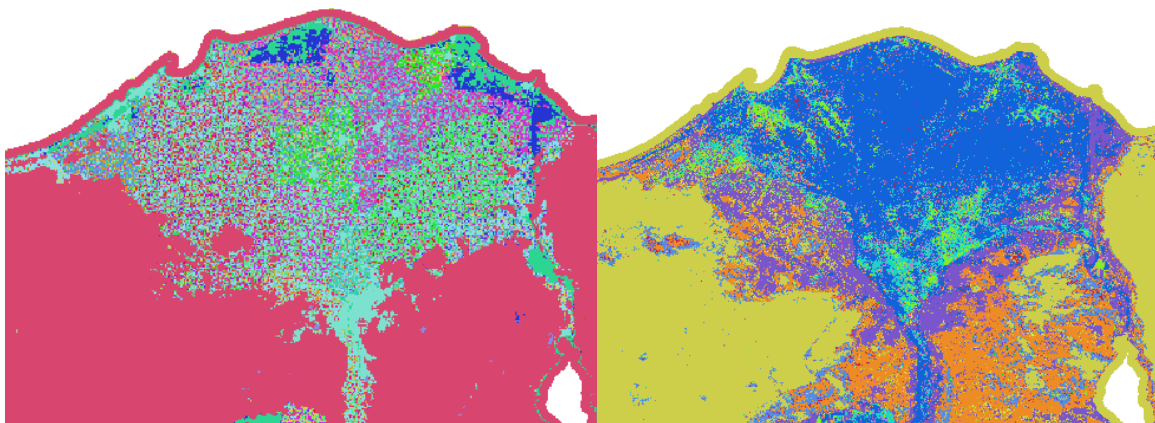


Figure B.2: Input rasters for HRU creation step for Delta region. Left: Landuse raster; right: Soil raster.

We use the inbuilt 'gwflow' (Bailey, Bieger, Arnold, & Bosch, 2020) model to develop this groundwater model. This model utilises the Global Hydrogeology Maps (Gleeson, 2018; Huscroft, Gleeson, Hartmann, & Börker, 2018) and depth to bedrock (Hengl et al., 2017) datasets to define the aquifer properties and thickness.

The final stage of SWAT+ model development involves inputting several key datasets: daily climate and streamflow data; crop management information; and decision tables. Once these inputs are incorporated, the model is ready for execution.

Crops used to model different land use types are included in Table B.1.

Table B.1: Land use type and SWAT+ modelled crop and growing season.

Crop group	SWAT+ plant type (code)	Season
Wheat	Spring wheat (swht)	Winter
Legumes	Dry beans (dryb)	Winter
Field.crops	Onion (onio)	Winter/Summer
Main.veg	Tomato (toma)	Winter/Summer
Other.veg	Potato (pota)	Winter/Summer
Fodder.seasonal	Berseem (brsm)	Winter/Summer
Maize	Corn (corn)	Summer
Fibre	Cotton (cotp)	Summer
Rice	Rice (rice)	Summer
Oil.crops	Peanuts (pnut)	Summer
Alfalfa	Alfalfa (alfa)	Perennial
Fruit.trees	Orange (oran)	Perennial
Date.palm	Date palm (datp)	Perennial
Sugar.cane	Sugarcane (sugc)	Perennial

SWAT+ includes a library of common crops and their properties. Date palm and berseem was not included in this list. After initially running the model, it was clear that some crops were not performing as expected. These include potato and cotton. Therefore, the optimal and minimum temperatures were edited based on the literature of common cultivars being used in Egypt and an iterative manual calibration process. Additionally, date palm and berseem

were added. Table B.2 includes key details of plant types. These values are calibrated for each region during the calibration stage of the modelling.

Table B.2: Key plant before calibration. This includes plant type, days to maturity, optimal and base temperature, biomass-energy conversion rate, years to maturity.

name	plnt_typ	days_mat	tmp_opt	tmp_base	bm_e	yrs_mat
swht	cold_annual	100	23	0	38	0
dryb	warm_annual	90	28	8	28	0
cotp	warm_annual	160	30	17	15	0
rice	warm_annual	160	25	10	22	0
corn	warm_annual	120	25	8	40	0
pnut	warm_annual_t uber	110	28	14	18	0
brsm	warm_annual	120	25	8	25	0
toma	warm_annual	90	29	10	27	0
pota	cold_annual_tub er	100	20	4.4	30	0
onio	cold_annual	100	30	1.6	34	0
sugc	perennial	0	28	11	25	2
datp	perennial	0	28	7	26	10
alfa	perennial	0	21	4	20	2
oran	perennial	0	24	7	15	10

Table B.3 includes details of the fertiliser application rate as derived from Food and Agriculture Organization of the United Nations (2005).

Table B.3: Fertiliser use by crop in the old lands

	n_stress	fert_N_ amount	max_N_fert	P_stress	fert_P_amount	max_P_fert
swht	0.9	18	10	0.9	10	2
dryb	0.9	20	2	0.9	17.5	2
cotp	0.9	17	10	0.9	13.75	2
rice	0.9	14.5	10	0.9	10	2

	n_stress	fert_N_amount	max_N_fert	P_stress	fert_P_amount	max_P_fert
corn	0.9	29	10	0.9	13.75	2
pnut	0.9	20	2	0.9	20	2
brsm	0.9	10	2	0.9	22.5	2
toma	0.9	30	10	0.9	27.5	2
pota	0.9	30	10	0.9	36.25	2
onio	0.9	37	10	0.9	27.5	2
sugc	0.9	38	10	0.9	27.5	2
datp	0.9	85	10	0.9	36.25	2
alfa	0.9	20	2	0.9	13.75	2
oran	0.9	43	10	0.9	17.5	2

We repeated the model development process outlined above for each of the 6 regional submodels. Table B.4 summarises the total and agricultural areas for each submodel and compares this to the national areas.

Table B.4: Areas of hydrological models: Total area, agricultural area, and their percentages of national territories

Region	Total Area (km ²)	Agricultural Area (km ²)	% of Total area	% of Agricultural area
Med	22280	4027	2.16	8.02
Delta	53094	28169	5.14	56.08
Middle	37400	4846	3.62	9.65
Upper	64760	2245	6.27	4.47
Qena	50948	4342	4.93	8.64
Aswan	61172	2505	5.92	4.99
Model total	289655	46132	28.05	91.84
National	1032498	50228.91	100	100

B.2 SWAT+ calibration

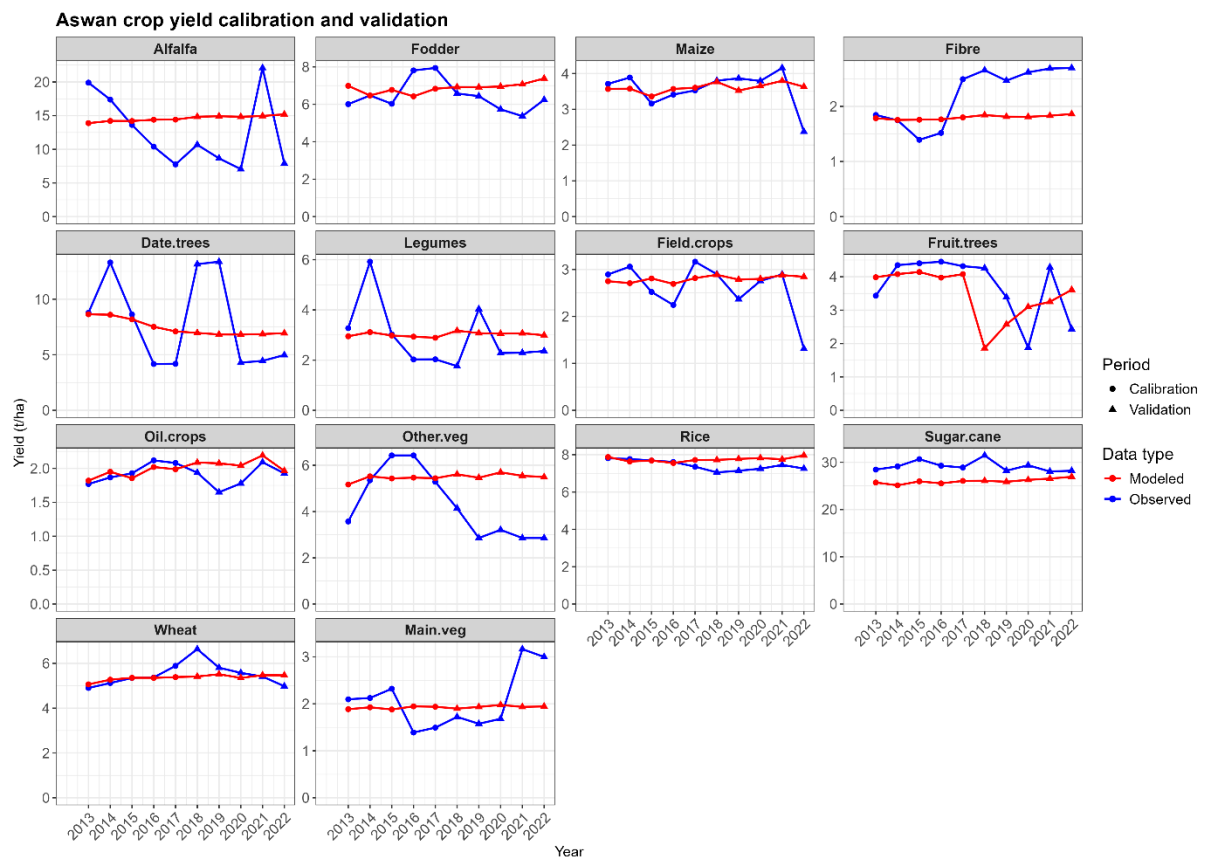
SWAT+ calculates the dry weight of each crop. Therefore, it is necessary to define the moisture content for each crop. Moisture content varies for each crop based on a range of

