

ADDIS ABABA UNIVERSITY

COLLEGE OF BUSINESS AND ECONOMICS
DEPARTMENT OF ECONOMICS

ADOPTION DYNAMICS OF SUSTAINABLE AGRICULTURAL INTENSIFICATION PRACTICES AND THEIR IMPACTS ON HOUSEHOLD WHEAT PRODUCTIVITY UNDER RECURRENT CLIMATE SHOCKS: EVIDENCE FROM RURAL ETHIOPIA

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By
Mihretu Abera

Advisor
Hailu Elias (PhD)

Addis Ababa, Ethiopia
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Approved by Board of Examiners

1. Hailu Elias (PhD) Signature _____ Date _____
   Advisor

2. Worku Gebeyehu (PhD) Signature _____ Date _____
   Internal Examiner

3. Nuredin Juhar (PhD) Signature _____ Date 09\09\2026
   External Examiner

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I, Mihretu Abera, hereby declare that this thesis entitled "Adoption Dynamics of Sustainable Agricultural Intensification Practices and Their Impacts on Household Wheat Productivity under Recurrent Climate Shocks: Evidence from Rural Ethiopia" is my original work, carried out through my own effort. It has been prepared and is submitted to the College of Business and Economics of Addis Ababa University in partial fulfillment of the requirements for the degree of Master of Science (MSc) in Development Economics. To the best of my knowledge, this thesis has not been submitted, in whole or in part, for any other degree or diploma at this or any other institution.

Stated by: Mihretu Abera

Signature: _____

Date: 28/08/2026

Place of Submission: College of Business and Economics, AAU

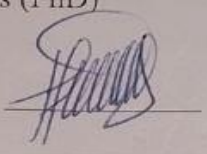
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STATEMENT OF CERTIFICATION

I hereby certify that this thesis entitled "Adoption Dynamics of Sustainable Agricultural Intensification Practices and Their Impacts on Household Wheat Productivity under Recurrent Climate Shocks: Evidence from Rural Ethiopia" was carried out by Mihretu Abera under my supervision. I confirm that the thesis is an original work, meets the required academic standards, and is recommended for submission for the award of the degree of Master of Science (MSc) in Development Economics at the College of Business and Economics, Addis Ababa University.

Hailu Elias (PhD)

Advisor

Signature: 

Date: _____

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ABSTRACT

Sustainable Agricultural Intensification (SAI) is widely promoted to raise wheat productivity among smallholder farmers in Ethiopia. However, recurrent climate shocks and weak insurance and credit markets make sustained adoption difficult. Most existing studies rely on cross-sectional or short-panel data and therefore cannot adequately capture true state dependence, complementarities, or reverse causality. This study examines the adoption dynamics of seven SAI practices and their impact on household wheat productivity under recurrent climate shocks in rural Ethiopia. Using three waves (2021, 2023, and 2025) of the Resilience to Climate Change (RCC) panel covering 598 households, the study applies a Conditional Mixed Process (CMP) framework that jointly estimates seven adoption equations and a wheat yield equation, controlling for self-selection, unobserved heterogeneity, and reverse causality.

Three main findings emerge. First, past adoption significantly raises the probability of current adoption for six of the seven practices, indicating true state dependence; the exception is Soil and Water Conservation (SWC), whose lagged effect is insignificant. Second, no individual SAI practice significantly increases wheat yield on its own (joint Wald $\chi^2(7) = 11.73$, $p = 0.110$). Strong error correlations particularly between improved seed and row planting ($\rho = 0.478$, $p < 0.01$) and between intercropping and row planting ($\rho = 0.428$, $p < 0.01$) show that practices function as complementary bundles. Third, households that persistently adopt the integrated input-plus-NRM package (regime R_3) achieve a 57% higher wheat yield than non-adopters (R_0). Recurrent climate shocks erode the persistence of chemical fertilizer and SWC adoption by 4.4 and 4.5 percentage points, respectively, and push households toward low-cost fallback practices such as organic manure.

These results imply that agricultural policy should move beyond promoting isolated technologies toward supporting integrated, shock-resilient adoption strategies. This insight forms the basis of the Triple-P (Promote–Protect–Persist) framework proposed in the study.

Keywords: Sustainable Agricultural Intensification, Technology Complementarities, State Dependence, Recurrent Climate Shocks, Conditional Mixed Process, Ethiopia

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LIST OF ACRONYMS AND ABBREVIATIONS

Acronym	Full form
AAU	Addis Ababa University
AGP	Agricultural Growth Programme
AHM	Agricultural Household Model
AME	Average Marginal Effect(s)
ANOVA	Analysis of Variance
ATT	Average Treatment Effect on the Treated
CA	Conservation Agriculture
CMP	Conditional Mixed Process
CRGE	Climate Resilient Green Economy
DA	Development Agent
DFP	Davidon-Fletcher-Powell
ESR	Endogenous Switching Regression
FAO	Food and Agriculture Organization of the United Nations
FE	Fixed Effects
FFS	Farmer Field Schools
FIML	Full Information Maximum Likelihood
GDP	Gross Domestic Product
Ha	Hectare
HGER	Homegrown Economic Reform Agenda
HH	Household
IMVP	Inter-temporal Multivariate Probit
IPCC	Intergovernmental Panel on Climate Change
Kg	Kilogram
kg/ha	Kilograms per Hectare
MLE	Maximum Likelihood Estimation
MVP	Multivariate Probit
NBE	National Bank of Ethiopia
NPC	National Planning Commission
NR	Newton-Raphson
NRM	Natural Resource Management
OLS	Ordinary Least Squares
OPM	Oxford Policy Management
PES	Payments for Ecosystem Services
Pp	Percentage Points
PSI	Policy Studies Institute
PSNP	Productive Safety Net Programme
R0	No Adoption Regime (Traditional Practices)
R1	Input Intensification Only Regime
R2	Natural Resource Management Only Regime
R3	Integrated SAI Synergy Regime (Input + NRM)
RA	Regression Adjustment
RCC	Resilience to Climate Change Survey

RE	Random Effects
SAI	Sustainable Agricultural Intensification
SLMP	Sustainable Land Management Programme
SNNPR	Southern Nations, Nationalities, and Peoples' Region
SSA	Sub-Saharan Africa
SWC	Soil and Water Conservation
TLU	Tropical Livestock Unit
UCPH	University of Copenhagen

Note: Acronyms are listed in alphabetical order. All abbreviations appear in full at their first use in the text.

CHAPTER ONE

1. Introduction

1.1 Background of the Study

Agriculture remains the backbone of the Ethiopian economy. It accounts for 34.6% of GDP and employs nearly 80% of the population (FAO, 2025). More than 95% of agricultural output comes from smallholder farms averaging less than two hectares (FAO, 2025; World Bank, 2023; Zerssa et al., 2021). Given such a high dependence, any reduction in the productivity of this sector will translate into increased food insecurity and an unstable political economy.

Wheat is one of the critical food-security crops in Ethiopia and is considered one of the priority crops for national policy (Tadesse et al., 2022). The government has expanded irrigated wheat production from almost none in 2015 to over 400,000 hectares by 2022, aiming at import substitution and eventual surplus production. USDA projects wheat output at 7.0 million metric tons in 2026/27, an 8% increase from the previous year, driven by irrigation, improved seeds, and cluster farming (USDA FAS, 2026). Nevertheless, Ethiopia still imports about 1.4 million metric tons commercially, showing that self-sufficiency remains an unfinished goal. For this reason, wheat productivity is both a farm-level welfare issue and a matter of current economic importance, making it a highly relevant crop for studying technology adoption dynamics.

Ethiopian agriculture faces persistent constraints, including low technology uptake, soil degradation, limited input access, weak infrastructure, and high climate variability. The period 2020–2023 brought some of the most severe droughts in four decades, followed by excessive rains in 2023 and 2024 that damaged assets and livelihoods (Kimutai et al., 2025). Even modest rainfall shortfalls significantly reduce yields, and rising temperatures threaten further declines in staple production across sub-Saharan Africa (IPCC, 2022; Abebaw, 2025).

In this regard, much emphasis has been given to sustainable agricultural intensification and climate-smart agriculture, which are based on three interlinked pillars: sustainably increasing productivity and incomes; adapting and building resilience to climate change; and reducing greenhouse-gas emissions from agriculture (FAO, 2023). Conservation

practices that improve soil fertility and stabilize yields are especially relevant in drought-prone areas such as Ethiopia (Di Falco, Veronesi and Yesuf, 2011; Abegaz et al., 2024).

A major limitation of much of the existing literature is its reliance on cross-sectional or short-panel data. These data treat the decision to adopt as a one-off event and thus cannot capture whether a farmer continues to use a given technology, discontinues its use, or newly adopts it after a given period. Evidence from sub-Saharan Africa shows that many farmers use improved seed and fertilizer for only one season before discontinuing them (Dercon and Christiaensen, 2011; Arslan et al., 2013). Adoption dynamics refer to inter-temporal changes in technology use over different survey waves, such as continuous use, dis-adoption, and first-time adoption. Only when adoption persists over several seasons will the technology fully contribute to higher productivity at the household level; thus, it is a crucial determinant of the household's food and nutrition security and resilience to climate shocks (Tadesse et al., 2021; Di Falco, Veronesi and Yesuf, 2011; Pangapanga-Phiri et al., 2024). Theoretical perspectives support this view. For example, induced innovation theory (Hayami and Ruttan, 1971) posits that continuing resource scarcities in land, labor, and soil fertility provide an incentive for ongoing technological change. Further, the agricultural household model implies that, in the absence of well-functioning markets or when markets are imperfect, production and consumption decisions are made jointly, so that technology choices in one period will influence household capabilities in subsequent periods (Singh, Squire and Strauss, 1986; Di Falco, Veronesi and Yesuf, 2011). Moreover, some recent studies have shown that households with continuous use of climate-smart technologies achieve higher food security and reduced poverty than households with intermittent use of the technologies (Abegaz et al., 2024).

In practice, many factors have made this difficult, Such as high input costs, seed and fertilizer availability, rainfall uncertainty, credit constraints, information asymmetries, fragmented landholdings, poor infrastructure, and gender constraints; female-headed households, which are constrained in access to land, credit, education, and extension, have lower adoption rates than male-headed households (Gebre, Amekawa and Rahut, 2023; Antwi-Agyei and Nyantakyi-Frimpong, 2021). Many farmers therefore revert to traditional low-input methods (Kassie et al., 2013).

The interaction of different technologies also partly explains productivity puzzles. While there is a strong complementarity between improved seeds and fertilizer, the synergy effects that could be derived from both inputs are not achievable when either input is used independently (Tabe-Ojong and Geffersa, 2024).

A farmer will be more likely to sustain yield gains if he or she adopts technologies in bundles rather than one at a time. However, at the national level, adoption rates of modern inputs, whether as stand-alone technologies or in bundles, are still low compared to their economically justified levels.

This study addresses these issues by using three waves (2021, 2023, and 2025) of the Resilience to Climate Change (RCC) panel survey. Since the same households are tracked over time, the survey data can identify persistent and dis-adopters and the characteristics, including the effect of climate shocks, that explain these paths. In this way, the study contributes to the understanding of the dynamics of SAI adoption and its implications for wheat productivity under climate stress in rural Ethiopia.

1.2 Statement of the Problem

Sustaining the adoption of improved agricultural technologies remains one of the central challenges facing Ethiopian smallholder agriculture. While many farmers are willing to try new practices, far fewer continue using them long enough to generate lasting productivity gains. Most empirical studies, however, conceptualize adoption as a one-time irreversible event and have relied on cross-section or short-panel data (Wooldridge, 2010; Feder, Just and Zilberman, 1985). Such an approach may be enough to identify correlates of adoption, but the very nature of such data means that persistence, dis-adoption, and transitions cannot be studied, and important mechanisms through which households may revise earlier adoption decisions in the face of climate shocks, learning, or changing market conditions are entirely missed (Feder and Umali, 1993; Moser and Barrett, 2006).

Given that each season's decisions are made in the face of uncertainty and, more recently, chronic liquidity constraints induced by climatic variability, a static approach is likely to overestimate the extent of technology use and understate the severity of the true challenge of sustaining use (Diagne, Tamini and Fall, 2022).

A further limitation is the inability of static designs to distinguish true state dependence from spurious state dependence. True state dependence arises when early adoption builds

experience, skills, and confidence that raise the probability of continued use. Spurious state dependence is due to temporary factors, such as input subsidies, short-term credit, or good weather, that induce adoption but which are then later reversed (Birhanu and Jensen, 2023). When the two mechanisms are not separated, one obtains evidence of pervasive partial or fragmented adoption, such as the use of fertilizer but not improved seed or failure to engage in soil conservation. Such fragmented adoption yields lower returns, weakens farmers' motivation to invest further, and slows agricultural transformation (Dercon and Christiaensen, 2011; Tabe-Ojong and Geffersa, 2024).

Most of the literature treated climate shocks as independent, single-period events rather than repeated stresses with potentially accumulating impacts (Dercon and Christiaensen, 2011; Dell, Jones and Olken, 2012). In this respect, shocks measured at one point in time can only capture the impact on production or adoption contemporaneous to the measurement and cannot capture changes in adoption trajectories induced by asset depletion and increased risk aversion following droughts and irregular rainfall over several periods (Carleton et al., 2024; Alem and Abebe, 2023). In Ethiopia, where farmers frequently face consecutive climate stresses, this cumulative dimension is especially important.

These limitations point to three interrelated gaps in the literature.

First, there is a dynamics and persistence gap. While Moser and Barrett (2006) and Birhanu and Jensen (2023) show rapid dis-adoption or very strong state dependence for specific technologies, they do not consider how persistence might be eroded by repeated climatic shocks or how persistence might differ across technologies or bundles of technologies. Second, most other studies are cross-sectional and hence do not provide any evidence on intertemporal patterns of continuation, upgrading, or abandonment (Ruzzante, Labarta and Bilton, 2021).

Second, there is a cumulative climate shock gap. Since most studies treat shocks as single events, they do not explain how recurrent droughts and rainfall irregularities gradually erode assets and undermine the long-term adoption of improved technologies and practices (Dercon and Christiaensen, 2011; Diagne, Tamini and Fall, 2022).

Third, there is a methodological and causal gap. Cross-sectional and two-wave designs fail to control for unobserved household characteristics that do not vary over time, such as

farming ability, soil quality, and risk preferences, all of which could confound the relationship between adoption and productivity. They are also blind to the reverse causality of productivity on adoption (Wooldridge, 2010). Against this background, the current paper applies a dynamic modeling framework to three waves (2021, 2023, and 2025) of the Resilience to Climate Change (RCC) panel.

The three-wave structure provides two adoption transitions per household, allowing direct examination of state dependence and the effects of cumulative climate shocks. Lagged adoption serves as an exclusion restriction in the yield equation, supporting stronger causal identification. By jointly modeling seven SAI practices and wheat yield within a Conditional Mixed Process framework, the study separates true state dependence from spurious persistence, accounts for complementarities among practices, and estimates the productivity returns to integrated versus partial adoption under recurrent climate stress. In doing so, it shifts the policy focus from simply promoting initial adoption toward ensuring that technologies are sustained long enough to deliver lasting productivity gains.

1.3 Research Objectives

1.3.1 General Objective

The general objective of this study is to examine the adoption dynamics of SAI practices and their impact on wheat productivity under recurrent climate shocks in rural Ethiopia.

1.3.2 Specific Objectives

This broad objective will be achieved through three specific objectives.

1. To examine the adoption, persistence, and transition patterns of each of the seven wheat-related sustainable agricultural intensification practices over the period 2021–2025, and to determine whether past adoption increases the likelihood of continued use.
2. To assess how repeated climate shocks affect the continued use or abandonment of sustainable agricultural intensification practices.
3. To estimate the effect of adopting sustainable agricultural intensification practices on household wheat productivity, while accounting for the fact that farmers who adopt these practices may differ systematically from those who do not.

1.4 Research Questions

Main research question: To what extent do SAI practices affect wheat productivity, measured in kg/ha, when adoption decisions are modeled jointly through a CMP framework that accounts for interdependence among the seven SAI practices, their lagged effects, and cross-equation error correlation?

Addressing this research question entails examining the following sub-questions:

1. What are the adoption, persistence, and transition patterns associated with adoption of SAI technologies based on wheat at the individual practice level and the extent to which households undergo transitions from one of the four technology adoption regimes: No Adoption [R_0], Input Technology Adoption [R_1], Natural Resource Management Technology Adoption [R_2], or Input-Natural Resource Management Synergy Technology Adoption [R3], through the years 2021, 2023, and 2025?
2. How can repeated climate shocks such as consecutive droughts and irregular rainfall weaken technology adoption persistence and increase technology dis-adoption or downward transitions within technology adoption regimes?
3. What are the increased productivity due to continued adoption of SAI technologies in terms of increased yield in kilograms per hectare, adjusting for potential bias from self-selection, time invariant unobserved heterogeneity, reverse causality, and contemporaneous and lagged relationships between different practices as well as cumulative impacts of climate shocks?

1.5 Research Hypotheses

The study formulates the following hypotheses to guide the empirical analysis of adoption dynamics and their impacts on household wheat productivity. It focused on wheat productivity among smallholder farmers in rural Ethiopia.

Null Hypothesis (H_0): Given a CMP estimation that allows for the interdependencies of the SAI practices, lagged adoption, cumulative climate shocks, and unobserved heterogeneity, none of the individual SAI practices has a statistically significant positive causal impact on wheat productivity (Kg/ha).

Alternative Hypothesis (H_1): At least one individual practice can positively affect wheat productivity (Kg/ha).

State dependence hypothesis (H_2): Past adoption of each individual wheat-related SAI practices increase the probability of current adoption of that same practice.

Climate shock hypothesis (H_3): Repeated and successive climate shocks disrupt the likelihood of adoption.

1.6 Significance of the Study

Ethiopia has experienced repeated droughts, floods, and rising agricultural input costs in recent years. These challenges have made it difficult for smallholder farmers to adopt and continue using sustainable agricultural intensification (SAI) practices. This study examines how smallholder wheat farmers adopt, continue, or stop using SAI practices over three survey rounds. The findings provide useful evidence for improving agricultural policies and programs.

The significance of this study can be explained in three ways: **methodological, empirical, and policy**.

Methodologically, many previous studies relied on one-time surveys or two-wave panel data. These approaches cannot clearly distinguish between farmers who adopt technologies because of their long-term characteristics and those who continue adopting because of their previous adoption decisions (Wooldridge, 2010; Kassie et al., 2013). By using three waves of the Resilience to Climate Change (RCC) panel dataset (2021–2025) and the Conditional Mixed Process (CMP) model developed by Roodman (2011), this study jointly analyzes seven SAI adoption decisions together with wheat yield.

