Hacettepe University Graduate School of Social Sciences

Department of Economics

LAND INEQUALITY AND CLIMATE CHANGE ADAPTATION: AN AGENT-BASED APPROACH

Leyla Gizem EREN

Ph. D. Dissertation

Ankara, 2025

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ETİK BEYAN

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ABSTRACT

EREN, Leyla Gizem. *Land Inequality and Climate Change Adaptation: An Agent-Based Approach*, Ph. D. Dissertation, Ankara, 2025.

As an alternative to traditional agricultural practices, no-till farming can increase farmers' resilience to climate change by reducing their dependence on high-input techniques. However, the lack of a comprehensive support system for such practices in Türkiye hinders widespread adoption. The presence of farmers unconvinced of the benefits of no-till farming is also a barrier, as their influential position and views within the farming community can influence the decisions of other farmers.

To understand the adoption and diffusion process of no-till farming, it is crucial to understand the complex interplay of factors that influence farmers' decision-making processes. This thesis explores the factors contributing to the diffusion of alternative production systems, such as no-till farming, considering social interaction mechanisms, market price dynamics, and farmers' perceptions of climate change. For this purpose, an agent-based model is used as a modeling technique. Agent-based models, which have a bottom-up modeling methodology by analyzing micro components to draw macro conclusions, have been widely used in modeling climate change in recent years.

In our model, we simulated farmers' decision-making processes by developing an agent typology to analyze wheat farmers' decision processes based on data from various farmer reports on their experiences with no-tillage farming in Turkey. For this, we used NetLogo software.

As the first study to model wheat farmers' adaptation to climate change in Türkiye using agent-based modeling, this thesis analyzes the potential contribution of farmers with previous direct cultivation experience to regional climate change adaptation.

In line with the literature, the findings show that the number of conservation farmers in a region can influence the adoption and diffusion of conservation agriculture. However, it also emphasizes the importance of the average land size of these farmers in the diffusion of conservation agriculture.

In conclusion, this thesis contributes to the growing knowledge of the complex diffusion dynamics of sustainable agricultural innovations, ultimately promoting farmers' adaptation to climate change.

Keywords:

Agent-Based Model, No-Till Farming, NetLogo, Social Learning, Decision-Making

ÖZET

EREN, Leyla Gizem. *Arazi Eşitsizliği ve İklim Değişikliğine Uyum: Ajan Temelli Bir Yaklaşım*, Doktora Tezi, Ankara, 2025.

Pulluksuz tarım, çiftçilerin yüksek girdili tekniklere olan bağımlılığını azaltarak, yoğun toprak işlemeye dayalı geleneksel tarım uygulamalarına alternatif bir uygulamadır. Bu uygulama iklim değişikliğine karşı çiftçilerin dayanıklılıklarını arttırmayı hedefler. Ancak, Türkiye'de bu tür uygulamalar için kapsamlı bir destek sisteminin olmaması, bu uygulamaların yaygın olarak benimsenmesini engeller. Pulluksuz tarımın faydalarına ikna olmayan geleneksel çiftçilerin varlığı da bu uygulamaların benimsenmesini geciktirir. Çünkü bu çiftçilerin tarım topluluğu içindeki etkili konumları ve görüşleri diğer çiftçilerin kararlarını etkileme potansiyeline sahiptir.

Pulluksuz tarımın benimsenme ve yayılma sürecini anlamak için, çiftçilerin karar verme süreçlerini etkileyen faktörlerin karmaşık etkileşimini anlamak çok önemlidir. Bu tez, sosyal etkileşim mekanizmalarını, piyasa fiyat dinamiklerini ve çiftçilerin iklim değişikliği algılarını göz önünde bulundurarak pulluksuz tarım gibi alternatif üretim sistemlerinin yayılmasına katkıda bulunan faktörleri araştırmaktadır. Bu amaçla, modelleme tekniği olarak ajan-tabanlı bir model kullanılmıştır. Makro sonuçlar çıkarmak için mikro bileşenleri analiz ederek aşağıdan yukarıya bir modelleme metodolojisine sahip olan ajan temelli modeller, son yıllarda iklim değişikliğinin modellenmesinde yaygın olarak kullanılmaktadır.

Modelimizde, Türkiye'deki pulluksuz tarım deneyimlerine yönelik çeşitli çiftçi raporlarından elde edilen verilere dayanarak buğday çiftçilerinin karar süreçlerini analiz etmek için bir ajan tipolojisi geliştirerek çiftçilerin karar verme süreçlerini simüle ettik. Bunun için NetLogo yazılımını kullandık.

Türkiye'de buğday çiftçilerinin iklim değişikliğine uyumunu ajan tabanlı modelleme kullanarak modelleyen ilk çalışma olan bu tez, daha önce pulluksuz deneyimi olan çiftçilerin bölgesel iklim değişikliğine uyuma potansiyel katkısını analiz etmektedir. Literatürle uyumlu olarak bulgular, bir bölgedeki korumacı çiftçi sayısının korumacı tarımın benimsenmesini ve yayılmasını etkileyebileceğini göstermektedir. Bununla birlikte, bu çiftçilerin ortalama arazi büyüklüğünün bu gibi koruyucu tarım uygulamalarının yayılmasındaki önemini de vurgulamaktadır.

Sonuç olarak bu tez, sürdürülebilir tarımsal yeniliklerin karmaşık yayılma dinamiklerine ilişkin artan bilgi birikimine katkıda bulunmakta ve nihayetinde çiftçilerin iklim değişikliğine uyumunu teşvik etmektedir.

Anahtar Sözcükler:

Ajan Temelli Model, Pulluksuz Tarım, NetLogo, Sosyal Öğrenme, Karar Verme

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ABBREVIATIONS

ABM	Agent-Based Model
CSA	Climate-Smart Agriculture
FAO	The Food and Agriculture Organization
WWF	World Wildlife Fund
ÇATAK	Environmentally Friendly Agricultural Land Protection Program
SDG	Sustainable Development Goals
OECD	the Organization for Economic Co-operation and Development
IPCC	Intergovernmental Panel on Climate Change
ILC	International Labor Coalition
CGE	General Equilibrium Model
IAM	Integrated Assessment Management

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INTRODUCTION

Despite decades of global efforts to reduce inequality, 71% of the world's population lives in countries where inequality is growing (United Nations, 2020, p. 3). Recent studies show that climate change exacerbates socioeconomic inequalities and disproportionately affects regions where vulnerable households live (Dasgupta et al., 2023; Gazzotti et al., 2021; IPCC, 2023; Vogt-Schilb, Adrien, 2016). Especially in regions where agricultural production is labor-intensive, climate-induced income losses increase existing inequalities within and across countries (Dasgupta et al., 2023; Méjean et al., 2024). This reopens the debate on how land distribution inequalities affect agricultural productivity (Borras & Franco, 2018; Franco & Borras, 2021). For example, the United Nations Economic and Social Council (UN ESC, 2016) has highlighted the links between sustainable development goals (SDG) and land distribution inequality, emphasizing the importance of its implications for distribution and welfare.

The sustainable development goals also implicitly address land distribution inequality through various indicators. However, analyses based on the global indicators of these goals may not produce an accurate result at the national level. For example, SDG 5.a aims to implement reforms that give women equal rights to economic resources, including land ownership and control (UNSD, 2024). For this, it defines a dataset based on the gender structure of ownership of agricultural holdings in countries. The defined dataset reveals the gender distribution of land distribution in the region. Based on this result, the extent to which regions can achieve sustainable development goals can be analyzed. However, the results arising from the regions' current structure are not considered. In other words, the education level of the people of the region, the size of the education expenditures made in the region, whether there is an effort by non-governmental organizations for girls to study in the region, in short, the patriarchal roots of the region are not considered. A solution is proposed according to the statistical result obtained. While this solution does not coincide with the social structure of that region, the same statistical value in another region may be a correct indicator for a solution. As a result, the SDGs, which are very important in expressing a measurable value, need to develop region-specific solutions to achieve these goals.

Agriculture remains the primary source of livelihood for many rural households in developing countries, so land can either serve as a catalyst for economic development or be a source of persistent inequality (Guereña & Wegerif, 2019, p. 2). The International Land Coalition (ILC) emphasizes that growing land inequality jeopardizes the livelihoods of around 2.5 billion people engaged in small-scale agriculture and that inequality in land distribution negatively affects food security, soil degradation, and the sustainability of agricultural production (Anseeuw & Baldinelli, 2020). Addressing land inequality is central to enhancing climate resilience in developing regions (Dombrowsky et al., 2025) because unequal access to land use worsens environmental degradation and ultimately hinders the achievement of sustainable development goals (Faus Onbargi, 2022).

Land distribution inequality is a multifaceted issue beyond simple ownership patterns. From an economic perspective, unequal land distribution can concentrate wealth and productive resources in the hands of a few, affecting agricultural productivity and income generation opportunities for the wider population. The political dimension is manifested through power dynamics, where largeholders often significantly influence policy decisions and governance structures. This influence can perpetuate existing inequalities through favorable legislation and resource allocation. Socially, land inequality often reinforces existing class structures and can limit social mobility. Communities with limited access to land may face reduced opportunities for subsistence agriculture, housing, and economic advancement. There are environmental consequences as different scales of land ownership tend to encourage different patterns of land use. Largeholders can lead to monoculture farming or resource extraction, while smaller distributions encourage more diverse and sustainable practices. The spatial dimension addresses how land inequality affects settlement patterns, urban-rural dynamics, and access to resources and services across geographical areas. Researchers primarily use the Gini coefficient of land distribution to measure and analyze these inequalities. This mathematical tool provides a single numerical value between 0 and 1, where 0 indicates perfect equality (everyone owns the same amount of land) and 1 indicates complete inequality (one entity owns all the land). This coefficient has become the standard benchmark due to its ability to capture the full spectrum of land distribution patterns in a given area.

This multidimensional nature of land inequality has important implications for agricultural productivity and development. Empirical research in the development literature shows an inverse relationship between land distribution and agricultural productivity (Ali & Deininger, 2014; Deininger & Squire, 1998; Unal, 2009; Vollrath, 2007). That is, as a basic stylized fact, small farms are more successful than large farms, and in regions with inequitable land distribution, as the area cultivated by large farms increases, the fairness of land distribution deteriorates, leading to a decline in agricultural productivity. However, Chand et al. (2011) show that this relationship has changed over time due to technological progress. According to the results of this study, while the productivity of small farms is higher than that of large farms, the productivity of small farms decreases relatively over time due to technological developments. Small farmers' increasing vulnerability to climate change's impacts may further accelerate this productivity decline, as these farms often lack the financial resources and technological access needed to adapt to changing environmental conditions. Thus, regions in the agricultural production system where small farms are concentrated may be more vulnerable to the impacts of climate change. In 2023, Blanz's empirical study found that agricultural productivity losses due to climate change disproportionately affect the poorest households and increase wealth inequality in 92 developing countries (Blanz, 2023). Therefore, the impacts of climate change need to be analyzed at the regional level.

These regional differences in vulnerability to climate change emphasize the need for targeted adaptation strategies considering environmental and structural inequalities, especially in regions with a high concentration of small farms.

To develop such targeted strategies, it is crucial to understand how climate change modeling approaches have evolved to address regional challenges. Initially, climate change was analyzed through global general equilibrium models that focused primarily on reducing greenhouse gas emissions through tax and subsidies. These models develop a top-down approach that assumes that adaptation will automatically occur in response to mitigation measures. However, the failure of these globally developed models to consider regions' socio-economic development levels, institutional capacities, and local adaptation needs has been subject to intense criticism. As Dasgupta et al. (2023) note, addressing climate change challenges requires an assessment of regional vulnerability as part of adaptive capacity, defined as the ability of a region to absorb climate-related impacts through social, economic, and technological adjustments. The main problem in vulnerable regions remains the growing population outstripping food production, reflecting the concerns of (Malthus, 1798). The solution to this is increased technological progress. However, technology adoption in agriculture requires access to affordable inputs, an area where smallholder farmers in regions with land inequality are often marginalized (Franco & Borras, 2021). These farmers face systemic barriers such as poor market integration, inadequate support systems, and limited institutional capacity (Méjean et al., 2024). As a result, technology adoption slows down, exacerbating agricultural productivity declines in regions already burdened by inequitable land distribution and climate change impacts (Ali & Deininger, 2014). Regions with limited technological progress are considered less developed and more vulnerable (Borras & Franco, 2018). Climate change thus adds as a new reinforcing link in the vicious circle of underdevelopment, where land inequality, limited technological progress, and climate vulnerability perpetuate each other.

Modeling approaches then evolve towards a bottom-up, coupled with the need to understand regional adaptation processes. Since adaptation decisions ultimately occur at the farmer level and are influenced by local conditions, social networks, and individual capabilities, agent-based modeling (ABM) emerges as a particularly appropriate methodology. ABMs can capture the heterogeneity in farmers' decision-making processes, their interactions with each other and their environment, and the emergence of regional patterns from individual choices. The bottom-up approach of ABM has been used extensively in studies of agricultural technology adoption (Sanga et al., 2021), climate adaptation strategies (Bazzana et al., 2022), and policy implementation (Berger & Troost, 2014).

By modeling individual farmer decisions and their interactions, ABMs can help identify potential barriers to adaptation to climate change and assess the effectiveness of targeted support programs. They can model how farmers learn from their neighbors' experiences, how environmental awareness spreads through social networks, and how different types of farmers respond to new technologies and practices. However, instead of focusing on learning process heterogeneity, some existing models often rely on simplified thresholds to explain learning processes, which fails to capture the nuanced social dynamics of agricultural communities (Alexander et al., 2013; Drogoul et al., 2016; Williams et al., 2020). While some studies demonstrate that climate-aware farmers can accelerate adaptation strategy adoption through their influence on neighboring farms (Asseng et al., 2010; Marvuglia et al., 2022), the mechanisms behind this influence remain inadequately explored.

The complexity of peer learning in agriculture extends far beyond simple proximity effects. Research has shown that their neighbors' outcomes and experiences significantly influence farmers' adoption decisions. For instance, (Conley & Udry, 2010) demonstrate how closely farmers observe and adjust their practices based on their neighbors' results. This effect is quantified in an empirical study from Ethiopia, where a one standard deviation increase in neighbors' adoption of new seeds increased an individual farmer's likelihood of adoption by 11% in 1999, 19% in 2004, and 12% in 2009 (Krishnan & Patnam, 2014). However, climate change adaptation presents a fundamentally different challenge from traditional agricultural innovations. It demands radical transformations in production processes - from adopting new technologies and altered cropping patterns to shifting from monoculture to mixed cropping systems and implementing sustainable practices like preventing stubble burning. These adaptations require farmers to make complex risk assessments and commit to substantial changes in their operations. In this context, trust and social relationships become particularly crucial in the decision-making process.

To effectively model climate change adaptation, we must incorporate farmers' attitudes toward their neighbors and the social dynamics that influence learning and adoption decisions. Recent research has begun to address this complexity. Ambrosius et al. (2022) employ social identity theory to examine how group identity and social network position shape farmers' choices. Brown et al. (2016) investigate farmers' willingness to adopt mitigation strategies by examining their relationships with neighbors and the influence of peers' decisions on their own choices.

Understanding these social dynamics reveals multiple pathways of influence. A farmer might be more likely to adopt new practices when they observe success on a larger neighboring farm, when the innovation comes from a respected community member, or when a relative implement it they trust. These varied influence patterns show the importance of incorporating social dimensions into agent-based modeling to better represent the complexity of farmers' decision-making and adaptation processes.

Methodology

In this thesis, we created an ABM to examine the climate change adaptation strategies of eight wheat-producing provinces of Türkiye. We selected no-till farming as a climate adaptation strategy among the strategies developed by the ÇATAK project implemented within Türkiye's climate change adaptation strategies. In the model, we analyzed the impact of social learning mechanisms, the presence of environmentally sensitive farmers, and land distribution across regions on the adoption and diffusion of no-till farming. We conducted this analysis to answer the following questions:

1. What role does the regional distribution of environmentally awareness farmers play in adopting no-till farming?

2. How does inequality in land distribution affect the diffusion of no-till farming through social networks?

3. How can policymakers better target support programs by understanding the interplay between social identity, land distribution, and farmers' adaptation decisions?

In the first part of the thesis, we reviewed the modeling approaches developed for climate change adaptation in agriculture. We compared general equilibrium and agent-based models, assessing the limitations of top-down approaches and the advantages of bottom-up modeling. We then examined ABM applications in agricultural systems, focusing on social learning mechanisms, environmental awareness diffusion, and policy support analysis. In this review, we developed a critical perspective on the social learning mechanism of the models. We emphasized that combining social learning mechanisms with theories such as social identity and the theory of planned behavior can increase the effectiveness of ABM. Finally, we concluded that a hybrid modelling approach may be necessary to analyze the policy supports developed in the region.

In the second part, we built an agent-based model of climate adaptation among Turkish wheat farmers. The model incorporates social identity theory to capture learning processes and farmer interactions and examines how land distribution and environmental awareness affect adaptation patterns. We analyzed the effectiveness of policy interventions and support programs using data from eight major wheat-producing provinces. The model aims to provide an overview of related studies investigating the adaptive capacity of wheat farmers in different regions and the factors influencing their adaptation strategies.

Each of the chapters presents critical messages:

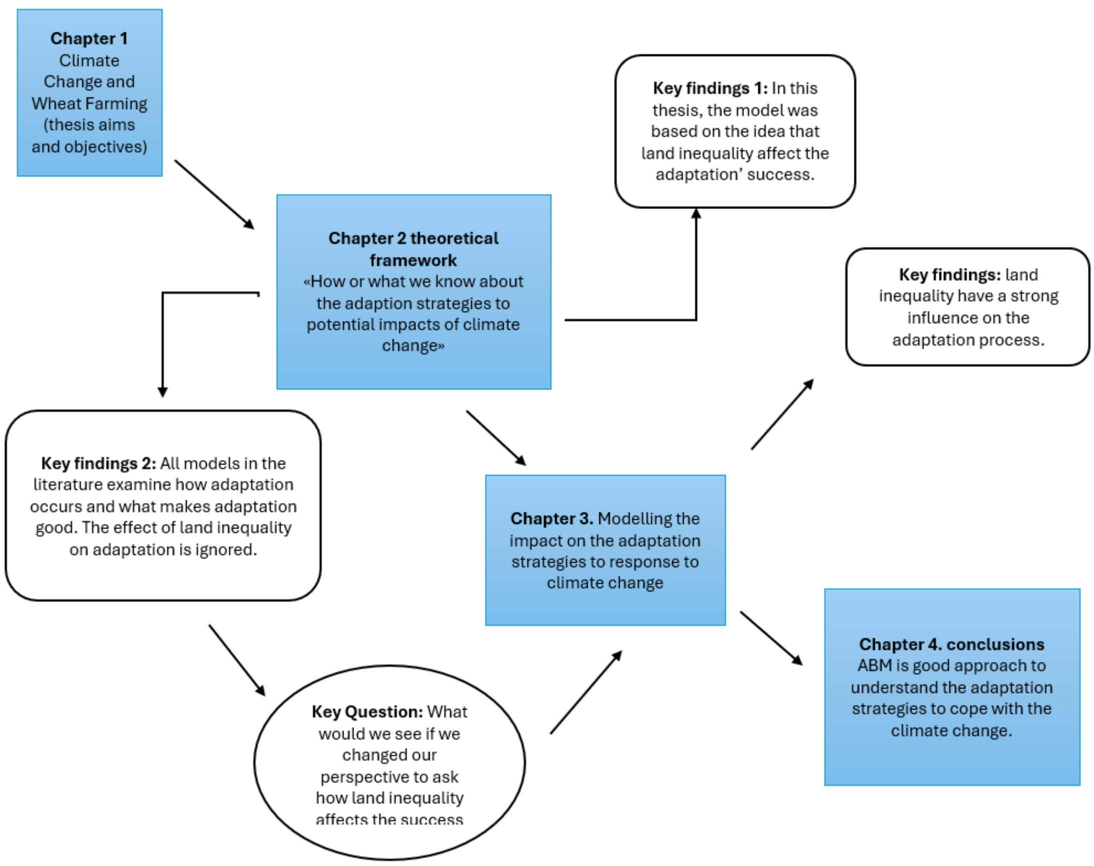
-The use of Agent-Based Models helps to understand the adaptive capacity of agricultural systems to climate change.

-Farmers' environmental awareness can lead to earlier adoption of new practices. However, for this to happen, farmers must first be dissatisfied with the status quo.

The social learning mechanism must work for sustainable techniques practiced by dissatisfied farmers to become widespread through interactions between farmers. However, the social identity of environmental farmers may determine their effectiveness in disseminating this information. Thus, factors such as land distribution, resource utilization, and the extent to which regions are affected by climate change may determine the motivations of farmers who learn from environmental farmers.

Our study's outline is below:

Figure 1: Outline of This Thesis



CHAPTER 1
THEORETICAL FRAMEWORK

Climate change is one of the most extensively researched and debated global phenomena. While natural climatic variability has historically shaped the Earth's climate, sustained warming coincides directly with the Industrial Revolution and the associated increase in greenhouse gas emissions (Block et al., 2004). The observed warming over the last 160 years has significantly exceeded similar warming periods in previous millennia (0.6°- 0.9°C compared to less than approximately ±0.2°C for any other century) (Jones & Mann, 2004).

Increasing greenhouse gas emissions is an environmental problem and a multidimensional issue that threatens agricultural production, food security, and rural development (Carozzi et al., 2022; Howden et al., 2007). Climate Change impacts on agricultural systems are complex and far-reaching, necessitating the development of comprehensive strategies to build resilience and adapt to changing conditions.

Two main strategies have emerged to address the impacts of climate change on agricultural systems: mitigation and adaptation. According to the Intergovernmental Panel on Climate Change (IPCC), mitigation involves human interventions to minimize pressure on Earth's climate systems - strategies include reducing greenhouse gas emissions from industrial activities and improving natural carbon sinks, and adaptation requires developing systems and infrastructure to withstand climate-induced stressors such as rising sea levels, intensifying weather events, and long-term ecosystem changes (IPCC, 2023).

In response to this challenge, international organizations have developed comprehensive strategies to increase agricultural systems' resilience by aligning sustainable development goals (SDG) with climate change. Of the 17 targets of the Sustainable Development Goals, some targets are directly related to climate change and include agricultural systems, such as ensuring food security (SDG 2, Zero Hunger), water management (SDG 6, Clean Water and Sanitation), and promoting rural development (SDG 15, Life on Land) (UN, 2020).

Aligning the Sustainable Development Goals with climate change adaptation and mitigation efforts in agriculture underscores the need for an integrated approach that considers multiple sustainability dimensions. However, it is important to examine how adaptation and mitigation are conceptualized and operationalized in different agricultural systems and regions to develop target- and context-specific interventions. The IPCC's approach to adaptation and mitigation emphasizes human emphasis on mitigation to anthropogenically-caused climate change, while adaptation emphasizes an externality decoupled from anthropogenic factors. This conceptualization creates a dichotomy in the mitigation and adaptation process. For instance, reducing greenhouse gas emissions from agriculture may require changes in land use and management practices, which in turn affects the system's adaptive capacity to respond to climate change impacts. In other words, the production system that causes emissions also determines the ability of regions to adapt to changing conditions.

Due to this conceptualization of climate change, early studies of climate change modeling in agricultural systems adopted a top-down approach to analyze how agricultural systems adapt to mitigation policies. These studies often focused on the broad-scale impacts of climate change and the effectiveness of different mitigation strategies without fully considering the complex interactions between mitigation and adaptation at the local level.