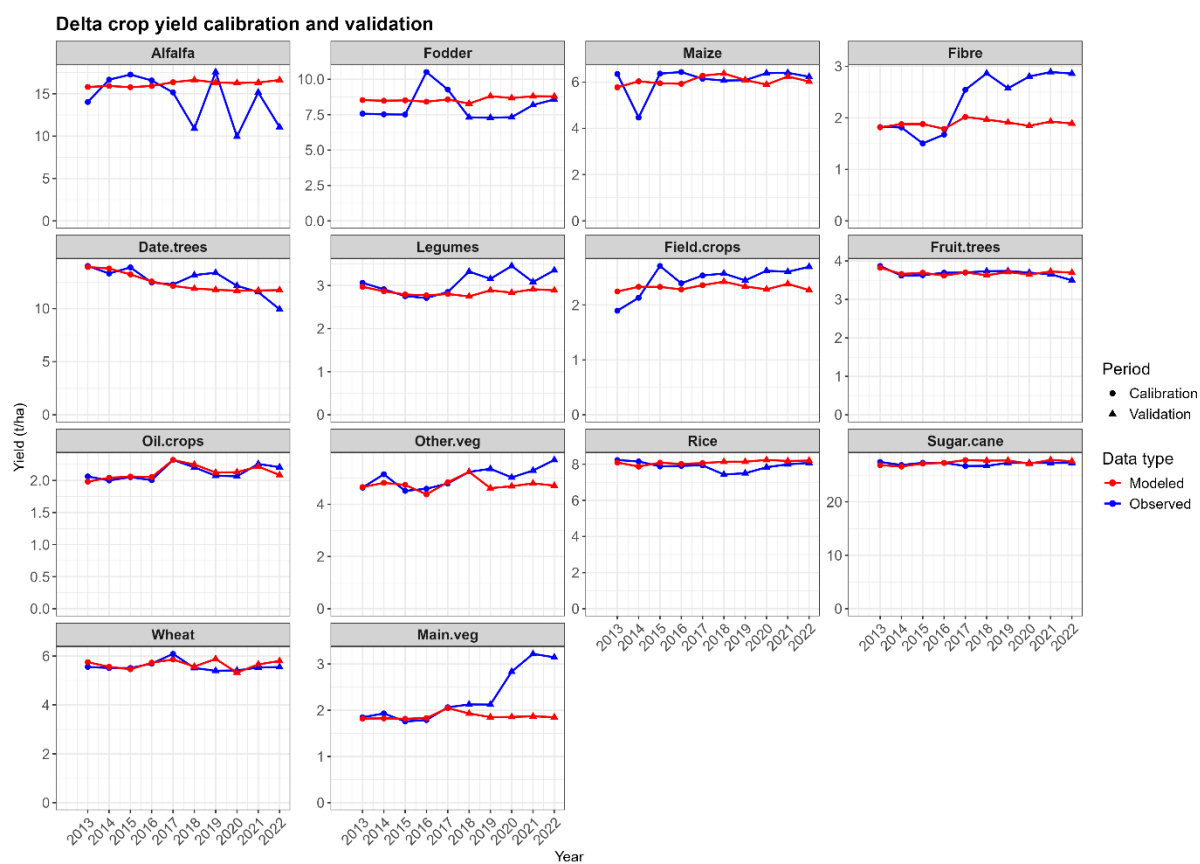
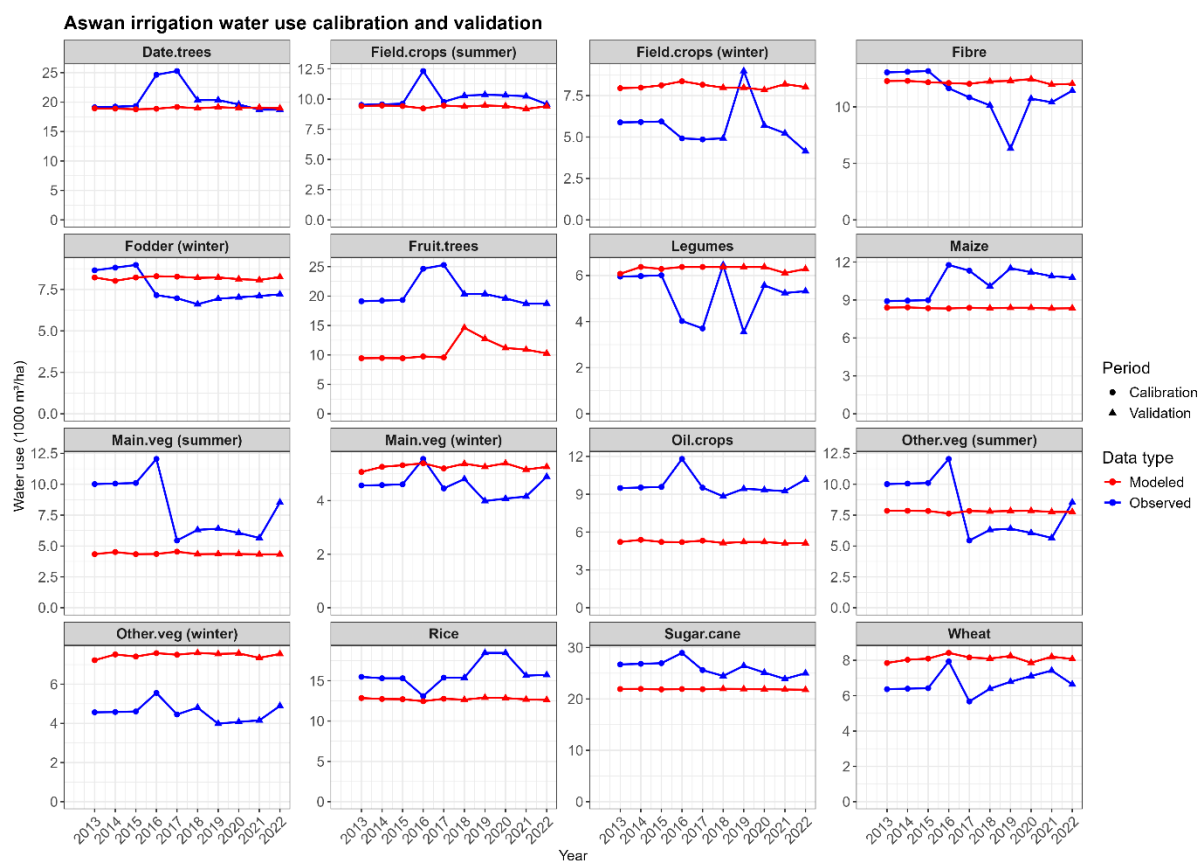
factors. Therefore, using literature, it was possible to define the possible range of the moisture content for each crop (Table B.5). Observed data was scaled by this range, and each calibration run was evaluated against the range of moisture content. The most common moisture content level for each crop and region (minimum, maximum or average) is used to convert the output dry weight yields to wet yields.

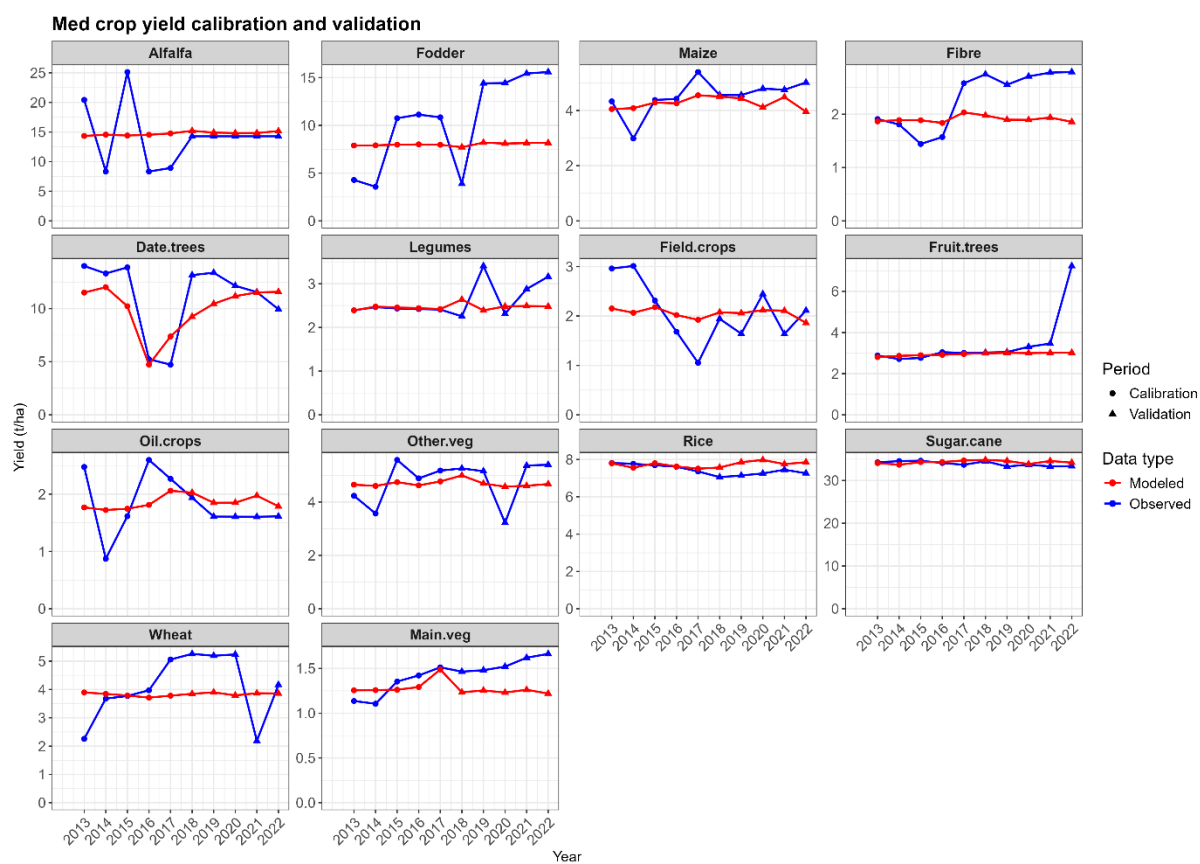
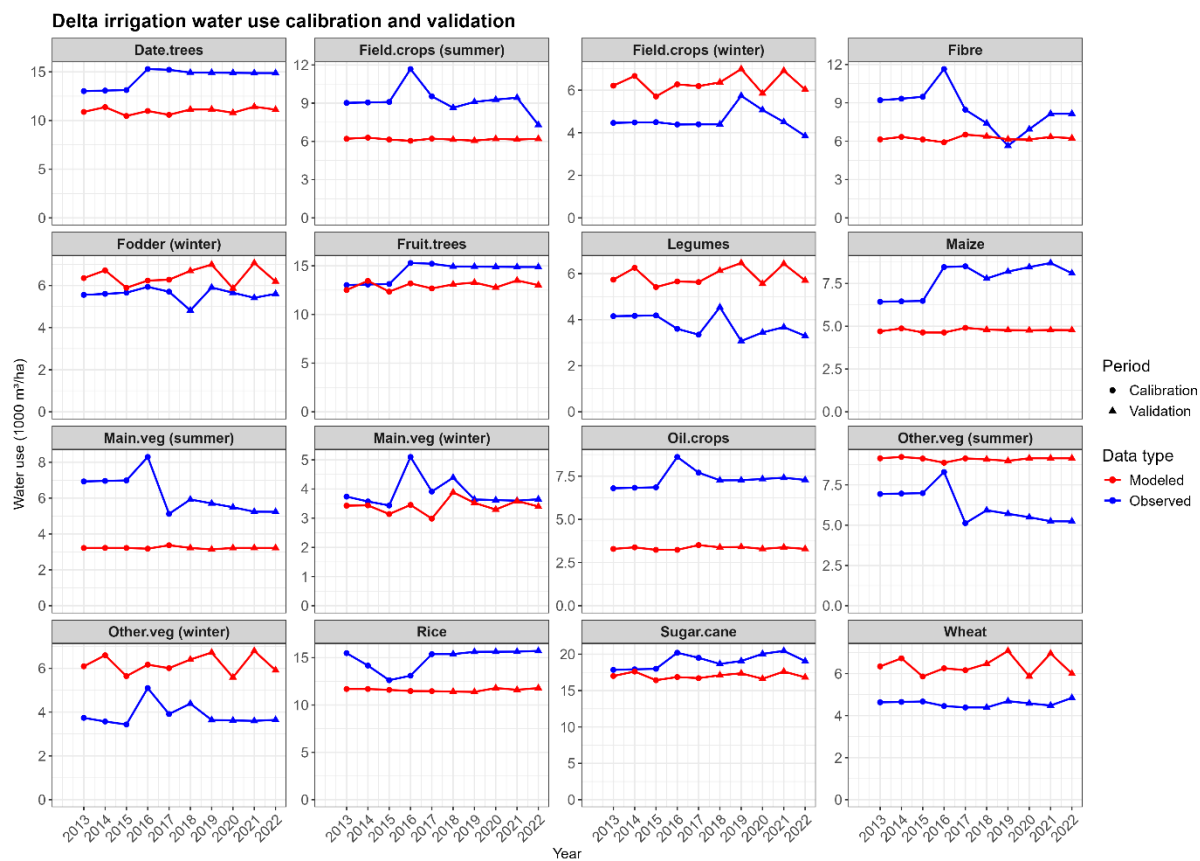
Table B.5: Minimum and maximum moisture content.

name	min	max	References
alfa	75	82.83	https://ucanr.edu/sites/default/files/2011-08/117607.pdf
datp	20	60	(Falade & Abbo, 2007)
oran	72.8	89.8	(Mbogo, Mubofu, Othman, & e, 2010)
sugc	65	75	(Abdelhady, Ibrahim, Mansour, El-Shafie, & Abd El Rahman, 2023; Sindhu, Gnansounou, Binod, & Pandey, 2016)
swht	12	20	(Abo EL-Naga, 2010)
pnut	25	50	(Dey, Mukherjee, & Bal, 1999; Muhammad, Ahmad, & Lawan, 2017)
corn	20	28	(Bo et al., 2021)
rice	12	25	(Nalley, Dixon, Tack, Barkley, & Jagadish, 2016)
dryb	12	20	(Hassan, Afify, El-Shal, & Abd El-Atty, 2015)
cotp	6	12	https://cotton.tamu.edu/wp-content/uploads/sites/27/legacy-files/Harvest/Moisture%20PUB.pdf
pota	75	85	https://felixinstruments.com/blog/why-is-measuring-dry-matter-important-in-potatoes/#:~:text=Potatoes%20have%20a%20water%20content,for%20which%20potatoes%20are%20gr own.
onio	83	92	(Bahnasawy, El-Haddad, El-Ansary, & Sorour, 2004)
brsm	75	85	(Khan, Imtiaz, Sana, Afzal, & Siddiqi, 2018)
toma	89.9106	95.245 9	(Degwale et al., 2022)

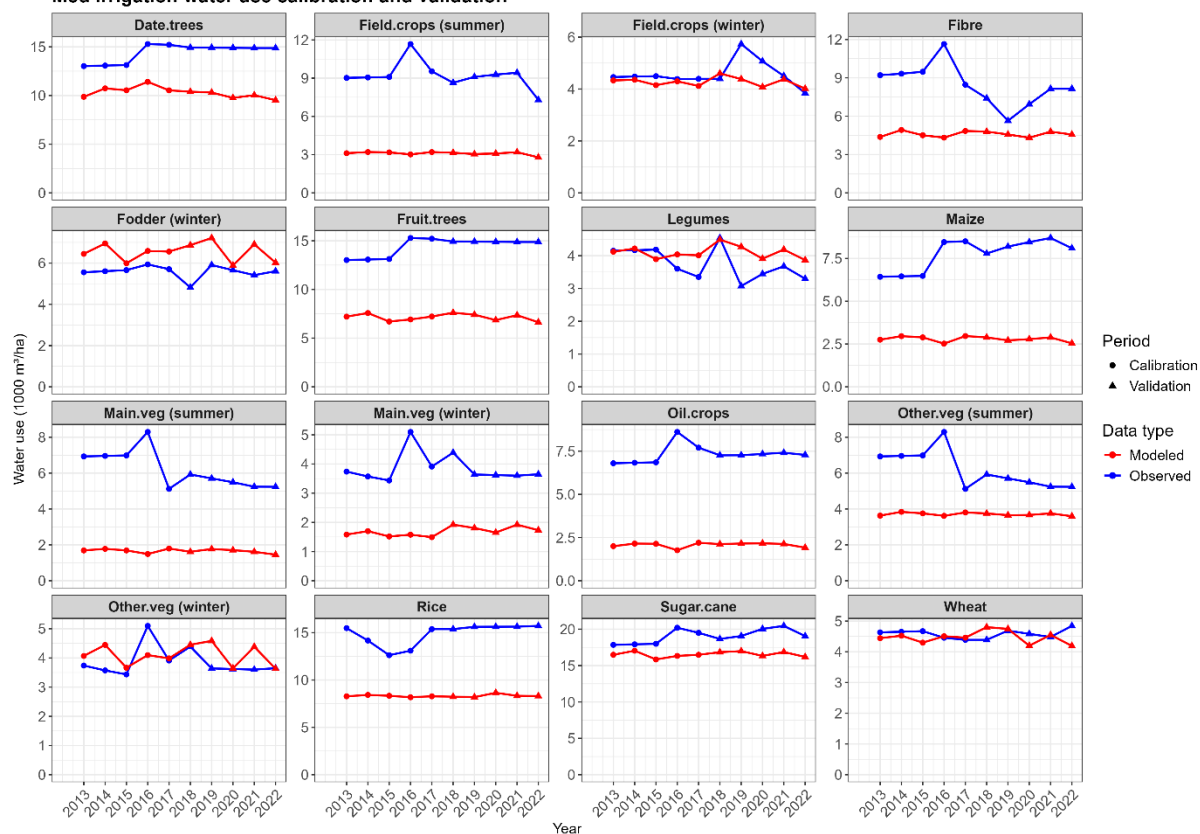
The figures below show the calibration and validation plots for the all crops and regions.



