Addis Ababa University

Doctoral Thesis

Essays on Agricultural Productivity and Climate Resilience in Ethiopia: Insights into Conservation Practices, Public Works, and Land Cover Change

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Declaration of Authorship

I, **Gemeda Olani Akuma**, hereby declare that this doctoral thesis, titled **“Essays on Agricultural Productivity and Climate Resilience in Ethiopia: Insights into Conservation Practices, Public Works, and Land Cover Change”**, and the work presented within are entirely my own. I affirm that:

- This research was primarily conducted during my doctoral studies at Addis Ababa University, in collaboration with the University of Gothenburg.
- Any sections of this thesis previously submitted for a degree or qualification at this or any other institution are acknowledged.
- All references to the work of others have been properly acknowledged and attributed.
- All sources quoted in this dissertation are properly cited, and except for these quotations, the work presented is entirely my own.
- I have made sure to acknowledge all key sources of assistance, guidance, and support that have contributed significantly to the completion of this research.
- Where this dissertation includes work conducted collaboratively with others, I have clearly distinguished the contributions made by my collaborators and those made by myself.

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Certificate

I hereby certify that the research presented in this Doctoral Thesis, titled **"Essays on Agricultural Productivity and Climate Resilience in Ethiopia: Insights into Conservation Practices, Public Works, and Land Cover Change"**, authored **by Gemeda Olani Akuma**, in fulfillment of the requirements for the degree of Doctor of Philosophy in Economics, has been conducted under my supervision and has not been submitted for a degree at any other institution.

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"*I am deeply grateful to my parents for their unwavering belief in the power of education, which laid the foundation for my academic journey. Their support has been instrumental in shaping my path. Guided by a deep passion for economics, I strive to generate original insights, cultivate inclusive learning, and engage in collaborative outreach that drives innovation and meaningful societal change.*"

Gemeda Olani Akuma

ADDIS ABABA UNIVERSITY

Abstract

College of Business and Economics
Department of Economics

Doctor of Philosophy in Economics

Essays on Agricultural Productivity and Climate Resilience in Ethiopia: Insights into Conservation Practices, Public Works, and Land Cover Change

by Gemeda Olani Akuma

This dissertation explores the interconnected dynamics of agricultural productivity, climate resilience, and sustainable land management in rural Ethiopia. It evaluates the effects of targeted conservation information on productivity, examines the role of public works in resource conservation and labor engagement, and analyzes the impact of land cover changes on agricultural output. The first essay assesses the influence of plot-specific conservation practices on productivity, highlighting the role of tailored information in promoting recommended practices and enhancing productivity. Through multi-year (2015-2021) randomized controlled trials, the study demonstrates that site-specific conservation recommendations significantly improve the adoption of conservation practices and increase maize land productivity across diverse agroecological contexts. The findings further suggest that such interventions lower costs by saving labor and improving soil fertility, thereby increasing productivity. These findings highlight the potential of targeted conservation strategies to improve agricultural productivity and promote long-term sustainability across diverse agroecological regions. The second essay examines the impact of public works programs on soil and water conservation and their effect on labor engagement in rural Ethiopia. By utilizing unbalanced panel data from the Ethiopian socioeconomic survey across three periods (2011/12, 2013/14, and 2015/16), this study illustrates that public works programs enhance soil and water conservation, reallocate labor to agricultural production, and reduce labor participation in non-agricultural activities. These programs support immediate livelihoods and long-term sustainability, particularly as adaptive strategies in drought-prone areas, by strengthening conservation efforts, reshaping household labor allocation, and enhancing food security. The third essay explores the impact of weather shocks on agricultural productivity in rural Ethiopia, focusing on the role of land cover dynamics. This study employs balanced panel data from the 2011/12, 2013/14, and 2015/16 waves of the Ethiopian Socioeconomic Survey, combined with satellite-based vegetation indices, drought severity, and temperature data. Using a multiway fixed-effects estimator, the analysis shows that weather shocks significantly reduce agricultural productivity, while improved land cover mitigates these effects and increases productivity. The study finds that enhanced land cover change better mitigates climatic stress in tropical-cool zones and high-productivity households. The paper emphasizes the critical importance of sustainable land management in strengthening resilience to climate variability in vulnerable regions. Collectively, these essays advance the understanding of sustainable practices and resilience strategies, offering valuable insights for policies that promote livelihoods, food security, sustainability, and climate resilience in rural Ethiopia. This dissertation synthesizes key findings and offers evidence-based recommendations to enhance agricultural productivity and climate resilience in Ethiopia, with broader applicability to regions sharing similar agroecological and farming contexts.

Keywords: Agricultural productivity, Climate resilience, conservation, information, Public works, Land cover change

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List of Abbreviations

AAU	**A**ddis **A**baba **U**niversity
ATE	**A**verage **T**eatment **E**ffect
ATT	**A**verage **T**eatment Effect on **T**reated
CA	**C**onservation **A**griculture
CSA	**C**entral **S**tatistics **A**gency
EAs	**E**numeration **A**reas
EfD	**E**nvironment for **D**evelopment
ESPS	**E**thiopia **S**ocioeconomic **P**anel **S**urvey
ESS	**E**thiopia **S**ocioeconomic **S**urvey
EVI	**E**nhanced **V**egetation **I**ndex
FA	**F**armer **A**ssociation
FE	**F**ixed **E**ffects
FIML	**F**ull **I**nformation **M**aximum **L**ikelihood
IFAD	**I**nternational **F**und for **A**gricultural **D**evelopment
ITT	**I**ntent-to-**T**reat
IV	**I**nstrumental **V**ariables
LPM	**L**inear **P**robability **M**odel
LR	**L**ikelihood **R**atio
LSMS-ISA	**L**iving **S**tandards **M**easurement **S**tudy-**I**ntegrated **S**urveys of **A**griculture
MODIS	**M**oderate **I**maging **S**pectroradiometer
MWFE	**M**ulti-Way **F**ixed **E**ffects
NDVI	**N**ormalized **D**ifference **V**egetation **I**ndex
POLS	**P**ooled **O**dinary **L**east **S**quares
PSNP	**P**oductive **S**afety **N**et **P**rogram
RCTs	**R**andomized **C**ontrrolled **T**rials
Sida	**S**wedish **I**nternational **D**evelopment **C**ooperation **A**gency
SPI	**S**tandardized **P**recipitation **I**ndex
SWC	**S**oil and **W**ater **C**onservation
TSM	**T**wo-**S**tage method of **M**oments
UGOT	**U**niversity of **G**othenburg
VCI	**V**egetation **C**ondition **I**ndex

List of Publications

Publications from Thesis

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To my beloved wife and cherished children, whose unwavering love, support, and presence have been a constant source of strength and inspiration.

Chapter 1

Introduction

1.1 Background and Context

Agriculture remains the backbone of Ethiopia's economy, accounting for nearly 50% of the country's GDP and more than 80% of its export earnings (Stellmacher and Kelboro, 2019), and sustaining millions of rural households, where smallholder farming is the dominant livelihood strategy (Haile et al., 2022; Zerssa et al., 2021; Aweke, 2017; Rapsomanikis, 2015; Dercon and Gollin, 2014). Approximately 80% of the population relies on the agricultural sector for their livelihoods (Njeru et al., 2016), with smallholder farms contributing over 90% of the nation's agricultural production (Getahun, 2020; Gebre-Selassie and T. Bekele, 2012). However, the sector is increasingly vulnerable to multifaceted challenges, including climate variability, land degradation, and constrained access to adaptive farming technologies. These undermine agricultural productivity and threaten food security (Demem, 2023). Erratic rainfall patterns, prolonged droughts, and other climate-induced shocks exacerbate yield instability, disproportionately affecting resource-poor farmers with limited capacity to adapt (Jayne et al., 2014). Furthermore, suboptimal land use, soil erosion, and declining soil fertility accelerate environmental degradation, compounding the risks to long-term agricultural sector resilience to climate change (Spielman et al., 2011). Addressing these challenges requires integrated solutions, including climate-smart agriculture such as conservation agriculture (CA) practices, sustainable land management, and information-driven policies. Enhancing smallholder resilience to climate variability through adaptive strategies and innovative technologies can improve productivity while ensuring environmental sustainability and food security.

Addressing challenges in agriculture requires an integrated approach that combines research, policy, and farmer-led solutions. Expanding access to conservation knowledge promotes sustainable agricultural practices like soil and water conservation (SWC), agroforestry, and climate-smart agriculture (Pretty et al., 2012). Targeted policies, including extension services and rural investments, bridge knowledge gaps and support adoption (Kassie et al., 2011). Sustainable land management practices, including watershed restoration and CA, enhance soil fertility, increase productivity, and strengthen resilience to climate shocks (Hussein, 2024; Solomon et al., 2024; Hadgu et al., 2019; Were et al., 2016). Aligning scientific advances with locally adapted strategies is key to long-term agricultural sustainability and food security. Thus, ensuring agricultural sector resilience in Ethiopia demands a comprehensive approach that integrates climate adaptation, institutional support, and better farmer decision-making, reducing vulnerabilities and promoting long-term sustainability and food security.

Access to tailored conservation information is essential for boosting agricultural productivity through CA practices, such as minimum tillage and crop residue retention. Studies have shown that these technologies are cost-effective and sustainable solutions that enhance soil health and water retention. However, adoption remains low, constrained by limited awareness, inadequate capacity-building, and institutional challenges, particularly in sub-Saharan African countries such as Ethiopia. The first paper in Chapter 2, *Enhancing Agricultural Productivity through Tailored Information on Conservation Practices: Evidence from Ethiopia*, addresses this concern. Providing context-specific information addresses these challenges, improving productivity, resource management, and environmental resilience for long-term sustainability.

Additionally, public works programs in rural Ethiopia, primarily designed for social protection and infrastructure development, play a crucial role in supporting conservation practices for drought adaptation and mitigation. These programs also influence labor allocation, allowing farmers to meet immediate agricultural needs while contributing to long-term conservation goals. The second paper, Chapter 3, *Adapting to Drought: How Do Public Works Affect Conservation and Labor Engagement in Rural Ethiopia?*, examines the impact of these programs on SWC practices and household labor allocation between on-farm and off-farm activities. By incentivizing labor-intensive activities such as SWC practices, these programs promote sustainable farming and help address immediate livelihood challenges in drought-prone regions. Understanding their impact is key to crafting policies that balance labor needs with long-term sustainability, fostering resilient agricultural systems.

Moreover, in rural Ethiopia, agricultural productivity is increasingly shaped by environmental challenges, particularly land cover changes and vulnerability to weather shocks. For example, deforestation, soil degradation, and land use changes intensify the negative impacts of climate variability on crop yields, increasing the vulnerability of farming systems to extreme weather events. The third paper, Chapter 4, *Weather Shocks and Agricultural Productivity in Rural Ethiopia: Role of Land Cover Dynamics*, addresses this issue. The interaction between land cover changes and weather shocks provides key insights into farmers' adaptive strategies for managing climate risks, highlighting the need for policies that promote sustainable land use and resource management. Such policies can strengthen resilience, reduce environmental degradation, and ensure long-term agricultural productivity amid climate challenges.

These studies collectively enhance our understanding of how access to information, social protection policy interventions, changes in land cover, climate variability, and environmental challenges affect agricultural productivity and rural livelihoods in Ethiopia. This dissertation builds on these insights by investigating the role of conservation practices, institutional support (public work programs), and climate resilience strategies in promoting long-term productivity, rural livelihoods, and sustainable agriculture.

1.2 Problem Statement and Research Objectives

This section presents the general and specific problem statements, along with the research objectives for each paper in the dissertation.

1.2.1 General Problem Statement

Climate variability, land degradation, and limited access to adaptive practices threaten agricultural productivity and rural livelihoods in developing countries, including Ethiopia. Unregulated land use accelerates deforestation and soil degradation, worsening vulnerability to extreme weather events (Deche et al., 2023; Maru et al., 2023; Mekonnen et al., 2023; Demem, 2023; Call and Gray, 2020). Despite the potential of conservation agriculture (CA) and public works programs to mitigate these impacts, low adoption rates persist due to knowledge gaps and institutional barriers. Integrating sustainable land management, social protection, and public works is critical for enhancing resilience, reducing climate vulnerability, and ensuring long-term food security in high-risk areas.

1.2.2 Paper 1: Problem Statement and Research Objectives

Paper Title: *"Enhancing Agricultural Productivity through Tailored Information on Conservation Practices: Evidence from Ethiopia"*

Problem Statement:

Conservation agriculture addresses soil degradation, low productivity, and climate vulnerability in rural Ethiopia. However, its adoption remains low due to knowledge gaps, limited access to information, and institutional barriers. There is a need to explore how tailored conservation information can promote CA adoption and enhance productivity.

General Objective:

To examine the impact of providing tailored information on conservation practices and agricultural productivity in Ethiopia.

Specific Objectives:

- To evaluate farmers' adoption of conservation practices based on plot-specific recommendations aligned with household characteristics, soil type, slope, and agroecological conditions, and
- To evaluate the impact of disseminating tailored conservation information on agricultural productivity.

1.2.3 Paper 2: Problem Statement and Research Objectives

Paper Title: *"Adapting to Drought: How Do Public Works Affect Conservation and Labor Engagement in Rural Ethiopia?"*

Problem Statement:

Public works programs in Ethiopia aim to improve livelihoods and build resilience to climate shocks through soil and water conservation. While these programs enhance land management and productivity, their impact on labor allocation between on-farm and off-farm activities remains unclear (Quisumbing and Yohannes, 2005; Subbarao et al., 2012; Berhane et al., 2014; M. Bekele et al., 2020; Fre et al., 2022; Franklin et al., 2024). Furthermore, the balance between meeting immediate agricultural needs and achieving long-term sustainability in high-risk regions is poorly understood.

General Objective:

To investigate the role of public works programs in shaping conservation efforts and labor allocation decisions in rural Ethiopia, particularly in response to drought conditions.

Specific Objectives:

- To assess how participation in public works programs affects the adoption of soil and water conservation measures, and

- To examine how public works programs differentially impact labor engagement, focusing on household labor allocation between farm and off-farm activities.

1.2.4 Paper 3: Problem Statement and Research Objectives

Paper Title: *“Weather Shocks and Agricultural Productivity in Rural Ethiopia: Role of Land Cover Dynamics"*

Problem Statement:

Changes in land cover, particularly improvements in vegetation and soil health, can enhance resilience to climate shocks and boost agricultural productivity. However, the impact of land cover dynamics on productivity under varying climatic conditions, especially in tropical-cool regions, remains underexplored. There is a need to investigate how land cover improvements can buffer the effects of weather shocks, such as droughts and heat waves, and support long-term agricultural sustainability in climate-vulnerable regions.

General Objective:

To explore the relationship between weather shocks, land cover changes, and agricultural productivity in rural Ethiopia.

Specific Objectives:

- To analyze the impact of weather shocks, such as drought and extreme temperatures, on agricultural productivity and the extent to which these impacts differ across distinct agroecological zones,

- To evaluate how land cover dynamics, as reflected by changes in greenness—indicating afforestation, deforestation, and vegetation loss—can mitigate against the adverse effects of such shocks, and (iii) how does the heterogeneity of weather shock impacts, and

- To assess how variations in weather shock impacts, alongside land cover changes, affect agricultural productivity across agroecological zones.

1.3 Methodology

The methods employed in the individual papers of this dissertation are outlined below, with detailed descriptions provided in the respective chapters (Chapters 2 - 4) and their corresponding sections (2.5, 3.4, and 4.4). Each chapter presents a unique methodological approach specifically designed to address its corresponding research questions.

- The first paper, *Enhancing Agricultural Productivity through Tailored Information on Conservation Practices: Evidence from Ethiopia*, employs multi-year randomized controlled trials (RCTs) with stratified random sampling across agroecological zones to assess the impact of tailored conservation information on agricultural productivity. Using panel data and applying fixed effects estimators, the analysis isolates causal effects, offering robust evidence of the effectiveness of information-based interventions in enhancing sustainable practices and productivity.
- The second paper, *Adapting to Drought: How Do Public Works Affect Conservation and Labor Engagement in Rural Ethiopia?*, employs the full-information maximum likelihood method and instrumental variables approach, integrating an endogenous treatment model to analyze the effects of public works programs on conservation efforts and household labor allocation.
- The third paper, *Weather Shocks and Agricultural Productivity in Rural Ethiopia: The Role of Land Cover Dynamics*, utilizes satellite-based measurements of drought and temperature to assess weather variability. It employs a multi-way fixed effects linear regression to estimate the impact of changes in land cover on agricultural productivity. This approach accounts for unobserved differences over time, location, and households, allowing for a robust analysis of the effects of land cover under various climatic conditions.

1.4 Key Findings

This dissertation investigates three critical dimensions of agricultural resilience in Ethiopia. The first paper examines the impact of providing tailored conservation information on farmers' adoption of sustainable practices. The findings demonstrate that information customized to the specific characteristics of each plot, including soil type and agroecological conditions, significantly enhances the likelihood of farmers adopting these practices. As a result, this tailored approach leads to notable improvements in agricultural productivity, emphasizing the importance of context-specific interventions in fostering more sustainable and resilient farming systems.

The second paper examines the impact of public works programs on agricultural resilience, focusing on their role in soil and water conservation. The study finds that public works programs significantly improve soil and water conservation, enhancing land management and sustainability. These programs also influence labor allocation, increasing agricultural labor and reducing off-farm activities. Hence, this suggests that public works earnings contribute to farm income stability and resilience against weather-related shocks, such as droughts. The findings underscore the effectiveness of public works programs in strengthening agricultural resilience and supporting long-term rural development in climate-vulnerable regions.

The third paper's findings suggest that changes in land cover, particularly vegetation and greenness, can alleviate the adverse effects of weather shocks on agricultural productivity. Enhanced land cover dynamics, such as increased vegetation and improved soil health, bolster resilience by buffering agricultural systems from climate extremes like droughts and heat waves. The study finds that enhanced land cover change more effectively mitigates climatic stress in tropical-cool zones and among high-productivity households across regions, as these households benefit more due to their greater exposure and vulnerability to climate variability. These results emphasize the critical need for sustainable land management practices to build resilience and mitigate climate change's impact on agriculture.

1.5 Contributions

This dissertation contributes to the discourse on climate resilience and agricultural productivity by analyzing three interrelated dimensions: the adoption of recommended CA practices, participation in public works programs, and land cover changes in rural Ethiopia. First, it investigates how plot-specific, tailored conservation information affects farmers' adoption of sustainable practices by focusing on the interaction between agroecological conditions, farm characteristics, and the delivery of conservation information and its subsequent influence on productivity outcomes. Second, it explores the impact of public works programs on conservation efforts and shifts in labor allocation between agricultural and non-agricultural activities, emphasizing their dual role in strengthening resilience through SWC while reshaping labor dynamics. Lastly, it assesses the role of land cover dynamics—measured through vegetation shifts and land cover changes—in mediating the effects of weather shocks on agricultural productivity, offering new perspectives on the nexus between environmental stressors and rural livelihoods. Together, these studies add to the understanding of climate-smart agriculture, how households adapt through social protection programs and labor shifts, and the crucial role of land cover changes in maintaining sustainable agriculture during climate change.

1.6 Limitations and Directions for Future Research

While this dissertation provides valuable insights into improving agricultural productivity, conservation practices, and climate resilience, it is not without its limitations. Notably, the dissertation focuses on a single-country analysis of rural Ethiopia, limiting the generalizability of its findings to regions with different socioeconomic and environmental contexts. Therefore, future research should expand its scope by incorporating comparative analyses across multiple countries or regions within sub-Saharan Africa and other developing regions to enhance the generalizability and relevance of the findings. This multi-country synthesis approach would enrich our understanding of the diverse factors influencing climate adaptation and agricultural productivity across varying contexts.

Secondly, while the second and third papers explore associations between the dependent and explanatory variables, establishing causality is challenging due to potential endogeneity, where unobserved factors may bias estimates. Despite several robustness checks, the strict exogeneity assumption remains unverified, suggesting potential endogeneity that may impact the validity of the causal inferences. Future research could address this by employing advanced identification methods, such as instrumental variables (this empirical strategy is applied in the second paper but not in the third), difference-in-differences, or natural experiments to establish causal relationships and claim causal inference. Therefore, advanced empirical strategies and more rigorous analyses are essential for examining the causal relationships between public works and conservation practices, labor allocation, and, simultaneously, between land cover changes and agricultural productivity.

Additionally, while this dissertation provides valuable contributions to understanding climate adaptation in Ethiopia, future research could extend these insights by investigating the long-term impacts of such interventions. Employing longitudinal data would allow for a systematic assessment of the sustainability of adaptation outcomes, offering a nuanced understanding of their enduring effectiveness. This methodological approach facilitates the evaluation of evolving impacts, the identification of adaptation gaps, and the refinement of policies to enhance resilience and adaptive capacity.

To this end, examining the interplay between individual-level factors, such as gender, household wealth, resource access, and climate adaptation strategies, would be highly valuable. This analysis could uncover disparities in how different demographic groups experience and respond to climate interventions, offering critical insights for more inclusive and targeted adaptation policies. Furthermore, examining the influence of national policy interventions in enabling or constraining local adaptation efforts would provide a more holistic understanding of the scalability of effective climate adaptation strategies. Such an analysis could contribute to designing more inclusive and context-specific policy frameworks that enhance resilience across diverse socio-economic and environmental contexts.

1.7 Organization of the Dissertation

Chapter 1 provides an overview of the dissertation, outlining the background, problem statement, research objectives, methodology, key findings, contributions, limitations, and directions for future research. The subsequent chapters of the dissertation are structured as follows. Chapter 2 presents the first research paper; Chapter 3 analyzes the second; and Chapter 4 examines the third. Finally, Chapter 5 synthesizes the main findings, discusses policy implications, and concludes the study.

References

Aweke, M Gelaw (2017). “Climate-smart agriculture in Ethiopia: CSA country profiles for Africa series”. *International Center for Tropical Agriculture: Washington, DC, USA*.

Bekele, Mekonnen et al. (2020). “Development economics research group”. *Development economics research group*.

Berhane, Guush, Daniel O. Gilligan, John Hoddinott, Neha Kumar, and Alemayehu Seyoum Taffesse (2014). “Can social protection work in Africa? The impact of Ethiopia’s productive safety net programme”. *Economic Development and Cultural Change* 63.1, pp. 1–26.

Call, Maia and Clark Gray (2020). “Climate anomalies, land degradation, and rural out-migration in Uganda”. *Population and Environment* 41, pp. 507–528.

Deche, Almaz, Mohammed Assen, Shimeles Damene, Jessica Budds, and Amanuel Kumsa (2023). “Dynamics and drivers of land use and land cover change in the Upper Awash Basin, Central Rift Valley of Ethiopia”. *Environmental management* 72.1, pp. 160–178.

Demem, Mulat Shibabaw (2023). “Impact and adaptation of climate variability and change on small-holders and agriculture in Ethiopia: A review”. *Heliyon*.

Dercon, Stefan and Douglas Gollin (2014). “Agriculture in African development: theories and strategies”. *Annu. Rev. Resour. Econ.* 6.1, pp. 471–492.

Franklin, Simon, Clement Imbert, Girum Abebe, and Carolina Mejia-Mantilla (2024). “Urban public works in spatial equilibrium: Experimental evidence from Ethiopia”. *American Economic Review* 114.5, pp. 1382–1414.

Fre, Zeremariam, Bereket Tsegay, Araya M. Teka, Nicole Kenton, and John Livingstone (2022). *Social Protection, Pastoralism and Resilience in Ethiopia*. TAYLOR FRANCIS Limited.

Gebre-Selassie, Atsbaha and Tessema Bekele (2012). “A review of Ethiopian agriculture: roles, policy and small-scale farming systems”. *C. Bell & J. Prammer (Researchers), C. Eder, D. Kyd-Rebenburg, & J. Prammer (Eds.), Global growing casebook: Insights into African agriculture*, pp. 36–65.

Getahun, Addisu (2020). “Review on Smallholders Agricultural Commercialization in Ethiopia”.

Hadgu, Kiros Meles, Badege Bishaw, Miyuki Iiyama, Emiru Birhane, Aklilu Negussie, Caryn M. Davis, and Bryan Bernart (2019). “Climate-smart agriculture: enhancing resilient agricultural systems, landscapes, and livelihoods in Ethiopia and beyond”.

Haile, Kusse, Engida Gebre, and Agegnehu Workye (2022). “Determinants of market participation among smallholder farmers in Southwest Ethiopia: double-hurdle model approach”. *Agriculture & Food Security* 11.1, p. 18.

Hussein, Abdulbasit (2024). “Climate smart agriculture strategies for enhanced agricultural resilience and food security under a changing climate in Ethiopia”. *Sustainable Environment* 10.1, p. 2345433.

Jayne, Thomas S, Jordan Chamberlin, and Derek D Headey (2014). “Land pressures, the evolution of farming systems, and development strategies in Africa: A synthesis”. *Food policy* 48, pp. 1–17.

Kassie, Menale, Bekele Shiferaw, and Geoffrey Muricho (2011). "Agricultural technology, crop income, and poverty alleviation in Uganda". *World development* 39.10, pp. 1784–1795.

Maru, Molla, Mohammed Assen, Asnake Mekuriaw, and Arragaw Alemayehu (2023). "Land Use/Cover Dynamics and its Implication in Alwero Watershed, Western Ethiopia". *Proceedings of the National Academy of Sciences, India Section A: Physical Sciences* 93.2, pp. 377–389.

Mekonnen, Esubalew Nebebe, Shimeles Damene, Ephrem Gebremariam, and Alemu Nebebe (2023). "Geospatially-Based Land Use/Land Cover Dynamics Detection, Central Ethiopian Rift Valley". *GeoJournal* 88.3, pp. 3399–3417.

Njeru, Esther, S Grey, and E Kilawe (2016). "Eastern Africa climate-smart agriculture scoping study: Ethiopia, Kenya and Uganda".

Pretty, Jules N., Stella Williams, and Camilla Toulmin (2012). *Sustainable intensification: increasing productivity in African food and agricultural systems*. Routledge.

Quisumbing, Maria Agnes R. and Yisehac Yohannes (2005). *How fair is workfare?: Gender, public works, and employment in rural Ethiopia*. Vol. 3492. World Bank Publications.

Rapsomanikis, George (2015). "The economic lives of smallholder farmers".

Solomon, Negasi, Emiru Birhane, Mesfin Tilahun, Mark Schauer, Mewcha Amha Gebremedhin, Filmon Tquabo Gebremariam, Tesfay Gidey, and Solomon W. Newete (2024). "Revitalizing Ethiopia's highland soil degradation: a comprehensive review on land degradation and effective management interventions". *Discover Sustainability* 5.1, p. 106.

Spielman, David J., Dawit Kelemwork, and Dawit Alemu (2011). "Seed, fertilizer, and agricultural extension in Ethiopia". *Food and agriculture in Ethiopia: Progress and policy challenges* 74, p. 84.

Stellmacher, Till and Girma Kelboro (2019). "Family farms, agricultural productivity, and the terrain of food (In) security in Ethiopia". *Sustainability* 11.18, p. 4981.

Subbarao, Kalanidhi, Carlo Del Ninno, Colin Andrews, and Claudia Rodríguez-Alas (2012). *Public works as a safety net: design, evidence, and implementation*. World Bank Publications.

Were, Kennedy, Aweke Mulualem Gelaw, and Bal Ram Singh (2016). "Smart strategies for enhanced agricultural resilience and food security under a changing climate in sub-Saharan Africa". *Climate Change and Multi-Dimensional Sustainability in African Agriculture: Climate Change and Sustainability in Agriculture*, pp. 431–453.

Zerssa, Gebeyanesh, Debela Feyssa, Dong-Gill Kim, and Bettina Eichler-Löbermann (2021). "Challenges of smallholder farming in Ethiopia and opportunities by adopting climate-smart agriculture". *Agriculture* 11.3, p. 192.

Chapter 2

Enhancing Agricultural Productivity through Tailored Information on Conservation Practices: Evidence from Ethiopia

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(Ongoing work)[5]

Abstract

Using a set of multi-year randomized controlled trials conducted in Ethiopia, this study examines the impact of tailored, plot-specific information on conservation practices and their effects on agricultural land productivity in the medium term. The findings reveal that providing tailored information drives a notable increase in the uptake of sustainable farming practices, resulting in improved land productivity for maize farmers. The findings suggest that customized plot information targeting sustainable agricultural technologies reduces costs, substantially increases productivity for maize farmers, and is conducive to enhancing the welfare of the farmers. Hence, this approach presents a promising pathway for enhancing agricultural resilience and long-term welfare for maize-growing communities, particularly in regions with diverse plot-specific and agroecological conditions.

JEL Classification: Q56

Keywords: Conservation agriculture | Land productivity | Sustainability science | Randomized controlled trials

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[5] Two important notes about this paper. First, it was presented at several international conferences by: **(1) Gemeda Olani Akuma -** The 15^{th} EfD Annual Meeting 2021 - https://www.efdinitiative.org/events/efds-15th-annual-meeting; and **(2) Salvatore Di Falco:** (i) Nordic Conference in Development Economics 2023 - https://www.gu.se/en/school-business-economics-law/economics/our-research/research-areas/development-economics/nordic-conference-in-development-economics-ncde-2023; (ii) University of Chicago Advance with Fields Experiments Conference (September 22, 2023); (iii) Center for the Study of African Economies (CSAE) Conference, Oxford University, March 17, 2024, and at multiple seminars. Second, it has been circulated under various titles, including: "The Impact of Information on Technology Adoption and Productivity: A Randomized Controlled Trial in Rural Ethiopia", "What's Sustainability Worth? Evidence from Ethiopia", "Conservation Agriculture and Welfare: Experimental Evidence from Ethiopia", "Environmental Conservation Technology and Productivity: Evidence from Ethiopia", "Learning about Environmental Conservation Technologies: Evidence from Ethiopia", and "Welfare implications of Conservation Agriculture: Experimental Evidence from Ethiopia"(https://www.conservation.cam.ac.uk/events/cci-conservation-seminar-prof-salvatore-di-falco-joint-cciceenrg).

2.1 Introduction

Enhancing agricultural productivity while preventing land degradation is crucial for food security and sustainability in Sub-Saharan Africa. The interplay of stagnant crop yields and rising food demand drives agriculture to encroach on less fertile lands, accelerating soil degradation and perpetuating cycles of poverty and economic insecurity (Jayne et al., 2014; Barbier and Hochard, 2018; Barrett and Bevis, 2015). A low agricultural productivity hampers structural transformation, a key driver of economic development. For agriculture to support this process, it must generate surpluses that can stabilize urban wages and release labor from low-productivity rural sectors to more productive growth-oriented industries (Gollin et al., 2014; Bustos et al., 2016; Gollin, 2023; Barrett et al., 2022).

Conservation agriculture (CA), which combines no-till, residue retention, and crop rotation (a form of diversification), improves productivity, soil health, and moisture retention while reducing degradation and environmental impact, especially in dry, rainfed areas (Atwood et al., 2024; Mitchell et al., 2024; Saha et al., 2024; Teng et al., 2024; Bazrafkan et al., 2022; Su et al., 2021; Corsi and Muminjanov, 2019; A. Kassam et al., 2019). By preventing erosion, improving organic matter, and breaking pest cycles, CA supports long-term soil fertility and resilience (FAO, 2001; Farooq and Siddique, 2015; Pooniya et al., 2022; Pittelkow et al., 2015a; Pittelkow et al., 2015b; Evans et al., 2020; M. Jat et al., 2020). Hence, it is an innovative farming approach designed to regenerate soil health, increase productivity, and strengthen resilience and adaptive capacity in the face of climate variability and environmental challenges. A. Kassam et al. (2019) highlighted that while CA adoption has increased steadily recently, its expansion has been disproportionately concentrated in developed regions, while uptake in developing areas remains relatively limited. Despite its promising potential, the adoption of CA in Sub-Saharan Africa remains minimal, covering only 0.8% of cropland. Slow adoption is due to awareness gaps, uncertain benefits, delayed returns, and limited access to input. Socioeconomic and institutional barriers further limit uptake. As indicated in Pretty et al. (2012), the adoption of CA faces several barriers, including high initial costs, labor-intensive cover cropping, and the critical need for effective knowledge transfer through targeted training programs. Hence, targeted extension, training, and policies are essential to realize the sustainability and resilience potential of CA (Ambler et al., 2023; Arslan et al., 2022; Suri and Udry, 2022; Christian Thierfelder and Mhlanga, 2022; M. Jat et al., 2020; Pittelkow et al., 2015a; Abdulai and Huffman, 2014; Corbeels et al., 2014; Hobbs et al., 2008; World Bank, 2007). Unlike capital-intensive soil conservation technologies, such as water harvesting (Aker and Jack, 2023), CA requires the knowledge-intensive management of three interdependent practices. Although crop rotation is widely known, minimum tillage and residue management are new to many farmers.

This study investigates the impact of addressing information barriers on medium-term crop productivity. To investigate this, this study implemented a series of field experiments monitoring maize productivity among a diverse group of farmers in the Ethiopian highlands over five years (2015–2021). During this time, the study exogenously varied farmers' access to tailored CA information both spatially—by providing treatment to some farmers while others remained in a control group—and temporally—where some farmers received the information only once, others twice, and some never at all. This experimental design introduced random variation within a longitudinal panel data framework, enabling a robust causal analysis of how access to information influences agricultural productivity over time (Ferraro and Pattanayak, 2006; Ferraro and Hanauer, 2014a; Ferraro and Hanauer, 2014b; Barrett, 2021).

The study demonstrates that personalized information significantly accelerates the adoption of CA practices and enhances maize productivity in the medium term. Tailored guidance improves farmers' understanding and implementation of CA, strengthening agricultural resilience and food security. The findings underscore the critical role of context-specific information in overcoming adoption barriers, particularly in settings characterized by heterogeneous agro-ecological conditions such as soil fertility and terrain variability (Hobbs et al., 2008; World Bank, 2007; A. Kassam et al., 2009; Pittelkow et al., 2015a). Furthermore, this study highlights the importance of conducting long-term experiments in sustainability science. By tracking outcomes over multiple years, such studies can identify key factors such as yield stabilization, adaptation, and learning effects (Pittelkow et al., 2015a; Barrett, 2021). In complex, coupled human-natural systems, causal inference often requires long-term experiments to capture these dynamics, which cannot be fully understood through short-term observations alone (Ferraro et al., 2019).

The rest of the paper proceeds as follows. Section 2.2 offers a comprehensive overview of Conservation Agriculture, detailing its principles, applicability, inherent limitations, and the contextual experiences within Ethiopia. Section 2.3 discusses the context and experimental design. Section 2.4 provides data. Section 2.5 discusses the empirical strategy. Section 2.6 presents the results and discussion. Section 2.7 gives the concluding remarks.

2.2 Conservation Agriculture: Principles, Applicability, and Limitations

CA is an ecologically grounded farming approach that relies on three core principles: limiting soil disruption through reduced or zero tillage, preserving continuous soil cover using crop residues or living vegetation, and diversifying crops through rotations or intercropping. These interrelated practices contribute to better soil structure, improved water retention, and more effective nutrient use. By enhancing soil health and ecosystem stability, CA promotes durable productivity and greater resilience to climatic and environmental challenges (A. Kassam et al., 2019; Thierfelder and Wall, 2010).

The effectiveness of CA is highly dependent on crop type and agroecological context. Maize generally exhibits stronger yield responses due to its high sensitivity to enhanced soil conditions, whereas crops like wheat and tubers may derive fewer benefits or require context-specific modifications (Corbeels et al., 2014; Thierfelder and Wall, 2010). Adoption remains constrained by delayed agronomic returns, competing uses for crop residues, substantial initial labor and knowledge requirements, and limited suitability for certain crop types (Valbuena et al., 2012; Giller et al., 2009).

In Ethiopia, CA is incorporated into national policy frameworks, including the Climate Resilient Green Economy (CRGE) strategy and the Sustainable Land Management Program (SLMP), which aim to advance sustainable and climate-resilient agriculture. Nonetheless, adoption remains limited and spatially concentrated, primarily due to competing demands for crop residues, inadequate technical capacity, and the limited compatibility of key CA practices—such as residue retention and minimal tillage—with prevailing smallholder farming systems (L. Hailu and Teka, 2024; Z. Hailu and Teshome, 2022; A. Araya and Stroosnijder, 2010).