1.1. CLIMATE CHANGE MODELING APPROACHES: FROM THE BOTTOM-UP TO THE TOP-DOWN: AGENT-BASED MODELLING

In agricultural systems, two main strategies have emerged to address the impacts of climate change: mitigation and adaptation. Mitigation focuses on reducing greenhouse gas emissions, while adaptation aims to build resilience to the consequences of climate change. Climate change modeling in agricultural systems has evolved significantly in response to the complex challenges of mitigation and adaptation. Initially, Integrated Assessment Models (IAMs) and Computable General Equilibrium (CGE) models dominated the field, offering broad perspectives on climate change impacts and policy responses (Fujimori et al., 2014; Hasegawa et al., 2014; Nelson et al., 2014; Popp et al., 2014; Thepkhun et al., 2013). In the agricultural context, prominent examples such as GCAM, IMAGE, and REMIND-MAgPIE calculate how much emissions can be reduced by analyzing the land use change of agricultural systems in line with the 2050 targets of the Paris Agreement on Climate Change. The Global Change Assessment Model GCAM provides a detailed understanding of how agricultural practices contribute to GHG emissions and how they can be optimized under various climate scenarios. REMIND-MAgPIE assesses trade-offs and synergies between energy production and land use. The Integrated Model for Assessing the Global Environment (IMAGE) includes a detailed representation of agricultural systems, essential for assessing land use changes' impacts on food production and environmental sustainability. Integrated models such as GCAM, IMAGE, and REMIND-MAgPIE aim to predict the impacts of climate change by linking economic, environmental, and social factors (Hertel et al., 2010; Van Meijl et al., 2006). These models comprehensively analyze economy-wide impacts and sector interactions. However, these top-down approaches face significant limitations in representing agricultural adaptation processes. The fundamental assumption of rational economic actors responding predictably to price signals and policy incentives fails to capture the complexity of farmer decision-making (Howden et al., 2007; Simutowe et al., 2024; Van Asseldonk et al., 2023). While useful, these models often ignore critical societal changes and emerging technologies that can significantly affect outcomes (Hertel et al., 2010; Popp et al., 2014; Van Meijl et al., 2006). Mitigation modeling often uses a "top-down" approach, where policy instruments such as incentives and taxes determine compliance rates among rational economic actors. However, empirical evidence consistently shows that factors such as risk aversion, cultural traditions, and resource constraints significantly influence farmers' adoption of new practices, even when economic incentives are present (Williamson et al., 2018). As Kahneman (2003) emphasizes, the rationality assumption of traditional economic models often differs significantly from real-world scenarios. Real-world problems are complex because they result from the behavior and interaction of multiple entities, such as people, markets, and the natural environment (Macal & North, 2010). Models are used to understand this complexity better. While valuable for macro-level analysis, the top-down approach of CGE models often fails to capture the nuanced complexity of farmer behavior in agricultural systems, suggesting the need to reconsider the climate change modeling approach fundamentally. This reconsideration involves shifting from a mitigation/adaptation framework to an adaptation/mitigation perspective that better reflects the realities of agricultural systems. The transition from top-down to bottom-up modeling approaches represents a paradigm shift in understanding and analyzing complex agricultural systems under climate change. Agent-Based Models (ABMs) emerge as a powerful methodological bridge between these approaches, the ability to capture both micro-level behavioral dynamics and macro-level system outcomes (de Vries, 2010; Delli Gatti et al., 2011). Unlike traditional economic models that assume rational behavior, ABMs acknowledge the heterogeneity of decision-making processes and allow for the emergence of complex system behaviors from relatively simple individual interactions. ABMs are valuable because they depict individual elements within a system and their behavior (Railsback & Grimm, 2019, p. 10). Agent-based models create an artificial environment of various agents through simulations, allowing for the study of the interactions between these agents and how interactions between agents and additional elements, such as time and space, contribute to the emergence of observed patterns (Hamill & Gilbert, 2016).

This modeling approach becomes particularly valuable when examining climate change adaptation strategies because it can capture the bottom-up nature of adaptation decisions while providing insights relevant to top-down policymaking. By simulating how individual farmers respond to climate pressures and policy interventions, ABMs can help identify potential barriers to adaptation and evaluate the effectiveness of different policy instruments. This makes them especially useful for developing targeted interventions considering local contexts and individual circumstances rather than assuming a one-size-fits-all approach.

Agents, environments, and interactions form the anatomy of agent-based models. ABM anatomy conceptualizes climate change modeling by providing a framework for translating complex real-world systems into analyzable elements.

The conceptualization phase is crucial in ABMs because it lays the foundation for the model's subsequent design, implementation, and analysis. How agents are defined, which environmental factors are prioritized, and which interactions are modeled vary greatly depending on regional challenges and the main purpose of climate change adaptation. Given these variations in adaptation needs and modeling approaches, a systematic framework is needed to analyze how ABMs represent different adaptation challenges and solutions. A systematic climate adaptation framework identifies the root causes driving adaptation needs and then examines how different studies conceptualize adaptation strategies and their effectiveness for specific regional challenges. While this conceptualization framework provides the basis for modeling agricultural adaptation, how agents are defined, which environmental factors are prioritized, and which interactions are modeled varies greatly depending on regional challenges and the main purpose of climate change adaptation. Given these variations in adaptation needs and modeling approaches, a systematic framework is needed to analyze how ABMs represent different adaptation challenges and solutions. A systematic analysis of climate adaptation in ABMs begins with identifying the root causes of driving adaptation needs and then examining how different studies conceptualize adaptation strategies and their effectiveness for specific regional challenges.

The conceptualization phase in ABMs starts with the identification of *agents*. In agricultural systems, agents are farmers or farms. Farmers in ABMs developed for climate change adaptation can be defined in many ways, such as farmers who are aware of climate change, farmers who learn from farmers who are aware of climate change, and farmers who benefit from policy support developed for climate change adaptation. Climate change awareness among farmers in farming communities influences farmers' short- and long-term decisions (Troost, 2014), catalyzes knowledge diffusion (Ado et al., 2019), and, thanks to knowledge diffusion, reduces information costs for adaptation strategies (Liu & Ruebeck, 2020). After the identification of agents, the *rules of behavior* of these agents should be determined. Determining agent behavior is part of the population-building process of ABMs. Farmer populations are usually composed of agent typologies. Developing farm typologies helps in targeting policy interventions more effectively. Through agent typologies, uncertainty in decision-making processes becomes visible. Agent-based models (ABMs) and other simulation tools are valuable for predicting the impacts of policy interventions on land use and landscape changes. These models consider the heterogeneity of farm agents and their interactions, providing insights into the emergent properties of agricultural systems. ABMs typically represent a system of a large number of heterogeneous agents, each with bounded rationality, i.e., making decisions based on limited information and cognitive constraints (Castro et al., 2020; Findlater et al., 2019; Gerst et al., 2013; Savin et al., 2023).

The third conceptualization stage defines the system the agents represent, i.e., the *environment*. The environment encompasses the external conditions and resources available to agents, including climatic variables, soil conditions, and market dynamics. It includes biophysical factors such as climate and soil conditions and socio-economic factors such as market prices and policy incentives. The environment can change dynamically depending on agents' actions (land-use change) and external events (climate and market price dynamics), allowing the model to simulate the effects of different adaptation strategies under various scenarios (Marvuglia et al., 2022). Agents in ABMs display complex adaptive behaviors by interacting with each other and their environment (Savin et al., 2023).

Interactions between agents are the final stage of conceptualization. In agriculture, interactions reveal the complex structure between actors and their environment (Amadou et al., 2018; Marvuglia et al., 2022). For example, interactions may involve the distribution of irrigation water among intermediaries (Arnold et al., 2015; Baeza et al., 2019; Wossen et al., 2018), the diffusion of new practices developed in response to climate change impacts (Bazzana et al., 2022; Musayev et al., 2021; Wossen et al., 2018) or collaboration among farmers to increase farmer awareness of climate change risks (Wens et al., 2022; Williams et al., 2020).

This conceptualization emphasizes the bottom-up approach of ABM. Instead of a top-down approach, a bottom-up approach explains the agent behavior that leads to the emergence of system structures (Tesfatsion, 2002). By focusing on the micro-level interactions and decision-making processes of individual agents, the bottom-up approach of ABM allows for a more nuanced understanding of how complex systems, such as agricultural communities, respond to and adapt to the challenges posed by climate change.

1.2. EXAMPLES OF THE USE OF AGENT-BASED MODELS IN CLIMATE CHANGE ANALYSIS

The impacts of climate change on agricultural systems have traditionally been assessed through crop yield decline, as this provides a quantifiable metric with established measurement protocols, historical data sets and clear economic significance. However, from a regional perspective, impacts are much more complex and interconnected than yield measurements alone can capture.

1.2.1. Regional Patterns in Climate Change Challenges

ABMs address climate change adaptation, varying by regional context and primary challenges faced. These patterns form the basis for analyzing regional variations in climate change challenges and specific adaptation options implemented across different contexts.

1.2.1.1. Food Security Challenges in Rain-fed Agricultural Regions: In regions heavily dependent on rain-fed agriculture, climate change threatens food security (Berger & Troost, 2014; Musayev et al., 2021; Wossen et al., 2018). These regions' economic activities are mainly dependent on agricultural sector (Amadou et al., 2018). Studies in these areas, particularly in parts of Africa and South Asia, focus on modeling adaptation strategies that maintain agricultural productivity despite increasing climate variability. For example, research in Ethiopia (Bharwani et al. 2005) and Ghana (Wossen et al., 2014) demonstrates how small-scale farmers adapt their practices to maintain food production under changing rainfall patterns. These studies particularly emphasize the role of social networks in spreading adaptation strategies among farming communities.

1.2.1.2. Water Management in Irrigation-Dependent Regions: Regions with developed irrigation systems face different challenges, primarily centered on water resource management. Studies in these areas (Arnold et al., 2015; Babaeian et al., 2023) focus on modeling how farmers adapt their water use practices in response to increasing scarcity. The models developed for these regions often incorporate complex water rights systems and market mechanisms, reflecting the institutional frameworks that govern water distribution.

1.2.1.3. Emission Reduction in Industrialized Agricultural Systems: In regions with industrialized agriculture, mainly Europe and North America, modeling efforts often focus on emission reduction strategies. Studies in these areas (Brown et al., 2016; Salvini et al., 2016) examine how farmers adapt their practices to meet climate mitigation targets while maintaining productivity. These models typically incorporate policy incentives and technological innovation as key drivers of change.

The effectiveness of adaptation strategies varies significantly across these different contexts. For instance, European models emphasize bioenergy adoption and efficiency improvements (Brown et al., 2016; Gevers et al., 2011). In contrast, African studies emphasize food security and community-based adaptation (Bazzana et al., 2022; Bharwani et al., 2005; Hailegiorgis et al., 2018), some studies in Africa integrating water management concerns with food security objectives (Wossen et al., 2014). In America and Asia, study areas typically basin, examining water scarcity management through policy-driven adaptation strategies.

These diverse regional challenges demonstrate how ABMs must adapt to local contexts while maintaining consistent modeling principles. Understanding how these models represent adaptation requires examining the range of options farmers employ to address climate change impacts. From technological solutions to changes in agricultural practices, adaptation strategies vary in both scope and implementation.

1.2.2. Adaptation Options

Climate change adaptation strategies focus on land use change in the agricultural sector. The importance of adaptation strategies lies in their ability to provide practical solutions to the complex problems posed by climate change and to enable agricultural systems to cope with and recover from climate-related stresses. Adaptation strategies in the agricultural sector are developed by combining technological, policy, and sustainable practices or by applying them individually.

1.2.2.1. Precision Agriculture: Precision agriculture refers to a process in which farmers' self-directed decisions are supported by technological advances, such as changing planting dates, using weather information systems, and developing early warning systems. Some studies (Gezimu Gebre et al., 2023; Hailegiorgis et al., 2018; Wossen et al., 2014) show that when farmers adjust their traditional cropping calendar to changing weather conditions, they significantly reduce crop losses due to unexpected temperature changes or rainfall fluctuations and achieve beneficial results in ensuring food security. However, the successful implementation of this cropping calendar strategy depends on farmers having access to accurate weather information systems. These systems enable farmers to make informed decisions such as adjusting planting dates or harvesting early, minimizing potential losses, and improving food security (Bharwani et al., 2005; Musayev et al., 2021; Williams et al., 2020). It also forms the technological backbone of precision agriculture by providing farmers with the data they need to make informed decisions. Early warning systems are another strategy proposed to improve food security by enabling farmers to make timely and informed decisions (Wens et al., 2022). However, the development and diffusion of these strategies require government support. Governments play a crucial role in developing such technologies by investing in meteorological infrastructure and improving communication networks among farmers.

1.2.2.2. Use of adapted crops and varieties: Developing new crop varieties can provide farmers with a broader range of options, helping to improve food security (Berger & Troost, 2014), meet greenhouse gas emission reduction targets (Brown et al., 2016) and increase the sustainability of water resources (Babaeian et al., 2023; Harik et al., 2023; Truong et al., 2023). For example, drought-tolerant crops with low water demand contribute significantly to food security by providing stable yields even during prolonged droughts while at the same time helping to conserve water resources. One study in Ethiopia shows that poor households without access to irrigation are more likely to choose these crops (Bharwani et al., 2005), while another study shows that relatively largeholders and experienced farmers are more likely to choose these crops (Gezimu Gebre et al., 2023). A study in Ghana shows that drought-resistant crops are selected because they are cash-crops (Wossen et al., 2014).

1.2.2.3. Conservation agriculture: Conservation agriculture practices include several key practices that increase climate resilience in agricultural systems. These practices include crop rotation, contour plowing, terracing and cover crops, soil conservation practices that prevent soil erosion and increase water holding capacity, crop diversification, and CSA. Crop rotations protect crop yields against climate risks and free farmers from dependence on chemical inputs (Findlater et al., 2019; Marvuglia et al., 2022). Soil conservation practices help restore degraded lands and maintain production capacity despite climate challenges (Ding et al., 2021; Egger et al., 2022; Yang et al., 2020). Crop diversification strategies increase food security by spreading risk among different crops (Hailegiorgis et al., 2018) and contribute to agricultural sustainability by increasing biodiversity (Truong et al., 2023). CSA offers a comprehensive approach to climate adaptation by fundamentally transforming production technology and agricultural practices. This approach includes innovative practices such as reduced tillage and intercropping. These practices simultaneously address multiple goals: enhancing food security (Bazzana et al., 2022), while reducing emissions (Salvini et al., 2016), and forms resilience to climate variability (FAO, 2014).

1.2.2.4. Improving irrigation efficiency: Public investment in large-scale irrigation projects is a policy response to address water scarcity exacerbated by climate change. By supporting the development and maintenance of improved irrigation systems, governments can ensure a more equitable and sustainable distribution of water resources. Infrastructure investments in irrigation systems are vital for sustaining agricultural productivity in regions facing drought and water scarcity (Chen, 2017; Zagaria et al., 2021). Irrigation investments, especially when combined with access to credit, can help mitigate the impacts of climate variability on farm households (Wossen et al., 2014). Another critical technological development is the implementation of more efficient irrigation systems such as drip irrigation, precision irrigation, and sprinkler systems. These methods deliver controlled amounts of water directly to plants, significantly reducing water wastage. Improved irrigation supports sustainable water management and increases crop productivity even in regions experiencing severe water stress (Mirzaei & Zibaei, 2021; Wens et al., 2022).

1.2.2.5. Water restrictions and water rationing: Agricultural regions can better manage increasingly scarce water resources by combining water rights arrangements, market mechanisms, rationing schemes, pricing structures, and use restrictions. These strategies make adapting to changing climatic conditions possible while promoting more sustainable and efficient water use in agriculture. The choice and implementation of specific water management strategies depends on local institutional, environmental, and socioeconomic contexts. However, all aim to increase resilience and productivity due to climate variability and water scarcity.

In Chile, where water rights are separate from land ownership, farmers often “stack” or accumulate water rights over typical irrigation needs per hectare as a risk management strategy for drought periods (Arnold et al., 2015). Similarly, groundwater markets and quota systems can help manage limited water resources in the face of heterogeneous hydrogeological conditions and climate variability (Khan & Brown, 2019). These market mechanisms enable the reallocation of water rights, while quotas restrict total water use. During droughts, water management authorities can impose cuts in water deliveries to farmers and implement water scarcity-sharing schemes to distribute limited resources more equitably (Yang et al., 2020). In addition, the price of water from reservoirs and other sources can be increased when drought is expected (Ding et al., 2021). Some systems impose penalties on farmers who use too much water for irrigation, indirectly encouraging wiser use and discouraging the overuse of limited resources (Babaeian et al., 2023).

The review reveals an important pattern in adaptation strategies: rather than developing specific solutions for individual challenges, most studies implement strategies that simultaneously address multiple aspects of climate change adaptation. This multi-purpose approach is evident in how adaptation strategies are modeled and implemented across different contexts.

1.3. CONCEPTUALIZING THE ADAPTATION PROCESS IN THESE STUDIES

In agent-based models (ABMs), conceptualization refers to identifying the underlying components, interactions, and rules that govern agents' behavior and the environment in which they operate. When modeling farmers' adaptation to climate change in these studies, we evaluate this conceptualization addresses four key questions following the framework of Smit et al. (2000):

-Who or what adapts?

- Adaptation to what?

-How does adaptation occur?

-How good is the adaptation?

These questions can further clarify how farmers conceptualize adaptation processes through ABMs.

We can answer the first question simply as farmers. However, the role of farmers as decision-makers in agricultural production can be complicated when adapting to climate change. It is, therefore, necessary to clearly define farmers as adaptation actors.

Climate change awareness of farmers is necessary but insufficient for adaptation to climate change. Economic constraints (sunk cost or financial limits), and external factors (climate variability and input costs) lead to outcomes that differ from idealized equilibrium situations (Balmann, 1997). For this reason, farmers can be defined in some models as small farmers, wheat farmers, traditional farmers, etc., based on factors that influence their decision processes.

The second question addresses the climate change problems farmers face. The environment they adapt to encompasses both existing agricultural problems and new problems created by climate change. The environment is conceptualized by multiple dimensions. Climate-related challenges, market dynamics, agricultural patterns.

The third question focuses on adaptations' mechanisms. It is part of the conceptualization process to understand the interactions between agents themselves and their environment. Interactions heavily realized agent-to-agent and agent-to-environment. This process is a part of social learning. Social learning means that farmers learn from the experiences of others and thus benefit from less uncertainty and higher returns (Conley & Udry, 2010; Le et al., 2020; Wu et al., 2022). These learning mechanisms are part of farmers' adaptation processes to climate change as they help to spread knowledge, promote innovation and support sustainable agricultural practices. The learning mechanism in the agricultural sector operates primarily through peer-to-peer learning or self-learning based on farmers' experiences and beliefs. The peer mechanism, where farmers learn from each other, is critical for climate change adaptation (Apetrei et al., 2024). Therefore, modeling farmers' learning of new knowledge can take place within the social learning process, such as peer learning, community knowledge sharing and social networks.

The forth question is how successful adaptation is also related to the success of the process of defining rules of farmer behavior. These rules need to be as representative as possible of the structure of the region. In this way, adaptation can achieve its goal.

This is how conceptualization is done in the studies modeled with ABM. These studies show that increasing farmers' environmental awareness through social learning is an effective adaptation strategy. Climate change awareness of farmers is essential for adaptation to climate change. Increasing the number of farmers with high awareness in regions can affect the speed and quality of adaptation. However, how this mechanism affects the adaptation process in the existing agricultural structure is also important. Peer-to-peer learning mechanisms among farmers may proceed by observing and imitating the behavior of successful or respected farmers in the community. In this case, the climate change perception of farmers trusted in the community may influence the course of adaptation to climate change in that region. Therefore, it is crucial to consider the social dynamics and power structures within the farming community when analyzing the effectiveness of the learning mechanism. While these models have significantly improved our understanding of adaptation processes, their perception of the learning mechanism must be improved to better capture the complex social dynamics that influence adaptation processes. The literature reveals an evolution from simple threshold-based adoption models (Babaeian et al., 2023; Zagaria et al., 2021), to more sophisticated representations of farmer decision-making processes. For example, in Ambrosius' study, the learning mechanism is analyzed regarding farmers' perspectives on each other in the context of social identity theory (Ambrosius et al., 2022), Brown (2016) heterogeneous decision processes in his study using a questionnaire survey, including whether the farmer trusts her/his neighbors enough to learn about bioenergy crop adoption (Brown et al., 2016). Nevertheless, there are important gaps in modeling social learning mechanisms.

Studies perceptions are far away from bounded-rationality. They used some decisions rules for agents and agents who defined these rules, rational. They observe neighbors, successful neighbors, and their constraints reflect rationality. Some papers shows farmers' perceptions of climate change are closely linked to their socioeconomic status and land ownership (Egger et al., 2022). Almost all papers shows that small-scale farmers operating on limited land are generally more vulnerable to climate impacts and have fewer resources to adapt than largeholders (Awazi et al., 2021; Musayev et al., 2021). But they use decision rules, and these rules lack this vulnerability.

In a region where smallholders are concentrated in the agricultural production system, adaptation to climate change may be delayed due to this cycle of vulnerability. This vulnerability cycle may further complicated by how land distribution influences the adoption of agricultural innovations. Papers ignore this reality. Unequal land distribution may create significant barriers, particularly in terms of knowledge sharing between farmers and their ability to implement innovative farming practices. This social dimension is crucial because land inequality creates deep social divisions between farmers. These divisions naturally reduce cooperation between different groups within the farming community. As cooperation decreases, there's less peer-to-peer learning taking place, which ultimately slows down the spread of innovations that could improve agricultural productivity. Considering the inverse relationship to farm size and agricultural productivity, land distribution pattern may be an important factor to understand regions' climate change adaptation capacity.

Social identity reinforces group norms that influence learning and behavior change (Dooley, 2020; Tisch & Hamilton-Hart, 2019). For example, a farmer who strongly identifies with an environmentally conscious group may adopt sustainable practices in line with group norms (Fielding et al., 2008). The interaction between social identity and norms accelerates the adoption of practices that benefit individual farmers and wider agroecosystems (Burke & Running, 2019). This conceptualization illustrates how adaptation emerges through complex social interactions where individual and community factors shape learning and decision-making.

In rural India, for example, dominant classes, often linked to particular castes, monopolize economic benefits, exacerbating existing inequalities and inhibiting collective action among marginalized groups (Levien, 2015). This monopolization of resources creates a scenario in which the marginalized lack the social ties necessary for practical cooperation, thus hindering the diffusion of innovations that could improve agricultural practices. These findings from rural India align with broader research on the impact of land distribution on agricultural innovation. In regions with significant land inequality, the ability of farmers to engage in collaborative learning and knowledge-sharing activities is often compromised. This is because larger landholders may dominate resources and decision-making processes, leaving smaller farmers with fewer opportunities to participate in innovation networks (Mahmood et al., 2020; Tole, 2004). Social networks are crucial for knowledge diffusion in agriculture. In contexts where land distribution is unequal, these networks may be less effective, as smaller farmers might have limited access to the same networks as larger landholders (Fielding et al., 2008; Kabirigi et al., 2022). These findings underscore the importance of considering the social dynamics and power structures that shape knowledge diffusion in agricultural communities. The complex interplay of land distribution, social networks, and power dynamics in agricultural communities highlights the need for a more nuanced understanding of the social learning processes that drive climate change adaptation. For this reason, ABM conceptualizing must include social learning with social identity.

These findings have important implications for both modeling approaches and policy development. For modeling social identity theory for social learning, the influence of land ownership patterns on knowledge diffusion, power dynamics, and social hierarchies in adoption processes must be explicitly used. For policy, adaptation strategies must account for existing social structures and inequalities; technical solutions alone may be insufficient without addressing social barriers to adoption, land reform and social equity issues may be integral to adaptation, and building community trust networks may be as important as developing technical solutions.

CHAPTER 2
IMPACT OF LAND DISTRIBUTION ON NO-TILL FARMING IN TÜRKİYE ON THE CLIMATE CHANGE ERA: AN AGENT-BASED APPROACH

One of the most critical crops affected by climate change is wheat, a staple food source for a significant portion of the world's population. Wheat production highly depends on rainfall and temperature variables in many parts of the world. This dependence leads to losses in wheat yields because of climate change. The Agricultural Model Intercomparison and Improvement Project estimates that for every 1 °C increase in temperature, global wheat production is estimated to decrease by 6% (Asseng et al., 2010). However, climate change's impact on agricultural productivity varies by region; while some regions experience positive effects such as longer growing seasons, others face challenges such as drought stress and limited crop yields (Mueller et al., 2015; Praveen & Sharma, 2020). These changes have the potential to significantly affect trade patterns, food security, and the economic viability of wheat agriculture in different regions of the world (Stevanović et al., 2016; Zhang et al., 2016; Zimmermann, 2023).

In Türkiye, wheat agriculture is important to the country's agricultural sector and economy. Türkiye ranks tenth among the world's top wheat producers (FAO, 2024), with an annual production of 22 million tons in 2023. Wheat is a primary staple in the Turkish diet, with an average per capita consumption of 199 kg per year (TURKSTAT, 2023) at the same time. But the wheat production area has decreased from 9.3 million hectares in 1988 to 6.8 million hectares in 2019 in Türkiye (Bishaw et al., 2021, p. 3). The wheat production area's decline can be attributed to several factors. Wheat cultivation is generally mono-cropping, and almost all wheat production regions are based on the rain-fed system. According to the 2001 Census of Agricultural, small-scale farming and land fragmentated are prevalent in Türkiye (DİE, 2004)[1].