Empirically, this study provides evidence on how farmers' adoption of SAI practices changed during a period of severe climate and economic challenges in Ethiopia (UNDRR, 2024; OCHA, 2023). Because the same households were followed over time, the study can also examine whether higher wheat yields come from using individual practices or from combining several practices, which is difficult to assess with a one-time survey (Ruzzante, Labarta and Bilton, 2021; Tabe-Ojong and Geffersa, 2024).

From a policy perspective, the findings support Ethiopia's Ten-Year Development Plan (2021–2030) and the second phase of the Homegrown Economic Reform Agenda, which both promote climate-resilient and technology-based agricultural development (NPC, 2020; FAO, 2025; NBE, 2025). The results will help policymakers decide whether extension and credit programs should promote single practices or groups of practices, how

safety-net and insurance programs can help farmers continue using SAI practices after climate shocks, and how the proposed **Triple-P (Promote–Protect–Persist)** framework can support long-term adoption of sustainable agricultural practices.

1.7 Scope of the Study

This study focuses on 598 smallholder wheat farming households from 40 rural woredas in six regions of Ethiopia: Oromia, Amhara, Sidama, Central Ethiopia, South Ethiopia, and Somali. These areas were selected to represent different agroecological conditions, including high-rainfall highlands and dry lowlands, as well as areas with and without major agricultural programs such as AGP, PSNP, and SLMP.

The analysis uses three rounds of panel data collected in 2021, 2023, and 2025 through the Resilience to Climate Change (RCC) survey.

The study focuses only on wheat production and does not include other crops such as maize or teff. Therefore, the findings should not be applied to other crops. In addition, since the data cover the period only up to 2025, the results describe farmers' adoption of sustainable agricultural intensification (SAI) practices and wheat productivity only during that period and do not reflect changes that may have occurred after 2025.

1.8 Organization of the Thesis

The remainder of the thesis is organized as follows. Chapter Two reviews the conceptual and empirical literature relevant to sustainable agricultural intensification, technology adoption and persistence, and the impacts of climate shocks.

Chapter Three outlines the methodology, presenting the conceptual framework, data, and econometric approach to modeling the dynamics of adoption and the impacts of regimes of adoption on wheat productivity, in particular, the CMP framework.

Chapter Four presents the results and discussion: descriptive statistics and adoption transitions, climate shock analysis, econometric results and impacts on wheat productivity, robustness checks of the CMP relative to its simpler alternatives, and discussions of the study's limitations arising from the short panel window, binary measurement of stock practices, and boundaries of generalizability. Chapter Five presents the conclusions and policy implications of the main findings. Finally, references are given.

CHAPTER TWO

2. Literature Review

2.1 Theoretical and Conceptual Framework

Sustainable Agricultural Intensification (SAI) choices are never a simple yes or no decision at a given moment in time. Rather, the choices are inter-temporal and involve learning, adaptation, and sometimes reversals. Based on this intuition, microeconomic household theory, behavioral learning models, and dynamic welfare economics are combined into one framework that integrates initial household endowments, risk preferences, and exposure to climate shocks with the potential for institutional support to either push or pull smallholders into or away from high-yielding agricultural production.

2.1.1 Microeconomic Foundations: The Agricultural Household Model (AHM)

Most profit-maximizing models fail to explain the resistance to adopting high-yield technologies such as chemical fertilizer and improved seed varieties among the majority of smallholders in developing countries. According to Hayami and Ruttan's Theory of Induced Innovation (1971), technological change is induced by factor endowments and relative prices.

However, in rural Ethiopia, smallholders operate under severe market failures. Hence, the model of the agricultural household by Singh, Squire, and Strauss (1986) argued that in such circumstances, when credit, insurance, and labor markets are absent or do not work, the decisions about production and consumption become inseparable. As both a firm and a consuming unit, the household does not allocate resources based only on expected profitability, liquidity constraints and risk preferences predominantly drive the decision. Against this background, the considerable productivity gains from improved technologies are insignificant compared to the risks of crop failure and subsequent food insecurity in an institutionally weak and highly risky environment. hus, non-adoption or even dis-adoption of a previously used technology can be rationally explained by risk-avoiding strategies. Dercon and Christiaensen (2011) noted that under such conditions, assets such as livestock are disinvested, and inputs are cut, falling back on subsistence agriculture, characterized by low inputs and low risk.

2.1.2 Learning Dynamics and Diffusion

If market imperfections induce caution, adoption and momentum must occur through a dynamic process of information acquisition and cognitive evaluation. n the learning-by-doing model of Foster and Rosenzweig (2010), farmers first test new technologies on a small scale and then observe their performance. This allows them to update their subjective beliefs and reduces uncertainty about the technology; thus, if the experience is positive, the level of confidence increases, while it decreases when a shock further strengthens negative prior beliefs.

Extending this to social learning and diffusion, early risk-taking sets up a visible demonstration effect in Rogers' (2003) classical diffusion theory. A neighbor will trust what he can see, such as a good harvest next door, more than a suggestion by an extension worker. Social observation creates the S-curve in adoption; with growing adoption, uncertainty decreases, leading to even faster adoption.

According to Ajzen's (1991) Theory of Planned Behavior, social norms and perceived behavioral control over resources shape the adoption decision; thus, an expected return to the practice will translate into adoption only when the farmer believes that he or she has the actual capacity to perform it, an aspect where the role of the institution is crucial.

2.1.3 Explaining Persistence: State Dependence vs. Stochastic Wealth Effects

Two competing economic mechanisms may explain whether the farmer continues with or ceases to use the technology once he/she adopts it. The first is the genuine state dependence postulated in learning models such as Foster and Rosenzweig's, according to which prior adoption makes future adoption more likely, given that the use of the practice changes the farmer. Indeed, experience in using a practice builds human capital and farm-specific skills that reduce the perceived riskiness of the new practice. More importantly, it facilitates the integration of the farmer into networks that provide access to credit and subsidized inputs, which further reduce future transaction costs and make it a routine rather than an experiment.

The second explanation is stochastic wealth effects, rooted in household liquidity. When credit and insurance markets fail, input use depends strictly on cash reserves. After abundant years, the household has enough liquidity to fund input purchases for the

following season, while a bad year results in negative cash balances and a forced return to traditional farming. Carter, Laajaj, and Yang (2021) show that these two mechanisms can operate jointly: temporary subsidies can start the learning process and state dependence while allowing the household to build up liquidity to sustain adoption. However, a major climate shock can disrupt both processes at once: accumulated knowledge and confidence are lost, and financial liquidity is wiped out.

2.1.4 Mechanisms of Shock-Induced Dis-Adoption

Adoption momentum in Ethiopia's wheat-producing regions is highly vulnerable to climate shocks, which trigger dis-adoption through three distinct channels. First, in the absence of insurance, crop failure forces asset liquidation and liquidity depletion. Households must sell productive assets, such as oxen, to meet immediate consumption needs, forcing a return to traditional methods out of sheer necessity. Crucially, failed adopters lose both their crop and the cash invested in expensive inputs, making them far more vulnerable than those who never adopted. Second, experiencing a crop failure alters subjective risk perceptions because losses loom larger than equivalent gains, causing farmers to cut back on modern inputs to avoid further cash exposure even if objective long-term returns remain high. Third, a temporal discounting of natural resource management occurs because inputs like seeds and fertilizer can boost yields in a single season, whereas conservation practices require years of labor before yielding visible benefits. Under the threat of immediate climate shocks, households experience high subjective discount rates and abandon long-term soil conservation to focus on immediate survival, causing dropouts to revert to high-risk, input-only or traditional regimes.

2.1.5 The Integrated Conceptual Flow

This study models adoption as a four-stage dynamic process, with initial conditions, climate shocks, and institutional buffering interacting to affect long-term productivity outcomes.

Stage 1: Initial Drivers and Entry Barriers

At the baseline, a farmer's predisposition to adopt is determined by demographic characteristics, household resource endowments, climatic shock history, and access to

institutional services. Demographic variables include the age, gender, and education of the household head. Resource endowments include landholding, asset wealth, and livestock holdings measured in Tropical Livestock Units. Institutional service access reflects proximity to agricultural extension, credit, and development programs such as the Agricultural Growth Program, the Sustainable Land Management Program, and the Productive Safety Net Programme. At this stage, severe resource constraints and climate risks lock households into the No Adoption regime.

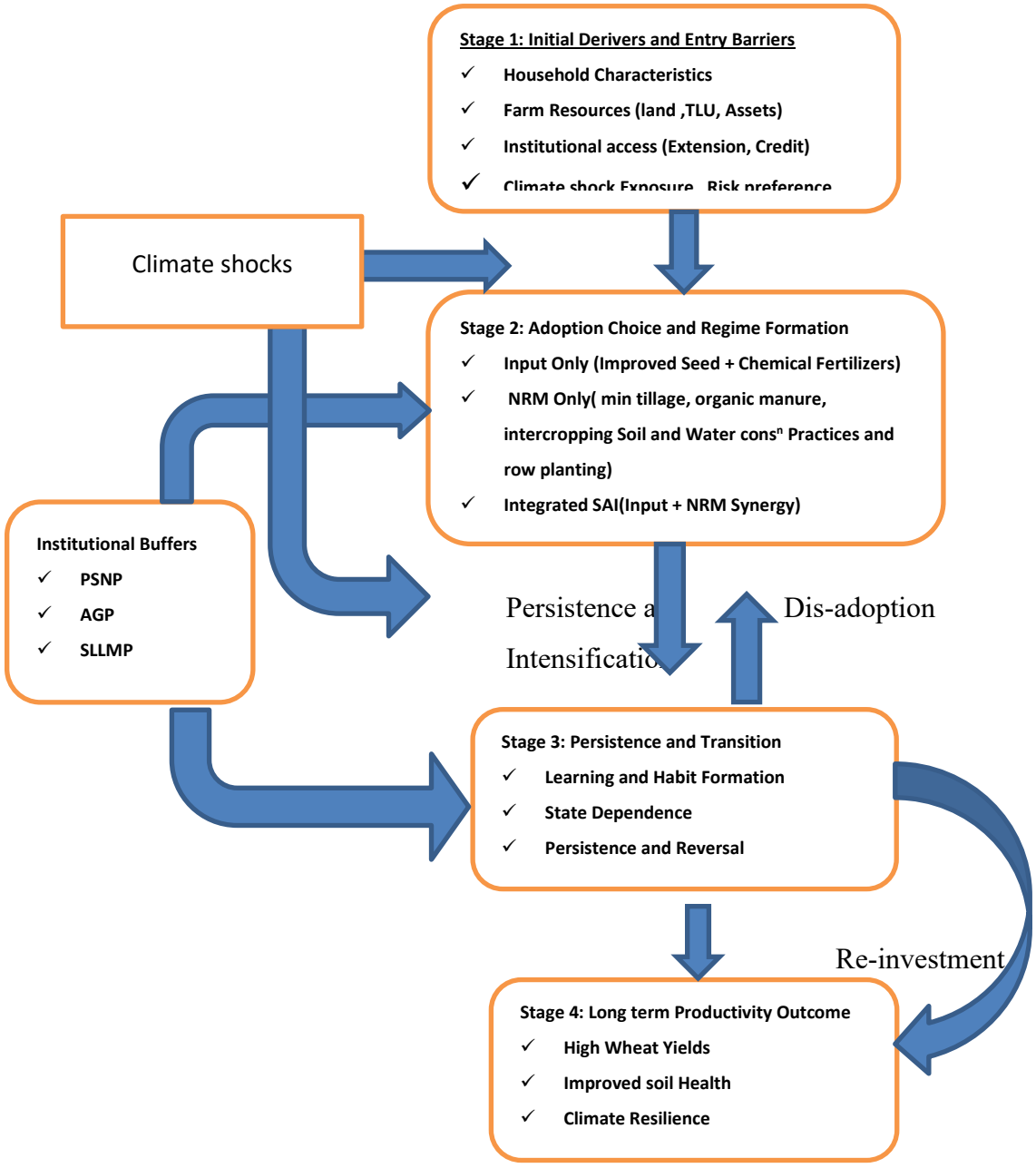
Stage 2: Adoption Choice and Regime Formation

Once the initial barrier is overcome, the household selects one of four mutually exclusive adoption regimes based on relative benefits, constraints, and complementarities as perceived by the household. These regimes include Regime 0: No Adoption and continuation with traditional practices; Regime 1: Input-Only, using chemical fertilizer and improved seed; Regime 2: Natural Resource Management-Only, using organic manure, minimum tillage, row planting, and soil and water conservation; and Regime 3: Integrated SAI Synergy, combining improved inputs and conservation practices. Experience shows that farmers start with the lowest-risk components and then move to the full package of integrated adoption as experience accumulates.

Stage 3: Persistence, Transition, and Institutional Buffering

Over time, households transition between these regimes. Positive experiences with high-yield, low-risk technologies may lead to true state dependence, which will tend to ensure continued membership in the high-yield Integrated SAI Synergy regime. In contrast, climate shocks act as a disruptive force that drives households toward simpler, less productive regimes. This is why institutional buffering plays a critical stabilizing role: the Productive Safety Net Programme, for example, provides a consumption safety net during drought, thus reducing the need for distress sales of productive assets. For example, during drought, the Productive Safety Net Programme acts as a consumption safety net, reducing the need for distress sales of productive assets. Concurrently, the Agricultural Growth Program and Sustainable Land Management Program subsidize input distribution, offer credit, and lower learning costs through organized demonstration plots, facilitating a return to integrated practices.

Figure 2.1: Conceptual framework of Smallholder Adoption Dynamics:



Source: own depiction using the concept of conceptual flow

Stage 4: Long-Term Productivity Outcomes:

The final stage examines the causal impacts of regimes on wheat productivity, soil quality, and vulnerability to climate shocks. Only those regimes that induce persistent adoption of integrated synergies will allow households to benefit in the long run from biophysical complementarities. For example, moisture conservation increases fertilizer efficiency,

ensuring high and stable levels of wheat production that enable households to escape the vulnerability trap associated with climate shocks. In contrast, households that persistently transition between regimes or ultimately settle in a non-adoption regime never accumulate soil capital, and their vulnerability to climate shocks remains high.

2.1.6 Linkage to Empirical Strategy

In an empirical implementation, all these theoretical mechanisms will be jointly tested in one system of equations within the framework of a Conditional Mixed Process (CMP). The first step will estimate an inter-temporal multivariate probit model of seven SAI practices that control for unobserved household heterogeneity, allowing the separation of true state dependence from complementarity. At the same time, the logarithm of wheat yield is modeled continuously. This system addresses potential self-selection, unobserved heterogeneity, and reverse causality issues and gives a credible causal estimate of the effect of integrated SAI adoption on smallholder wheat productivity in a context of repeated climate shocks.

2.2 Empirical Literature

This literature broadly documents what determines adoption, how practice changes affect yields, and under what circumstances early gains are reversed or sustained. However, much of it relies on cross-section or short-panel data, capturing only the moment, not the trajectory. Therefore, questions remain about whether yields are persistent under accumulating climate stresses and whether gains from technology packages are permanent or not. That is the focus of this study.

2.2.1 Determinants and Patterns of Adoption

Technology adoption patterns in Ethiopia mirror those across Sub-Saharan Africa. Household heads with higher education, better access to extension and credit, cooperative membership, and larger livestock holdings and farm sizes consistently show higher adoption of modern agricultural technologies (Wordofa et al., 2021; Tesfaye et al., 2024; Lankamo et al., 2025).

Institutional support greatly influences adoption of productivity-enhancing and climate-smart practices. Extension contact, field days and demonstrations, credit access, and social organization membership are consistently identified as key determinants of adopting

improved crop varieties and adaptation measures (Weli and Mohammed, 2021; Deressa et al., 2011). Extension services and training significantly affect adoption in both Zambia and Ethiopia. In eastern Zambia, Khonje et al. (2018) report double-digit increases in adoption probabilities associated with extension. In Ethiopia, Mogess and Ayen (2023) find extension service use raises the probability of jointly adopting improved seed and crop rotation by about 10 percentage points. Deressa et al. (2011) show extension access significantly increases the likelihood of adapting to climate change in the Nile Basin.

Cooperative membership reinforces these effects. Zambian panel data show membership raises adoption of improved maize, fertilizer, and crop rotation by 11–24 percentage points and shortens adoption lags by 1.6–4.3 years (Manda et al., 2020). Ethiopian evidence finds cooperative members more likely than non-members to use fertilizers and pesticides, showing how farmer organizations relax market and information constraints (Abebaw and Haile, 2013).

Not all determinants favor adoption. Remoteness from markets, older household headship, and female-headed households are generally associated with lower adoption of climate-smart and improved technologies, suggesting structural rather than purely informational constraints.In Ethiopia's Sidaama Region, the sex and age of the household head and distance to market significantly affect adoption of multiple climate-smart practices, with female-headed and older households and those farther from markets less likely to adopt (Lankamo et al., 2025). Similarly, in the Nile Basin, male-headed households are significantly more likely to adapt to climate change than female-headed ones. Education, household size, livestock ownership, extension access, and credit availability all raise adaptation probability, while distance to markets constrains it (Deressa et al., 2011). Hence, extension systems and farmer organizations jointly determine who adopts, how fast adoption occurs, and by how much, but there are stubborn structural divides by gender and age and access to markets.

Climate shocks are among the strongest barriers to adoption. Repeated bad seasons erode the assets and liquidity needed to sustain adoption, not just its initial attractiveness. In rural Ethiopia, production shocks significantly reduce adoption of high-cost innovations such as improved seeds, chemical fertilizer, and irrigation, while sometimes raising use of lower-cost options like organic fertilizer (Gebremariam and Tesfaye, 2018). Panel evidence

shows consumption risk and rainfall shocks discourage fertilizer use even among potentially profitable adopters, because households fear harvest failure without insurance and credit (Dercon and Christiaensen, 2011). Tanzanian evidence indicates weather shocks and rainfall variability reduce adoption primarily through income and credit constraints rather than information gaps (Arslan et al., 2017). When drought coincides with other stresses, the effect magnifies: in Ethiopia, conflict combined with drought reduces fertilizer and improved seed use by about 25 and 22 percentage points respectively (Abay et al., 2026). Climatic risk thus appears as a cumulative and persistent constraint that continually drains the financial and physical capital necessary to use technologies over time. This matters because existing literature largely treats climate shocks as isolated events. In Ethiopia, repeated droughts and erratic rainfall gradually erode household assets and reduce their ability to withstand further shocks-a process of cumulative erosion that cannot be captured by cross-sectional analysis. This is why this study seeks to fill this gap by constructing a cumulative measure of exposure to climate shocks over time to capture how repeated shocks influence adoption and dis-adoption behavior.