CA adoption in Ethiopia remains low due to institutional constraints. Key practices—such as reduced tillage, residue retention, and crop diversification—are relatively new to smallholders and often misaligned with traditional systems. Limited extension support, poor access to inputs and credit, and competing demands for crop residues further hinder uptake (Valbuena et al., 2012; T. Araya et al., 2011; Giller et al., 2009). Additionally, CA promotion lacks local adaptation and suffers from weak institutional coordination, while existing policies continue to favor conventional tillage (L. Hailu and Teka, 2024; Z. Hailu and Teshome, 2022).

While the short-term productivity gains of CA may be modest outside of maize-based systems, its core value lies in its capacity to improve soil health, prevent land degradation, and promote sustainable agricultural intensification over time (Giller et al., 2009). These long-term ecological benefits are particularly relevant in contexts facing soil fertility decline and climate variability. A clear understanding of the advantages and inherent limitations of CA is essential for designing context-specific adaptations and for informing strategies aimed at scaling its adoption effectively and sustainably.

2.3 Context and Experimental Design

2.3.1 Context

The motivation for the customized information experiment dates back to a survey conducted by the Nile Basin in 2013. The data collected mapped the extent of adoption of existing CA practices and evaluated the net farm incomes of plots with varying slopes and soil fertility levels. The experiment began in September 2015 to raise the historically low adoption rates of CA technologies. In doing so, reduce the gap between actual lower and potentially higher predicted net farm incomes based on the 2013 data from a randomly drawn sample of farm households growing major cereal crops and residing in randomly chosen 50 villages, one village from one *woreda* refers to a district-level administrative unit, typically comprising 9 to 15 kebeles or villages on average Abate et al. (2020).

A multi-stage random sampling strategy was implemented within the Ethiopian Blue Nile Basin to select study sites for the field experiment. In the first stage, 20 woredas were randomly selected from five regions intersecting the basin—Tigray, Amhara, Oromia, Benishangul-Gumuz, and Southern Nations, Nationalities, and Peoples' Region (SNNP)—forming the sampling frame. In the second stage, five villages were randomly drawn from each selected woreda, resulting in a total sample of 100 villages. This sampling design ensured geographic, agroecological, and socioeconomic representativeness while maintaining operational feasibility. The structure remained consistent across survey rounds, supporting longitudinal analysis.

The experimental design incorporated treatment and control groups, initially distributed across 15 of the 20 sampled woredas (see Figure 2.1 for locations). At baseline in 2015, the treatment group consisted of 5 woredas (25 villages), and the control group comprised 10 woredas (50 villages). In 2016, five additional woredas and 25 villages were reassigned from the control to the treatment group, reversing the allocation: 10 woredas (50 villages) received the intervention, while 5 woredas (25 villages) served as controls. This design enabled comparative analysis of treatment effects while retaining the original sample for panel data purposes.

The 20 selected woredas and 100 villages span diverse agroecological zones, rainfall patterns, farming systems, and irrigation practices, ensuring broad representativeness of Ethiopia's agricultural landscapes. Reflecting dominant land-use and agroecological classifications across the five regions, this diversity provided a suitable context for a tailored information intervention targeting farm households. The experiment promoted the adoption of CA practices—minimum tillage, crop residue management, and crop rotation—implemented individually or in combination.

As argued by Ferraro and Agrawal (2021), harmonized experiments using RCTs across multiple sites enhance both internal and external validity and reduce biases commonly associated with small-scale observational studies. The design adopted here aligns with this approach, leveraging Ethiopia's ecological and institutional heterogeneity to generate policy-relevant insights on the adoption and effectiveness of sustainable agricultural practices.

2.3.2 Experimental Design

The experiment assesses the impact of tailored information on CA practices to improve land productivity and farmers' welfare, benefiting both households and the broader community. Although the technologies differ, this study employs a technological learning framework similar to that of Hanna et al. (2014), who showed that providing farmers with information on technology returns—supplemented by individual-specific yield data—can drive behavioral change and increase adoption.

In this study, net farm incomes were projected for plots with specified characteristics, assuming full adoption of recommended CA practices, including minimum tillage, crop

Fig. 2.1 Locations of sample households in treatment and control villages

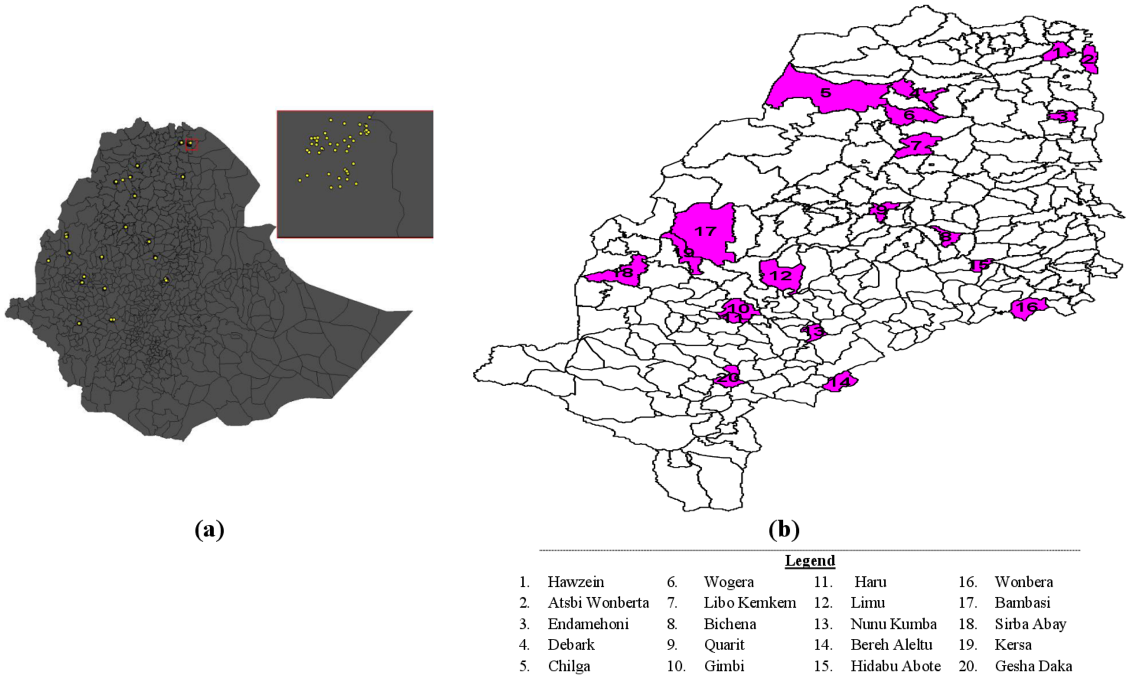


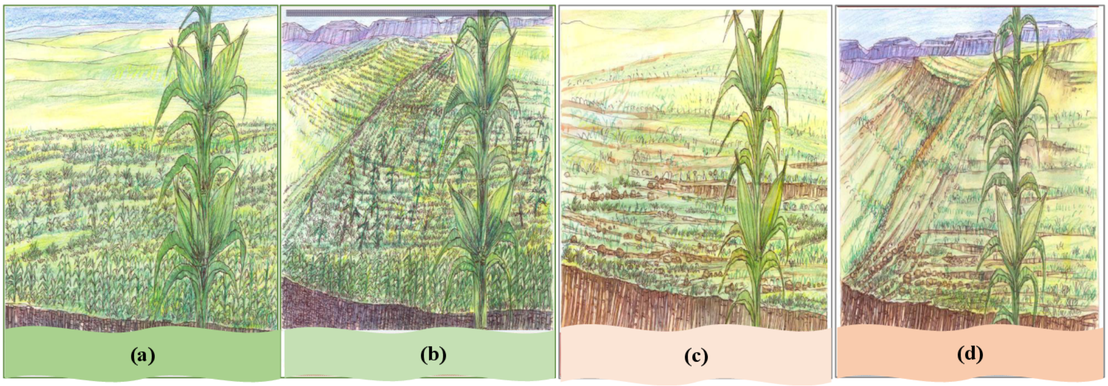
Figure 2.1 presents the geographic distribution of the sample villages across 20 woredas in the Ethiopian Blue Nile Basin, covering a total of 100 villages surveyed during the 2015–2017 period. The woredas are listed at the bottom of the figure under Panel (b). Panels (a) and (b) illustrate the spatial distribution of these villages across the five regions intersecting the basin: Tigray, Amhara, Oromia, Benishangul-Gumuz, and SNNP. In Panel (a), yellow dots indicate the locations of the sampled woredas. In the subsequent follow-up surveys conducted in 2019 and 2021, the sample was expanded to include 35 woredas by incorporating 15 additional woredas across various regions. These newly included woredas are Tarma-ber, Dera, Dembia, Gidan, Efrata-ena-Gidim, Menge, Guto Gida, Ejere (Adis Alem), Sasiga, Wayu Tuka, Gobu Seyo, Jeldu, Goma, Wuchale, and Endegagn. This expansion aimed to enhance the geographic and agroecological coverage of the study, thereby increasing the external validity of the analysis and allowing for a more comprehensive assessment of the intervention across diverse farming systems and environmental conditions.

residue retention, and legume-based crop rotation. The intervention was implemented at the village level, providing tailored information to farmers based on their partial or non-adoption of these practices.

Although Hanna et al. (2014) focused on raising seaweed farmers' awareness of a specific, previously unrecognized productivity factor (pod size), both studies share the common objective of addressing information gaps that constrain adoption decisions. Both utilize targeted information interventions to improve farmers' understanding of key factors influencing productivity and technology adoption. Thus, the fundamental similarity lies in employing information provision as a behavioral catalyst to overcome knowledge constraints and stimulate the adoption of beneficial agricultural technologies, ultimately enhancing productivity and livelihoods.

The tailored information intervention focused on achieving full adoption of three CA practices, motivated by the observed benefits, particularly in net farm income, resulting from full adoption compared to partial or no adoption. The experiment, conducted in two phases before each cereal crop planting season, assessed adoption rates for each household to provide tailored information. Encouraging farmers to adopt these practices targets to increase farm incomes and land productivity, often surpassing projected values based on each farm plot's slope and soil fertility characteristics, as shown in the posters in Figure 2.2, and detailed in Appendix A Figures A.1 (written information) and A.2 (visual information), along with estimated net incomes across various farm plots.

Fig. 2.2 Tailored information posters



In Figure 2.2, tailored information communication focuses on farm plot characteristics such as steepness and soil fertility in cereal crop cultivation. The four panels depict plots with varying soil fertility and landscape/slope, showing the potential percentage changes in target outcomes after adopting the recommended CA practices. Panel (a) represents fertile soil with a flat landscape, panel (b) shows a fertile, steep plot, panel (c) illustrates a less fertile, flat plot, and panel (d) depicts a less fertile, steep plot.

The present study employs a plot-specific treatment design (see Figure 2.2 and Appendix A, Figures A.1 and A.2, pages 144 and 145, respectively) that explicitly accounts for variations in landscape features and soil fertility. This approach enables the targeted promotion of tailored CA practices to increase agricultural productivity and improve environmental sustainability at the micro-level. By integrating biophysical heterogeneity into the treatment assignment, the study aims to generate more precise estimates of the benefits associated with context-specific CA adoption, thereby enhancing the relevance and effectiveness of recommended practices across diverse agroecological conditions.

The four sets of posters used in the intervention conveyed tailored information based on key plot characteristics—soil fertility and slope, which are critical determinants of agricultural productivity and management practices. Specifically, the posters depicted four categories: fertile-flat, fertile-steep, less fertile-flat, and less fertile-steep plots. Each visual illustrated the recommended CA practices most suitable for those specific conditions, such as minimum tillage, crop residue retention, and crop rotation, alongside their anticipated benefits.

To enhance farmers' understanding and motivation, the posters presented projected net benefits of adopting Conservation Agriculture practices across four plot types categorized by soil fertility and slope (fertile-flat, fertile-steep, less fertile-flat, and less fertile-steep). These projections were derived from modeled estimates of yield gains and cost savings, calibrated using 2013 household survey data from a separate study in the Ethiopian Blue Nile Basin. The estimated percentage changes in benefits were corroborated by peer experiences, ensuring the information was evidence-based and locally relevant.

Tailored information was disseminated based on key farm characteristics—soil fertility and plot topography—to address knowledge gaps through practical, context-specific recommendations. This approach aligns with behavioral economics principles that suggest personalized and relatable information enhances comprehension and uptake. By framing the benefits of CA adoption in terms familiar to farmers' land conditions, the intervention sought to promote broader and more informed adoption of sustainable practices across diverse farming systems.

To enhance accessibility and inclusivity, the information was disseminated through both written and visual formats, ensuring effective communication across diverse literacy levels. It was prepared in three languages, namely Amharic, Afan Oromo, and Tigrigna, to facilitate comprehension and engagement among farmers in their native languages. Additionally, farm-specific recommendations were translated into English, with the corresponding written information presented in Appendix A, Figure A.1 on page 144, while the visual representation in Amharic is provided in Appendix A, Figure A.2 on page 145.

Farm households were encouraged to adopt the recommended technologies most relevant to their specific plots through tailored information. Posters effectively convey tailored information on recommended CA technologies, using clear visuals to help farmers understand and adopt the practices. This approach also allows for comparison with past results, aiding the assessment of the intervention's impact and progress over time. The process effectively summarizes the benefits to farmers by detailing the percentage increase in net farm incomes per hectare that results from the full adoption of suggested CA practices. This approach provides clear insights into the financial impact of these practices on farmers' productivity. Furthermore, control farmers reside in 25 villages, geographically distinct from the 25 treatment villages. These control farmers did not receive any tailored information or plot-level poster demonstrations, allowing for a clear comparison between those exposed to the intervention and those who were not.

Fig. 2.3 Tailored information rollout schedule for maize growers

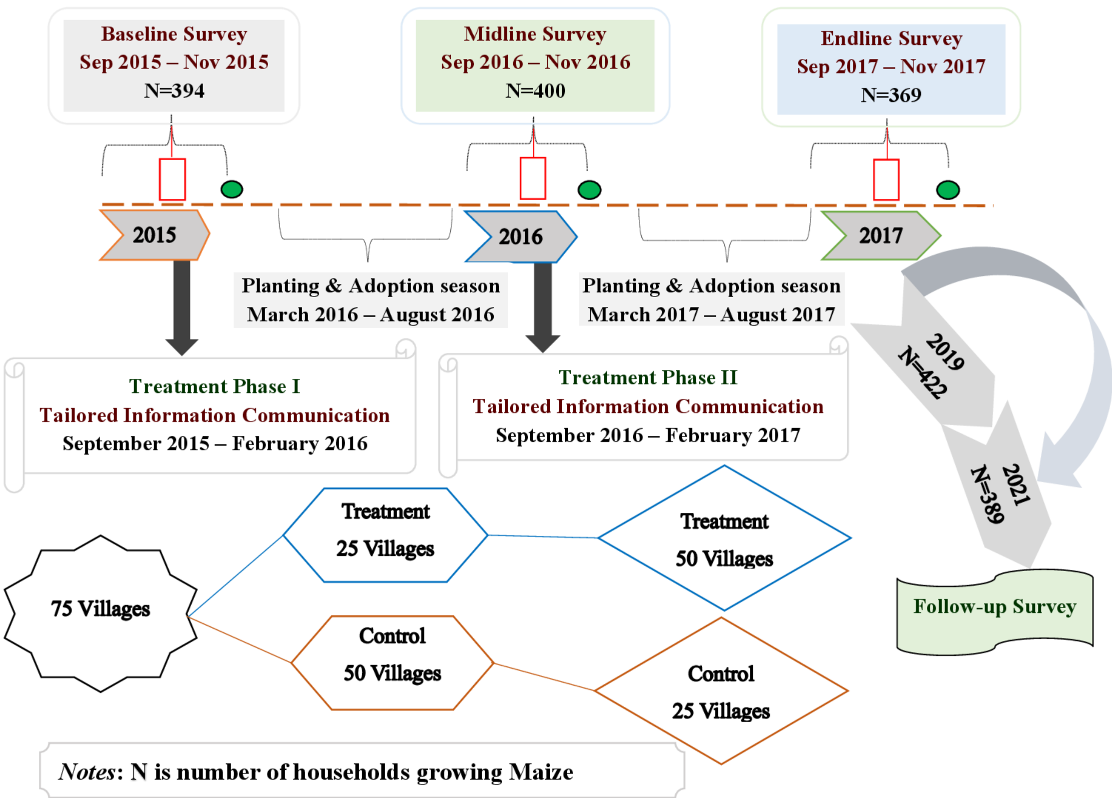


Figure 2.3 illustrates the activity timeline designed to promote the adoption of recommended CA practices through targeted information delivery for maize farmers. The planting and adoption period runs from March to August, followed by harvest, typically from November to January.

Figure 2.3 presents the timing and implementation of the activities in the experiment for maize-growing farm households. The number of maize producers fluctuates across survey years as farmers implement crop rotation, a key CA practice (Giller et al., 2009; Pittelkow et al., 2015a). Driven by soil fertility, markets, inputs, and climate variability, crop rotation and diversification strategies sustain yields, enhance soil health, and reduce environmental and economic risks (A. H. Kassam et al., 2016). Consequently, rather than specializing in maize cultivation, farmers adapt their cropping decisions dynamically, selecting cereal crops based on prevailing conditions. This adaptability results in variations in the number of maize growers over time, as shown in Figure 2.3.

The intervention in each agricultural production season consists of two main periods with distinct activities. The first involves a tailored information communication period in the first six months of an agricultural season, September to February. The second period consists of the next six months, March to August, of the crop production season, when farmers are engaged in planting and adoption activities. The tailored information communication also overlaps with the survey periods, during which farmers visited twice during the pre-harvest and post-harvest agricultural production seasons. This allows us to notice the adoption of CA practices when they are most visible. Hence, our fieldwork spanned from September to February across multiple seasons, involved in the tailored information delivery experiment, covering the years 2015 (Baseline and first phase treatment), 2016 (Midline), 2017 (Endline), and follow-up surveys in 2019 and 2021. The livestock questionnaire and post-planting visit were conducted from September to November, while the household and post-harvest agriculture questionnaires were administered from December to February, aligning with the recording of agricultural output data.

2.4 Data

2.4.1 Survey Design and Administration

This section provides an overview of the household survey that underpins the empirical analysis in this study. The data were collected through a structured panel survey implemented in collaboration with the Ethiopia Policy Studies Institute (PSI), formerly the Ethiopian Development Research Institute (EDRI), with financial support from the Swiss National Science Foundation. The survey aimed to evaluate how targeted information provision influences the adoption of CA practices and their effects on productivity among smallholder farmers.

To capture Ethiopia's agro-ecological diversity, the survey used woreda- and village-level stratified sampling, enhancing external validity and enabling analysis of heterogeneous impacts. It combined experimental variation in information provision with panel data to estimate the medium-term effects of CA adoption. The focus on information reflects evidence of its importance as a behavioral and institutional constraint. The author contributed to data analysis and interpretation but was not involved in the survey's design or implementation.

The baseline survey, first-phase treatment, second-phase treatment, and endline survey were conducted in 2015, 2016, and 2017, respectively, with follow-up rounds administered in 2019 and 2021. The detailed timeline and implementation of the experimental design are presented in Figure 2.3. By integrating experimental variation in information exposure with longitudinal household data, the survey enables credible estimation of the medium-term impacts of CA adoption on both uptake and productivity. The comprehensive and context-sensitive design of the survey provides a strong basis for causal inference and offers valuable evidence to inform policy and practice in sustainable agriculture.

2.4.2 Baseline Balance Checks

Table 2.1 primarily draws from the baseline household survey of the Blue Nile Basin, providing insights into agricultural practices and socio-economic conditions. The intervention includes three-panel waves (2015–2017) and two follow-up surveys (2019, 2021) for longitudinal impact analysis. A rapid baseline survey was conducted alongside the first treatment phase (Sept-Dec 2015), followed by an end-line assessment in 2017 to evaluate initial outcomes. The experiment spanned two agricultural seasons, allowing consideration of variations in weather, soil conditions, and farming practices across diverse environments. Follow-up surveys in 2019 and 2021 helped examine long-term impacts, track progress, and refine subsequent interventions. Figure 2.3 outlines the timeline and key activities of the experiment.

The data includes information on CA adoption, maize production, household characteristics, resource endowments, and over 30 years of climate data from CHIRPS. Follow-up surveys in 2019 and 2021 with the same households assessed farmers' knowledge and implementation of CA practices, allowing for long-term impact analysis. These surveys examined technology adoption, recall of informational materials, and behavioral changes over six years, offering insights into the dynamic effects of tailored information on adoption, productivity, and well-being.

Table 2.1 presents the baseline balance checks for the outcome variable and additional controls. The primary focus is on evaluating the impact of the full CA adoption on maize land productivity. Full CA adoption is a binary variable, with "1" indicating the adoption of all three CA practices (minimum tillage, crop rotation, and crop residue retention) in treatment villages and "0" indicating no adoption in control villages. The comparison groups are "full adopters in treatment villages" versus "non-adopters in control villages." Maize land productivity is measured as the ratio of total yield (quintals) to plot area (hectares). CA practices are particularly effective for maize among the five cereals.[6]

Table 2.1 Baseline balance checks

	Full Sample	Treatment	Control	Mean Difference
	(1)	(2)	(3)	(4)
Maize land productivity (quintal/ha)	29.053	28.538	30.215	-1.677
	(19.34)	(19.19)	(19.71)	(2.113)
CA partial adoption (1=yes)	0.896	0.886	0.917	-0.031
	(0.306)	(0.318)	(0.276)	(0.033)
CA full adoption (1=yes)	0.056	0.059	0.050	0.009
	(0.230)	(0.235)	(0.218)	(0.025)
Gender (1=Male)	0.858	0.850	0.876	-0.026
	(0.350)	(0.358)	(0.331)	(0.038)
Household size (number)	6.505	6.385	6.777	-0.392
	(2.239)	(2.198)	(2.315)	(0.244)
Average age (years)	25.452	24.948	26.588	-1.640
	(9.493)	(9.236)	(9.996)	(1.035)
Highest education (years)	8.036	7.846	8.463	-0.617*
	(3.405)	(3.487)	(3.183)	(0.371)
Non-farm income (1=yes)	0.236	0.223	0.264	-0.041
	(0.425)	(0.417)	(0.443)	(0.046)
Credit access (1=yes)	0.482	0.440	0.579	-0.139**
	(0.500)	(0.497)	(0.496)	(0.054)
Tenure security (1=yes)	0.741	0.799	0.612	0.187***
	(0.439)	(0.402)	(0.489)	(0.047)
Migration (1=yes)	0.424	0.414	0.446	-0.032
	(0.495)	(0.493)	(0.499)	(0.054)
Observations	394	273	121	394

The standard errors are in parentheses, and asterisks indicate significance at the * 10%, ** 5%, & *** 1% levels.

Control variables include household characteristics (such as gender, household size, average age, and highest education level), economic and social factors (including non-farm income, access to credit, tenure security, and migration status), and the area of maize plots to measure land productivity. Village-level factors, such as average rainfall during the summer, spring, and across all seasons, are included to account for climatic influences. These variables enable the assessment of the impact of CA practices by controlling for external factors.

The differences in most control variables between farmers in the treatment and control villages (shown in column (4) of Table 2.1) are small and statistically

[6] The five main cereal crops include maize, wheat, teff, barley, and sorghum.

insignificant, indicating that the groups are comparable. However, there are a few exceptions: farmers in treatment villages tend to have lower education levels and less access to credit, with significant differences at the 10% and 5% levels, respectively. These disparities, likely reflecting pre-existing conditions, are vital to consider as they could influence the adoption and effectiveness of CA practices.

On the other hand, farm households in the treatment villages exhibit greater tenure security for their plots, with the mean difference being statistically significant at the 1% level. This increased tenure security promotes sustainable practices like CA, as secure land rights are typically associated with a greater willingness to invest in long-term land improvement. These differences highlight the importance of factoring in tenure security, as this existing situation could influence both CA adoption and productivity outcomes.

2.5 Empirical Strategy

2.5.1 Tailored Information

Tailored information for CA offers personalized guidance based on farmers' unique conditions. Research highlights the importance of context-specific strategies and experimental designs in boosting CA adoption. However, no long-term study has concurrently assessed CA adoption and its economic impact. Such research could provide vital insights into CA's effects on productivity and broader economic outcomes, helping policymakers promote sustainable farming practices.

Studies show that context-specific information enhances CA adoption. Giller et al. (2009) found that farmers adopt CA more with tailored advice, while Gibbon (2012) emphasized the importance of designing knowledge transfer to suit local conditions to overcome skepticism and knowledge gaps.

Moreover, tailored information is crucial for maximizing CA benefits. Pittelkow et al. (2015a) showed that context-specific guidance improves outcomes like soil fertility and moisture retention, boosting adoption and ensuring sustainability across different settings. In conclusion, it helps overcome barriers and adapts CA practices to local conditions.

RCTs using tailored information are crucial for estimating CA adoption and its economic benefits by providing plot-specific, personalized guidance to overcome adoption barriers and enhance recommendation relevance. A framed field experiment in northern Ghana evaluated strategies to promote CA adoption. The results showed that incentives significantly boosted adoption during and after their provision, while peer information had no significant effect (Ambler et al., 2023). Additionally, a non-experimental study in Southern Africa used a multivariate probit model and other methods to analyze data from thousands of households, identifying key drivers and barriers to CA adoption. Despite its benefits, smallholder adoption remained low, highlighting the need for tailored strategies (Tufa et al., 2023).

Therefore, this experimental study contributes to the literature by offering a tailored, personalized approach to promoting CA adoption and its effects on agricultural productivity. By focusing on plot-specific factors like soil type, slope, resources, and agroecological conditions, it offers evidence-based recommendations to enhance the adoption of CA practices. The study encourages sustainable practices like no-till farming, crop rotation, and residue management, which improve productivity, soil health, and climate resilience, supporting long-term regional and broader sustainability.

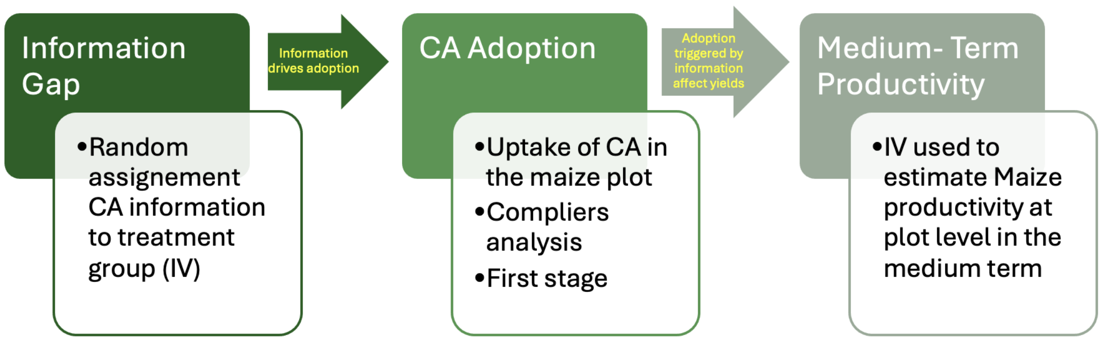
2.5.2 Method

Various sources highlight the crucial role of randomization in reducing selection bias and strengthening causal inference in Randomized Controlled Trials (RCTs). As the most rigorous method for establishing causality, RCTs eliminate baseline selection bias by randomly assigning subjects to treatment and control groups (Imbens and Rubin, 2015; Alexander et al., 2015) and additionally provide the most robust scientific evidence for policy and practice, overcoming spurious causality and bias (Schulz and Grimes, 2002). This ensures that the only systematic difference between treatment and control groups is the treatment itself.

In observational conservation studies, factors like soil fertility, farmer abilities, and institutional influences can bias treatment effect estimates. Randomization helps identify effective conservation practices by isolating treatment effects from these confounders. RCTs are essential for establishing causal relationships in human-natural systems and evaluating conservation policies (Ferraro et al., 2019). Without causal inference, sustainability efforts may misidentify drivers of environmental change, misallocate resources, and implement ineffective policies with unintended consequences. As such, RCTs provide rigorous estimates that clarify the effectiveness of interventions in complex systems (Ferraro and Hanauer, 2014a).

Reduced-form analyses alone are insufficient for establishing causality in sustainability science. To understand interventions' impact, we must examine the pathways to medium- and long-term outcomes, requiring a design that identifies causal effects and explores underlying mechanisms. Additionally, follow-up monitoring is crucial for capturing outcomes over time and obtaining medium- and long-term estimates. This design not only deepens our understanding but also strengthens sustainability strategies. Thus, the research should incorporate a causal framework that clarifies the pathways from intervention to outcome (Pittelkow et al., 2015a; Ferraro and Hanauer, 2014a; Ferraro et al., 2019; Barrett, 2021). As illustrated in Figure 2.4, this approach ensures a comprehensive analysis of both mechanisms and causal pathways.

Fig. 2.4 Research Design and Causal Framework



Instrumental Variables (IV) and Intent-to-Treat (ITT) are key methods in experimental design for addressing non-compliance. IV uses an external variable to estimate causal effects despite non-compliance, while ITT analyzes participants based on their original treatment group, preserving randomization and providing unbiased estimates. Both methods ensure accurate causal inference in studies with imperfect compliance. Using ITT and IV methods in conservation agriculture research ensures robust, unbiased intervention evaluations, offering valuable policy insights.

The ITT principle is crucial in research areas like conservation agriculture, where accurately evaluating treatment effects is essential. It ensures unbiased estimates by analyzing participants based on their original group assignments, regardless of adherence. ITT preserves randomization, reduces biases from non-compliance and dropouts, and enhances the generalization of findings for real-world policy decisions. This method strengthens causal inference by preventing biases from self-selection, attrition, or non-compliance, making results more reliable for policy applications

(Pathak et al., 2024; Molero-Calafell et al., 2024; Ahn and Kang, 2023).

In RCTs, non-compliance can bias treatment estimates, and IV methods strengthen causal inference by addressing unmeasured confounding (Bastardoz et al., 2023). IV techniques use external variables that influence treatment assignment but not outcomes, estimating causal effects among compliers. IV methods are applied in conservation programs to manage non-compliance and confounding. They estimate the Local Average Treatment Effect (LATE), with randomization acting as an IV (Cook et al., 2018; Brookhart et al., 2010). Additionally, Richardson et al. (2023) highlights IV's role in trials with nonadherence, offering methods that do not rely on the exclusion restriction assumption. When non-compliance is significant, random assignment can serve as an IV to estimate LATE, mitigating selection bias and endogeneity. This two-stage least squares (2SLS) approach uses treatment assignment as an exogenous instrument for actual treatment uptake. IV methods not only correct for non-compliance but also reveal the mechanisms of causality, particularly in contexts with around 60% compliance. IV uses exogenous variation in treatment assignment to clarify direct and indirect effects, enhancing policy insights and program design.

In the analysis, the study applies both specifications. The ITT estimate is:

$$ITT = \frac{1}{N} \sum_{n=1}^{\infty} (Y_i(traetment) - Y_i(control)) \tag{2.1}$$

Where N is the number of participants and Y_i and Y_i represent the observed outcomes in treatment and control groups.

To conduct an IV estimate, we follow these steps:

Step 1: Choose the Instrument (Z): In an RCT, treatment assignment (randomized encouragement or ITT) serves as a natural instrument, impacting treatment receipt but affecting the outcome only through treatment.

Step 2: Check Instrument Validity:

Relevance: The instrument must strongly predict the treatment received, verified by the first-stage regression:

$$T_i = \pi_0 + \pi_1 Z_i + \varepsilon_i \tag{2.2}$$

In Equation 2.2, T_i represents the actual treatment received, while Z_{it} denotes the assigned treatment.

Exogeneity (Exclusion Restriction): The instrument should affect the outcome only through treatment, not other pathways.

Step 3: Estimate Treatment Effect (Second Stage): Using Two-Stage Least Squares (2SLS): Stage 1: Predict actual treatment using assignment:

$$\hat{T}_i = \pi_0 + \pi_1 Z_i + \varepsilon_i \tag{2.3}$$

Stage 2: Use predicted treatment to estimate the outcome:

$$Y_i = \beta_0 + \beta_1 \hat{T}_i + u_i \tag{2.4}$$

Here, β_1 in Equation 2.4 represents the IV estimate of the Local Average Treatment Effect (LATE).

Step 4: Interpret Results: The IV estimate corrects non-compliance bias but applies only to compliers.

Equations 2.5 and 2.6 present the ITT and IV estimates. Equation 2.5 captures the overall effect on maize productivity for all farmers, while Equation 2.6 isolates the causal impact for adopters, offering a focused evaluation of the intervention's effectiveness. Together, they provide a complete view of the intervention's impacts.

$$ln(Productivity)_{it} = \beta_0 + \gamma Treat_{it} + \beta_i X_{it} + \eta_t + \mu_i + \epsilon_{it} \tag{2.5}$$

$$ln(Productivity)_{it} = \beta_0 + \delta Assign_v + \beta_i X_{it} + \eta_t + \mu_i + \epsilon_{it} \tag{2.6}$$

$Treat_{it}$ denotes full adoption of all three CA elements (minimum tillage, crop rotation, and crop residue retention) by household i at time t, taking a value of 1 if adopted and 0 otherwise. $Assign_v$ represents the random treatment assignment to village v and serves as an instrument for CA uptake in the ITT equation. The ITT and IV impact estimators are γ and δ, respectively. β_i are coefficients for household characteristics $X's$ to enhance treatment effect precision. η_t and μ_i account for time-specific and household-level variations, respectively, while ϵ_{it} is the random error term. All estimations use robust standard errors clustered at the district level.

2.6 Results and Discussion

2.6.1 Main Results

2.6.1.1 Effects of Treatment on CA Adoption among Maize Farmers

Table 2.2 presents the first-stage estimation, examining the impact of the treatment on the adoption of CA among maize farmers. This analysis provides insights into how exposure to tailored information and support influences farmers' decision-making and uptake of CA practices.

Table 2.2 Tailored information and CA adoption for maize growers

	T=1 (2015)		T=2 (2015 & 2016)		T=3 (2015-2017)		T=5 (2015-2021)	
Dept var: CA uptake (1=yes)	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Treatment	0.165***	0.143***	0.384***	0.395***	0.493***	0.462***	0.533***	0.473***
	(0.052)	(0.053)	(0.033)	(0.033)	(0.025)	(0.025)	(0.018)	(0.018)
HH head gender		0.032		-0.025		0.013		0.009
		(0.061)		(0.045)		(0.036)		(0.028)
Household size		-0.035***		-0.014*		-0.017***		-0.017***
		(0.012)		(0.009)		(0.007)		(0.005)
HH highest education		0.019***		0.014***		0.008*		0.003
		(0.007)		(0.005)		(0.004)		(0.003)
HH average age		-0.003		-0.002		-0.003*		-0.003***
		(0.003)		(0.002)		(0.001)		(0.001)
Off-farm income		-0.016		-0.002		-0.018		0.025
		(0.047)		(0.034)		(0.028)		(0.019)
Credit access		0.080**		0.069**		0.036		0.021
		(0.040)		(0.029)		(0.024)		(0.017)
Tenure security		-0.147***		-0.122***		-0.096***		-0.124***
		(0.048)		(0.036)		(0.030)		(0.026)
Migration		0.005		-0.017		-0.027		-0.035*
		(0.042)		(0.030)		(0.025)		(0.018)
Average rainfall (summer)		-0.001**		0.002***		0.002***		0.003***
		(0.001)		(0.000)		(0.000)		(0.000)
Average rainfall (spring)		-0.000		-0.001**		-0.001**		-0.002***
		(0.001)		(0.001)		(0.000)		(0.000)
Year (reference year=2015)								
2016			0.391***	0.399***	0.371***	0.383***	0.363***	0.384***
			(0.030)	(0.029)	(0.028)	(0.028)	(0.027)	(0.026)
2017					0.303***	0.318***	0.289***	0.317***
					(0.029)	(0.030)	(0.028)	(0.028)
2019							0.386***	0.288***
							(0.027)	(0.033)
2021							0.290***	0.299***
							(0.028)	(0.029)
Constant	0.178***	0.750***	0.137***	-0.096	0.117***	-0.054	0.109***	-0.216***
	(0.022)	(0.176)	(0.021)	(0.126)	(0.020)	(0.100)	(0.019)	(0.079)
Additional controls	—	✓	—	✓	—	✓	—	✓
Number of observations	394	394	794	794	1163	1163	1974	1974
F-value	10.012	4.868	196.058	37.426	255.721	64.261	269.925	108.000
Prob > F	0.002	0.000	0.000	0.000	0.000	0.000	0.000	0.000
R-squared	0.025	0.123	0.331	0.365	0.398	0.421	0.407	0.453

In all instances, the regression analysis utilizes pooled ordinary least squares (POLS). Standard errors in parentheses. * 10%, ** 5%, & *** 1%.