The wheat production season is from October to July in Türkiye. Research shows that temperature increase can significantly decrease wheat yields, with a 1.5 °C increase causing a significant 9% decrease in yield in Türkiye (Demirdogen et al., 2024). Therefore, to enhance the capacity of wheat farmers in Türkiye to adapt to climate change, the ÇATAK (Environmentally Friendly Agricultural Land Protection Program) Support Program was implemented between 2006 and 2019. The ÇATAK Support Program offered financial incentives to farmers committed to implementing environmentally friendly agricultural practices. Empirical studies on the results of this program emphasize the importance of government support for the spread of sustainable agricultural practices while also showing that socioeconomic factors such as farm size, education level, and environmental awareness of farmers are also important (Boz, 2016; Canan & Ceyhan, 2021; Olhan et al., 2010).

The implementation of region-specific policies is crucial for promoting sustainable agricultural practices in Türkiye's diverse farming landscape. A recent study by WWF (2022), titled "Policy Implementation and Communication Recommendations for Mainstreaming Sustainable Agricultural Practices" examining the process of adoption and diffusion of *direct seeding* techniques in Türkiye (Karakoç et al., 2022). Direct seeding, also known as no-till farming, is a conservation agriculture method that involves planting crops directly into the residue of the previous crop without disturbing the soil through tillage. This approach aims to minimize soil disturbance, reduce erosion, and improve soil health. Although no-till farming has shown potential for sustainable wheat production, the effectiveness of no-till farming in wheat production presents a complex picture in the literature, so research is needed on the impact of tillage on wheat yield (Bailey et al., 2001; Gathala et al., 2011; Jug et al., 2011). While some studies have reported increased yields under no-till farming (Adil et al.,

[1] Although there is a lack of recent farm survey data, the Turkish agricultural subsidy system has included to support small-scale farmers with maximum of five decares of land since 2016. So, we can infer that small scale farming is still important in Türkiye's agricultural environment.

2022; Gültekin et al., 2017; Jabran & Aulakh, 2015), the results of tillage's impact on crop yields remain uncertain. Pittelkow's meta-analysis study indicates that no-till farming leads to wheat yield loss of about 2.6% (Pittelkow et al., 2015), while a more recent comprehensive meta-analysis of 25565 yield records from 30 long-term experiments across Europe and Africa showed that different tillage intensities and reducing tillage did not significantly affect yields (MacLaren et al., 2022). While the impact on yields may be variable, there is consensus on the economic benefits of no-till farming in the literature. According to studies direct seeding showed the lowest total fuel consumption (0.91 L/ha) and saved significantly compared to conventional tillage (5.15 L/ha) (Marakoğlu & Çarman, 2008), fuel use can be reduced by up to 50% (Sanford & Go, 2022; Yudina et al., 2024). Eliminating multiple tillage operations also decreases labor requirements, contributing to lower production costs (Kawa, 2021; Laukkanen & Nauges, 2009; Tadjiev et al., 2023).

Despite these clear economic benefits, farmers' adoption decisions are influenced by a combination of external and internal factors, including economic incentives, social networks, and personal values. For example, the framing of policies and the degree of control (mandatory vs. voluntary) significantly affect farmers' adoption of sustainable practices (Thomas et al., 2019). According to the WWF report, while the primary motivation for farmers to practice direct seeding is its economic advantages, there are various barriers to adoption. Farmers who heard about this method but did not want to implement it stated that they did not implement it due to the perception of risk and lack of resources. Some farmers who have tried it have stopped due to problems such as reduced yields, increased weeds, and crop diseases. According to the report, the reason for the lack of widespread adoption of direct seeding in Türkiye is that such innovations are not suitable for local conditions, an institutional environment that encourages innovation has not been created, there is a lack of social networks among farmers, and the short and long-term benefits of the innovation have not been explained to farmers.

Given these complex challenges in promoting sustainable agricultural practices and the critical role of understanding farmers' decision-making processes in adoption processes, this study aims to examine the dynamics of the adoption of sustainable agricultural practices among wheat farmers in Türkiye through the lens of the ÇATAK support program (2006-2020). Specific objectives are:

-To analyze how farmer decision-making processes influenced by both internal factors (cognitive limitations, behavioral preferences, risk perceptions) and external pressures (climate change, input costs) affect the adoption of sustainable agricultural practices

-To investigate the role of social learning and peer networks in promoting sustainable agricultural practices among wheat farmers

-To examine systemic feedback between individual farmer decisions and regional land use dynamics in the context of climate change adaptation

Through agent-based modeling, this research aims to understand the complex interactions between policy interventions, farmer behavior, and environmental outcomes in wheat farming systems in Türkiye.

2.1. METHODOLOGY

2.1.1. Study Area

This study builds on the findings of the 2022 WWF report that analyzed farmers' attitudes towards sustainable agricultural practices, focusing on the adoption of no-till farming under the ÇATAK project in Türkiye. The 2022 WWF report was selected as the foundation for this study because it provides a highly representative sample of farmers in key wheat-producing regions of Türkiye.

The WWF study used a two-stage approach. In the first phase, extensive interviews were conducted with leading farmers, academics, experts and civil society activists working in agriculture. These interviews aimed to assess the potential roles of government, the private sector and civil society in promoting sustainable agricultural practices and innovations such as local seeds, conservation agriculture and regenerative agriculture. The interviews also included village visits in Konya, Edirne and Şanlıurfa, where ideas and experiences shared by experts were discussed with farmers, public officials and agricultural machinery manufacturers.

In the second phase, a survey was conducted among 545 wheat farmers using stratified random sampling. The survey focused on five broadly defined regions: Ankara-Eskişehir, Konya, Şanlıurfa, Edirne-Tekirdag, and Kayseri-Sivas. These regions were selected based on their importance in wheat production and their experience with direct seeding (no-till farming), which was used as the main indicator to measure farmers' responsiveness to innovative practices. Within these regions, 19 districts were identified using a second stratification based on the amount of irrigated and dry agricultural land. The total number of surveys was distributed among these districts according to the number of farmers using data from the Provincial Investment Guide published by the Ministry of Agriculture and Forestry. The final sample included 545 wheat farmers distributed by province as follows: Ankara (115), Edirne (52), Eskişehir (32), Kayseri (86), Konya (108), Sivas (40), Tekirdağ (34), and Şanlıurfa (79).

The significance of these regions is evident in their agricultural patterns and production capacity - wheat is the primary crop in all selected provinces, and together, these regions account for approximately 40 percent of Türkiye's total wheat production (see tables in APPENDIX 1). Furthermore, their distribution across different geographical regions of Türkiye, each with distinct climatic characteristics and agricultural structures, makes them valuable for analyzing regional variations in climate change adaptation strategies. The cropping patterns data presented will be used to parameterize our agent-based model and analyze its results. This data provides information on regional differences in agricultural practices and farm characteristics, which are necessary to accurately represent wheat farmers' decision-making in our model.

2.1.2. Conceptualization

Our study investigates the impact of Türkiye's Environmentally Friendly Agricultural Land Protection Program (ÇATAK) on wheat farmers' adoption of sustainable production practices between 2006 and 2020. In this context, we aim to analyze how a ÇATAK-like program designed for climate change adaptation would affect the adaptation processes of wheat farmers in Türkiye under various price dynamics and climate change scenarios. ÇATAK program is a support program that offers various support options for the implementation of several sustainable techniques. Sustainable production techniques are very diverse (discussed in chapter two), depending on the region, the crop produced, and the willingness and ability of farmers to implement them. The sustainable production technique we use in this thesis is no-tillage farming, piloted in Türkiye under the ÇATAK program.

1. Agents: Agents are wheat farmers. We heterogenized wheat farmers to reflect the bounded rationality of their decision-making processes, i.e., farmers are not perfect rational optimizers but agents who make decisions based on limited information, cognitive constraints, and local interactions.

2. Environment: Environment refers to wheat production areas in Türkiye that are exposed to various climate change impacts and price dynamics. Environmental characteristics such as local climatic conditions and fertilizer use influence farmers' decisions and the effectiveness of adaptation strategies.

3. Interactions: Farmers' interactions with their environment and other farmers shape their decision-making processes. In this context, farmers learn from past experiences and observe the practices of neighboring farmers. These interactions, often local, contribute to the diffusion of knowledge and the adoption of sustainable practices such as no-tillage farming.

By examining these three components - wheat farmers with limited rationality (agents), wheat production areas in Türkiye (environment), and learning from past experiences and neighbors (interactions) - this study aims to capture the complex and heterogeneous nature of farmers' decision-making processes in the context of climate change adaptation.

This conceptualization sets the stage for a comprehensive analysis of the interplay between individual decision-making, environmental factors, and policy interventions in shaping farmers' adaptation to climate change in Türkiye's wheat production sector.

2.1.3. Input Data

Our study needs multiple data types to analyze the social and physical aspects of agricultural decision-making. Our data collection approach comprises complementary quantitative and qualitative data combinations commonly used in ABMs (Janssen & Ostrom, 2006; L. Yang & Gilbert, 2008).

We started data collection by analyzing the eligibility conditions for the ÇATAK program. The ÇATAK program includes three types of support: minimum tillage, protection of soil and water structure and prevention of erosion, and environmentally friendly agricultural techniques and cultural practices. In this study, we analyzed the decision-making processes of farmers implementing minimum tillage (no-till farming) support. The main criterion of the program is to have a minimum land size of fifty decares. Based on this requirement and the WWF (2022) report's focus on ÇATAK participants, we assumed that the 575 farmers interviewed in the report met this minimum size threshold. We also included farmers below this threshold to fully model social learning mechanisms through social identity theory. For this, we used the most recent agricultural census data:

To ensure that our model is representative of all farm sizes and captures social learning mechanisms across different farmer types, we expanded the sample of 575 farmers in the WWF report to include small farms. We use recent agricultural census data for this expansion for the study regions.

First, we categorized the 575 farmers in the WWF report as large farms (≥50 decares), assuming they meet the minimum land size threshold to participate in the ÇATAK program. We then calculated the regional distribution of these large farms across the five study regions (Ankara-Eskisehir, Konya, Sanliurfa, Edirne-Tekirdag and Kayseri-Sivas).

Next, we obtained the total number of farms and their size distribution in each region from the agricultural census data. Using this information, we calculated the ratio of small farms (<50 decares) to large farms (≥50 decares) in each region.

Finally, we added a proportional number of small farms to the sample of large farms in each region, preserving the regional distribution of farm sizes observed in the agricultural census data. After these calculations, our sample expanded from 575 to 798.

The final regional breakdown and farmer numbers are shown in Table 1:

Table 1. Number of Farmers in the Study area

Regions	Number of Farmers (report)	Number of Farmers (adjusted)
Ankara-Eskişehir	147	188
Konya	108	162
Şanlıurfa	79	106
Edirne-Tekirdağ	86	136
Kayseri-Sivas	126	206

The expanded sample comprises 575 large and 223 small farms, offering a more comprehensive representation of regional farming communities. This diversity in farm sizes enables our model to capture the heterogeneity in farming operations better and examine the potential for social learning and diffusion of no-till farming among different types of farmers. This representation allows us to model the decision-making processes and interactions of farms that can participate in the ÇATAK program and farmers who may be indirectly affected by the program through social learning. The inclusion of small farms in the model is crucial for understanding the broader impacts of the ÇATAK program on the adoption of no-till farming practices and the overall sustainability of farming systems in the study regions.

In our model, we extend ÇATAK's three-year commitment to five years. The transition to no-till farming often involves an initial period where soil compaction and reduced crop yields can be observed. This period can last several years as the soil structure adjusts to the new management practice (Bakirov et al., 2021; Carretta et al., 2021). The decision to use five years is supported by Turkish agricultural reports, which recommend uninterrupted support during this period (Redman & Hemmami, 2008).

Our main source is the WWF report to identify the farmer typology, but we also used other reports (DOKTAR, 2018, 2019) to identify factors influencing the decision processes of farmers in Türkiye. These reports provided information on the factors influencing farmers' decision-making processes and the challenges and opportunities they face in adopting sustainable agricultural practices.

We used the WWF report to identify key variables and thresholds farmers consider when adopting no-till farming practices. These include expected costs and benefits, perceived risks and uncertainties, and the influence of social norms and peer behavior. To identify how peer learning, a key determinant of farmer behavior, influences farm decisions across regions, we drew on the WWF report, as well as other reports which allowed us to identify a diverse profile of farmers with different levels of resources, skills, and motivation, ranging from subsistence smallholders to large holders. We used this information to create different types of agents in the model, each with its own characteristics and decision rules, reflecting the real-world heterogeneity of farmers in the study regions.

To estimate the wheat yields equation, we constructed a panel regression model using wheat yields, fertilizer use per decare, and climate data from 1994-2023 for the eight provinces in the study area. We calculated average monthly rainfall and temperature values separately for each stage of the crop cycle (sowing, growing, and maturing phases) (see appendix 2). For this analysis, we obtained wheat yield data from TurkStat for 2004 and onwards and agricultural structure statistics for 1994-2003; data on inputs per decare from MoAF for 2000-2023 and agricultural structure statistics for 1994-2000; and meteorological data on seasonal variables from the World Bank's climate change unit.

Using the World Bank data, we also conducted a trend analysis of climate change impacts on wheat yields, temperature, and precipitation for the period 1994-2023. This involved calculating the long-term mean and standard deviation values of temperature and precipitation variables for each stage of the wheat production cycle. By incorporating these historical trends into the panel regression model, we effectively endogenized the observed changes in yield, temperature and precipitation due to climate change. This approach allows our model to capture the dynamic relationships between climate variables and wheat yields over time, providing a more realistic representation of the agricultural systems' response to changing environmental conditions.

Finally, we used the household size of farms to calculate the average annual consumption of producer-consumer subsistence farmers, which affects their production decisions.

2.2. MODEL

The model was simulated with NetLogo version 6.0.4 (Wilensky & Rand, 2015). NetLogo is a valuable tool for modeling and simulating climate change impacts and adaptation strategies (Svihla & Linn, 2012). Integrating NetLogo into the software facilitates parameter estimation, sensitivity analysis, and simulation experiments in agent-based models (Thiele et al., 2014).

ABM was developed to analyze the impact of annual climate variability and changes in wheat yields obtained using inputs per decare on agricultural decision-making processes.

The ABM incorporates key insights from the ÇATAK program and the regional differences in cropping patterns and farm sizes discussed in the previous section. First, the model includes a policy component that simulates the financial incentives the ÇATAK program provides to farmers who adopt environmentally friendly agricultural practices, such as no-till farming. This allows us to explore how different levels of support or targeting incentives may influence farmers' decision-making and the overall adoption of sustainable practices.

Second, the model accounts for regional heterogeneity in cropping patterns and farm sizes by initializing the farmer agents with characteristics that reflect the distributions observed in the empirical data.

2.2.1. Agents

Wheat farmers are the main agents in our model. We can categorize the decision-making processes of wheat farmers in Türkiye in many ways depending on various factors such as agricultural practices, land size, and resource access. In the farmer typology we developed in this model, we designed farmers' decision-making process as a multifaceted interaction of factors such as their willingness and ability (Zagaria et al., 2017). This is because even though agents in the same agent typology share a similar willingness, differences in their abilities (e.g., socio-economic conditions and different agent characteristics) can affect [agents'] decision-making processes (Valbuena et al., 2010).

We used some published reports, notably the WWF report, to define the farmer typology. With the farmer typology defined according to farmers' willingness and abilities, we defined four different farmer types:

Subsistence farmers: These farmers have a land size of less than 50 decares. Therefore, even if they want to try no-till farming, they cannot. Their aim of farming is their consumption instead of agricultural production. So, they have off-farm income.

Observer farmers: These farmers are open to peer-to-peer learning and follow the same agricultural production method as the neighboring farm.

Environmental-awareness farmers: According to the report, we included farmers with no-till farming experience as environmental-awareness farmers in the model. These farmers are adaptive farmers who learn from their own experience.

Traditional farmers: These farmers are not convinced about the benefits of no-till farming based on the information in the WWF report.

Following the identification of farmer typologies, we categorized farmers by enterprise size scale to identify factors that increase or decrease the adaptive capacity of regions. Farmers' objectives for agricultural production differ according to enterprise size. This difference in their objectives reflects their farming style, as van der Ploeg (2008) defined. Farming style (or land use) can be defined as the dominant structure of relations between producers, objects of labor, and tools (van der Ploeg, 2008, p. 12). While the farm size category does not fully reflect farming style, as the model neglects farmer labor, one can speak of a farming style in terms of whether the primary purpose of farms is agricultural production or not, depending on their size. Based on this, a distinction can be made between family and commercial farms. Family farms can be categorized into farms with and without agricultural production as their primary purpose. The resulting farming styles represent the heterogeneity of farmers' decision processes.

The enterprise size of farms categorization used in Türkiye is as in the table:

Table 2: Enterprise size of farms categorized by enterprise type

Enterprise Size	Enterprise Type
1- 499	**Small farm enterprise**
1- 99	Small family farm enterprise
100- 199	Medium-size family farm enterprise
200- 499	Large-size family farm enterprise
500- 5000	**Medium-size farm enterprise**
5000+	**Large-size farm enterprise**

Source: (Anonymous, 2018)

The decision-making process heterogeneity of farmers in our model is shaped by enterprise type and farmer type. The learning process of the defined farmer types varies according to their desires and abilities. Some farmers observe their neighbors, while others learn from past experiences. A farmer who learns from past experience can be considered an experienced farmer, and this experience also reveals their approach to risk-taking. For farmers capable of making their own decisions, this willingness may be determined by their experience as well as the size of their production area.

Decision processes can be influenced by many components. Therefore, in addition to the farmer typology, we have included farmers' enterprise sizes to reflect the heterogeneity of decision processes. In the typologies we defined, we did not explicitly specify the average land size of farmers other than subsistence farmers due to the lack of data. However, it is possible to make assumptions about the determinants of farmers' learning processes based on empirical studies that support the relationship between farmers' risk perception, farming experience, and land size.

For example, when adding farmers who have learned from the past to the model, we indicated that they might be experienced and largeholders. Although we cannot state this explicitly, we can assume that the land size of a traditional farmer who does not believe in the benefits of conservation agriculture may be a determinant of the learning mechanism. For a traditional farmer to be a farmer who learns from their past, farming should be their main purpose, and they should have an agricultural enterprise of a size that is not affected by anyone else's decision.

However, the fact that these farmers do not believe in the benefits of no-till farming reflects their beliefs, regardless of land size. This belief or attitude may be driven by the resources available to the farmers or influenced by the norms of the society in which they live. In this case, the traditional farmer is likely to be a small-scale farmer who is not willing to change their approach and does not know how to compensate for the loss of yield.

The learning mechanisms of traditional farmers are, therefore, a function of their land size. This is true only for traditional farmers. Unlike farmers who learn from their neighbors and carry out the learning process by looking at their neighbors objectively, we can infer that if traditional farmers are small-scale farmers, they will only observe their neighbors who do not practice no-till farming. If they are largeholders, they do not consult anyone while continuing their production with traditional methods such as adjusting the amount of inputs.

Table 3. Farmer Typology

Farmer Type	Behavior Type	Willingness	Ability	Result
Subsistence	Social learner	N.A. (- / +)	No (-)	Social learner but lack of resources
Observer	Social learner	Yes (+)	Yes	Adaptive
Environment-awareness	Autonomous decision-maker	Yes (+)	Yes	Adaptive
Traditional	Autonomous decision-maker and social learner	No (-)	Yes	Social learner but resistance to change

This farmer typology provides a concise overview of the key characteristics and decision-making processes of each farmer type in our model.

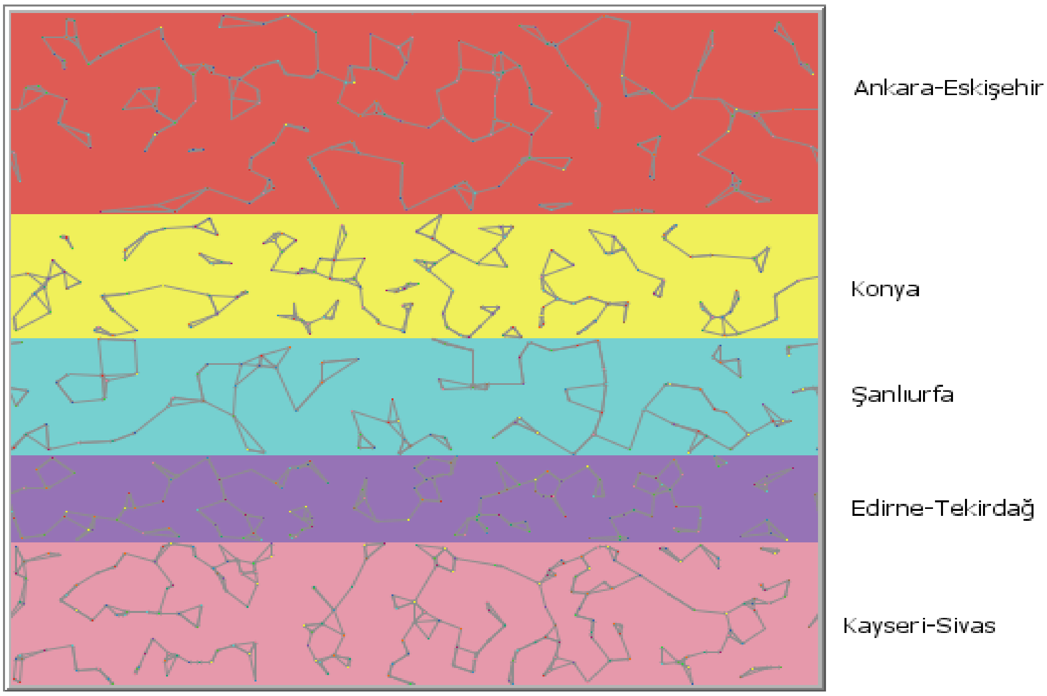
The willingness of each farmer type to adopt new practices, such as no-till farming, indicated by a positive (+) or negative (-) sign. N/A is used for subsistence farmers, as their willingness is not a determining factor due to their land-size constraints. The ability of each farmer type to adopt new practices, indicated by a positive (+) or negative (-) sign. For subsistence farmers, the ability is listed as (- / +) No, suggesting that their ability is limited and ultimately results in a negative outcome.

2.2.2. Environment

The landscape is a 200 by 200 grid (40000 cells) of 1 decare arable plots representing the five regions in the study area. Each plot's wheat yield differs according to the amount of inputs used and rainfall and temperature values (for which the wheat yield equation was derived).

We use NetLogo interface to show the regions. Our environment has five regions; Ankara-Eskişehir, Konya, Şanlıurfa, Edirne-Tekirdag, and Kayseri-Sivas. Figure 2: provides the environment of study areas in NetLogo interface.

Figure 2: Study area in NetLogo interface



All regions have different numbers of farmers with farmer typology and business type. Table 4 shows the regional distribution of farmer typologies as percentages of the total number of farmers in each region.

Table 4. Farmer Typology's Regional Distribution (%)

	Subsistence	Observer	Environmental-Awareness	Traditional
Ankara-Eskişehir	0.22	0.25	0.25	0.29
Konya	0.33	0.22	0.17	0.28
Şanlıurfa	0.25	0.64	0.03	0.08
Edirne-Tekirdağ	0.37	0.27	0.14	0.22
Kayseri-Sivas	0.39	0.28	0.12	0.21

The distribution of farmer typologies varies significantly across regions. For example, Şanlıurfa has the highest proportion of observer farmers (64%) and the lowest proportion of environmentalist-awareness farmers (3%), while Kayseri-Sivas has the highest proportion of subsistence farmers (39%) and a relatively low proportion of environmentalist-awareness farmers (12%).

These regional differences in farmer typologies are important for understanding the heterogeneity of decision-making processes and the potential for adopting sustainable agricultural practices, such as no-till farming. These regional differences in farmer typologies are important for understanding the heterogeneity of decision-making processes and the potential for adopting sustainable agricultural practices, such as no-till farming. Table 5 shows the regional distribution of farmer typologies as percentages of the total number of farmers in each region.