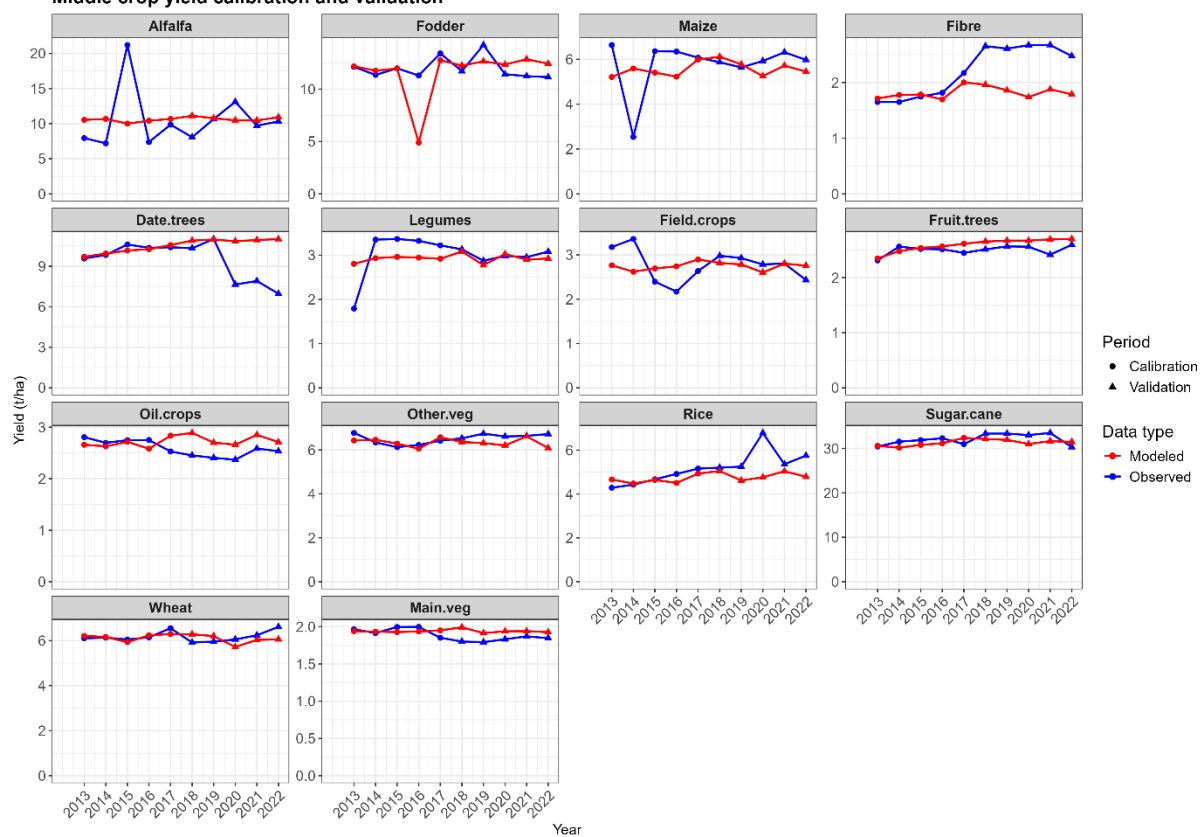


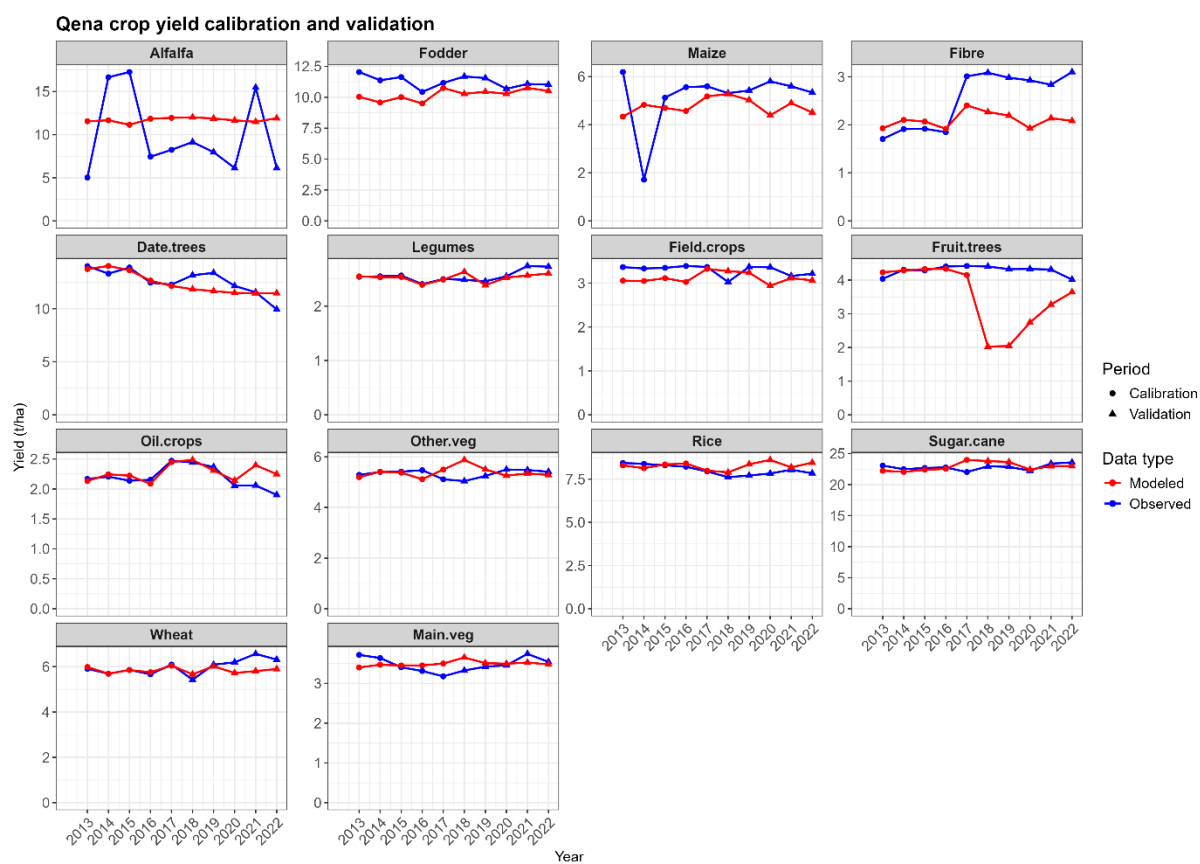
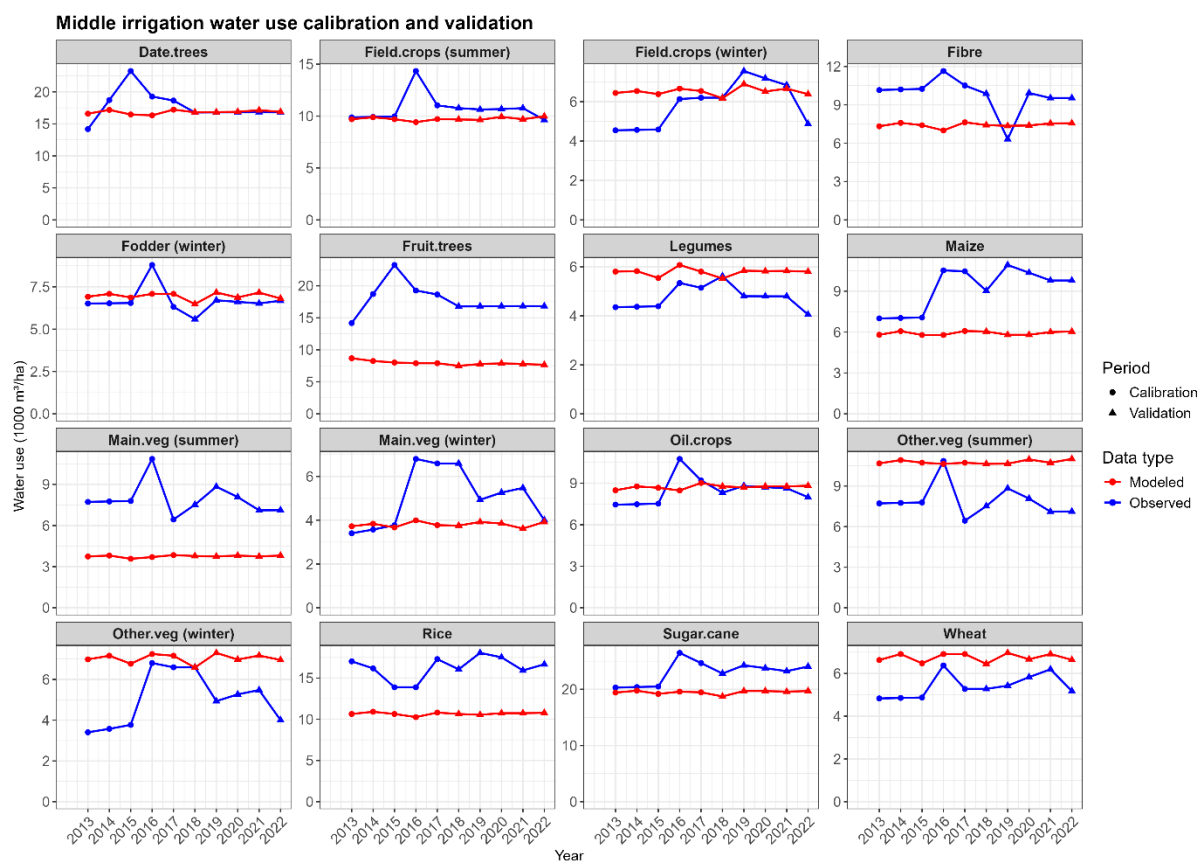