Specifically, Table 2.2 presents four estimations assessing the impact of tailored information on CA adoption over one to five seasons. With full controls, adoption rates range from 0.143 to 0.473, a significant difference at the 1% level. Hence, this highlights the importance of tailored information in promoting CA practices. By including time as a control variable, the analysis isolates the true impact of the intervention, providing insights into how tailored information drives CA adoption over time.

Appendix Table A.1 also presents the first-stage estimation of CA practice adoption across all five major cereal crops, including maize. The results show that the treatment positively impacts adoption rates for all crops, not just maize, highlighting the intervention's effectiveness across diverse cereals. This consistency underscores the robustness of tailored CA information as a strategy for improving agricultural productivity and sustainability, regardless of crop type.

2.6.1.2 Treatment Effects on Maize Productivity

The decision to begin with maize reflects strong empirical evidence that it responds more consistently and positively to CA than other cereals. This is mainly due to its physiological traits and greater sensitivity to improvements in soil moisture, nutrient availability, and structure—benefits amplified under CA in rainfed and drought-prone areas (Zerihun et al., 2014; Christian Thierfelder et al., 2013; Thierfelder and Wall, 2010). A. Kassam et al. (2019) also notes that maize's longer growing season and responsiveness to soil water conservation make it particularly well-suited to CA. Thus, the analysis starts with maize to capture the core productivity effects of CA systems.

Table 2.3 presents the estimates of the IV and ITT impacts of fully adopting CA practices on maize land productivity. The results show that households implementing CA practices consistently achieve higher productivity than those in control villages, highlighting the positive effect of CA on agricultural productivity and sustainability. Specifically, on average, maize-growing households in the treatment group harvested about 18% more maize yield than control households, exceeding the baseline control average of 2,994 kg/ha, which is evidence of increased productivity.

In particular, Table 2.3 presents the IV estimates in columns (1)-(4) and the corresponding ITT estimates in columns (5)-(8), all following a similar structure of control variables. Columns (1) and (5) represent baseline regressions, including the treatment variable, household, and time-fixed effects. Columns (2) and (6) expand the

Table 2.3 Conservation Practices & Maize Land Productivity: IV & ITT Estimates

	Dependent variable: ln(Maize land productivity)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Treatment: IV	0.169**	0.173**	0.177**	0.182***				
	(0.072)	(0.072)	(0.069)	(0.067)				
Treatment: ITT					0.098**	0.100**	0.102**	0.105***
					(0.041)	(0.042)	(0.040)	(0.039)
Household FE	✓	✓	✓	✓	✓	✓	✓	✓
Time FE	✓	✓	✓	✓	✓	✓	✓	✓
Additional controls	—	✓	✓	✓	—	✓	✓	✓
Improved seed	—	—	✓	✓	—	—	✓	✓
Avg. rainfall (mm) (summer & spring)	—	—	—	✓	—	—	—	✓
Number of observations	1962	1962	1962	1962	1962	1962	1962	1962

Source: Nile Basin five-wave panel data: 2015, 2016, 2017, 2019, 2021.
The regressions include IV estimates based on random village assignments within a district. Columns (1) and (5) show baseline regressions with the treatment variable, household, and time-fixed effects. Columns (2)–(4) report IV estimates with varying controls, while Columns (6)–(8) present ITT estimates with a similar control structure. Controls include household size (number), average age (years), highest education (years), improved seed use, CA partial practice, non-farm income, credit access, tenure security, and migration status (all dummies except where noted in the bracket). Constants are not reported. District-level multi-way clustered robust standard errors are in parentheses. Statistical significance: * 10%, ** 5%, & *** 1%.

model by adding additional control variables. Columns (3) and (7) incorporate improved seed adoption as a control to examine whether technology adoption drives productivity improvements more than the treatment variable. Finally, columns (4) and (8) include full specifications of controls by adding average rainfall as an additional control, providing a more comprehensive understanding of the factors influencing productivity.

Furthermore, the long-term impact of the intervention remains substantial, with instrumented average maize productivity consistently about 17% to 18% higher in treatment villages compared to control villages, even after accounting for various control variables. These results demonstrate the intervention's effectiveness in enhancing productivity over time, and the findings remain robust with the inclusion of additional controls, reinforcing the reliability of the observed impact. These enduring improvements in productivity suggest the intervention's substantial role in building resilience and fostering sustainable maize production practices. The continued productivity increases enhance food security and contribute to long-term agricultural stability, safeguarding the livelihoods of participating households. As a result, this sustained productivity increase drives the economic well-being of farmers while paving the way for a more stable and prosperous future, fostering broader community development and long-term sustainability.

Robustness checks validate the impact estimates of tailored information on technology adoption and land productivity among maize farmers, with results remaining consistent after controlling for extensive covariates and fixed effects.

2.6.2 Evidence on Differential Cereal Crop Responses

The subsequent analysis across all cereal crops is not a robustness check but a complementary assessment to evaluate whether CA benefits extend beyond maize. While maize is often cited as the most responsive crop to CA, the comparable or greater effects observed on other cereals in this study indicate significant heterogeneity in crop-level responses.

Table 2.4 presents the estimated impacts of the treatment on agricultural productivity across all cereal crops, including maize. On average, treatment households harvested 19% more cereal crops than control households, surpassing the baseline control mean of 2,459 kg/ha, highlighting the lasting impact of tailored information interventions on productivity. The results align closely with those observed for maize-growing farmers, indicating that the intervention's effect is not limited to a single crop but extends to other cereals. The estimations follow the same rigorous structure, incorporating both control variables, IV, and ITT estimation approaches, ensuring consistency and robustness in the findings.

Table 2.4 Conservation Practices & Land Productivity: IV & ITT Estimates for all Cereals

	Dependent variable: ln(land productivity) - all cereals							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Treatment: IV	0.184***	0.179**	0.180**	0.190**				
	(0.069)	(0.076)	(0.076)	(0.075)				
Treatment: ITT					0.118***	0.115**	0.115**	0.122**
					(0.044)	(0.049)	(0.048)	(0.048)
Household FE	✓	✓	✓	✓	✓	✓	✓	✓
Time FE	✓	✓	✓	✓	✓	✓	✓	✓
Additional controls	—	✓	✓	✓	—	✓	✓	✓
Improved seed	—	—	✓	✓	—	—	✓	✓
Average rainfall (mm) (all seasons)	—	—	—	✓	—	—	—	✓
Number of observations	3181	3174	3174	3174	3181	3174	3174	3174

Source: Nile Basin five-wave panel data: 2015, 2016, 2017, 2019, 2021.
The regressions include IV estimates based on random village assignments within a district. Columns (1) and (5) show baseline regressions with the treatment variable, household, and time-fixed effects. Columns (2)–(4) report IV estimates with varying controls, while Columns (6)–(8) present ITT estimates with a similar control structure. Controls include household size (number), average age (years), highest education (years), improved seed use, CA partial practice, non-farm income, credit access, tenure security, and migration status (all dummies except where noted in the bracket). Constants are not reported. District-level multi-way clustered robust standard errors are in parentheses. Statistical significance: * 10%, ** 5%, & *** 1%.

The impact ranges from 17.9% to 19% for IV estimates, highlighting a significant increase in productivity when considering additional controls. ITT estimates show a slightly lower impact of 11.5% to 12.2%, reflecting the effects across the entire sample, including non-compliance. These findings highlight the broader applicability of CA practices across diverse cropping systems and confirm the positive, differentiated impacts of tailored agronomic information on productivity and sustainability. The consistency of results across IV and ITT approaches further reinforces the reliability of the evidence, providing robust support for policy and program interventions.

2.6.3 Mechanisms

As the literature suggests, CA enhances productivity and rural livelihoods by improving soil health, reducing costs, and promoting sustainable land use. Practices like minimum tillage, crop rotation, and residue retention conserve moisture, replenish nutrients, and build organic matter. Additionally, CA mitigates environmental degradation, lowers labor demands, and strengthens climate resilience, making it essential for food security and rural economic stability. These benefits position CA as a key strategy for sustainable agriculture and long-term socio-economic development.

For instance, according to Giller et al. (2009), CA practices enhance soil fertility, increasing crop yields while reducing labor costs through more efficient farming methods. Minimum tillage maintains soil structure and moisture, while crop rotation restores essential nutrients, decreasing reliance on synthetic fertilizers (Giller et al., 2009). Additionally, retaining crop residues improves soil organic matter, promoting long-term soil health and sustainability (Diacono and Montemurro, 2011). These benefits collectively enhance farm productivity, profitability, and food security, positioning CA as a vital approach for resilient and sustainable agriculture.

Consequently, the results in Tables 2.5 and 2.6 confirm that CA enhances soil fertility and reduces labor demand on farm plots. By minimizing soil disturbance, CA improves structure, moisture retention, and organic matter content while promoting natural nutrient cycling through crop rotation and residue retention. Reduced tillage and natural weed suppression minimize labor demands, decreasing production costs while enhancing long-term agricultural sustainability. These findings align with existing research, reinforcing CA's role in increasing productivity and long-term sustainable farming.

Table 2.5 CA Practices & Soil Fertility: IV & ITT Estimates

	Dependent variable: Soil Fertility (dummy: 1=fertile)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Treatment: IV	0.145***	0.163**	0.162**	0.163***				
	(0.053)	(0.072)	(0.072)	(0.051)				
Treatment: ITT					0.104***	0.116**	0.116**	0.116***
					(0.038)	(0.051)	(0.052)	(0.037)
Household FE	✓	✓	✓	✓	✓	✓	✓	✓
Time FE	✓	✓	✓	✓	✓	✓	✓	✓
Additional controls	—	✓	✓	✓	—	✓	✓	✓
Improved seed	—	—	✓	✓	—	—	✓	✓
Average rainfall (mm) (summer & spring)	—	—	—	✓	—	—	—	✓
Number of observations	1152	1152	1152	1152	1152	1152	1152	1152

Source: Nile Basin five-wave panel data: 2015, 2016, 2017.
The regressions include IV estimates based on random village assignments within a district. Columns (1) and (5) show baseline regressions with the treatment variable, household, and time-fixed effects. Columns (2)–(4) report IV estimates with varying controls, while Columns (6)–(8) present ITT estimates with a similar control structure. Controls include household size (number), average age (years), highest education (years), improved seed use, CA partial practice, non-farm income, credit access, tenure security, and migration status (all dummies except where noted in the bracket). Constants are not reported. District-level multi-way clustered robust standard errors are in parentheses. Statistical significance: * 10%, ** 5%, & *** 1%.

The estimations in Tables 2.5 and 2.6 cover three intervention periods: 2015, 2016, and 2017. IV estimates indicate that soil fertility in treatment villages is, on average, 0.145 to 0.163 higher than in control villages, highlighting the positive impact of CA practices.

Table 2.6 presents the estimated effects of the treatment on the daily allocation of labor hours to agricultural activities. The results illustrate variations in labor input across treatment and control groups, providing insights into the impact of the intervention on household labor allocation patterns. The distribution of daily labor hour allocation in the data exhibits positive skewness, with a minimum of 0 (observed in 13 households), a maximum of 14.17 hours per day, and an average of 4.26 hours per day. Therefore, this indicates that approximately 50% of households dedicate around 4 hours per day to agricultural activities, reflecting a concentration of labor input around the median, with a smaller proportion of households allocating significantly higher hours.

The results in Table 2.6 show that farmers in treatment villages use significantly less labor than those in control villages, with reductions averaging over 27%, ranging from 27.5% to 27.9% across model specifications. This consistent decline highlights a key advantage of CA: its potential to lower labor demands in smallholder farming systems. In addition to enhancing soil health and productivity, CA practices—through reduced tillage and efficient crop management—significantly lower labor demands, a key advantage in labor-scarce or high-cost settings. This dual benefit strengthens environmental sustainability and economic efficiency, supporting CA as a scalable, resilient strategy for sustainable intensification in climate-vulnerable, labor-constrained contexts.

Table 2.6 CA Practices & labor use: IV & ITT Estimates

	Dependent variable: ln(1 + HH average adult labor use (hours/day)[a])							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Treatment: IV	-0.279***	-0.277***	-0.276***	-0.275**				
	(0.100)	(0.099)	(0.100)	(0.112)				
Treatment: ITT					-0.171***	-0.169***	-0.169***	-0.168**
					(0.061)	(0.061)	(0.061)	(0.068)
Household FE	✓	✓	✓	✓	✓	✓	✓	✓
Time FE	✓	✓	✓	✓	✓	✓	✓	✓
Additional controls	—	✓	✓	✓	—	✓	✓	✓
Improved seed	—	—	✓	✓	—	—	✓	✓
Average rainfall (mm) (summer & spring)	—	—	—	✓	—	—	—	✓
Number of observations	1916	1909	1909	1909	1916	1909	1909	1909

Source: Nile Basin five-wave panel data: 2015, 2016, 2017.
The regressions include IV estimates based on random village assignments within a district. Columns (1) and (5) show baseline regressions with the treatment variable, household, and time-fixed effects. Columns (2)–(4) report IV estimates with varying controls, while Columns (6)–(8) present ITT estimates with a similar control structure. Controls include household size (number), average age (years), highest education (years), improved seed use, CA partial practice, non-farm income, credit access, tenure security, and migration status (all dummies except where noted in the bracket). Constants are not reported. District-level multi-way clustered robust standard errors are in parentheses. Statistical significance: * 10%, ** 5%, & *** 1%.

[a] The addition of +1 in the log transformation accounts for the 13 households reporting 0 labor hours.

2.6.4 Discussion

Policymakers and extension services should prioritize site-specific CA practice recommendations over uniform approaches. Tailored information enhances technology adoption and land productivity among maize farmers, aligning with recent observational and large-scale experimental findings across Africa. Our approach, customized to household and farm plot characteristics, proves effective in increasing the adoption of recommended CA practices. In essence, the findings of this study align with other research, emphasizing the importance of tailored information in promoting CA adoption. While delivery methods may differ, the key takeaway is clear: Context-specific, personalized guidance is crucial for overcoming adoption barriers and encouraging sustainable farming practices (Ayalew et al., 2022; Magar et al., 2022; Akter et al., 2021; A. Kumar et al., 2020; Chiputwa et al., 2020; Abrahamse et al., 2007; Knowler and Bradshaw, 2007).

Adopting CA practices yields economic, welfare, and productivity gains, with greater uptake driving farming improvements. The findings in this study align with broader objectives of sustainable agricultural productivity increase, which aims to improve food security, alleviate poverty, and enhance the well-being of farmers (Magar et al., 2022). Additionally, the findings of this study resonate with long-term evidence from Sub-Saharan Africa and other developing regions, emphasizing CA's benefits, including higher yields, increased income, and improved revenues, across crops such as maize, soybeans, lentils, mustard, and wheat, ultimately boosting productivity and economic resilience (Miah et al., 2023; Myers, 2023; Tambo and Mockshell, 2018; Teklewold et al., 2017; Giller et al., 2015; Di Falco and Veronesi, 2013; Teklewold et al., 2013; FAO, 2001; Council et al., 2010). These studies highlight that CA improves soil productivity by enhancing organic matter, water retention, soil structure, and nutrient exchange. It also reduces costs by lowering labor and farm-power needs while stabilizing yields and increasing agricultural productivity.

Furthermore, the adoption of sustainable land management training for technology diffusion also significantly increased farmers' maize revenue in Mozambique (Kondylis et al., 2017). The results are also in line with recent studies that confirm that the adoption and diffusion of sustainable agricultural technologies have a great potential to advance productivity in agriculture and maintain the resilience of agroecosystems (Mwalupaso et al., 2019; Skaf et al., 2019). Similarly, information diffusion improves technology adoption and promotes productivity, profits, and other related outcomes in agricultural production. For instance, though the mode of delivery is different from our tailored information, a study by Ayalew et al. (2022) states that targeted extension advice focusing on site-specific agronomic information led smallholder farmers to increase fertilizer adoption, which in turn encouraged productivity and profits as well. In addition, CA practices complemented with improved seed adoption increased land productivity in line with the recommendations in Vanlauwe et al. (2014) and Andersson and D'Souza (2014). However, differential effects tests reveal that the impact estimates for the full adoption of CA practices and CAT practices on land productivity in maize production are similar.

These findings contribute to different strands of literature. First, the scarce causal literature on the economics of environmental technologies in the developing and emerging world Aker and Jack (2023), Barrett et al. (2022), and Michler et al. (2019). We document the welfare-improving role of a low-cost (albeit information-intensive) technology. Second, we contribute to the literature on relaxing informational constraints to improve technology adoption Kondylis et al. (2017), Emerick and Dar (2021), and Beaman et al. (2021). We show the importance of tailored information Ayalew et al. (2022) in a context where we have a 'package' technology rather than one single technology or input.

2.7 Conclusions

Tailored information dissemination significantly accelerates the adoption of CA practices, enhancing land productivity for maize and other cereal crops while improving farm household welfare. Our study highlights that customized information, accounting for plot-specific characteristics such as soil fertility, slope, and agroecological conditions, fosters adoption through experiential learning. The findings confirm that the intervention effectively increases adoption rates and productivity, yielding positive short- and long-term benefits for farmers by enhancing food security and sustainable agriculture.

The intervention improves soil fertility and reduces labor hours for treatment farmers compared to controls, driven by sustainable CA practices that enhance land use and prevent soil degradation. Although the analysis centers on maize, the results are consistent across other cereal crops, at least on average, demonstrating the broad applicability of CA practices. Therefore, this underscores the effectiveness of tailored information in improving agricultural sustainability and productivity across diverse crops.

Moreover, although region-specific, the findings in this study have global relevance, as many farming regions share similar plot features like soil fertility, slope, and moisture retention. The intervention's positive impact on soil fertility and labor efficiency suggests it can be adapted to improve agricultural outcomes worldwide, offering valuable insights for sustainable global agricultural development.

The findings are robust, even with control variables. A substantial long-term impact on treatment farmers than control farmers, particularly for maize growers and all cereals production, emphasizes the role of tailored information in promoting sustainable CA practices. Optimizing these interventions boosts land productivity and economic benefits, enhancing farmers' welfare. Hence, this highlights the crucial role of context-specific information about CA practices in fostering productivity with broader implications on environmental sustainability and resilience for improved rural livelihoods.

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Author Contributions:

Gemeda Olani Akuma: Conceptualization, Methodology, Data curation, Software, Formal analysis, Writing-original draft. **Salvatore Di Falco:** Conceptualization, Methodology, Writing-review & editing. **Gunnar Köhlin:** Conceptualization, Methodology, Writing-review & editing, Supervision. **Hailemariam Teklewold:** Conceptualization, Methodology, Data curation.

References

Abate, Gashaw T, Mekdim Dereje, Kalle Hirvonen, and Bart Minten (2020). “Geography of public service delivery in rural Ethiopia”. *World development* 136, p. 105133.

Abdulai, Awudu and Wallace Huffman (2014). “The adoption and impact of soil and water conservation technology: An endogenous switching regression application”. *Land economics* 90.1, pp. 26–43.

Abrahamse, Wokje, Linda Steg, Charles Vlek, and Talib Rothengatter (2007). “The effect of tailored information, goal setting, and tailored feedback on household energy use, energy-related behaviors, and behavioral antecedents”. *Journal of environmental psychology* 27.4, pp. 265–276.

Ahn, EunJin and Hyun Kang (2023). “Intention-to-treat versus as-treated versus per-protocol approaches to analysis”. *Korean Journal of Anesthesiology* 76.6, pp. 531–539.

Aker, Jenny C and B Kelsey Jack (2023). “Harvesting the rain: The adoption of environmental technologies in the Sahel”. *Review of Economics and Statistics*, pp. 1–52.

Akter, Shaheen, Mahesh K. Gathala, Jagadish Timsina, Saiful Islam, Mahbubur Rahman, Mustafa Kamrul Hassan, and Anup Kumar Ghosh (2021). “Adoption of conservation agriculture-based tillage practices in the rice-maize systems in Bangladesh”. *World Development Perspectives* 21, p. 100297.

Alexander, Lorraine K, Brettania Lopes, K Richetti-Masterson, and KR Yeatts (2015). *Randomized controlled trials (experimental studies)*.

Ambler, Kate, Alan De Brauw, and Mike Murphy (2023). “Increasing the adoption of conservation agriculture: A framed field experiment in Northern Ghana”. *Agricultural Economics* 54.5, pp. 742–756.

Andersson, Jens A. and Shereen D’Souza (2014). “From adoption claims to understanding farmers and contexts: A literature review of Conservation Agriculture (CA) adoption among smallholder farmers in southern Africa”. *Agriculture, ecosystems & environment* 187, pp. 116–132.

Araya, Alemie and L Stroosnijder (2010). “Effects of tied ridges and mulch on barley (Hordeum vulgare) rainwater use efficiency and production in Northern Ethiopia”. *Agricultural water management* 97.6, pp. 841–847.

Araya, Tesfay et al. (2011). “Effects of conservation agriculture on runoff, soil loss and crop yield under rainfed conditions in Tigray, Northern Ethiopia”. *Soil Use and Management* 27.3, pp. 404–414.

Arslan, Aslihan, Kristin Floress, Christine Lamanna, Leslie Lipper, and Todd S Rosenstock (2022). “A meta-analysis of the adoption of agricultural technology in Sub-Saharan Africa”. *PLOS Sustainability and Transformation* 1.7, e0000018.

Atwood, Lesley, Maria Gannett, and Stephen A. Wood (2024). “AgEvidence: A dataset to explore agro-ecological effects of conservation agriculture”. *Scientific Data* 11.1, p. 581.

Ayalew, Hailemariam, Jordan Chamberlin, and Carol Newman (2022). "Site-specific agronomic information and technology adoption: A field experiment from Ethiopia". *Journal of Development Economics* 156, p. 102788.

Barbier, Edward B. and Jacob P. Hochard (2018). "Land degradation and poverty". *Nature Sustainability* 1.11, pp. 623–631.

Barrett, Christopher B. (2021). "On design-based empirical research and its interpretation and ethics in sustainability science". *Proceedings of the National Academy of Sciences* 118.29, e2023343118.

Barrett, Christopher B. and Leah E. M. Bevis (2015). "The self-reinforcing feedback between low soil fertility and chronic poverty". *Nature Geoscience* 8.12, pp. 907–912.

Barrett, Christopher B., Asad Islam, Abdul Mohammad Malek, Debayan Pakrashi, and Ummul Ruthbah (2022). "Experimental evidence on adoption and impact of the system of rice intensification". *American Journal of Agricultural Economics* 104.1, pp. 4–32.

Bastardoz, Nicolas, Michael J. Matthews, Gwendolin B. Sajons, Tyler Ransom, Thomas K. Kelemen, and Samuel H. Matthews (2023). "Instrumental variables estimation: Assumptions, pitfalls, and guidelines". *The Leadership Quarterly* 34.1, p. 101673.

Bazrafkan, Khadijeh, Naser Valizadeh, Setareh Khannejad, Nazanin Kianmehr, Masoud Bijani, and Dariush Hayati (2022). "What drives farmers to use conservation agriculture? Application of mediated protection motivation theory". *Frontiers in Psychology* 13, p. 991323.

Beaman, Lori, Ariel BenYishay, Jeremy Magruder, and Ahmed Mushfiq Mobarak (2021). "Can network theory-based targeting increase technology adoption?" *American Economic Review* 111.6, pp. 1918–43.

Brookhart, M. Alan, Jeremy A. Rassen, and Sebastian Schneeweiss (2010). "Instrumental variable methods in comparative safety and effectiveness research". *Pharmacoepidemiology and drug safety* 19.6, pp. 537–554.

Bustos, Paula, Bruno Caprettini, and Jacopo Ponticelli (2016). "Agricultural productivity and structural transformation: Evidence from Brazil". *American Economic Review* 106.6, pp. 1320–1365.

Chiputwa, Brian, Priscilla Wainaina, Tebila Nakelse, Parmutia Makui, Robert B. Zougmoré, Ousmane Ndiaye, and Peter A. Minang (2020). "Transforming climate science into usable services: The effectiveness of co-production in promoting uptake of climate information by smallholder farmers in Senegal". *Climate Services* 20, p. 100203.

Cook, Jonathan A., Graeme S. MacLennan, Tom Palmer, Noemi Lois, and Richard Emsley (2018). "Instrumental variable methods for a binary outcome were used to informatively address noncompliance in a randomized trial in surgery". *Journal of Clinical Epidemiology* 96, pp. 126–132.

Corbeels, Marc, Christian Thierfelder, and Leonard Rusinamhodzi (2014). "Conservation agriculture in sub-Saharan Africa". *Conservation agriculture*. Springer, pp. 443–476.

Corsi, Sandra and Hafiz Muminjanov (2019). *Conservation agriculture*. FAO;

Council, National Research, Division on Earth, Life Studies, and Committee on Twenty-First Century Systems Agriculture (2010). *Toward sustainable agricultural systems in the 21st century*. National Academies Press.

Di Falco, Salvatore and Marcella Veronesi (2013). "How can African agriculture adapt to climate change? A counterfactual analysis from Ethiopia". *Land Economics* 89.4, pp. 743–766.

Diacono, Mariangela and Francesco Montemurro (2011). "Long-term effects of organic amendments on soil fertility". *Sustainable agriculture volume 2*, pp. 761–786.

Emerick, Kyle and Manzoor H. Dar (2021). “Farmer field days and demonstrator selection for increasing technology adoption”. *Review of Economics and Statistics* 103.4, pp. 680–693.

Evans, DL, John N Quinton, Jessica AC Davies, Jianlin Zhao, and Gerard Govers (2020). “Soil lifespans and how they can be extended by land use and management change”. *Environmental Research Letters* 15.9, 0940b2.

FAO (2001). *The Economics of Conservation Agriculture*. Soils Bulletin, Rome.

Farooq, Muhammad and Kadambot H. M. Siddique (2015). *Conservation agriculture: concepts, brief history, and impacts on agricultural systems*. Springer.

Ferraro, Paul J and Arun Agrawal (2021). “Synthesizing evidence in sustainability science through harmonized experiments: Community monitoring in common pool resources”. *Proceedings of the National Academy of Sciences* 118.29, e2106489118.

Ferraro, Paul J and Merlin M Hanauer (2014a). “Advances in measuring the environmental and social impacts of environmental programs”. *Annual review of environment and resources* 39.1, pp. 495–517.

— (2014b). “Quantifying causal mechanisms to determine how protected areas affect poverty through changes in ecosystem services and infrastructure”. *Proceedings of the national academy of sciences* 111.11, pp. 4332–4337.

Ferraro, Paul J and Subhrendu K Pattanayak (2006). “Money for nothing? A call for empirical evaluation of biodiversity conservation investments”. *PLoS biology* 4.4, e105.

Ferraro, Paul J, James N. Sanchirico, and Martin D. Smith (2019). “Causal inference in coupled human and natural systems”. *Proceedings of the National Academy of Sciences* 116.12, pp. 5311–5318.

Gibbon, David (2012). “Save and Grow: A Policymaker’s Guide to the Sustainable Intensification of Smallholder Crop Production. Rome, Italy: Food and Agriculture Organization of the United Nations (2011), pp. 112, ISBN 978-92-5-106871-7”. *Experimental Agriculture* 48.1, pp. 154–154.

Giller, Ken E., Jens A. Andersson, Marc Corbeels, John Kirkegaard, David Mortensen, Olaf Erenstein, and Bernard Vanlauwe (2015). “Beyond conservation agriculture”. *Frontiers in plant science* 6, p. 870.

Giller, Ken E., Ernst Witter, Marc Corbeels, and Pablo Tittonell (2009). “Conservation agriculture and smallholder farming in Africa: the heretics’ view”. *Field crops research* 114.1, pp. 23–34.

Gollin, Douglas (2023). “Agricultural productivity and structural transformation: evidence and questions for African development”. *Oxford Development Studies* 51.4, pp. 375–396.

Gollin, Douglas, David Lagakos, and Michael E Waugh (2014). “Agricultural productivity differences across countries”. *American Economic Review* 104.5, pp. 165–170.

Hailu, Leta and Wondimagn Teka (2024). “Potential of conservation agriculture practice in climate change adaptation and mitigation in Ethiopia: a review”. *Frontiers in Climate* 6, p. 1478923.

Hailu, Ziade and Kinde Teshome (2022). “Adoption Rate and Trends in Adoption of Conservation Agriculture in Ethiopia”.

Hanna, Rema, Sendhil Mullainathan, and Joshua Schwartzstein (2014). “Learning through noticing: Theory and evidence from a field experiment”. *The Quarterly Journal of Economics* 129.3, pp. 1311–1353.

Hobbs, Peter R, Ken Sayre, and Raj Gupta (2008). “The role of conservation agriculture in sustainable agriculture”. *Philosophical Transactions of the Royal Society B: Biological Sciences* 363.1491, pp. 543–555.

Imbens, Guido W. and Donald B. Rubin (2015). *Causal inference in statistics, social, and biomedical sciences*. Cambridge university press.

Jat, Mang Lal, Debashis Chakraborty, Jagdish Kumar Ladha, Dharamvir Singh Rana, Mahesh Kumar Gathala, Andrew McDonald, and Bruno Gerard (2020). "Conservation agriculture for sustainable intensification in South Asia". *Nature Sustainability* 3.4, pp. 336–343.

Jayne, Thomas S, Jordan Chamberlin, and Derek D Headey (2014). "Land pressures, the evolution of farming systems, and development strategies in Africa: A synthesis". *Food policy* 48, pp. 1–17.

Kassam, Amir, Theodor Friedrich, and Rolf Derpsch (2019). "Global spread of conservation agriculture". *International Journal of Environmental Studies* 76.1, pp. 29–51.

Kassam, Amir, Theodor Friedrich, Francis Shaxson, and Jules Pretty (2009). "The spread of conservation agriculture: justification, sustainability and uptake". *International journal of agricultural sustainability* 7.4, pp. 292–320.

Kassam, Amir H., Saidi Mkomwa, and Theodor Friedrich (2016). *Conservation agriculture for Africa: building resilient farming systems in a changing climate*. CABI.

Knowler, Duncan and Ben Bradshaw (2007). "Farmers' adoption of conservation agriculture: A review and synthesis of recent research". *Food policy* 32.1, pp. 25–48.

Kondylis, Florence, Valerie Mueller, and Jessica Zhu (2017). "Seeing is believing? Evidence from an extension network experiment". *Journal of Development Economics* 125, pp. 1–20.

Kumar, Anjani, Hiroyuki Takeshima, Ganesh Thapa, Naveen Adhikari, Sunil Saroj, Madhab Karkee, and P. K. Joshi (2020). "Adoption and diffusion of improved technologies and production practices in agriculture: Insights from a donor-led intervention in Nepal". *Land Use Policy* 95, p. 104621.

Magar, Shikha Thapa, Jagadish Timsina, Krishna Prasad Devkota, Liang Weili, and Neeranjan Rajbhandari (2022). "Conservation agriculture for increasing productivity, profitability and water productivity in rice-wheat system of the Eastern Gangetic Plain". *Environmental Challenges* 7, p. 100468.

Miah, M. A. Monayem, Richard W. Bell, Enamul Haque, Md Wakilur Rahman, Md Abdur Rouf Sarkar, and M. A. Rashid (2023). "Conservation agriculture practices improve crop productivity and farm profitability when adopted by Bangladeshi smallholders in the Eastern Gangetic Plain". *Outlook on agriculture* 52.1, pp. 11–21.

Michler, Jeffrey D., Kathy Baylis, Mary Arends-Kuenning, and Kizito Mazvimavi (2019). "Conservation agriculture and climate resilience". *Journal of environmental economics and management* 93, pp. 148–169.

Mitchell, Jeffrey P. et al. (2024). "No-tillage, surface residue retention, and cover crops improved San Joaquin Valley soil health in the long term". *California Agriculture* 78.2.

Molero-Calafell, Javier, Andrea Burón, Xavier Castells, and Miquel Porta (2024). "Intention to treat and per protocol analyses: differences and similarities". *Journal of Clinical Epidemiology* 173, p. 111457.

Mwalupaso, Gershom Endelani, Mariko Korotoumou, Aseres Mamo Eshetie, John-Philippe Essiagnon Alavo, and Xu Tian (2019). "Recuperating dynamism in agriculture through adoption of sustainable agricultural technology-Implications for cleaner production". *Journal of cleaner production* 232, pp. 639–647.

Myers, R. (2023). "How Conservation Practices Influence Agricultural Economic Returns". *Agree: Washington, DC, USA*, pp. 1–19.

Pathak, Santosh, Hua Wang, and Naveen C. Adusumilli (2024). "Contract noncompliance in agricultural conservation programs: Panel evidence from Louisiana, USA". *Agricultural and Resource Economics Review* 53.2, pp. 251–276.

Pittelkow, Cameron M. et al. (2015a). "Productivity limits and potentials of the principles of conservation agriculture". *Nature* 517.7534, pp. 365–368.

Pittelkow, Cameron M. et al. (2015b). "When does no-till yield more? A global meta-analysis". *Field crops research* 183, pp. 156–168.

Pooniya, Vijay et al. (2022). "Conservation agriculture based integrated crop management sustains productivity and economic profitability along with soil properties of the maize-wheat rotation". *Scientific Reports* 12.1, p. 1962.

Pretty, Jules N., Stella Williams, and Camilla Toulmin (2012). *Sustainable intensification: increasing productivity in African food and agricultural systems*. Routledge.

Richardson, David B., Oliver Dukes, and Eric J. Tchetgen Tchetgen (2023). "Estimating the effect of a treatment when there is nonadherence in a trial". *American Journal of Epidemiology* 192.10, pp. 1772–1780.

Saha, Ajoy Kumar, John T. McMaine, Todd Trooien, Peter Sexton, and Christopher Graham (2024). "Impact of no-till, crop rotation, cover crop, and drainage on soil physical and hydraulic properties". *Soil Science Society of America Journal* 88.2, pp. 239–257.

Schulz, Kenneth F. and David A. Grimes (2002). "Generation of allocation sequences in randomised trials: chance, not choice". *The Lancet* 359.9305, pp. 515–519.

Skaf, Ludmila, Elvira Buonocore, Stefano Dumontet, Roberto Capone, and Pier Paolo Franzese (2019). "Food security and sustainable agriculture in Lebanon: An environmental accounting framework". *Journal of cleaner production* 209, pp. 1025–1032.

Su, Yang, Benoit Gabrielle, Damien Beillouin, and David Makowski (2021). "High probability of yield gain through conservation agriculture in dry regions for major staple crops". *Scientific reports* 11.1, p. 3344.

Suri, Tavneet and Christopher Udry (2022). "Agricultural technology in Africa". *Journal of Economic Perspectives* 36.1, pp. 33–56.

Tambo, Justice A. and Jonathan Mockshell (2018). "Differential impacts of conservation agriculture technology options on household income in Sub-Saharan Africa". *Ecological Economics* 151, pp. 95–105.

Teklewold, Hailemariam, Menale Kassie, Bekele Shiferaw, and Gunnar Köhlin (2013). "Cropping system diversification, conservation tillage and modern seed adoption in Ethiopia: Impacts on household income, agrochemical use and demand for labor". *Ecological Economics* 93, pp. 85–93.

Teklewold, Hailemariam, Alemu Mekonnen, Gunnar Köhlin, and Salvatore Di Falco (2017). "Does adoption of multiple climate-smart practices improve farmers' climate resilience? Empirical Evidence from the Nile Basin of Ethiopia". *Climate Change Economics* 8.01, p. 1750001.

Teng, Jialing et al. (2024). "Conservation agriculture improves soil health and sustains crop yields after long-term warming". *Nature Communications* 15.1, p. 8785.

Thierfelder, C and PC Wall (2010). "Rotation in conservation agriculture systems of Zambia: effects on soil quality and water relations". *Experimental agriculture* 46.3, pp. 309–325.

Thierfelder, Christian and Blessing Mhlanga (2022). "Short-term yield gains or long-term sustainability?–a synthesis of Conservation Agriculture long-term experiments in Southern Africa". *Agriculture, Ecosystems & Environment* 326, p. 107812.

Thierfelder, Christian, Mulundu Mwila, and Leonard Rusinamhodzi (2013). “Conservation agriculture in eastern and southern provinces of Zambia: long-term effects on soil quality and maize productivity”. *Soil and tillage research* 126, pp. 246–258.