This is especially relevant for wheat systems in Ethiopia, where productivity is limited by several constraints: soil degradation, moisture stress, and weak input markets for both inputs and outputs. herefore, bundling input-intensive practices such as using fertilizer and improved seed with NRM practices like mulching, terracing, and crop rotation allows one to address several binding constraints simultaneously. Indeed, this study shows that the integrated regime (R3) is superior to partial adoption. This also fits well with the evidence that membership in a cooperative combined with extension services can reduce the lags in adoption and improve performance (Manda et al., 2020). Therefore, the case for integrated technology packages through collective action and institutional support is further enhanced (Abebaw & Haile, 2013; Kassie et al., 2013).

2.2.2 Complementarities and Superiority of Integrated Technology Adoption

In Ethiopian wheat systems, soil degradation, irregular rainfall, and weak input and output markets constrain productivity simultaneously. Improved seeds need adequate moisture and nutrients to express yield advantages, while fertilizer on degraded soils with low organic content often yields low, risky returns. Each practice has a ceiling that complementary practices can raise the joint effect exceeds the sum of individual parts. This

is the core rationale for promoting integrated SAI packages combining improved seeds, fertilizers, and natural resource management (Teklewold et al., 2013; Kassie et al., 2018). Evidence supports this complementarity. In Zambia, Khonje et al. (2018) show farmers who simultaneously adopt improved maize, minimum tillage, and legumes achieve larger gains in output and poverty reduction than those adopting any single component alone. In Ethiopian wheat systems, Zenbaba and Ketema (2025) find combining improved seed and chemical fertilizer rather than either input alone drives meaningful improvements: the bundle raises dietary diversity by 8.88%, food consumption scores by 15.5%, and wheat income by 2.3%, consistent with the integrated regime (R3) effects observed in this study. Meta-analyses for Sub-Saharan Africa reinforce these findings. Across crops and environments, technology bundles generate 25–35% larger productivity impacts than single technologies, with integrated packages showing even greater advantages under drought and climate stress (Habtewold and Heshmati, 2023). Integrated soil fertility management and climate-smart agriculture studies similarly show combining mineral fertilizer with organic amendments, soil and water conservation, and improved varieties generates more stable and resilient yield gains than stand-alone practices.

Two methodological implications follow. First, classifying farmers into four regimes (R0 = none; R1 = input-only; R2 = NRM-only; R3 = integrated) reflects that the package matters more than individual elements. Second, the Conditional Mixed Process (CMP) framework is appropriate because it allows correlated error terms across adoption equations, capturing unobserved factors and testing for complementarities rather than imposing them a priori.

Most existing studies on integrated SAI adoption rely on cross-sectional or short-panel data, comparing adopters with non-adopters at one point in time. They cannot fully assess whether benefits persist, grow, or decline over time, nor systematically identify which bundles perform best under repeated climate shocks. This study contributes by applying a CMP model to panel data, using estimated correlations across adoption decisions to identify complementarities directly from the data and evaluate dynamic performance of different SAI combinations under cumulative climate stress.

2.2.3 The dynamic nature of adoption

Most studies ask: "Did the farmer use the practice last season?" This treats adoption as a one-time decision rather than a process that changes over time. In reality, farmers may adopt, continue, or stop using practices because of drought, rising input prices, financial conditions, or previous experiences (Wordofa et al., 2021; Lankamo et al., 2025a). Looking at only one point in time can be misleading. Two farmers may both appear to be using improved seed in a survey, but one may have used it continuously for years while the other used it only once under a temporary subsidy and then stopped. Though they look similar in a cross-section, their experiences and support needs differ greatly. Birhanu and Jensen (2023) found farmers who adopted improved seed in earlier years were more likely to adopt it again later because they gained knowledge and experience. However, their study focused on only one technology and did not examine persistence under repeated climate shocks or for combinations of SAI practices.

Very little is known about the transition dynamics of adoption, non-adoption, partial adoption, and full adoption over time among farmers living in areas prone to climate change. It is crucial because, many farmers adopt technologies during the period of subsidy or demonstration programs but discontinue after external support ceases or after drought. Therefore, measuring adoption only once after a program has finished is likely to give a very biased impression of the success of such programs.

Moser and Barrett (2006) found many farmers in Madagascar initially adopted the System of Rice Intensification but later abandoned it due to high labor requirements and limited resources, especially among poorer households. Panel data are also often presented only as averages, masking substantial heterogeneity in adoption pathways.

This study will use a unique three-wave panel of survey data collected between 2021 and 2025, a period marked by serious climatic stress in Ethiopia. Against this background, the Conditional Mixed Process (CMP) framework will allow testing the effects of previous adoption, interactions among SAI practices, and repeated climate shocks on farmers' decisions to adopt SAI practices over time. In other words, this framework will allow testing not only whether farmers adopt SAI practices but also whether they continue to do so for long enough to increase wheat productivity.

2.2.4 The compounding benefit of persistence

Most studies look at the effect of technology on the very first season of adoption, and only very few go beyond that to examine what happens when a farmer uses a technology continuously for a couple of seasons. There is, however, a strand of literature that suggests that the benefits associated with continued adoption accumulate and increase with time. The more experienced farmers become in using the technology, the better they can improve aspects such as the timing of planting, adjusting input use, or the interaction of multiple practices. In that regard, even if input levels remain constant, yields can still increase (Foster and Rosenzweig, 2010).

For practices, such as organic manure, zero tillage, intercropping, or soil conservation, productivity gains will only gradually appear because such practices only slowly improve the quality of the soil and its capacity to retain water. In the long run, soils with improved properties enable better performance of improved seed and fertilizer, which is a biological multiplier effect described by Antle and Capalbo (2001) and Wollni et al. (2010). Indeed, improved soil quality increases the marginal productivity of modern inputs over time.

Some recent studies provide evidence on this. Khonje et al. (2018) found long-term poverty reduction benefits of technology packages exceeded short-term effects because soil quality improved over time. Mogess and Ayen (2023) showed Ethiopian farmers who consistently used improved seed with crop rotation achieved larger yield gains than those using practices only briefly. Mume et al. (2024) found households continuing conservation agriculture became more resilient over time.

If a farmer in Ethiopia who cultivates wheat stops using one or more technologies included in the package, he or she not only loses the flow of current-season benefits but also the accrued benefits of soil quality and farming experience built up over the previous years. Few studies try to measure these long-run effects because most panel datasets are short. With three waves of panel data and the inclusion of previous adoption in the econometric specification, this study offers a better perspective on the productivity impacts of SAI technologies under repeated climate stress conditions.

2.2.5 Fragility of adoption gains: The “reset button” effect of climate shocks

The benefits of SAI practices increase over time. Farmers gradually improve skills, build healthier soils, and become more resilient through continued use. However, repeated

climate shocks can interrupt this process. RCC survey evidence shows as drought worsened between 2021 and 2023, many households reduced food consumption and sold livestock to cope (Policy Studies Institute, 2025). While these strategies help families survive short-term, they reduce resources needed to continue using improved practices in later seasons. Climate shocks also affect farmers' willingness to invest. After crop losses, many farmers become more cautious and spend less on costly inputs fearing future losses (Tesfaye et al., 2024). NRM practices are especially vulnerable. Soil conservation, organic manure, and minimum tillage usually take several years to show clear benefits. When households face financial pressure, they often stop these practices first because they must meet immediate needs. Researchers describe this as the "reset button" effect (Dercon and Christiaensen, 2011; Oumer et al., 2025). A severe climate shock can cause farmers to abandon previously adopted practices not because they no longer believe in them, but because they lack resources to continue. Farmers lose not only current-season benefits but also long-term gains built over previous years improved soil quality, farming experience, and resilience. This study examines this issue using the three-wave RCC panel (2021–2025), covering repeated droughts and irregular rainfall. It uses a cumulative shock index to measure repeated climate shocks and a dynamic adoption model to examine how these shocks affect farmers' ability to continue using SAI practices over time.

2.3 Research gap

The review of panel studies in agricultural technology adoption has revealed significant gaps in the dynamics of sustainable agricultural intensification in contexts prone to repeated shocks, such as rural Ethiopia Such gaps compromise the internal validity of existing empirical evidence, reduce their applicability, and may misguide policy and program design toward short-run "quick fixes" that may never result in long-run improvements in productivity, yield stability, and resilience among smallholder farmers. Three interrelated aspects are discussed in the succeeding paragraphs based on the most recent empirical evidence and their relation to the justification for this study. **Gap 1: Predominance of Static or Short-Term Analyses** The vast majority of empirical work on technology adoption in Ethiopia and comparable developing country settings continues to use cross-sectional data or, at best, very short panels, most often consisting of only two waves. In these data and methodologies, the adoption decision is thus treated as a single

point or fixed state, rather than a process that is temporally dynamic and may evolve over the course of a season, even reversing in some case (Wordofa et al., 2021; Lankamo et al., 2025a). Even when panel data are used, the time coverage is often short. Most studies focus on average effects rather than the intra-household time dimension of adoption, such as persistence, scale-up, partial adoption, or abandonment of adoption (Khonje et al., 2018; Mogess & Ayen, 2023). This approach disregards the idea of "transitory adoption" in which farmers try improved inputs, for example, high-yielding seed and fertilizer, for one or two seasons, possibly because of subsidies or favorable weather, but discontinue their use after a while due to cash constraints, poor returns, or other shocks. Here, the positive initial outcomes may fail to endure, and wheat yields may prove to be volatile and even diminish over time, according to Birhanu and Jensen (2023).

Gap 2: Lack of True State Dependence and Compounding Persistence Modeling: There are very few pieces of research work that address the issue of true state dependence, which states that an increase in the likelihood of adoption due to learning-by-doing, skill acquisition, lower adjustment costs, and habit formation, while considering spurious persistence arising from unobserved heterogeneity like soil productivity, management skills, and risk attitude (Wooldridge, 2010; Oumer et al., 2025). It thus means that the literature lacks much knowledge of the factors that drive sustained adoption after the initial stage of promotion, the process by which farmers make progress from using technologies partially and in isolation to adopting technology bundles for several seasons, and under what circumstances trial adoptions could turn into sustainable intensifications in order to create compounding effects in terms of yields per hectare, technical efficiency, and sustainability (Mume et al., 2024; Zenbaba et al., 2025). Since most analyses do not incorporate lags or dynamic specification, they fail to capture these compounding processes such as cumulative learning and soil fertility replenishment. This deprives policy advice of clear-cut evidence regarding the incremental returns to persistence over time.

Gap 3: Insufficient Attention to Cumulative Shocks and the "Reset Button" Effect: The climatic shocks farmers face are repeatedly stressed in the literature as one of the largest single threats to farm productivity, yet they are usually modeled as independent or single-period shocks instead of accumulative stress that eats away at the persistence of adoption and any gains in productivity over time (Dercon & Christiaensen, 2011).

First, in terms of dynamics, to fill the knowledge gap regarding the dynamics of adoption, this study draws on a balanced three-wave panel survey data from 2021, 2023, and 2025, capturing years of severe climatic shocks. This allows tracing the adoption, continued use, switching, or discontinuation of SAI practices by the same households over time, as opposed to once-off or two-period data. Second, in terms of shocks, it builds a running cumulative shocks index of drought and erratic rainfall to which the household is exposed in all three waves. This index thus captures the compounding erosion of adoption persistence that single-period shocks indicators do not. And third, methodologically, this study uses a Conditional Mixed Process (CMP) framework to jointly model seven SAI adoption decisions alongside a wheat yield equation in a single step. By estimating these interrelated probit equations and the yield outcome within a unified likelihood function, the approach accounts for cross-practice synergies, unobserved heterogeneity, and causal identification. This joint estimation simultaneously corrects for self-selection, unobserved heterogeneity, and reverse causality—an integration that traditional cross-sectional multivariate probit models, endogenous switching regressions, and two-stage instrumental variable estimators cannot achieve. While Oumer et al. (2025) apply an inter-temporal multivariate probit model to analyze SAI persistence in Ethiopia, they neither jointly estimate productivity outcomes within the same likelihood system nor incorporate a cumulative shock index to capture compounding climate exposure. Our study directly extends their framework to address these key gaps.

CHAPTER THREE

3. Methodology

This chapter discusses the methodology applied in analyzing the impact of technology adoption, climate shocks, and persistence in farming practices on wheat productivity in Ethiopia. Given that technology adoption decisions vary with endowments, constraints, and risk preferences, the simple methods of analysis will lead to biased results. Appropriate econometric approach should, therefore, be adopted to handle the self-selection into the adoption of technology by farmers and dynamic decisions over time.

3.1 Description of the Study Area

The data used for this analysis was collected from a total of 40 rural woredas representing different agro-ecological zones of Oromia, Amhara, Sidama, Central Ethiopia, South Ethiopia, and Somali regions. The woredas were chosen to ensure variation in relation to the differential farming potentials and climate shocks experienced. The woredas are also located inside and outside the geographical coverage of the country's flagship programs: Agricultural Growth Programme (AGP), Sustainable Land Management Program (SLMP), and Productive Safety Net Program (PSNP), thus providing a rich source of comparative information (PSI, UCPH, & AAU, 2022).The sample woredas thus vary from the highland high rainfall areas of the staple crop-producing zone to the dry and semi-arid lowland pastoral/agro-pastoral areas. This becomes critical in examining the effects of adopting long-term technologies in terms of productivity.

The RCC panel survey covers 1919 households across six regions of Ethiopia: Amhara, Oromia, SNNPRG, Somali, Gambela, and Dire Dawa. Since wheat is not a major crop in Gambela and Dire Dawa, the wheat-specific estimation sample used in this study (N = 1,061 observations) comes from only four regions: Amhara, Oromia, SNNPRG, and Somali, with Amhara as the reference category in the regression tables.

My estimation model is an inter-temporal multivariate probit (MVP) model that simultaneously estimates multiple SAI adoption decisions by farmers, allowing for correlated choices, persistence over time, and unobserved heterogeneity. The wheat productivity equation is estimated jointly with the adoption equations.

The CMP model jointly estimates productivity and technology adoption, thus correcting for self-selection and unobserved heterogeneity in one step without recourse to a separate two-step procedure. It also incorporates lagged terms to account for path dependence. As a result, the model provides a more accurate estimate of the effect of adoption on wheat yield by accounting for both persistent technology use and changes in adoption behavior over time.

3.2 Data sources, type and method of data collection

The RCC panel is owned and collected by PSI, UCPH, and AAU (2022). It is not publicly available data, access was granted through my advisor, Dr. Hailu Elias. The RCC panel dataset provides detailed information on rural households in Ethiopia, including agricultural technology use, responses to climate change, resilience strategies, and welfare outcomes. It includes data on farming practices such as improved seeds, fertilizer use, and natural resource management; shocks to the environment; asset ownership; education levels; coping strategies; and participation in government programs such as AGP, SLMP, and PSNP.

The RCC survey retained 1,964 of the original 2,000 sampled households across all three waves, a survey-level attrition rate of 1.8% (PSI, OPM, & UCPH-DERG, 2025). After cleaning the data and dropping households with missing values on any of the variables used in the model, the working analytical panel for this thesis contains 1,919 households, which constitute a strongly balanced panel over the years 2021, 2023, and 2025 (5,757 household-year observations; confirmed by Stata's xtset panel diagnostics). The wheat-growing sub-sample used for estimation is 598 households.

3.3 Research Design

The research design is deductive, wherein hypotheses are first formulated from theoretical frameworks, such as the expected utility framework of technology adoption by Feder et al. (1985) and dynamic state dependence following Wooldridge (2010), and then tested using real data from rural Ethiopian households. For instance, one of the hypotheses tested is whether continuous use of improved practices leads to higher wheat productivity. Depending on the empirical evidence, the hypothesis is either accepted or rejected.

3.4 Variable Description

3.4.1 Dependent Variable: Wheat Productivity

Wheat productivity is defined as the total quantity of wheat harvested divided by the total land area planted to wheat, expressed in kilograms per hectare. Both the quantity harvested and the land area are summed across all wheat plots cultivated by the household in a given year.

Formally, the wheat productivity for household i at time t is expressed as:

$$y_{it} = \frac{\sum_{p=1}^{n} Q_{ipt}}{\sum_{p=1}^{n} A_{ipt}} \quad \text{---------- (1)}$$

Where:

y_{it} : is wheat yield (kg/ha) for household $i$in year t,

Q_{ipt} : is the quantity of wheat harvested from plot $p$by household $i$in year t,

A_{ipt} : is the area (in hectares) of plot $p$allocated to wheat by household $i$in year t, and

n : is the number of wheat plots cultivated by the household in that year.

The vector X_{it} in the yield equation includes household- and plot-level characteristics expected to influence wheat productivity independently of SAI adoption:

Table 3.4.1: Description of Covariates in the Wheat Yield Estimation

Variable	Measurement	Expected Sign	Rationale
Household Head Age	Years	Ambiguous	Older heads may have more farming experience (raising yield) but also more risk-averse, conservative input use (lowering yield)
Household Head Gender	Binary: 1 = male	Ambiguous	Male-headed households often have better access to extension, mobility, and labor, but the effect on yield itself is not theoretically determinate

Total Land Size	Hectares allocated to wheat (log-transformed)	–	Captures diminishing returns to scale and dilution of management intensity across larger holdings
Livestock (TLU)	Tropical Livestock Units owned (log-transformed)	+	Livestock provide draft power for timely land preparation and serve as a liquid asset buffer that finances input purchases
Extension Plot	Binary: 1 if household has an extension demonstration plot	+	Direct exposure to demonstrated practices reduces uncertainty about correct input use and management, raising realized yield
Mean Distance to Parcel	Kilometers (log-transformed)	–	Greater distance raises monitoring and transport costs, reducing timeliness and quality of management
Credit Access	Binary: 1 if household has access to formal credit	+	Eases liquidity constraints on purchasing yield-enhancing inputs
Region	Regional fixed effects (Amhara, Oromia, SNNPRG, Somali); Amhara reference	Region-specific	Captures unobserved agro-ecological and institutional differences (rainfall reliability, soil type, market access, program coverage)
Year	Survey wave fixed effects (2021, 2023); 2025 reference	Year-specific	Captures common shocks, price changes, and time trends affecting all households in a given wave

Land size, TLU, and mean distance to parcel are log-transformed prior to estimation to avoid distortion from combining variables measured in very different units. Head age and head gender are excluded from transformation on distributional grounds (symmetric scale, homogeneous variance across waves per Bartlett's test, p = 0.982); the remaining variables are binary (0/1), for which log-transformation is not meaningful.

3.4.2 Seven SAI practices

This study models seven SAI practices as separate binary adoption decisions:

Improved wheat seed - high-yielding or drought-tolerant varieties; flow input, raises yield within the same season.

Chemical fertilizer - flow input; complements improved seed by supplying nutrients the variety is bred to use.