Med irrigation water use calibration and validation

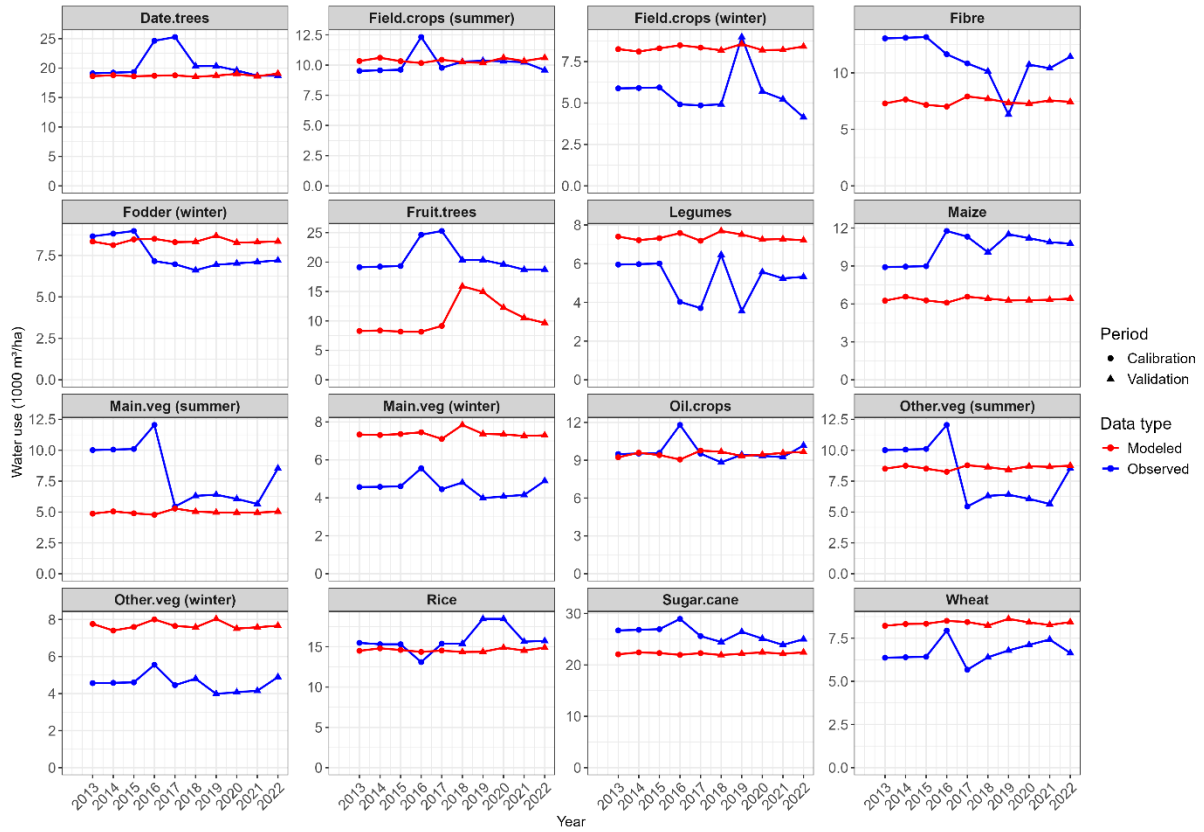


Middle crop yield calibration and validation

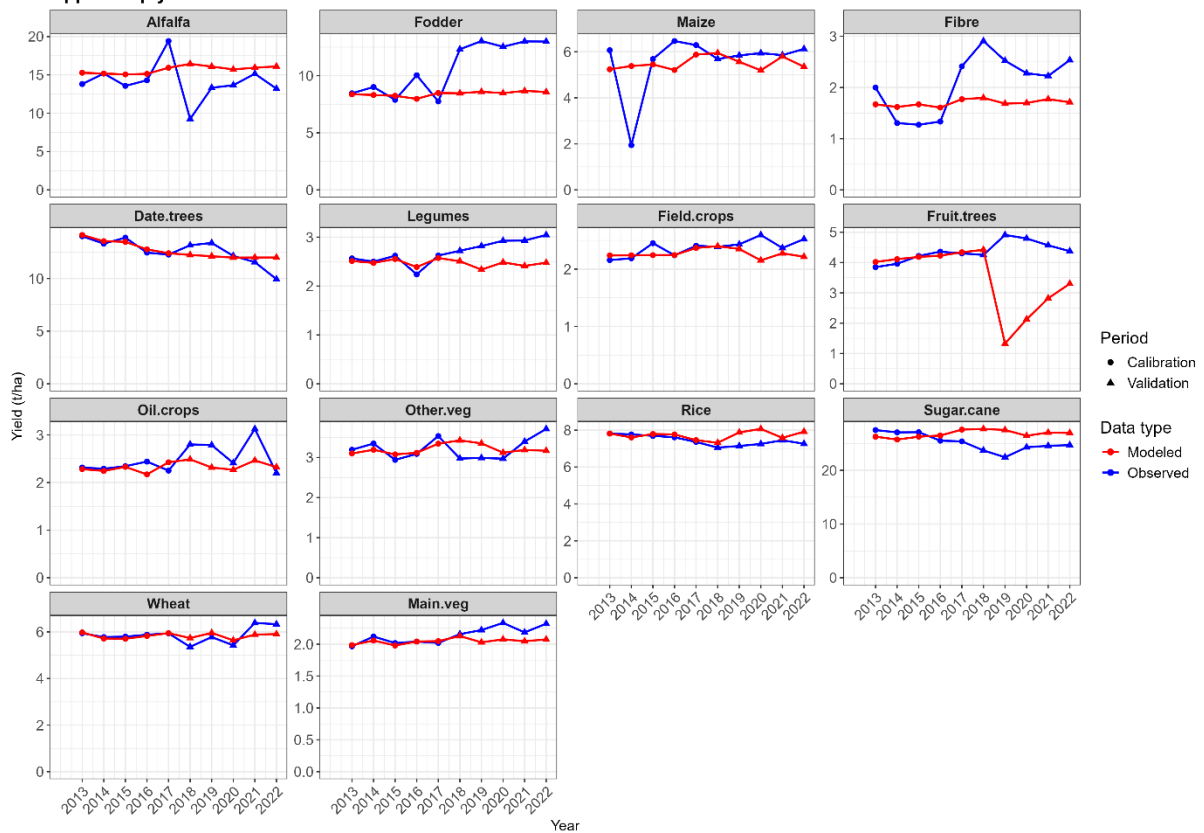


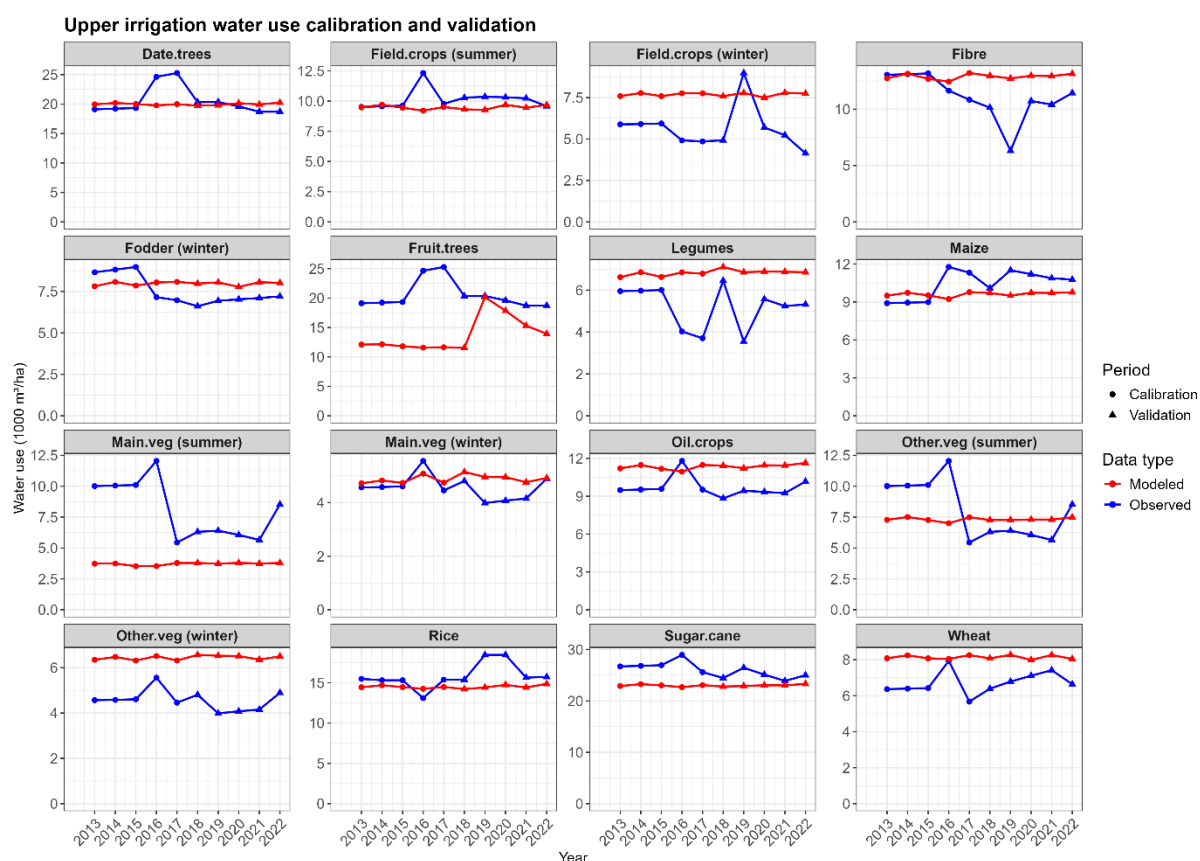


Qena irrigation water use calibration and validation



Upper crop yield calibration and validation





B.3 Cropping patterns

Table B.6 details the cropped areas in 2009/2010 in each of the three growing seasons. Due to the relatively small area of the Nile season, this has not been included in the modelling. Table B.7 includes areas of season crops based on crop groupings used in this model development for the winter and summer seasons.

Table B.6: Total area grown of seasonal crops in each season in feddan in 2009/2010 agricultural year.

Season	Area (feddan)	Percent of total cropped area
Nile	596887	4.53
Summer	5992474	45.50
Winter	6579093	49.96
Total	13168454	100

Table B.7: Total area by crop and season and percentage of total cropped area in 2009/10 agricultural year.

Season	Crops	Total area	Percent of total area
Summer	Fibre.crops.	369124	2.94
Summer	Fodder.seasonal.	613654	4.88
Summer	Main.vegetables.	440303	3.50
Summer	Maize.	1998248	15.89
Summer	Oil.crops.	318311	2.53
Summer	Other.field.crops.	378496	3.01

Summer	Other.vegetables.	781073	6.21
Summer	Rice.	1093264	8.70
Winter	Fodder.seasonal.	1922330	15.29
Winter	Legumes.	231709	1.84
Winter	Main.vegetables.	367425	2.92
Winter	Other.field.crops.	608249	4.84
Winter	Other.vegetables.	359896	2.86
Winter	Wheat.	3089484	24.58
Total		12,571,566	100.00

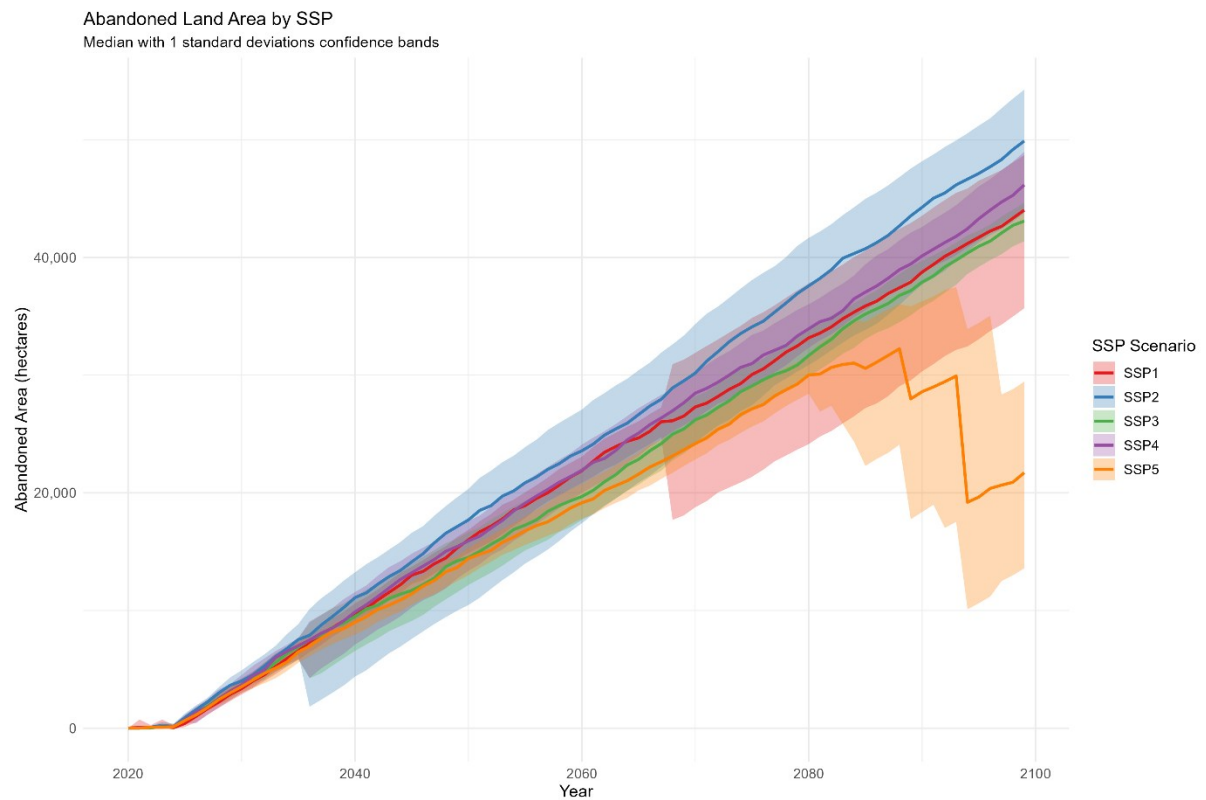
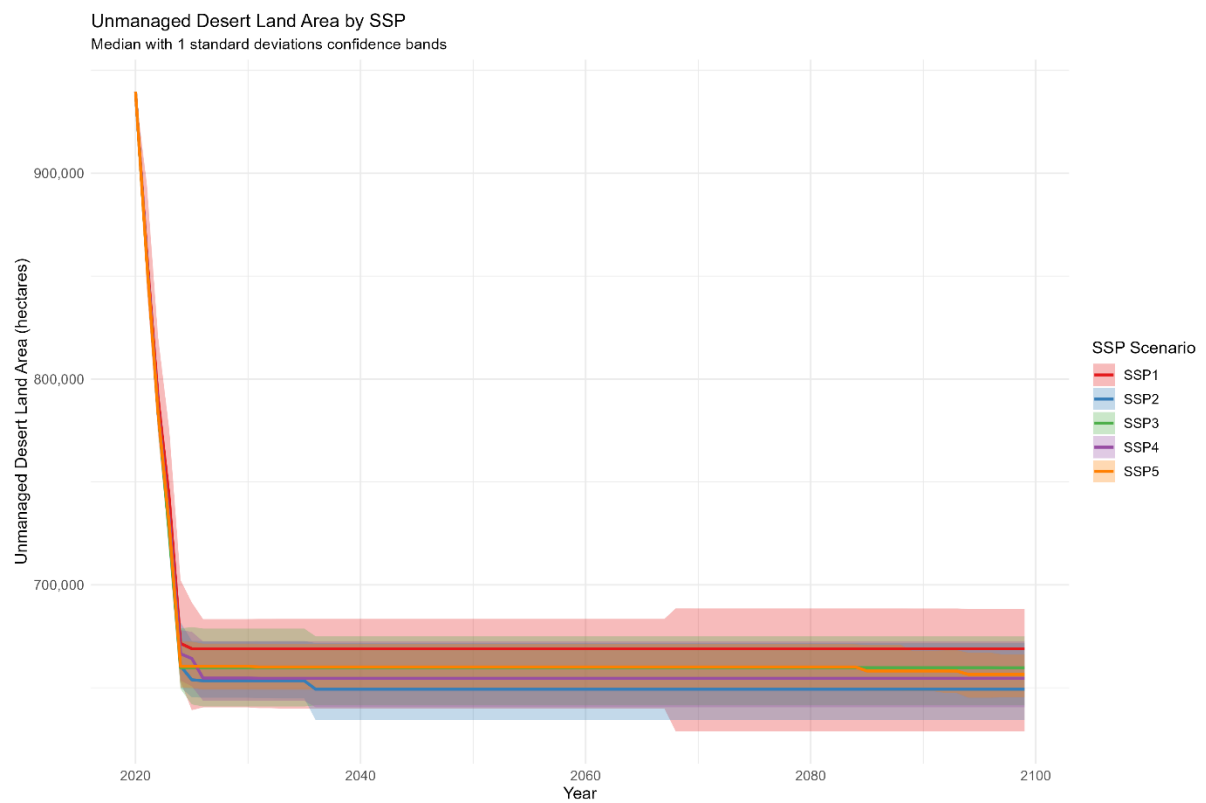
Table B.8: CRAFTY-Egypt AFTs, including labels, names, and descriptions