Table 5: Farmer Farm Enterprice Type's Regional Distribution (%)

Regions	Smallholder Family Farm Enterprise (1-100 de)	Medium-Size Family Farm Enterprise (101-250 de)	Large-Size Family Farm Enterprise (251-500 de)	Commercial Farm Enterprise (501-5000 de)
Ankara-Eskişehir	0.41	0.36	0.19	0.04
Konya	0.52	0.31	0.14	0.02
Şanlıurfa	0.51	0.28	0.15	0.06
Edirne-Tekirdağ	0.65	0.26	0.05	0.03
Kayseri-Sivas	0.64	0.23	0.12	0.01

By incorporating these regional variations into our agent-based model, we can understand how the interactions between farmers with different typologies and business types influence the overall dynamics of the agricultural system and its response to policy interventions and changing environmental conditions.

2.2.3. Interactions

Farmer agents interact with each other and their environment through land use decisions driven by their characteristics, experiences, and learning processes. The decision farmers make in the model is whether to continue or stop wheat production. This decision is influenced by several factors, including the farmer's typology, their past yields, the behavior of their neighbors, and the availability of policy support for conservation agriculture.

Farmers who continue wheat production can choose between two options: (1) adopt no-till farming practices that the agricultural support program can support, or (2) maintain conventional tillage methods. The choice to adopt no-till farming is based on the farmer’s perception of climate change and knowledge of its potential benefits (e.g. reduced input costs), as well as their interactions of environmental-awareness farmers with the environment, observer farmers with other farmers who have adopted the no-till farming.

Farmers who decide to stop wheat production can either (1) change the cropping pattern in their region and switch to the second most crop in their region’s cropping pattern, or (2) completely withdraw from agricultural production and leave their land uncultivated.

As a result of these individual decisions, the overall land use pattern in the region evolves, with changes in the area devoted to wheat cultivation, other crops, and uncultivated wheat area. These changes, in turn, affect the environment (e.g., through migration from rural to urban areas) and the social and economic conditions of the farming community (e.g., through changes in overall yields and incomes). The model captures these feedback effects and allows complex dynamics to emerge at the regional scale based on interactions between heterogeneous agents and their environment.

2.3. MODEL PROCESS

The model represents the economy as an iterative system. At each time step representing the year (t = 1, ... T), farmers iterate their decision-making process based on their current resource situation, accumulated knowledge, and social interactions and take the following actions

1. Deciding whether to continue wheat production: Farmers' decisions on whether to continue wheat production are determined by threshold rules assigned according to their farm enterprise size and farmer type.

2. Wheat production using the selected support system: Farmers who continue wheat production choose between two support systems: Conventional tillage or conservational tillage.

3. Evaluating the wheat production process: Farmers evaluate the results of wheat production in terms of revenue, farming aim, and yield. Farmers whose yields are lower than the average yield of the last five years engage in a decision process within their typology.

4. Operating the learning mechanism: Farmers update their knowledge and expectations based on their own experience and the experience of other farmers in their neighborhood. This learning process influences their future decisions to adopt or continue with no-till farming. This process works differently for each typology.

5. Analyzing the effectiveness of the subsidy program: The model tracks adoption rates of no-till farming and changes in wheat yields, costs, and profitability over time. By comparing these results under different scenarios (e.g., with and without the no-till farming support program or different levels of support), the model assesses the effectiveness of the subsidy program in promoting the adoption of sustainable agricultural practices and improving the economic and environmental performance of the farming system[2].

These five components of the model process are implemented through a set of sub-models, which include the decision-making process of farmers. These sub-models are described in more detail in the following subsections.

2.3.1. Sub-models

2.3.1.1. Production decision model: The production decision model in our ABM calculates the average net revenue of farmers based on their farm

[2] The farmer who chooses the no-till farming support policy has to continue this support policy for five years. Under this support policy, farmers received higher support than traditional support. In the ÇATAK program, the government also gave the farmer a 50 percent grant for a planting machine. However, this model assumes that the state provides the planting machine free of charge for five years. Farmers who have not experienced a decline in revenue at the end of five years become lead farmers. After that, farmers do not decide to change their production methods again. In the case of lead farmers, it is assumed that the farmer who has not experienced a revenue loss at the end of five years will invest in a new production technology by purchasing a seeder. Given that the economic life of the agricultural investment is 23 years, it is unlikely that the seeder will complete its economic life in the simulation period (2021-2050). Under the assumption that farmers will consider sunk costs, lead farmers are always assumed to practice conservation agriculture. After becoming a lead farmer, farmers do not benefit from subsidies for conservation agriculture but from subsidies for conventional agriculture. After five years, farmers who experience welfare losses start producing in the old way again and continue as conventional farmers.

enterprise type, which is used as a measure of their welfare. Farmers' welfare is determined by the cost of inputs per decare, and this plays a crucial role in their decision to adopt environmental policies, such as conservation agriculture.

Continuing wheat production: Farmers' decisions to continue or stop wheat production are independent of their decisions regarding the adoption of conservation policies. Each farmer has a specific threshold for continuing wheat production, which varies based on their farming objectives and farm type. For subsistence farmers, the threshold is related to production costs. If the cost of wheat production exceeds the cost of consumption for five consecutive years, these farmers stop wheat production. For non-subsistence farmers, the threshold is determined by the wheat input parity, which includes the costs of oil and fertilizer. If the previous year's parity is higher than the current year's parity for five consecutive years, these farmers either quit farming altogether or stop wheat production, depending on their farm size category. Farmers with smaller land holdings (less than 250 decares) are more likely to quit farming entirely if the threshold is crossed, while those with larger holdings are more likely to switch to alternative crops.

The production decision model captures the complex interactions between farmers' welfare, input costs, and the adoption of conservation agricultural policies. It highlights the role of heterogeneous adoption behavior and the influence of farm size and farming objectives on farmers' decisions to continue or stop wheat production. By incorporating these factors, the model provides a more realistic representation of the decision-making processes and outcomes in the context of sustainable agriculture adoption in Türkiye.

The wheat yield is a critical component of the agent-based model, as it determines the actual yields for each farmer based on their input use and climate conditions. To estimate the yield model, we use a panel regression approach with data on wheat yields, fertilizer use, and climate variables for the eight provinces in the study area over the period 1994-2023.

The specific functional form of the yield equation is as follows:

$$Y_{f,r,t} = \beta_r + \beta_f NPK_{f,t} + \beta_{sow} sow_{r,t} + \beta_{grw} grw_{r,t} + \beta_{mtr} mtr_{r,t} + \varepsilon_{f,r,t} \quad (1)$$

Where:

- $Y_{f,r,t}$ is the wheat yield for farmer f in region r at year t
- $NPK_{f,t}$ is the amount of fertilizer (Nitrogen-phosphorus-potassium) used by farmer f at year t (individual decision)
- $sow_{r,t}$, $grw_{r,t}$ are the average yearly temperatures during the sowing, growing phases of the wheat cycle in region r and year t (in ℃)
- $mtr_{r,t}$ is the average yearly precipitation during the maturing phases of the wheat cycle in region r and year t (in mm)
- β_r is the region-specific fixed effect
- $\varepsilon_{f,r,t}$ is an error term for farmer f in region r at year t

The estimated coefficients from the yield are used to calculate total wheat production for each farmer agent in the ABM. Total wheat production for each farmer is calculated with wheat yield and farm size, farm size is equal to total number of patches for farmer;

$$A_f = \sum A_{f,p} \quad (2)$$

Where;

A_f : Total farm size for farmer f

$A_{f,p}$: Number of patches p owned by farmer f

From the yield and farm size we can calculate total wheat production per farmer:

$$Q_{f,t} = Y_{f,r,t} \times \mathrm{A_f} \quad (3)$$

Where:

$Q_{f,t}$: Total wheat production for farmer f at year t

$Y_{f,r,t}$: Wheat yield per decare for farmer f in region r at year t

A_f : Total farm size for farmer f

With the wheat production value, farmer production decision model is evaluated. First, we can look at farmers' farming aims. The only subsistence farmers farming aim is production to consumption. Others' main aim is agricultural production. So, their decision is different because of this. We explain this section above. Decision processes affect their thresholds. These thresholds related to farmers' wheat production value. This value reflects the size of economics normally. But in this model because of the lack of data, we can differentiate farmers' wheat production value based on wheat market. The wheat market reflects price dynamics to buyer and seller of wheat. This market is related to farmers' abilities. These abilities are related to farmers' farm size. So, we can differentiate farmers' wheat market dynamics depending on the farmers farm enterprise type. Subsistence farmers production is not to market. They produce wheat for consumption. So, their production decision is based on their production amount and cost of production. We can define a decision rule from this point of view.

Price is based on market structure. Farmers may also differ in terms of the means of production they own and the market structure in which they sell their products. For example, the market structure in which wheat farmers sell their products is different from each other. There are three main buyers in Türkiye's wheat market: merchants, TMO, and wheat stock-exchange (KKB, 2020). In our model, we assumed that the sales channel of small and medium-sized family enterprises is merchants, the sales channel of large family enterprises is TMO, and the sales channel of medium and large enterprises is wheat exchange. This assumption is based on the understanding that small and medium-sized family farms lack the transportation facilities to deliver their products to TMO silos, while large family farms have the means to transport their products to state silos but do not have their own storage facilities. Medium and large-scale enterprises, on the other hand, have silos on their farms and can store their products until they can sell at the highest price on the wheat exchange.

We can calculate wheat production value $V_{f,t}$ in the equation (3):

$$V_{f,t} = P_{f,t} \times Q_{f,t} \tag{3}$$

where:

- $V_{f,t}$the wheat production value for farmer f
- $P_{f,t}$: Wheat Price for farmer f

- $Q_{f,t}$: Wheat Production Amount for farmer f

Farmers' production decisions first part is wheat production value is calculated and, as we said above, the wheat production value equation reflects distinct sales channels.

The second part of the decision-making process concerns input costs and subsidies. Input costs include fertilizer and oil costs. This cost differs according to the type of tillage. In no-till farming, farmers tilled only once. In conventional tillage systems, farms are tilled four times. Therefore, oil costs are different. Studies on fertilizer use in a no-till farming show that the land's need for nitrogen fertilizer is reduced when wheat production is combined with legumes. It was also found that pesticide use increased in the first years of no-till farming. Since our study is not based on some land-related data, we cannot include fertilizers and pesticides. Therefore, we can only focus on diesel demand.

The amount of support differs according to farm size and tillage type. In the support system in Türkiye, farmers with a maximum of five decares of land are supported as additional support for small family farms. In the years when ÇATAK support was provided, the amount of support received by the implementing farmers differed from that of the traditional farmers. Based on this information, our model has three types of support systems. These different support systems influence farmers' production decisions, which can be analyzed through a series of economic calculations that account for both revenue and costs.

We can calculate the returns on per area (de^{-1}) for each farmer in equation (4):

$$G_{f,t} = V_{f,t} - (F_{f,t} + O_{f,t}) + S_{f,k,t} \qquad (4)$$

where:

- $G_{f,t}$: the gross margin per decare for wheat for farmer f
- $V_{f,t}$: the wheat production value for farmer f
- $F_{f,t}$: fertilizer cost for farmer f
- $O_{f,t}$: oil cost for farmer f

- $S_{f,k,t}$: subsidy amount for farmer f under support system k

The model calculates revenue. Let’s consider $\mathrm{R_f}$ revenue for farmer f:

$$\mathrm{R_f} = V_f \ / \ C_f \tag{5}$$

Where:

- V_f: the wheat production value for farmer f
- C_f: the wheat production cost for farmer f

These equations to determine the economic performance of each farmer agent based on their individual yields, input costs, and subsidy levels. The gross margin per decare is a key indicator of profitability, as it represents the difference between the production value and the variable costs (fertilizer and oil), plus any subsidies received.

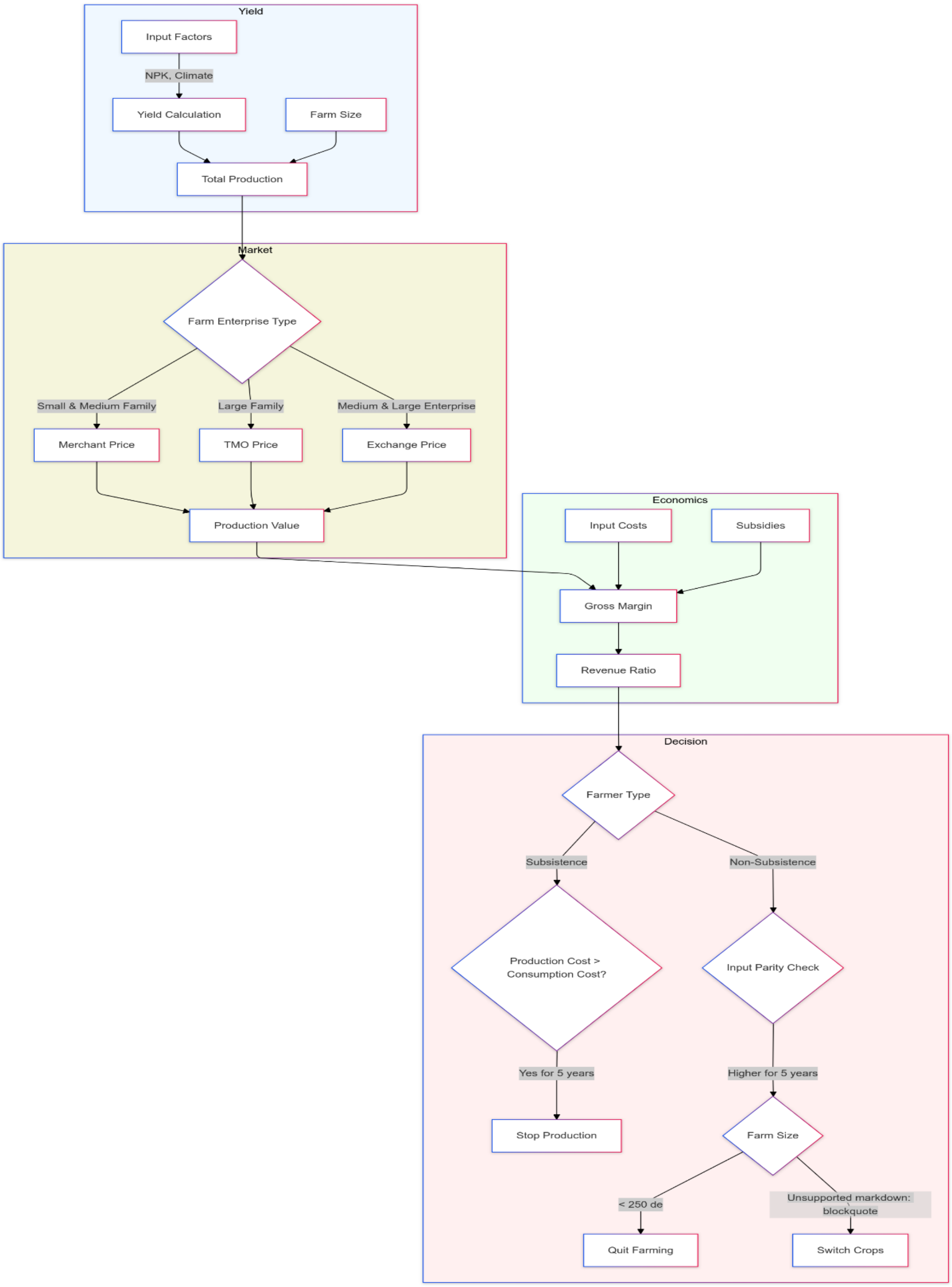
The wheat production value is calculated by multiplying the wheat price by the production amount, which is determined by the yield model described in the previous subsection. The revenue is then obtained by subtracting the variable costs from the production value.

These economic variables are updated at each time step of the model based on the realized yields, input use, and market prices. Farmers use this information to assess their financial performance, compare their outcomes with those of other farmers, and make decisions about whether to continue wheat production or switch to alternative crops or practices.

The economic model also includes additional components to capture the costs and benefits of participating in the no-till farming support program. Farmers who adopt no-till farming practices receive higher subsidy payments for the first 5 years. The model accounts for these factors when calculating the net returns for each farmer and assessing the overall impact of the program on the profitability and sustainability of wheat production in the study area.

Flow cart of production decision model is below:

Figure 3: Flow cart of production decision model



Note: The flowchart consists of four main interconnected sections, each marked by different background colors and representing distinct aspects of agricultural decision-making: The Yield Section (Blue Background), The Market Section (Beige Background), The Economics Section (Green Background), and The Decision Section (Pink Background). Farmers' actions and decisions related to interactions. The initial point for the decision process is light blue box: mean production amount of last 5 years > actual production.

2.3.1.2. Learning model: Peer learning is important in farmers' decision-making, but complex social dynamics and identity considerations shape its effectiveness. When farmers observe their neighbors' practices, their evaluations are shaped by social identity rather than economic rationality. The decision to learn from a neighbor is based on the neighbor's success and how farmers perceive their neighbors within their own social context. Farmers tend to pay more attention to the experiences of neighboring farms that they perceive as similar to their own regarding social status, farming approach, and scale of operation. A farmer may ignore the practices of a neighbor from a different social or operational category, even if these practices could improve their economic outcomes for learning.

In our model, we do not have qualitative data to observe the process of farmers' evaluation of each other, so we evaluate them using quantitative data, using farmers' enterprise size categories. Accordingly, a farmer whose neighbor is in the same farm enterprise category is similar in terms of neighbors, and farmers observe their similar neighbors without defining any thresholds in line with their perception. We assume that a farmer does not observe a neighbor in a different farm enterprise size category if the neighbor is in a smaller category. However, if the different neighbor is in a larger enterprise size category, the farmer can learn by observing within certain thresholds. This framework reflects the heterogeneity in farmers' learning processes. It increases the ability to interpret the results of peer learning regarding regional differences.

The learning model in our ABM addresses the individual and social learning processes that shape farmers' adoption and maintenance of no-till farming practices. We assume that farmers update their beliefs about the feasibility of no-till farming based on two main sources of information: (1) their experiences and evaluations of no-till farming on their farms and (2) the observed experiences and outcomes of other farmers who have adopted no-till farming in their communities. In both cases, assessing the processes that forced the farmer to change the production model is necessary. In the model, we define a five-year memory for farmers in which they compare the average of their production over the last five years with the current year's production (we assume that farmers prioritize production quantity over production gains). If the farmer achieves a higher production than the average of the last five years, then is willing to change. Following this willingness to change, farmers learning from neighbors check whether their neighbors are similar or different. They then compare their revenues with their neighbors' revenues. If a similar neighbor achieves a higher revenue, they will follow the similar neighbor. If not, they look at the different neighbors and compare their revenues with different neighbors. This process is different in each typology:

Subsistence farmers: Since these farmers do not have enough land to practice no-till farming, they only look at the tillage system of their neighbors, regardless of whether their neighbors are similar or different. They adjust their input usage according to the amount of inputs of their neighbors who practice conventional cultivation (if any). If their neighbors practice no-till farming, they continue producing in their own way.

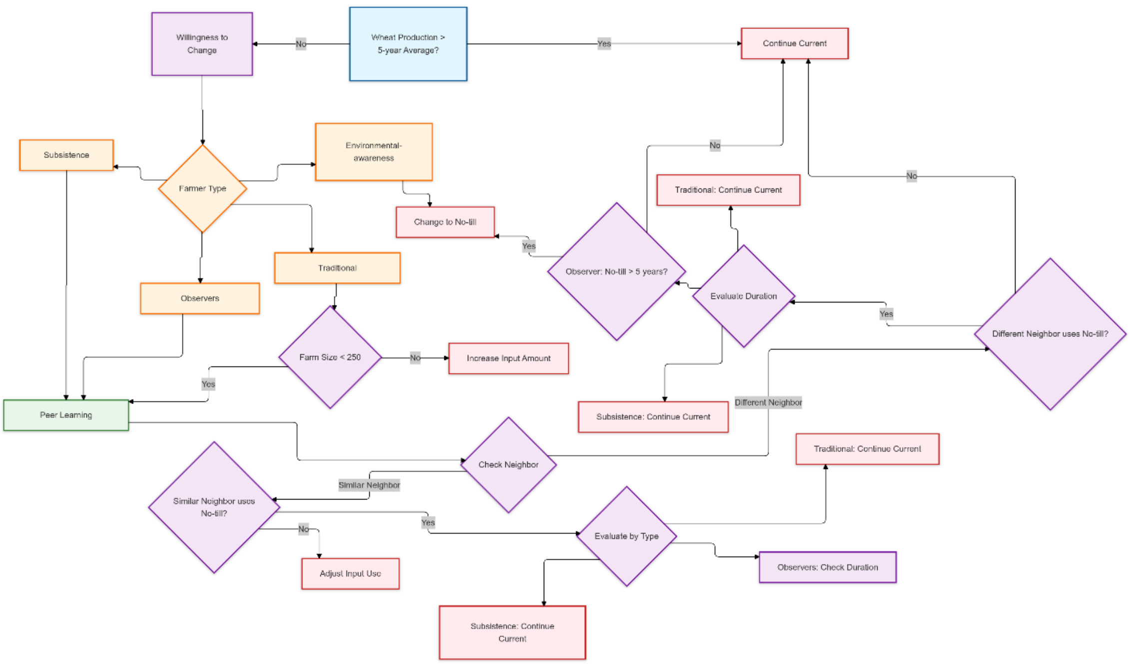
Observers: If a similar neighbor is a no-till farmer, they change the support system; if in the traditional system, they adjust the amount of inputs according to their neighbors. The situation is different for the different neighbors. If the different neighbor (in the larger category) is practicing no-till farming, they check whether the different neighbor has been doing so for at least five years. They continue with the current system if it has been no-till for less than five years. If a different neighbor is practicing a conventional tillage system, they adjust the amount of inputs accordingly. This describes a decision mechanism in which farmers consider risk factors when changing their production technology and focus on the economic benefit obtained when adjusting the amount of input used in the current technology. Farmers are aware that the risk structures of farmers different from them may differ due to resource inequality. Since their similar neighbors produce under the same conditions, they rely on their neighbors who buy the risk in advance. When they do not have a neighbor to learn from, they continue to produce as they know how.

Environmental-awareness farmers: These farmers learn from past experiences. They have previous no-till farming experience, so they know the cost advantage of this system. Therefore, they choose the support policy for no-till farming as a result of the reduction in the amount of production.

Traditional Farmers: The decision mechanism of these farmers is determined by their land size. Those with less than 250 decares of land learn from their neighbors who practice conventional cultivation, while those with more than 250 decares learn from their own experiences. While learning from neighbors is realized by adjusting the amount of inputs according to the neighbor, learning from their own experience is realized by increasing the amount of inputs.

The flowchart below identifies how the learning model is updated based on farmers' individual and social learning experiences:

Figure 4: Flowchart of Decision-Making process of Learning



Note: Farmers' actions and decisions related to interactions. The initial point for the decision process is light blue box: Wheat Production > 5-year Average, farmers' decisions are shown in purple diamond boxes; actions are shown in red/pink rectangle boxes and linked by arrows; farmers' decision process is shown purple diamond boxes; farmer types are shown in yellow rectangle boxes. Decision related to learning is shown in green rectangle box.

2.3.2. Scenarios

2.3.2.1. Model setup: Netlogo's interface allows the user to choose which policy scenarios to simulate. The model can simulate the impacts of both conventional and environmental policies on land use. The baseline scenario aims to represent land-use changes in the absence of environmental support policies. Based on this information, it uses data from the current agricultural system and updates land use at each time step. The result of applying environmental policy scenarios is that farmers' decisions are updated, and these decisions subsequent land use changes. Environmental agricultural policies include an additional support program.

The model was initialized with 798 wheat farmers distributed across five regions. Initially, it is assumed that all farmers practice conventional agriculture. Each region has different input use per decare, climatic characteristics, and land distribution (seen as Table 6: 1994-2023 years variables).

Table 6: 1994-2023 years variables

Regions	Wheat Yield (per decares/kg)	NPK (per decares/kg)	Sowing Temperature (℃)	Growing Temperature (℃)	Maturing Rainfall (mm)
Ankara-Eskişehir	234	6.2	10.06	2.73	149.69
Konya	246	8.2	9.63	2.5	125.4
Şanlıurfa	280	11.1	16.38	7.96	82.63
Edirne-Tekirdağ	367	16	12.83	6.04	140.58
Kayseri-Sivas	189.5	4.3	7.47	-0.65	159.15

2.4. EXPERIMENTS AND SENSITIVITY ANALYSIS

We conducted two sets of simulation experiments. The first is the “agricultural policy effects on climate change adaptation” simulation. With this simulation experiment, we analyze the impacts of agricultural support policies on wheat production, farmer revenue, farmer numbers, and land use change under different price dynamics in the climate change era. We focused on analyzing agricultural subsidy policies and their interaction with price scenarios in the context of climate change adaptation.