Organic manure - stock/NRM input; builds soil organic matter and fertility gradually.

Minimum tillage - stock/NRM practice; reduces soil disturbance and moisture loss over multiple seasons.

Soil and Water Conservation (SWC) - stock/NRM practice (terracing, bunding); reduces erosion and runoff.

Intercropping (legume rotation) - stock/NRM practice; improves soil nitrogen and diversifies risk.

Row planting - flow practice; improves plant spacing and input-use efficiency, often paired with intercropping.

Each of the seven SAI practices is measured as a binary variable for each household in each survey year (1 = adopted on at least one wheat plot; 0 = not adopted). These variables are used in two ways. First, each practice is analyzed separately in the seven adoption equations of the Conditional Mixed Process (CMP) model to estimate persistence and relationships among practices. Second, the practices are combined into four adoption regimes (R_0–R_3, Section 3.4.4) for describing adoption patterns and changes over time. A simple count of practices (0–7) was not used because farmers with the same number of practices may use very different combinations. For example, a farmer using improved seed and fertilizer is different from one using organic manure and soil and water conservation, even though both use two practices. The regime approach preserves these important differences.

The study takes an inter-temporal approach to technology adoption. Seven key SAI practices are modeled as separate binary (yes/no) decisions and estimated jointly using a multivariate probit framework. Persistence is modeled as the lagged adoption of the individual practice. The correlation of error terms across equations allows us to assess whether practices are complements or substitutes.

For interpretative convenience, practices are broadly categorized into the following groups:

Input-intensive: This means higher-quality seeds and fertilizer inputs that will increase production rapidly.

Natural Resource Management (NRM): This consists of organic fertilizer, reduced tillage, SWC, intercropping, and row cropping. All these techniques aim at ensuring soil productivity for the longer term.

Lagged adoption variables were constructed on the full RCC panel (1,919 households, 5,757 observations), with the panel declared using a two-year delta (xtset HH_ID year, delta(2)) to correctly reflect the true two-year spacing between survey waves (2021, 2023, 2025). This ensures that lagged terms are computed relative to genuine prior-wave adoption rather than an assumed annual periodicity. The wheat-specific estimation sample (598 households, 1,061 household-year observations) was then extracted from this correctly-lagged panel using keep if e(sample), preserving the validity of state-dependence terms even for the small number of households with a gap in wheat cultivation between waves.

The improved seed, chemical fertilizer, and row planting variables are only recorded in years when the household grew wheat. So, if a household skipped wheat in one wave, its lagged value is missing for the next wave. The CMP model does not drop the household because of this it simply leaves that one equation out for that observation, while still using the household's data in the other equations. This is why the full model uses N=1,058, while running the improved-seed equation alone (which requires every row to be non-missing) gives a smaller number, N=607.

3.4.3 Cumulative climate shocks

This is defined as wheat_cumulative_shocks, which is the total of the climate shocks faced by households cultivating wheat.

For each year, different rainfall problems; rainfall was late, rain was not enough, rainfall ceased early, distribution was poor, or it rained during harvest and drought experience were recorded as binary variables (1 if the problem occurred, 0 otherwise).

These were then warped into a single variable, any_shock_this_year, taking the value 1 if the household experienced at least one climate shock in that year.

The annual shock experiences are then cumulated over time for each household to construct the cumulative shock index.

This variable increases with each additional shock and captures long-term exposure to climate stress during the study period.

Mathemathical epression:

$S_{it} = \sum_{\tau=1}^{t} C_{i\tau}$ ---------- *(2)*

Where:

S_{it}: The history of Stress or cumulative shock count for household i up to period t.

$C_{i\tau}$: The year specific Climate Shock (the binary input). It is 1 if the farmer reported a shock in year k and 0 otherwise.

A farmer who said "Yes" to a drought in 2021 and "Yes" in 2023 has a cumulative score of 2.

Institutional variables (extension_plot, program participation): These variables proxy for access to extension services and participation in programs such as PSNP, AGP, or SLMP. Through extension services, households are made aware of improved seeds, fertilizer application, and conservation measures. Various programs provide input support, training, and social safety nets, all aimed at increasing wheat production capacity. For these reasons, these variables are expected to relate positively to wheat productivity.

Year dummies control for changes that occur through time that affect all households simultaneously, such as changes in input prices, policy reforms, or national extension campaigns. Their inclusion ensures that the household- and regime-specific effects identified in the model are not conflated with other wave-specific variations.

We measure cumulative climate shocks by counting the number of times a household has experienced a shock across survey waves rather than using a weighted index of the shock's severity, such as the rainfall deficit or the intensity of drought. Because this variable reflects the recurrence of shocks rather than their physical magnitude, it is better suited to

reflect behavioral and asset-erosion channels through which repeated shocks discourage sustained technology adoption than direct, contemporaneous agronomic effects on crop growth. For this reason, the variable for cumulative shocks is included in the seven adoption equations to capture discouragement and dis-adoption responses, as documented in Section 2.2.5, but excluded from the yield equation, where it can serve as an exclusion restriction aiding the identification of the system.

3.4.4 Construction of Adoption Regimes

This study recognizes that Sustainable Agricultural Intensification (SAI) is not a single decision but a combination of different practices that work in different ways. Some deliver quick results in one season, while others build long-term benefits over multiple years. To reflect this reality, the study distinguishes between flow and stock variables.

Flow practices (used up within a season) include improved wheat seeds, chemical fertilizers, and row planting. These are short-term inputs that mainly affect current yields.

Stock practices (Natural Resource Management – NRM) practices. These are longer-term investments that gradually improve soil health, water retention, and fertility over several seasons.

All practices are standardized at the household-year level for consistency in the analysis. Plot-level data for flow practices are aggregated to the household level (whether the household used the practice on any wheat plot), while NRM practices are naturally measured at the household level.

For descriptive analysis and clearer interpretation, the individual practices are grouped into four mutually exclusive adoption regimes:

R_0 (No Adoption): Households using none of the practices.

R_1 (Input Only): Households using only flow practices (improved seeds, fertilizer, and/or row planting).

R_2 (NRM Only): Households using only natural resource management practices.

R_3 (Integrated SAI Synergy): Households combining both input-intensive and NRM practices.

Such a dual approach analyzing practices individually in the econometric model and regimes in descriptive and transition analyses allows for high statistical precision while

retaining a broad, meaningful picture of farmer trajectories toward (or away from) more sustainable intensification. The essential element that distinguishes flow from stock adoption measures relates to the timing of measurement between the point of adoption and the point at which productivity impacts are felt.

3.5 Econometric Analysis and Discussion

3.5.1 Model Specification

Farmers' decisions are rarely made in isolation. Practices are often adopted together because of synergies, and decisions change over time through experience and respond to climate conditions.

Following the dynamic approach of Oumer et al. (2025), this study estimates an inter-temporal Multivariate Probit (MVP) model using the Conditional Mixed Process (CMP) estimator.

The specified model has the following desirable properties:

First, it allows contemporaneous correlation between the seven practices by modeling multiple adoption decisions simultaneously.

Second, it accounts for state dependence by including the lagged adoption variables to assess whether past adoption increases the probability of continued use in subsequent periods.

Third, it allows for unobserved household heterogeneity that can be correlated between practices and over time.

For each household i, practice k, and time period t, the model estimates the latent utility (unobserved net benefit) of adopting practice k. If this latent utility exceeds a certain threshold, the farmer adopts the practice.

In this regard, the intertemporal MVP appropriately captures the simultaneous joint nature of the adoption decision and its dynamic evolution in an environment of climatic uncertainty and repeated climate shocks.

$$A^{*}_{ikt} = \alpha_{ik,t}\ \delta_k A_{ik,t-1} + \beta_{\ k} X_{it} + \gamma_k S_{it} \ + \varepsilon_{itk} \quad \text{----------} \quad \textit{(3)}$$

Where: k = 1, 2 … 7

A^*_{ikt} : represents the unobserved latent utility determining whether household i adopts practice k in period t (A_{ikt} = 1 if A^*_{ikt}>0, and 0 otherwise).

$A_{ik,t-1,}$: is the lagged adoption indicator for the same practice k in the previous wave (e.g., adoption in 2023 influencing 2025), capturing true state dependence.

X_{it} : is a vector covariate.

S_{it}: denotes cumulative climate shocks up to period t, constructed as a running sum of erratic rainfall and drought events experienced by the household across waves.

In this study, we focus on seven specific SAI practices: improved seed, chemical fertilizer, organic manure, minimum tillage, SWC (Soil and Water conservation Practices), and legume intercropping and row planting.

Table 3.5.1 Expected Signs and Rationale for Covariates in the SAI Adoption Equations

Variable	Expected Sign (Adoption)	Rationale
Household head age	–	Older heads more risk-averse, shorter planning horizon
Head gender (male=1)	+	Better access to extension, mobility, land decision authority
Log(Land size)	+ (inputs), – (labor-intensive NRM)	Scale economies for purchased inputs; labor constraints for manure/intercropping on large plots
Log(Livestock, TLU)	+	Draft power, manure supply, and liquidity buffer
Extension contacts	+	Reduces information constraints
Log (Distance to parcel)	–	Raises monitoring/transport cost of intensive practices
Credit access	+ (NRM/labor inputs), possibly –	Liquidity vs. competing uses

	(seed, in tight periods)	
Cumulative climate shocks	–	Asset loss and risk aversion reduce input use
Year dummies	+/-	Capture price shocks, policy changes, campaigns

Three covariates exhibiting scale heterogeneity across households were log-transformed prior to estimation: total land size, livestock holdings (TLU), and mean distance to parcel, the latter two with a +1 adjustment to accommodate zero values. This transformation was confirmed using Bartlett's test for equal variances across survey waves, which showed that logging resolved variance heterogeneity for livestock (raw p=0.000, logged p=0.347) and distance (raw p=0.007, logged p=0.467), and materially reduced it for land size (raw p=0.000, logged p=0.005). By contrast, household head age and gender were tested and found not to require transformation: age is a naturally bounded, roughly symmetric continuous variable with homogeneous variance across waves (Bartlett p=0.982), and gender is a binary indicator, for which a log transformation is neither meaningful nor defined. Cumulative climate shocks and credit access were likewise left untransformed, as both are count/binary-type indicators bounded over a narrow, discrete range rather than continuous, right-skewed magnitudes, so the scale-distortion problem that motivates log-transformation for land, livestock, and distance does not arise for these variables.

3.5.2 Outcome Stage: Joint Estimation of Adoption and Productivity Impacts

While the inter-temporal Multivariate Probit model effectively captures the drivers and interdependencies of SAI adoption. wheat productivity is not included here

A major challenge is that adoption is endogenous, farmers who adopt certain practices often differ in unobserved ways (such as managerial ability, soil quality, or risk preferences) that also affect yields. Failing to account for this would lead to biased estimates.

Seven correlated binary adoption equations (one for each SAI practice), which include lagged adoption terms to capture state dependence.

Linear productivity equation for log (wheat yield in kg/ha), where the seven adoption indicators enter directly as explanatory variables.

By jointly estimating the adoption and productivity equations, the model exploits the structure of correlated errors to correct for selection bias and endogeneity and thus provides consistent estimates of the impact of the seven SAI practices on productivity.

The CMP approach adopted here allows the researcher to treat the seven SAI practices as multiple, potentially simultaneous, adoption decisions rather than mutually exclusive choices. It allows the researcher to consistently estimate the partial impact of a given SAI practice on productivity, net of the other SAI practices.

3.5.3 The Outcome Equations

Based on the commands, the productivity model is specified as a continuous linear equation integrated with the probit selection equations:

$$ln_{y_{it}} = \alpha_{it} + \sum_{k=1}^{7} \delta_k A_{ikt} + \beta X_{it} + \eta_{it} \text{ ---------- } (4)$$

Where:

ln_y_{it}: The natural log of wheat yield (kg/ha), calculated after excluding outliers below 50 and above 8000 kg/ha.

A_{ikt} : Endogenous binary indicators for the adoption of the SEVEN SAI practices: improved seed, chemical fertilizer, organic manure, minimum tillage, SWC, intercropping and row planting.

η_{it}: The idiosyncratic error term (ε_{ikt}).

So, following Roodman (2011), the model allows for a 'mixed process' where the adoption equations are modeled as a Multivariate Probit (MVP) while the outcome equation (ln_y) is modeled as a continuous linear process, all linked by a correlated multidimensional error structure.

3.5.4 Impact Estimation: Treatment Effects

This section details the computation of treatment effects. Standard errors for these effects are obtained through standard in margins to account for the complex covariance structure. Thus, this allows providing convincing evidence on the returns to integrated intensification in the shock-prone wheat systems of Ethiopia.

3.5.5 Identification Strategy

The key issue is that yield regressions would be confounded by unobserved household characteristics affecting adoption and productivity, such as farming skill or risk attitudes. Hence, lagged adoption is included in the adoption equations but not in the yield equation. Past experience with adoption would facilitate current adoption through learning by doing, skill-building, and lower switching costs. Past adoption does not enter the current yield equation because it affects current yield only through the current adoption decision and accumulated soil quality changes, captured by the "stock" practice variables. Past practices aren't a direct input into this year's harvest. Lagged adoption is thus an ideal exclusion restriction, as it strongly predicts current adoption (see Table 4.3.2) and has no direct effect on yields. This identification restriction is imposed within the FIML estimation of the full system of eight equations, allowing for the identification of the true causal effect of adoption net of unobserved heterogeneity at the household level without the need for external instruments, which are difficult to find in farm-level contexts.

Cumulative climate shocks measures the cumulative number of climate shocks experienced by a household over the survey waves; it does not measure the magnitude of a given shock. The idea is that the focus is on how a household responds over time in terms of adoption after being hit by one or more shocks and not on the immediate impact of any given shock on yield. More specifically, multiple shocks hitting the household have been hypothesized to dis-incentivize the adoption of SAIs, thus increasing the likelihood of switching from one regime to another.

Therefore, climate shocks enter only the adoption equations and not the yield equation. To verify this exclusion restriction, the yield equation was estimated with cumulative shocks directly included in two separate specifications. First, in the seven-practice CMP model, the coefficient on cumulative shocks was very small and statistically insignificant ($\beta = -0.010$, $p = 0.857$), indicating no direct impact of cumulative climate shocks on yield net of the seven SAI adoption decisions and other covariates. Second, in the CMP model with the integrated R_3 adoption indicator, the coefficient on cumulative shocks was also small and insignificant ($\beta = -0.027$, SE = 0.058, $p = 0.646$), further validating the exclusion restriction. Both results support the validity of excluding cumulative shocks from the yield equation as an identification strategy.

3.6 Ethical Considerations

This study uses secondary data from the Resilience to Climate Change (RCC) panel survey, obtained through the researcher's academic supervisor, Dr. Hailu Elias, who participated in the original data collection as part of the Policy Studies Institute (PSI) and University of Copenhagen (UCPH) research collaboration. Since the data were originally collected by that research team under its own ethical approval procedures, the researcher did not take part in field-level data collection.

The ethical responsibility in this thesis therefore concerns the proper, confidential, and honest use of the data. The data were provided to the researcher in a de-identified form, with no information about respondents or households that would allow identification of any respondent or household. Confidentiality was maintained during the analysis. Aggregate results have been reported; no attempt has been made to identify any individual household or respondent.

The data have been used exclusively for academic purposes under the conditions by which they were provided to the researcher and advisor. This study follows Addis Ababa University research ethics requirements and generally accepted standards for the responsible handling and reporting of secondary data.

CHAPTER FOUR

4. Empirical Results and Discussion

4.1 Introduction to the Analysis Chapter

This chapter provides empirical evidence using panel data of rural smallholder households in Ethiopia from the three waves of the Resilience to Climate Change (RCC) survey from 2021 to 2025. The data comes from the three waves of the Resilience to Climate Change (RCC) survey for 2021–2025. The analysis will shed light on the nature and dynamics of adoption of SAI technologies among wheat-producing smallholder farmers; whether past adoption history influences future decisions; how repeated exposure to climate shocks modifies this mechanism; and, finally, how these mechanisms cumulatively impact wheat output per unit area. This study takes a simple and straightforward approach to measuring productivity: total output of wheat (kg) divided by the total wheat area (hectares) for each household in each survey year. To avoid unusual or outlier values, wheat productivity observations of less than 50 kg/ha and more than 8,000 kg/ha are excluded from the estimation. In all, the data provide a relatively rich, detailed picture of crop-specific technology adoption over a strongly balanced panel that enables us researcher to examine the dynamics of adoption over time and its impact on wheat productivity.

4.2 Descriptive Analysis

4.2.1 Analysis of Socio-Economic Characteristics

This part of the section will describe the characteristics of wheat-producing households and changes in those characteristics between 2021 and 2025, as observed in the three rounds of the survey. Such socio-economic and agro-ecological household characteristics have been used to distinguish between relatively homogeneous groups and identify emerging challenges faced by wheat-producing households in rural Ethiopia. Hence, two sets of statistical tests are used to characterize the description. The first set uses one-way ANOVA to test whether the mean age of households significantly differs across survey years. The second uses Bartlett's test to check the homogeneity of variance across survey

years. These are among the major descriptive statistics to be reported in the subsequent econometric analysis.

Household Demographics and Asset Holdings: The demographic profile and asset holdings of households from the three waves indicate a steady increase in the age of household heads. While the average age of household heads in 2021 was 47.4 years, it increased to 50.9 years in 2025. This is also supported by the ANOVA test, which gives F = 7.52, with p = 0.0006, meaning the means differ between the three periods of the survey. However, the test for homogeneity of variances showed no differences in age variance across survey waves, with ρ = 0.982. Other demographic characteristics remained stable, with about 84% male-headed households, an average family size of 5.5 persons, and minor changes in educational attainment levels.

Table 4.2.1: Summary Statistics and ANOVA Results (2021–2025)

Variable	2021 (Mean)	2023 (Mean)	2025 (Mean)	ANOVA F	Prob > F	Bartlett's (p-value)
Household Head Age	47.40	49.15	50.94	7.52	0.0006	0.982
Head Gender	0.855	0.838	0.839	0.29	0.7466	0.579
Head Education (Yrs)	4.537	4.821	4.161	1.58	0.2066	0.006
Household Size	5.500	5.551	5.419	0.43	0.6478	0.331
Log(Total Land Size)	0.390	0.175	0.348	9.16	0.0001	0.005
Log(Livestock, TLU)	1.431	1.335	1.313	4.64	0.0098	0.347
Extension Contact	0.584	0.821	0.760	34.34	0.0000	0.000
Credit Access	0.227	0.133	0.118	11.11	0.0000	0.000
Program Participation	2.720	2.635	2.788	2.07	0.1268	0.918
Log(Mean Parcel Distance)	2.163	2.211	2.247	0.63	0.5316	0.467
Climate Shocks	0.729	1.321	1.852	264.10	0.0000	0.000

Source: Own computation using RCC Panel Waves (2021, 2023, and 2025). Land size, livestock holdings, and mean parcel distance are log-transformed, consistent with the specification used in the econometric models (Section 3.4.1).