Label	Name	Description
FSFSS	Fodder_ Fodder_Specialised	Fodder, Fodder cropping pattern by commercial farmer
FSFSV	Fodder_ Fodder_Village	Fodder, Fodder cropping pattern by subsistence farmer
WHOVS	Wheat_Other veg_Specialised	Wheat, Other veg cropping pattern by commercial farmer
WHOVV	Wheat_Other veg_Village	Wheat, Other veg cropping pattern by subsistence farmer
FCMAS	Field crop_Maize_Specialised	Field crop, Maize cropping pattern by commercial farmer
FCMAV	Field crop_Maize_Village	Field crop, Maize cropping pattern by subsistence farmer
FSMVS	Fodder_Main veg_Specialised	Fodder, Main veg cropping pattern by commercial farmer
FSMVV	Fodder_Main veg_Village	Fodder, Main veg cropping pattern by subsistence farmer
WHRIS	Wheat_Rice_Specialised	Wheat, Rice cropping pattern by commercial farmer
WHRIV	Wheat_Rice_Village	Wheat, Rice cropping pattern by subsistence farmer
WHMVS	Wheat_ Main veg_Specialised	Wheat, Main veg cropping pattern by commercial farmer
WHMVV	Wheat_ Main veg_Village	Wheat, Main veg cropping pattern by subsistence farmer
WHMAS	Wheat_Maize_Specialised	Wheat, Maize cropping pattern by commercial farmer
WHMAV	Wheat_Maize_Village	Wheat, Maize cropping pattern by subsistence farmer

Label	Name	Description
WHFCS	Wheat_Field Crop_Specialised	Wheat, Field Crop cropping pattern by commercial farmer
WHFCV	Wheat_Field Crop_Village	Wheat, Field Crop cropping pattern by subsistence farmer
MVMVS	Main veg_Main veg_Specialised	Main veg, Main veg cropping pattern by commercial farmer
MVMVV	Main veg_Main veg_Village	Main veg, Main veg cropping pattern by subsistence farmer
MVOVS	Main veg_Other veg_Specialised	Main veg, Other veg cropping pattern by commercial farmer
MVOVV	Main veg_Other veg_Village	Main veg, Other veg cropping pattern by subsistence farmer
FSMAS	Fodder_Maize_Specialised	Fodder, Maize cropping pattern by commercial farmer
FSMAV	Fodder_Maize_Village	Fodder, Maize cropping pattern by subsistence farmer
WHS	Wheat_ Specialised	Wheat cropping pattern by commercial farmer
WHV	Wheat_ Village	Wheat cropping pattern by subsistence farmer
WHOIS	Wheat_Oil_Specialised	Wheat, Oil cropping pattern by commercial farmer
WHOIV	Wheat_Oil_Village	Wheat, Oil cropping pattern by subsistence farmer
OVFSS	Other veg_Fodder_Specialised	Other veg, Fodder cropping pattern by commercial farmer
OVFSV	Other veg_Fodder_Village	Other veg, Fodder cropping pattern by subsistence farmer
WHFSS	Wheat_Fodder_Specialised	Wheat, Fodder cropping pattern by commercial farmer
WHFSV	Wheat_Fodder_Village	Wheat, Fodder cropping pattern by subsistence farmer
OVOVS	Other veg_Other veg_Specialised	Other veg, Other veg cropping pattern by commercial farmer
OVOVV	Other veg_Other veg_Village	Other veg, Other veg cropping pattern by subsistence farmer
FSOVS	Fodder_Other veg_Specialised	Fodder, Other veg cropping pattern by commercial farmer

Label	Name	Description
FSOVV	Fodder_Other veg_Village	Fodder, Other veg cropping pattern by subsistence farmer
LERIS	Legumes_Rice_Specialised	Legumes, Rice cropping pattern by commercial farmer
LERIV	Legumes_Rice_Village	Legumes, Rice cropping pattern by subsistence farmer
FSFIS	Fodder_Fibre_Specialised	Fodder, Fibre cropping pattern by commercial farmer
FSFIV	Fodder_Fibre_Village	Fodder, Fibre cropping pattern by subsistence farmer
FSRIS	Fodder_Rice_Specialised	Fodder, Rice cropping pattern by commercial farmer
FSRIV	Fodder_Rice_Village	Fodder, Rice cropping pattern by subsistence farmer
FCRIS	Field crop_Rice_Specialised	Field crop, Rice cropping pattern by commercial farmer
FCRIV	Field crop_Rice_Village	Field crop, Rice cropping pattern by subsistence farmer
FSOIS	Fodder_Oil_Specialised	Fodder, Oil cropping pattern by commercial farmer
FSOIV	Fodder_Oil_Village	Fodder, Oil cropping pattern by subsistence farmer
FCFSS	Field crop_Fodder_Specialised	Field crop, Fodder cropping pattern by commercial farmer
FCFSV	Field crop_Fodder_Village	Field crop, Fodder cropping pattern by subsistence farmer
FCMVS	Field crop_Main veg_Specialised	Field crop, Main veg cropping pattern by commercial farmer
FCMVV	Field crop_Main veg_Village	Field crop, Main veg cropping pattern by subsistence farmer
SCS	Sugarcane_Specialised	Sugarcane cropping pattern by commercial farmer
ALS	Alfalfa_Specialised	Alfalfa cropping pattern by commercial farmer
FTS	Fruit tree_Specialised	Fruit tree cropping pattern by commercial farmer
DPS	Date tree_Specialised	Date tree cropping pattern by commercial farmer
SCV	Sugarcane_Village	Sugarcane cropping pattern by subsistence farmer
ALV	Alfalfa_Village	Alfalfa cropping pattern by subsistence farmer
FTV	Fruit tree_Village	Fruit tree cropping pattern by subsistence farmer
DPV	Date tree_Village	Date tree cropping pattern by subsistence farmer

B.4 Unmanaged land and abandoned land area



B.5 Demand

Table B.9: Domestic production in 2020 for food and fibre ecosystem services (Adopted from CAPMAS, 2025). * Fibre is measured in local volumetric units of kantar.

Service	Domestic production
	1000s tonnes
Main.veg	10040
Other.veg	10262
Date.trees	1711
Fruit.trees	13247
Meat.milk	6098
Oil.crop	455
Sugar.cane	15336
Legumes	259
Wheat	9211
Maize	7593
Rice	4804
Other.field	14811
Fibre*	1442916

B.6 Capital sensitivities

Table B.10: Capital sensitivities summary, capital vs services for subsistence and commercial agents

Aspect	Subsistence Agents	Commercial Agents
Crop Production		
Capital Sensitivities	Human: 0.03, Social: 0.05, Manufactured: 0.03, Financial: 0.02, Water: 0.05	Human: 0.06, Social: 0.02, Manufactured: 0.05, Financial: 0.04, Water: 0.02
Production Value	1.5(perennial crops),1(single crop),0.5(multiple crops)	1.5 (perennial crops),1 (single crop),0.6 (multiple crops)
Employment		

Capital Sensitivities	Human: 0.015, Social: 0.025, Manufactured: 0.015, Financial: 0.01, Water: 0.02	Human: 0.03, Social: 0.01, Manufactured: 0.025, Financial: 0.02, Water: 0.03
Production Value	0.1 * number of crops	0.3 * number of crops
Meat and Milk		
Capital Sensitivities	Human: 0.015, Social: 0.025, Manufactured: 0.015, Financial: 0.01, Water: 0.00	Human: 0.03, Social: 0.01, Manufactured: 0.025, Financial: 0.02, Water: 0.00
Production Value	1(if Alfalfa), +0.5 per Fodder crop (max 1),0.6(mixed feed crops)	1 (if Alfalfa), + 0.5 per Fodder crop (max 1),0.6 (mixed feed crops)
Suitability	1 for all meat/milk crops (Fodder, Alfalfa, Wheat, Maize, etc.)	1 for all meat/milk crops (Fodder, Alfalfa, Wheat, Maize, etc.)
Water Use Efficiency		
Capital Sensitivities	Human: 0.04, Social: 0.04, Manufactured: 0.04, Financial: 0.05, Water: 0.05	Human: 0.05, Social: 0.02, Manufactured: 0.05, Financial: 0.05, Water: 0.05
Production Value	0.03(water-intensive crops),0.05(other crops)	0.1(water-intensive crops),0.2(other crops)

B.7 AFT properties

Table B.11: Example AFT parameters. Commercial and subsistence “other field crop”-“rice” agents

AFT	givingIn Mean	givingIn SD	givingUp Mean	givingUp SD	NoiseMin	NoiseMax	givingUp Prob
FCRIS	0.03	0	0.2	0	1	1	0.1
FCRIV	0.2	0	0.02	0	1	1	0.01

B.8 CRAFTY sensitivity results

The zipped folder below includes all plots for the CRAFTY supply-demand sensitivity plots, details of each sensitivity run, and the resulting impact on land abandonment and reclamation for each run.



CRAFTY_sensitivity_analysis.zip

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C Appendix C

This appendix include:

- C.1: Details of the AFTs under different scenarios.
- C.2: Details of the production sensitivity under different scenarios.
- C.3: Details of the capital indicator projections for all scenarios.
- C.4: Details of demand projections under different scenarios.
- C.5: Scenario CRAFTY model configuration settings.
- C.6: Weighting factor.
- C.7: Details of crop groupings.

C.1 Agent functional Types

AFTs are modified to represent the changing behaviours in different scenarios. Table C.1 includes details of the multiplication factor used to modify the give-in and give-up distribution means as well as the give-up probability. For example, for SSP 1, the specialised AFTs are 20% less likely to give up land or give in to another agent compared to the current/business-as-usual state (SSP 2).

Table C.1: AFT parameter scenario factors. These are scenario-specific multiplication factors for “give-in” and “give-up” distribution means, and give-up probability.

	Specialised			Village		
	GiveIn Mean	GiveUp Mean	GiveUp Prob	GiveIn Mean	GiveUp Mean	GiveUp Prob
SSP1	1.2	0.9	0.8	1.2	0.9	0.9
SSP2	-	-	-	-	-	-
SSP3	1.2	0.9	0.9	1.5	0.75	0.8
SSP4	1.1	0.95	0.95	1.2	0.8	0.8
SSP5	1.3	0.7	0.7	1.2	0.9	0.8

C.2 Production tables

Table C.2 includes details of the scaling factors for non-natural capital sensitivities and production for specialised and village AFTs for all SSPs. This means for the production table for a specialised AFT, the services-capital figure is scaled by a factor of 2 for SSP1. The baseline production sensitivity tables are outlined in detail in (Sattar, Moulds, Brown, Rounsevell, & Alexander, 2026).