To create price scenarios, we use trend extrapolation method. Trend extrapolation is a valuable method for scenario analysis as it allows for estimating future trends based on historical data. Scenario development can, therefore, benefit from trend extrapolation techniques as they provide a basis for estimating future scenarios (Schosser, 2022). These scenarios were completed in two different periods starting from the base year 2002. The first price scenario (PS1) considers data from 2002 to 2019, while the second (PS2) considers data from 2002 to 2021. The end year of the first price scenario is essential as it is the last period before COVID-19.

In this price scenario, the increase in input costs is offset by subsidies and the wheat price. In the second price scenario, due to the exchange rate crisis that started in the second half of 2021, the increase in production costs was much higher than the amount of support, leading to a price shock in input costs. The price of DAP fertilizer, 3700 TL in the first half of 2021, increased to 14600 TL in the second half of 2021. Since the annual averages of the variables used in the model are considered, the 2021 DAP fertilizer price is calculated as 9150 TL. Since subsidies are announced at the beginning of the year and evaluated according to the annual price average, the increase in input prices in 2021 could not be compensated by the increase in subsidies. Fertilizer and oil prices, agricultural subsidies, wheat prices (heterogeneous), and TMO wheat sales prices are considered when constructing price scenarios. Table 7 shows the annual rate of increase after accounting for price changes. 2021 prices are taken as a starting point.

Table 7: Annual growth rates of scenario parameters

	PS1	**PS2**
Wheat Price	7.11 %	8.26 %
TMO Market Price	7.10 %	8.77 %
Oil Price	7.36 %	8.21 %
Fertilizer Price	5.09 %	8.10 %
Subsidy Amount	0.44 %	2.51 %
Smallholder Family farmers subsidy amount	10 %	10 %

After the calculations, we developed three main scenarios in the first experiment (see Table 8).

Table 8: Scenarios for first experiment

Scenario	**Input price dynamics**	**Price scenarios**	**Subsidy policy**
Baseline	Exogeneous	PS1	Conventional
A	Exogeneous	PS2	Conventional
B	Exogeneous	PS2	Conventional and conservational

The model incorporates multiple price-related variables to capture the economic dynamics of wheat production. Price scenarios are constructed using a comprehensive set of variables: fertilizer and oil prices represent input costs, while agricultural subsidies and wheat prices (which vary by region) represent revenue sources. The Turkish Grain Board (TMO) wheat sales prices are included to reflect market intervention effects. All these variables are initialized using 2021 base prices and adjusted annually according to the respective price scenarios (Table **9**). The annual rates of change for these variables differ between PS1 and PS2, reflecting the distinct economic conditions of each scenario period.

Table 9: First Experiment' Scenario's parameters

Variables	Unit	Initial value	Data access	Notes
TMO-price	TL	2.25	Turkish Grain Board (TMO)	The wheat used in this study is white/red bread wheat with the code 1211/1221.
Merchant Price	TL	1.81	TMEX	The rate of change in this price is indexed to the rate of change in the TMO price.
Stakeholder Price	TL	2.73	TMEX	The rate of change in this price is indexed to the rate of change in the TMO price.
TMO-selling-price	TL	2.32	Turkish Grain Board (TMO)	The wheat used in this study is white/red bread wheat with the code 1211/1221.
Fertilizer price	TL	9.15	Turkish Chamber of Agricultural Engineering (ZMO)	The price of DAP fertilizer is considered because it is a very suitable plant nutrient for wheat to be grown in Central Anatolia and the transition regions.
Oil price	TL	7.65	Turkish Chamber of Agricultural Engineering (ZMO)	-
Subsidies	TL	42	Ministry of Agricultural and Forestry	The subsidies cover oil and fertilizer prices. Since wheat yield is analyzed based on fertilizer and climate, the cost of seed is not considered. for this reason, the amount of certified seed included in the subsidies is not included in the subsidies.
Additional subsidies	TL	100	Ministry of Agricultural and Forestry	Small farmers (at least 5 decares of land)
Subsidies NT	TL	70	Ministry of Agricultural and Forestry	ÇATAK subsidies 2018 deflates dollar

The second simulation experiment is "environmental-awareness farmers farm size effect on adaptation rate." In the model, the learning mechanism takes place through peer-to-peer learning of farmers. For this reason, we analyze whether the adaptation rate results are changed to the land size of the environmental-awareness farmers. In the first simulation experiment, we randomly distributed the farm sizes of the farmer typology. The area cultivated by farmers in the region, excluding subsistence farmers (max 49 decares of land they have), varies in each simulation experiment. The first is the B scenario (from the first experiment), the second is environmental-awareness farmers' farm sizes larger than traditional farmers' farm sizes, and the third is environmental-awareness farmers' farm sizes smaller than traditional farmers. In all these scenarios, the price scenario is PS2. This experiment analysis is crucial for identifying which regions and land sizes should be prioritized for support to optimize adaptation outcomes.

The scenarios are Table 10: Scenarios for second experiment below.

Table 10: Scenarios for second experiment

Scenario	**Input price dynamics**	**Price scenarios**	**Environmental-awareness farmers' farm size**
B	Exogeneous	PS2	Randomly distributed
B1	Exogeneous	PS2	Larger than traditional farmers
B2	Exogeneous	PS2	Smaller than traditional farmers

We ran the simulation 1000 times for three scenarios to analyze the effect of environmental-awareness of farmers' land size on the adoption rate. We obtained the production area sizes of the environmental-awareness farmers in each region, as shown in Table 11.

Table 11: Mean farm size (de) of environmental-awareness farmers

Scenarios	Ankara-Eskişehir	Konya	Şanlıurfa	Edirne-Tekirdağ	Kayseri-Sivas
B	230	215	270	170	180
B1	310	290	1100	270	300
B2	150	130	190	110	130

We compare the scenarios developed for the two simulations with the BAU. This ABM simulated for a 30-year period starting from the base year 2021. Table 12 summarizes the two experiments and the main results.

Table 12: Summary of experiments

Experiments	Scenarios	Results	
Price and agricultural support mechanism	**BAU:** PS1 prices, no environmental support policy	• Wheat production ↓ • Farm number ↓ • Wheat area ↓	
	A: PS2 prices, no environmental support policy	**Compared to BAU:** • Wheat production ↓ • Farm number ↓ • Wheat area ↓	
	B: PS2 prices, with environmental support policy	**Compared to BAU:** • Wheat production ↓ • Farm number ↓ • Wheat area ↓	**Compared to A:** • Wheat production ↓ • Farm number ↓ • Wheat area ↓
Peer learning mechanism	**B:** Environmental farm size defined randomly	• Wheat production ↓ • Wheat area ↓	
	B1: environmental farm size larger than traditional	**Compare to B:** • Wheat production ↑ • Wheat area ↑ • Revenue ↑ • Adoption rate ↑ Input productivity ↑	
	B2: environmental farm size smaller than traditional	**Compare to B:** • Wheat production ↓ • Wheat area ↓ • Revenue ↓ • Adoption rate ↓ • Input productivity ↓	**Compared to BAU:** • Wheat production ↓ • Wheat area ↓ • Revenue ↓ • Adoption rate ↓ • Input productivity ↓

Note: ↑ indicates an increase or improvement, ↓ indicates a decrease or decline.

2.5. RESULTS

We assessed the impacts of the scenarios on wheat production, farmer income, number of farms, and land use change by examining regional differences.

Experiment 1: agricultural policy effects on climate change adaptation

We summarize the scenarios' impact on the main outcomes at the end of 30 years in Table 13.

Table 13: Results of the first experiment

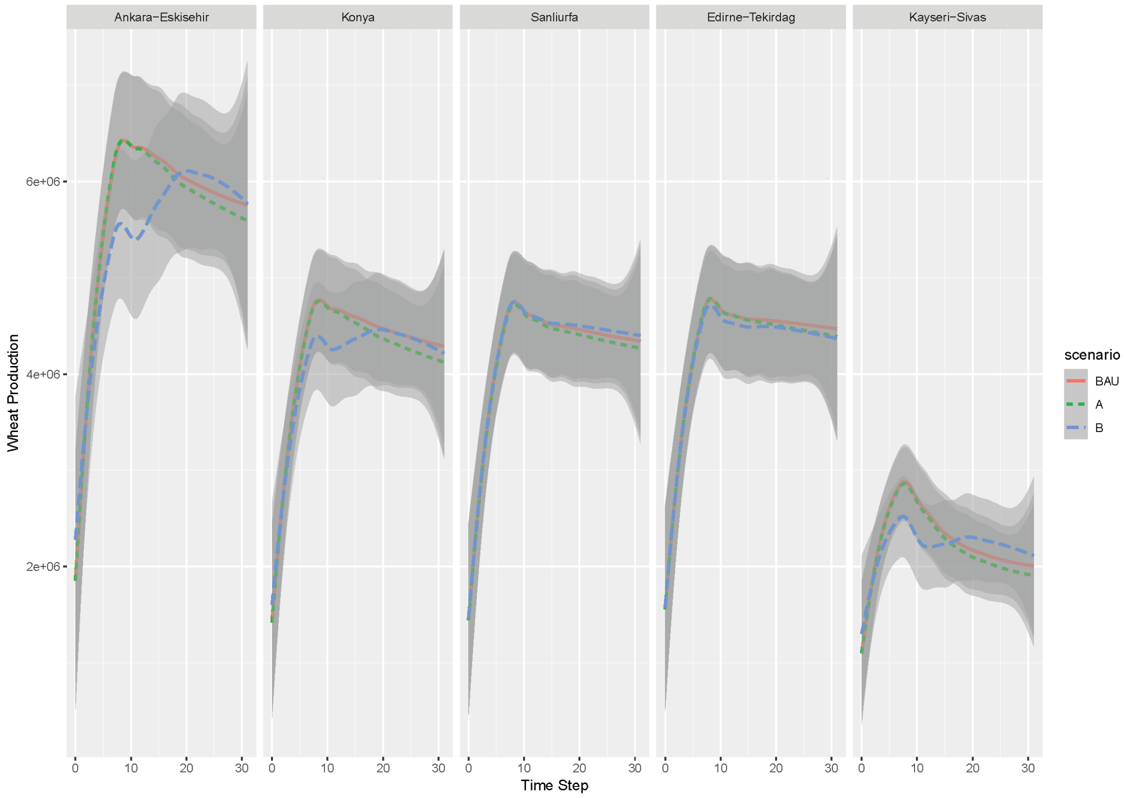
Region	Outputs	Indicator	Unit	Scenarios BAU	A	B
Ankara-Eskişehir	Wheat production change		(%)	18.1↓	20.8↓	17.3↓
	LUC	Wheat area	(%)	30.8↓	33.0↓	30.4↓
		Other area		14.7↑	15.5↑	14.9↑
		Uncultivated		16.2↑	17.5↑	15.5↑
	Revenue		TL	1.84	1.69	1.83
	Farmer numbers	Smallholder	(%)	35↓	37↓	38↓
		Medium-size		40↓	44↓	40↓
		Large-size		27↓	30↓	27↓
		Commercial		21↓	20↓	22↓
Konya	Wheat production change		(%)	17.8↓	20.5↓	18.1↓
	LUC	Wheat area	(%)	26.7↓	29.4↓	27.9↓
		Other area		11.1↑	11.8↑	11.5↑
		Uncultivated		15.6↑	17.6↑	16.3↑
	Revenue		TL	1.86	1.70	1.83
	Farmer numbers	Smallholder	(%)	27↓	30↓	34↓
		Medium-size		34↓	38↓	32↓
		Large-size		22↓	24↓	24↓
		Commercial		17↓	17↓	17↓
Şanlıurfa	Wheat production change		(%)	14.2↓	15.3↓	13.2↓
	LUC	Wheat area	(%)	17.0↓	18.9↓	17.5↓
		Other area		8.6	9.1	8.3
		Uncultivated		8.4	9.8	9.1
	Revenue		TL	2.01	1.86	1.90
	Farmer numbers	Smallholder	(%)	22↓	25↓	26↓
		Medium-size		23↓	27↓	24↓
		Large-size		16↓	17↓	15↓
		Commercial		12↓	11↓	11↓
Edirne-Tekirdağ	Wheat production change		(%)	15.9↓	17.7↓	17.6↓
	LUC	Wheat area	(%)	6.0↓	9.2↓	8.8↓
		Other area		1.0↑	1.5↑	1.3↑
		Uncultivated		5.0↑	7.8↑	7.4↑
	Revenue		TL	2.08	1.82	1.90
	Farmer numbers	Smallholder		8↓	12↓	13↓
		Medium-size		8↓	13↓	12↓
		Large-size		3↓	5↓	4↓
		Commercial		2↓	2↓	2↓
Kayseri-Sivas	Wheat production change		(%)	46.7↓	49.2↓	43.5↓
	LUC	Wheat area	(%)	62.5↓	64.6↓	60.1↓
		Other area		24.6↑	25.6↑	23.7↑
		Uncultivated		37.9↑	39.0↑	36.4↑
	Revenue		TL	1.69	1.59	1.70
	Farmer numbers	Smallholder	(%)	63↓	64↓	66↓
		Medium-size		70↓	73↓	65↓
		Large-size		57↓	59↓	55↓
		Commercial		47↓	50↓	45↓

Note: Average value of main outputs for the 'BAU', 'A', B scenario for the last year of the 30-year simulation period.

Wheat Production

In all regions, wheat production increased rapidly in the first decade, followed by a downward trend. Despite climate change, wheat production increased in all three scenarios during the first decade. These results are in line with Dudu & Çakmak (2017)' study, which calculates yield changes for 35 crops (including wheat) in NUTS-3 regions in Türkiye using an approach based on the Penman-Monteith method and indicates that climate change will not have a profound impact in Türkiye until the late 2030s, but negative impacts will prevail afterward. At the end of 30 years, the regional analysis of the change in wheat production is shown in the Figure 5.

Figure 5: Wheat production over time by region (first experiment)

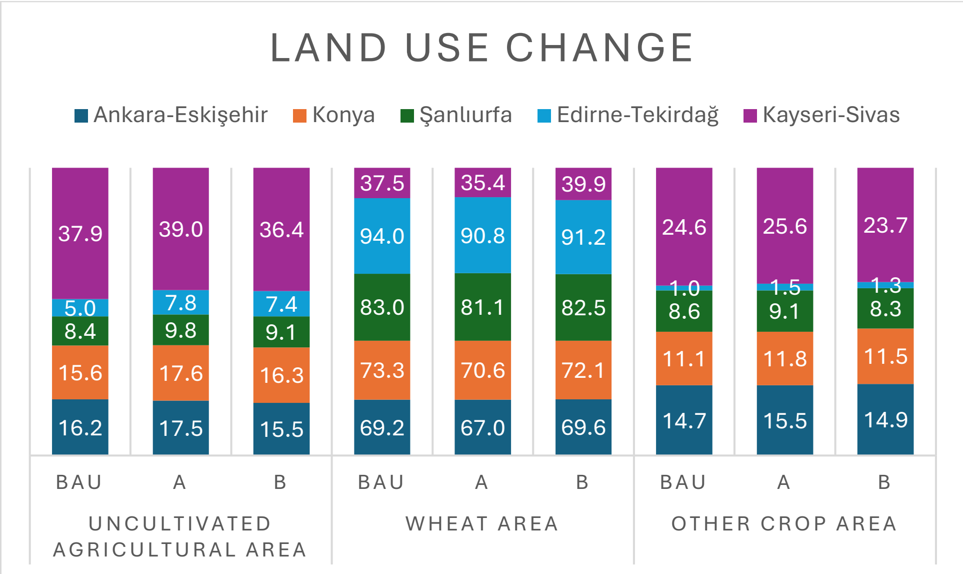


Note: The graphs in Figure 5 show the impact of the scenarios on wheat production for five different regions (Ankara-Eskişehir, Konya, Şanlıurfa, Edirne-Tekirdağ, Kayseri-Sivas) during the climate change period. The total wheat production time series for each region is given according to the scenarios. For the y-axes, all results are averaged over 250 runs. The colored lines represent the scenarios: (i) the red solid line is "BAU," where agricultural policy supports only conventional production and the price scenario is PS1; (ii) the green shortdash line is "A," where agricultural policy supports only conventional production and the price scenario is PS2; (iii) the blue longdash line is "B," where agricultural policy supports conventional and sustainable production and the price scenario is PS2 (see Table 8).

Land-use change

Farmers' production decisions result in three types of land use: uncultivated agricultural area, wheat area, and other crop area. The land use changes shown in Figure 6 reveal complex patterns of regional adaptation in response to different scenarios. The changing proportions of wheat area, other crops, and uncultivated agricultural areas reveal how farmers' production decisions differ across regions.

Figure 6: Land use change (first experiment)

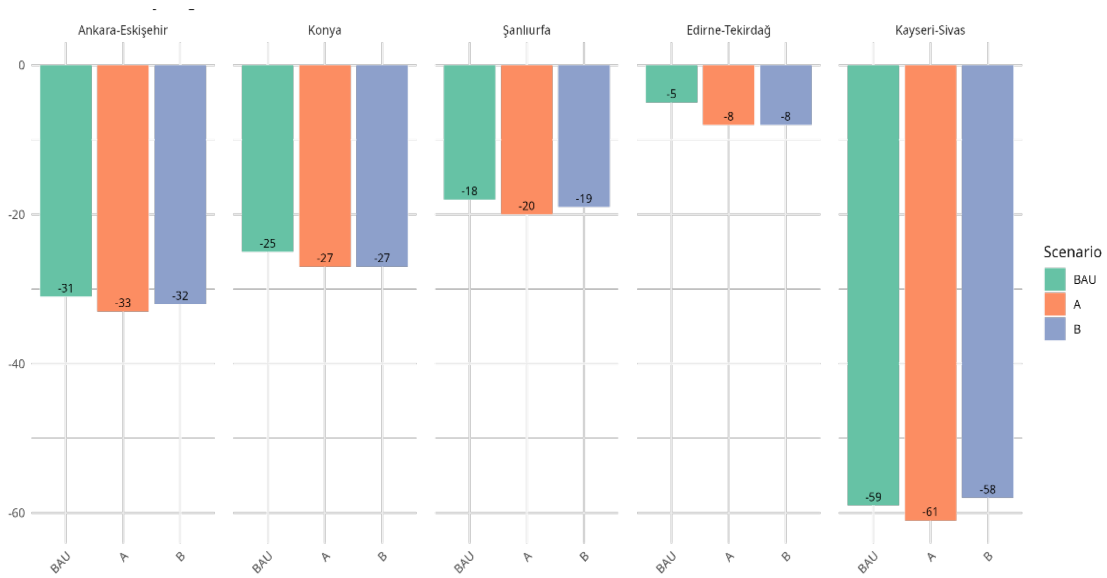


In Scenario A, each region's area of uncultivated wheat and other crops area is increased. This shows that the revenues of small farmers, as well as large farmers, are sensitive to changes in prices. With no-till farming (scenario B), all regions compensate for this upward trend in uncultivated agricultural and other crop areas. However, the impact of price dynamics is reduced compared to BAU (baseline scenario). Ankara-Eskişehir and Kayseri-Sivas reduce the area of uncultivated agricultural land compared to the baseline scenario (BAU). This suggests that no-till farming increases the resilience of farmers, with 250 decares or fewer to price changes in these regions. In other regions, no-till farming compensates for the negative impact of scenario A. In other words, price changes do not fully protect farmers with 250 decares or less in regions other than Ankara-Eskişehir and Kayseri-Sivas, despite the support of no-till farming.

Farm numbers

Compared to the initial 798 farms in 2021, there is a consistently significant reduction in wheat farmers in each region in all scenarios until 2050. Although scenario assumptions differ significantly, simulations under BAU (average: -28%) and B (average: -29%) result in very similar future farm numbers, while the decline is higher under scenario A (average: -30%) (see Figure 7).

Figure 7: Farm numbers by region (first experiment)



These results differ regionally. Different results emerge for each farm size and scenario (see Table 12).

In all regions, Scenario A reduces the number of farms of all farm types. The highest declines occur in medium-sized family farms. The resilience of these farm types after conservational agricultural subsidies differs regionally. Medium-sized family farms are the most vulnerable group in all regions. No-till farming support has increased their resilience, with the most significant improvement observed in the Kayseri-Sivas region. Compared to the baseline scenario, medium-scale farms increased in the Ankara-Eskişehir and Kayseri-Sivas regions. In contrast, the number of such farms decreased in the other regions. Price fluctuations do not increase the resilience of these farms much, despite conservation agriculture.

Small-scale family farms represent the second most vulnerable group in all regions. The introduction of no-till farming subsidies has increased their vulnerability in Ankara-Eskişehir, Konya, and Kayseri-Sivas regions, while it has increased their resilience in Şanlıurfa and Edirne-Tekirdağ regions.

Large-scale family farms represent the third most vulnerable group in all regions. While the introduction of support for no-till farming increases the resilience of these farms in all regions, comparisons with the baseline scenario reveal that regional impacts vary. In Şanlıurfa and Kayseri-Sivas regions, the number of these farms is higher under no-till farming scenario than under the baseline scenario, while in Ankara-Eskişehir, Konya and Edirne-Tekirdağ regions, their number decreases.

Commercial farms represent the most resilient group in all regions. Under scenario A, their numbers show a slight decrease in all regions. The introduction of no-till farming support increases the resilience of these farms in all regions except Ankara-Eskişehir. Regional differences emerge when compared to the baseline scenario: Konya, Şanlıurfa, and Kayseri-Sivas regions increase the number of these farms with no-till, while Ankara-Eskişehir and Edirne-Tekirdağ regions show a decrease.

Revenue

Revenue represents wheat production value and is calculated according to input cost, like a wheat input parity. Each farmer's revenue is changed by its enterprise type. This parity is important to farmers' decision-making process.

Revenues from wheat production increased steadily in all scenarios after a decade of decline. At the end of 30 years, the Kayseri-Sivas region maximizes revenues in scenario B, while in Ankara-Eskisehir, the income level is very close to the BAU scenario. In Konya, after the twentieth year, the rate of increase in the

BAU scenario exceeds that of the B scenario, and at the end of 30 years, it is above the B scenario. In Şanlıurfa and Edirne-Tekirdağ, the income level in scenario B is below the BAU scenario. However, it compensates for income losses due to increased input costs in scenario A.

Table 14: Comparison table (first experiment)

Regions	**A vs. B scenarios**	**B vs. BAU scenarios**
Ankara-Eskişehir	5.53↑	0.03↓
Konya	4.61↑	1.13↓
Şanlıurfa	1.37↑	3.83↓
Edirne-Tekirdağ	2.86↑	5.73↓
Kayseri-Sivas	3.96↑	0.12↑

Table 14 reveals complex patterns in revenue responses across regions and scenarios. When comparing Scenarios A and B, all regions show positive revenue changes, indicating that no-till farming support (Scenario B) consistently improves farm incomes relative to conventional farming under challenging price conditions (Scenario A). Ankara-Eskişehir demonstrates the strongest improvement (5.53%), followed by Konya (4.61%), suggesting that these central regions benefit most from transitioning to sustainable practices when facing adverse price conditions.

However, when comparing Scenario B with the baseline (BAU), most regions show declining revenues, with Edirne-Tekirdağ experiencing the most significant decrease (5.73%). Only Kayseri-Sivas maintains a slight positive change (0.12%), indicating unique regional factors that enable it to exceed baseline performance even under more challenging price conditions with sustainable practices.

These contrasting results between the two comparisons reveal important insights about policy effectiveness. While sustainable farming practices help mitigate the negative impacts of adverse price scenarios (as shown in the A vs. B comparison), they generally cannot fully compensate for the more favorable price conditions in the BAU scenario (as evidenced in the B vs. BAU comparison). The exception is Kayseri-Sivas, where combining sustainable practices and support policies creates a more resilient agricultural system.

Experiment 2: **Environmental-Awareness Farmers Farm Size Effect on Adaptation Rate**

The relationship between adoption rates and wheat production shows complex regional differences. Despite having the highest adoption rate (22 percent), Ankara-Eskisehir shows only a 3.5 percentage point improvement in production. In contrast, Kayseri-Sivas achieves a more significant production increase (5.7 percentage points) with a lower adoption rate (18 percent). Similar differences are seen between Konya (15% adoption, 2.4 percentage points improvement) and Şanlıurfa (3% adoption, 2.1 percentage points improvement), while Edirne-Tekirdağ achieves minimal improvement in wheat production (0.1 percentage points) despite a 10% adoption rate.