Since total land size, livestock holdings (in TLU), and mean parcel distance are all strongly right-skewed, they are log-transformed before being included in the econometric models

(see Section 3.4.1). Visually, the log transformation also improves the assumption of homogeneous variance across the survey waves. For livestock, the Bartlett test rejects equal variances on the raw scale (p=0.000) but fails to reject on the log scale (p=0.347). This is similarly the case for mean parcel distance (raw p=0.007 vs. logged p=0.467). For land size, the log transformation reduces but does not remove variance heterogeneity across waves (raw p=0.000 vs. logged p=0.005). This is consistent with the land fragmentation dynamics discussed below. Thus, the log specification in the yield and adoption equations is justified on distributional grounds and improves the homogeneity of variance assumption underlying the ANOVA comparisons.

Asset ownership

Land ownership showed more noticeable changes. Average landholding size (in log terms) declined significantly between 2021 and 2023 before partially recovering by 2025 ($F = 9.16$, $p = 0.0001$), consistent with the raw-hectare pattern (2.04 ha in 2021, declining to approximately 1.57 ha by 2023, before recovering to roughly 1.81 ha in 2025). This is consistent with asset fragmentation via inheritance or forced sales.

Livestock ownership (in log terms) also declined steadily by about 17% in raw terms ($F = 4.64$, $p = 0.0098$). which may significantly decrease the livelihood capabilities of the households to absorb shocks other than livestock, one of the main productive and safety-net assets of rural households in Ethiopia. Bartlett's test shows that variance heterogeneity in land size persists even after log transformation ($p = 0.005$), supporting the increasing level of inequality in asset ownership, while the livestock variance issue is resolved once logged ($p = 0.347$). This further testifies that technology benefits are captured by relatively better-endowed households and contribute to increasing inequality in rural areas.

Institutional Access and Environmental Pressure

First, there is imbalance in institutional support over time. Extension service access increased significantly, with the share of households receiving extension contact rising from 58% to 76% ($F = 34.34$, $p = 0.0000$). Conversely, credit accessibility reduced from 22.7% to 11.8% ($F = 11.11$, $p = 0.0000$). It implies that extension agents have contacted all the farmers concerning improved technologies, but the lack of money prohibits them from adopting these technologies. Program participation did not vary statistically across

the three waves (F = 2.07, p = 0.1268), implying that the coverage of institutional programs was neither expanded nor contracted during the study period.

But, environmental factors worsened over time. The climate shock index increased by about three times to 1.85 from 0.73 (F = 264.10, p = 0.0000). Climate shocks seem to be more concentrated within vulnerable household units, according to Bartlett's test (p = 0.000). This suggests that such vulnerable or poor households experience a greater level of climate shocks than other households and that their production and food security would be under severe pressure. In such a context, farmers' capacity to respond is constrained by reduced credit access, greater exposure to climate shocks, aging household heads, and declining livestock assets. These factors, taken together, represent a vulnerability trap that may prevent a sustained increase in productivity.

4.2.2 Distribution of Climate Shocks across Technology Adoption Regimes

Table 4.2.2 Cross-tabulation of Cumulative Climate Shocks by Adoption Regime

Cumulative Shocks	No Adoption	Input Only	NRM Only	SAI (Synergistic)	Total
0 Shocks	1 (0.52%)	4 (2.08%)	7 (3.65%)	180 (93.75%)	192 (100%)
1 Shock	3 (0.47%)	18 (2.80%)	33 (5.13%)	589 (91.60%)	643 (100%)
2 Shocks	0 (0.00%)	10 (3.14%)	9 (2.83%)	299 (94.03%)	318 (100%)
3 Shocks	3 (2.54%)	31 (26.27%)	3 (2.54%)	81 (68.64%)	118 (100%)
Total	7 (0.55%)	63 (4.96%)	52 (4.09%)	1,149 (90.40%)	1,271 (100%)

Pearson $\chi^2(9) = 140.5359$, $p < 0.001$, $df = (rows - 1) \times (columns - 1)$

Source: Own computation using RCC Panel data (2021, 2023, and 2025).

Table 4.2.2 displays the distribution of cumulative climate shocks across the four regimes of technology adoption. For each category of shocks, the Synergistic group dominates and stays above the 90% threshold in zero, one, and two cumulative shocks (93.75%, 91.60%, and 94.03%, respectively). This suggests that integrated intensification is the preferred

strategy for wheat production under moderate levels of shocks. The non-adoption regime stays very low and does not exceed 2.54% in any category of cumulative shocks, meaning that farming with no modern inputs is almost non-existent.

This trend substantially reverses for higher shock levels. For households with three cumulative shocks, the share of SAI adopters drops sharply to 68.64%, while the Input Only strategy jumps to 26.27% after being around 3% at lower shock levels. These associations are also highly significant in the Chi-square test, $\chi^2(9) = 140.5359$, $p < 0.001$. Repeated shocks likely constrain households' options to pursue integrated, relatively laborious SAI strategies. Thus, at three or more shocks, they tend to adopt the relatively simple Input Only strategy, a strategy that makes sense from a short-term survival perspective but is counterproductive to the long-run goal of integrated intensification.

4.2.3 Comparative Analysis of Wheat Productivity by Adoption Regime

Table 4.2.3 compares the average yields for wheat across the four adoption regimes to test whether complementarity results in higher productivity. This produces a clear productivity pattern, where the average wheat yield of households in the SAI adoption regime is the highest (1,710.76 kg/ha), followed by Input Only adopters (1,285.07 kg/ha), NRM Only adopters (1,138.74 kg/ha), and non-adopters (900.00 kg/ha). In other words, the productivity of the combined technology, improved inputs, and NRM, exceeds their separate contributions. However, a one-way ANOVA suggests that the differences in means are only marginally significant at the 10% level ($F = 2.18$, $p = 0.0896$), thus providing only weak statistical evidence for the above differences in means. The differences in yields are economically meaningful, especially for SAI adopters compared to non-adopters.

Table 4.2.3 Mean Wheat Yield and ANOVA Results by Adoption Regime

Adoption Regime	Mean Yield (kg/ha)	Std. Deviation	Frequency
No Adoption	900.00	757.19	4
Input Only	1,285.07	1,249.79	39
NRM Only	1,138.74	1,652.01	28
SAI (Synergistic)	1,710.76	1,637.96	650
Total	1,661.02	1,621.49	721

ANOVA: F(3, 717) = 2.18, Prob > F = 0.0896; Bartlett's Test: $\chi^2(3) = 6.4462$, Prob > χ^2 = 0.092, Source: Own computation using RCC Panel Waves (2021, 2023, and 2025).

However, it is worth noting that all these average yields, from the lowest of 900 kg/ha for non-adopters to the highest of 1,711 kg/ha for SAI adopters, fall well below the national average yield for wheat, which ranges between 2,000 and 3,000 kg/ha. Three factors explain this. First, the No Adoption category contains only four observations, making its mean highly unstable and not representative. Second, the RCC sample covers some semi-arid and pastoral woredas that lie outside the high-potential wheat belt, where most commercial wheat production occurs Third, yield data is based on farmer self-reports, and there is abundant evidence that farmers under-report yields relative to the crop-cut estimates used by the Central Statistical Agency. Within this context, however, the relative ordering of regimes is informative, with integrated adopters outperforming partial adopters and non-adopters, even in a relatively low-yielding environment.

It is also evident that the variance differs between groups; indeed, Bartlett's test rejects the null hypothesis of equal variance at the 10% level. The highest variance is shown for the NRM Only group, indicating that conservation practices without the complementarity of modern inputs are highly variable.

Thus, in general, the descriptive statistics reveal that productivity gains are the highest for the integrated SAI regime. Because the sample is largely concentrated on SAI adopters and these descriptive statistics do not control for selection bias and unobserved heterogeneity, I will estimate the CMP model, which explicitly accounts for these dimensions.

4.2.4 Distributional Properties of Wheat Yield

Because the raw yield data showed significant skewness, a log-transformation was applied. Table 4.2.5 shows the formal results of the Skewness/Kurtosis test.

Table 4.2.4: Normality test

Variable	Obs	Pr(Skew)	Pr(Kurt)	Adj Chi^2	Prob > Chi^2
Wheat Yield	721	0.0000	0.0000	--	0.0000
Log Yield (ln_y)	721	0.0000	0.9410	28.37	0.0000

Source: Own computation using RCC Panel Waves (2021, 2023, and 2025).

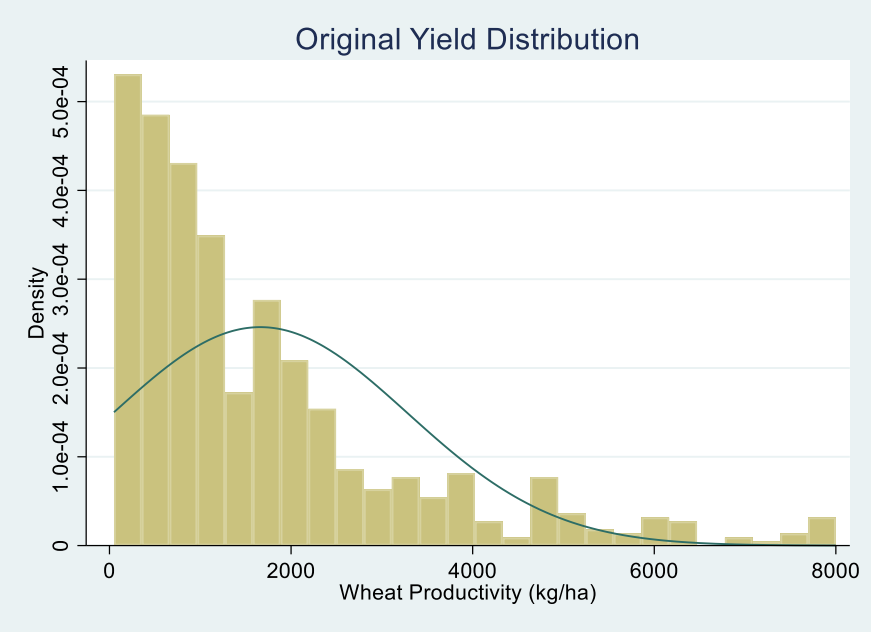


Figure 4.2.1 original wheat_yield distribution

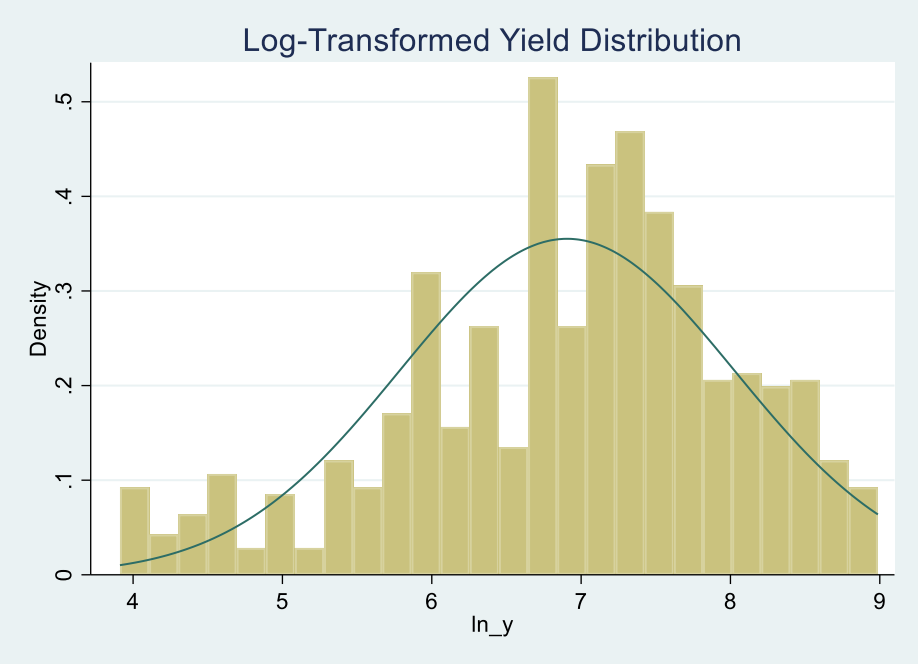


Figure 4.2.2 wheat_yield transformed to natural logarithm

Source: Own computation using RCC Panel Waves (2021, 2023, and 2025).

Clearly, the distribution of wheat productivity among sampled households is right-skewed. Most farmers fall in the lower productivity bracket, mostly between 0 and 2,000 kg/ha. However, a few farmers reach higher productivity levels, up to 8,000 kg/ha, forming a long right tail. It means that household-level productivity is highly dispersed. As expected, the

distribution of data is not normal, and the normal curve does not represent the data well. The skewness test for normality is rejected at a 1% significance level, with p = 0.0000. Therefore, to mitigate this problem and enhance the robustness of the results, wheat yield is log-transformed. This reduces the influence of outliers and makes the distribution more balanced. Log-transformed yield (ln_y) is much closer to a normal distribution. This happens because the log-transformation compresses extreme values at the upper tail and spreads out values at the lower tail, producing a bell-shaped distribution. After log transformation, the data better fit the normal curve and pass the Skewness/Kurtosis test for normality. This further justifies the use of log-transformed yield in the subsequent econometric analysis, as this reduces the effect of outliers and more closely meets the assumptions underlying the model.

4.2.5 Analysis of Inter-temporal Transition Dynamics

Table 4.2.5 shows a transition matrix; that is, it shows the proportions with which households move between regimes of adoption from one period to the next. Accordingly, the analysis allows for observing dynamic patterns of persistence, upgrading, and dis-adoption in wheat production strategies.

Table 4.2.5: Transition Matrix of Adoption Regimes (2021–2025)

(t-1) \ (t)	**R0 (No Adop)**	**R1 (Input Only)**	**R2 (NRM Only)**	**R3 (SAI)**	**Total**
R_0: No Adoption	69 (21.10%)	0 (0.00%)	245 (74.92%)	13 (3.98%)	327 (100%)
R_1: Input Only	0 (0.00%)	0 (0.00%)	5 (31.25%)	11 (68.75%)	16 (100%)
R_2: NRM Only	259 (9.72%)	13 (0.49%)	2,201 (82.62%)	191 (7.17%)	2,664 (100%)
R_3: SAI (Synergy)	25 (3.01%)	44 (5.29%)	236 (28.40%)	526 (63.30%)	831 (100%)
Total	353 (9.20%)	57 (1.49%)	2,687 (70.01%)	741 (19.31%)	3,838 (100%)

Source: Own computation using RCC Panel Waves (2021, 2023, and 2025).

Persistence (Diagonal Elements): Diagonal elements reveal high persistence for the NRM Only and SAI synergies at 82.62% and 63.30%, respectively. Thus, these two adoption regimes are persistent over time. Persistence is lowest in the No Adoption state at 21.10%, suggesting that, in the long run, most farmers adopt at least one improved technology. Finally, the Input Only regime shows no persistence at all, which is a transitory stage farmers go through toward more integrated systems.

Upgrading or Intensification (Above the Diagonal): The most frequent upward transition is from No Adoption to NRM Only (74.92%), suggesting that the main technologies adopted by the farmers are low-cost soil and water conservation technologies. The most common subsequent upgrading by Input Only farmers (68.75%) is to full SAI, suggesting that integrating inputs with NRM technologies is perceived as more rewarding. Very few households go directly from No Adoption to full SAI (3.98%), which can only be rationalized as a consequence of strong external interventions.

Downgrading or Dis-adoption (Below the Diagonal): Upward transitions may sometimes be reversed due to several constraints. For example, 9.72% of those who at some point in time adopted NRM Only went back to No Adoption, perhaps due to the labor constraints or any other constraint. The most common form of dis-adoption is from SAI to NRM Only (28.40%), indicating that farmers dis-adopt inputs, especially fertilizers, but continue with conservation measures. Very few households (3.01%) dis-adopt inputs and conservation measures simultaneously and go directly from SAI to No Adoption.

In summary, upward transitions tend to persist over time once a household reaches a higher level of practices. Dis-adoption is quite common, mainly when there are shocks or the continuation of relatively costly inputs, especially modern inputs.

A Note on the Transition Matrix:

Table 4.2.5 reports the movement of households across adoption regimes between consecutive survey waves, rather than the cross-sectional distribution of regimes in a single wave. For this reason, the transition counts cannot be directly compared with the summary proportions reported in Table 4.2.2. The matrix shows that adoption behavior is dynamic: households move not only from no adoption to higher adoption regimes, but also between partial and synergistic adoption states over time. For example, among households in the no-adoption regime at t−1, 74.92 percent moved to the NRM-only regime and 3.98 percent

moved to the SAI regime, while only 21.10 percent remained in no adoption. Similarly, among households in the SAI regime at t−1, 63.30 percent remained in SAI, 28.40 percent moved to NRM only, 5.29 percent moved to input only, and 3.01 percent reverted to no adoption. These patterns indicate that adoption regimes are not static end states but evolving behavioral choices shaped by changing household conditions, climate exposure, and institutional support.

4.3 Econometric Results and Discussion

4.3.1 Evidence of Endogeneity and Justification of Methodology

What matters here is that the correlation coefficient ρ between the error term in each adoption equation and the error term in the yield equation is significantly different from zero. Three of the seven ρ coefficients linking an adoption decision to the yield equation are statistically significant. Intercropping shows the strongest link (ρ_{68} = 0.397, SE = 0.117, p = 0.003, significant at 1%), followed by improved wheat seed (ρ_{18} = 0.228, SE = 0.104, p = 0.034, significant at 5%), with row planting marginally significant (ρ_{78} = 0.215, SE = 0.107, p = 0.052, borderline at 10%). The remaining four practices chemical fertilizer (ρ_{28} = −0.055, p = 0.716), organic manure (ρ_{38} = 0.125, p = 0.283), minimum tillage (ρ 48 = 0.151, p = 0.186), and SWC (ρ_{58}= 0.030, p = 0.783) show correlations with the yield equation that are not statistically distinguishable from zero.

It is informative that endogeneity is not a general problem across all seven technologies but is confined to improved seed, intercropping, and row planting. For these, the unobserved household attributes such as farming skills, soil quality, and risk orientation that induce higher probabilities of adoption are also correlated with unobserved determinants of yield, leading to biased coefficients in a single-equation OLS regression of yield on the practice. The CMP framework addresses this by estimating adoption and yield equations jointly to isolate the correlated unobservables from the coefficient of interest. For the other four technologies with insignificant ρs, the single-equation estimator would not be subject to the bias of this nature. However, joint system estimation is still preferable to ensure that the whole model is consistent and efficient.