Table C.2: Scaling factors for capital sensitivity and production table for specialised and village AFTs

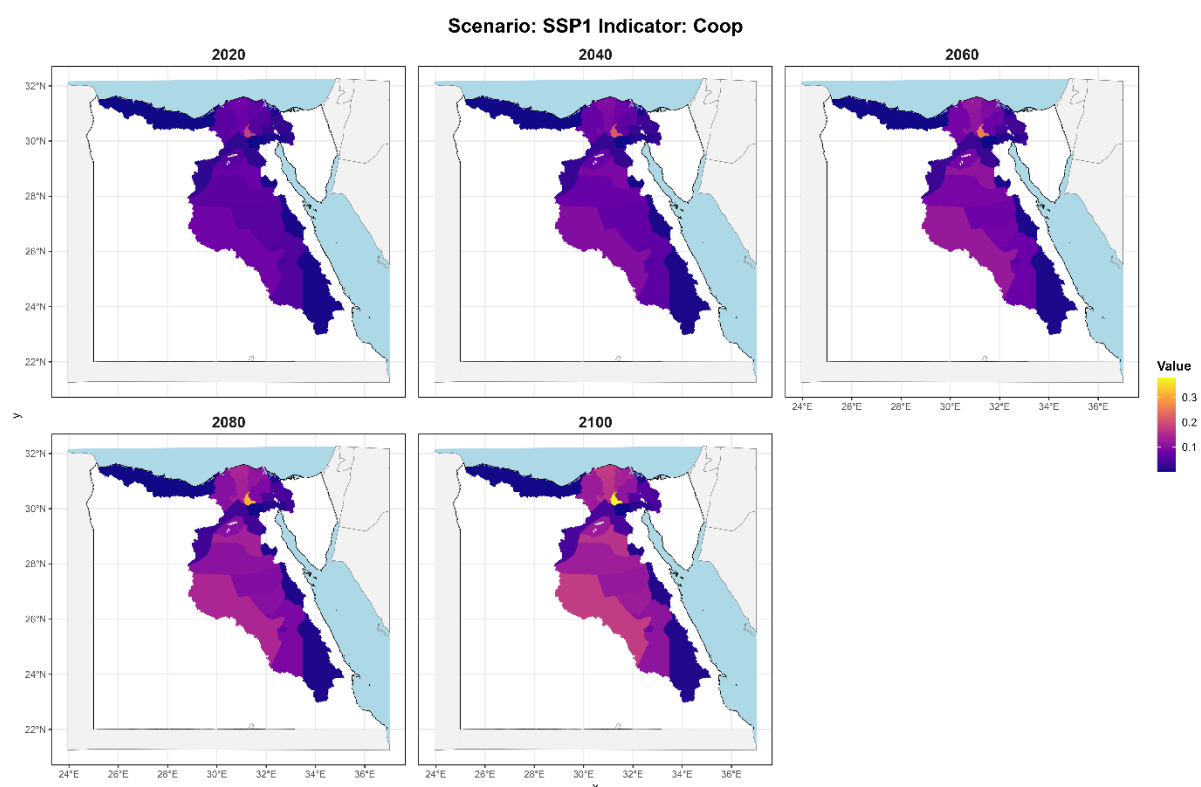
SSP	Agent Type	Human	Financial	Social	Manufactured	Water	Production
SSP1	Specialised	2	0.75	1.5	0.8	1.5	1.25
	Village	1.9	0.7	1.75	0.5	1.25	1.25
SSP2	Specialised	-	-	-	-	-	-
	Village	-	-	-	-	-	-
SSP3	Specialised	0.9	0.9	1.3	0.75	1	0.9
	Village	1.1	0.7	1.25	0.6	1.1	0.9
SSP4	Specialised	1.1	0.9	0.75	1.1	1.1	1.1
	Village	0.6	0.9	0.75	0.8	1	0.9
SSP5	Specialised	0.9	2	0.8	2	0.9	2
	Village	1.25	1.5	0.9	1.75	0.95	1.75

C.3 Capitals

The first step to project capital layers for different SSPs required the projection of the constituent indicators for the capital layers. Utilising some aspects of the method defined by (Merkle et al., 2023), indicators were defined in 2020 on a sub-national level (either gridded, at the governorate or sub-governorate level). Using the downscaled narratives, the decadal national-level projections were developed. These are included in Table C.3 to Table C.10 below. Details of the baseline indicators are included in Chapter 3.

Table C.3: Cooperative membership per capita

SSP	2020	2030	2040	2050	2060	2070	2080	2090	2100
SSP1	0.053	0.058	0.064	0.070	0.077	0.085	0.093	0.103	0.113
SSP2	0.053	0.051	0.050	0.049	0.047	0.046	0.045	0.044	0.042
SSP3	0.053	0.055	0.058	0.061	0.064	0.067	0.071	0.074	0.078
SSP4	0.053	0.051	0.050	0.048	0.047	0.045	0.044	0.043	0.041
SSP5	0.053	0.047	0.043	0.038	0.035	0.031	0.028	0.025	0.023



SSP1: 10% increase each decade reaching 0.113 in 2100 – 11.3% of the population are members of cooperatives in 2100, up from 5.3% in 2020.

SSP2: Continued reduction at 2010 to 2020 rate (2.7%) reaching 4.2% of population being members of cooperatives by 2100.

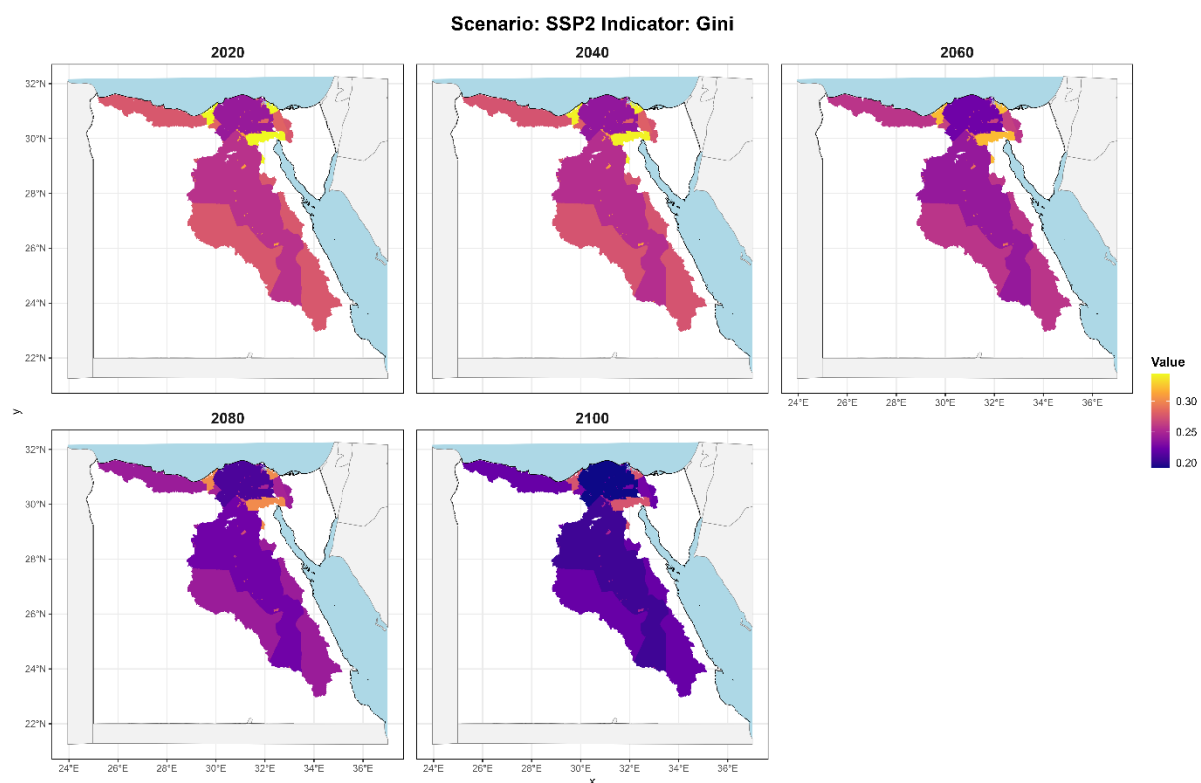
SSP3: 5% increase each decade in the membership of cooperatives, reaching a 7.8% of population being members of cooperatives by 2100.

SSP4: 3% reduction per decade in membership to cooperatives, reaching 4.1% in 2100.

SSP5: Cooperative membership reduces by 10% per decade, reaching 2.3% of the population by 2100.

Table C.4: Gini index projections

SSP	2020	2030	2040	2050	2060	2070	2080	2090	2100
SSP1	0.292	0.285	0.273	0.256	0.228	0.191	0.155	0.136	0.125
SSP2	0.292	0.291	0.290	0.281	0.273	0.263	0.255	0.242	0.233
SSP3	0.292	0.288	0.281	0.270	0.261	0.252	0.243	0.236	0.236
SSP4	0.292	0.310	0.329	0.349	0.371	0.394	0.418	0.444	0.471
SSP5	0.292	0.314	0.328	0.292	0.273	0.255	0.246	0.237	0.228



SSP1: The Gini index continues to reduce from 2020 to 2100. The rate of reduction in Gini Index increases from around 2% between 2030 and 2020 to a peak of decadal reduction of 19% between 2070 to 2090. The rate of reduction then reduces until the Gini Index reaches 0.125 in 2100.

SSP2: The Gini Index reduces slowly, representing a slow reduction in inequality between 2020 and 2100. The rate of reduction each decade increases from below 1% in 2020 to 5% in 2090. The Gini Index reaches a value of 0.233 in 2100.

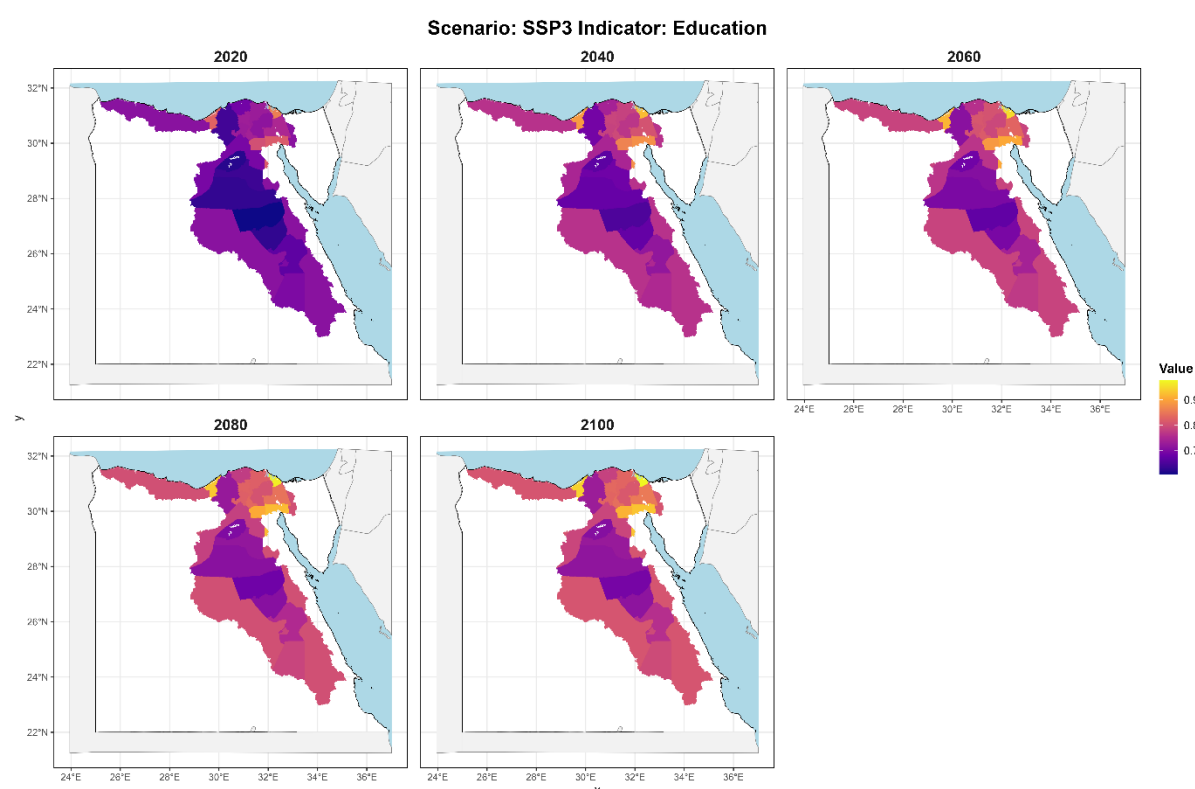
SSP3: The Gini index reduces at an increasing rate at first from 1.5% between 2030 and 2020 to a rate of 3.6% in 2050. The rate of decadal change in the Gini Index reduces slowly to 3% until it reaches 0.236 in 2090 where it remains constant to 2100.

SSP4: The Gini index continues to increase at a rate equal to the rate of increase between 2010 and 2020 (6.1% each decade) until it reaches 0.471 in 2100.

SSP5: Index peaks in 2040 at 0.328 then reduces, at first quite fast then more slowly, reaching 0.228 in 2100.