Table 15: Results of the Second Experiment

Region	Outputs	Indicator	Unit	Scenarios		
				B	**B1**	**B2**
Ankara-Eskişehir	Adoption Rate	No-till farmers	(%)	22	26	20
	Wheat production change	Wheat yield	(%)	17.3↓	6↓	28↓
	LUC	Wheat area	(%)	30.4↓	26.2↓	34.6↓
		Other area	(%)	14.9↑	11.6↑	19.1↑
		Uncultivated	(%)	15.5↑	14.6↑	15.5↑
	Input productivity	Input per production	kg	35.2	39.6	25.6
	Farmer numbers	Smallholder	(%)	38↓	49↓	46↓
		Medium-size	(%)	40↓	41↓	44↓
		Large-size	(%)	27↓	29↓	46↓
		Commercial	(%)	22↓	22↓	34↓
Konya	Adoption Rate	No-till farmers	(%)	15	20	14
	Wheat production change	Wheat yield	(%)	18.1↓	13↓	24↓
	LUC	Wheat area	(%)	27.9↓	25.4↓	30.1↓
		Other area	(%)	11.5↑	10.1↑	13.4↑
		Uncultivated	(%)	16.3↑	15.2↑	16.7↑
	Input productivity	Input per production		34.1	37.1	27.8
	Farmer numbers	Smallholder	(%)	34↓	50↓	47↓
		Medium-size	(%)	32↓	46↓	52↓
		Large-size	(%)	24↓	32↓	46↓
		Commercial	(%)	17↓	24↓	33↓
Şanlıurfa	Adoption Rate	No-till farmers	(%)	3	7	3
	Wheat production change	Wheat yield	(%)	13.2↓	10↓	15↓
	LUC	Wheat area	(%)	17.5↓	16.6↓	18.4↓
		Other area	(%)	8.3↑	7.3↑	8.9↑
		Uncultivated	(%)	9.1↑	9.3↑	9.6↑
	Input productivity	Input per production		29.1	33.0	27.9
		Smallholder	(%)	26↓	45↓	45↓

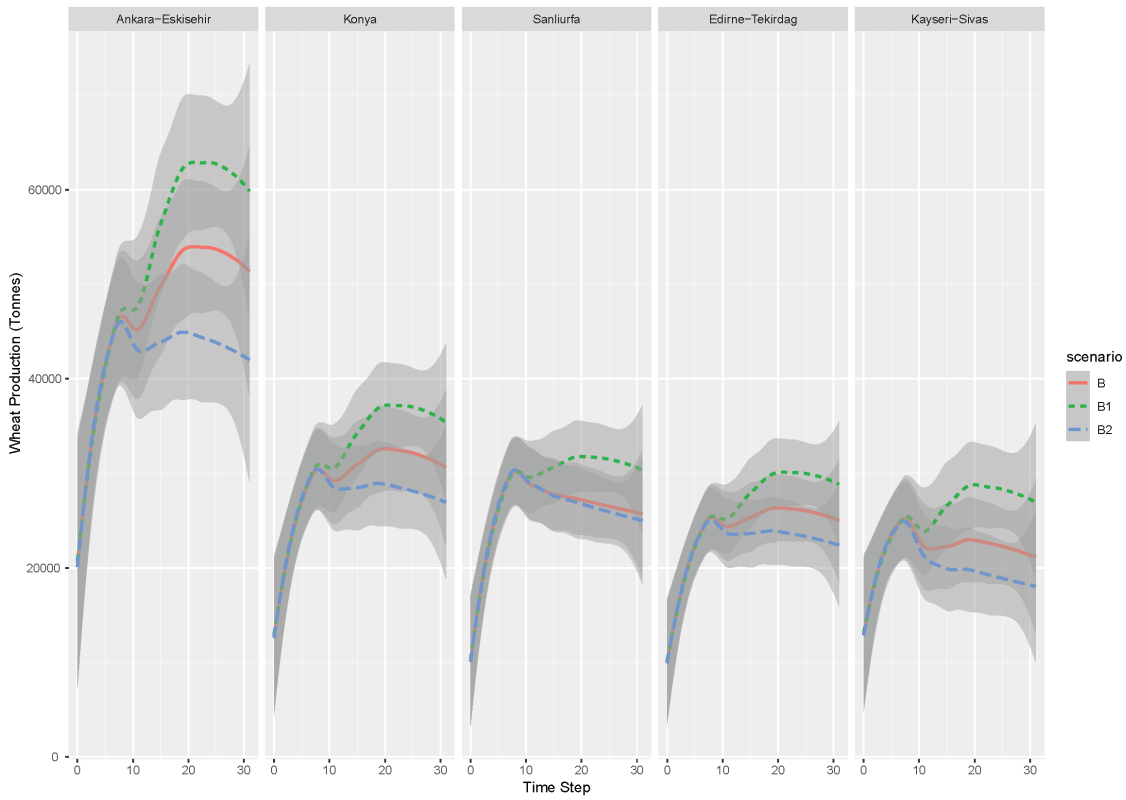
	Farmer numbers	Medium-size	(%)	24↓	46↓	46↓
		Large-size	(%)	15↓	33↓	35↓
		Commercial	(%)	11↓	15↓	28↓
Edirne-Tekirdağ	Adoption Rate	No-till farmers		10	17	10
	Wheat production change	Wheat yield	(%)	17.6↓	16↓	19↓
	LUC	Wheat area	(%)	8.8↓	8.2↓	8.6↓
		Other area	(%)	1.3↑	1.5↑	1.4↑
		Uncultivated	(%)	7.4↑	6.7↑	7.2↑
	Input productivity	Input per production		36.6	38.8	34.3
	Farmer numbers	Smallholder	(%)	13↓	40↓	38↓
		Medium-size	(%)	12↓	34↓	42↓
		Large-size	(%)	4↓	22↓	34↓
		Commercial	(%)	2↓	13↓	24↓
Kayseri-Sivas	Adoption Rate	No-till farmers		18	22	18
	Wheat production change	Wheat yield	(%)	43.5↓	26↓	53↓
	LUC	Wheat area	(%)	60.1↓	52.4↓	65.3↓
		Other area	(%)	23.7↑	17.5↑	28.0↑
		Uncultivated	(%)	36.4↑	34.9↑	37.2↑
	Input productivity	Input per production		34.1	40.8	23.0
	Farmer numbers	Smallholder	(%)	66↓	66↓	64↓
		Medium-size	(%)	65↓	61↓	69↓
		Large-size	(%)	55↓	42↓	62↓
		Commercial	(%)	45↓	30↓	52↓

Wheat production

Our findings show a clear relationship between environmental-awareness farmers farm size and adaptation rate. Regions consistently show higher adoption rates under the B1 scenario, ranging from 7% in Şanlıurfa to 26% in Ankara-Eskişehir—the B2 scenario results in lower adaptation rates.

The relationship between adoption rates and improvements shows complex regional differences. Despite having the highest adoption rate (22 percent), Ankara-Eskisehir shows only a 3.5 percentage point improvement in production. In contrast, Kayseri-Sivas achieves a more significant production increase (5.7 percentage points) with a lower adoption rate (18 percent). Similar differences are seen between Konya (15% adoption, 2.4 percentage points improvement) and Şanlıurfa (3% adoption, 2.1 percentage points improvement), while Edirne-Tekirdağ achieves minimal improvement in wheat production (0.1 percentage points) despite a 10% adoption rate. At the end of 30 years, the regional analysis of the change in wheat production is shown in the Figure 8: Wheat Production: No-till farming Adoption Effects

Figure 8: Wheat Production: No-till farming Adoption Effects



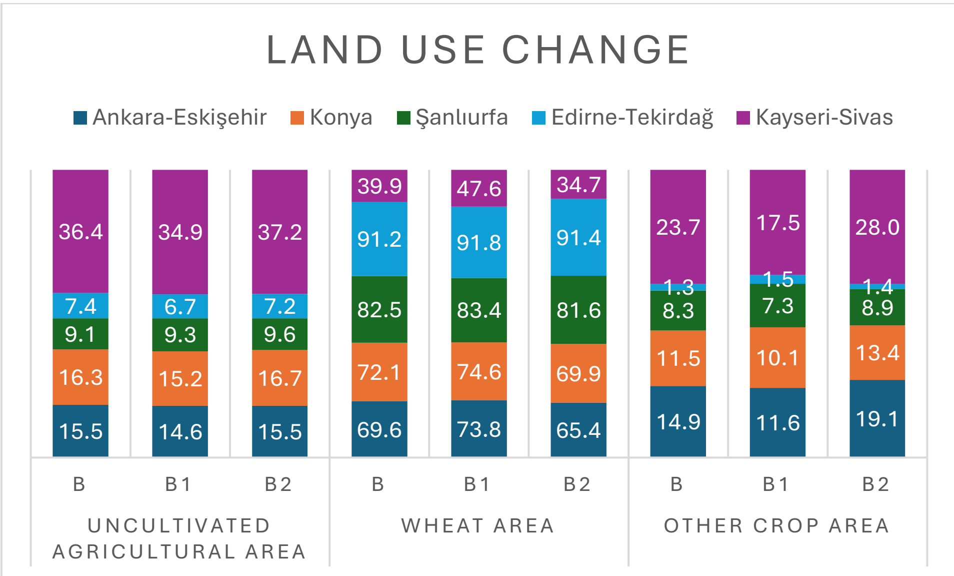
Note: The graphs in Figure 8: Wheat Production: No-till farming Adoption Effects show the impact of the scenarios on wheat production for five different regions (Ankara-Eskişehir, Konya, Şanlıurfa, Edirne-Tekirdağ, Kayseri-Sivas) during the climate change period. The total wheat production time series for each region is given according to the scenarios. For the y-axes, all results are averaged over 250 runs. The colored lines represent the scenarios: (i) the red solid line is “B”, environmental-awareness farmers' farm sizes assigned randomly (ii) the green shortdash line is “B1” environmental-awareness farmers' farm sizes larger than traditional farmers' farm sizes; (iii) the blue longdash line is “B2,” environmental-awareness farmers' farm sizes smaller than traditional farmers' farm sizes (see Table 8).

In all regions, wheat production increased rapidly in the first decade. Production peaks around time-step 10-15. After the peak, there's a gradual decline in all scenarios. This visualization effectively demonstrates that the impact of different scenarios varies significantly by region, with B1 consistently providing the most favorable outcomes for wheat production. The regional variations suggest that local conditions and characteristics play a crucial role in determining the effectiveness of different agricultural strategies.

Land-use Change

Farmers' production decisions result in three types of land use: uncultivated agricultural area, wheat area, and other crop area. The land use changes shown in Figure 9 reveal complex patterns of regional adaptation in response to different scenarios. The changing proportions of wheat area, other crops, and uncultivated agricultural areas reveal how farmers' production decisions differ across regions.

Figure 9: Land use change (second experiment)

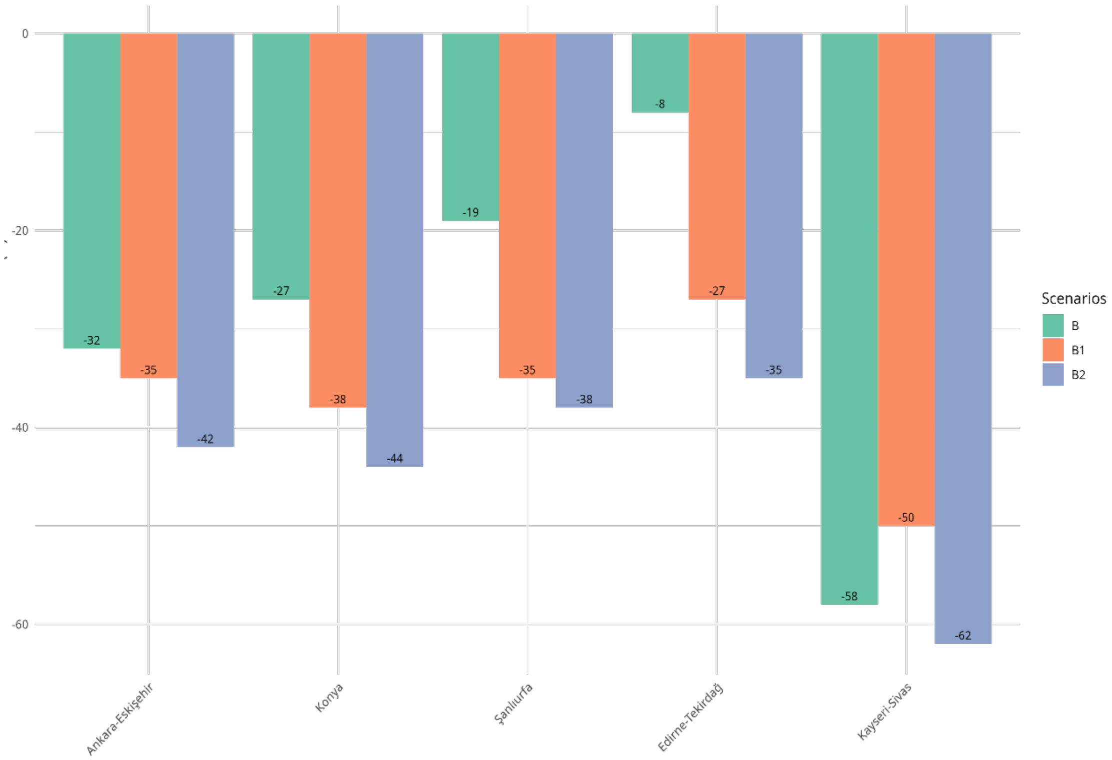


Regarding production areas, scenario B1 showed the most positive impact on farmers' production decisions, with 250 decares of land or less in most regions. The scenario with the lowest percentage of uncultivated land is scenario B1. Our analysis reveals different regional results regarding secondary crop areas and uncultivated land. In scenario B1, the area under secondary production is the lowest in all regions except Edirne-Tekirdağ. However, in Edirne-Tekirdağ, the change in the area under secondary crops between scenarios is minimal. However, scenario B1 shows the smallest regional reduction in farmers operating above 250 decares, highlighting the differential impact of adopting conservation agriculture across farm sizes. Scenario B1 shows overall better results for small-scale (below 250 decares) and large-scale farmers in most regions.

Farm numbers

Compared to the initial 798 farms in 2021, there is a consistently significant reduction in wheat farmers in each region in all scenarios until 2050. Simulations under B (average: -29%), B1 (average: -37%), and B2 (average: -44%) (see Figure 10).

Figure 10: Farm numbers by region and scenario experiment 2



These results differ regionally. Different results emerge for each farm size and scenario.

The resilience of these farm types differs regionally when environmental-awareness farmers farm size is changed. In scenario B1, except Şanlıurfa, in all regions, smallholder family farms are the most vulnerable group in all regions. In Şanlıurfa while smallholder family farms decreased at 0.45 rate, medium-sized family farms decreased at 0.46 rate. In B2 scenario, when environmental-awareness farmers are relatively smallholders, increased smallholder family farms' resilience, with the most significant improvement observed in the Kayseri-Sivas region.

Medium-size family farms represent the second most vulnerable group in all regions. When environmental-awareness farmers are relatively largeholders, medium-size family farms' vulnerability is increased in all regions.

Large-scale family farms represent the third most vulnerable group in all regions. When environmental-awareness farmers are relatively largeholders, the resilience of these farms is increased in all regions, comparisons with the B2 scenario.

Commercial farms represent the most resilient group in all regions. When environmental-awareness farmers are relatively largeholders, their resilience is increased in all regions. But compared to the B scenario, only Kayseri-Sivas region is increased resilience. The worst effect on resilience is shows in Edirne-Tekirdag region.

Input productivity

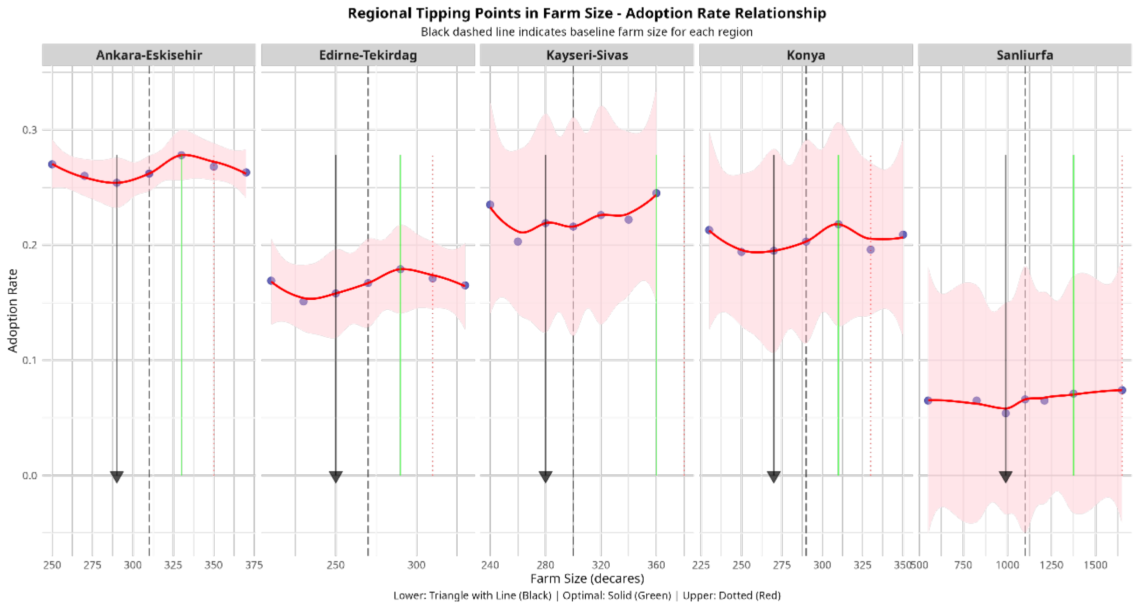
Scenario B shows an improvement in input productivity across regions; Input productivity shows how many kg of wheat is produced per decare with one input unit. This amount increases in each region with no-till farming. In other words, no-till farming increases the amount of wheat produced with one unit of input in each region. However, this result is changed by environmental-awareness farmers' farm size. In B2 scenarios (when environmental-awareness farmers' farm sizes were larger than traditional farmers'), input efficiency increased. In this situation, the average farm size of environmental-awareness farmers is simultaneously larger than the region's farm size. So, when environmental-awareness farmers are relatively largeholders, input efficiency increases. In B3 scenarios (when environmental-awareness farmers' farm sizes were smaller than traditional farmers), input efficiency decreased. In this situation, the average farm size of environmental awareness farmers is smaller than that of the region. So, when environmental-awareness farmers are relatively smallholders, input efficiency is decreased. However, this scenario shows that input efficiency decreases when environmental-awareness farmers are smaller than traditional or when environmental-awareness farmers are smallholders compared to the absence of no-till farming support. So, when environmental-awareness farmers are relatively smallholders, no-till farming creates inefficiency in input usage all regions.

2.5.1. Sensitivity analysis

To assess how farm size changes affect adoption rates of no-tillage farming under policy scenario 'B,' we conducted One-at-a-Time (OAT) sensitivity analysis in five regions. OAT reveals the mechanisms and patterns generated by ABM by changing one parameter at a time while holding other parameters constant (ten Broeke et al., 2016).

We defined intervals for land size changes to test this finding's sensitivity. These intervals are critical points where small changes in parameters lead to significant changes in the system's behavior. Identifying these points is essential for understanding the system's sensitivity and potential for dramatic shifts. Sensitivity analysis is a key tool here, as it helps in exploring how changes in parameters affect model output. We conducted a One-at-a-time (OAT) sensitivity analysis in five regions to assess how farm size changes affect adoption rates under policy scenario 'B.' OAT reveals mechanisms and patterns produced by ABM by changing one parameter at a time while keeping others constant regional results show how adoption rates respond to changing farm sizes of environmental-awareness farmers.

Figure 11: Results of the Sensitivity Analysis



Note: The graph shows the relationship between land size (x-axis) and adoption rate (y-axis) for five regions: Ankara-Eskişehir, Edirne-Tekirdağ, Kayseri-Sivas, Konya and Şanlıurfa. Three important tipping points are marked in each region: Lower Tipping Point (Black Triangle with Solid Line): Refers to the minimum farm size at which adoption becomes feasible. Below this point, adoption rates are typically low or unstable. Optimal Tipping Point (Green Solid Line): The farm size at which adoption rates stabilize and reach the most efficient level. It represents the ideal balance between land size and adoption rate. Upper Tipping Point (Red Dotted Line): The maximum farm size at which adoption rates peak. Beyond this point, adoption rates may plateau or fall, indicating diminishing returns. The red curve shows the adoption rate trend, and the pink shaded area shows the confidence interval indicating the variability in the data.

The analysis reveals several crucial relationships between environmental awareness, land size, and adoption rates. Regions with lower environmental sensitivity consistently demonstrate higher adoption sensitivity, while larger land size requirements correlate strongly with increased sensitivity levels. Stability appears most robust in regions with narrow tipping point ranges and higher environmental awareness levels.

Table 16: Regional comparison of sensitivity analysis

Regions	Adoption rate	Optimum size (decares)	Tipping point	Tipping range
Ankara-Eskişehir	26.2	310	Primary: At 330 ha (+6.11% increase) Secondary: At 270 ha (-3.70% decrease)	250-370
Konya	20.3	290	more gradual changes without dramatic tipping points	230-350
Şanlıurfa	6.6	1100	No clear tipping points*	550-1650
Edirne-Tekirdağ	16.7	270	Notable; sharp decrease at 230 de (-10.65%), increase at 290 de (7.19%)	210-330
Kayseri-Sivas	21.6	300	Significant; decrease t 260 de (-13.62%)	240-360

Note: * changes are gradual, high variability makes it difficult to distinguish true shifts from random variation.

Based on the results of the agent-based model, we propose the following region-specific policy recommendations to promote the adoption of no-till farming in Türkiye:

Ankara-Eskisehir Region: Optimization & Maintenance

The Ankara-Eskisehir region has high adoption rates (26-28%) even at lower farm sizes, with a narrow optimal farm size range of 300-330 decares. The policy focus for this region should be on maintaining the existing high adoption rates and providing technical support to optimize current operations. This region can serve as a model for best practices in no-till farming adoption. Additionally, supporting the consolidation of farms below 300 decares to reach the optimal size range could further enhance the region's performance.

Konya Region: Targeted Growth

The Konya region has moderate adoption rates (20-22%), with an optimal farm size around 310 decares. To promote further adoption in this region, policies should incentivize farms to reach the optimal size of 310 decares and provide technical support for farms near the current average farm size. Focusing on farms between 250-310 decares is likely to have the maximum impact. Furthermore, developing specific programs for farms below 250 decares to encourage consolidation could help improve the overall adoption rates in the region.

Sanliurfa Region: Structural Reform

The Sanliurfa region faces significant challenges, with very low adoption rates (7-7%) and requiring much larger farm sizes (around 1650 decares) for optimal adoption. This region needs special support programs and a focus on structural reforms. Policies should prioritize the consolidation of smallholder farms to reach larger, more viable sizes. Additionally, investigating and addressing barriers to adoption beyond farm size is crucial. Considering alternative agricultural models that may be better suited to the region's specific conditions could also help improve the adoption of no-till farming practices.

Edirne-Tekirdağ Region: Steady Enhancement

The Edirne-Tekirdağ region has stable adoption rates (15-18%), with an optimal farm size range of 250-290 decares. Policies should focus on supporting gradual farm size optimization, particularly for farms near 250 decares, to reach the optimal size of 270 decares. Providing incentives for reaching the optimal size and developing programs for technical efficiency improvement can help enhance the adoption of no-till farming in this region.

Kayseri-Sivas Region: Growth Optimization

The Kayseri-Sivas region shows a strong positive trend in adoption rates (20-25%), with a wide optimal farm size range of 260-360 decares. Policies should aim to support farms in reaching at least 300 decares and provide incentives for optimization. Focusing on technical support for farms near the lower end of the optimal range can help maintain the region's growth trajectory. Developing programs to sustain the positive trend in adoption rates is also important for this region.

By tailoring policies to the specific characteristics and needs of each region, policymakers can more effectively promote the adoption of no-till farming practices and contribute to the sustainable development of Türkiye's agricultural sector.