Tufa, Adane H., Joseph S. Kanyamuka, Arega Alene, Hambulo Ngoma, Paswel P. Marenya, Christian Thierfelder, Happy Banda, and David Chikoye (2023). “Analysis of adoption of conservation agriculture practices in southern Africa: mixed-methods approach”. *Frontiers in Sustainable Food Systems* 7, p. 1151876.

Valbuena, Diego et al. (2012). “Conservation agriculture in mixed crop–livestock systems: scoping crop residue trade-offs in Sub-Saharan Africa and South Asia”. *Field crops research* 132, pp. 175–184.

Vanlauwe, Bernard, J. Wendt, Ken E. Giller, Marc Corbeels, B. Gerard, and Christian Nolte (2014). “A fourth principle is required to define conservation agriculture in sub-Saharan Africa: the appropriate use of fertilizer to enhance crop productivity”. *Field Crops Research* 155, pp. 10–13.

World Bank (2007). *World development report 2008: Agriculture for development.* The World Bank.

Zerihun, Abebe, Birhanu Tadesse, Tadesse Shiferaw, and Degefa Kifle (2014). “Conservation agriculture: maize-legume intensification for yield, profitability and soil fertility improvement in maize belt areas of western Ethiopia”. *International Journal of Plant and Soil Science* 3.8, pp. 969–985.

Chapter 3

Adapting to drought: how do public works affect conservation and labor engagement in rural Ethiopia?

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Abstract

This paper explores the effects of public works on soil and water conservation practices and labor participation in rural Ethiopia, aligning with the UN Sustainable Development Goals for life on land. By using unbalanced panel data across three periods (2011/12, 2013/14, and 2015/16), this study examines the relationship between drought and public works employment, utilizing satellite-based Enhanced Vegetation Index anomalies as a proxy for drought shock. Findings indicate that public works positively impact soil and water conservation practices despite concerns about crowding out individual efforts. Moreover, participation in public works increases labor allocation to agricultural activities while reducing hours in non-agricultural work. This shift suggests that public works can promote sustainable land use and enhance food security. The study highlights the role of public works employment within the Productive Safety Net Program in improving resource conservation and livelihoods, emphasizing its potential as a pathway for sustainable development in rural areas facing environmental challenges like drought.

Keywords: Drought, Food security, Public works, Resource conservation, Household labor, Ethiopia

JEL Classification: Q54, Q18, I38, Q2, J22, O55

3.1 Introduction

Extreme weather shocks (for instance, drought) frequently affect various aspects of society in developing economies. Drought weakens adaptive capacities (Das et al., 2023;

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Matewos, 2020), influences agricultural production and income (Demem, 2023; Berhe et al., 2017; Letta et al., 2018), hence reducing consumption (Letta et al., 2018) and welfare (Baez et al., 2017), disrupt food security (Ajefu and Abiona, 2020; Mandal and Sarma, 2020), worsen health outcomes (Meierrieks, 2021), and increase migration (Kubik and Maurel, 2016). Studies recommend various adaptation strategies, including social safety nets (Gao and Mills, 2018; Mersha and Laerhoven, 2018) and public works programs (Scognamillo et al., 2024; Bekele et al., 2020; Schwan and Yu, 2018; Dasgupta, 2017) to support vulnerable populations and promote greater resilience in adverse weather conditions.

Public works programs, known as cash-for-work schemes, provide temporary employment opportunities for shock-affected and chronically food-insecure households. They offer a chance to build or restore public infrastructure (Gazeaud and Stephane, 2023), generate income, and provide insurance for poor people (Gehrke and Hartwig, 2018). These programs are tools to facilitate asset-building objectives and transform lives in the face of shocks. While some studies suggest mixed effects of the programs on food security, they remain a popular developmental tool. Evaluations have shown that, with careful follow-up, they can contribute to ecosystem benefits. Programs such as the India National Rural Employment Guarantee Act (NREGA) and Ethiopia Productive Safety Net Program (PSNP) have benefited millions of poor people (World Bank, 2015), improving household welfare and ecosystem services (Anantha et al., 2021). Similarly, programs in Mexico, Indonesia, and Brazil have shown promising results, offering the potential to improve the lives of those engaged in such activities (Dyngeland et al., 2020).

Public works are vital components of Ethiopia's PSNP and comprise about 80 percent of the program beneficiaries. The program aimed at improving community-level investments in conservation measures (World Bank, 2020), but its micro-level effects on soil and water conservation (SWC) efforts remain uncertain. This program serves a dual purpose. First, public works serve as a social protection instrument to improve livelihoods and food security by providing temporary wage employment. The public works program offers five-day temporary employment to eligible households per month for at least six months per year.

Public works employment eligibility demands being a member of the community, facing chronic food insecurity-sustained food shortages (food gap for three months or more a year) in the last three years, and sudden food insecurity due to a severe loss of assets (financial, livestock, means of production, assets). Chronic illness, lack of adequate family support, or not being a beneficiary in any other social protection programs are conditions for selection into the program for participation of at least one adult member in a household. Early periods of pregnancy, first-year breastfeeding, illness, or disability rule out participating in public works, where these members become clients in temporary direct support, receiving cash transfers (Ministry of Agriculture, 2014). Second, public works help generate access to public social services. Support for life on land is the concern of Goal 15 within the UN Sustainable Development Goals (SDGs) and requires protection, restoration, and sustainable utilization of terrestrial ecosystems (Regeringskansliet, 2015). Hence, public works are supposed to rehabilitate degraded land by repairing and building its productive capacity, enabling essential support to smallholder farm households. In other words, family members with labor capacity work on an integrated, community-based, wide range of projects that may cover SWC practices in highland areas, range-land management in pastoral areas, and infrastructure or community assets development projects, including roads, water infrastructure, schools, and health centers.

The dual objectives of public works employment—improving livelihoods and developing public infrastructure—are integral to social protection and development efforts. However, if not carefully designed, such programs may lead to unintended consequences. Diverting labor from on-farm activities, particularly during peak agricultural periods, can reduce household agricultural output and compromise food security. Additionally, sustained reliance on public works may weaken incentives for private investment and self-sufficiency, potentially fostering long-term aid dependence. Addressing these risks is essential to ensure that public works contribute to sustainable livelihoods and efficient labor allocation. According to a study by Holden et al. (2006), food for work (FFW) programs can either promote or hinder private investments and affect sustainable land use negatively. Although conceptually similar, the FFW programs, implemented before 2005, primarily provided food in exchange for labor. In contrast, the public works component delivers either cash or food transfers as part of a broader, institutionalized social protection framework that also includes direct support for labor-constrained households (GFDRE, 2004). Therefore, the potential risks of large annual transfers and taking appropriate measures to mitigate them, given that the government and donors have already contributed over 2.2 billion dollars since the program's inception in 2005. Hence, the outcome of a thorough analysis may recommend that farm households adopt conservation measures and help vulnerable families escape poverty.

The SWC practices are vital tools applied worldwide that can mitigate the impacts of weather shocks, enhance productivity, and improve food security. These conservation practices include labor-intensive physical measures such as terracing, check-dams/water catchments, or vegetative or biological measures like afforestation and plowing along the contour. Physical measures involve building structures for soil and water conservation. The vegetative conservation measures work through their protective impact on an improved vegetation cover by planting crops. Therefore, these conservation practices help overcome the adverse effects of climate change and land degradation, which threaten worldwide livelihoods (Mirzabaev et al., 2023; Barbier and Hochard, 2018).

Soil erosion, soil nutrient deterioration, biodiversity losses, and deforestation are all signs of land degradation (Viju et al., 2023). Soil erosion is the primary cause of environmental degradation in developing economies, posing a significant threat to global food security (Piñeiro et al., 2020; Pozza and Field, 2020; Agidew and Singh, 2017). Cropland expansion is the main reason for soil erosion in sub-Saharan Africa, South America, and Southeast Asia (Borrelli et al., 2017). As a result, SWC practices require specific localized activities and contexts to be effective (Graaff et al., 2013; Nigussie et al., 2017), helping to improve sustainable land use and agricultural production (Hishe et al., 2017; Chesterman et al., 2019; Sileshi et al., 2019; Amfo et al., 2021).

This paper focuses on two fundamental questions regarding the impact of drought shock-induced participation in public works on conservation and household labor engagement outcomes. These outcomes are akin to the living standards of rural households in Ethiopia in particular and sub-Saharan Africa in general. These targets differ from the outcomes of interest in previous studies in Ethiopia. For instance, earlier investigations focus on the effects of PSNP on livelihood outcomes, including food security (Devereux, 2016; Berhane et al., 2014; Gilligan et al., 2009), poverty (Subbarao, 1997; Khosla and Jena, 2022), children's nutrition and human capital accumulation (Favara et al., 2019; Berhane et al., 2017; Porter and Goyal, 2016; Debela et al., 2015), and the adoption of productivity-enhancing agricultural technologies (Araya, 2020; Alem and Broussard, 2018). The first aspect of this study investigates whether participation in public works projects, which focus on constructing SWC infrastructure at the community level, influences the adoption of these practices on participants' plots. In other words, this aspect investigates how drought-induced public works employment can make a difference in the resource conservation of farm households in rural areas. This feature is significant as it explores strategies to help farmers invest in drought adaptation and resilience-building measures, potentially reducing their future dependence on public works. Additionally, the paper evaluates how participation in public works can affect the time spent in agricultural and off-farm work in rural areas. This aspect aims to contribute to the empirical literature on the potential theoretical crowding-out effects of public works on productive activities.

This study contributes to the literature on how public works employment can make a difference in resource conservation and labor engagement, particularly in the face of drought shock in rural areas. Our contribution builds upon previous literature examining the impacts of public works programs on sustainable land use, including tree cover (Hirvonen et al., 2022) and tree holdings (Andersson et al., 2011) and investments in sustainable land management activities (Adimassu and Kessler, 2015). This study primarily aims to fill the gap in the literature by evaluating the effects of public works programs on household-level SWC practices, which are crucial for promoting agricultural production and food security, safeguarding soil and environmental health, and enhancing social and economic sustainability. Furthermore, our study also explores the association between public works programs and household labor engagements in on-farm and off-farm activities. These agricultural and non-agricultural activities compete for different resources (e.g., labor, time, capital) in rural areas. Therefore, rural income earnings from both on-farm and off-farm activities can improve sustainable land use, agricultural production, and food security. Hence, environmental conservation efforts and family labor reallocation are vital areas of inquiry for smallholder farm households, as these outcomes can directly link to farm income, productivity, and food security, particularly in the face of weather shocks. We use Ethiopia's Socioeconomic Survey (ESS) panel data in three waves to evaluate how public works employment influences conservation measures and household labor engagements in different activities in rural Ethiopia.

The paper is structured as follows: Section 3.2 provides the context and program overview, Section 3.3 describes the data, Section 3.4 illustrates the empirical strategy, Section 3.5 presents and discusses the results, and Section 3.6 concludes.

3.2 Context and overview

3.2.1 The context

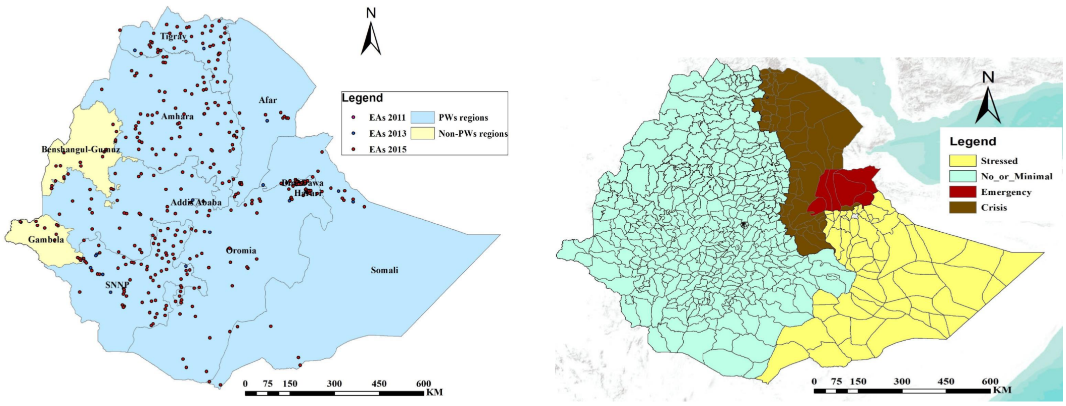
The agricultural sector in Ethiopia primarily relies on rainfed farming and is characterized by subsistence agriculture. Most crop production occurs during the long rainy 'Meher' season, which includes the planting period from June to August and the harvesting period from September to February. Agricultural production is vulnerable to weather shocks and environmental degradation. Consequently, there has been frequent food insecurity in different parts of the country since the 2002/03 severe drought, flooding, and crop failure (Mahoo et al., 2013). Similarly, Tofu et al. (2022) stated that high temperature, rainfall variability, droughts, crop and livestock pests and diseases, and pasture and water scarcity are widespread weather shocks in northern Ethiopia. The 2015/16 El Niño drought[4] was one of the most severe shocks that affected many areas, particularly in the northern, central, and eastern parts. This drought resulted in significant rainfall deficits in millimeters compared to the long-term average, as indicated in the Climate Hazards Group InfraRed Precipitation with Station (CHIRPS) rainfall data. Additionally, R. Singh et al. (2016) indicated a rainfall shortage below expectations from February through September 2015/16, as illustrated in panel (b) of Figure 3.1. The 2015/16 El Niño-induced drought affected nearly 10 million people, as shown in Drechsler and Soer (2016).

The interactions between weather shocks and environmental degradation can adversely affect the livelihoods and sustainable land use of smallholder farmers (He and Chen, 2022; Girard et al., 2021; Crook et al., 2020). Various studies have shown that human activities accelerate this process (Ahmed et al., 2018), leading to low land productivity and ineffective water resources management (Gazeaud and Stephane, 2023). In response, smallholder farmers employ different climate change adaptation strategies, such as soil and water conservation practices (Tofu et al., 2022; Delgado et al., 2021; Amfo et al., 2021; Tambet and Stopnitzky, 2021; Geremu, 2019).

Climate change has affected Ethiopia's highland areas for 30 years (Wolka et al., 2023a; Temesgen et al., 2014; Hurni et al., 1993). Previous land management policies failed due to a top-down approach. Later, conservation agriculture and targeted interventions became

[4] El Niño intensity experienced during planting and growing seasons of 2015/16 in different districts or *woredas*. In Ethiopia, *woredas* refers to districts, which are the 2^{nd} higher level administrative stage next to zones in the regional states. Figure 3.1 panel (b) presents the 2015/16 El Niño situations in different districts of Ethiopia.

Fig. 3.1 Public works employment areas by regions and 2015/16 El Niño intensity by *woredas*



(a) PWs regions **(b)** El Niño intensity in 2015/16

Figure 3.1 refers to information on public works (PWs) employment by regions across the survey years and 2015/16 El Niño prone areas. Panel (a) indicates the PWs and non-PWs-regions, and the dots refer to Enumeration areas (EAs). Panel (b) shows the 2015/16 El Niño drought intensity consisting of four categories: (1) No or minimal, (2) Stressed, (3) Crisis, and (4) Emergency.
Source: Both figures are authors' sketches using longitudinal and latitudinal coordinates for Enumeration areas (EAs) given in the household geospatial variables of the Living Standards Measurement Study-Integrated Surveys of Agriculture (LSMS-ISA).

popular for sustainable land management (Selvakumar and Sivakumar, 2021; Graaff et al., 2013).

Landscape restoration activities such as area closures, physical SWC activities, and planting trees and shrubs can contribute to the land cover dynamics of the watersheds (Wolka et al., 2023a). Such initiatives can improve the sustainability of livelihoods of smallholder farmers and land use in Ethiopia, as shown in Tofu and Wolka (2023) and Wolka et al. (2023b).

3.2.2 Overview of public works

The PSNP in Ethiopia has supported millions of people since its inception in 2005. The Ethiopian government and various donors, including the World Bank and other organizations, have funded it. The program aims to address the challenges of vulnerable farming households by providing a mix of cash and food transfers to meet their basic food needs (Hoddinott et al., 2012). Beneficiaries are selected based on both geographical and community-based criteria. Some of the program beneficiaries receive unconditional cash or in-kind food transfers, including those who are pregnant, elderly, or disabled. The amount of support provided to each household can vary based on household size, but the median total payment over five years was approximately 200 USD. This payment contributes to the well-being of beneficiaries and their household members. The program also helps improve resilience to various risks and hazards with a positive impact on their livelihoods.

The PSNP has expanded its reach from 263 chronically food-insecure districts (*woredas*) in 2005 to over 318 districts by 2020, progressing through four phases. Initially, the program aimed to support around five million people residing in Tigray, Amhara, Oromia, and Southern Nations and Nationalities Peoples (SNNP) regions (Siyoum, 2012). Five years later, Afar, Somali, Harari, and Dire Dawa were included in the program, expanding operational area coverage. Hence, the PSNP operates in eight regional states in Ethiopia. They later expanded to ten administrative regions after SNNP split into SNNP, Sidama, and South West Ethiopia Peoples (SWEP) regions. These regions cover almost 93% of rural households in Ethiopia (Kosmowski et al., 2020). Therefore, effective implementation of the PSNP can improve the living standards of millions of people in Ethiopia.

About 80 percent of the PSNP receive conditional cash transfers for contributions to public works employment to address underlying chronic food insecurity in drought-affected areas. Figure 3.2, for instance, depicts the sketch for the conceptual framework adapted from the "PSNP Implementation Manual" for addressing food insecurity (Ministry of Agriculture, 2014). Eligible households with able contributing adult members receive transfer payments for participating in public works.

In Ethiopia, the PSNP requires able-bodied beneficiaries to participate in public works to receive support, while labor-constrained households, such as those with elderly or disabled members, receive direct support (Berhane et al., 2014). Unjustified non-participation may result in suspended benefits, though re-entry is possible upon reassessment during annual targeting (Hoddinott et al., 2012). While the program balances short-term support with long-term asset creation, it risks excluding households facing temporary labor constraints (Gebrehiwot and Castilla, 2019).

The average payment to each member was initially 2,364 Ethiopian Birr (ETB). However, it was later revised to benefit the entire family. Under the revised system, each family member is offered five days of work per month for six months at a wage rate of 10 ETB per day.[5] This means that each family member will receive a total payment of 300 ETB over six months. Therefore, the total payment will be 1,500 ETB for a household with five members (Berhane et al., 2017).

[5] On average, 1 USD was about 16.97 ETB in 2011, 18.71 ETB in 2013, and 20.69 ETB in 2015.

Fig. 3.2 Conceptual framework

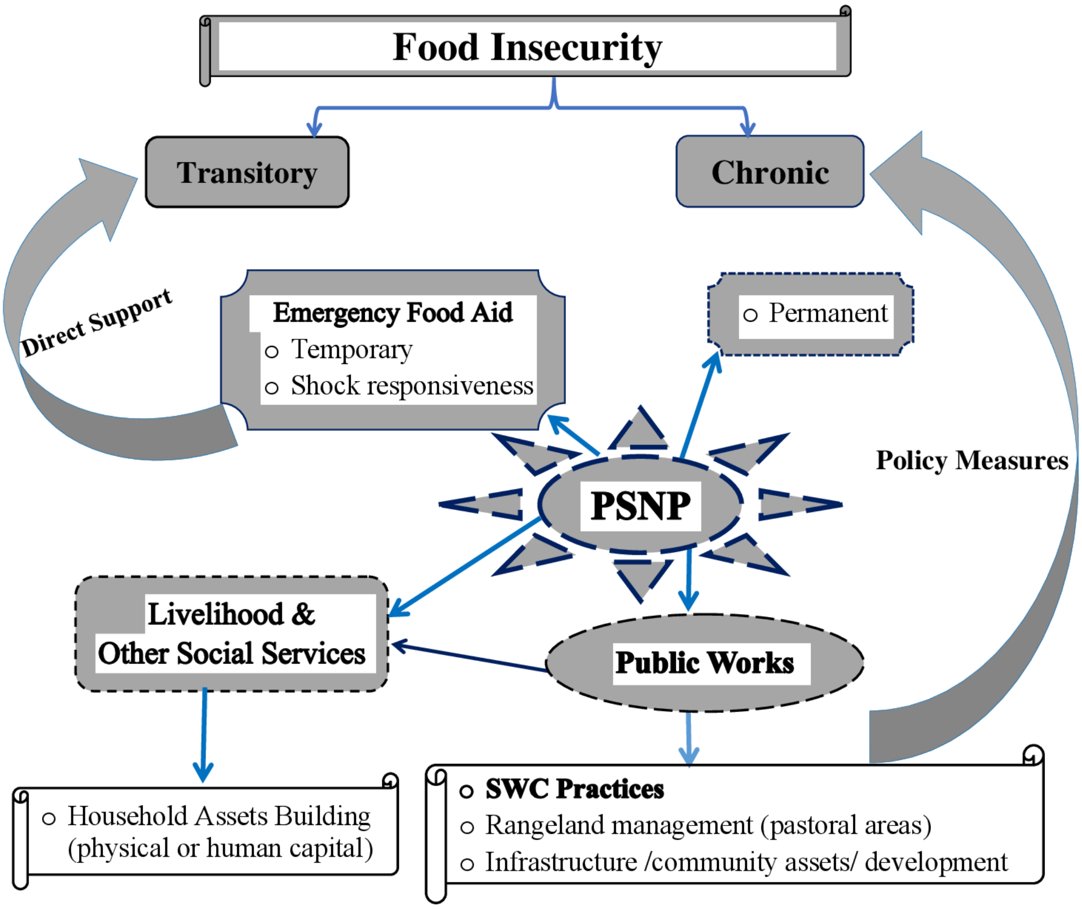


Figure 3.2 describes a framework for addressing food insecurity.

Public works can have direct and indirect pathways for different outcomes. Although there is limited evidence for the effects of the program on SWC measures, many studies in other contexts confirmed that off-farm employment can supplement farm incomes and productivity while also assisting in safeguarding against the effects of climate change, to a certain extent (Davies et al., 2008). Furthermore, off-farm employment can directly affect farm household savings, reducing liquidity constraints and lessening credit snags in rural areas. Hence, this helps adjust farm household spending, investment, and risk-bearing behavior and improves farmers' adoption of adaptable SWC practices. These are particularly crucial in rural areas where households face challenges meeting their daily needs. In addition, off-farm incomes generated from public works can increase the safety net for ensuring weather-induced production shocks and allow consumption smoothing (Tirivayi et al., 2013). These findings suggest that households can better cope with unexpected shocks and maintain their living standards. For instance, a recent study confirms that participation in the PSNP can enhance undertakings in high-risk and high-return activities that could reduce the probability of taking customary adverse risk-coping practices, such as selling agricultural assets and improving agriculture outcomes (Alem and Broussard, 2018). These are particularly important in areas where households may have limited access to resources and face high levels of uncertainty in their day-to-day lives. In general, the PSNP's focus on public works and off-farm employment has the potential to bring about a range of positive outcomes for rural households.

Some argued that public work programs had a limited impact on sustainable agricultural practices, particularly on SWC and intercropping activities (Deressa et al., 2009). Farmers who devote their time to off-farm employment may have less time to focus on these practices, which can impede efforts to adapt to climate change. In particular, SWC practices can involve significant labor and opportunity costs, especially during peak periods (Deressa et al., 2009). The critiques include their poor timing or schedule, despite being scheduled during slack labor periods to minimize disruptions to livelihood activities (Ministry of Agriculture, 2014). Furthermore, these programs can divert family labor away from agricultural production and investments (Andersson et al., 2011), reducing investment in productivity-enhancing and sustainable conservation practices, such as intercropping and SWC (Adimassu and Kessler, 2015; Deressa et al., 2009). While smallholder farmers in different parts of Asia are more likely to adapt to frequent drought through diversification into off-farm activities, such opportunities may not always be available for smallholder farmers in isolated and less-favored rain-fed agriculture under different economic settings in Africa (Cooper et al., 2008). Public works programs can also pose social risks, such as area closures, damage to physical assets, and loss of social capital related to health or safety problems arising from disruption to downstream water use or inequitable benefits from small-scale irrigation. Therefore, it is essential to take cautious measures to ensure the implementation of public works programs is effective and does not pose any social risks (Ministry of Agriculture, 2014).

On the contrary, others argue that public work programs stimulate economic growth and development. Participation in PSNP improves the use of complementary agricultural inputs (e.g., fertilizer) (Hoddinott et al., 2012) and the use of improved crop varieties that are risky but have high returns (Taraz, 2021; Merfeld, 2020; Gehrke, 2019; Alem and Broussard, 2018). In other words, income earnings might help invest in new and innovative technologies like improved seeds, irrigation technologies, and planting more trees on limited land areas. Moreover, Banerjee et al. (2017) states that participants of PSNP can remove some plots from cultivation when agricultural productivity increases. In addition, (Adimassu and Kessler, 2015) also indicates that public work programs can create labor movements toward agriculture due to the labor-intensive nature of the program. However, this could induce agricultural labor crowding out engagements despite the total output being intact as output per labor increases. Finally, public works programs can affect migration dynamics and availability of labor for agricultural productions, influencing agricultural productivity, labor markets, and economic growth (Gazeaud et al., 2023; Hidrobo et al., 2022; Imbert and Papp, 2020).

To this end, it is crucial to understand the theory of change results chain guiding the practical evaluation of the impact of development programs on a choice of outcome indicators (Tengberg and Valencia, 2018; Gertler et al., 2016a; Gertler et al., 2016b; Khandker et al., 2009). In this particular case, the theory of change is based on an asset-income-conservation outcome to describe adaptation to drought vulnerability. Natural resource conservation (e.g., soil, water, and so on) is among the adaptation strategies to weather shocks (Gaworek-Michalczenia et al., 2022; Pinto et al., 2022; Lavorel et al., 2019; Muchuru and Nhamo, 2019). An adaptive capacity to weather shocks might depend on multiple interconnected factors, including access to public programs (Sam et al., 2019), property/asset holdings, social safety nets (Kundo et al., 2023; Bowen et al., 2020; Paul Jr et al., 2020; Mekuyie et al., 2018; Smith and Frankenberger, 2018; Shiferaw et al., 2014), and support services (Beegle et al., 2018).

3.2.3 Drought occurrence and major activities timeline

In Ethiopia, there are two rainy seasons. The 'Kiremt' or 'Meher' season, also known as summer, is the heavy rainy season with a planting period ranging from June to August. It accounts for 50%-80% annual rainfall and 85%-95% of food crop production. The harvest period for the 'Meher' season spans from September to February. The secondary wet (rainy) season is called 'Belg' (Autumn). The planting occurs from March to April while harvesting runs from May to June during this season. This season typically experiences significantly less rainfall in the central and northern regions of the country.[6] The timeline

[6] This is available at https://climateknowledgeportal.worldbank.org/country/ethiopia/climate-data-historical.

of activities and occurrence of a drought situation directly related to the 'Meher' season are presented in Figure 3.3. 'Meher' season drought occurs when rain fails during the planting and adoption agriculture season (June-August).

As shown in the basic information of the ESS and Figure 3.3, the reference periods of the survey can capture the timing of participation in public works related to the adoption of the SWC. The data enumeration for household characteristics, community-level variables, and post-harvest agriculture information for the panel occurs between February and April. This period roughly corresponds to an overlap between the end of the previous agricultural season and the beginning of the next agricultural season. Figure 3.3 presents the timing and sequencing of activities in an agricultural season. The figure shows that the timing of SWC practices follows drought incidence and public works participation. A failure or erratic rainfall in the 'Meher' season leads to an impactful drought.

Fig. 3.3 The sequence of major activities timeline in different agriculture seasons in rural Ethiopia

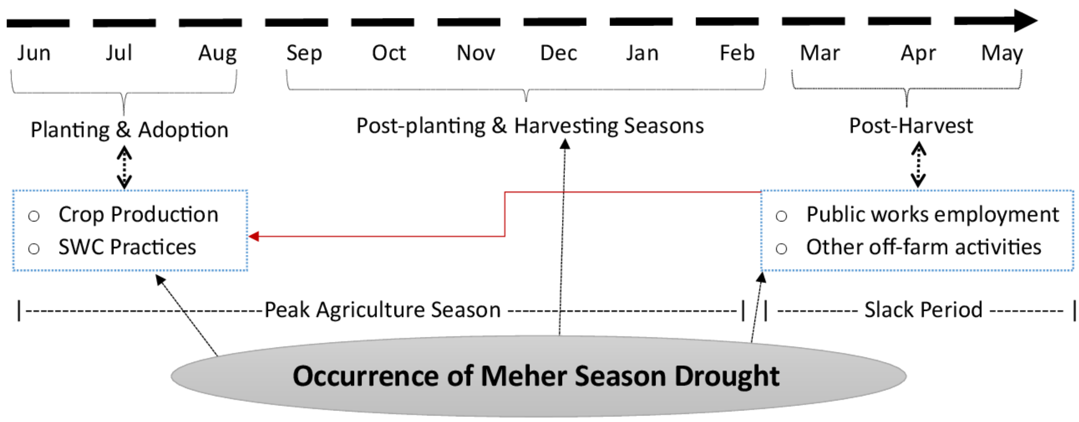


Figure 3.3 presents the major activities timeline and effects of 'Meher' Season Drought on various outcomes.

Literature indicates that droughts have occurred in various parts of Ethiopia at different times, such as in 2011/12 and 2015/16 (Abara, Budiastuti, et al., 2020). Drought causes harvest failure and weakens farmers' investment capacity in the following agricultural season. Hence, this situation forces farmers to adopt an appropriate adaptation strategy to drought. SWC practices serve as key adaptation strategies and productivity-enhancing tools in rural areas. Therefore, we can hypothesize that income earnings due to drought-induced public works employment can contribute to sustainable agriculture by enhancing SWC practices and altering labor engagements in different activities.

3.3 The Data

We use the publicly available World Bank Living Standards Measurement Study-Integrated Surveys of Agriculture (LSMS-ISA) panel datasets collected in 2011/12, 2013/14, and 2015/16 through collaborative efforts between the World Bank and the Central Statistics Agency (CSA) in Ethiopia.[7] The panel data is valuable because it includes detailed information about household socioeconomic characteristics and community-level variables. Additionally, it provides insights into SWC practices and self-reported weather-shock variables such as drought (too little rainfall) and other idiosyncratic shocks. To enhance the reliability of the self-reported data, we can also consider supplementing the panel data with vegetation remote sensing satellite-based data.

The most recent Ethiopia Socioeconomic Panel Survey (ESPS) had some limitations. Hence, we only stick to the earliest ESS three-panel datasets conducted in 2011/12, 2013/14, and 2015/16. To elaborate, the surveys conducted in 2018/19 and 2021/22 faced volatile security situations in the northern and western parts of the country. In particular, the ESPS-5 in 2021/22 covered limited enumeration areas (EAs), excluding all EAs in the Tigray region and partial data collection in the Afar region. In addition, security issues were problematic in both the Amhara and Oromia regions during ESPS-5 (fifth wave), consistently reducing the number of households and EAs coverage.

The study uses unbalanced panel households of 3226 in 2011/12, 3106 in 2013/14, and 3063 in 2015/16, respectively. The attrition rates were only 3.72 percent between 2011/12 and 2013/14 and 1.38 percent between 2013/14 and 2015/16, respectively. Therefore, we use a panel of 9395 households surveyed in 2011/12, 2013/14, and 2015/16. Even though it is the most extensive survey national data including all regions of the country, this paper is limited to sample households in ten rural administrative regions, namely Tigray, Amhara, Oromia, SNNP, Sidama, SWEP, Afar, Somali, Harari, and Dire Dawa city where the public works program operated. The regions have similar livelihood diversification, agricultural production, and population density characteristics. Public works employment is the primary target of the PSNP across these regions. However, the lowland areas focus on infrastructural development schemes.

[7] The LSMS-ISA datasets for Ethiopia are publicly available at `https://www.worldbank.org/en/programs/lsms/initiatives/lsms-ISA#2`.

One data limit for this study refers to the area coverage used for the analysis. First, it excluded two regional states, specifically Beneshangul Gumuz and Gambella, from the analysis since they had no public works operation till the end of the 2015/16 agriculture season (end of the evaluation period). In addition, it does not include sample households from the Addis Ababa city administration since the primary focus of this study is rural areas. Figure 3.1 shows the details of the enumeration areas across the three waves and administrative regions. Therefore, the interpretation of the results aligns with this context. In other words, there remains doubt about the possibility of bias or inaccuracies in interpreting the relationship between drought and public works employment in all regions.

3.3.1 Construction of key variables

3.3.1.1 Outcome variables

The two key outcome variables of interest are SWC practice and labor allocation. Various studies show that conservation and labor reallocation are adaptation measures to extreme weather shocks such as drought (Mulungu and Kilimani, 2023; Colmer, 2021; Girard et al., 2021). The construction of aggregate soil and water conservation (SWC) practices uses four widely promoted individual conservation measures. These measures consist of two broad categories. They include (1) structural activities, including terracing and check dams, and (2) vegetative conservation practices, namely afforestation and contour farming. Distinct analyses are conducted for physical measures (including structures built, such as terracing and check dams) and biological measures (consisting of planting crops related to afforestation and plowing along the contour) for soil and water conservation. Focusing on such categories aims to ensure the robustness of the main results. The other related outcome variables include aggregate family labor hours allocated to agricultural and non-agricultural activities over the last seven days.

3.3.1.2 Enhanced Vegetation Index anomaly as a proxy measure for drought

The most widely employed measures to characterize droughts include the Standardized Precipitation Index (SPI) (McKee et al., 1993) and the Palmer Drought Severity Index (Palmer, 1965). Wilhite and Glantz (1985) and Dracup et al. (1980) also independently provided dozens of drought definitions. These indices generally agree that drought is a condition of insufficient moisture triggered by a deficit in precipitation over some time. Hence, these measures have been developed by synthesizing meteorological, climatological, atmospheric, agricultural, hydrological, and water management-related variables such as precipitation, stream flow, and soil moisture. These require developed systems for recording and management to satisfy adequacy in spatial coverage and obtain quality data. However, fulfilling such requirements might be challenging in developing economies like Ethiopia, with missing or underdeveloped systems.

Alternative measures to monitor droughts employ satellite-based vegetation indices with advancements in remote sensing for wide spatial and temporal resolutions over large areas. These indices use the 12 months of vegetation index from the Moderate Resolution Imaging Spectroradiometer (MODIS). The MODIS-based indices include the Normalized Difference Vegetation Index (NDVI) (Svoboda, Fuchs, et al., 2016), the National Oceanic and Atmospheric Administration (NOAA) designed Vegetation Condition Index (VCI) (Kogan, 1995), and Enhanced Vegetation Index (EVI) (Huete et al., 2002). Furthermore, evaluating the sensitivity of the two MODIS vegetation indices (VI) to differences in vegetation cover showed that while the EVI is sensitive to canopy variations, the NDVI is only asymptotic to high biomass areas with dense vegetation cover. That is, NDVI, widely used for vegetation monitoring, saturates in high-biomass areas, reducing sensitivity to dense vegetation. Near 0.8–0.9, distinguishing moderate from dense cover is difficult, limiting its effectiveness. EVI performs better in these cases (Huete et al., 2002; Pettorelli et al., 2005).