Table C.5: Education index projections

SSP	2020	2030	2040	2050	2060	2070	2080	2090	2100
SSP1	0.702	0.755	0.795	0.850	0.900	0.943	0.975	1.000	1.000
SSP2	0.702	0.755	0.785	0.825	0.855	0.877	0.900	0.925	0.950
SSP3	0.702	0.735	0.755	0.767	0.777	0.786	0.792	0.795	0.799
SSP4	0.702	0.745	0.790	0.835	0.880	0.902	0.900	0.875	0.850
SSP5	0.702	0.755	0.815	0.895	0.955	0.985	1.000	1.000	1.000



SSP1: The education index gradually increases at a slowing rate (7.5% between 2020 and 2030 to 2.6% between 2080 to 2090) until it reaches 1 in 2090.

SSP2: The index continues to increase at a slowing rate until it reaches 0.95 in 2100. The rate of increases appears to stagnate around 2.5% from 2070.

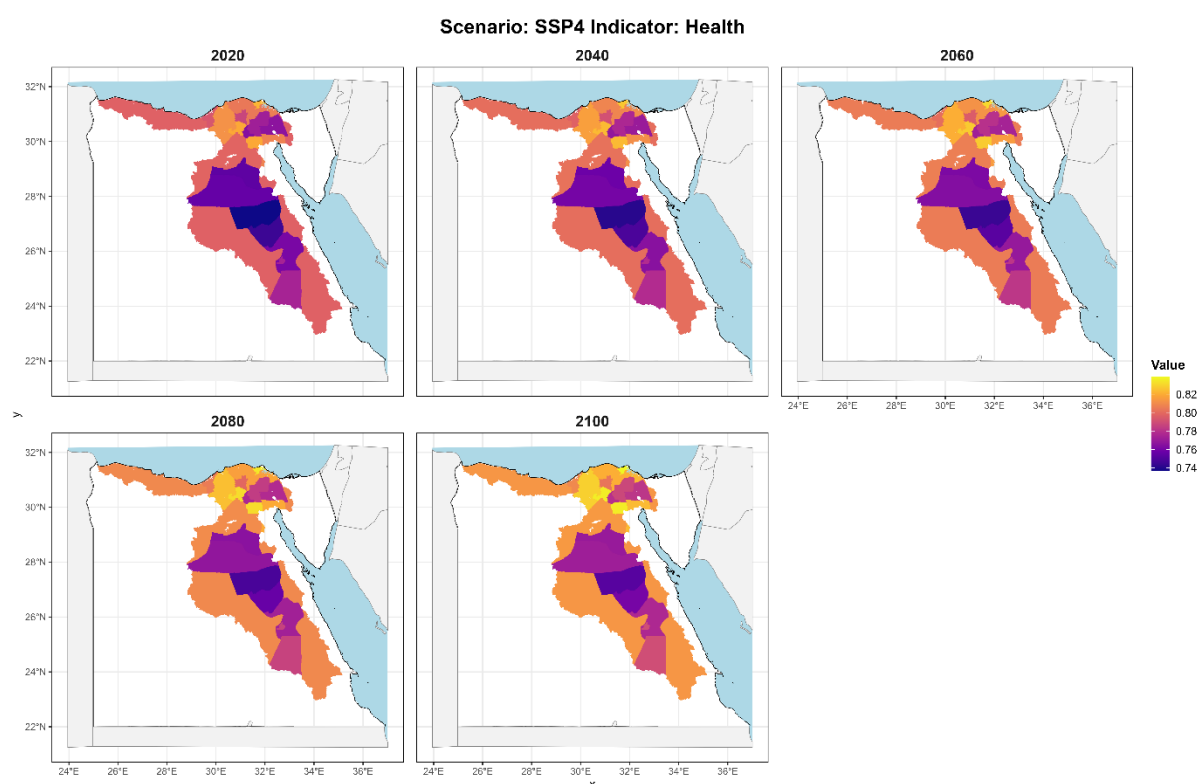
SSP3: Slow increase of the education index until 2100 of a rate of 4.7% in 2030 to >1% from 2080, where it peaks at 0.799 in 2100.

SSP4: Peak in education levels in 2070 at 0.902 followed by a reduction to 0.85 in 2100.

SSP5: Approximately 8-10% increase until 2050. The rate of increase of the index reduces after 2050 until the index reaches 2080 when it peaks at that value and remains constant until 2100.

Table C.6: Health index projections

SSP	2020	2030	2040	2050	2060	2070	2080	2090	2100
SSP1	0.784	0.824	0.868	0.910	0.950	0.970	0.980	0.990	1.000
SSP2	0.784	0.805	0.826	0.847	0.869	0.892	0.915	0.939	0.964
SSP3	0.784	0.794	0.805	0.820	0.840	0.862	0.890	0.912	0.922
SSP4	0.784	0.786	0.788	0.790	0.792	0.794	0.796	0.798	0.800
SSP5	0.784	0.795	0.810	0.828	0.865	0.900	0.930	0.950	0.950



SSP1: The health index continues to increase at a gradually reducing rate, starting at 5% between 2030 and 2020 and 1% in 2100. The final index is 1.

SSP2: The health index continues to increase at 2.6% as per the increase between 2010 and 2020.

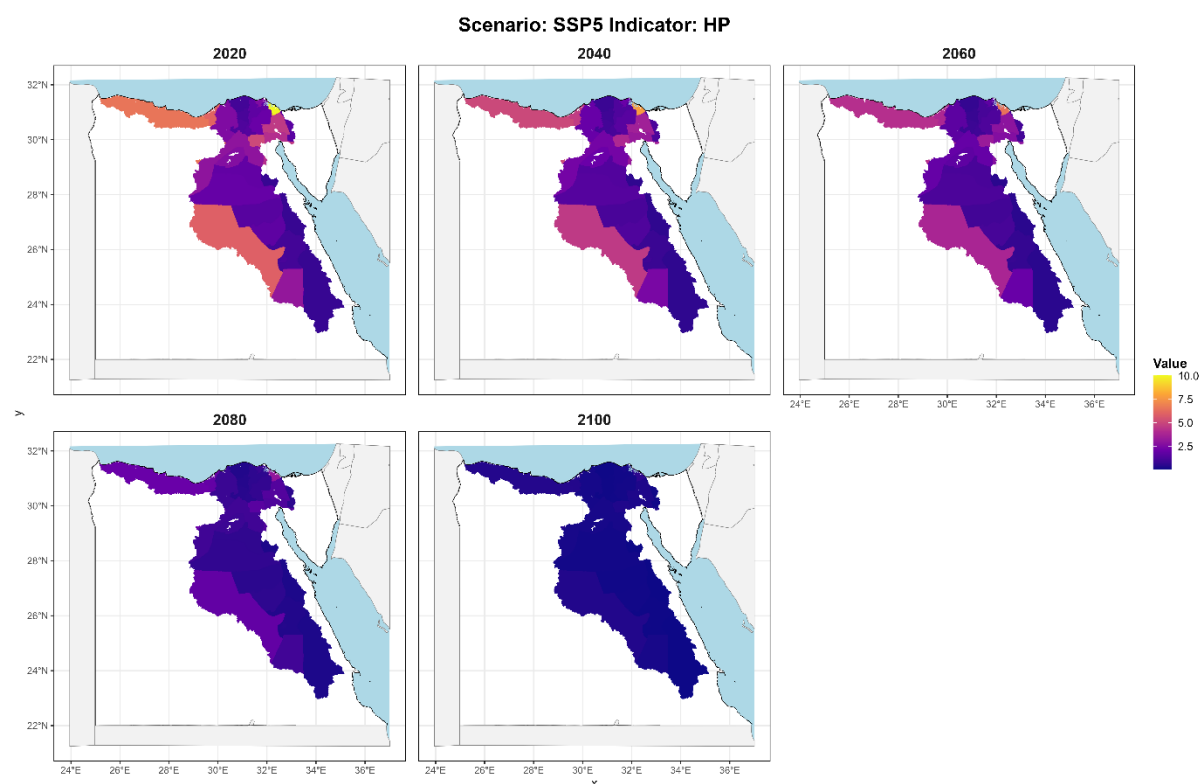
SSP3: The index increases at a gradually increasing rate between 1% and 3% until it reaches 0.89 in 2080. Between 2080 to 2100 the health index continues to increase but at a reducing rate to reach 0.922 in 2100.

SSP4: Approximately a 0.25% increase in the health index from 2020 to 2100, where the health index is 0.8.

SSP5: The health index increases at an increasing rate until 2060, when the rate of increase reaches 5.5% in a decade. The rate of increase drops until it reaches 0 between 2090 and 2100 and a health index of 0.95.

Table C.7: Feddan per horsepower indicator projections

SSP	2020	2030	2040	2050	2060	2070	2080	2090	2100
SSP1	1.95	1.62	1.36	1.14	0.97	0.82	0.70	0.59	0.50
SSP2	1.95	1.65	1.45	1.30	1.18	1.10	1.04	1.00	1.00
SSP3	1.95	1.93	1.92	1.90	1.90	1.89	1.85	1.80	1.75
SSP4	1.95	1.85	1.78	1.72	1.67	1.70	1.74	1.79	1.85
SSP5	1.95	1.80	1.50	1.30	1.25	0.95	0.60	0.30	0.10



SSP1: The feddan per horsepower indicator reduces at a rate of around 15% per decade until it reaches 0.5 feddan per horsepower in 2100.

SSP2: The indicator gradually decreases at a reducing rate, starting at 15% per decade in 20230 to 4% in 2090 until it reaches 1 in 2090. From 2090, it remains constant at 1.

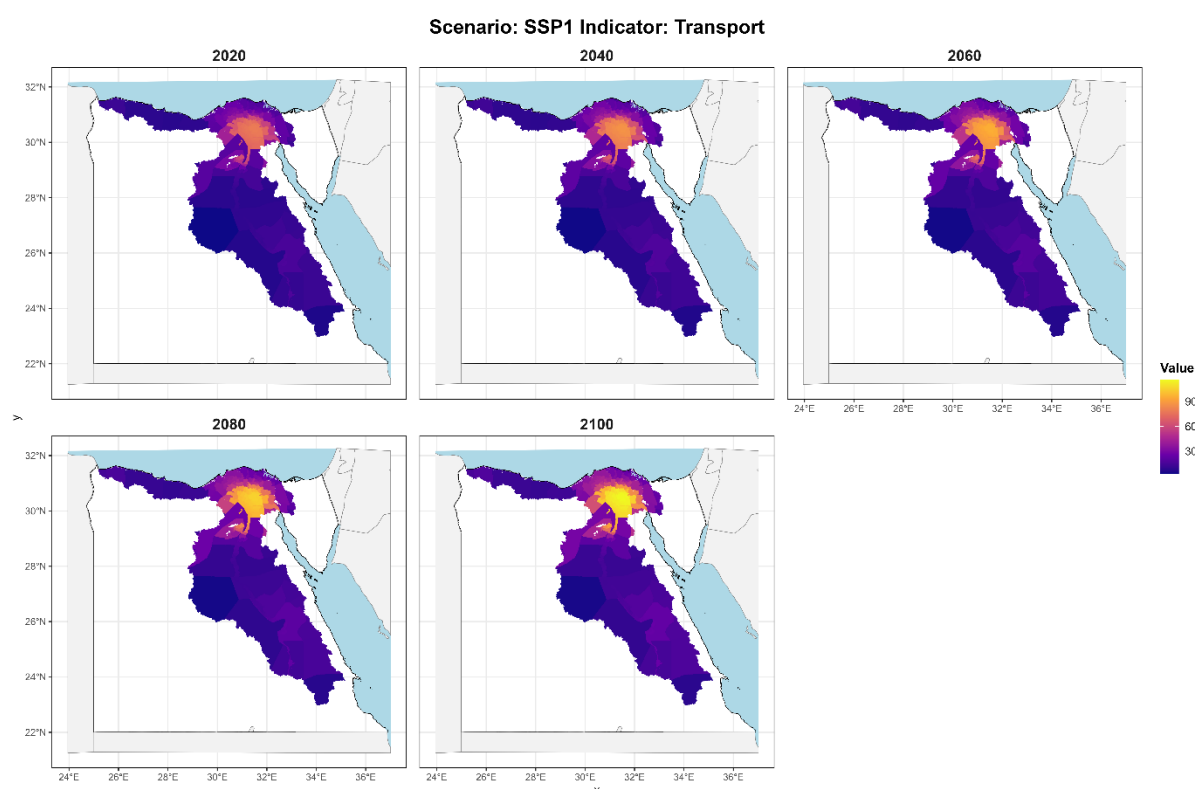
SSP3: Slow reduction in feddan per horsepower from 0.2%-4% until 1.75 feddan per horsepower is achieved in 2100.

SSP4: Feddan per horsepower reduces to 1.67 in 2060. After this point, it increases gradually to 1.85 feddan per horsepower.

SSP5: The rate of reduction in feddan per horsepower increases until the indicator reaches a value of 0.1 feddan per horsepower.