2.6. DISCUSSION

In this study, we tried to analyze the extent to which wheat farmers in Türkiye can be made resilient to input costs and climate change through agricultural support through various scenarios. In this context, we created an agent-based model based on reports that evaluate farmers' perception of climate change and their attitudes towards input costs through the results of the ÇATAK program implemented between 2006-2019. In this model, we conducted a regional analysis of farmers' vulnerabilities and tried to understand how climate-compatible systems such as conservation agriculture can increase their resilience. For this purpose, we conducted two different simulation experiments in our agent-based model. In the first one, we compared the impact of sustainable and traditional agricultural support systems. We investigated how price increases in input costs and support systems affect adaptation decisions. In the second simulation experiment, we analyzed the impact of the adoption rate of conservation agriculture on key outcomes across regions. In the first simulation experiment, we observed that the proportional size of environmental-awareness farmers affects the adoption rate but produces different results on key outcomes. Therefore, we analyzed the effects on the adoption rate of no-till farming for two cases where the average land size of environmental-awareness farmers is larger and smaller than that of traditional farmers.

As a result of the first simulation experiment, we observed that the input use of regions impacts the results. We analyzed the results regarding production, land use, and number of farmers.

2.6.1. Discussion of the first simulation experiment:

Table 17 below shows the fertilizer use per decare and the rate of increase of fertilizer use in the regions at the end of 30 years (see Table 6 for the initial input use of the regions):

Table 17: Fertilizer Use (kg/de) and Fertilizer Increase Rates (%) of the Regions

	Npk per decares			Increase rate		
	BAU	A	B	BAU	A	B
Ankara-Eskişehir	11.2	10.6	8.6	0.9	0.8	0.46
Konya	11.9	11.5	10.1	0.44	0.4	0.24
Şanlıurfa	11.4	11.1	11.2	0.2	0.1	0.04
Edirne-Tekirdağ	17.8	17.7	17	0.13	0.12	0.08
Kayseri-Sivas	6.8	6.4	5.7	0.59	0.49	0.33

Kayseri-Sivas experienced a production loss of 4.61% despite a 49% increase in fertilizer input use. This region is the most vulnerable. This vulnerability stems from the region's unequal land distribution (Gini coefficient of 0.54) and the agricultural system's heavy dependence on smallholder farmers, who make up 64% of all farmers in the region. As input use per decare increases, costs increase, affecting smallholder farmers the most.

The Ankara-Eskişehir region is the second most vulnerable. Fertilizer use in Ankara-Eskişehir increases by 80 percent to 10.6 kg/decare. However, this large increase in input use leads to a lower production decline of 3.34 percent despite the more equitable land distribution in the region. Konya experiences similar production impacts with a 3.31% decline despite a 40% increase in fertilizer use.

Although land distribution is more inequitable (0.53), the initial high input use per decare makes this region less vulnerable than Ankara-Eskişehir.

Edirne-Tekirdağ ranks fourth in vulnerability despite having the highest input use per decare (16 kg/decare). The 12% increase in input use could not compensate for rising costs, leading to a 9% reduction in wheat production area. Şanlıurfa shows the greatest resilience to price changes, experiencing only a 1.21% decline in production despite being the second highest input user (11.1 kg/decare). This resilience can be attributed to the region's minimal increase in input use per decare (1%). The results of the production analysis are in the Table 18:

Table 18: Comparative analysis of the rate of change in wheat production amount between scenarios

Regions	Wheat production amount decreasing rate (%)		
	Compared BAU with A	**Compared A with B**	**Compared B with BAU**
Ankara-Eskişehir	-3.34	4.52	1.03
Konya	-3.31	2.96	-0.45
Şanlıurfa	-1.21	2.41	1.17
Edirne-Tekirdağ	-2.18	0.10	-2.09
Kayseri-Sivas	-4.61	11.21	6.08

Note: these numbers represent the changing rate of wheat production, but this calculation is based on wheat production amount.

Our model shows regional resilience to input costs and climate change depends on land distribution (represented by Gini coefficients) and input use (fertilizer). Regions with lower input use per decare increase their input use substantially (40-80%) to protect yields in the face of climate change. However, this increase increases their vulnerability to input cost increases. However, more equitable land distribution helps mitigate these challenges, increasing regional resilience. This comprehensive analysis reveals that regional resilience to price changes depends on a complex interplay of factors such as land distribution patterns, input use intensity, and structural characteristics of farming activities.

This spatial variation in vulnerability underlines the need for regionally tailored agricultural policies. Scenario analysis of different support systems reveals that regions most vulnerable to price changes show the greatest potential for improvement through sustainable agricultural practices (Scenario B). This relationship is particularly evident in Kayseri-Sivas, where no-till farming significantly reduces losses due to unfavorable price conditions. This result holds across all regions, albeit at different magnitudes. In Kayseri-Sivas, Scenario B yields an 11.21% increase in production compared to Scenario A, demonstrating the potential for adaptation of no-till farming to climate change in this region. Ankara-Eskişehir, which experienced a decrease of 3.34% when moving from BAU to Scenario A, showed an improvement of 4.52% under Scenario B. Similarly, Konya's initial 3.31% decline under Scenario A is partially offset by a 2.96% improvement under Scenario B. These regions illustrate how adaptive agricultural practices can partially offset the negative impacts of price scenarios. The changing price structure (BAU scenario compared to scenario A) negatively affects the regions' wheat production. Kayseri-Sivas is the most affected region, with 4.61 percent, while Şanlıurfa's production loss of 1.21 percent.

Changing prices affect the Kayseri-Sivas region the most, with the lowest input use per decare. These results suggest that price shocks have a negative impact on wheat production in regions with low fertilizer use per decare. Our findings are consistent with the results of the study by Vos et al. (2025), which focuses on how low fertilizer use by African smallholder farmers makes them less vulnerable to global fertilizer price shocks (Vos et al., 2025). Despite being the second highest fertilizer user after Edirne-Tekirdağ, Şanlıurfa has shown a higher resilience to rising input costs in wheat production than Edirne-Tekirdağ. This resilience is because large farmers who create the change in production in Şanlıurfa, which has the highest inequality (Gini coefficient of 0.57) among the analyzed regions, are less sensitive to price changes. This result is consistent with Assefa et al., (2025)'s, who found that farmers with smaller land sizes than the average in the region are more sensitive to changes in fertilizer prices. The proportion of smallholder farmers is larger in Edirne-Tekirdağ than in Şanlıurfa. Although Edirne-Tekirdağ has a more equitable land distribution, the higher proportion of smallholder farmers makes the region more vulnerable to increases in input prices, especially given the high input use per decare. This suggests that regions with unequal land distribution but a higher proportion of largeholder farmers in production are more resilient to price changes. However, higher input use per decare does not lead to significant production losses; it primarily affects farmers' production decisions. The results suggest that the support system's structure significantly affects wheat production and overall land use decisions. With no-till farming, we observed a reduction in both the area of secondary crops and uncultivated crop areas.

2.6.2. Discussion of the second simulation experiment

The impact of no-till farming on production is shaped by complex regional endogenous dynamics rather than the proportional size of adopting farmers. The results of this analysis suggest that adoption rates do not linearly predict changes in input efficiency or farmer returns. The adoption effectiveness depends on the spatial distribution of environmental-awareness farmers, the proportion of observer farmers in regions, and the differences between traditional and environmental-awareness farmers. We, therefore, conducted this simulation experiment to assess the impact of the land size of environmental-awareness farmers on regional adoption rates within specific parameters.

First of all, in each region, the adaptation rate and the impact of adaptation differ for both scenarios, where environmental-awareness farmers produce in larger and smaller areas than traditional farmers.

As a result of this simulation, we observe that the highest production levels in each region are realized in scenario B1 and the lowest in scenario B2. Below is the table where we compare the results with the results obtained in the absence of the initial support policies:

As can be seen, in the B2 scenario, the production level is even lower than in the BAU scenario. In contrast, in the B1 scenario, the production level is higher than in the A scenario. This result aligns with studies that confirm that the proportional size of environmental-awareness farmers is as influential as the size of their impact in the region.

Regarding production areas, scenario B1 showed the most positive impact on farmers' production decisions, with 250 decares of land or less in most regions. The scenario with the lowest percentage of vacant land is scenario B1. However, an important nuance emerged in the analysis of farmer numbers: In scenario B1, the highest reduction in smallholder family farms is observed in all regions, while the lowest reduction in medium-sized family farms is observed in all regions except Şanlıurfa. In Şanlıurfa, the reduction rate of medium-sized family farmers remains constant across scenarios, indicating that there are not enough environmental-awareness farmers to influence the learning mechanism. The positive impact of scenario B1 on wheat production area primarily reflects the production decisions of medium-scale farmers. This pattern suggests that no-till farming disadvantages the smallest farmers. The most important reason for this is that the learning mechanism becomes ineffective. As the number of farmers practicing no-till farming increases in the regions, the effectiveness of neighborhood-based learning decreases, as farmers below 50 decares cannot benefit from no-till subsidies. This effect is more pronounced in regions with low input use per decare, such as Ankara-Eskişehir (49%) and Kayseri-Sivas (66%).

Our analysis reveals different regional results regarding secondary crop areas and uncultivated land. In scenario B1, the area under secondary production is the lowest in all regions except Edirne-Tekirdağ. However, in Edirne-Tekirdağ, the change in the area under secondary crops between scenarios is minimal. However, scenario B1 shows the smallest regional reduction in farmers operating above 250 decares, highlighting the differential impact of adopting conservation agriculture across farm sizes. Scenario B1 shows better results for both small-scale (under 250 decares) and largeholder farmers in most regions.

2.6.3. Model Limitations

Our model has some limitations. The first one is related to the process of identifying farmer typologies. This study utilized the results of the WWF report and various agricultural reports organized for the regions. Existing typologies defined in the literature were used rather than actual data on farmers in the study area. Elaborating on the differences in the markets where farmers sell their products, including the farm enterprise size type, as it affects farmers' decisions and behavior. However, information on which farm size farmers sell to which market in Türkiye is hypothetically included. Considering this situation, conducting further studies by including this information in future studies would be helpful.

While modeling farmers according to their typology and farm size, farm inputs were not included (e.g., rent, wage, and family labor). Future studies can be expanded to include the labor factor and investigate the potential of agricultural support policies to affect rural-urban migration by affecting agricultural production and employment. In this context, there are many studies modeled with ABM.

The other limitation concerns model parameterization. This model is based on data and parameter values from literature. To increase the reliability of the findings, the model will need to be calibrated and validated with empirical data from the study area. Data scarcity, an essential problem in the regions studied, may limit the accuracy and applicability of ABMs (Hailegiorgis et al., 2018). Data scarcity in the agricultural sector is also a matter of debate in Türkiye (Kasnakoğlu, 2022).

A last limitation is the simplistic representation of price and sustainable agricultural policy scenarios. This model's climate change adaptation process does not consider other adaptation measures, such as crop diversification, water management practices, or drought-tolerant varieties. This study is seen no-till farming as a climate change adaptation strategy. However, when considering this method, farmers are assumed to have access to the production technology required by this system. The economic life of agricultural production technologies is not considered, except that farmers have the monetary conditions to invest in this technology. One of the important issues affecting farmer decisions is sunk costs. There are many studies in literature on this topic. The model is incomplete in this respect, but thanks to the flexible structure of ABMs, it can be used in another study that considers these shortcomings.

CONCLUSION

Climate change is one of the main threats to Türkiye's agricultural productivity, food security, and economic development. There are opportunities for wheat farmers to cope with and adapt to the impacts of climate change, including through the adoption of climate adaptation strategies such as climate-smart agriculture (CSA) - a strategy increasingly promoted by both government and civil society organizations as a way to meet the "triple win" benefits of simultaneously increasing production and food security, adapting agriculture to climate change and improving mitigation (FAO, 2014). Despite the worldwide acceptance of conservation tillage systems as sustainable alternatives, farmers in Türkiye continue to predominantly use traditional intensive tillage practices (Celik et al., 2012). The study by Sertoglu et al., (2021) emphasizes the importance of assessing the role of agriculture in environmental sustainability, pointing to the need to address the factors affecting agricultural practices in Türkiye. In Türkiye, the ÇATAK support program was put into practice in this context, and the capacity of farmers to adapt to climate change was tried to be increased. This program aimed to increase farmers' awareness of climate change and motivate the adoption of sustainable production technologies in this context. This thesis aims to uncover the critical motivations for farmers' willingness to adopt sustainable techniques. Therefore, an agent-based model was developed to understand the determinants of farmers' decision-making structures, namely their willingness and abilities.

In this study, we built a model with ABM to assess climate change adaptation regarding the number of environmental-awareness farmers and the social identity of environmental-awareness farmers. Previous studies focus on the social identity of farmers, the number of environmental-awareness farmers, and the land ownership structure of regions in terms of climate change adaptation. This study reveals again that climate change awareness is an important factor for adaptation. However, it also claims that the region's internal dynamics influence the increase in this rate and change the adoption rate. Accordingly, an increase in the proportion of environmental-awareness farmers in regions with low fertilizer use per decare affects the adoption rate. A peer-to-peer learning process driven by farmers' social identities is central to the model. Accordingly, an agricultural support system developed for adaptation to climate change, such as no-till farming, creates two types of farming categories: conventional farming, where farming is increasingly dependent on fertilizers due to climate change, and no-till farmers, who produce more efficiently with fewer inputs, offsetting the decrease in production quantity with an increase in income thanks to cost advantages. Farmers may develop resilience to climate change and input costs as these farming types diversify. The resulting farm types emerge as shifting representations of households practicing different production systems, which can have many unexpected consequences on climate change adaptation patterns and food security. In summary, the model's perspective provides new insights into many consequences for farmers' decisions in the climate change adaptation process.

Simulation results demonstrate the potential of an agent-based modeling approach to understand the complex dynamics of climate change adaptation in the agricultural sector.

The main findings of the thesis are: (i) fertilizer use per decare and soil distribution of regions can be used to determine the vulnerability of regions, (ii) the impact of no-tillage on production, land use, and farmers' income is not linearly related to the rate of adaptation, (iii) the proportional size of environmental-awareness farmers in regions as well as their land size and position relative to other farmers in the region affect the success of adaptation.

Fertilizer use per decare, and soil distribution of regions can be used to determine the vulnerability of regions.

In our first simulation experiment, we analyzed the effects of changes in price dynamics on regions' wheat production, land use, and number of farmers without a support mechanism for conservation agriculture. Accordingly, we found that regions with low input use per decare are the most vulnerable, but land distribution has changed this degree of vulnerability. For example, although Edirne-Tekirdağ has the highest fertilizer use per decare, it is more vulnerable than Şanlıurfa. This is because production in Şanlıurfa is concentrated among large-scale farmers. Since large farmers are more resilient to price changes than small farmers, they are less affected by increases in input costs. This shows that the distribution of land in regions is important in determining the vulnerability of regions. At the same time, inequitable land distribution increases vulnerability in regions with low input use per decare. In the Kayseri-Sivas region, input use per decare is low. This increases the vulnerability of farmers trying to adapt to climate change by increasing their input use. As a result, inequitable land distribution is a factor that increases vulnerability in regions with relatively low input use per decare.

The impact of no-till farming on production, land use, and farmers' income is not linearly related to the rate of adaptation.

The relationship between adoption rates and wheat production complex relation shows regional differences. Despite having the highest adoption rate (22%), Ankara-Eskisehir shows only a 3.5 percentage increase in production. In contrast, Kayseri-Sivas achieves a more significant production increase (5.7%) with a lower adoption rate (18%). Similar differences are seen between Konya (15% adoption, 2.4 percentage improvement) and Şanlıurfa (3% adoption, 2.1% increase), while Edirne-Tekirdağ achieves a minimal increase in wheat production (0.1 percent) despite a 10% adoption rate.

The proportional size of environmental-awareness farmers in regions as well as their land size and position relative to other farmers in the region affect the success of adaptation.

Our findings show a clear relationship between environmental-awareness farmers farm size and adaptation rate. Regions consistently show higher adoption rates under the B1 scenario, ranging from 7% in Şanlıurfa to 26% in Ankara-Eskişehir—the B2 scenario results in lower adaptation rates.

In scenario B1, the highest reduction of small family farms is observed in all regions, while the lowest reduction of medium-scale family farms is observed in all regions except Şanlıurfa. In Şanlıurfa, medium-scale farmers' reduction rate remains constant across scenarios, indicating that there are not enough environmental-awareness farmers to influence the learning mechanism. The positive impact of scenario B1 on wheat production area primarily reflects the production decisions of medium-scale farmers. This pattern suggests that no-till farming disadvantages the smallest farmers in scenario B1. The most important reason for this is that the learning mechanism becomes ineffective. As the number of farmers practicing no-till farming increases across regions, the effectiveness of neighborhood-based learning decreases, as farmers with less than 50 decares cannot benefit from no-till supports. In regions where environmentalist farmers are large landowners, additional support for small farmers' input use can help them stay in production. However, these subsidies must be designed to protect small farmers from price shocks. While the cost advantage of conservation agriculture may create farmers who do not need additional support, it may make small farmers more dependent on input subsidies. Therefore, small farmers need different support mechanisms. However, support for them may make them more dependent on inputs and the state more dependent on input trade, which may have a negative impact on the terms of trade, or supporting these farmers with inputs may reduce wheat imports because of the smallholders producer-consumer while supporting them with inputs may increase input imports. General equilibrium models are needed to see the overall outcome of these two values. So, the economy needs agent-based models, but the results must be analyzed with general equilibrium models.

Our analysis of policy effectiveness reveals striking regional variations in outcomes. The most vulnerable regions show the strongest response to adaptation measures, with Kayseri-Sivas achieving an 11.21% production improvement, while high-input regions like Edirne-Tekirdağ show minimal gains of 0.10%. These disparities in policy effectiveness underscore the importance of regionally tailored approaches that account for existing agricultural practices and structural characteristics.

This research opens crucial avenues for future investigation. First, the long-term stability of adoption patterns requires careful examination, particularly in regions showing initial success. Second, the mechanisms of peer learning across different farm sizes warrant deeper investigation to enhance knowledge transfer effectiveness. Finally, the interaction between multiple policy interventions needs systematic evaluation to optimize adaptation strategies.

In conclusion, this thesis provides compelling evidence that successful climate change adaptation in Turkish agriculture requires a sophisticated understanding of regional characteristics and their interaction with adaptation mechanisms. Our findings challenge policymakers to move beyond one-size-fits-all approaches and develop regionally tailored strategies that account for the complex interplay between environmental awareness, structural characteristics, and social learning networks. This research contributes significantly to our understanding of agricultural adaptation to climate change and provides a robust foundation for developing more effective and equitable adaptation policies in Türkiye.

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APPENDIX 1. STUDY AREA’S DESCRIPTION

Table 19: Crop Pattern of Study Area (%)

Region		2019	2020	2021	2022	2023
Ankara	Main crop (wheat)	53	45	45	44	45
	Secondary crop (Barley)	30	35	35	35	35
Eskişehir	Main crop (wheat)	48	43	40	40	45
	Secondary crop (Barley)	26	28	28	28	25
Konya	Main crop (wheat)	36	41	39	48	39
	Secondary crop (Barley)	21	21	22	22	22
Şanlıurfa	Main crop (wheat)	17	11	15	17	15
	Secondary crop (Cotton)	17	36	25	21	23
Edirne	Main crop (wheat)	43	44	41	38	40
	Secondary crop (Sunflower)	31	30	33	37	38
Tekirdağ	Main crop (wheat)	50	51	48	48	48
	Secondary crop (Sunflower)	36	37	41	42	43
Kayseri	Main crop (wheat)	43	48	45	43	41
	Secondary crop (Barley)	30	25	26	26	27
Sivas	Main crop (wheat)	52	48	47	45	47
	Secondary crop (Barley)	25	26	25	25	24

Table 20: Wheat yield of provinces in the study area per decares (kg/de)

	Ankara	Eskişehir	Konya	Şanlıurfa	Edirne	Tekirdağ	Kayseri	Sivas	Türkiye
2019	253	273	309	304	381	451	234	218	276
2020	270	272	307	368	358	392	237	245	292
2021	166	242	276	383	474	534	203	163	266
2022	247	289	335	332	407	421	233	243	296
2023	297	344	386	550	536	351	313	247	318

Table 21: Share of provinces in the study region in wheat production in Türkiye

	2019	2020	2021	2022	2023
Ankara	981611	887869	562099	822387	1021120
Eskişehir	501362	459296	389972	449841	603160
Konya	1271728	1301497	1098193	1313200	1556550
Şanlıurfa	419371	790319	589522	459409	839526
Edirne	497094	478412	641384	522535	724119
Tekirdağ	857020	769915	1026611	811950	687601
Kayseri	325808	362217	267910	316344	416358
Sivas	523687	560413	361938	539189	560721
Türkiye	15850000	16500000	14500000	16000000	17700000
Share (%)	34	34	34	33	36

Table 22: Agricultural holdings by size and number

Region	Size of holdings	Number of holdings	Area (decare)
Ankara	-5	40 885	6 700 871
	5- 9	131	466
	10-19	446	2 540
	20-49	3 514	54 826
	50- 99	4 152	145 342
	100- 199	7 946	582 635
	200- 499	13 901	2 029 062
	500-999	9 005	2 462 606
	1000- 2499	1 503	908 822
	2500- 4999	285	357 111
	5000+	-	-
Eskişehir	-5	24 522	4 071 322
	5- 9	460	1 196
	10-19	955	6 716
	20-49	1 285	19 359
	50- 99	3 972	135 909
	100- 199	4 621	328 836
	200- 499	6 097	867 025
	500-999	6 100	1 784 316
	1000- 2499	800	539 025
	2500- 4999	197	243 509
	5000+	34	100 506
Konya	-5	98 567	13 036 853
	5- 9	3 367	7 917
	10-19	3 448	21 816
	20-49	6 802	94 165
	50- 99	19 102	645 691
	100- 199	18 524	1 306 012
	200- 499	26 722	3 682 115
	500-999	18 271	4 880 462
	1000- 2499	2 153	1 567 991
	2500- 4999	175	176 201
	5000+	-	-
Sanliurfa	-5	50 406	9 821 677
	5- 9	295	867
	10-19	375	2 565
	20-49	2 230	28 738
	50- 99	9 700	325 347
	100- 199	12 660	852 635
	200- 499	12 600	1 665 838
	500-999	9 667	2 679 931
	1000- 2499	2 088	1 442 601
	2500- 4999	747	1 103 427
	5000+	43	148 628

Region	Size of holdings	Number of holdings	Area (decare)
Edirne	-5	37 390	3 630 484
	5- 9	274	842
	10-19	941	6 242
	20-49	2 830	40 581
	50- 99	10 253	347 488
	100- 199	11 149	786 330
	200- 499	8 594	1 150 771
	500-999	2 476	700 049
	1000- 2499	739	455 470
	2500- 4999	134	142 711
	5000+	-	-
Tekirdag	-5	28 026	2 929 595
	5- 9	248	956
	10-19	845	5 787
	20-49	2 264	31 761
	50- 99	5 815	199 858
	100- 199	8 445	607 282
	200- 499	6 889	961 313
	500-999	3 189	874 102
	1000- 2499	270	178 521
	2500- 4999	60	65 289
	5000+	1	4 726
Kayseri	-5	29 393	3 423 990
	5- 9	1 115	2 897
	10-19	1 229	8 913
	20-49	2 366	30 543
	50- 99	5 886	187 955
	100- 199	7 266	512 971
	200- 499	6 540	947 714
	500-999	4 249	1 232 022
	1000- 2499	677	423 891
	2500- 4999	65	77 084
	5000+	-	-
Sivas	-5	77 957	7 467 539
	5- 9	911	3 278
	10-19	1 171	7 390
	20-49	6 314	84 081
	50- 99	25 464	822 686
	100- 199	19 505	1 253 989
	200- 499	15 322	2 055 341
	500-999	8 775	2 644 048
	1000- 2499	284	155 661
	2500- 4999	209	347 490
	5000+	-	-

APPENDIX 2. MANN-KENDALL ANALYSIS

For temperature and precipitation parameters, trend analysis for 1994-2023 was performed using Sen's Slope and Mann-Kendall (Sen, 1968) techniques. Sen's slope method was applied to quantify the magnitude of the observed trends. All analysis was performed using the Excel XLSLAT software program. The Mann-Kendall test is a nonparametric tool that detects trends in time series data that do not follow a normal distribution. In weather forecast analysis, the Mann-Kendall test is used to identify trends in variables such as precipitation (Alemu & Dioha, 2020; Ruwangika et al., 2020) and temperature (Romanić et al., 2016).