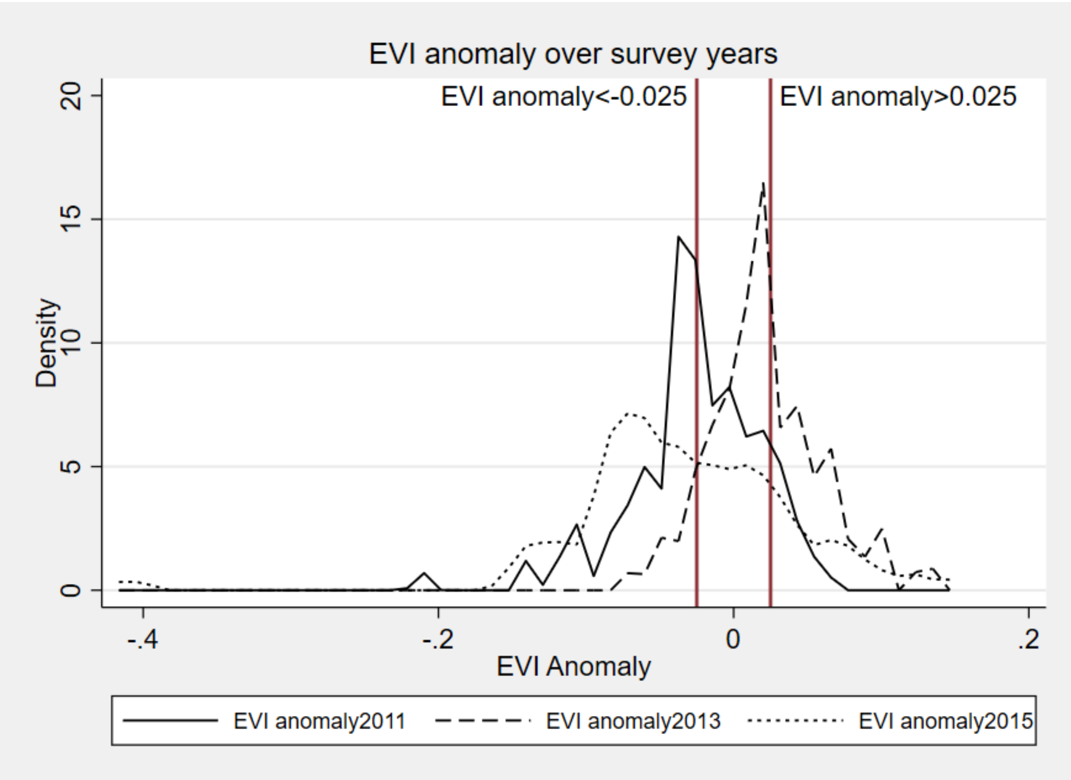
As a result, we construct an objective proxy measure of drought by utilizing the average EVI data obtained from the MODIS Land Cover Dynamics images. The LSMS-ISA includes the EVI values for respective growing periods and the long-term average from 2001 to the respective survey years, averaged by zone within the main ('Meher') growing season. The vegetation stress due to drought for a given zone over a given year characterizes the health of the vegetation in a given time series. As shown in Equation 3.1, we calculate the EVI anomalies of a zone by subtracting the long-term average from the respective survey year average values for the 'Meher' growing periods. Hence, the EVI anomalies can reflect the common drought incidence during the growing season in Ethiopia.

$$\textbf{NEVI Anomaly}_{i,t} = \textbf{Average EVI Value}_{v(i),t} - \textbf{Average EVI Value}_{v(i),long} \quad (3.1)$$

In Equation 3.1, *Average EVI Value*$_{v(i),t}$ denotes the average Enhanced Vegetation Index (EVI) value for the zone corresponding to household i during the Meher growing season in survey year t, while *Average EVI Value*$_{v(i),long}$ represents the long-term zonal average EVI for the Meher season. Here, i denotes the household index, and $v(i)$ represents the village to which household i belongs. Accordingly, the EVI anomaly is measured at the zone level and uniformly assigned to all households within that zone.

The MODIS EVI product suite accuracy within $\pm[0.025/2.5\%]$[8] threshold range characterizes the normal vegetation conditions. However, EVI anomaly values classified to the left of -2.5% and the right of +2.5% are below and above normal vegetation conditions, respectively. Therefore, an EVI anomaly value below -2.5% using remote sensing is the proxy for drought shock. Figure 3.4 presents the continuous EVI anomaly drought shock threshold. Hence, sample households residing in areas exhibiting the lower EVI anomaly threshold are drought-affected and considered the treatment group compared to those living in the non-drought-affected areas. Note that the normal EVI anomaly range includes -0.025≤EVI anomaly≤0.025.

Fig. 3.4 The distribution density of EVI anomalies for the survey years



In Figure 3.4, there is a continuous EVI anomaly illustrating a threshold for **drought shock** categorized as **EVI anomaly**< -0.025. The households falling into this category are the treatment group. The comparison households are villages within the EVI anomaly that fall in the range of **-0.025≤EVI anomaly≤0.025**, defined as the EVI anomaly standard for plant health and growth.

The EVI anomaly constructed using satellite-based data can overcome three limitations of self-reported data that rely on individual perceptions and recall abilities.

[8] The MODIS EVI product suite accuracy information is available at `https://modis-land.gsfc.nasa.gov/ValStatus.php?ProductID=MOD13`.

First, self-reported data is a subjective measure that can overstate or understate the situation. Secondly, it can overcome the limitations of self-reported data, which depend on households' recollections of recent rainfall patterns. Even if farmers likely remember the adverse effects of drought shocks on livelihoods, their recollections tend to be time-bound and subjective. Thirdly, the variability in impact can be high when using self-reported data. That means a slight rainfall decline might relatively affect the most vulnerable households with fewer coping strategies and experiencing other idiosyncratic shocks, likely to report them as droughts, than relatively more resilient farmers. Hence, the self-reported drought shock indicator is likely endogenous, which will have an upward bias on the impact estimates of extreme weather shocks.

3.3.2 Description and summary statistics

Table 3.1 presents details of the description and summary statistics for variables of interest. The pooled sample comprises 9395 households in the three waves, including participants and non-participants of the public works program. Additional controls involve different categories. First, household size is a household background characteristic referring to a family composition directly related to the public works program. Second, economic indicators include assets, land size, and oxen holdings. These are crucial resource endowments to enhance resilience capacity and adaptation to drought by mitigating its adverse effects. Note that household asset holdings are indices generated using principal component analysis as shown in Table 3.1. In addition, institutional variables consist of irrigation access, tenure security, and credit access. These are also fundamental factors that promote investment in conservation measures and proper family labor allocation. Moreover, community-level variables include weather shocks, food security status, elevation, and distance to central administration.

As shown in Table 3.1, the mean differences across the survey years presented in the last three columns for most variables are significant. Hence, these reports indicate significant mean changes over time for most variables, except for asset holdings, plot elevation, and residence distance to the central administration. The pooled sample mean shows that, on average, about 64% of households adopted the aggregate SWC practice, but relatively lower adoption rates for physical and biological conservation measures. The public works program employs only around 12% of the pooled sample households. Although many households allocate family labor hours to agricultural activities, only a few are engaged in non-agricultural activities.

Table 3.1 Description and summary statistics

Variable	Description of variables	Pooled Mean (1)	Pooled Min (2)	Pooled Max (3)	Mean across survey years 2011/12 (4)	2013/14 (5)	2015/16 (6)	Mean Difference (5)−(4)	(6)−(4)	(6)−(5)
Soil and Water Conservation (SWC) Practices	1 if a household practiced either of the four conservation measures, namely terracing, check dams, afforestation, and contour farming, and 0 otherwise	0.637	0	1	0.502	0.614	0.675	0.113***	0.173***	0.061***
Physical SWC measure	1 if a household has practiced physical or structural conservation measures that include either terracing or check dams; and 0 otherwise	0.437	0	1	0.349	0.433	0.451	0.084***	0.102***	0.018
Biological SWC measures	1 if a household reported biological or vegetative conservation measures, including either afforestation or contour farming; and 0 otherwise	0.342	0	1	0.241	0.310	0.384	0.069**	0.143***	0.074***
Public Works	1 if a household member reported participation in the public works of the PSNP over the preceding 12 months, and 0 otherwise	0.121	0	1	0.137	0.110	0.117	-0.027***	-0.019**	0.007
Agricultural labor	Family labor hours allocated to agriculture activities by all members of a household in the last seven days	50.452	0	432	51.896	52.310	47.046	0.415	-4.849***	-5.264***
Non-agricultural labor	Family labor hours allocated to non-agricultural activities by all members of a household in the last seven days	9.036	0	258	16.5	5.671	4.587	-10.83***	-11.91***	-1.084**
Food security	1 if a household was food secure during the last 12 months, 0 otherwise	0.679	0	1	0.687	0.646	0.702	-0.040***	0.015	0.056***
Drought (satellite-based)	A dummy for EVI anomaly less than -0.025 (1 if EVI anomaly $\leq$ -0.025; and 0 if it is $\geq$ -0.025 and $\leq$ 0.025).[a]	0.503	0	1	0.591	0.121	0.712	-0.470***	0.121***	0.590***
Drought (self-reported)	It is a measure showing whether a household had drought (too little rain) experience in the 'Meher' season (1=yes; 0 otherwise)	0.365	0	1	0.252	0.196	0.578	-0.056***	0.326***	0.382***
Asset holdings	Asset Quintile nq(5) indices constructed from 35 asset items a household has held in the last 12 months, using principal component analysis (PCA)[b]	2.804	1	5	2.826	2.800	2.784	-0.025	-0.042	-0.017
Household size	Number of household members in an adult equivalent[c]	4.485	0.74	14.58	4.107	4.581	4.781	0.474***	0.674***	0.201***
Land size	Total current land size holding in hectares	1.460	0.003	19.844	1.742	1.346	1.278	-0.396***	-0.463***	-0.068*
Ox	Total number of oxen used in previous 'Meher' season	1.009	0	25	1.056	0.965	1.013	-0.091***	-0.044	0.048
Irrigation access	1 if a household had access to small-scale irrigation practices, 0 otherwise	0.105	0	1	0.111	0.103	0.102	-0.008	-0.010	-0.001
Tenure security	1 if a household received a certificate for any of the parcels, and 0 otherwise	0.370	0	1	0.274	0.397	0.443	0.123***	0.169***	0.046***
Credit access	Whether a household member had access to credit over the last 12 months (1=yes; 0 otherwise)	0.221	0	1	0.281	0.215	0.171	-0.067***	-0.110***	-0.043***
Elevation	It is a geospatial variable measuring the field elevation in meters	1881.737	201	3451	1876.669	1880.751	1888.076	4.082	11.41	7.325
Distance to central admin	It is a geospatial variable measuring a household residence distance in kilometers to the Population Center with $\geq$20,000. It is a proxy measure for central administration in a locality (in Ethiopia, this refers to a district)	38.399	0	208.2	38.829	38.171	38.184	-0.658	-0.645	0.013
Observations		9395			3226	3106	3063	6332	6289	6169

Note: The data comes from the Ethiopian Socioeconomic Survey (ESS) conducted in 2011/12, 2013/14, and 2015/16. Columns (1), (2), and (3) present the mean, minimum, and maximum values for the pooled sample. Columns (4) through (6) present the mean for each survey year. The last three columns indicate the mean difference across the survey years. Asterisks indicate significance at * 10%, ** 5%, and *** 1% levels.

[a] Section 3.3.1 on page 59 discusses how to construct EVI anomaly. It is the average daily EVI value of the current year minus the long-term average daily EVI value. Both current and long-term EVI values refer to the average by zone within the main ('Meher') growing season (reference periods: 2001-2011, 2001-2013 & 2001-2015).

[b] nq(5) describes asset holding quintiles ranging from 1 to 5; "1" is the lower 20% (an index category in 1-20%), "2" middle in 21-40%, "3" signifies an index category in 41-60%, "4" is an index category in 61-80%, and "5" indicates the upper 20% (an index category in 81-100%). The details to construct the scores in the PCA are given in Eriksson et al. (2013).

[c] An adult equivalent household size is generated based on weights adapted from Krishnan et al. (1998).

The data also shows that over 30% of households are food insecure. Appendix B Figure B.2 also confirms that households employed in public works are more prone to chronic food insecurity than unemployed households. The difference holds across all survey years. About half of the pooled sample is prone to the EVI anomaly drought indicator. The self-reported drought measure was relatively lower, reporting that 37% of the pooled sample was affected by the shock. Household resource holdings measured in terms of assets, land, and the number of oxen on average are limited. Appendix B Figure B.3 also presents detailed comparisons for resource endowment and asset holdings for public work participants and non-participant households. Participants are endowed with fewer resources and assets but are more vulnerable to shocks and chronic food insecurity. These are not surprising results. In other words, food insecurity, shocks, and limited resources are the main criteria for participation in public works. As per the program design, participants in public works experience more severe shocks and food insecurity than non-participants. As expected, participants own fewer resources and assets. We refer to footnote *b* under Table 3.1 to interpret the asset holdings. The asset holdings show quantile indices 1 to 5. An index of "1" refers to a category less than or equal to the bottom 20%, but "5" represents a category of asset holding in the top 20%.

Moreover, eligible households participate in public works since the program requires able-bodied temporary family labor participation. The average household size is more than four members per household, measured in the adult equivalent, with high variability. On average, land size for cultivation is about 1.46 hectares, and ox holding is about 1 per household, indicating the existence of resource constraints. Hence, this confirms that the public works program targets relatively poorer households with a smaller resource endowment. Access to irrigation is small, which is only about 11% of the pooled sample. While less than 40% of the households have tenure security for their farm plots, only about 22% of the households have credit access. The average elevation of the farm plots is about 1882 meters above sea level. Finally, on average, the household residence distance to the central administration is about 38 kilometers, with high variability ranging from 0 to 208. Figure 3.5 presents the distribution density of distance to central administration for treatment and control households. The figure shows that there is no difference between the two groups. Most households reside within less than 50 kilometers, and the right tail of the distribution density consists of only a small proportion of households in both groups.

3.4 Empirical strategy

3.4.1 Empirical specifications

We aim to evaluate the effects of public works on (a) SWC practices and (b) the allocation of household labor hours to agricultural and non-agricultural activities.[9] In a randomized intervention scenario, the outcome of non-participant households becomes an estimate of the counterfactual. However, sustained severe shocks, fewer asset holdings, low income, and inadequate support are observable characteristics that create differences in the outcome for participants and non-participants in public works. Hence, comparing the two groups will lead to a biased estimate.

Let $y_{0,it}$ and $y_{1,it}$ be untreated and treated outcomes for household i at time t, respectively. T_{it} refers to the binary treatment status for household i at time t equal to "1" if a household is employed, "0" otherwise. Then, the Average Treatment Effect on Treated (ATT) is given by:

$$ATT = E(y_{1it} - y_{0it}|T_{it} = 1) = E(y_{1it}|T_{it} = 1) - E(Y_{0it}|T_{it} = 1)$$

We cannot observe the untreated outcome for the treated group given by $E(y_{0it}|T_{it} = 1)$. Using the outcome for untreated households as an estimate of the counterfactual comparison generates bias that becomes:

$$Bias = E(y_{0it}|T_{it} = 1) - E(y_{0it}|T_{it} = 0)$$

The above bias applies to either group and is the difference between the expected outcome of the treated and untreated households before any treatment. We need to address this bias.

A more comprehensive approach is necessary to identify ATT. For example, we can model $y_{0,it}$ and $y_{1,it}$ as:

$$y_{0,it} = \alpha_0 + x'_{it}\beta_0 + \epsilon_{0,it}, \qquad E(\epsilon_{0,it}|x_{it}) = 0 \tag{3.2}$$

$$y_{1,it} = \alpha_1 + x'_{it}\beta_1 + \epsilon_{1,it}, \qquad E(\epsilon_{1,it}|x_{it}) = 0 \tag{3.3}$$

[9] The data enumeration for household, community, and post-harvest agriculture for all survey years in the panel takes place between February and April, roughly corresponding to the end of the 'Meher' agriculture season. This period also partly includes the slack period (as shown in Figure 3.3) when farmers look for non-farm income employment.

The observed outcome is given by:

$$\begin{aligned} y_{it} &= \alpha_0 + x'_{it}\beta_0 + \epsilon_{0,it} + T_{it}[(\alpha_1 - \alpha_0) + x'_{it}(\beta_1 - \beta_0) + (\epsilon_{1,it} - \epsilon_{0,it})] \\ &= \alpha_0 + x'_{it}\beta_0 + \delta T_{it} + T_{it}x'_{it}\gamma + \epsilon_{it}, \quad \epsilon_{it} = (1 - T_{it})\epsilon_{0,it} + T_{it}\epsilon_{1,it} \end{aligned} \tag{3.4}$$

where δ=$\alpha_1 - \alpha_0$ and γ=$\beta_1 - \beta_0$.

In the above model, the Average Treatment Effect (ATE) for households with characteristics x_{it} is given by

$$ATE(x_{it}) = \delta + x'_{it}\gamma$$

while ATT is given by

$$ATT(x_{it}) = \delta + x'_{it}\gamma + E\{\epsilon_{1,it} - \epsilon_{0,it}|x_{it}, T_{it} = 1\} \tag{3.5}$$

Suppose the treatment decision is specified as a probit equation:

$$\begin{aligned} T^*_{it} = \mu + \beta_z Z_{it} + \beta_x X_{it} + \eta_{it} = w'_{it}\beta_2 + \eta_{it}, \\ T_{it} = \begin{cases} 1, & \text{if } T^*_{it} > 0 \\ 0, & \text{otherwise} \end{cases} \end{aligned} \tag{3.6}$$

where T_{it} is the likelihood of participating in public works, Z_{it} is the vector of instruments, X_{it} is additional controls, and vector w'_{it} includes both instruments and additional controls.

Assume that $\eta_{it} \sim NID(0, 1)$, independent of z_{it} and x_{it}. Furthermore, assume that the error terms denoted by $\epsilon_{0,it}$ $\epsilon_{1,it}$ in Equations 3.2 and 3.3 for control and treatment groups respectively are also normal, with variances σ_0^2 and σ_1^2, and covariance σ_{02} and σ_{12} with η_{it}, i.e.,

$$cov(\epsilon_{0,it}, \eta_{it}|x_{it}) = \sigma_{02} \quad and \quad cov(\epsilon_{1,it}, \eta_{it}|x_{it}) = \sigma_{12},$$

Then, given these assumptions, one can show that

$$E[\epsilon_{0,it}|x_{it}, T_{it} = 0] = \sigma_{02}E[\eta_{it}|x_{it}, \eta_{it} < -w'_{it}\beta_2] = \sigma_{02}\lambda_{it}(w'_{it}\beta_2)$$

$$E[\epsilon_{1,it}|x_{it}, T_{it} = 1] = \sigma_{12}E[\eta_{it}|x_{it}, \eta_{it} > -w'_{it}\beta_2] = \sigma_{12}\lambda_{it}(w'_{it}\beta_2)$$

where

$$\lambda_{it}(w'_{it}\beta_2) = E[\eta_{it}|x_{it}, \eta_{it}] = \frac{T_{it} - \Phi(w'_{it}\beta_2)}{\Phi(w'_{it}\beta_2)[1 - \Phi(w'_{it}\beta_2)]}\phi(w'_{it}\beta_2)$$

In the first stage, we estimate the probit model to get $\lambda_{it}(w'_{it}\hat{\beta}_2)$. The identification strongly rests upon distributional assumptions, and it is advisable to have exclusion restrictions in Equations 3.3 and 3.4. That is, ideally, an instrumental variable that affects the decision whether to participate in the program, but not the actual and counterfactual outcomes of y_{it} can be found. Under these assumptions, the ATT from Equation 3.6 equals

$$ATT(x_{it}) = \delta + w'_{it}\gamma + (\sigma_{12} - \sigma_{02})\lambda_{it}(x'_{it}\beta_2)$$

If it is imposed that $\beta_0 = \beta_1 = \beta$, it follows that

$$E\{y_{it}|x_{it}, T_{it}\} = \alpha_0 + w'_{it}\beta + E\{\epsilon_{it}|x_{it}, T_{it}\}$$

$$= \alpha_0 + w'_{it}\beta + \sigma_{12}T_{it}\lambda_{it}(w'_{it}\beta_2) + \sigma_{02}(1 - T_{it})\lambda_{it}(w'_{it}\beta_2)$$

The above discussions show that we can consistently estimate α_0, β, and δ from a single regression provided that we include the generalized residual interaction with the treatment dummy. If it can be assumed that $\sigma_{02} = \sigma_{12}$, in which case $ATE(x_{it})$ and $ATT(x_{it})$ are identical.

3.4.2 Does drought shock drive public works employment?

According to the PSNP implementation manual, households facing severe shocks and chronic food insecurity are typically the poorest, with few assets, and are more likely to participate in the program. Guided by this, we examine whether drought shock is associated with household participation in public works and engagement in SWC practices, the primary outcomes of interest.

Drought is treated as an exogenous covariate, as its occurrence is independent of household behavior, and the PSNP provides a fixed monthly budget per participating household member. Hence, this reduces concerns of reverse causality or program-induced behavioral responses that could bias the estimates. Accordingly, Table 3.2 presents Linear Probability Model (LPM) estimates of participation in public works and SWC activities. These estimates assess whether drought triggers public works participation and influences the likelihood of adopting SWC practices. The results clarify whether participation is shock-driven and whether drought exposure significantly affects conservation adoption.

Table 3.2 Correlates of public works employment and SWC practices using satellite-based drought measure

	Public works employment(1=treated)			SWC practices (1=yes)		
	(1)	(2)	(3)	(4)	(5)	(6)
Drought (dummy EVI anomaly)	0.074***	0.067***	0.068***	0.030	0.017	0.008
	(0.008)	(0.008)	(0.008)	(0.018)	(0.019)	(0.019)
ln(Distance to central admin)	-0.019***	-0.014***	-0.019***	-0.015	-0.008	0.007
	(0.006)	(0.006)	(0.005)	(0.010)	(0.010)	(0.010)
Household size			0.008***			0.010***
			(0.002)			(0.004)
Land size			-0.001***			0.000
			(0.000)			(0.001)
Irrigation access			0.057***			0.108***
			(0.016)			(0.020)
Tenure security			-0.024***			0.057***
			(0.008)			(0.015)
Credit access			0.010			0.099***
			(0.009)			(0.017)
Asset holding			-0.007***			-0.018***
			(0.002)			(0.005)
Food security			-0.027***			0.059***
			(0.009)			(0.015)
Elevation			-0.000			0.000***
			(0.000)			(0.000)
Constant	0.014	-0.024	0.003	0.537***	0.503***	0.139**
	(0.016)	(0.019)	(0.028)	(0.042)	(0.046)	(0.059)
Time Fixed Effects	✓	✓	✓	✓	✓	✓
District Fixed Effects (21)	—	✓	✓	—	✓	✓
Additional controls	—	—	✓	—	—	✓
R^2	0.057	0.076	0.094	0.014	0.038	0.075
$F-stat$	73.264	16.242	10.783	14.245	8.496	13.012
$Prob > F$	0.000	0.000	0.000	0.000	0.000	0.000
Observations	4239	4239	4238	4239	4239	4238

The coefficient estimates represent the probabilities of (a) public works employment in columns (1)–(3) and (b) SWC practices in columns (4)–(6). The standard errors in parentheses are robust. Asterisks indicate significance at * 10%, ** 5%, and *** 1% levels.

Columns (1)-(3) reveal the probability estimates of public works employment and columns (4)-(6) control for drought shock, distance to central administration, household characteristics, and other relevant community-level variables. The results show that drought shock increases program participation and SWC practices, though the effects are insignificant in the latter case. Households in drought-affected villages are more likely to participate in the public work program and tend to adopt drought-adaptation SWC practices. In addition, an increase in household size increases public works employment and SWC practices. However, distance to central administration, land size, tenure security, asset holding, and food security negatively correlate with the probability of public works employment. The positive coefficient on irrigation access in public works estimation is unexpected, though it likely increases the likelihood of SWC practices.

In particular, columns (1) and (4) of Table 3.2 present the baseline likelihood estimations respectively for public works employment and SWC practices by controlling for drought shock, distance to central administration, and year and district-fixed effects. Public works' likelihood of participation is higher for households in drought-affected villages (about 7.4%) than in non-drought villages. On the other hand, a 1% increase in household distance away from the central administration reduces the likelihood of public works participation by 1.9%. The coefficient estimates on drought shock and distance to central administration are non-significant for SWC practices, irrespective of the specifications.

Furthermore, columns (2) and (5) present the probability estimates of public works employment and SWC practices by adding district-fixed effects on preceding specifications. The results are consistent and comparable to the baseline estimation results. Public works participation is likely higher for households in drought-prone villages by about 6.7%. An increase in household distance to central administration by 1% leads to a decrease in public work participation by about 1.4%.

Finally, columns (3) and (6) report the likelihood of employment for public works and SWC practices under full specifications, respectively. The interpretation of the probability estimates under full specifications follows a similar pattern. The results show that the probability of public works employment is higher by about 6.8% with the presence of drought shock.

The results, in general, show that drought shock and distance to the central administration are crucial factors that would make program participation more visible. That means being in drought-prone villages increases the likelihood of participation in safety net programs such as public works employment. On the contrary, households residing in distant areas away from the central administration are less likely to participate in public works. Moreover, households with more resources (e.g., land size) and asset holdings are better equipped to cope with severe shocks and are less likely to participate in safety net programs.

In conclusion, the results are robust using the self-reported drought indicator. As a result, Appendix B Table B.1 presents the re-estimation of Table 3.2. The results are consistent and comparable despite differences in size and significance of the coefficient estimates in some cases. The likelihood of public works employment and SWC practices are higher for households with reported drought. Household residence distance to central administration negatively correlates to public works participation and adoption of SWC practices, and its coefficient is non-significant for SWC practices under full specification.

3.4.3 Identification and estimation issues

When participation is random, public works employment and sets of other controls can determine the probability of adopting drought adaptation SWC practices and household labor engagement in agricultural and non-agricultural activities. Due to the absence of random participation in the public works program, our study faces multiple identification and estimation challenges. One major threat relates to the identification of the impact estimate. In particular, household participation in public works might be endogenous to the outcome variables of interest, the adoption of SWC practices, and household labor allocation to different activities. That is, participation in public works involves selection bias that we need to address. Selection bias arises from the inability to determine the outcome for a household participating in the program if not employed.

We are aware of the problem of selection bias. We can address it by an appropriate model specification under suitable assumptions about its error terms. Hence, we have developed a multifaceted approach. First, we want to rely on the justification provided in the program implementation manual to guide our efforts. As shown in the manual, the basis for public works employment is observable characteristics, including severe shocks, less resource endowment, small asset holding, low income, and less support status for a household in the preceding twelve months. These characteristics result in chronic food insecurity, which calls for appropriate social protection programs and interventions. Therefore, it is crucial to control exhaustively for these variables, as well as other confounding factors that may affect the likelihood of adopting SWC practices and household labor allocation to agricultural and non-agricultural activities. By doing so, we can attenuate the bias due to omitted variables and improve the efficiency of the estimates. However, some argue that unobservable individual behaviors might still affect the program's impacts. To counter this argument, we refer to Sharp et al. (2006), which suggests that unobservable characteristics such as assertiveness to participate in the program are low. Additionally, Andersson et al. (2011) shows that both eligible and non-eligible groups supported the official selection criteria publicized for why they had or had not participated in the program. These findings suggest that selection criteria are crucial and can lead to a higher chance of compliance in determining program participation.

Second, various studies, including Msuha et al. (2024), confirm that public work programs set the wage rate at or below the prevailing market rate, requiring beneficiaries to work in exchange for the transfer by focusing on infrastructure in poor communities. Therefore, deliberately choosing participants can help reduce the benefits that flow to the non-poor group of a community.

Third, we utilize an instrumental variable approach to address the potential endogeneity of public works employment. The choice of an instrument is complex as we need a variable that correlates with participation in public works but is uncorrelated with the error terms of the outcome variables. The first stage predicts the probability of binary treatment based on a set of instruments. In the second stage, we assess the likelihood of adopting SWC practices and the level of household labor allocated to agricultural and non-agricultural activities, using the predicted probabilities of participation obtained from the first stage. The second stage primarily employs the endogenous switching model, with detailed elaboration for model selection in later paragraphs under the same section. Public works employment targets households vulnerable to chronic food insecurity due to severe shocks, poverty (low income), inadequate support (such as limited access to credit), and fewer asset holdings (Coll-Black et al., 2012; Andersson et al., 2011; Ministry of Agriculture, 2014; Kosmowski et al., 2020). However, these variables are likely correlated with public works participation and might also directly influence investment in SWC measures and household labor allocation to various activities, thus violating the exclusion restriction.

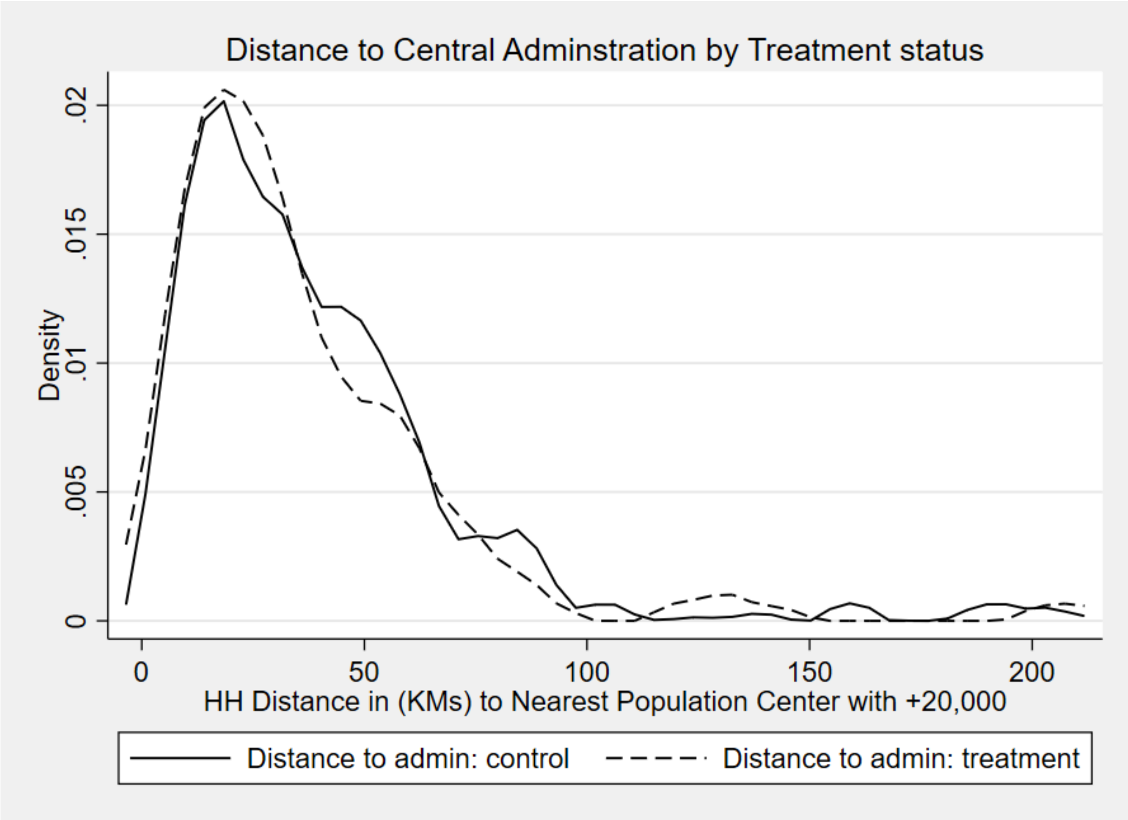
As a result, we need to find an instrument that could meet the first-stage requirements and the second-stage exclusion restriction for identification. Our data consists of the geographical distance in kilometers between households and the central administration responsible for deciding public works participation. Consequently, household residence distance to central administration for public works registration and participation can satisfy the requirements. Equation 3.6 describes a probit model that predicts program participation status in the first stage, utilizing the instrument to obtain consistent estimates for the β's coefficients. The argument might proceed as follows. An increase in the distance to central administration increases the transaction costs for registration and opportunity costs of participation, hence can discourage participation in the program, potentially reducing the incentive to participate without directly affecting the likelihood of adopting SWC practices and labor hour allocation decisions to different activities if public works participation is absent.

Recall that the geospatial distance variable in Table 3.1 shows considerable variability, with a minimum of 0 km and a maximum of 208 km. In addition, Table 3.1 depicts no significant mean difference between any two survey years in the panel. Figure 3.5 presents the distribution density of distance to the central administration by treatment status. The figure depicts that the two groups do not have any systematic differences in their distance from the central administration. Moreover, estimation in Table 3.2 shows that the distance of households from central administration negatively correlates with participation in public works regardless of the inclusion of additional controls in the specifications. However, it has no significant correlation with SWC practices across different specifications.

We want to stress that the chosen instrument might not be perfect, but we demonstrate its appropriateness by referring to the validity of the statistical tests. The first stage estimation shows a strong correlation between the instrument and public works, implying that the instrument has a statistically strong effect on program participation. An increase in distance to central administration likely discourages participation in the program. In addition, the coefficient estimates on the instrument variable in the probit and LPM models are negative and statistically significant at the 1% level (refer to Table 3.2 for estimations under different specifications from LPM). The Likelihood Ratio (LR) statistic associated with the instrument from the Probit model is 15.11, while the F-statistic from the LPM stands at 15.86. Both first-stage IV estimations are formally not reported here. These statistics are noticeably large relative to the LR test statistic that needs to exceed 10, as per the recommendation in White and Raitzer (2017).

Furthermore, the second-stage tests for the appropriateness of the Endogenous Switching model in the presence of selection bias are also satisfied. Accordingly, these include tests for correlation between the error terms in the treatment and outcome models ($atanh\ \rho$), heteroscedastic error terms ($ln\ \sigma$), and the Wald test of independent equations ($\rho = 0$), and they are all valid. To elaborate, the calculated values of the

Fig. 3.5 Distribution density of distance to central administration in kilometers by public works employment status



In Figure 3.5, we can see the continuous distance to central administration based on public works employment status. The figure demonstrates that there are no systematic differences between the two groups, and the mean difference tests across the years in Table 3.1 support this conclusion.

chi-square statistics are significant, indicating that we need to reject the hypothesis $\rho = 0$, implying that the two equations (Treatment and Outcome) are not independent. That means the endogenous switching model helps to handle when selection bias, heteroscedastic errors, and correlated error terms exist. The details of these test statistics are given in the bottom parts of Tables 3.3, 3.4, 3.5, 3.6, and 3.7.

The second stage determines a household's SWC adoption status and the level of labor hours allocated to agricultural and non-agricultural activities using the predicted participation status in the first stage. Not all farm households adopt SWC practices. The individual conservation measures in the aggregate SWC practices include terracing, check dams, afforestation, and contour farming. The households practice these measures either in isolation or in combination. A farm household practicing and maintaining at least one of these conservation measures either as recommended or with some modification refers to an adopter, where "1" denotes households that practice (hereafter, adopters), and "0" stands for non-adoption (hence, non-adopters). The T_{it} in Equation 3.6 is a dummy treatment variable denoting the situation of a household i being an adopter or not at time t. The impact estimate on the probability of adopting SWC practice and the level of labor hours allocation is depicted and interpreted as either ATE for the entire sample or ATT for those community members who received the treatment. The additional controls (X_{it}) include household size (number in adult equivalent), land size (in hectares), irrigation access (dummy), tenure security (dummy), credit access (dummy), and the farm plot's elevation (in meters).

Fourth, we employ the Full Information Maximum Likelihood (FIML) approach, one of the variants of the endogenous-switching regression model. This approach helps in dealing with selection bias. Terza (1998) states that the two-stage method of moments (TSM) estimator is relatively robust. It is a nonlinear least-squares estimator equivalent to the popular Heckman two-stage or "Heckit" approach Heckman (1979). It helps to deal with selection bias, assuming a binary switch, which is endogenous for the outcome. This empirical specification applies to outcome variables of interest, including SWC practices and labor engagement in agricultural and non-agricultural activities in rural areas.

Fifth, we implement two additional alternative empirical specifications to probe the robustness of the main results. The first of these alternative specifications is regression analysis. In this case, we estimate the ATE for the entire sample using the Pooled Ordinary Least Squares (POLS) estimation. The justification for this approach is that the basis of selection for public works employment is observable to policymakers and analysts. Hence, controlling for these observable variables with other controls using regression analysis can improve the efficiency of the estimate. Recall that both Sharp et al. (2006) and Andersson et al. (2011) supported this approach for the reason stated in earlier discussions.

Finally, we conducted additional robustness checks using an alternative identification strategy. Here, we employed the Lewbel two-step IV method (Lewbel, 2012). This approach exploits heteroskedasticity-based instruments to provide an efficient estimate with the existence of endogenous explanatory regressors or measurement errors as stated in Lewbel (2018) and Baum et al. (2013). In this approach, identification requires regressors to be uncorrelated with the product of heteroscedastic error terms. This assumption is a feature of many models where the correlation of error terms in the two models happens due to an unobserved common factor. This approach can be applied when valid external instruments are missing. Or else, when we use external instruments to improve the efficiency of the IV estimator. This approach also allows 'Sargan–Hansen' orthogonality condition tests or over-identifying restrictions. This statistical test is missing in the just-identified cases using external instruments. Hence, this allows for simultaneous testing of the validity of external and constructed or generated instruments. The Lewbel approach is similar to the dynamic panel data estimators presented in Arellano and Bond (1991) since the latter estimators use lagged values for endogenous regressors for identification. However, the Lewbel approach has an advantage in applying purely cross-sectional, time series, or panel datasets.