Table C.8: Road infrastructure indicator projections (speed weighted km/km2)

SSP	2020	2030	2040	2050	2060	2070	2080	2090	2100
SSP1	8.812	9.253	9.716	10.201	10.711	11.247	11.809	12.400	13.020
SSP2	8.812	8.989	9.168	9.352	9.539	9.730	9.924	10.123	10.325
SSP3	8.812	8.900	8.989	9.079	9.170	8.987	8.807	8.631	8.458
SSP4	8.812	8.989	9.168	9.352	9.539	9.730	9.243	8.781	8.342
SSP5	8.812	9.429	10.089	10.796	11.551	12.360	13.225	14.151	15.141



SSP1: Road infrastructure sees a 5% increase per decade to reach 13.020 km/km² in 2100.

SSP2: Investment in roads results in a decadal increase in road infrastructure of 2% until 2100.

SSP3: Road infrastructure indicator increases at a rate of 1% until 2060 when it begins to reduce at a rate of 2% per decade. Until it reaches 8.458 km/km².

SSP4: A national average of 2% increase in road infrastructure is implemented until 2070, at which point the road infrastructure is at 9.730 speed weighted km/km². Between 2070 and 2100, there is a decadal reduction of 5% in road infrastructure.

SSP5: A consistent decadal increase of road infrastructure of 7% results in the average national speed weighted road infrastructure of 15.141 km/km² in 2100.

Table C.9: Distance to surface water (m)

SSP	2020	2030	2040	2050	2060	2070	2080	2090	2100
SSP1	58563	57465	56367	55269	54171	53073	51974	50876	49778
SSP2	58563	57831	57099	56367	55635	54903	54171	53439	52707
SSP3	58563	58124	57684	57245	56806	56367	55927	55488	55049
SSP4	58563	58270	57977	57684	57392	57099	56806	56513	56220
SSP5	58563	57099	55635	54171	52707	51242	49778	48314	46850

SSP1: Distance to surface water reduces by 15% between 2020 and 2100.

SSP2: Distance to surface water reduces 10% between 2020 and 2100.

SSP3: Distance to surface water reduces 6% between 2020 and 2100.

SSP4: Distance to surface water reduces 4% between 2020 and 2100.

SSP5: Distance to surface water reduces by 20% between 2020 to 2100.

Table C.10: Hydraulic head of confined aquifer – elevation(m)

SSP	2020	2030	2040	2050	2060	2070	2080	2090	2100
SSP1	-187.77	-186.59	-185.42	-184.25	-183.07	-181.90	-180.73	-179.55	-178.38
SSP2	-187.77	-185.42	-183.07	-180.73	-178.38	-176.03	-173.69	-171.34	-168.99
SSP3	-187.77	-184.25	-180.73	-177.21	-173.69	-170.16	-166.64	-163.12	-159.60
SSP4	-187.77	-184.25	-180.73	-177.21	-173.69	-170.16	-166.64	-163.12	-159.60
SSP5	-187.77	-183.07	-178.38	-173.69	-168.99	-164.30	-159.60	-154.91	-150.21

SSP1: Hydraulic head increases by 5% between 2020 and 2100.

SSP2: Hydraulic head increases by 10% between 2020 and 2100.

SSP3: Hydraulic head increases by 15% between 2020 and 2100.

SSP4: Hydraulic head increases by 15% between 2020 and 2100.

SSP5: Hydraulic head increases by 20% between 2020 and 2100.

Table C.11: Population projections for SSP1 to SSP5 (in millions) (Koch & Leimbach, 2023)

SSP	2020	2030	2040	2050	2060	2070	2080	2090	2100
SSP1	107.47	123.49	136.06	146.08	152.69	156.38	157.04	155.11	151.22
SSP2	107.47	124.05	138.32	150.21	158.75	164.43	167.06	166.93	164.08
SSP3	107.47	125.77	145.52	164.53	181.96	197.87	211.86	223.77	232.93
SSP4	107.47	122.47	131.36	136.37	136.91	133.76	127.24	118.13	106.95
SSP5	107.47	123.18	134.86	143.86	149.33	151.82	151.26	148.17	143.2

The gridded GDP and population values are outlined in Chapter 3 and derived based on (T. Wang & Sun, 2022; X. Wang, Meng, & Long, 2022). These are developed to consistent with

the SSPs. Koch and Leimbach (2023) update the national GDP and population projection for the SSPs. These are used to scale the gridded population and GDP for Egypt for each scenario.

Table C.12: GDP projections for SSP1 to SSP5 (in millions 2017\$PPP) (Koch & Leimbach, 2023)

SSP	2020	2030	2040	2050	2060	2070	2080	2090	2100
SSP1	1223044	2034429	3500065	5352458	7435106	9588258	11586646	13458793	15171647
SSP2	1223044	1953405	2979234	4286059	5859015	7668446	9605996	11623354	13607714
SSP3	1223044	1878024	2567639	3297701	4123533	5096250	6162122	7288254	8454238
SSP4	1223044	1912871	2782324	3766077	4845074	5936961	6904922	7737236	8359682
SSP5	1223044	2098485	3912907	6352870	9315706	12668072	16147767	19831361	23695036

The rainfall indicator (Yukimoto et al., 2019) is a gridded daily dataset summed annually for each SSP. These values are directly used in the model.

Table C.13: Summary of average rainfall for each SSP for MRI-ESM2-0 downscaled and biased corrected as per ISIMIP3b (Lange & Büchner, 2021)

SSP	2020	2030	2040	2050	2060	2070	2080	2090
SSP1	35.43	27.08	16.54	38.34	24.46	29.97	25.76	22.43
SSP2	22.14	25.01	29.53	15.93	16.72	22.68	22.06	23.57
SSP3	16.75	17.67	28.38	38.09	30.19	20.50	19.40	19.47
SSP4	19.16	29.96	26.38	56.31	19.22	27.59	21.02	29.08
SSP5	55.80	36.78	22.45	26.51	10.31	24.04	32.78	21.82

C.4 Demand projections

Demand for food ecosystem services was calculated for 2020 based on national statistical reports (CAPMAS, 2025). Projections are based on the interpretations of the downscaled narratives in Section 3 of the manuscript. The tables below detail the values for daily calorific intake per capita, losses, imports, exports, and non-food projections for 2020 and 2100 for each scenario.

C.4.1 Daily calorific intake projections

Table C.14: Daily calorific intake per capita in 2020 and 2100 for each scenario.

Service	2020	SSP1	SSP2	SSP3	SSP4	SSP5
Main.veg	27	66	29	58	58	66
Other.veg	84	51	91	180	180	51
Date.trees	35	30	38	75	75	30
Fruit.trees	77	245	83	165	165	245
Meat.milk	253	219	542	274	274	500
Oil.crop	400	668	433	433	433	354
Sugar.cane	75	120	148	161	161	120
Legumes	50	172	107	107	107	172
Wheat	1497	511	1274	993	993	511
Maize	914	250	778	393	393	250
Rice	286	50	264	123	123	250
Other.field	43	35	64	64	64	35
Total	3741	2417	3850	3026	3026	2584

C.4.2 Losses

Table C.15: Percentage losses by crop type in 2020 and 2100 for each scenario.

Service	2020	SSP1	SSP2	SSP3	SSP4	SSP5
Main.veg	25.87	11.14	17.16	2.59	2.59	22.01
Other.veg	19.63	8.45	13.02	1.97	1.97	16.70
Date.trees	16.57	7.13	10.99	1.66	1.66	14.09
Fruit.trees	17.01	7.32	11.29	1.70	1.70	14.47
Meat.milk	1.06	0.46	0.70	0.11	0.11	0.90
Oil.crop	5.93	2.55	3.93	0.59	0.59	5.04
Sugar.cane	6.00	2.58	3.98	0.60	0.60	5.10
Legumes	7.07	3.04	4.69	0.71	0.71	6.02
Wheat	11.21	4.83	7.44	1.12	1.12	9.54
Maize	6.20	2.67	4.11	0.62	0.62	5.28
Rice	5.95	2.56	3.95	0.60	0.60	5.06
Other.field	13.45	5.79	8.92	1.35	1.35	11.44

C.4.3 Imports

Table C.16: Percentage imports for crop types for each crop in 2020 and each scenario.

Service	2020	SSP1	SSP2	SSP3	SSP4	SSP5
Main.veg	0.00	0.00	0.00	0.00	0.00	0.00
Other.veg	0.22	0.00	0.00	0.00	0.00	0.00
Date.trees	0.30	0.00	0.00	0.00	0.00	0.00
Fruit.trees	4.41	4.41	2.00	0.00	2.00	2.00
Meat.milk	6.80	5.00	10.00	0.00	10.00	15.00
Oil.crop	92.47	60.00	75.00	0.00	75.00	75.00
Sugar.cane	0.00	0.00	0.00	0.00	0.00	0.00
Legumes	88.08	60.00	25.00	0.00	25.00	60.00
Wheat	58.29	20.00	25.00	0.00	25.00	50.00
Maize	55.24	55.24	25.00	0.00	25.00	50.00
Rice	1.88	0.00	0.00	0.00	0.00	0.00
Other.field	0.84	2.00	0.00	0.00	0.00	0.00
Fiber	33.96	20.00	35.00	0.00	50.00	25.00

C.4.4 Exports

Table C.17: Percentage exports for crop types for each crop in 2020 and each scenario.

Service	2020	SSP1	SSP2	SSP3	SSP4	SSP5
Main.veg	1.27	5.00	10.00	5.00	10.00	20.00
Other.veg	11.75	20.00	20.00	10.00	25.00	30.00
Date.trees	2.22	15.00	20.00	10.00	20.00	25.00
Fruit.trees	16.32	25.00	25.00	25.00	30.00	30.00
Meat.milk	0.00	0.00	0.00	0.00	0.00	0.00
Oil.crop	16.92	20.00	20.00	20.00	25.00	30.00
Sugar.cane	0.00	0.00	0.00	0.00	0.00	0.00
Legumes	54.44	40.00	60.00	20.00	60.00	60.00
Wheat	0.00	0.00	0.00	0.00	0.00	0.00
Maize	0.00	0.00	0.00	0.00	0.00	0.00
Rice	0.00	0.00	0.00	0.00	0.00	0.00
Other.field	4.10	10.00	10.00	10.00	20.00	25.00
Fiber	60.57	30.00	50.00	75.00	80.00	40.00

C.4.5 Non-food projections

Table C.18: Domestic production of non-food and non-fibre ecosystem services in 2020 and 2100. Water use efficiency (WUE) is an index with 100 at 2020. Agricultural employment (Employ.) is the percentage of the population working in agriculture.

SSP	Service	2020	SSP1	SSP2	SSP3	SSP4	SSP5
SSP1	Fibre	861430	215358	646073	947573	1292145	1076788
	Employ.	20	8	10	15	20	2
	WUE	100	400	250	150	150	200

C.5 Configuration scenario changes

Table C.19: CRAFTY configuration settings for different scenarios.

Configuration	SSP1	SSP2	SSP3	SSP4	SSP5
Neighbour priority probability	0.7	0.7	0.9	0.8	0.5
Neighbour radius	6	5	3	3	10
Percentage of cells participating	0.15	0.1	0.05	0.1	0.3
Land abandonment percentage	0.01	0.01	0.001	0.02	0.1
Marginal utility per tick	5	4	3	2	6
Takeover unmanaged cell percentage	0.02	0.04	0.01	0.01	0.1

C.6 Weighting factor

The weighting factor (Table C.20) is calculated by determining the highest service value in 2020 and scaling all other services.

In addition to this weighting to ensure that all services are of equal magnitude to enable equal competition, it is possible to multiply this weighting by a scaling factor to represent the effect of price differences. The high-value crops in Egypt are fibre, fruit, main veg, other veg, and dates. Additionally, key staples are included in the wheat and maize. This represents targeted subsidies for these staples.

Table C.20: Demand weighting factor for key crops (high value and key staples).

Crop	SSP1	SSP2	SSP3	SSP4	SSP5
Fruit	1.5	2	1	2	3
Date trees	1.5	2	1	2	3
Fibre	0.75	1.5	2	3	3
Main veg	0.75	1	1	2	1.5
Other veg	2	2	1	2	3
Wheat	2	2	1	2	3
Maize	1.5	2	3	2	1.5

C.7 Crop groupings

Table C.21 includes details of the ecosystem service groups, their constituent crop groupings in CRAFTY and the crops used to model them in SWAT+.

Table C.21: Ecosystem services, CRAFTY crops, and modelled SWAT+ crops

Ecosystem service	CRAFTY crop grouping	SWAT+ modelled crop (code)
Fibre	Fibre	Cotton (cotp)
Fruits	Fruit trees	Orange (oran)
Fruits	Date trees	Dates (datp)
Staple crops	Wheat	Spring wheat (swht)
Staple crops	Maize	Corn (corn)
Staple crops	Rice	Rice (rice)
Sugarcane	Sugarcane	Sugarcane (sugc)
Vegetables	Main vegetables	Tomatoes (toma)
Vegetables	Other vegetables	Potatoes (pota)
Other	Other field crops	Onion (onio)
Other	Legumes	Dry beans (dryb)
Other	Oil crops	Peanuts (pnut)
-	Alfalfa	Alfalfa (alfa)
-	Seasonal fodder	Berseem (brsm)

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