While estimation flagged several regressor matrices as ill-conditioned, the model converged after four Newton-Raphson iterations followed by a switch to DFP, reaching a stable log pseudolikelihood of −3,680.15.

Table 4.3.1: Evidence Diagnostics for Methodological and Model Choices

Diagnostic Component	Detail	Value	Significance
Model Fit	Total Observations (N)	1,058	—
	Time Period	3 Waves (2021, 2023, and 2025)	—
	Standard Errors	Robust (Clustered at HH Level, 597 clusters)	—
	Log Pseudolikelihood	−3,680.15	—
	Wald $\chi^2(89)$	775.29	p < 0.0001
Endogeneity Evidence	ρ_{68} (Intercropping ↔ Yield equation)	0.397 (SE = 0.117)	*** (1%)
	ρ_{18} (Improved Seed ↔ Yield equation)	0.228 (SE = 0.104)	** (5%)
	ρ_{78} (Row Planting ↔ Yield equation)	0.215 (SE = 0.107)	* (10%, borderline)
	ρ_{28}, ρ_{38}, ρ_{48}, ρ_{58} (Fertilizer, Manure, Min. Tillage, SWC ↔ Yield)	−0.055 to 0.151	not significant

*Source: Own computation using RCC Panel Waves (2021, 2023, and 2025). Significant ρ values confirm selective adoption endogeneity for improved seed, intercropping, and row planting, justifying CMP over single-equation OLS. *** p<0.01, ** p<0.05, * p<0.10.*

Therefore, ill-conditioning warnings do not indicate model failure but rather the complex process of estimating eight correlated equations simultaneously over a covariate set with several log-transformed variables and region/year fixed effects. The final estimation uses 1,058 observations, with standard errors clustered at the household level (597 clusters) across the three survey waves (2021–2025). The overall significance of the model is

established with a strong Wald test ($\chi^2(89) = 775.29$, $p < 0.001$). A single-equation VIF check for the same covariate set finds no material multicollinearity problem, with a mean VIF of 1.24 and a maximum of 1.82 both well below any conventional thresholds of concern (usually, VIF > 10), confirming Including a set of closely related practices in the model does not bias coefficient estimates. In sum, selective significance of ρ_{xy}, overall significant Wald test results, and low VIF values all justify the CMP framework as the correct approach to obtaining reliable impact estimates of SAI on wheat productivity under climate stress.

Note that for the main model (CMP), all 1,058 observations were used. The model is specified so that an entire record for a farmer does not need to be dropped just because data for the previous year is missing. However, the calculation of real-world impacts average marginal effects requires the sample to be reduced to 607 observations because such calculations rely on strictly before-and-after comparison data, which does not exist for the starting year of 2021. In contrast, our simpler baseline model (random effects) does not use any information on past behavior. Because it does not require any data from the previous year, the 2021 batch was retained, and the number of observations used was 717.

4.3.2 Inter-temporal Adoption Patterns and Drivers of SAI Practices.

This section presents the results of the inter-temporal multivariate probit model estimated within the Conditional Mixed Process framework. The model jointly estimates the determinants of the seven SAI practices while allowing for state dependence through lagged adoption and for correlation across practices. Table 4.3.2 reports the coefficient estimates.

Persistence in Adoption

It indicates that most of the SAI practices show persistence, indicating that past adoption behavior might be a significant indicator of current adoption behavior of SAI practices. The strongest persistence is recorded for chemical fertilizer ($\beta = 1.064$, $p < 0.01$), followed by improved seed ($\beta = 0.703$, $p < 0.01$) and intercropping ($\beta = 0.483$, $p < 0.01$). Organic manure ($\beta = 0.281$, $p < 0.01$) and minimum tillage ($\beta = 0.172$, $p = 0.049$) show moderate but significant persistence, while row planting is only marginally persistent ($\beta = 0.223$, $p = 0.051$, borderline at 10%). Meanwhile, SWC is insignificant ($\beta = 0.070$, $p = 0.544$). Hence, adoption behavior in SWC seems to be more influenced by exogenous variables

than by farmers' previous experiences. Physical structures like stone bunds or terraces are also semi-permanent; once built, "adopting" them in the next wave is a matter of maintenance rather than a brand-new, active behavioral decision.

Table 4.3.2: Inter-temporal Multivariate Probit (IMVP) Results for SAI Adoption Dynamics

Variables	Improved Seed	Chemical Fert.	Organic Manure	Min. Tillage	SWC	Intercropping	Row Planting
Lagged Adoption	0.703*** (0.120)	1.064*** (0.337)	0.281*** (0.101)	0.172** (0.088)	0.070 (0.115)	0.483*** (0.103)	0.223* (0.114)
Head age	-0.003 (0.004)	-0.002 (0.006)	0.007** (0.003)	-0.001 (0.004)	0.004 (0.004)	-0.001 (0.004)	-0.003 (0.004)
Gender	0.042 (0.165)	-0.018 (0.190)	0.587*** (0.126)	0.116 (0.120)	0.159 (0.133)	0.329** (0.143)	0.413*** (0.141)
ln_total_land_size	0.289*** (0.108)	0.079 (0.164)	-0.212*** (0.080)	-0.022 (0.083)	0.159* (0.089)	-0.169* (0.089)	0.086 (0.102)
Log Livestock (ln_TLU)	0.305** (0.136)	0.571*** (0.206)	0.287*** (0.099)	0.388*** (0.100)	0.160 (0.107)	0.120 (0.107)	0.308** (0.126)
Extension Plot	0.831*** (0.147)	0.621*** (0.199)	-0.026 (0.113)	0.231** (0.110)	0.897*** (0.122)	0.097 (0.126)	0.478*** (0.130)
Dist. to Parcel	-0.163*** (0.062)	0.036 (0.081)	-0.219*** (0.046)	-0.114** (0.045)	-0.105** (0.053)	-0.259*** (0.051)	-0.220*** (0.056)
Credit Access	-0.425** (0.166)	-0.018 (0.251)	0.370*** (0.128)	0.259** (0.131)	0.042 (0.140)	-0.085 (0.142)	-0.104 (0.155)
Climate Shocks	-0.093 (0.083)	-0.572*** (0.221)	0.106* (0.057)	-0.015 (0.054)	-0.154** (0.064)	-0.015 (0.061)	0.056 (0.073)

Year (2023)	0.307** (0.127)	-0.775*** (0.244)	0.187* (0.100)	0.054 (0.096)	0.462*** (0.106)	0.216* (0.111)	0.208* (0.117)
Constant	-0.617 (0.393)	1.227 (0.867)	-1.076*** (0.281)	-0.800*** (0.291)	-0.430 (0.314)	-0.849*** (0.291)	-0.722** (0.367)

*Source: Own computation based on RCC Panel Waves (2021, 2023, and 2025). Land size, TLU, and Distance to Parcel are log-transformed. *, **, *** denote significance at p<0.1, p<0.05, p<0.01 levels, respectively.*

Role of Extension Services

Extension services have a considerable effect on adoption of improved seeds ($\beta = 0.831$, $p < 0.01$), chemical fertilizer ($\beta = 0.621$, $p < 0.01$), minimum tillage ($\beta = 0.231$, $p < 0.05$), SWC ($\beta = 0.897$, $p < 0.01$), and row planting ($\beta = 0.478$, $p < 0.01$). This implies that extension services promote knowledge-intensive technologies, such as improved seeds, chemical fertilizer, minimum tillage, SWC, and row planting, which need training and technical support. But it has no significant effect on organic manure and intercropping. Thus, it can be concluded that extension systems perform better in disseminating modern inputs than traditional farming practices.

Credit Access

Credit access favors the adoption of organic manure ($\beta = 0.370$, $p < 0.01$) and minimum tillage ($\beta = 0.259$, $p < 0.05$), but hinders that of improved seed ($\beta = -0.425$, $p < 0.05$). Access to credit facilitates the adoption of labor-related and equipment-based SAI, such as organic manure and minimum tillage; however, it reduces the adoption of improved seed because of its competition with other variables during lean financial periods. On the other hand, credit access has no significant effect on the adoption of fertilizer, SWC, intercropping, and row planting because these variables do not depend on credit access but rather on extension services.

Household/Farm Characteristics

Land holding has a positive relationship with adopting improved seeds ($\beta = 0.289$, $p < 0.01$) while it negatively impacts organic manure ($\beta = -0.212$, $p < 0.01$) and, marginally,

intercropping (β = -0.169, p = 0.057, borderline at 10%). Livestock ownership (TLU) increases the probability of adopting improved seed (β = 0.305, p < 0.05), chemical fertilizer (β = 0.571, p < 0.01), organic manure (β = 0.287, p < 0.01), minimum tillage (β = 0.388, p < 0.01), and row planting (β = 0.308, p < 0.05). Larger landholdings favor adopting improved seeds, a purchased input that can be scaled with commercial production. On the other hand, large farm sizes have difficulty with labor-intensive activities such as applying organic manure and intercropping. TLU broadly increases the viability of SAI adoption because livestock provides draft power and manure, reducing the cost of investment and increasing returns.

Gender and Access Factors

Male-headed households are more likely to use organic manure (β = 0.587, p < 0.01), row planting (β = 0.413, p < 0.01), and intercropping (β = 0.329, p < 0.05). Being farther from plots hampers the adoption of almost all technologies, with distance coefficients ranging from -0.105 to -0.259 across equations (improved seed, organic manure, minimum tillage, SWC, intercropping, and row planting all significant). These findings suggest that the use of practices requiring more effort and knowledge is characteristic of male-headed households, given their comparatively better access to extension services, mobility, and decision-making control over farms. Female-headed households, by contrast, face considerable time and resource constraints. The consistently negative effect of distance from the plot reflects the higher transport and supervision costs associated with managing dispersed technologies.

Climate Shocks

Cumulative climate shocks significantly reduce the probability of adopting chemical fertilizer (β = -0.572, p < 0.01) and SWC practices (β = -0.154, p < 0.05). The effect on improved seed adoption is negative but no longer statistically significant (β = -0.093, p = 0.267). By contrast, cumulative shocks significantly increase the probability of adopting organic manure (β = 0.106, p = 0.060, borderline at 10%). Since organic manure can be produced on-farm at relatively low cost, it represents a safer, more resilient choice for households facing repeated climate stress, whereas purchased inputs like fertilizer and labor/capital-intensive practices like SWC become harder to sustain.

This finding directly addresses Specific Objective 2: repeated climate shocks significantly weaken the persistence of chemical fertilizer and SWC adoption, while pushing households toward low-cost fallback practices such as organic manure. The cumulative shock measure captures the compounding erosion of adoption persistence that single-period shock indicators cannot reveal.

Temporal Effects (Year 2023)

Relative to 2025 (the omitted reference year), adoption in 2023 was significantly higher for improved seed ($\beta = 0.307$, $p < 0.05$), organic manure ($\beta = 0.187$, $p < 0.10$), SWC ($\beta = 0.462$, $p < 0.01$), intercropping ($\beta = 0.216$, $p < 0.10$), and row planting ($\beta = 0.208$, $p < 0.10$), while chemical fertilizer adoption was significantly lower in 2023 relative to 2025 ($\beta = -0.775$, $p < 0.01$). Minimum tillage showed no significant year effect ($\beta = 0.054$, $p = 0.574$). The broad-based increase in most practices by 2023 is consistent with a general upward trend in SAI uptake over the panel period, while the decline in fertilizer adoption likely reflects rising input costs or supply disruptions specific to that wave, a pattern also consistent with the negative and significant effect of cumulative climate shocks on fertilizer adoption discussed above.

4.3.3 Average Marginal Effects Analysis

Table 4.3.3 presents the AMEs from the CMP model, providing policy-relevant effects for the 607 observations used to estimate each adoption equation. It presents the predicted probability of adopting SAI technologies in percentage points. Among all technologies, past adoption is the most important predictor of current adoption status. Better seeds have the highest coefficient on past adoption, at 21.0 percentage points, organic manure and intercropping follow at 10.2 and 13.5 percentage points respectively, and row planting adds 8.1 percentage points indicating highly reinforcing relationships in each respective technology. In other words, if farmers have already adopted the respective technology and have gained some experience in using it, then the chances of its future adoption are extremely high. Soil and water conservation is the one exception: its own-lag effect (2.1 pp) is not statistically distinguishable from zero, suggesting SWC adoption is driven less by habit persistence than by contemporaneous conditions such as extension access.

Extension demonstration plots strongly support this initial step, with learning in the field resulting in a 26.4 pp increase in SWC adoption and a 24.8 pp increase in improved seed

adoption. These findings further support the argument that, for most farmers, the main binding constraint to adoption is not input prices but the lack of information and the opportunity to learn about the returns to adoption. In addition to issues of institutions, farm structure is crucial in determining the nature of technology adopted. Larger landholdings favor inputs with high economies of scale, such as improved seed (+8.6 pp) and SWC (+4.7 pp), while pulling away from labor-intensive inputs such as organic manure (-7.7 pp) and intercropping (-4.7 pp). Livestock-intensive farm structures tend strongly toward minimum tillage (+14.7 pp), since draft power and manure both flow from livestock ownership; the corresponding relationship with SWC is positive but not statistically significant at conventional levels in this specification. Credit access works through complex channels; rather than uniformly pushing toward intensification, it instead pushes toward cheaper options like organic manure (+13.5 pp) and minimum tillage (+9.8 pp), and away from improved seed (-12.7 pp). Liquidity alone, therefore, does not override risk aversion in the face of high production uncertainty. This uncertainty is compounded by climate shocks, which significantly reduce purchased-input adoption chemical fertilizer (-4.4 pp) and, notably, SWC (-4.5 pp) while significantly raising the odds of falling back on organic manure (+3.9 pp), the lowest-cost, on-farm option. This dynamic traps the most vulnerable households in low productivity when, in fact, technology investments are most needed.

Table 4.3.3: Average Marginal Effects of the Intertemporal Multivariate Probit (CMP) Model

Explanatory Variable	Imp. Seed	Chem. Fert	Org. Manure	Min. Till	SWC	Intercrop	Row Plant
Lagged Practice	0.210***	0.082***	0.102***	0.065**	0.021	0.135***	0.081**
Extension Plot	0.248***	0.048***	-0.010	0.088**	0.264***	0.027	0.175***
ln_Total Land Size	0.086***	0.006	-0.077***	-0.009	0.047*	-0.047*	0.032
Livestock (ln_TLU)	0.091***	0.044***	0.105***	0.147***	0.047	0.033	0.113**
Credit Access	-0.127**	-0.001	0.135***	0.098**	0.012	-0.024	-0.038

Cumulative Shocks	-0.028	-0.044**	0.039*	-0.006	-0.045**	-0.004	0.021
Ln_dist. To Plot	-0.049***	0.003	-0.080***	-0.043**	-0.031**	-0.072***	-0.081***
Head gender (M=1)	0.013	-0.001	0.214***	0.044	0.047	0.092**	0.151***

Source: Own computation using RCC Panel Waves (2021, 2023, and 2025).

*Notes: AMEs represent the marginal change in adoption probability. Significance: p<0.01***, p<0.05**, p<0.1*. Sample size: 607 observations per equation.*

On top of this, female-headed households lag in adopting labor-coordinating practices organic manure, intercropping, and row planting all show significant male-headed-household premiums (+21.4, +9.2, and +15.1 pp respectively) suggesting mobility, time burden, and extension access issues that asset transfers cannot address. In other words, these results suggest that no single policy lever is effective. The package of policies required to induce sustainable adoption of SAI would have to be based on a holistic approach to field-based extension, flexible, outcome-contingent credit, weather insurance and safety nets, investment in rural infrastructure, and gender-responsive programming.

The reinforcing relationships identified above are not limited to a practice's own history — the CMP framework's error correlations also show that adoption decisions are interlinked across practices. Improved seed correlates most strongly with row planting (ρ=0.478) and intercropping (ρ=0.357), and intercropping and row planting are themselves strongly linked (ρ=0.428), consistent with these three functioning as parts of a coordinated crop-management package rather than independent choices. Chemical fertilizer stands somewhat apart, showing weak or even negative correlations with the NRM practices (e.g., ρ=-0.136 with intercropping), suggesting fertilizer use follows a largely separate adoption logic from the labor-coordination-dependent practices. The full correlation matrix is reported in Table 4.3.4.

4.3.4 Pairwise Error Correlations in SAI Adoption Decisions

These error terms show the connections among the practices that have been used, as Table 4.3.4 illustrates. They refer to complementarity/substitutability of technology use, when

the influences of the observable variables are controlled. Therefore, farmers do not adopt these technologies independently, which is evidenced from the findings.

Table 4.3.4: Pairwise Error Correlations (ρ) among 7 SAI Practices

Practice	Imp_Seed	Chem_Fert	Org_Manure	Min_Till	SWC	Intercrop	Row_ Plan
Imp_Seed	1.000						
Chem_Fert	0.209	1.000					
Org_Manure	0.224	0.062	1.000				
Min_Tillage	0.339	-0.008	0.263	1.000			
SWC	0.133	0.041	0.135	0.144	1.000		
Intercrop	0.357	-0.136	0.089	0.254	0.079	1.000	
Row_Planti	0.478	0.086	0.167	0.303	0.154	0.428	1.000

Source: Own computation using RCC Panel Waves (2021, 2023, and 2025).

Twelve of the twenty-one pairwise correlations are statistically significant at conventional levels. The strongest and most significant correlations are improved seed with row planting ($\rho=0.478$, $p<0.01$), intercropping with row planting ($\rho=0.428$, $p<0.01$), and improved seed with intercropping ($\rho=0.357$, $p<0.01$). Improved seed also correlates significantly with minimum tillage ($\rho=0.339$, $p<0.01$) and organic manure ($\rho=0.224$, $p<0.01$), making it the practice most broadly and significantly connected to the rest of the system. Beyond improved seed, minimum tillage shows significant links with row planting ($\rho=0.303$, $p<0.01$), organic manure ($\rho=0.263$, $p<0.01$), and intercropping ($\rho=0.254$, $p<0.01$), reinforcing the picture of an integrated soil–crop management cluster anchored by minimum tillage alongside improved seed. Organic manure is also significantly linked to row planting ($\rho=0.167$, $p<0.05$) and SWC ($\rho=0.135$, $p<0.05$), while minimum tillage and SWC are also significantly linked ($\rho=0.144$, $p<0.05$), and SWC to row planting ($\rho=0.154$, $p<0.05$).

The correlation between improved seed and chemical fertilizer conceptually the dominant pairing in the conventional-input package, since improved seed is agronomically most productive when combined with fertilizer is positive at $\rho=0.209$, ranking ninth by magnitude among the 21 pairwise correlations. However, it does not reach statistical significance in this specification ($p=0.129$), so while the sign is consistent with the expected input-package effect, it should be read as suggestive rather than confirmed

complementarity, and should not be given the same evidentiary weight as the significant pairs above.