In summary, here are a few additional notes on the alternative empirical approaches to improve the consistency of the estimates. Both endogenous-switching regression and the Lewbel method employ an instrumental variable approach to deal with potential endogeneity due to selection bias. The inference in this paper sticks to the main estimation results from the endogenous-switching regression model. The regression analysis and the Lewbel approach are employed to scrutinize the robustness of the main results. In addition, we included time-fixed effects or the year dummy (in the Lewbel method) to address unobserved heterogeneity over time. Since there are 21 districts, we include district-fixed effects to handle heterogeneity in the residence location of the households. Finally, additional controls in the estimations include household size, land size, irrigation, tenure security, credit access, and farm plot elevation.

3.5 Results and discussion

This section presents empirical results for the impact of drought shock-induced public works employment on the adoption of SWC practices and the level of household labor allocation to different activities in rural areas. Public works employment is a significant part of the PSNP, which aims to deliver resource conservation and improve livelihoods for people in rural areas. This paper further evaluates the program's role in household labor allocation decisions for agricultural and non-agricultural activities. Therefore, we consider household adjustment in labor engagement as one possible mechanism through which public works employment can influence conservation measures in rural areas. Specifically, Section 3.5.1 provides the main results. Section 3.5.2 explains possible mechanisms through which public works employment affects investments in SWC practices via household labor supply adjustments. Section 3.5.3 scrutinizes the robustness of the main results.

3.5.1 Main results

3.5.1.1 Public works and aggregate soil and water conservation

In this section, we gauge the effects of public works employment on SWC practices. In particular, Table 3.3 presents the likelihood of adoption for aggregate SWC practices. Tables 3.4 and 3.5 provide the probability of adoption for the two broad categories of SWC practices (physical and biological SWC measures), respectively.

In particular, Table 3.3 reports the ATE and ATT coefficient estimates of public works employment on aggregate SWC practice. The analysis employs the Poisson regression with endogenous treatment effects. The results show that public works employment increases the likelihood of adopting SWC practice under different specifications. The impact estimates in all cases are statistically significant at the 1% level. The estimated ATE on public works employment in the first row of Table 3.3 ranges from about 0.106 to 0.118 for the different specifications of controls. The estimated values imply that the average sample households increase investment in aggregate SWC practices if employed in public works. The ATT in the second row of Table 3.3 is close to the ATE estimates in the first row. The similarity between the ATT and ATE values indicates that the average households employed in public works would respond with similar adoption of SWC practices if they did not get employment in the program.

The first two columns of Table 3.3 provide the ATE and ATT estimates of the baseline regression results without including additional controls. Public works employment likely increases SWC practices in both cases. The ATE estimate on public works employment in column (1) is 0.118, implying that the average household of the entire sample practices results in 0.118 higher additional SWC practices when employed in public works. Similarly, the ATT estimate on public works employment in column (2) is 0.124. Thus, the average household in the treated population might likely practice SWC with a 0.124 higher probability than it would if they were not participants in the public works program.

Moreover, the ATE and ATT estimates in columns (3) and (4), respectively, are robust to the additional controls. Columns (5) and (6) report ATE and ATT coefficient estimates under full specifications, considering farm plot elevation in addition to the preceding additional controls under columns (3) and (4). The inclusion of farm plot elevation aims to

Table 3.3 Effects of public works employment on aggregate SWC practices

	Full Information Maximum Likelihood (FIML) approach[a]					
Depend. var: Aggregate SWC practice (1=yes)	(1)	(2)	(3)	(4)	(5)	(6)
Public works: ATE	0.118***		0.106***		0.111***	
	(0.023)		(0.022)		(0.022)	
ATT		0.124***		0.113***		0.118***
		(0.024)		(0.023)		(0.023)
Time Fixed Effects	✓	✓	✓	✓	✓	✓
District Fixed Effects (21)	✓	✓	✓	✓	✓	✓
Additional controls	—	—	✓	✓	✓	✓
Elevation	—	—	—	—	✓	✓
Instrument	✓	✓	✓	✓	✓	✓
Dependent variable control mean	0.621					
/atanh ρ	-1.353***		-1.326***		-1.232***	
/ln σ	-6.754***		-7.082***		-8.215***	
Wald test of Indep. Eqns. ($\rho = 0$): $\chi^2_{(1)}$	409.32***		427.07***		90.22***	
Observations	5801	5801	5800	5800	5800	5800

In all cases, estimations demonstrate the impact of public works employment, instrumented by distance to central administration, on a binary measure aggregate SWC practices indicator, including terracing, check dams, afforestation, and contour farming. The FIML approach is a variant of the endogenous switching regression model that employs the two-stage method of moments (TSM). The coefficient estimates on public works refer to marginal effects corresponding to ATE and ATT under different specifications. Columns (1) and (2) present baseline estimates without additional controls, while columns (3) and (4) include additional controls such as household size (in adult equivalent), land size (in hectares), irrigation access (dummy), tenure security (dummy), and credit access (dummy). Columns (5) and (6) are full specifications by incorporating the farm plot's elevation (in meters) in addition to earlier controls in columns (3) and (4). All estimations report robust standard errors in parentheses, and asterisks show significance at the * 10%, ** 5%, and *** 1% levels.

[a] The FIML approach is a variant of the Endogenous Switching Model that employs the Poisson regression with endogenous treatment effects. It uses *"etpoisson"* command to estimate both the Average Treatment Effect (ATE) and Average Treatment Effect on the Treated (ATT) with robust standard errors. The details of estimation procedures are available at https://www.stata.com/manuals/teetpoisson.pdf.

test the sensitivity of the estimated coefficients to differences in altitude. The coefficient estimate on elevation in the Poisson regression with endogenous treatment is positive and statistically significant at 1% (not formally reported), confirming that public works target highland areas, as shown in the program implementation manual. In addition, the ATE and ATT estimates that include elevation are slightly higher, suggesting the exclusion of this variable might understate the impact estimate. Furthermore, the results in columns (5) and (6) are consistent and comparable with the baseline and estimations with additional controls. The average predicted aggregate SWC practice for households in the entire sample (ATE estimates) and those employed in the program (ATT estimates) are similar but slightly higher for participants (0.118 as compared to 0.111).

We stick to the explanation provided in Terza (1998) for slight differences in the ATE and ATT estimates from similar specifications. While using the Endogenous treatment model, the ATE and ATT will only be the same under specific conditions. These conditions include the absence of correlation between errors from treatment and outcome equations and the exogenous covariates X's having the same distribution in the overall population and treated sub-population. Despite the slight differences, all specifications reveal a positive effect of public works employment on the likelihood of SWC practices. The results suggest that public works employment enhances investments in SWC practices at the household level.

Finally, the bottom part of Table 3.3 reports the statistical test results required in the second stage of the Endogenous Switching Model. As we can recall from discussions under Section 3.4.3, the vital tests for adequacy and reliability of this model include checking for the significance of the estimated correlation coefficient between the error terms in the treatment and outcome model ($atanh\ \rho$), heteroskedastic error terms ($ln\ \sigma$), and the Wald test of independent equations ($\rho = 0$). In all cases, the test statistics are significant under different specifications. These imply that the statistical test results are all valid and that the selection of the endogenous switching model is appropriate for gauging the effects of public works on SWC adoption.

3.5.1.2 Heterogeneous effects of public works on different categories of SWC measures

Tables 3.4 and 3.5 focus on the physical/structures and biological/vegetative measures of SWC practices, respectively. Such categorization intends to examine the robustness of the main results. The two categories require different labor intensities for practice. Accordingly, building structural measures such as terracing and check dams are relatively more labor-intensive than vegetative SWC measures. Afforestation and contour farming practices are related to tree planting and tilling/planting across sloped land consistent with lines of elevation to conserve rainwater and reduce soil losses by controlling run-off.

Results in Table 3.4 indicate the effects of public works employment on physical conservation measures. Hence, drought shock-induced public works likely increase the probability of adopting physical conservation measures. Focusing on the first row of

Table 3.4, the ATE estimates range approximately from 0.15 to 0.18 under different specifications of the Endogenous Switching Model.

Table 3.4 Effects of public works employment on Physical SWC measures

	Full Information Maximum Likelihood approach					
Dependent var: Physical SWC practices (1=yes)	(1)	(2)	(3)	(4)	(5)	(6)
Public works: ATE	0.183***		0.149***		0.153***	
	(0.028)		(0.026)		(0.026)	
ATT		0.187***		0.160***		0.164***
		(0.027)		(0.027)		(0.027)
Time Fixed Effects	✓	✓	✓	✓	✓	✓
District Fixed Effects (21)	✓	✓	✓	✓	✓	✓
Additional controls	—	—	✓	✓	✓	✓
Elevation	—	—	—	—	✓	✓
Dependent variable control mean	0.414					
$/atanh\ \rho$	-1.421***		-1.353***		-1.256***	
$/ln\ \sigma$	-5.908***		-6.483***		-8.450***	
Wald test of Indep. Eqns. ($\rho = 0$): $\chi^2_{(1)}$	293.01***		285.28***		361.14***	
Observations	5801	5801	5800	5800	5800	5800

In all cases, estimations demonstrate the impact of public works employment, as influenced by the distance to central administration, on a binary measure of structural/physical SWC practices indicator, including terracing & check dams. The coefficient estimates on public works employment are marginal effects from the endogenous switching model corresponding to ATE and ATT under different specifications. Columns (1) and (2) present baseline estimates without additional controls, while columns (3) and (4) include additional controls such as household size (in adult equivalent), land size (in hectares), irrigation access (dummy), tenure security (dummy), and credit access (dummy). Columns (5) and (6) are full specifications by incorporating the farm plot's elevation (in meters) in addition to earlier controls in columns (3) and (4). All estimations report robust standard errors in parentheses, and asterisks show significance at the * 10%, ** 5%, and *** 1% levels.

Table 3.4 further presents that the magnitudes of ATE and ATT estimates for physical measures are relatively higher than similar estimates of the aggregate SWC practices in 3.3. The results show that the average households in the sample invest more in physical/structural SWC practices when participating in public works. For instance, the estimation in the full specification of column (5) shows that the average household of the whole sample likely had about 0.153 higher predicted physical/structural SWC practices when employed in public works. In other words, participation in public works employment yields a greater probability of adopting physical SWC measures for employed households than the control sample. In addition, the ATT estimates in the second row of Table 3.4 are also close in magnitude to the ATE estimates in the first row.

Table 3.5 presents the estimates of the effects of public works employment on biological conservation measures. Irrespective of the employed specifications, the ATE and ATT estimates are negative and insignificant. Moreover, the results are stable and not sensitive to the inclusion of additional controls in the estimations. The results suggest that the program has limited effects on biological/vegetative SWC measures, which are relatively less labor-intensive but long-term investments in conservation measures. Hence, the results further highlight that while public works influence physical/structural SWC practices, they do not affect the vegetative SWC measures despite the former being relatively labor-intensive but might require a short time to promote sustainable land management, hence improving productivity and food security in rural areas.

Table 3.5 Effects of public works employment on biological SWC measures

	Full Information Maximum Likelihood approach					
Dependent var: Biological SWC practices (1=yes)	(1)	(2)	(3)	(4)	(5)	(6)
Public works: ATE	-0.023		-0.015		-0.014	
	(0.026)		(0.026)		(0.026)	
ATT		-0.025		-0.016		-0.015
		(0.028)		(0.028)		(0.028)
Time Fixed Effects	✓	✓	✓	✓	✓	✓
District Fixed Effects (21)	✓	✓	✓	✓	✓	✓
Additional controls	—	—	✓	✓	✓	✓
Elevation	—	—	—	—	✓	✓
Dependent variable control mean	0.347					
$/atanh\ \rho$	1.385***		1.416***		1.431***	
$/ln\ \sigma$	-5.900***		-5.612***		-5.490***	
Wald test of Indep. Eqns. ($\rho = 0$): $\chi^2_{(1)}$	157.11***		177.54***		177.42***	
Observations	5801	5801	5800	5800	5800	5800

In all cases, estimations demonstrate the impact of public works employment, instrumented by the distance to central administration, on a binary measure of biological SWC practices indicator that includes afforestation & contour farming. The coefficient estimates on public works employment are marginal effects from the endogenous switching model corresponding to ATE and ATT under different specifications. Columns (1) and (2) present baseline estimates without additional controls, while columns (3) and (4) include additional controls such as household size (in adult equivalent), land size (in hectares), irrigation access (dummy), tenure security (dummy), and credit access (dummy). Columns (5) and (6) are full specifications, incorporating the farm plot's elevation (in meters) in addition to earlier controls in columns (3) and (4). All estimations report robust standard errors in parentheses, and asterisks show significance at the * 10%, ** 5%, and *** 1% levels.

In general, investment decisions are higher for households participating in public works despite the two broad categories of SWC measures that might be complementary in rural areas. These variations in investment decisions might be due to relative differences in technical skill or specific know-how, capital, land, and other resource requirements to implement these conservation measures. For instance, relatively permanent check dams, afforestation, and contour farming require advanced technical skills, capital investments, marginal land (e.g., afforestation), and additional resources compared to terracing activities. However, public works employment targets households with able-bodied family labor but with different constraints related to resource endowment (land holding, oxen ownership) and asset holdings. A relatively lower resource endowment might be due to households' vulnerability to drought shock, among other factors. This results in chronic food insecurity that calls for social protection programs and assistance from different parties. Hence, the successful implementation of conservation measures might require technical skills and capacity-building services that can complement public works to promote sustainable land management and conservation practices as an adaptation to drought.

In conclusion, participation in public works likely increases the adoption of SWC measures in rural Ethiopia. Drought shock significantly drives program participation. Despite concerns in the literature about public works potentially crowding out participants' own soil and water conservation and agricultural efforts, the results suggest that public works likely contribute to enhanced soil and water conservation practices. To put it differently, social protection targeting public works employment increases investments in labor-intensive SWC practices at the household level. The average difference is higher and more significant for participants than non-participants. That means community-level employment in infrastructure-building activities can trickle down to household-level investments, contributing to two main reasons. First, household employment in public works generates additional income, enhancing SWC practices. Second, the experiences gained at the community level can encourage farmers to participate in their farms' conservation efforts.

The program mainly helps with labor-intensive physical resource conservation measures, like building structures to prevent soil erosion, but has less effect on biological/vegetative conservation measures, such as planting trees to protect the soil. The differential effects of the program on the two categories of conservation measures might be due to the nature of these practices. The labor-intensive resource conservation measures often require relatively more technical skills, capital, and labor intensity that can benefit from provisions and support to households participating in public works programs. However, biological/vegetative conservation measures often require a long time for their restoration.

The results highlight that public works programs can complement and enhance individual soil and water conservation efforts. Public work programs often provide resources (for instance, training, tools, and financial incentives) that individuals or small farmers might not have access to independently. Additionally, these programs can create a network of support that encourages better practices and greater participation, helping to improve conservation outcomes. Moreover, such social protection programs might give people behavioral incentives by providing job opportunities and financial compensation and can motivate individuals to engage in practices they might have otherwise neglected.

The results can also have broader implications for different outcomes in rural areas. The argument proceeds as follows. Public works programs improve soil and water conservation, enhancing agricultural productivity through improved soil health, leading to higher crop yields and economic gains. They also help develop skills, mobilize labor, and increase productivity, resulting in higher incomes. Furthermore, effective conservation reduces future environmental degradation, preventing losses and lowering costs. Finally, healthier agricultural sectors can boost rural incomes, increase local goods and services demand, and stimulate broader economic growth, leading to long-term benefits that far outweigh the initial costs.

Our empirical findings align with the positive and statistically significant Average Treatment Effect (ATE) estimate reported in Bahru and Zeller (2022). This study employed a targeted maximum likelihood estimation procedure to conclude that participation in the Productive Safety Net Program (PSNP) enhances household involvement in watershed activities, which are essential for conservation efforts. Similarly, participation in the PSNP significantly increased tree cover in less densely populated areas and on steeply sloped terrain, and in the long run (Hirvonen et al., 2022). Besides, our finding supports a statistically significant ATT estimate in Andersson et al. (2011) using regression analysis. That study estimated the effects of PSNP participation on the number of tree holdings and confirmed involvement in PSNP increased tree holdings[10], and the difference between participants and non-participants was statistically significant. Of course, households' tree holdings can be either household assets or part of long-term investment efforts to improve land cover by complementing

[10] Both tree holdings by Andersson et al. (2011), and tree cover analysis in Hirvonen et al. (2022) can equivalently signify farm households afforestation practices, which is one major component of promoted conservation measures in the current study.

the SWC practices and promoting better agricultural production. However, our results contradict the finding in Adimassu and Kessler (2015) that stated that households who participated in highly labor-intensive public works of the PSNP had less investment in soil erosion control measures than non-participating households.

3.5.2 Mechanisms

Recall the previous discussions in Section 3.2.2 on page 52 in which public works employment could directly or indirectly affect different aspects of society in rural areas. The direct effects work through investments in sustainable land management, such as SWC measures, and several potential pathways for the indirect effects of the program. Therefore, this section discusses these issues as mechanisms through which public works employment could indirectly enhance farm-level investment in conservation measures. In other words, evaluations focus on how public works employment can create a difference in labor hours allocated to agricultural and non-agricultural activities, referring to Adimassu and Kessler (2015), Deininger et al. (2016), Imbert and Papp (2020), Bhargava (2023), and Gazeaud et al. (2023).

An inquiry about whether public works employment could create a crowding-in effect of labor engagements in agricultural activities is inconclusive and widely debatable in the literature. For instance, Koohi-Kamali (2010) states that public works employment can increase labor hours spent on private farm plots and investments in marginal land. Gehrke and Hartwig (2018) also showed that public works employment can induce productive investments via income and insurance effects when the program is sufficiently reliable and long-term. Furthermore, Zimmermann (2024) confirmed that participation in public works could improve welfare by allowing participants to shift from work for pay to self-employment activities, hence limited evidence of a crowding out of private-sector jobs. On the contrary, Ajefu, Joseph Boniface and Abiona, Olukorede (2019) indicated that public works likely increase non-agricultural labor as excess informal labor market opportunity reduces school engagements for children during positive shock periods in rural India.

Therefore, our regressions in the subsequent subsections focus on household labor engagements in agricultural and non-agricultural activities in the past seven days. The empirical estimations for these outcome variables also apply the FIML approach of the Endogenous Switching Model and the household distance to central administration to instrument the public works employment endogenous regressor, similar to the analysis for identifying SWC practices.

3.5.2.1 Public works employment and agricultural labor

Table 3.6 presents the effects of public works employment on household labor hours allocated to agricultural activities. In all cases, the dependent variables are dummies for three different thresholds for household labor hours allocated to agricultural activities in the last seven days. In addition, all estimations involve full specifications. The first, middle, and final two columns, respectively, refer to the proportion of a household's total labor allocation to agricultural activities in the *Bottom 25%*, *Middle 50%*, and *Top 25%* threshold.

Columns (1) through (6) of Table 3.6 present the ATE and ATT coefficient estimates of public works employment on different proportions of labor hours allocated to agricultural activities. Accordingly, the size of the ATE and ATT coefficient estimates are identical for the first two columns and close in the other remaining columns. On average, labor hours allocated to agricultural activities by participants in public works likely outweigh the allocation to similar activities by non-participants of the program, irrespective of the labor hours thresholds. Furthermore, the largest and strongest effect exists in the proportion equal to the Middle 50% threshold of total labor hours allocated to agricultural activities. That means columns (3) and (4) of Table 3.6 show about 10% greater total labor hours allocation to agricultural activities for the treated households than the control group for the total labor hours threshold in the middle 50%. The effects are similar for average households of the entire sample (ATE) and the treated group (ATT). We interpret the ATE and ATT estimates in columns (1), (2), (5), and (6) accordingly.

In summary, results in Table 3.6 show that labor hours allocated to agricultural activities by participants in public works are higher than non-participants, irrespective of the specified thresholds. Estimation results under similar labor allocation thresholds are almost the same for average households of the entire and treated samples. In other words, the ATE and ATT estimates are either identical or very close in magnitude under the subsequent pair of estimations. The positive and significant coefficient estimates imply that participants in public works allocated more labor hours to agricultural activities than the non-participants. The results suggest that the increase in labor engagements in agriculture may be one mechanism through which public works

Table 3.6 Effects of public works employment on agricultural labor hours

Dependent var: Agricultural labor hours (dummy)	Bottom 25%		Middle 50%		Top 25%	
	(1)	(2)	(3)	(4)	(5)	(6)
Public works: ATE	0.031^{**}		0.098^{***}		0.036^{**}	
	(0.016)		(0.019)		(0.017)	
ATT		0.031^{**}		0.099^{***}		0.038^{**}
		(0.015)		(0.019)		(0.018)
Time Fixed Effects	✓	✓	✓	✓	✓	✓
District Fixed Effects (21)	✓	✓	✓	✓	✓	✓
Additional controls	✓	✓	✓	✓	✓	✓
Elevation	✓	✓	✓	✓	✓	✓
Sample Mean (unemployed) (%)	0.746		0.496		0.245	
Number of Households (Underemployed)	8205		8205		8205	
$/atanh\ \rho$	1.915^{***}		1.920^{***}		1.955^{***}	
$/ln\ \sigma$	-7.592^{***}		-6.156^{***}		-4.564^{***}	
Wald test of Indep. Eqns. ($\rho = 0$): $\chi^2_{(1)}$	8.31^{***}		8.02^{***}		12.11^{***}	
Observations	8667	8667	8667	8667	8667	8667

The dependent variables refer to dummy agricultural labor hours for three different thresholds. The coefficient estimates on public works employment represent the marginal effects from the endogenous switching model corresponding to ATE and ATT. All columns (1) through (6) represent full specifications that include additional controls such as household size (in adult equivalent), land size (in hectares), irrigation access (dummy), tenure security (dummy), credit access (dummy), and farm plot's elevation (in meters). Furthermore, all estimations report robust standard errors in parentheses, and asterisks indicate significance at the * 10%, ** 5%, and *** 1% levels.

employment can promote investments in resource conservation. Hence, this can improve various economic outcomes, including agricultural production, sustainable land use, and food security in rural areas of developing economies.

3.5.2.2 Public works employment and non-agricultural labor

Columns (1) through (6) of Table 3.7 present the estimated effects of public works employment on the likelihood of household labor allocation to non-agricultural activities under specific thresholds. The estimations consider only the top 25% thresholds of non-agricultural labor engagements. The analysis is limited to only the top non-agricultural labor hours because the majority (about 77%) of the households in the entire sample were not engaged in non-agricultural activities where there are many zero labor hours to the left of the specified threshold. In other words, we only observe labor engagements in non-agricultural activity thresholds to the right of the top 25%. Accordingly, columns (1) and (2) show the *Top 25%*, columns (3) and (4) provide the

Top 10%, and columns (5) and (6) indicate the *Top 5%* of total labor hours that a household in rural areas allocated to non-agricultural activities.

Table 3.7 Effects of public works employment on non-agricultural labor hours

Dependent var: Non-agricultural labor hours (dummy)	Top 25%		Top 10%		Top 5%	
	(1)	(2)	(3)	(4)	(5)	(6)
Public works: ATE	-0.052***		-0.027		-0.014	
	(0.018)		(0.017)		(0.013)	
ATT		-0.037***		-0.018		-0.009
		(0.013)		(0.011)		(0.008)
Time Fixed Effects	✓	✓	✓	✓	✓	✓
District Fixed Effects (21)	✓	✓	✓	✓	✓	✓
Additional controls	✓	✓	✓	✓	✓	✓
Elevation	✓	✓	✓	✓	✓	✓
Sample Mean (unemployed) (%)	0.225		0.170		0.094	
Number of Households (Underemployed)	8205		8205		8205	
$/atanh\ \rho$	-1.917***		1.911***		1.912***	
$/ln\ \sigma$	-6.331***		-7.186***		-11.742***	
Wald test of Indep. Eqns. ($\rho = 0$): $\chi^2_{(1)}$	7.34***		6.42**		7.32***	
Observations	8667	8667	8667	8667	8667	8667

The dependent variables indicate dummy non-agricultural labor hours across three different thresholds. The coefficient estimates on public works employment represent the marginal effects from the endogenous switching model corresponding to ATE and ATT. All columns (1) through (6) represent full specifications that include additional controls such as household size (in adult equivalent), land size (in hectares), irrigation access (dummy), tenure security (dummy), credit access (dummy), and farm plot's elevation (in meters). Furthermore, all estimations report robust standard errors in parentheses, and asterisks indicate significance at the * 10%, ** 5%, and *** 1% levels.

The results in Table 3.7 show that the coefficients of public works employment are negative in all cases. They show that participation in public works had a downward pressure on non-agricultural labor hours and reduced the likelihood of non-agricultural labor hours allocation per week for the average household of the entire and treated samples. In other words, they imply that participants are less likely to allocate household labor to non-agricultural activities, irrespective of the thresholds specified. Focusing on columns (1) and (2) of Table 3.7, the estimated ATE and ATT coefficients are about -5.2% and -3.7%, respectively, implying that participants in public works allocate lower labor hours to non-agricultural activities than non-participants. In other words, non-agricultural labor hours are lower for households participating in public works for the proportion of total labor hours in the *Top 25%* threshold. The results suggest that participation is associated with lower non-agricultural labor hours among households in the top 25% of the labor distribution compared to non-participating households. We found no evidence for the differences in the effects of public works employment on non-agricultural labor hours allocation for relatively higher thresholds (i.e., labor allocation to non-agricultural activities for the proportion of labor in the *Top 10%* and *Top 5%*) in columns (3) through (6). Although the effects are not statistically significant for the top 10% and top 5%, this does not necessarily indicate a weak overall effect. The consistent negative sign of the coefficients across all thresholds points to a potential reduction in non-agricultural labor hours among high-intensity participants, even if the strength of the effect varies by threshold.

The results on household labor engagements in Table 3.6 and 3.7 indicate that while public works employment likely increases agricultural labor, it reduces non-agricultural labor hours per week. The results confirm that the two activities compete for labor hours, and an increase in labor hours allocated to agricultural activities means a reduction in its availability for non-farm activities since the total available hours per a given time is limited. The average differences in labor hour engagements in agricultural and non-agricultural activities, respectively, are higher and lower for participants than for non-participant households. The results suggest that farm households exert more effort on agricultural activities when employed in public works. In peasant agriculture, the increase in agricultural labor among public works participants likely reflects the reallocation of previously underutilized household labor. Given the prevalence of underemployment in such settings, public works may enable more efficient use of idle labor rather than crowding out other productive activities. Hence, both results support that household labor adjustments are mechanisms to promote investments in conservation measures that help rural households adapt to drought shock. Consequently, such improved resource conservation and altered labor allocation can enhance sustainable land use by increasing productivity and improving food security.

To this end, participation in the program is also more likely to increase labor engagement in agricultural activities but reduce work hours in non-agricultural activities. Such labor adjustments and engagement in different activities are the indirect mechanisms through which public works influence conservation efforts and agricultural production in rural areas of developing economies. Public works employment at the community level can trickle down and enhance micro-level investment in conservation measures. Accordingly, participation in public works significantly increased household labor hours allocation to agricultural activities but reduced hours in off-farm employment. In other words, farm households participating in the program typically spend more hours on agricultural activities while working fewer hours in off-farm activities. This finding aligns with one of the recent findings in Bahru and Zeller (2022) that stated participation in PSNP significantly increased time spent in agricultural work. In addition, the results support the findings in Maity (2020), which indicates that the participation of adults in India's National Rural Employment Guarantee Act (NREGA) increases the number of work days in agricultural activities for boys.

Moreover, the results on the effects of public works employment on household labor allocation support the idea that participation in the program can create crowding-in effects of labor hours engaged in agricultural activities. For instance, Koohi-Kamali (2010) states that public works employment increases labor hours spent on private farm plots and investments in marginal land. Gehrke and Hartwig (2018) also showed that public works employment induces productive investments via income and insurance effects when the program is sufficiently reliable and long-term. Furthermore, Zimmermann (2024) confirms that participation in public works could improve participants' welfare by allowing them to take on more risky self-employment activities, showing limited evidence for its crowding-out effects on private-sector jobs. On the contrary, participation in public works employment likely lowers household labor engagements in non-agricultural activities for a proportion of labor hours in the top 25%. The results suggest that public works employment helps farm households focus on agricultural activities and increase investment in conservation measures. The income earned, experience acquired, and reduced time and search costs of other off-farm employment in this regard might help. The results support the findings in Bahru and Zeller (2022), which state that participation in PSNP decreased time spent in non-agricultural work. However, the magnitude of the ATT in Bahru and Zeller (2022) is small and does not match the result in the current study.

3.5.3 Robustness checks

Robustness checks scrutinize the validity of the drought shock-induced effects of public works employment. We examine the robustness of the results using different methods. First, we analyze the impacts of self-reported drought on public works and SWC practices. Appendix B Table B.1 presents the effects of self-reported drought on public works participation and SWC practices, controlling for other confounding factors.

The results are robust to findings in Table 3.2. Accordingly, household self-reported drought shock likely increases participation in public works and SWC practice. In other words, the impact estimate for the drought shock indicator exhibits the expected signs. In addition, it influences the adoption of productivity-enhancing and drought-adaptation SWC practices. Appendix B Table B.1 also confirms the negative correlation between public works (endogenous regressor) and household residence distance to central administration (the instrumental variable), which aligns the results in Table 3.2. Hence, this suggests that the longer distance to central administration discourages participation in public works as it can create high transaction costs for registration and opportunity costs of participating in the program.

Moreover, the results are robust to alternative estimation approaches. Appendix B Table B.2 presents the effects of public works employment on aggregate and the two broad categories of conservation measures, controlling for distance to central administration and other confounding factors using POLS. The results are robust for aggregate, physical, and biological SWC practices. The estimated coefficients are comparable to the main results.

Furthermore, Appendix B Table B.3 reports estimation results from the Lewbel two-step IV-GMM estimation in identifying the adoption of aggregate SWC practices. The results are robust to the main findings under different specifications. In addition, the crucial statistical tests of this approach, including under-identification, weak identification, over-identification, and exclusion restriction conditions, are included at the bottom of the table. The test statistics confirm that the problems of under-identification, over-identification, and exclusion restrictions do not exist. Hence, the estimates from this approach are comparable to results from the FIML approach in the main results under Section 3.5.1 in Tables 3.3 through 3.5 and robustness checks using the Pooled Ordinary Least Squares (POLS) in Table B.2 to measure the effects of public works employment on SWC practices.

3.6 Conclusions

Weather shocks frequently affect various aspects of society in developing economies. Consequently, public works are vital development and social protection safety nets that target households facing extreme weather shocks (e.g., drought) and chronic food insecurity.

We use Enhanced Vegetation Index (EVI) anomalies, a proxy for a satellite-based drought shock indicator, to examine how drought determines the probability of participation in public works. In addition, we use rich and nationally representative World Bank Living Standards Measurement Study-Integrated Surveys of Agriculture (LSMS-ISA) panel datasets collected in 2011/12, 2013/14, and 2015/16 agriculture seasons to investigate how drought-induced public works employment influences SWC practices and household labor engagements in rural Ethiopia. Household labor allocation to different activities is the indirect mechanism through which public works might influence micro-level SWC practices. Public work employment is potentially endogenous due to selection bias. Consequently, we employ the endogenous switching regression model and instrumental variables approach to deal with selection bias. Household distance from the central administration serves as an instrumental variable for public works employment, showing a significant negative correlation with program participation but no significant association with the outcome of interest. In other words, the farthest distance might create the highest transaction costs of registration and opportunity costs of participation. The statistical tests confirm that the instrument is valid.

The results show that drought shock significantly drives participation in public works. Despite concerns in the literature about public works potentially crowding out participants' own soil and water conservation and agricultural efforts, the results suggest that public works employment likely contributes to enhanced soil and water conservation practices. Additionally, people who join the program tend to spend more hours working in agriculture but end up working fewer hours in jobs outside of farming activities. In particular, public works employment ATE coefficients vary from 0.106 to 0.118 for aggregate SWC practices, irrespective of the differences in approaches and additional controls in the specifications. Similarly, the ATT coefficient estimate for aggregate SWC practices is 0.111 under full specifications and is comparable to the ATE coefficient estimate. The results are significant at the 1% level. The findings suggest that community-based labor-intensive conservation practices can trickle down to household-level investments in conservation measures, where farmers increase investment in plot-level labor-intensive SWC practices. We infer that the skills, experience, and income benefits from participatory public works employment implemented at the community level can generate favorable conditions for farm-level investments in resource conservation to stimulate other linked outcomes in rural areas.

The program mainly helps with labor-intensive physical resource conservation measures, including building structures to prevent soil erosion, but has an insignificant effect on biological/vegetative conservation measures, such as planting trees to protect the soil. Hence, this shows that employment in public works affects conservation measures differently. Successfully implementing different conservation measures requires both technical skills and substantial capital investments. The differing impacts may stem from the complementary nature of resources needed for implementing these conservation strategies. Key constraints such as technical know-how, capital requirements, and land size can lead to variations in investment decisions related to conservation efforts. For example, conservation practices such as permanent check dams, afforestation, and contour farming typically require more advanced technical skills, substantial capital investments, and marginal land (e.g., for afforestation). Consequently, the successful implementation of widely advocated resource conservation measures in rural areas of developing economies may depend heavily on accessing critical resources that complement public works employment.

In conclusion, the findings show that public works programs provide employment opportunities for households in shock-prone and food-insecure areas of developing economies. In this case, the fear that participation in public works creates resource constraints is not substantiated. On the contrary, the uptake of SWC practices and time spent in agriculture are higher for households employed in public works. Given these findings, public works employment might benefit from supplementary investments in technical know-how about conservation measures, making it easier to access agricultural inputs and create incentives and provisions for capital. Consequently, enhanced investment in conservation measures, increased labor allocation to agricultural activities, and reduced labor allocation to non-agricultural activities can improve sustainable land management, farm income, agricultural productivity, and food security. In other words, public work programs improve soil and water conservation, which can reduce environmental degradation with other related benefits, such as preventing losses and lowering costs, and enhancing agricultural productivity through improved soil health, resulting in higher crop yields and incomes. These programs can also help develop skills, mobilize labor, and contribute to higher incomes and increased productivity. The findings highlight that public works can promote sustainable land use and improve food security by enhancing SWC practices and altering labor engagements in different activities. Despite its focus on rural Ethiopia, the findings can provide important insights into the global implications of climate change, food security, agriculture, and environmental sustainability in rural areas of developing economies.

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References

Abara, Magarsa, Sri Budiastuti, et al. (2020). “Drought frequency, severity, and duration monitoring based on climate change in southern and southeastern Ethiopia”. *IOP Conference Series: Earth and Environmental Science*. Vol. 477. 1. IOP Publishing, p. 012011.

Adimassu, Zenebe and Aad Kessler (2015). “Impact of the productive safety net program on farmers’ investments in sustainable land management in the Central Rift Valley of Ethiopia”. *Environmental Development* 16, pp. 54–62.

Agidew, Alem-meta Assefa and Singh (2017). “The implications of land use and land cover changes for rural household food insecurity in the Northeastern highlands of Ethiopia: the case of the Teleyayen sub-watershed”. *Agriculture & Food Security* 6, pp. 1–14.

Ahmed, Nafiu, Taherul Islam Khan, and Aboh Augustine (2018). “Climate change and environmental degradation: a serious threat to global security”. *European Journal of Social Sciences Studies.*

Ajefu, Joseph B. and Olukorede Abiona (2020). “The mitigating impact of land tenure security on drought-induced food insecurity: Evidence from rural Malawi”. *The Journal of Development Studies* 56.12, pp. 2169–2193.

Ajefu, Joseph Boniface and Abiona, Olukorede (2019). “Impact of shocks on labour and schooling outcomes and the role of public work programmes in rural India”. *The Journal of Development Studies* 55.6, pp. 1140–1157.

Alem, Yonas and Nzinga H. Broussard (2018). “The impact of safety nets on technology adoption: A difference-in-differences analysis”. *Agricultural economics* 49.1, pp. 13–24.

Amfo, Bismark, Ernest Baba Ali, and David Atinga (2021). “Climate change, soil water conservation, and productivity: Evidence from cocoa farmers in Ghana”. *Agricultural Systems* 191, p. 103172.

Anantha, K. H. et al. (2021). “Impact of natural resource management interventions on water resources and environmental services in different agroecological regions of India”. *Groundwater for Sustainable Development* 13, p. 100574.