The results are below:

Table 23: Results Mann-Kendall trend test for climate variables from 1994-2023

Time Series	Kendall's tau	p-value	Sen's slope	Interpretation
Sowing Temperature (℃)	0.356	**0.006**	0.057	Significant upward trend
Growing Temperature (℃)	0.260	**0.046**	0.065	Significant upward trend
Maturing Precipitation (mm)	-0.360	**0.007**	-0.996	Significant downward trend

According to the Sen's slope result, a steady increase in sowing and growing season temperatures is expected. The negative slope of the rainfall during the maturing period indicates that dry farming in the wheat production process will not be sustainable. The equations obtained based on these values were added to the model for the climate change projection of the regions. This analysis was done to endogenize the effects of climate change on the model.

Sowing Temperature (℃):

Kendall's Tau 0.356 indicates a positive correlation, meaning an upward trend in sowing temperature over time. Sen's Slope 0.057 shows the rate of change per unit of time (e.g., per year). This implies sowing temperatures are increasing by 0.057 units (e.g., degrees) annually.

Growing Temperature (℃):

Kendall's Tau, 0.260 also indicates a positive correlation, showing an upward trend in growing temperature. Sen's Slope 0.065 reflects a slightly higher rate of change per time unit compared to Sow_temp.

Maturing Rainfall (mm):

Kendall's Tau -0.360 reflects a strong negative correlation, indicating a downward trend in precipitation during the maturation phase. Sen's Slope -0.996 shows a substantial decrease in precipitation over time, with nearly 1 unit decline per time period.

Future projections using this formula:

$$\boldsymbol{future} = \boldsymbol{current} + (\boldsymbol{Sen's\ slope}\ \times \boldsymbol{years\ into\ future})$$

Projections for sowing stage for 2020;

Current value: 10 ℃

Sen’s slope: 0.065

2030: $10 + (0.065\ \times 10) = 10.55$ ℃

2040: $10 + (0.065\ \times 20) = 11.11$ ℃

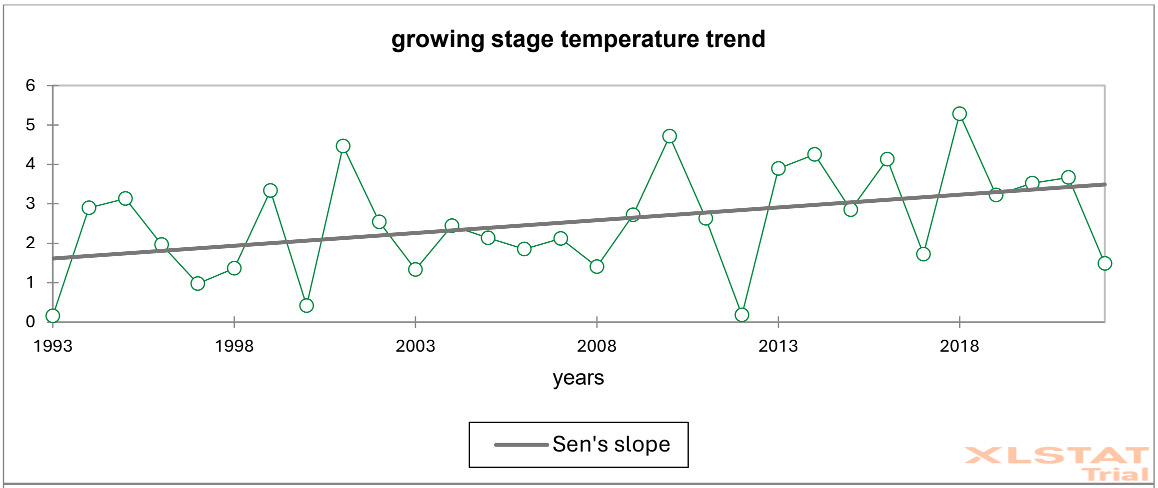
2050: $10 + (0.065\ \times 30) = 11.66$ ℃

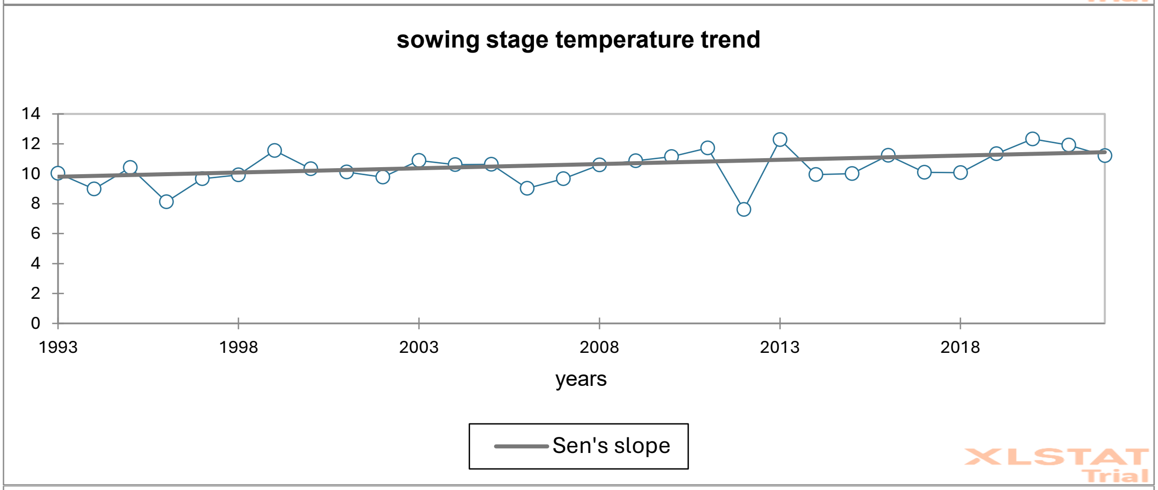
In time-series trend analysis (e.g., weather trends):

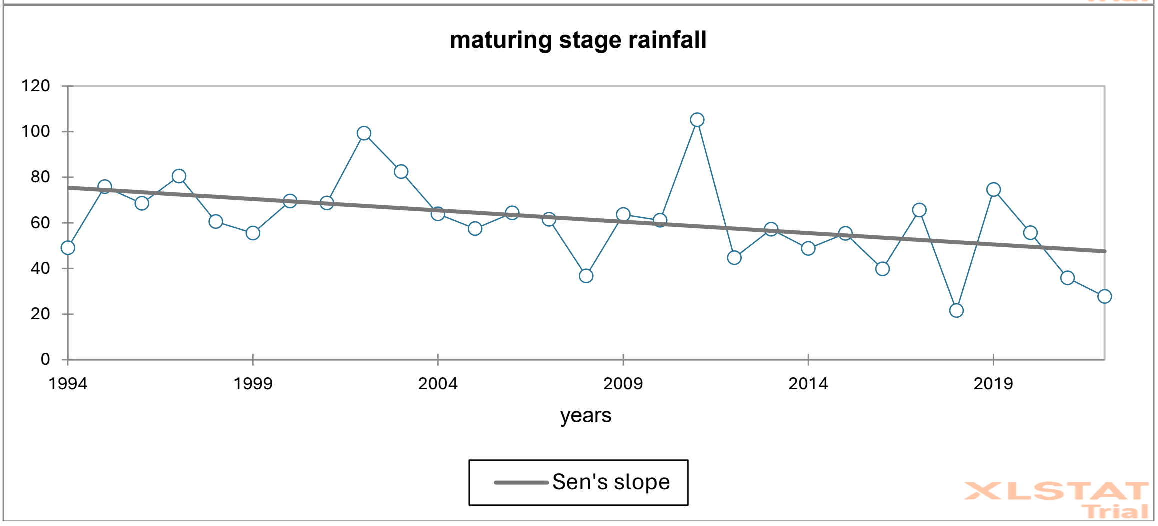
Kendall’s Tau indicates whether there is a statistically significant monotonic trend (upward or downward) over time. Often paired with the Mann-Kendall Test to determine if the trend is statistically significant.

The trend analysis results are below:

Figure 12: Results of the Mann-Kendall trend Analysis







APPENDIX 3. PANEL REGRESSION RESULTS

In this study, the factors affecting wheat yields are estimated by panel data methods using 1994-2023 data for eight provinces in the study area. This estimation aims to reveal the process of wheat yield being affected by climate change as a factor affecting farmers' production decisions on a provincial basis. Data on input use per decare were obtained from the Ministry of Food, Agriculture and Livestock. These data were compiled from plant nutrition statistics covering the period after 2000. The data between 1994 and 2000 were compiled from the Agricultural Structure (Production, Price, Value) Statistics published by TurkStat. Then, precipitation and temperature data for the sowing, growing, and maturing stages for the production period of wheat were calculated. World Bank's climate change data were used for these calculations.

Table 24: 1994-2023 years variables

Provinces	Wheat Yield (per decares/kg)	NPK (per decares/kg)	Sowing Temperature (℃)	Growing Temperature (℃)	Maturing Rainfall (mm)
Ankara-Eskişehir	234.34	6.22	10.06	2.73	149.69
Konya	245.8	8.15	9.63	2.5	125.4
Şanlıurfa	280.14	11.14	16.38	7.96	82.63
Edirne-Tekirdağ	366.56	15.8	12.83	6.04	140.58
Kayseri-Sivas	189.53	4.32	7.47	-0.65	159.15

Note: Average values of data between 1994 and 2023

Model

In equation (1), wheat yield (Y), fertilizer use per decare (f), sowing period temperature (℃) value (sow), growing period temperature (℃) value, and maturing period rainfall (mm) value (mtr) are included, respectively. These values refer to the data at the time series of the provinces in the study region (i = 1, ... , N; t = 1, ..., T).

Equation 1 is first estimated to estimate wheat yield, and yield coefficient values (β_f , β_{sow} , β_{grw} , β_{mtr}) are obtained.

$$Y_{it} = \beta_i + \beta_f f_{it} + \beta_{sow} sow_{it} + \beta_{grw} grw_{it} + \beta_{mtr} mtr_{it} + \varepsilon_{it} \quad (1)$$

This model has six independent variables:

1. npk_per_decare: Nitrogen-phosphorus-potassium fertilizer per decare.

2. npksq: Square npk_per_decare to capture diminishing returns.

3. grw: temperature value during the growing phase of wheat

4. sow: Sowing temperature during the sowing phase.

5. mtr: Rainfall during the maturing phase.

The table presents the results obtained using random effects, fixed effects, Generalized Least Squares (GLS), and Panel Corrected Standard errors (PCSE) estimation methods. The Hausman test in Table 3 supports the results of the random effects model. However, contrary to the findings of statistical tests, the FE model is used in this study. Because only eight cities were analyzed (small N), RE may not be reliable if unobserved heterogeneity is associated with explanatory variables. FE focuses on changes within cities over time, which aligns with this study's research objectives (effectiveness of agricultural policy and impact of climate change). FE controls unobservable, city-specific factors that do not change over time. Studies have shown that FE models can produce more reliable estimates than OLS in small samples, especially when unobserved heterogeneity is present (Wooldridge, 2010).

The Pesaran CD test (Pesaran, 2004), a horizontal cross-section dependence test, shows no horizontal cross-section dependence in the models (Table 25, last column). The short length of the series can explain this. Baltagi (2013), argues that horizontal cross-sectional dependence is not a problem when the time series dimension is not higher than 20-30. On the other hand, tests for heteroscedasticity and autocorrelation in the panel revealed heteroscedasticity in the data. FGLS and PCSE estimations solve this problem (columns 3 and 4 in Table 25). FGLS estimations were performed on panel data with variable variance. PCSE estimations are performed under correlated panel and variable variance errors (each panel has its variance). FGLS and PCSE estimations include the time dimension, not the city dimension. This is because, with only eight regions, adding i.city adds seven dummies (for eight regions), which may reduce the degrees of freedom. This may increase multicollinearity, leading to unstable coefficient estimates.

All estimations were performed in Stata version 17 software. In this model, PCSE, introduced by Beck & Katz (1995), provides a robust alternative to FGLS by allowing varying variance and simultaneous correlation across panels. The PCSE estimator adjusts the standard errors of OLS estimates to account for these problems without requiring a specific model for the error structure. This flexibility makes PCSE particularly useful in empirical applications where the basic assumptions of FGLS may be violated.

Table 25: Estimation results

VARIABLES Dependent variable (Y)	(1) Fixed Effects	(2) Random Effects	(3) FGLS	(4) PCSE
npk	23.95***	25.19***	19.09***	19.49***
	(2.56)	(2.21)	(2.27)	(2.42)
npksq	-0.475***	-0.51***	-0.34***	-0.36***
	(0.09)	(0.08)	(0.08)	(0.09)
sow	-0.14	1.27	-4.42**	-6.77***
	(2.54)	(1.94)	(2.23)	(2.38)
grw	-1.69	0.05	9.63***	12.67***
	(2.13)	(1.83)	(2.53)	(2.73)
mtr	0.31***	0.31***	0.43***	0.49***
	(0.08)	(0.07)	(0.08)	(0.09)
Constant	65.73**	37.63*	66.67***	63.05***
	(26.77)	(21.80)	(22.38)	(23.81)
Observations	240	240	240	240
R-squared	0.54			0.85
Number of city	8	8	8	8

According to the estimation results, the wheat yield (Y_t) depends on the amount of fertilizer used (NPK_t) and the effects of rainfall and temperature during the production period.

$$Y_t = 66.1 + (16.79 * NPK_t) - (0.31 * (NPK_t)^2) - \left(7.34 * temperature_{sowing}\right) + \left(15.76 * temperature_{growing}\right) + (0.42 * rainfall_{maturing})$$

Estimation results

According to the estimation results (Table 25, column (4)), the output coefficients of wheat yield in Türkiye are estimated as follows:

Each 1 percent increase in fertilizer use per acre increases yields by 20 percent. The negative npk_square coefficient (-0.36) indicates that the marginal return to fertilizer application decreases.

Sowing Temperature: The negative coefficient of this variable (-6.8) indicates that sub-optimal planting temperatures reduce yields.

Growing Temperature: Higher temperatures during the growing stage positively affect yield, as indicated by the coefficient (12.7).

Maturing Rainfall: Rainfall at the maturing stage increases yield (0.5).

R-square: 0.85 - The model explains 85% of the variation in wheat yield.

Wald Chi2(34): 1187.11 (p = 0.000) - The joint significance of the variables is confirmed.

APPENDIX 4. ODD + D Protocol

Table 26: The ABM description follows the template set out by the ODD + D protocol presented by (Müller et al., 2013)

<table>
<tr><th colspan="2">OUTLINE</th><th>ODD+D Model Description</th></tr>
<tr><td rowspan="3">I) Overview</td><td>Purpose</td><td>This agent-based model aims to investigate the factors contributing to the diffusion of no-tillage farming among wheat farmers in Turkey, considering social interaction mechanisms, market price dynamics, and farmers' perceptions of climate change. The model aims to analyze the potential contribution of farmers with previous experience in direct seeding to regional climate change adaptation.</td></tr>
<tr><td>Entities, state variables, and scales</td><td>Agents: Wheat farmers are characterized by their farm size, environmental awareness, and adoption of no-tillage practices.
Environment: Wheat production areas in Turkey have varying land distributions and input use levels.
State variables: see Table 27.
Spatial scale: Regional level (e.g., Ankara-Eskişehir, Konya, Şanlıurfa).
Temporal scale: Annual time steps represent growing seasons.</td></tr>
<tr><td>Process overview and scheduling</td><td>1. Initialization: Set initial values for farmer agents' state variables and environmental conditions.
2. Farmer decision-making: Farmers evaluate the adoption of no-tillage farming based on their environmental awareness, farm size, and social interactions.
3. Social learning: Farmers learn from their experiences or their peers—peer learning with learning thresholds is influenced by farm size and environmental awareness.
4. Policy interventions: Apply support policies (e.g., subsidies) to promote no-till adoption.
5. Update adoption status: Farmers update their no-till adoption status based on decision-making and policy interventions.
6. Output: Record and visualize adoption rates, land use changes, and farmer enterprise categories.</td></tr>
</table>

<table>
<tr><td rowspan="3">II) Design Concepts</td><td>Theoretical and Empirical Background</td><td>At the system level, the model builds upon the following theoretical foundations:
1. Diffusion of Innovations Theory: The model incorporates an inverse relationship between land distribution and innovation diffusion by considering the impact of farm size and social identity on forming social networks and learning thresholds. It recognizes that the power asymmetries arising from unequal land ownership can influence the effectiveness of social learning processes and the diffusion of no-tillage practices among farmers.
At the submodel level, the following theories and hypotheses are relevant:
1. Social Network Theory: The social learning submodel incorporates concepts from social network theory, emphasizing the role of network structure and social ties in facilitating information exchange and influencing behavior. The model considers the impact of farm size and social identity on forming social networks and learning thresholds.
2. Policy Intervention Theories: The policy intervention submodel builds upon policy design and implementation theories, such as the Policy Feedback Theory and the Multiple Streams Framework. These theories highlight the importance of considering the interplay between policy instruments, target populations, and broader socio-economic contexts in shaping policy outcomes.
By explicitly accounting for the role of land distribution in shaping innovation diffusion, the model aims to provide insights into the complex dynamics underlying the adoption of sustainable agricultural practices. It highlights the need for policies and interventions that address the power imbalances and create an enabling environment for all farmers, regardless of their land-holding size, to accelerate the diffusion of beneficial practices and technologies.
Including this concept in the model's design underscores the importance of considering social equity and power dynamics when studying adopting sustainable practices in the context of climate change adaptation. It emphasizes the need for a more holistic approach beyond individual decision-making. It considers the broader socio-economic and institutional factors that shape the diffusion of innovations in the agricultural sector.
Farmers make adoption decisions based on environmental awareness, farm size, social influences, and policy interventions. Bounded rationality and heterogeneous decision-making are incorporated through varying thresholds and social identities.</td></tr>
<tr><td>Individual Decision Making</td><td>Farmers' decisions change land use. The land of farmers who stop farming appears as uncultivated land. Farmers who stop wheat production have land that appears as secondary cropland. Farmers who continue to produce wheat continue to have wheat fields. They decide which support system to choose. This decision has led to two types of wheat farming: no-till farmers and traditional tillage farmers.
Farmers' purpose is defined through typologies. Each farmer is rational within his or her purpose. However, this rationality is bounded in their decision-making process. While their willingess limit their rationality, some farmers' abilities limit their rationality. In other words, their willingness and abilities limit farmers' rationality.
Farmers make adoption decisions based on a combination of environmental awareness, farm size, social norms, and policy interventions. Bounded rationality and heterogeneous decision-making are incorporated through varying thresholds and social identities.
Spatial characteristics play a role in decision-making when calculating annual yields (based on climate and inputs).
Temporal aspects play a role in decision-making based on the average yield value and production gain over five years.
Farmer representatives do not explicitly consider uncertainty or risk in their decision-making process.</td></tr>
<tr><td>Learning</td><td>Farmers learn from their experiences or peers. Farmers engage in social learning by observing and interacting with their peers. Learning thresholds</td></tr>
</table>

		are influenced by farm size and social identity, with large, environmentally-aware farmers having the highest probability of influencing others.
	Individual Sensing	Farmers sense changes in wheat prices, subsidies, and input prices. Some are aware of climate change. As farmers join environmental support programs, they start making use of extra subsidies. The model does not consider the costs of joining the environmental support program. Regarding the sensing process, it is important to acknowledge that it may be erroneous or subject to limitations.
	Individual Prediction	Farmers do not aim to predict future conditions; they base their yearly decision-making on their current situation and past actions and compare present and past returns.
	Interaction	Farmers interact through their neighbors, which are influenced by spatial proximity and social identity (e.g., farm size). These interactions facilitate knowledge exchange and social learning.
	Collectives	
	Heterogeneity	Farmers' heterogeneity is represented by farm size, typology, climate change perception, household size, and region.
	Stochasticity	Farm size of farmer typologies, except for subsistence farmers, is assigned randomly. So, farm enterprise categories of farmer typologies' are changed in each simulation process.
	Observation	The model outputs adoption rates of no-till farming, changes in land use patterns, and shifts in farmer enterprise categories over time. These outputs are analyzed to assess the impact of various factors on the diffusion of no-till farming practices and regional climate change adaptation. These emerging outputs are recorded in the ABM interface at every time step.
III) Details	Implementation	The model was built in NetLogo version 6.0.4
	Initialization	Initially, all farmers were wheat farmers, producing with the traditional cultivation method. Therefore, land use is seen only as a wheat production area. Land use changes with farmer decisions, i.e., it is stochastic. Since farmers who stop producing will completely exit the system, their production area is seen as uncultivated land. This also changes the initial number of farmers. Since farmer typologies and farm enterprise size categories are set based on the number of wheat farmers, their distribution across regions changes after 30 years.
	Input Data	Quantitative and qualitative data combinations. The quantitative data include Agricultural census data, National Statistical Data from TURKSTAT, and climate data from the World Bank. Qualitative data come from some studies survey-based, farmer reports
	Submodels	See Interactions section in this thesis.

Table 27: Attributes of model entities

Entity	Attribute name	Description	Values	Notes
Agents	Farmer-id	Individual farmer ID	1-798	Discrete
	Farmer-type	Typology is based on farmers' willingness and abilities.	1 = subsistence 2 = observer 3 = environmental awareness 4 = traditional	Categorical

	Farm enterprise category	Based on Turkish enterprise category	1 = smallholder family 2 = medium-sized family 3 = large-sized family 4 = commercial	Categorical
	Household size	Based on regions' data	4-7	Derived from TURKSTAT
	Off-farm	smallholder family farms have off-farm income	Minimum wage	No change
	Food requirement	Per capita wheat production	200 kg	Based on TURKSTAT data
	No-Till Transition Period	Subsidy years	Five years.	No change
Environment	Local Area	Patches	Grid of 1 decare plot.	No change
	Regions	Study area	1 = Ankara-Eskişehir 2 = Konya 3 = Şanlıurfa 4 = Edirne-Tekirdağ 5 = Kayseri-Sivas	Based on WWF (2022).
	Farm	Farms occur with several plots.	Agents have farms that have several plots.	All farms change with farmers' willingness and ability.
	Wheat yield	Per decare	Kg	Based on wheat yield equation.

APPENDIX 5. ORIGINALITY REPORT

	HACETTEPE ÜNİVERSİTESİ SOSYAL BİLİMLER ENSTİTÜSÜ	Doküman Kodu *Form No.*	FRM-DR-21
		Yayım Tarihi *Date of Pub.*	04.01.2023
	FRM-DR-21 **Doktora Tezi Orijinallik Raporu** *PhD Thesis Dissertation Originality Report*	Revizyon No *Rev. No.*	02
		Revizyon Tarihi *Rev.Date*	25.01.2024

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SOSYAL BİLİMLER ENSTİTÜSÜ
İKTİSAT ANABİLİM DALI BAŞKANLIĞINA

Tarih: 30/01/2025

Tez Başlığı Arazi Eşitsizliği ve İklim Değişikliğine Uyum: Ajan Temelli Bir Yaklaşım

Yukarıda başlığı verilen tezimin a) Kapak sayfası, b) Giriş, c) Ana bölümler ve d) Sonuç kısımlarından oluşan toplam 95 sayfalık kısmına ilişkin, 29/01/2025 tarihinde şahsım/tez danışmanım tarafından Turnitin adlı intihal tespit programından aşağıda işaretlenmiş filtrelemeler uygulanarak alınmış olan orijinallik raporuna göre, tezimin benzerlik oranı % 4'tür.

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	Programme	Economics - PhD		
	Status	**PhD** ☒	**Combined MA/MSc-PhD** ☐	

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	Öğrenci No	N17144209	
	Enstitü Anabilim Dalı	İktisat	
	Programı	İktisat (İngilizce) – Doktora	
	Statüsü	**Doktora** ☒	**Lisans Derecesi ile (Bütünleşik) Dr** ☐

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* Tez **Almanca** veya **Fransızca** yazılıyor ise bu kısımda tez başlığı **Tez Yazım Dilinde** yazılmalıdır.

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		Revizyon Tarihi *Rev.Date*	25.01.2024

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I respectfully submit this for approval.

Leyla Gizem EREN

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	Department	Economics		
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	Status	**PhD** ☒	**Combined MA/MSc-PhD** ☐	

SUPERVISOR'S APPROVAL

APPROVED
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