Chemical fertilizer is otherwise the practice most disconnected from the rest of the system: none of its remaining five pairwise correlations (with organic manure, minimum tillage, SWC, intercropping, or row planting) are statistically significant, and its correlation with intercropping is mildly negative (ρ=-0.136, not significant). This suggests fertilizer use follows a distinct adoption logic likely driven more by input-market access and affordability than by the labor-coordination and land-management factors that link the other six practices to one another.

This result strongly suggests that the decision to adopt one SAI technology cannot be viewed in isolation, but is embedded in a system of interrelated adoption decisions. Farmers adopt technologies in bundles, constrained by complementarities, resource endowments, and the general orientation of the farming system with improved seed as the practice most tightly and significantly woven into that broader bundle.

4.3.5 Links to Productivity: The Yield Equation

In addition to the seven adoption equations, a yield equation was estimated within the CMP framework. The coefficients may be interpreted as the approximate percentage change in yield associated with each SAI practice, correcting for self-selection and unobserved heterogeneity at the household level through the correlation in error terms across the system.

Chemical fertilizer shows a positive coefficient corresponding to a 40.07% higher yield, but this effect is only marginally significant at the 10% level (p=0.055), indicating weak statistical evidence of an effect. Minimum tillage shows a negative coefficient (-28.61%) that is statistically significant at the 5% level (p=0.034), and intercropping shows a negative coefficient (-25.84%) that is marginally significant at the 10% level (p=0.094). These negative signs should be interpreted as short-run transition costs or adjustment effects rather than evidence that these practices reduce productivity in the long term.

Improved wheat seed, organic manure, SWC, and row planting show effects that are not statistically distinguishable from zero when considered separately. Notably, improved wheat seed shows a small negative point estimate (-2.57%) that is far from significant (p=0.841, 95% CI: -24.4% to +25.4%); this should not be read as evidence that improved

seed harms yield, but as evidence that its direct, partial effect, net of selection into adoption is indistinguishable from zero, a pattern discussed further below. A joint Wald test across all seven SAI practice coefficients confirms that these individual effects are not jointly different from zero ($\chi^2(7) = 11.73$, p = 0.110), reinforcing that individual practice adoption alone is not a reliable predictor of yield gains in this sample.

Table 4.3.5: CMP Estimates of the Wheat Yield (ln_y) Equation

Covariate	Coef.	% Effect on Yield	Std. Err.	Z	P>|z|	Sig.
Improved Wheat Seed	-0.026	−2.57%	0.129	-0.20	0.841	—
Chemical Fertilizer	0.337	+40.07%	0.176	1.92	0.055	*
Organic Manure	-0.039	−3.82%	0.175	-0.23	0.821	—
Minimum Tillage	-0.337	−28.61%	0.159	-2.12	0.034	**
SWC	0.204	+22.63%	0.165	1.23	0.217	—
Intercropping	-0.299	−25.84%	0.178	-1.68	0.094	*
Row Planting	0.108	+11.40%	0.143	0.75	0.451	—
Head Age	0.003	+0.30%	0.003	1.11	0.267	—
Head Gender	-0.022	−2.18%	0.140	-0.16	0.876	—
Log (Total Land Size)	-0.506	−39.70%	0.077	-6.59	0.000	***
Log (Livestock, TLU)	0.332	+39.38%	0.091	3.66	0.000	***
Extension Plot	0.250	+28.40%	0.117	2.13	0.033	**
Log (Mean Distance to Parcel)	-0.085	−8.15%	0.056	-1.51	0.131	—
Credit Access	0.044	+4.50%	0.111	0.39	0.696	—
Region: Oromia	0.179	+19.61%	0.105	1.70	0.088	*
Region: Somali	-0.410	−33.64%	0.509	-0.81	0.420	—
Region: SNNPRG	-0.473	−37.69%	0.142	-3.33	0.001	***
Year: 2021	-0.207	−18.70%	0.124	-1.67	0.095	*
Year: 2023	-0.040	−3.92%	0.101	-0.40	0.691	—
Constant	6.262	—	0.287	21.81	0.000	***

*Significance: *** p<0.01, ** p<0.05, * p<0.10. N=1,058 (597 clusters on HH_ID); standard errors are cluster-robust. % effect = ($e^{\beta} - 1$) × 100. Reference categories: region = Amhara; year = 2025. Cumulative climate shocks are excluded from the yield equation as an identifying exclusion restriction (Section 3.4.5).*

The above supports the bundle argument in Chapter Two: if the individual SAI practices had effects, they would show them unconditionally and robustly regardless of what other practices are adopted. What gives strength to the story, in contrast, is the evidence on pairwise complementarities in Table 4.3.4 in particular, strong correlations between improved seed and row planting (ρ = 0.478, p<0.01) and between intercropping and row

planting (ρ = 0.428, p<0.01) indicating that these practices are components of a joint management system, not separate technologies. The positive correlation between improved seed adoption and the yield equation's error term (ρ = 0.228, p=0.034) is equally informative: it shows that households have some unobserved traits that improve yields (skills, soils) that are also more likely to lead to adopting improved seed. Once this selection is accounted for in the joint CMP system, no signal remains to explain the direct partial effect of improved seed on yields. That is why its coefficient in Table 4.3.5 is small, negative, and statistically null instead of positive, as a naive single-equation regression would indicate.

Aside from SAI practices, the two other strongest covariates in this model are land size and livestock holdings. A 1% increase in land size is associated with a 39.71% decrease in yield per hectare (p<0.01), consistent with diminishing returns to scale and lower per-hectare management intensity on larger holdings. Larger land holdings are strongly and precisely associated with lower yield per hectare, reflecting diminishing returns to scale and lower per-hectare management intensity on larger holdings. Access to an extension plot increases yield, supporting the idea that demonstration-based learning reduces uncertainty about the correct way to implement the practices.

Region effects. Region effects are estimated relative to Amhara, the reference category. Households in Oromia show higher yields than Amhara (+19.61%), marginally significant (p=0.088). Households in Somali show lower yields (-33.64%), not significant (p=0.420) and estimated imprecisely given the very small Somali subsample (13 of 1,058 observations). Finally, yields in SNNPRG are significantly lower than in Amhara by 37.69% (p<0.01). This makes sense, given SNNPRG's more diverse and lower-altitude agroecology and generally poorer access to wheat-specific extension services and input markets compared to Amhara. The sample from these three regions constitutes the bulk of the sample's wheat cultivation. Other regions, such as Gambela and Dire Dawa, are excluded because sampled households in those regions do not grow wheat to any meaningful extent.

Year effects. Year effects are estimated relative to 2025, the reference year. Relative to that year, yields in 2021 were 18.68% lower, marginally significant at the 10% level (p=0.095). This finding statistically corroborates the study's claim that the early years of

the study period, when drought conditions intensified, were associated with lower wheat productivity. Yields in 2023 were 3.93% lower than in 2025, not statistically significant (p=0.691).

4.3.6 Impact of SAI Practices on Wheat Productivity: ATT Analysis

The ATT results (Table 4.3.6) show clear differences between modern inputs and conservation practices in their short-term impact on wheat yields with practices splitting into those showing a positive association, and those showing short-term adjustment costs.

Table 4.3.6: ATT effect for SAI Practices

SAI Technology	ATT (dy/dx)	% Impact on Yield	Treated Obs. (N)	P-Value
Imp Wheat Seed	-0.026	-2.5%	402	0.841
Chemical Fertilizer	0.337*	+40.0%	578	0.055
Organic Manure	-0.039	-3.9%	323	0.821
Minimum Tillage	-0.337**	-28.6%	263	0.034
SWC	0.204	+22.6%	440	0.217
Intercropping	-0.299*	-25.9%	132	0.094
Row Planting	0.108	+11.4%	342	0.451

*Source: Own computation using RCC Panel Waves (2021, 2023, and 2025). ** p<0.05, * p<0.10.*

Chemical fertilizer shows the clearest yield-enhancing association (+40.0%, p=0.055, marginally significant). SWC and row planting are positive but insignificant. Improved seed and organic manure show small, statistically null negative estimates (p=0.841 and p=0.821) not evidence of harm, just noise. Improved seed's null result is further explained by its significant positive correlation with the yield equation's error term (ρ_{18}=0.228, p=0.034, Section 4.3): unobserved traits that raise adoption also raise yield, so once CMP purges that selection, no independent effect remains.

Minimum tillage (-28.6%, p=0.034) and intercropping (-25.9%, p=0.094) are significantly or marginally negative. The joint Wald test across all seven practices is $\chi^2(7)$ =11.73, p=0.110 confirming none are jointly different from zero.

These negative NRM coefficients likely reflect short-run transition costs rather than genuine productivity losses: farmers face learning costs and crop competition (in

intercropping) before soil-structure benefits materialize. This is reinforced by a measurement issue discussed in Section 3.4.3 since binary adoption indicators miss carryover soil-capital effects from prior NRM use, coefficients are biased toward zero or negative even when the true effect is positive. So negative ATTs here should be read as a lower bound, not evidence of ineffectiveness, and point to the same policy need: credit, extension, and safety-net support to help farmers through the transition period.

Synthesis of Findings: Bridging Descriptive and Econometric Evidence

The dual descriptive-econometric approach lets econometric analysis address causality and endogeneity issues that description alone cannot. While the descriptive analysis tracks patterns and transitions in adoption, the econometric approach seeks to explain these transitions and quantify their impacts.

The four central conclusions emerging from both strands of analysis are that SAI practices are strongly complementary and embedded within a bundle of practices; adoption is very sensitive to climate shocks; persistence and dis-adoption are more than idiosyncratic behaviors; and resource endowments and institutions are very important in shaping productivity outcomes. The high degree of consistency between the two strands of analysis further reinforces confidence in the results and their policy implications, as discussed in Chapter 5.

Descriptively, farmers using the full synergy bundle (R3) achieve the highest average yield, 1,710.76 kg/ha a 33–50% advantage over Input-Only and NRM-Only adopters, respectively. Econometrically, no single practice moves yield reliably on its own (joint Wald $\chi^2(7)=11.73$, $p=0.110$), and individual coefficients are mostly insignificant. This is not a contradiction: indeed, the significant error correlations between improved seed and row planting ($\rho=0.478$, $p<0.001$), improved seed and intercropping ($\rho=0.357$, $p<0.001$), and intercropping and row planting ($\rho=0.428$, $p<0.001$) confirm that these practices are adopted as an interlocking system rather than separately. However, caution is warranted in this respect: R3 exhibits the highest yield variability (SD=1,637.96) and an ANOVA result that is only marginally significant ($F=2.18$, $p=0.090$), confirming that environmental volatility is a major constraint, even in the highest-performing regime.

A shock-intensification trap compounds this vulnerability: participation in advanced "R3" farming remains near 94% during calm periods but drops to roughly 69% after three or

more shocks, while basic "Input-Only" farming surges from 3% to over 26% ($\chi^2(9) = 140.54, p < 0.001$). Rather than abandoning agriculture, farmers simplify their operations, shifting toward low-cost organic manure under stress (+3.9 percentage points). Transition data reveals that about 5% of advanced R3 farmers slide into the basic Input-Only tier—a short-lived regime that acts as a step down the productivity ladder rather than a stable alternative. Thus, shocks destroy integrated systems designed to protect farmers against them, erode the assets needed to rebuild those systems, and trap farmers in lower productivity equilibria without institutions such as insurance or asset restoration programs. The evidence presented here, therefore, points to three structural gaps: first, the most productive adoption regime, R_3, is also the most vulnerable to shocks; second, most practices exhibit strong state dependence except for SWC, which is more driven by program contact than experience; and, third, two divergent institutional trends work against one another: extension contacts rose sharply from 58.4% to 76.0% of households (χ^2=34.34, p<0.001), but credit access almost halved from 22.7 to 11.8% (χ^2=11.11, p<0.001). In other words, farmers are well aware of available technologies but financially constrained in pursuing them.

4.4 Robustness Checks and Model Validation

4.4.1 Why CMP Is Necessary

Two joint Wald tests confirm that the Conditional Mixed Process (CMP) framework is required rather than optional. First, adoption decisions are interdependent: the correlations across three key practice pairs (improved seed–chemical fertilizer, minimum tillage–SWC, and intercropping–row planting) are jointly non-zero (Wald $\chi^2(3) = 55.18$, $p < 0.001$). Second, adoption is endogenous to yield: the seven adoption-equation errors are jointly correlated with the yield-equation error (Wald $\chi^2(7) = 14.41$, $p = 0.044$). Ignoring either form of dependence would bias single-equation estimates.

Table 4.5.1: Joint Wald Tests for Interdependence and Endogeneity

Test	Null hypothesis	χ^2	D_f	p-value
Practice interdependence	$\rho_{12} = \rho_{34} = \rho_{67} = 0$	55.18	3	0.000
Adoption–yield endogeneity	$\rho_{18} = \rho_{28} = \ldots = \rho_{78} = 0$	14.41	7	0.044
Joint significance of SAI practices in yield equation	All seven practice coefficients = 0	11.73	7	0.110

Source: *Own computation using RCC Panel Waves (2021, 202 and 2025).*

Individual Practices Are Insignificant Alone: Only the Bundle Matters A joint Wald test of the seven individual SAI practice coefficients in the yield equation indicates that none of them, when considered separately, has a significant effect on yield (Wald $\chi^2(7) = 11.73$, p = 0.110).

This null result is not a weakness; it is a central finding of the study. It shows that individual-practice adoption alone has no robust productivity payoff. Only the integrated R3 bundle delivers a significant yield gain (Section 4.3.5). This result reinforces the complementarity evidence obtained from the pairwise error correlations (Table 4.3.4).

4.4.2 RE versus CMP: The Cost of Ignoring Endogeneity

If one runs a naïve random-effects model with adoption as an exogenous regressor, the integrated SAI regime (R_3) is not statistically significant (β = 0.458; SE = 0.536; p = 0.393), although predicted margins are quite large roughly 1,047 kg/ha for R_3 compared to 662 kg/ha for non-adopters.

Once endogenous selection is corrected within the CMP framework, the R_3 coefficient becomes significant and substantially more precise (β = 0.453, SE = 0.158, p = 0.004). This corresponds to an approximate 57 percent yield premium ($e^{0.453} - 1$). The standard error falls to roughly one-third of the RE estimate, confirming the efficiency gain from joint estimation.

When cumulative climate shocks were included in the yield equation alongside the R_3 adoption indicator, the coefficient remained small and statistically insignificant (β = -0.027, SE = 0.058, p = 0.646) in an earlier estimation run; this specific check is not present in the most recent estimation log used to verify this chapter's figures and should be re-run and re-confirmed before final submission, rather than cited from memory. The finding that individual practice coefficients in the eight-equation CMP system's yield equation are jointly indistinguishable from zero (Section 4.5.2) is independently confirmed in the current log and does not depend on this specific check. Together, these results are consistent with excluding cumulative climate shocks from the yield equation while retaining them in the adoption equations to capture their effect on adoption persistence and dis-adoption, though the exact magnitude of the shocks-included robustness check above should be reproduced and re-verified rather than treated as confirmed.

Table 4.5.2: Random-Effects (RE) Baseline Wheat Yield Model

Variable	Coefficient	Std. Err.	Z	p> | z |
Input Only (R_1)	−0.061	0.560	−0.11	0.913
NRM Only (R_2)	0.088	0.571	0.15	0.877
SAI Synergy (R_3)	0.458	0.536	0.85	0.393
Head age	0.004	0.003	1.07	0.286
Head gender (male = 1)	−0.136	0.125	−1.09	0.276
ln(Total land size)	−0.496***	0.074	−6.70	0.000
ln(TLU)	0.377***	0.087	4.34	0.000
ln(Distance to parcel)	0.058	0.044	1.30	0.194
Extension plot	0.184*	0.094	1.95	0.051
Credit access	−0.026	0.110	−0.23	0.817
Year 2023	0.157	0.095	1.65	0.100
Year 2025	0.191*	0.102	1.88	0.060
Constant	5.676***	0.584	9.72	0.000
Number of observations	717			
Number of groups	491			
Wald $\chi^2(12)$	77.50***			

Note: *Dependent variable is ln(wheat yield). Reference regime = No Adoption (R_0). * $p <$ 0.01, $p < 0.05$, * $p < 0.10$.*

Source: *Own computation using RCC Panel Waves (2021, 2023, and 2025).*

Table 4.5.3: Predictive Margins of Wheat Yield by Adoption Regime (RE Model)

Regime	Predictive Margin (ln_y)	Std. Err.	Approx. Yield (kg/ha)
No Adoption (R_0)	6.496	0.534	662
Input Only (R_1)	6.435	0.178	623
NRM Only (R_2)	6.584	0.208	723
SAI Synergy (R_3)	6.954	0.046	1,047

Note: *Approximate yields are obtained by exponentiating the predictive margins.*

Source: *Own computation using RCC Panel Waves (2021, 2023, and 2025).*

4.4.3 Covariate Stability

Core covariates maintain consistent sign, magnitude, and significance across the RE and CMP specifications: land size (RE: −0.496; CMP: −0.482; both $p < 0.01$), livestock (RE: 0.377; CMP: 0.314; both $p < 0.01$), and extension access (RE: $p = 0.051$; CMP: $p = 0.008$). This stability indicates that the significant R3 effect recovered by CMP is not an artifact of the choice of estimator.

Table 4.5.4: CMP Estimates of the Yield Equation with Integrated Package (R_3)

Variable	Coefficient	Robust Std. Err.	z	P>z	Sig.
R3 (Integrated SAI)	0.453	0.158	2.87	0.004	***
Head age	0.003	0.003	0.98	0.327	
Head gender (male = 1)	-0.062	0.135	-0.46	0.648	
ln(Total land size)	-0.482	0.076	-6.37	0.000	***
ln(TLU)	0.314	0.087	3.61	0.000	***
Extension plot	0.259	0.098	2.65	0.008	***
ln(Distance to parcel)	-0.050	0.054	-0.92	0.357	
Credit access	0.003	0.109	0.03	0.980	
Region: Oromia	0.070	0.102	0.69	0.488	
Region: Somali	-0.518	0.538	-0.96	0.336	
Region: SNNPRG	-0.522	0.145	-3.60	0.000	***
Year: 2021	-0.241	0.104	-2.31	0.021	**
Year: 2023	-0.092	0.095	-0.98	0.329	
Constant	6.215	0.284	21.87	0.000	***

*Note: Dependent variable is ln(wheat yield). Standard errors clustered at household level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. $N = 717$ (491 clusters on HH_ID). Log pseudolikelihood = 1268.27.* Source: *Own computation using RCC Panel Waves (2021, 2023, and 2025).*

4.4.4 Multicollinearity Check

A supplementary OLS regression of yield on the seven individual SAI practices and the full set of controls shows no material multicollinearity. The mean Variance Inflation Factor

(VIF) is 1.24 and the maximum VIF is 1.82 (land size). Both values lie well below the conventional threshold of 10.