Andersson, Camilla, Alemu Mekonnen, and Jesper Stage (2011). “Impacts of the Productive Safety Net Program in Ethiopia on livestock and tree holdings of rural households”. *Journal of Development Economics* 94.1, pp. 119–126.

Araya, Girmay Berhe (2020). “Impact of Ethiopia’s productive safety net program on manure use by rural households: Evidence from Tigrai, Northern Ethiopia”. *Agricultural Economics* 51.5, pp. 725–742.

Arellano, Manuel and Stephen Bond (1991). “Some tests of specification for panel data: Monte Carlo evidence and an application to employment equations”. *The review of economic studies* 58.2, pp. 277–297.

Baez, Javier E., Leonardo Lucchetti, Maria E. Genoni, and Mateo Salazar (2017). “Gone with the storm: rainfall shocks and household wellbeing in Guatemala”. *The Journal of Development Studies* 53.8, pp. 1253–1271.

Bahru, Bezawit Adugna and Manfred Zeller (2022). “Gauging the impact of Ethiopia’s productive safety net programme on agriculture: Application of targeted maximum likelihood estimation approach”. *Journal of Agricultural Economics* 73.1, pp. 257–276.

Banerjee, Abhijit V., Rema Hanna, Gabriel E. Kreindler, and Benjamin A. Olken (2017). "Debunking the stereotype of the lazy welfare recipient: Evidence from cash transfer programs". *The World Bank Research Observer* 32.2, pp. 155–184.

Barbier, Edward B. and Jacob P. Hochard (2018). "Land degradation and poverty". *Nature Sustainability* 1.11, pp. 623–631.

Baum, Christopher F. et al. (2013). "Implementing new econometric tools in Stata". *Mexican Stata Users' Group Meetings*. Vol. 9.

Beegle, Kathleen, Aline Coudouel, and Emma Monsalve (2018). *Realizing the full potential of social safety nets in Africa*. World Bank Publications.

Bekele, Mekonnen et al. (2020). *Building resilience to climate change in Ethiopia: What do we know so far?* University of Copenhagen, Faculty of Social Sciences, Department of Economics.

Berhane, Guush, Daniel O. Gilligan, John Hoddinott, Neha Kumar, and Alemayehu Seyoum Taffesse (2014). "Can social protection work in Africa? The impact of Ethiopia's productive safety net programme". *Economic Development and Cultural Change* 63.1, pp. 1–26.

Berhane, Guush, John F. Hoddinott, and Neha Kumar (2017). *The impact of Ethiopia's productive safety net programme on the nutritional status of children: 2008–2012*. Vol. 1604. Intl Food Policy Res Inst.

Berhe, Melaku, Dana Hoag, Girmay Tesfay, Tewodros Tadesse, Shunji Oniki, Masaru Kagatsume, and Catherine M. H. Keske (2017). "The effects of adaptation to climate change on income of households in rural Ethiopia". *Pastoralism* 7, pp. 1–15.

Bhargava, Anil K. (2023). "Do Labor Market Interventions Incentivize Technology Adoption? Unexpected Impacts of the World's Largest Rural Poverty Program". *Economic Development and Cultural Change* 71.2, pp. 000–000.

Borrelli, Pasquale et al. (2017). "An assessment of the global impact of 21st century land use change on soil erosion". *Nature communications* 8.1, p. 2013.

Bowen, Thomas, Carlo Del Ninno, Colin Andrews, Sarah Coll-Black, Kelly Johnson, Yasuhiro Kawasoe, Adea Kryeziu, Barry Maher, and Asha Williams (2020). *Adaptive social protection: building resilience to shocks*. World Bank Publications.

Chesterman, Nathan S., Julia Entwistle, Matthew C. Chambers, Hsiao-Chin Liu, Arun Agrawal, and Daniel G. Brown (2019). "The effects of trainings in soil and water conservation on farming practices, livelihoods, and land-use intensity in the Ethiopian highlands". *Land use policy* 87, p. 104051.

Coll-Black, Sarah, Daniel O. Gilligan, John Hoddinott, Neha Kumar, and William Wiseman (2012). "10 Targeting Food Security Interventions in Ethiopia: The Productive Safety Net". *Food and agriculture in Ethiopia: Progress and policy challenges* 74, p. 280.

Colmer, Jonathan (2021). "Temperature, labor reallocation, and industrial production: Evidence from India". *American Economic Journal: Applied Economics* 13.4, pp. 101–124.

Cooper, Peter J. M., J. Dimes, K. P. C. Rao, B. Shapiro, B. Shiferaw, and S. Twomlow (2008). "Coping better with current climatic variability in the rain-fed farming systems of sub-Saharan Africa: An essential first step in adapting to future climate change?" *Agriculture, ecosystems & environment* 126.1-2, pp. 24–35.

Crook, David R., Brian E. Robinson, and Ping Li (2020). "The impact of snowstorms, droughts and locust outbreaks on livestock production in Inner Mongolia: anticipation and adaptation to environmental shocks". *Ecological Economics* 177, p. 106761.

Das, Utsoree, Salvatore Di Falco, and Avichal Mahajan (2023). "Adaptive capacity and subsequent droughts: evidence from Ethiopia". *Environment and Development Economics* 28.6, pp. 511–537.

Dasgupta, Aparajita (2017). "Can the major public works policy buffer negative shocks in early childhood? Evidence from Andhra Pradesh, India". *Economic Development and Cultural Change* 65.4, pp. 767–804.

Davies, Mark, Jennifer Leavy, Tom Mitchell, and Thom Tanner (2008). "Social protection and climate change adaption". *Report prepared for the Commission on Climate Change and Development, Brighton.*

Debela, Bethelhem Legesse, Gerald Shively, and Stein T. Holden (2015). "Does Ethiopia's productive safety net program improve child nutrition?" *Food Security* 7, pp. 1273–1289.

Deininger, Klaus, Hari Nagarajan, Sudhir Singh, and Hari Krishnan Nagarajan (2016). "Short-term effects of India's employment guarantee program on labor markets and agricultural productivity". *World Bank Policy Research Working Paper* 7665.

Delgado, Jorge A., Victor H. Barrera Mosquera, Jeffrey R. Alwang, Alexis Villacis-Aveiga, Yamil E. Cartagena Ayala, Donna Neer, Carlos Monar, and Luis O. Escudero López (2021). "Potential use of cover crops for soil and water conservation, nutrient management, and climate change adaptation across the tropics". *Advances in Agronomy* 165, pp. 175–247.

Demem, Mulat Shibabaw (2023). "Impact and adaptation of climate variability and change on small-holders and agriculture in Ethiopia: A review". *Heliyon.*

Deressa, Temesgen Tadesse, Rashid M Hassan, Claudia Ringler, Tekie Alemu, and Mahmud Yesuf (2009). "Determinants of farmers' choice of adaptation methods to climate change in the Nile Basin of Ethiopia". *Global environmental change* 19.2, pp. 248–255.

Devereux, Stephen (2016). "Social protection for enhanced food security in sub-Saharan Africa". *Food policy* 60, pp. 52–62.

Dracup, John A., Kil Seong Lee, and Edwin G. Paulson Jr (1980). "On the definition of droughts". *Water resources research* 16.2, pp. 297–302.

Drechsler, Mareile Beate Stephanie and Wout Soer (2016). "Early warning, early action: the use of predictive tools in drought response through Ethiopia's productive safety net programme". *World Bank Policy Research Working Paper* 7716.

Dyngeland, Cecilie, Johan A. Oldekop, and Karl L. Evans (2020). "Assessing multidimensional sustainability: Lessons from Brazil's social protection programs". *Proceedings of the National Academy of Sciences* 117.34, pp. 20511–20519.

Eriksson, Lennart, Tamara Byrne, E. Johansson, Johan Trygg, and C. Vikström (2013). *Multi-and megavariate data analysis basic principles and applications.* Vol. 1. Umetrics Academy.

Favara, Marta, Catherine Porter, and Tassew Woldehanna (2019). "Smarter through social protection? Evaluating the impact of Ethiopia's safety-net on child cognitive abilities". *Oxford Development Studies* 47.1, pp. 79–96.

Gao, Jianfeng and Bradford F. Mills (2018). "Weather shocks, coping strategies, and consumption dynamics in rural Ethiopia". *World Development* 101, pp. 268–283.

Gaworek-Michalczenia, M. F., S. M. Sallu, M. Di Gregorio, N. Doggart, and J. Mbogo (2022). "Evaluating the impact of adaptation interventions on vulnerability and livelihood resilience". *Climate and Development* 14.10, pp. 867–883.

Gazeaud, Jules, Eric Mvukiyehe, and Olivier Sterck (2023). "Cash transfers and migration: Theory and evidence from a randomized controlled trial". *The Review of Economics and Statistics* 105.1, pp. 143–157.

Gazeaud, Jules and Victor Stephane (2023). “Productive Workfare? Evidence from Ethiopia’s Productive Safety Net Program”. *American Journal of Agricultural Economics* 105.1, pp. 265–290.

Gebrehiwot, Tagel and Carolina Castilla (2019). “Do safety net transfers improve diets and reduce undernutrition? Evidence from rural Ethiopia”. *The Journal of Development Studies* 55.9, pp. 1947–1966.

Gehrke, Esther (2019). “An employment guarantee as risk insurance? Assessing the effects of the NREGS on agricultural production decisions”. *The World Bank Economic Review* 33.2, pp. 413–435.

Gehrke, Esther and Renate Hartwig (2018). “Productive effects of public works programs: What do we know? What should we know?” *World development* 107, pp. 111–124.

Geremu, Tadele (2019). “Review on role of soil and water conservation measures on Soil Physico chemical properties and its implication to climate change mitigation and adaptation”. *Journal of Natural Sciences Research* 9.11, pp. 27–41.

Gertler, Paul J., Sebastian Martinez, Patrick Premand, Laura B. Rawlings, and Christel M. J. Vermeersch (2016a). *Impact evaluation in practice.* World Bank Publications.

Gertler, Paul J., Orie Shelef, Catherine D. Wolfram, and Alan Fuchs (2016b). “The demand for energy-using assets among the world’s rising middle classes”. *American Economic Review* 106.6, pp. 1366–1401.

GFDRE (2004). “Productive safety net programme: Programme implementation manual”.

Gilligan, Daniel O., John Hoddinott, and Alemayehu Seyoum Taffesse (2009). “The impact of Ethiopia’s Productive Safety Net Programme and its linkages”. *The journal of development studies* 45.10, pp. 1684–1706.

Girard, Julia, Philippe Delacote, and Antoine Leblois (2021). “Agricultural households’ adaptation to weather shocks in Sub-Saharan Africa: implications for land-use change and deforestation”. *Environment and Development Economics* 26.5-6, pp. 538–560.

Graaff, Jan de, Amsalu Aklilu, Mohamed Ouessar, Sabina Asins-Velis, and Aad Kessler (2013). “The development of soil and water conservation policies and practices in five selected countries from 1960 to 2010”. *Land Use Policy* 32, pp. 165–174.

He, Xi and Zhenshan Chen (2022). “Weather, cropland expansion, and deforestation in Ethiopia”. *Journal of Environmental Economics and Management* 111, p. 102586.

Heckman, James J. (1979). “Sample selection bias as a specification error”. *Econometrica: Journal of the econometric society*, pp. 153–161.

Hidrobo, Melissa, Valerie Mueller, and Shalini Roy (2022). “Cash transfers, migration, and gender norms”. *American Journal of Agricultural Economics* 104.2, pp. 550–568.

Hirvonen, Kalle, Elia A. Machado, Andrew M. Simons, and Vis Taraz (2022). “More than a safety net: Ethiopia’s flagship public works program increases tree cover”. *Global Environmental Change* 75, p. 102549.

Hishe, Solomon, James Lyimo, and Woldeamlak Bewket (2017). “Soil and water conservation effects on soil properties in the Middle Silluh Valley, northern Ethiopia”. *International Soil and Water Conservation Research* 5.3, pp. 231–240.

Hoddinott, John, Guush Berhane, Daniel O. Gilligan, Neha Kumar, and Alemayehu Seyoum Taffesse (2012). “The impact of Ethiopia’s Productive Safety Net Programme and related transfers on agricultural productivity”. *Journal of African Economies* 21.5, pp. 761–786.

Holden, Stein, Christopher B. Barrett, and Fitsum Hagos (2006). “Food-for-work for poverty reduction and the promotion of sustainable land use: can it work?” *Environment and Development Economics* 11.1, pp. 15–38.

Huete, Alfredo, Kamel Didan, Tomoaki Miura, E. Patricia Rodriguez, Xiang Gao, and Laerte G. Ferreira (2002). "Overview of the radiometric and biophysical performance of the MODIS vegetation indices". *Remote sensing of environment* 83.1-2, pp. 195–213.

Hurni, Hans et al. (1993). "Land degradation, famine, and land resource scenarios in Ethiopia." *World soil erosion and conservation.*, pp. 27–61.

Imbert, Clément and John Papp (2020). "Short-term migration, rural public works, and urban labor markets: Evidence from India". *Journal of the European Economic Association* 18.2, pp. 927–963.

Khandker, Shahidur R., Gayatri B. Koolwal, and Hussain A. Samad (2009). *Handbook on impact evaluation: quantitative methods and practices.* World Bank Publications.

Khosla, Sunil and Pradyot Ranjan Jena (2022). "Analyzing vulnerability to poverty and assessing the role of universal public works and food security programs to reduce it: Evidence from an eastern Indian state". *Review of Development Economics* 26.4, pp. 2296–2316.

Kogan, Felix N. (1995). "Application of vegetation index and brightness temperature for drought detection". *Advances in space research* 15.11, pp. 91–100.

Koohi-Kamali, Feridoon M. (2010). *Public works and social protection.* Tech. rep.

Kosmowski, Frederic, Solomon Alemu, Paola Mallia, James Stevenson, and Karen Macours (2020). "Shining a brighter light: Comprehensive evidence on adoption and diffusion of CGIAR-related innovations in Ethiopia". *SPIA Synthesis Report.*

Krishnan, Pramila, Stefan Dercon, and T. Selassie (1998). "The urban labour market during structural adjustment: Ethiopia 1990-1997".

Kubik, Zaneta and Mathilde Maurel (2016). "Weather shocks, agricultural production and migration: Evidence from Tanzania". *The Journal of Development Studies* 52.5, pp. 665–680.

Kundo, Hare Krisna, Martin Brueckner, Rochelle Spencer, and John K. Davis (2023). "Enhancing the resilience and well-being of rural poor to climate risks: are the economic functions of social protection enough?" *Disasters* 47.3, pp. 651–675.

Lavorel, Sandra, Matthew J. Colloff, Bruno Locatelli, Russell Gorddard, Suzanne M. Prober, Marine Gabillet, Caroline Devaux, Denis Laforgue, and Véronique Peyrache-Gadeau (2019). "Mustering the power of ecosystems for adaptation to climate change". *Environmental Science & Policy* 92, pp. 87–97.

Letta, Marco, Pierluigi Montalbano, and Richard S. J. Tol (2018). "Temperature shocks, short-term growth and poverty thresholds: Evidence from rural Tanzania". *World Development* 112, pp. 13–32.

Lewbel, Arthur (2012). "Using heteroscedasticity to identify and estimate mismeasured and endogenous regressor models". *Journal of Business & Economic Statistics* 30.1, pp. 67–80.

— (2018). "Identification and estimation using heteroscedasticity without instruments: The binary endogenous regressor case". *Economics Letters* 165, pp. 10–12.

Mahoo, H. F., Maren A. O. Radeny, James Kinyangi, and Laura Cramer (2013). "Climate change vulnerability and risk assessment of agriculture and food security in Ethiopia: which way forward?" *CCAFS Working Paper.*

Maity, Bipasha (2020). "Consumption and time-use effects of India's employment guarantee and women's participation". *Economic Development and Cultural Change* 68.4, pp. 1185–1231.

Mandal, Raju and Munmi Sarma (2020). "Impact of weather shock on food insecurity: a study on India". *Socio-economic and Eco-biological Dimensions in Resource use and Conservation: Strategies for Sustainability*, pp. 333–349.

Matewos, Tafesse (2020). “The state of local adaptive capacity to climate change in drought-prone districts of rural Sidama, southern Ethiopia”. *Climate Risk Management* 27, p. 100209.

McKee, Thomas B., Nolan J. Doesken, John Kleist, et al. (1993). “The relationship of drought frequency and duration to time scales”. *Proceedings of the 8th Conference on Applied Climatology*. Vol. 17. 22. Boston, pp. 179–183.

Meierrieks, Daniel (2021). “Weather shocks, climate change and human health”. *World Development* 138, p. 105228.

Mekuyie, Muluken, Andries Jordaan, and Yoseph Melka (2018). “Understanding resilience of pastoralists to climate change and variability in the Southern Afar Region, Ethiopia”. *Climate Risk Management* 20, pp. 64–77.

Merfeld, Joshua D. (2020). “Moving Up or Just Surviving? Nonfarm Self-Employment in India”. *American Journal of Agricultural Economics* 102.1, pp. 32–53.

Mersha, Azeb Assefa and Frank van Laerhoven (2018). “The interplay between planned and autonomous adaptation in response to climate change: Insights from rural Ethiopia”. *World Development* 107, pp. 87–97.

Ministry of Agriculture (2014). “Productive safety net programme phase IV programme implementation manual”. *Addis Ababa: Ethiopia*.

Mirzabaev, Alisher, Anton Strokov, and Pavel Krasilnikov (2023). “The impact of land degradation on agricultural profits and implications for poverty reduction in Central Asia”. *Land Use Policy* 126, p. 106530.

Msuha, Basil, Luitfred D. Kissoly, and Arnold Kihaule (2024). “Design and implementation of social safety nets in Tanzania: A systematic review”. *International Journal of Economics and Financial Issues* 14.1, pp. 180–203.

Muchuru, Shepherd and Godwell Nhamo (2019). “A review of climate change adaptation measures in the African crop sector”. *Climate and development* 11.10, pp. 873–885.

Mulungu, Kelvin and Nicholas Kilimani (2023). “Does forest access reduce reliance on costly shock-coping strategies? Evidence from Malawi”. *Ecological Economics* 209, p. 107827.

Nigussie, Zerihun, Atsushi Tsunekawa, Nigussie Haregeweyn, Enyew Adgo, Makoto Nohmi, Mitsuru Tsubo, Dagnachew Aklog, Derege Tsegaye Meshesha, and Steffen Abele (2017). “Factors influencing small-scale farmers’ adoption of sustainable land management technologies in north-western Ethiopia”. *Land use policy* 67, pp. 57–64.

Palmer, Wayne C. (1965). *Meteorological drought*. Vol. 30. US Department of Commerce, Weather Bureau.

Paul Jr, Martin, Joyce Anima Boakye, Mashauri Muliro, et al. (2020). “Mitigating the impacts of floods using adaptive and resilient coping strategies: The role of the emergency Livelihood Empowerment Against Poverty program (LEAP) in Ghana”. *Journal of Environmental Management* 270, p. 110809.

Pettorelli, Nathalie, Jon Olav Vik, Atle Mysterud, Jean-Michel Gaillard, Compton J Tucker, and Nils Chr Stenseth (2005). “Using the satellite-derived NDVI to assess ecological responses to environmental change”. *Trends in ecology & evolution* 20.9, pp. 503–510.

Piñeiro, Valeria et al. (2020). “A scoping review on incentives for adoption of sustainable agricultural practices and their outcomes”. *Nature Sustainability* 3.10, pp. 809–820.

Pinto, Elisabete et al. (2022). “Healthier and sustainable food systems: Integrating underutilised crops in a ‘Theory of change approach’”. *Biodiversity, Functional Ecosystems and Sustainable Food Production*. Springer, pp. 275–323.

Porter, Catherine and Radhika Goyal (2016). "Social protection for all ages? Impacts of Ethiopia's Productive Safety Net Program on child nutrition". *Social Science & Medicine* 159, pp. 92–99.

Pozza, Liana E. and Damien J. Field (2020). "The science of soil security and food security". *Soil Security* 1, p. 100002.

Regeringskansliet, Regeringen och (2015). "The Global Goals and the 2030 Agenda for Sustainable Development".

Sam, Anu Susan, Azhar Abbas, Subash Surendran Padmaja, Harald Kaechele, Ranjit Kumar, and Klaus Müller (2019). "Linking food security with household's adaptive capacity and drought risk: implications for sustainable rural development". *Social Indicators Research* 142, pp. 363–385.

Schwan, Susanne and Xiaohua Yu (2018). "Social protection as a strategy to address climate-induced migration". *International Journal of Climate Change Strategies and Management* 10.1, pp. 43–64.

Scognamillo, Antonio, Marina Mastrorillo, and Adriana Ignaciuk (2024). "One for all and all for one: Increasing the adaptive capacity of households and communities through a public work programme". *World Development* 175, p. 106467.

Selvakumar, S. and K. Sivakumar (2021). "Conservation agriculture: A way for soil water conservation". *Agricultural Reviews* 42.4, pp. 474–477.

Sharp, Kay, Taylor Brown, and Amdissa Teshome (2006). "Targeting Ethiopia's productive safety net programme (PSNP)". *London and Bristol, UK: Overseas Development Institute and the IDL Group.*

Shiferaw, Bekele, Kindie Tesfaye, Menale Kassie, Tsedeke Abate, Boddupalli M. Prasanna, and Abebe Menkir (2014). "Managing vulnerability to drought and enhancing livelihood resilience in sub-Saharan Africa: Technological, institutional and policy options". *Weather and climate extremes* 3, pp. 67–79.

Sileshi, Million, Reuben Kadigi, Khamaldin Mutabazi, and Stefan Sieber (2019). "Impact of soil and water conservation practices on household vulnerability to food insecurity in eastern Ethiopia: endogenous switching regression and propensity score matching approach". *Food Security* 11, pp. 797–815.

Singh, Roop, Mulugeta Worku, Solomon Bogale, Adrian Cullis, Alebachew Adem, Ben Irwin, Sheri Lim, Lorenzo Bosi, and Courtenay Cabot Venton (2016). "Reality of resilience: Perspectives of the 2015-16 drought in Ethiopia". *BRACED Resilience Intel* 6, pp. 1–28.

Siyoum, Aschale Dagnachew (2012). *Broken promises: food security interventions and rural livelihoods in Ethiopia.* Wageningen University and Research.

Smith, Lisa C. and Timothy R. Frankenberger (2018). "Does resilience capacity reduce the negative impact of shocks on household food security? Evidence from the 2014 floods in Northern Bangladesh". *World Development* 102, pp. 358–376.

Subbarao, Kalanidhi (1997). "Public works as an anti-poverty program: An overview of cross-country experience". *American journal of agricultural economics* 79.2, pp. 678–683.

Svoboda, Mark D., Brian A. Fuchs, et al. (2016). *Handbook of drought indicators and indices.* Vol. 2. World Meteorological Organization Geneva, Switzerland.

Tambet, Heleene and Yaniv Stopnitzky (2021). "Climate adaptation and conservation agriculture among Peruvian farmers". *American Journal of Agricultural Economics* 103.3, pp. 900–922.

Taraz, Vis (2021). "Public works programs and agricultural risk: Evidence from India". *Available at SSRN 3176705.*

Temesgen, Gashaw, Bantider Amare, Hagos G. Silassie, et al. (2014). “Land degradation in Ethiopia: causes, impacts and rehabilitation techniques.” *Journal of environment and earth science* 4.9, pp. 98–104.

Tengberg, Anna and Sandra Valencia (2018). “Integrated approaches to natural resources management—Theory and practice”. *Land Degradation & Development* 29.6, pp. 1845–1857.

Terza, Joseph V. (1998). “Estimating count data models with endogenous switching: Sample selection and endogenous treatment effects”. *Journal of econometrics* 84.1, pp. 129–154.

Tirivayi, Nyasha, Marco Knowles, and Benjamin Davis (2013). “The interaction between social protection and agriculture”. *A review of evidence. Rome: Food and Agriculture Organization of the United Nations (FAO).*

Tofu, Daniel Assefa, Teshale Woldeamanuel, and Firafis Haile (2022). “Smallholder farmers’ vulnerability and adaptation to climate change induced shocks: The case of Northern Ethiopia highlands”. *Journal of Agriculture and Food Research* 8, p. 100312.

Tofu, Daniel Assefa and Kebede Wolka (2023). “Transforming food insecure farmers from climate variability and land degradation susceptibility to resilient livelihoods”. *Research in Globalization* 7, p. 100168.

Viju, Tania et al. (2023). “Sustainable land management strategies, drivers of LULC change and degradation: An assessment of Malappuram Metropolitan region, Kerala, India”. *Water, Land, and Forest Susceptibility and Sustainability.* Elsevier, pp. 191–214.

White, Howard and David A. Raitzer (2017). *Impact evaluation of development interventions: A practical guide.* Asian Development Bank.

Wilhite, Donald A. and Michael H. Glantz (1985). “Understanding: the drought phenomenon: the role of definitions”. *Water international* 10.3, pp. 111–120.

Wolka, Kebede, Birhanu Biazin, Fikadu Getachew, Firehiywot Girma, and Gizaw Desta (2023a). “Towards sustainable watershed-based landscape restoration in degraded drylands: Perceived benefits and innovative pathways learnt from project-based interventions in Ethiopia”. *Journal of Environmental Management* 335, p. 117499.

Wolka, Kebede, Tadese Uma, and Daniel Assefa Tofu (2023b). “The role of integrated watershed management in climate change adaptation for small-scale farmers in Southwest Ethiopia”. *Environmental and Sustainability Indicators* 19, p. 100260.

World Bank (2015). *The state of social safety nets 2015.* The World Bank.

— (2020). *Ethiopia poverty assessment: Harnessing continued growth for accelerated poverty reduction.* https://doi.org/10.1596/33544.

Zimmermann, Laura V. (2024). “Why guarantee employment? Evidence from a large Indian public-works program”. *Economic Development and Cultural Change* 72.4, pp. 000–000.

Chapter 4

Weather shocks and agricultural productivity in rural Ethiopia: Role of land cover dynamics

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Highlights

- Weather shocks reduce agricultural productivity, underscoring the need for adaptation.
- Enhanced land cover change mitigates weather shock impacts, boosting productivity.
- Land cover mitigates drought in tropical cool and high-yield warm zones, requiring adaptation.

Abstract

Climate variability poses significant challenges to rainfed agriculture, necessitating effective adaptation. This study examines the effects of weather shocks on agricultural productivity and the mitigating role of land cover change in rural Ethiopia. Using balanced panel data from Ethiopia's LSMS-ISA (2011/12, 2013/14, 2015/16) and satellite-based indicators, such as the

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Enhanced Vegetation Index and climatological temperature data, the analysis employs a Multi-Way Fixed Effects estimator to address unobserved heterogeneity and endogeneity. Results show that weather shocks significantly reduce productivity, but enhanced land cover can buffer these effects. The mitigating effect is more pronounced across agroecological zones, especially in tropical-cool and high-yield warm areas. These findings highlight the importance of land cover management for boosting productivity, promoting sustainability, and enhancing food security. The study identifies sustainable land use planning as a potential mechanism for nature-based climate resilience in vulnerable rural areas.

Keywords: Climate variability, Agricultural productivity, Land cover change, Agroecological zones, Ethiopia

JEL Classification: Q54, Q11, Q12, Q15, Q24, O55

4.1 Introduction

Agricultural productivity in sub-Saharan Africa, including Ethiopia, remains highly susceptible to climate variability, particularly to weather shocks such as droughts, erratic rainfall, and extreme temperatures (Affoh et al., 2022; Bouteska et al., 2024; Sinore and Wang, 2024; Di Falco et al., 2011; Deressa et al., 2009). While previous studies in Ethiopia have analyzed the direct impact of weather shocks on crop yields, limited research has explored the mediating role of land cover dynamics—specifically, changes in forest cover, grasslands, and cultivated land—in shaping resilience to climate shocks (Woldesenbet, 2022; Ahmad et al., 2018; Jayachandran et al., 2017; Eric F. Lambin et al., 2003). Given Ethiopia's ongoing afforestation efforts under the Climate Resilient Green Economy (CRGE) strategy (FDRE, 2011), it is crucial to understand whether land cover changes exacerbate or mitigate the productivity effects of weather shocks.

Climate variability—manifested through extreme weather events such as irregular rainfall and rising temperatures—presents significant constraints for farm households in developing economies (Adom, 2024; Kosmowski et al., 2016). For instance, Hossain et al. (2024) documents the adverse impacts of heat stress on rice production and agricultural sustainability. Enhancing income, agricultural productivity, and food security—while strengthening resilience to climate change—remains a central development priority. Addressing these interconnected challenges is essential for improving local adaptive capacity and advancing global development objectives, particularly the Sustainable Development Goals focused on eradicating poverty and hunger (Braun et al., 2021; Fentie and Beyene, 2019). Within this framework, improving agricultural productivity remains a key pathway for elevating the economic well-being of rural populations (M. Amare et al., 2021; Shikur, 2020; Gollin, 2010).

Land productivity in sub-Saharan Africa remains significantly lower than in other developing regions, with widespread poverty posing persistent challenges. Despite ongoing interventions by governments and development partners, the productivity gap endures. Rural communities are particularly vulnerable, as weather shocks and socioeconomic constraints continue to decrease agricultural productivity (Makate et al., 2022; M. Amare et al., 2018). These pressures frequently exacerbate deforestation (He and Chen, 2022), drive food price volatility (Kakpo et al., 2022), and intensify food insecurity (Harvey et al., 2014). Addressing underlying factors such as land degradation, inadequate water management, limited technological adoption, and weak market infrastructure is critical to enhancing agricultural productivity in the region (Yigezu Wendimu, 2021; Asfaw et al., 2020; Wassie, 2020; Tarfasa et al., 2018; Dagnaw, 2007).

The relationship between land cover—particularly forests and grasslands—and agricultural productivity is underpinned by key ecosystem services such as soil moisture regulation, erosion control, nutrient cycling, and microclimate stabilization (FAO, 2011; Reid et al., 2005). These land cover types enhance soil quality and buffer agricultural systems against climatic shocks and land degradation (Lemenih and Itanna, 2005). In this study, vegetation greenness, measured using the Enhanced Vegetation Index (EVI), is employed as a proxy for these ecological functions, reflecting the role of natural vegetation in maintaining the biophysical conditions essential for sustained productivity. Although engineered soil conservation structures are not explicitly modeled, the framework incorporates land cover attributes associated with agricultural productivity (Teshome et al., 2022; M. Kassie et al., 2008).

The broader relationship between agricultural productivity and natural resource use highlights the need to integrate economic, environmental, and social dimensions in land management. Land expansion and intensification affect resource conservation and long-term sustainability, with outcomes contingent on the methods employed. While unsustainable expansion often contributes to environmental degradation, well-managed intensification can enhance productivity without compromising ecological integrity. Effective land management can mitigate forest loss, control soil erosion, and reduce environmental degradation (Barakat et al., 2019; Tadesse et al., 2017; Ananda and Herath, 2003), thereby enhancing both agricultural productivity (AbdelRahman, 2023; Mirzabaev et al., 2023) and rural livelihoods (Barbier and Hochard, 2018; Wubie et al., 2016; Bai et al., 2008). Sustainable practices enhance resource conservation by reducing deforestation and fostering responsible land use (Nguyen et al., 2022; Szerman et al., 2022). In Ethiopia, however, persistent challenges such as drought and land degradation (Zewdu et al., 2016; Ariti et al., 2015) threaten land use systems and biodiversity (Anteneh, 2022; Wassie, 2020). Addressing soil erosion and declining water availability is essential for ensuring agricultural sustainability (Gitima et al., 2023; Endalamaw et al., 2021), particularly for vulnerable subsistence farming communities. Understanding the interlinkages between economic conditions, land cover, and soil quality is vital for effective poverty reduction strategies (Barrett and Bevis, 2015).

A growing body of literature—globally and particularly in sub-Saharan Africa—highlights the essential role of enhanced green land cover, including trees, forests, and agroforestry systems, in strengthening rural households' resilience to environmental and economic shocks. These land-use strategies contribute to local resilience by enhancing ecosystem stability, supporting agricultural stability, diversifying income sources, and reducing vulnerability to climate-related risks. Tree-based systems and agroforestry support global climate goals by easing pressure on natural forests, boosting carbon storage, and promoting sustainable land use. These practices enhance biodiversity and contribute to long-term ecological resilience, while simultaneously increasing agricultural productivity and livelihoods through improved ecosystem health and soil fertility (Tebkew et al., 2024; Meyer, 2023; Mbow et al., 2014; Lasco et al., 2014).

Empirical research demonstrates a significant correlation between weather-induced shocks—such as droughts and extreme temperature events—and subsequent changes in land cover. These climatic disturbances often drive shifts in vegetation patterns, land use practices, and ecosystem structure, reflecting both direct biophysical impacts and adaptive human responses to environmental stressors (Thapa, 2021; Abd El-Hamid et al., 2020; Shukla et al., 2019; Sleeter et al., 2018). Weather events influence land use through disturbance patterns and suitability for various purposes (Sayyadi et al., 2019; Quan and Dyer, 2008). Additionally, human-environment interactions drive these changes (Siqi Yang et al., 2022; Wubie et al., 2016; Zewdu et al., 2016). Effective land use decisions are crucial for climate adaptation as they affect energy, water, and greenhouse gas exchanges between the land and the atmosphere (Barati et al., 2023; Mendoza-Ponce et al., 2021).

Enhanced land cover change refers to deliberate and intensified modifications in land cover, such as vegetation changes, to strengthen the resilience and functionality of ecological and agricultural systems. These changes include practices like agroforestry, reforestation, wetland restoration, and climate-smart agriculture (Patel et al., 2019; Pellikka et al., 2013; Eric F Lambin and Meyfroidt, 2011). Huete et al. (2002) developed the EVI to enhance vegetation assessment under high biomass and atmospheric interference. It is widely employed in environmental, agricultural, drought, and land-use studies for its accuracy in capturing vegetation dynamics. This study uses “land cover changes" and “land cover dynamics" interchangeably, as continuous changes generate dynamics. Practices like reforestation, agroforestry, and sustainable land management promote these changes, addressing environmental challenges like extreme weather, land degradation, and biodiversity loss while enhancing productivity and sustainability. Land cover dynamics are measured using the EVI, which tracks green vegetation during the Meher season, averaged across zones. EVI, a remote sensing tool, quantifies vegetation greenness while minimizing atmospheric effects and soil noise, offering insights into the resilience of natural systems under changing environmental conditions. EVI data from 2001–2011, 2001–2013, and 2001–2015 correspond to survey years in 2011/12, 2013/14, and 2015/16. Understanding the interactions between land use, weather, and ecological processes can improve natural resource management and enhance resilience to climate change.

While extensive research in Ethiopia has documented land use and land cover (LULC) dynamics—driven by factors such as population growth, agricultural expansion, deforestation, and climatic shifts (Belete et al., 2023; Gebeyehu et al., 2023; E. N. Mekonnen et al., 2023; Hishe et al., 2021)—limited attention has been given to how these changes interact with extreme weather events. In particular, the joint and varied effects of land cover transformation and climate-induced shocks on agricultural productivity across agroecological zones remain insufficiently understood. This relationship is critical, as changes in land cover—such as deforestation, reforestation, or the adoption of agroforestry—can significantly influence soil quality, water retention, and local micro-climatic conditions, thereby affecting the resilience of agricultural systems to climate extremes such as drought and heat stress. This study addresses this gap by examining how land cover change influences the effects of weather shocks on agricultural productivity, emphasizing agroecological differentiation to guide context-specific adaptation strategies.

This study investigates the interplay between weather shocks, agricultural productivity, and land cover dynamics in rural Ethiopia. By leveraging high-resolution satellite imagery and panel survey data, it assesses how changes in land cover—through improved vegetation cover and sustainable land use practices—can buffer the adverse effects of weather shocks by enhancing productivity and adaptive capacity. Specifically, the analysis focuses on (i) the impact of weather shocks on agricultural productivity, with an extended analysis across diverse agroecological zones, (ii) the role of land cover improvements in mitigating these impacts, and (iii) the interaction among agroecological heterogeneity, weather shock exposure, and land cover dynamics in shaping agricultural productivity.