Table 4.5.5: Variance Inflation Factors (VIF) for Yield Equation Covariates

Variable	**VIF**	**1/VIF**
ln(Total land size)	1.82	0.550
ln(TLU)	1.61	0.623
ln(Distance to parcel)	1.34	0.748
Row planting	1.29	0.776
Improved seed	1.29	0.776
Organic manure	1.18	0.849
Extension plot	1.16	0.861
Intercropping	1.14	0.876
SWC	1.12	0.892
Chemical fertilizer	1.09	0.914
Head gender	1.08	0.925
Minimum tillage	1.07	0.930
Credit	1.06	0.941
Head age	1.05	0.951
Mean VIF	1.24	

Source: Own computation using RCC Panel Waves (2021, 2023 and 2025).

4.4.5 Region Effects: Yield Equation Only

Region dummies were tested in the adoption equations but produced complete separation: specific regions perfectly predicted adoption in four of the seven equations. This is a known identification failure in binary choice models (Albert and Anderson, 1984). It reduced usable sample sizes (from 1,058 to as low as 606) and worsened matrix conditioning. Region indicators are therefore retained only in the yield equation, where they capture agroecological variation (soil, rainfall, altitude) without compromising estimation of the adoption system.

4.4.6 Summary of Robustness Checks

CMP is required by the data: both interdependence and endogeneity tests reject the simpler single-equation alternative.

No individual SAI practice significantly affects yield on its own (Wald $\chi^2(7) = 11.73$, p = 0.110); only the integrated R3 bundle does.

CMP recovers a statistically significant 57 percent yield premium for R_3 (p = 0.004); the naïve RE model finds a similar point estimate (β = 0.458) but with a standard error more than three times larger, which pushes it below conventional significance (p = 0.393) despite barely differing in magnitude from the CMP estimate.

Core covariates remain stable across estimators, and VIF diagnostics rule out multicollinearity.

Region effects are appropriately confined to the yield equation on documented statistical grounds.

Collectively, these checks demonstrate that the study's central conclusion—that practices matter primarily as an integrated bundle, and that the R3 regime raises yield once selection is corrected—is robust and not an artifact of model specification.

4.5 Limitations

Several limitations should be acknowledged.

First, this study is deliberately scoped to wheat and seven specific SAI practices; the findings should not be generalized to other leading crops such as maize or teff, nor to other farming practices such as irrigation or agroforestry. By implication, the results can only be interpreted for this crop, the practice set, and the time window considered here. In particular, this study does not address the longer-run soil regeneration dynamics beyond 2025, which is the last survey wave considered.

Second, while the RCC data include a variable on seeking off-farm employment and variables on off-farm income (wage and remittances), these variables represent quite different concepts of the household livelihood, and they do not appear to be substitutable. Seeking employment captures whether a household is currently looking for off-farm employment; wage and remittance income capture whether the household has received off-farm income. For instance, one household may receive remittances but not be seeking employment, or vice versa. Consistent with this, these two variables identify largely

separate groups of households. For example, 82.8% of households with off-farm income are not seeking off-farm employment, and only 38.7% of those seeking off-farm employment report off-farm income. Most importantly, more than 85% of the wheat-growing households report zero wage or remittance income, so this leaves very little variation to analyze statistically. For all these reasons, these variables were not combined into one variable capturing off-farm engagement, nor included in the yield model. Instead, household economic capacity is captured by more reliable and more populated variables: livestock holdings (TLU), land size, credit, and extension services.

Third, while the CMP allows for self-selection and cross-practice dependence, and state dependence, many other factors that could be influential and vary over time are not controlled for in the present data set. These include, for instance, changes in soil quality, dynamics of intra-household bargaining, and short-run variations in market prices.

Fourth, at various stages in estimating the CMP system, ill-conditioned regressor matrices were encountered. The highest condition number was 177.7 in the yield equation, and 147.4 was reached in the chemical fertilizer adoption equation. This was expected since seven interdependent adoption equations are simultaneously estimated with one productivity equation. Each equation includes its set of regressors, some log-transformed, others categorical, and others lagged. An auxiliary check reveals that this is not the classic form of multicollinearity: the mean variance inflation factor (VIF) across the covariates in the yield equation is 1.24, while the maximum is 1.82, both values being well below common thresholds of concern. Thus, the ill-conditioning arises from the complexity of the joint likelihood surface rather than from redundant regressors.

Despite the above warnings, convergence was attained smoothly using a mixture of Newton-Raphson and Davidon-Fletcher-Powell methods, with the log pseudolikelihood stabilizing within four iterations. The estimates are robust and economically plausible, given the similar patterns in descriptive analyses, regime-level comparisons, and robustness checks of RE versus CMP detailed in Section 4.5.

However, a larger sample would undoubtedly enhance the numerical stability of the solution, particularly for practices with the smallest adoption variation, such as intercropping in the Somali region.

CHAPTER FIVE

5. Conclusion and Policy Recommendation

5.1 Conclusion

Smallholder wheat farmers in rural Ethiopia do not adopt SAI practices as a one-off rational decision; adoption varies intertemporally with past experience, current liquidity constraints, and exposure to shocks. This study tracks that process across three survey rounds (2021, 2023, 2025) using a Conditional Mixed Process model suited to adoption as dynamic, interdependent behavior. **Six findings emerge.**

5.1.1 SAI Practices Function as a System, Not as Isolated Inputs

No individual SAI practice shows a statistically significant positive effect on wheat yield at the 5% level. Chemical fertilizer is marginally significant at the 10% level (p=0.055), while minimum tillage shows a negative and statistically significant coefficient at the 5% level (p=0.034). These results suggest that individual practices, when considered in isolation, do not reliably predict yield gains in this sample. The seven adoption indicators are jointly insignificant in the yield equation (Wald $\chi^2(7) = 11.73$, p = 0.110). Chemical fertilizer shows a positive but only marginally significant coefficient (p = 0.055), while minimum tillage (p = 0.034) and intercropping (p = 0.094) have negative coefficients, significant at the 5% and 10% levels, respectively. However, such effects may be consistent with adjustment costs and transition effects rather than representing any long-term negative effect on productivity. These findings also imply that, in assessing SAI practices separately, their complementary value when used jointly may be missed.

5.1.2 Strong Evidence of True State Dependence in SAI Adoption

Past adoption significantly predicts current adoption for six of the seven practices most strongly for chemical fertilizer and improved seed, and significantly (though more moderately) for organic manure, intercropping, minimum tillage, and row planting. This reflects learning-by-doing: repeated use lowers perceived risk and builds practical knowledge, consistent with Birhanu and Jensen (2023) and Oumer, Burton, and Kassie (2025). The policy implication: subsidies, credit, and demonstration plots matter most at first adoption, not afterward the entry point is the bottleneck. SWC is the exception: its

lagged effect is statistically insignificant, meaning past adoption does not predict continuation, and adoption here is more likely program-driven than experience-driven.

5.1.3 Significant Complementarities among SAI Practices

Adoption decisions across the seven SAI practices are not independent. The estimated error correlations reveal systematic pairings: improved seed with row planting (ρ = 0.478, p < 0.01), intercropping with row planting (ρ = 0.428, p < 0.01), and improved seed with intercropping (ρ = 0.357, p < 0.01). These significant positive correlations imply that farmers tend to adopt those practices in a bundle, supporting the complementary nature of their agronomic and economic returns. This evidence aligns with earlier research across Ethiopia and the region: combining improved seed and fertilizer with proper farm management produces far greater gains than using either approach on its own.

5.1.4 Flight to Safety under Cumulative Climate Shocks

Recurrent shocks erode adoption of purchased inputs. Cumulative climate shocks significantly reduce chemical fertilizer adoption (-4.4 percentage points, p=0.014) and SWC adoption (-4.5 pp, p=0.017), while significantly raising reliance on organic manure (+3.9 pp, p=0.058) a low-cost, on-farm fallback. This matches Dercon and Christiaensen (2011), who found harvest-failure risk alone suppresses fertilizer use in Ethiopia, and Oumer et al. (2025), who found the same dis-adoptive pattern across SAI practices more broadly. This addresses Specific Objective 2 directly: recurrent climate shocks build into a constraint on sustaining SAI, particularly purchased inputs (chemical fertilizer) and labor-intensive conservation activities (SWC).

5.1.5 Short-Run Costs and Long-Run Gains in NRM Adoption

Minimum tillage and intercropping show negative, and in some cases statistically significant, short-run yield coefficients; organic manure and SWC are not significant. The negative coefficients do not reflect the true productivity potential of these technologies but transition costs in terms of labor and management in the early years of adoption. For example, Arslan et al. (2014) found in Zambia that the positive yield effects of minimum tillage appear only after several seasons. Moser and Barrett (2006) and Dercon and Christiaensen (2011) show risk-averse smallholders avoid delayed-return technologies without support to bridge early losses matching the NRM dis-adoption pattern here. This

point to a specific policy gap: conditional cash transfers, input insurance, and assured extension during the transition period, not long-run NRM subsidies.

5.1.6 SAI as a System: Why the Whole Outperforms the Parts

Productivity gains from SAI appear to be a system property rather than the sum of individual effects. Full integration (regime R_3) outperforms partial adoption, which in turn outperforms non-adoption, yet the integrated regime is also the most vulnerable to resource and shock pressures. Improved seed and fertilizer help protect against immediate yield loss but are the first inputs reduced when liquidity tightens; NRM practices build longer-run resilience but require a degree of resource stability that many households lack. This dynamic can trap farmers in cycles of moving between full and partial adoption rather than sustaining integrated management.

The core finding is that, although no individual SAI practice reaches conventional significance in the yield equation, the integrated R_3 system delivers a statistically significant 57% yield premium over non-adopters ($\beta = 0.453$, SE = 0.158, $p = 0.004$). This is not a limitation of the analysis; it is the study's central argument. SAI productivity is a system property; evaluation frameworks that treat practices as separable will systematically undervalue integrated adoption and design programs too narrow to capture its returns. Extension and subsidy programs should therefore target technology bundles and integrated management packages, rather than promoting individual technologies in isolation.

5.2 Policy Recommendations

5.2.1 A Triple-P Framework for Sustainable Agricultural Transformation: From Input Supply to System Integration

Ethiopian smallholder farmers do adopt SAI practices, and yields improve when adoption is integrated rather than piecemeal. But adoption is fragile: it starts, produces results, and then unravels under a bad season, a cash shortfall, or the accumulated cost of conservation practices that haven't yet paid off. Farmers cycle back to partial or no adoption, rarely holding the full package together long enough to reach the productivity level sustained integration makes possible.

The Triple-P framework: -Promote, Protect, persist; addresses this. The three conditions are not sequential; they must hold simultaneously, because financial pressure,

climate stress, and transition costs arrive together, not one at a time. Promotion without protection collapses at the first shock. Protection without promotion traps farmers in low-productivity systems with no exit. Persistence without either is not a policy, just an aspiration.

PROMOTE: **Getting Farmers into the Full SAI System**

State dependence is strong for six of the seven practices (Section 5.1.2), meaning the first season of use is the critical barrier after that, continuation follows largely from experience and confidence, not fresh intervention. Combined with the significant complementarities across practices (improved seed–row planting, ρ=0.478; intercropping–row planting, ρ=0.428), the evidence points against single-technology entry. Yet most farmers start by adopting only part of the package; either inputs or conservation practices, but rarely both. This partial adoption keeps them on a lower productivity path than the full integrated system.

Three policy measures follow from this evidence:

Starter packages for first-time and partial adopters.

First-season input support (vouchers, partial subsidies, low-interest seasonal credit) has effects that outlast the support itself, as Carter, Laajaj and Yang (2021) document: one season of experience builds the confidence for subsequent adoption. Support should cover the full package (seed, fertilizer, relevant conservation practices) together, since the practices show no evidence of separable returns.

Full-package demonstration plots at the kebele level.

Direct observation drives adoption more than general advice (Krishnan and Patnam, 2014; Rogers, 2003). Development Agents should run full-package demonstration plots, not single-technology plots, and extension worker evaluation should shift from farmer contacts to sustained full-package adoption.

Subsidies restructured around integrated soil fertility.

Current subsidies target chemical fertilizer alone, discouraging long-run soil conservation. Zenbaba and Ketema (2025) show integrated packages fertilizer with organic manure, legumes, and lime where appropriate outperform single-input approaches in yield and soil condition over time. Subsidy and credit programs should reward integrated adoption, with

stronger incentives for combining organic and inorganic inputs particularly important in wheat-growing regions where climate stress is making soil resilience harder to maintain.

PROTECT: **Shielding Farmers and Their Adoption Investments from Shocks**

Cumulative climate shocks significantly erode adoption of purchased inputs chemical fertilizer falls 4.4 percentage points and SWC falls 4.5 percentage points per shock while organic manure use raises 3.9 pp as households retreat to cheaper, local alternatives. A shock does not just reduce yield in the year it hits; it forces an adoption reversal that erases progress built over several good seasons. Protection has to intervene precisely at the moment shocks occur, when adoption is most likely to unravel.

Index-based weather insurance linked to SAI adoption.

Administratively feasible even in remote areas, since payouts trigger on a rainfall or temperature threshold rather than measured farm-level loss. Linking lower premiums or higher coverage to full-package SAI adoption gives farmers a financial reason to stay in the system during stress rather than retreat from it, with government premium subsidies making this viable in drought-prone areas.

Shock-responsive reform of the Productive Safety Net Programme.

PSNP's fixed payment structure does not scale with shock severity. Hoddinott et al. (2012) show that linking safety-net support with agricultural inputs improves both welfare and adoption outcomes. PSNP should automatically supplement transfers with seed vouchers, fertilizer coupons, and livestock protection or restocking for households at risk of dropping out of SAI and keeping farmers in the system in a bad year is cheaper than reintegrating them afterward.

Climate-contingent credit with flexible repayment.

Formal credit access declined over the survey period even as climate stress rose, leaving farmers least protected exactly when they need credit most. Fixed repayment schedules force asset sales and input cuts after bad years, accelerating the dis-adoption documented in Section 5.1.4. Credit products should build in automatic repayment deferrals, interest relief, or rescheduling upon a verified climate event as standard contract terms, not case-by-case exceptions made financially sustainable at scale through government-backed guarantees and support to cooperatives and microfinance institutions.

PERSIST: Keeping Farmers in the Full SAI System Long Enough to Benefit

Farmers who reach full adoption often move backward later, typically dropping expensive modern inputs while retaining conservation practices; input-only adoption without conservation is rarely retained either way. Neither partial position is stable. This instability is not irrational it reflects a mismatch between the multi-season timeline over which SAI benefits accrue and the single-season timeline most households can self-finance. Without support through that formative period, farmers revert to simpler strategies before benefits materialize not because the system failed, but because they could not afford to wait.

Multi-year incentives for sustained integrated adoption.

One season of support gets farmers in; it does not keep them there. Mechanisms such as continued access to subsidized inputs at increasing levels, priority input access, or formal recognition as model farmers give an incentive to remain in the system season over season, matching the timeline over which soil, learning, and management benefits actually accumulate.

Payments for Ecosystem Services tied to conservation practices. Minimum tillage, intercropping, and organic matter use carry transition costs before soil-health benefits accrue — the reason they are most often abandoned early. Payments tied to verifiable conservation activity, monitored through Development Agents and community-based verification built on existing SLM infrastructure, can compensate for this gap while keeping administrative costs manageable.

Multi-season farmer field schools and peer learning networks.

Current extension relies on short, one-off training poorly matched to the multi-season learning full SAI adoption requires. Sseguya et al. (2021) find demonstration plots and farmer-to-farmer networks raise adoption substantially, but only when sustained across multiple seasons. Field schools should run continuously, not as isolated events, and farmers who sustain full adoption particularly women, who face access and recognition barriers should be supported as peer trainers connected to input supply networks.

The core message: adoption must be maintained, not just initiated. The full SAI system delivers its benefits slowly and requires conditions most smallholder households cannot create alone sustained incentives, shock protection, and continuous learning support are what determine whether promotion produces anything lasting.

Ethiopian smallholder farmers are not resistant to modern agricultural technology. Households that persistently adopt the full SAI bundle achieve yields roughly **57%** higher than non-adopters., alongside improved soil quality and greater resilience to climate risk. The potential is demonstrated, not hypothetical.

The open question is why this potential remains underused? The problem is not the technology, and it is not farmer behavior; it is the environment in which adoption decisions are made. Smallholders face four structural cost barriers: the cost of initiating a new practice, the cost of sustaining input use through drought, the cost of short-run yield loss during the conservation transition, and the cost of rebuilding after a shock.

The Triple-P framework responds directly to these four costs. It is not a call for new programs, but a reorientation of existing ones from encouraging adoption to sustaining it. In practice, this means: extension evaluated on sustained integrated adoption, not farmer contacts; safety nets that protect productive assets, not only address short-term food gaps; and credit designed to manage risk across seasons rather than become a liability after one bad harvest.

Agricultural transformation should be judged not by performance in good years, but by whether farmers have enough support to stay the course until conditions improve. That requires sustained commitment from policymakers, development partners, extension agents, researchers, and farmers themselves and institutions built for the long term.

5.3 Directions for Future Research

This study opens five immediate research directions:

1. Longer Panel:

Three waves over four years capture short-run adoption dynamics but cannot confirm whether the yield dips from intercropping and minimum tillage reverse over time as soil structure improves. A 10–15-year panel is needed to test whether these transition costs eventually give way to the gains that the agronomic literature predicts. Extending the existing RCC panel is the natural next step.

2. Agro-ecological Zoning:

SAI performance likely varies across highland, mid-elevation, and lowland zones. This study assumes regional homogeneity for a national-level estimate; future work should disaggregate by agro-ecological zone to identify which practice combinations perform best

in specific contexts. A one-size-fits-all recommendation likely understates the achievable gains.

3. Policy evaluation:

The Triple-P framework is grounded in this study's evidence, but its components starter packages, index insurance, shock-responsive safety nets, multi-year incentives, and ecosystem service payments have not been tested together in Ethiopia. Rigorous randomized or quasi-experimental evaluation, conducted with farming communities, is needed to move it from recommendation to evidence.

4. Realizing SAI's full promise:

Realizing SAI's full promise productivity, resilience, and equity for Ethiopian smallholders will require longer time horizons, finer geographic detail, deeper household-level data, and closer collaboration across disciplines.

The farmers this research serves have waited long enough for that investment.

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