This study contributes to the literature by combining high-resolution land cover data with a Multiway Fixed Effects econometric approach to investigate the underexplored relationship between weather shocks, land use changes, and agricultural productivity in Ethiopia. Using household-level data from the Ethiopian Socioeconomic Surveys (2011/12, 2013/14, 2015/16), the study offers new insights into how land cover changes influence household responses to climatic variability across tropical cool and warm agroecological zones. The study proposes an integrated policy approach to mitigate climate change impacts on agricultural productivity, emphasizing sustainable land use as vital for enhancing land cover, reducing vulnerability to weather shocks, and improving agricultural productivity. It offers policy-relevant recommendations aligned with Ethiopia's CRGE strategy, Climate-Smart Agriculture (CSA), and sustainable forestry goals. The findings underscore the importance of targeted investments, increased smallholder awareness, and coordinated stakeholder engagement to strengthen climate resilience and sustainability in rural Ethiopia and other similar developing contexts.

While the adverse effects of drought and extreme temperatures on agricultural productivity are well documented, this study advances the literature by integrating satellite-derived vegetation indices with high-resolution climate data to assess the moderating role of land cover. Employing a multi-level fixed effects framework, it provides context-specific evidence from Ethiopia and offers policy-relevant insights for targeted climate adaptation and sustainable land management. Enhancements in land cover—through practices such as reforestation and agroforestry—ameliorate these negative impacts by improving soil quality, water retention, and ecosystem resilience. This mitigating effect is most pronounced in tropical-cool and high-potential tropical-warm zones, underscoring their vulnerability to climate variability and the need for focused adaptation strategies. The findings emphasize the importance of coordinated efforts among rural communities, policymakers, and development partners to strengthen land cover, promote sustainable land management, and enhance agricultural productivity, food security, and long-term resilience.

The remainder of the paper is structured as follows: Section 4.2 provides the context and country experience, Section 4.3 describes the data and key variables, Section 4.4 details the empirical strategy, Section 4.5 presents the results and discusses, and Section 4.6 concludes.

4.2 Ethiopian Context and Experience

4.2.1 Context

Ethiopia's agriculture is primarily rainfed and dominated by smallholder, mixed, and subsistence farming systems (A. W. Degife et al., 2021; Lankford and Grasham, 2021; Adamseged, 2019; Lewis, 2017). Rural livelihoods largely depend on agriculture, with cereals comprising the primary staple crop output (CSA, 2017; Canton, 2021; Tolossa et al., 2015). However, the sector remains highly susceptible to increasingly frequent and severe weather shocks, which pose serious threats to rural well-being and economic stability (Bedeke et al., 2020; Tessema and Simane, 2019; Mohammed et al., 2018; A. Amare and Simane, 2017). Persistent climate risks, especially recurrent El Niño-related droughts, alongside natural disasters, pest invasions, and erratic rainfall patterns, contribute significantly to production volatility (B. T. Haile et al., 2021; Koo et al., 2019; Gizaw and Gan, 2017; Singh et al., 2016; Zaroug et al., 2014; Abtew et al., 2009; Dercon, 2004). These challenges have led to substantial variability in crop yields across space and time, aggravating rural poverty and food insecurity.

Weather shocks limit farmers' financial capacity, hindering investment in agricultural technologies and reducing consumption stability in rural areas of developing countries. Although weather-indexed insurance aims to enhance climate resilience and adaptation, its uptake and effectiveness remain limited in contexts such as Ethiopia (K. K. Haile et al., 2020; Hansen et al., 2019; De Janvry et al., 2016). Consequently, households often depend on alternative coping mechanisms, such as income diversification, livestock sales, and remittances, to manage financial shocks and sustain access to agricultural inputs and essential goods (Hussain et al., 2020; Kumar et al., 2020).

Weather shocks and environmental degradation pose critical threats to land use and smallholder livelihoods, exacerbated by human-induced pressures that diminish land productivity and impair water management systems (He and Chen, 2022; Girard et al., 2021; Crook et al., 2020; Ahmed et al., 2018; Gazeaud and Stephane, 2023). This growing vulnerability highlights the urgent need for adaptive, climate-resilient approaches to sustain agricultural output and protect rural communities. In response, smallholder farmers increasingly adopt resilience-enhancing measures—such as land cover restoration and soil and water conservation practices—to promote sustainability and secure their livelihoods (Tofu et al., 2022; Delgado et al., 2021; Amfo et al., 2021; Tambet and Stopnitzky, 2021; Geremu, 2019).

Declining land cover accelerates soil erosion and degrades soil quality, exacerbating climate hazards. In Ethiopia, watershed vegetation decreased by 91% between 2001 and 2010 but recovered by 88% from 2010 to 2015 due to land restoration efforts (Tadesse et al., 2017). Interventions such as area closures, soil and water conservation (SWC) measures, and reforestation have been instrumental in improving land cover, enhancing watershed functionality, and promoting sustainable rural livelihoods (Wolka et al., 2023; Tofu and Wolka, 2023). These measures mitigate soil loss, combat land degradation, and support long-term agricultural productivity.

Changes in land use have significant implications for agricultural productivity, food security, and household resilience. Such transitions influence labor allocation, income diversification, and access to ecosystem services. Agroforestry systems, in particular, enhance soil fertility, improve moisture retention, and increase crop yields, while also generating alternative income from timber, fuelwood, and non-timber forest products (Oeba and Illiassou, 2020; G. W. Kassie, 2018; Appiah and Pappinen, 2010; Babulo et al., 2008). These practices help reduce reliance on climate-sensitive agriculture and facilitate risk management (Holden and Otsuka, 2014).

Agroforestry also serves as a nature-based adaptation strategy, offering multiple co-benefits. It strengthens farmers' adaptive capacity by diversifying production, improving soil structure, and providing essential goods such as food and fodder (Tebkew et al., 2024; Partey et al., 2018; Gautier et al., 2016). Moreover, agroforestry delivers critical ecosystem services and contributes to sustainable intensification, though its impacts on land use are multifaceted (Girard et al., 2021). By reducing pressure on natural forests, agroforestry fosters conservation and supports more resilient agricultural landscapes.

4.2.2 Ethiopia's Afforestation: Achievements and Challenges

Ethiopia's land restoration efforts have evolved over several decades and political regimes. During Mengistu Haile Mariam's Derg regime, the Arengwade Zemecha campaign mobilized communities for soil and water conservation through terracing, check dams, and tree planting to combat land degradation despite centralized land ownership (Bewket, 2003; Taddese, 2001). Following the political transition, Prime Minister Meles Zenawi emphasized integrated watershed development that combined tree planting, soil conservation, and community participation, linking environmental rehabilitation with poverty reduction and climate resilience, thereby setting the foundation for initiatives like the Climate Resilient Green Economy (Gebreselassie et al., 2016; MoFED, 2011; Hurni et al., 2010). Over the past fifty years, Ethiopia has implemented extensive afforestation and land restoration programs, including the Sustainable Land Management Program (SLMP) and the Green Legacy Initiative (GLI) launched in 2019. These efforts, characterized by both state-led and community-based approaches, focus on tree planting, watershed management, and sustainable land use practices across diverse ecological zones, reflecting the government's sustained commitment to addressing land degradation, deforestation, and climate vulnerability (Gashaw et al., 2022; A. Degife et al., 2021; Gebreselassie et al., 2016; Gebreegziabher and Kooten, 2013; Bewket, 2003).

Despite notable afforestation efforts, Ethiopia's programs have encountered significant implementation challenges. The GLI, for instance, has struggled with seedling survival rates below optimal levels—reports indicate survival often falls under 60% due to insufficient post-planting care, inadequate watering, and poor soil preparation (Massrie, 2024). Institutional coordination challenges compound these limitations; forestry programs often operate within weak administrative frameworks, face shortages of technical capacity at the local level, and lack consistent long-term follow-up mechanisms to support tree establishment and ecological integration (Massrie, 2024; Gashaw et al., 2022). Additionally, the predominance of top-down approaches has sometimes undermined community ownership and participation, reducing program sustainability (Gebreselassie et al., 2016; Bewket, 2003). Ecological concerns also arise from the widespread planting of fast-growing exotic species like Eucalyptus, which can negatively affect soil health and water resources (Z. Mekonnen et al., 2007; Teketay, 2000). Furthermore, regional disparities in implementation and weak monitoring systems limit the ability to evaluate long-term impacts, and the linkage between afforestation and climate resilience strategies remains underdeveloped (Gashaw et al., 2022; Gebreselassie et al., 2016).

4.3 Data and key variables

4.3.1 The Data

This study utilizes the Ethiopian Socioeconomic Survey (ESS) panel datasets conducted in 2011/12, 2013/14, and 2015/16 through a collaborative effort between the World Bank Living Standards Measurement Study-Integrated Surveys of Agriculture (LSMS-ISA) and the Central Statistical Agency (CSA).[2] The panel data is particularly valuable as it is nationally representative, offering the most comprehensive survey data that covers all regions of the country, including rural and small-town households. Additionally, it provides in-depth information on household socioeconomic characteristics and community-level variables.

[2] The LSMS-ISA datasets for Ethiopia are open data and publicly available at `https://www.worldbank.org/en/programs/lsms/initiatives/lsms-ISA#2`. In addition, detailed information about the survey's management, design, implementation, and dissemination is available alongside the datasets at this link.

The most recent Ethiopia Socioeconomic Panel Survey (ESPS) had certain limitations. Hence, this study focuses solely on the earlier ESS three-panel datasets from 2011/12, 2013/14, and 2015/16. The surveys conducted in 2018/19 and 2021/22 faced significant challenges due to volatile security situations in the northern and western parts of the country. Specifically, the ESPS-5 survey in 2021/22 had a restricted coverage of enumeration areas (EAs), excluding the entire Tigray region and partially collecting data in the Afar region. Additionally, security issues in the Amhara and Oromia regions during the ESPS-5 further limited household and EA coverage.

This study draws on a panel dataset of rural households from twelve administrative regions in Ethiopia: Tigray, Afar, Amhara, Oromia, Somali, Benishangul-Gumuz, SNNP, Sidama, South West Ethiopia Peoples' Region (SWEP), Gambella, Harari, and Dire Dawa. These regions exhibit comparable patterns in livelihood diversification, agricultural practices, and population density. The analysis focuses on households engaged in the cultivation of six primary cereal crops, teff, wheat, barley, maize, sorghum, and millet, using survey data collected in three waves: 2011/12, 2013/14, and 2015/16, with corresponding sample sizes of 3,466, 3,323, and 3,272 households. Sample attrition rates between waves are low, approximately 4% between the first and second rounds and 1.5% between the second and third. To ensure consistency and mitigate potential bias from attrition, the final empirical analysis relies on a balanced panel of 3,222 households observed in all three rounds, resulting in 9,666 household-year observations.

The datasets offer detailed information on agricultural inputs and outputs, weather-related shocks, household socioeconomic characteristics, and a wide range of community-level variables. They include both subjective and objective measures of weather shocks, such as self-reported drought (insufficient rainfall), crop damage, production loss, and exposure to extreme temperatures. Recurrent shocks—particularly droughts, yield reductions, and temperature extremes—are empirically associated with adverse impacts on cereal productivity.

The explanatory variables comprise binary indicators for self-reported drought, crop damage, and a continuous measure of production loss expressed as the percentage reduction in yield. The analysis additionally accounts for a comprehensive set of control variables related to agricultural productivity and household welfare. These include demographic characteristics (e.g., household size and age composition), economic indicators (e.g., landholding size, use of improved agricultural inputs such as seeds and fertilizers, food security status, and non-farm income), as well as institutional factors (e.g., land tenure security, access to credit, and irrigation practices).

In addition, the data leverage geo-referenced household locations provided through the LSMS-ISA community-level modules, which offer spatial insights into local infrastructure, including proximity to roads, markets, and service centers—factors that shape both exposure to and resilience against weather shocks.

To overcome the limitations of self-reported weather shock variables, this study integrates two geo-referenced environmental datasets to develop objective measures of weather shocks. The first primarily utilizes the Enhanced Vegetation Index (EVI), a satellite-derived remote sensing metric from the Moderate Resolution Imaging Spectroradiometer (MODIS), to capture land cover dynamics corresponding to the LSMS-ISA survey data.

Additionally, the study integrates an alternative specification of weather shocks based on long-term temperature extremes. This measure uses the annual mean temperature thresholds derived from monthly climatological data, capturing cumulative exposure to long-term heat stress, to construct the temperature thresholds to test its effect on agricultural productivity. By leveraging historical temperature patterns, this approach enables a more objective and temporally consistent assessment of heat-related shocks, complementing self-reported measures and enhancing the robustness of the climate risk analysis.

The satellite-based data under consideration addresses two critical limitations of self-reported weather shock data. First, it minimizes reliance on households' recollections of recent rainfall patterns, which, although farmers may remember the adverse impacts of weather shocks such as droughts, are often constrained by time-bound memory biases. Second, marginal reductions in rainfall can disproportionately affect the most vulnerable households—those with limited coping mechanisms and exposure to additional idiosyncratic shocks—leading them to classify such events as droughts more frequently than relatively resilient farmers. Consequently, self-reported weather shock indicators are susceptible to partial endogeneity, potentially resulting in an upward bias in estimating the impacts of extreme weather shocks.

4.3.2 Key variables and descriptive statistics

4.3.2.1 Outcome variable: Agricultural productivity

This paper investigates the impact of weather shocks on agricultural productivity. The analysis also explores how changes in land cover can help mitigate the negative impacts of weather-related shocks, particularly those related to rainfall shortages (defined as drought) and temperature extremes. The study evaluates the impact of weather shocks on agricultural productivity, using productivity thresholds for sensitivity checks. A heterogeneity analysis explores variations in productivity, spatial weather shocks, and land cover changes across two agroecological zones.

As a result, the outcome variable, agricultural productivity, is measured in monetary terms (ETB) and is derived from six primary cereal crops: teff, wheat, barley, maize, sorghum, and millet. It refers to calculated values as the ratio of income derived from cereal crops to the area of cultivated land (in hectares). To evaluate the sensitivity of productivity to weather shocks and the potential mitigating role of land cover change, productivity thresholds are defined by categorizing the data into three levels: the bottom 25%, the middle 50%, and the top 25%. While Table 4.1 presents summary statistics, a detailed description of all variables used in the analysis, including definitions and measurement methods, is provided in Appendix Table C.1. A heterogeneity analysis is also performed based on the country's traditional agroecological classifications. This methodology facilitates a nuanced assessment of the varying impacts of weather shocks on agricultural productivity across different productivity levels and agroecological zones.

4.3.2.2 Key explanatory variables

(a) Enhanced Vegetation Index (EVI):

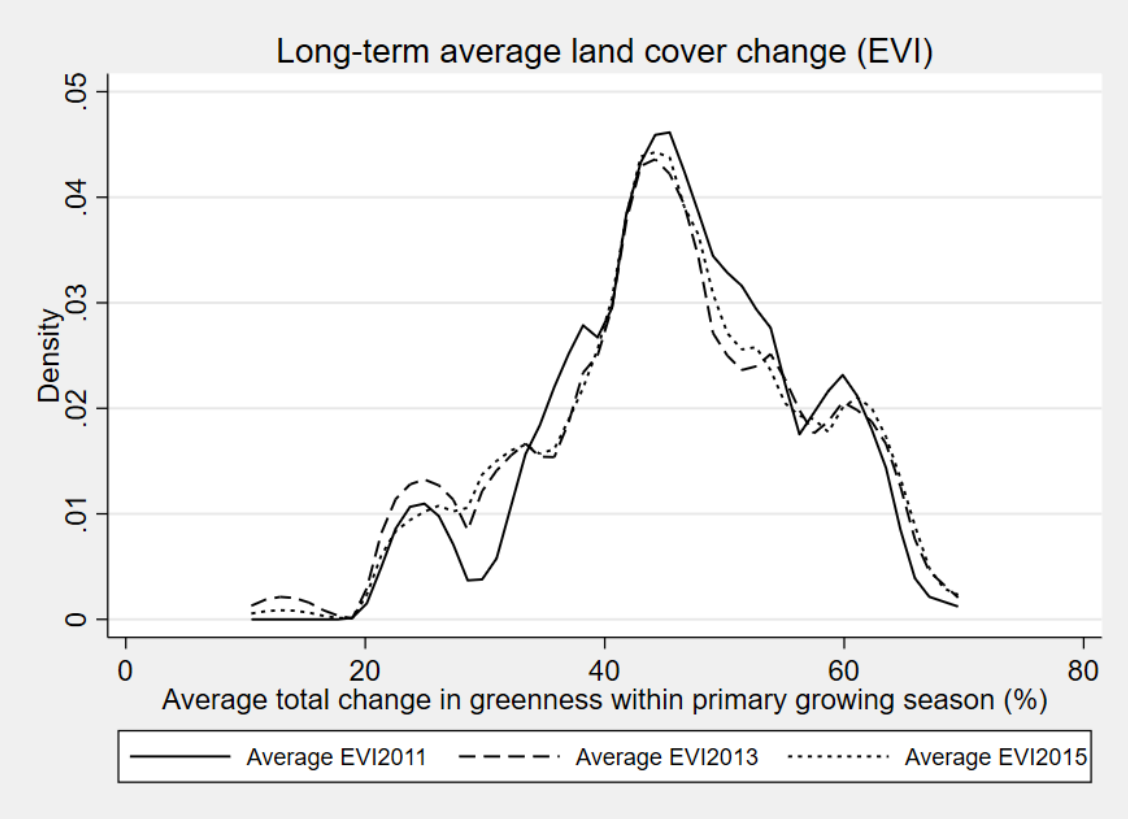
The EVI is a crucial tool for assessing land cover dynamics both globally and in Ethiopia. Worldwide, EVI is used to classify land cover types, such as urban areas, and to monitor vegetation changes in high-biomass regions, providing insights into shifts in land cover (Mehra and Swain, 2023). In Ethiopia, EVI has been used to monitor vegetation trends through remote sensing, highlighting the effects of climate change and human activity (Alemu et al., 2024; Shengjie Yang et al., 2022). EVI from Landsat imagery tracks forest cover changes and estimates biomass and carbon storage, supporting climate mitigation in the Alemsaga forest (Tigabu and Gessesse, 2025). These applications highlight EVI's effectiveness in monitoring land cover dynamics and their significant regional implications for environmental management in Ethiopia.

As a result, this study develops an objective, spatially explicit proxy for drought conditions using EVI, a satellite-based metric derived from MODIS Land Cover Dynamics imagery. Figure 4.1 presents the average percentage change in EVI values across the three survey years during the primary cereal crop growing season, capturing variations in vegetation greenness and long-term land cover dynamics. As illustrated in Figure 4.1, the inter-annual distribution of vegetation greenness, measured by the integral of EVI values, generally follows a normal distribution across the survey years. However, 2011 exhibits increased variability relative to the more stable patterns observed in 2013 and 2015, indicating more pronounced deviations in vegetation health—likely driven by climatic or environmental disturbances—compared to the relative stability of the later years.

Therefore, the EVI helps construct a viable alternative to conventional drought indicators, enhancing the systematic detection of vegetation stress linked to drought events through high-resolution remote sensing data. By capitalizing on advancements in satellite observation technologies, this approach enables consistent and scalable assessment of land surface conditions using 12-month EVI composites, ensuring broad spatial coverage and refined temporal resolution.

To capture intra-annual and inter-annual vegetation dynamics, the analysis utilizes average EVI values corresponding to the primary agricultural season (Meher) linked to the LSMS-ISA survey data. The EVI data are aggregated at the zonal level for each survey year and benchmarked against a long-term average from 2001 to the respective survey year in the LSMS-ISA dataset. Vegetation stress, indicative of drought severity, is assessed through EVI anomalies, calculated as the deviation of the current season's EVI from its long-term zonal mean. As illustrated in Figure

Fig. 4.1 Mean long-term land cover change, measured by EVI (%)



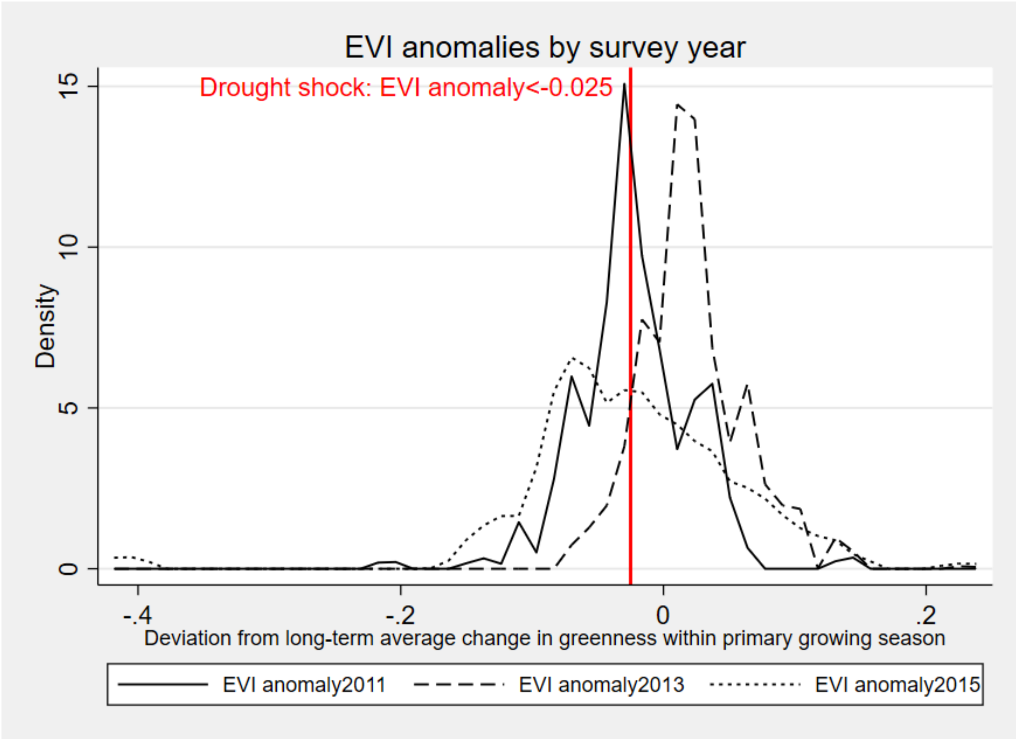
4.2, these anomalies provide a reliable proxy for detecting drought incidence during the critical growing season, reflecting variations in vegetative health attributed to climatic stressors compared to the long-term local historical average across Ethiopia.

The MODIS EVI product, with anomalies in the range of -0.025 $\leq$ EVI anomaly $\leq$ 0.025, defines normal vegetation conditions. An EVI anomaly below -0.025 (-2.5%) serves as a proxy for drought shock, indicating vegetation stress defining the threshold for identifying drought-affected areas, as shown in Figure 4.2. Households in these areas constitute the treatment group, while those within the normal EVI anomaly range form the comparison group.

(b) Extreme Temperature:

Extreme temperatures in Ethiopia have exacerbated drought conditions, leading to a decline in yields of crops such as teff, wheat, and barley. Most farmers depend on rain-fed agriculture, but erratic rainfall and rising temperatures increase food insecurity and economic instability. Agriculture is vital to Ethiopia's GDP but faces significant threats due to declining productivity, which impacts rural livelihoods and exacerbates poverty. Drought-adaptation strategies, such as improved irrigation, agroforestry, and climate-smart practices like soil and water conservation (Akuma et al., 2025), are vital for enhancing resilience against climatic challenges. These

Fig. 4.2 EVI anomalies calculated relative to the long-term average

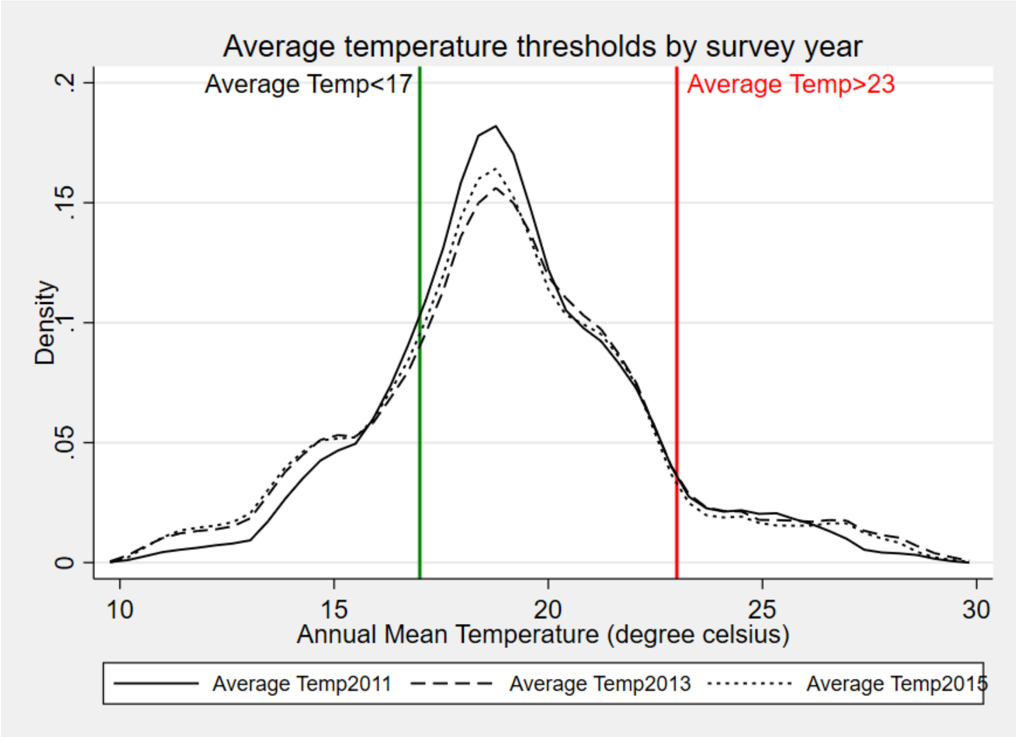


methods help optimize water use, improve soil health, and sustain agricultural productivity despite changing climatic conditions, reducing dependence on unpredictable weather across sub-Saharan Africa (Otieno, 2024; Sinore and Wang, 2025).

The average annual temperature is calculated as the mean of monthly temperature values over a defined reference period, offering a robust estimate of long-term climatic conditions. This approach captures deviations from historical temperature norms to identify periods of anomalous heat stress. These temperature-based shock indicators are geo-referenced and matched to the LSMS-ISA for each corresponding survey year, ensuring a consistent link between climatic variability and household outcomes. This methodology enhances the precision of weather shock measurement by accounting for localized, long-term climate patterns.

Furthermore, it is crucial to emphasize the temporal and spatial heterogeneity of average temperature in the datasets. As depicted in Figure 4.3, the average annual temperature is calculated as the mean of monthly values over a specified reference period, with distributions generally following a relatively normal pattern. Notably, the temperature in 2011/12 exhibited high fluctuation compared to the more stable periods of 2013/14 and 2015/16. Figure 4.3 also categorizes temperature thresholds into low, moderate, and high for each agricultural season preceding the survey years (2011, 2013, and 2015). These maps further emphasize the asymmetric distribution of temperature variations spatially across regions and temporally across the observed periods.

Fig. 4.3 Average annual temperature thresholds (°C)



4.3.2.3 Descriptive statistics

Table 4.1 presents the mean values of the variables included in the analysis across the survey rounds and the whole pooled sample. These descriptive statistics provide crucial insights into the distribution of the variables, serving as a foundation for the subsequent analysis. The average agricultural productivity for the pooled sample is about 7.96 in natural logarithmic terms, which approximately equates to 2,900 ETB per hectare. This figure ranges from a minimum of 6.60 to a maximum of 8.38, with the lowest value observed in 2011 and the highest in 2013. The mean difference in agricultural productivity, expressed in natural logarithmic terms across the survey years, reflects the rainfed nature of the sector. This variability underscores the sector's vulnerability to climate change, as agricultural output is highly dependent on prevailing weather patterns in the country.

As shown in the pooled sample means in Table 4.1, approximately 30% of households reported experiencing food insecurity, indicating that a substantial proportion was affected by food shortages. Additionally, most households fall within the second-lowest quintile (approximately 1.87), representing 21-40% of non-farm income. This indicates that many households earn little income from non-agricultural activities, which may heighten their vulnerability to economic shocks and food insecurity.

As indicated in Table 4.1, the data reveal that the average age of household heads is approximately 47 years, with an average household size of five adult equivalents. This demographic structure suggests moderate labor availability for agricultural activities, which may influence the household's capacity to manage farming operations effectively. Moreover, the mean landholding size is 1.70 hectares, reflecting limited access to sufficient arable cropland. Such land constraints hinder households' ability to expand agricultural production, restricting opportunities for increased income and improved food security.

Table 4.1 Summary statistics

	2011/12		2013/14		2015/16		Pooled	
	Mean	Sd	Mean	Sd	Mean	Sd	Mean	Sd
ln(Productivity)[a] (ETB/ha)	6.595	1.847	8.383	1.097	8.216	1.191	7.961	1.482
Food security (1=secure; 0=insecure)	0.717	0.451	0.672	0.470	0.730	0.444	0.704	0.457
Non-farm income (Quintile Index: 1-5)	1.897	1.575	1.895	1.581	1.820	1.536	1.866	1.563
Age (years)	45.036	14.807	46.549	14.798	48.362	14.595	46.935	14.774
Household size (number)	4.570	1.835	4.888	1.962	5.034	2.048	4.881	1.979
Cropland area (hectares)	2.283	2.377	1.571	1.613	1.524	1.669	1.695	1.835
Improved seed (1=improved; 0=local)	0.196	0.397	0.199	0.399	0.218	0.413	0.206	0.404
Chemical fertilizer use (1=yes; 0 otherwise)	0.585	0.493	0.554	0.497	0.584	0.493	0.572	0.495
Tenure security (1=certified; 0 otherwise)	0.389	0.488	0.436	0.496	0.514	0.500	0.457	0.498
Credit access (1=yes; 0 otherwise)	0.309	0.462	0.239	0.426	0.200	0.400	0.237	0.426
Irrigation access (1=yes; 0 otherwise)	0.137	0.344	0.119	0.324	0.111	0.314	0.119	0.324
Distance to market (KM)	47.196	20.884	47.194	21.408	47.407	21.555	47.278	21.359
Agro-ecological zone (1=Tropical cool; 0 otherwise)	0.937	0.243	0.921	0.270	0.928	0.258	0.927	0.260
$LandCoverChange_{v,t}$ (%)	46.021	9.948	44.941	11.581	45.601	11.013	45.414	11.056
$DroughtShock_{v,t-1}$(Satellite: 1=yes; 0=no)	0.177	0.382	0.182	0.386	0.182	0.386	0.181	0.385
$AverageTemp_{v,t-1}$ ($^{\circ}C$)	19.031	2.859	19.008	3.308	18.850	3.235	18.951	3.195
$DroughtShock_{v,t-1}$(Self-report: 1=yes; 0=no)	0.141	0.348	0.189	0.392	0.180	0.384	0.176	0.381

Source: Ethiopian LSMS-ISA survey: 2011/12, 2013/14, and 2015/16.

[a] "ln" denotes natural logarithm.

There is significant variation in the adoption of agricultural technologies among the sample households. The uptake of improved seeds is relatively low, with only 21% of households using this technology. In contrast, approximately 57% of households utilize chemical fertilizers, reflecting a higher adoption rate for this input. This disparity highlights unequal access to productivity-enhancing technologies within the agricultural sector, suggesting that while some households benefit from advanced practices, others face limitations in access or affordability, potentially hindering broader sectoral growth and agricultural modernization.

Regarding institutional factors, 46% of households report having tenure security, indicating that nearly half of the sample enjoy stable land ownership or use rights, an essential prerequisite for long-term agricultural planning and investment. Although secure tenure supports productivity improvements and encourages on-farm investments, access to other key institutional resources remains constrained. Only 24% of households report access to credit, which is critical for financing agricultural inputs and modern technologies. Furthermore, just 12% have access to irrigation infrastructure, a vital mechanism for mitigating rainfall variability and enhancing yield stability. These figures reflect enduring institutional barriers, particularly in access to credit and irrigation, that inhibit the widespread adoption of productivity-enhancing practices and undermine the agricultural sector's capacity to build resilience against climate and economic shocks.

As shown in Table 4.1, the average distance to the nearest market is 47.28 kilometers, indicating significant spatial isolation that may limit access to inputs, services, and markets. Moreover, approximately 93% of households are located in the tropical cool agroecological zone, characterized by moderate temperatures and distinct rainfall patterns. These geographic and agroecological conditions highlight the importance of accounting for spatial heterogeneity when analyzing agricultural productivity and resilience.

The long-term average EVI value during the main agricultural seasons is approximately 45.41%, reflecting vegetation greenness as a proxy for land cover and photosynthetic activity relevant to drought conditions. Mean EVI values remain consistent across survey years, indicating minimal inter-annual variation in average greenness, as supported by the density distribution in Figure 4.1, indicating stable aggregate vegetation conditions over time despite potential localized climatic variations.

Table 4.1 reports both satellite-based and self-reported measures of drought shock from the previous agricultural season, capturing complementary perspectives on household exposure. Satellite data indicate that 18.1% of households experienced drought, while 17.6% self-reported rainfall insufficiency. The close alignment suggests consistency between objective and subjective assessments, though minor discrepancies may reflect differences in perception, timing, or spatial resolution. Together, these measures provide a more comprehensive understanding of drought exposure by combining biophysical data with localized household experiences.

The average long-term annual temperature for the previous agricultural season was approximately $19°C$, with consistent mean values and distribution across the three survey years, as shown in Figure 4.3. While this stability indicates minimal interannual variation at the aggregate level, it may obscure substantial area-specific differences across agroecological zones.

4.4 Empirical strategy

4.4.1 Empirical specification

This study investigates the impact of weather shocks on agricultural productivity in rural Ethiopia, emphasizing the role of land cover dynamics. The analysis employs a fixed effects (FE) estimator to control for unobserved heterogeneity across households and districts. This approach is particularly appropriate for panel data settings, as it effectively controls for latent characteristics, such as inherent soil properties or historical patterns of land use, that do not vary over time but could confound the results. By exploiting temporal variation within observational units, the FE methodology allows for more credible identification of causal impacts stemming from continuous variables, such as fluctuations in weather conditions and changes in land cover across both spatial and temporal contexts (Wooldridge, 2010).

Moreover, to efficiently handle high-dimensional fixed effects, the study applies the efficient Multi-Way Fixed Effects (MWFE) estimator, which extends the traditional within transformation by using iterative projection techniques to absorb multiple layers of fixed effects. This method is a linear regression model that includes many types of fixed effects. The MWFE estimator is an efficient method for estimating linear regression models with high-dimensional fixed effects. It extends the standard within transformation through iterative projections to absorb multiple types of fixed effects, thereby enabling consistent estimation in the presence of multi-way unobserved heterogeneity. Instead of estimating numerous fixed effect coefficients directly, the MWFE approach absorbs them computationally, greatly enhancing efficiency and scalability in models with intricate fixed effect structures (Correia, 2017). This approach also excludes singleton groups in linear regressions with nested fixed effects to prevent inflated statistical significance (Correia, 2015).

The econometric model is specified as follows:

$$\begin{aligned} Y_{i,t} = \beta_1 WeatherShock_{v,t-1} + \beta_2 LandCoverChange_{v,t} + \\ \beta_3 (WeatherShock_{v,t-1} \times LandCoverChange_{v,t}) + X_{i,t}\gamma + \alpha_i + \delta_t + \epsilon_{i,t} \end{aligned} \tag{4.1}$$

In Equation 4.1, $Y_{i,t}$ denotes agricultural productivity, measured as the value of yield per hectare for household i at time t. $WeatherShock_{v,t-1}$ captures the drought shock in village v at time t. $LandCoverChange_{v,t}$ a proxy measure for changes like forest, cropland, or grassland cover. $WeatherShock_{v,t-1} \times LandCoverChange_{v,t}$ represents the interaction term measuring moderation effects. $X_{i,t}$ includes control variables at the household level—such as household size, tenure security, fertilizer use, improved seed adoption, credit access, and irrigation—as well as community-level factors like distance to the nearest road and market. α_i denotes district-fixed effects, controlling for time-invariant factors. δ_t represents year-fixed effects, capturing macroeconomic trends. $\epsilon_{i,t}$ is the error term.

4.4.2 Identification

This study employs objective, satellite-derived indicators of drought and extreme temperatures from reputable climatological data sources to evaluate the effects of weather shocks on agricultural productivity. Drought exposure is measured using remotely sensed EVI data, providing a consistent and spatially comprehensive proxy for vegetation stress associated with moisture deficits. Extreme temperature exposure is quantified based on long-term annual mean temperature thresholds, capturing cumulative heat stress relevant to crop development and growth cycles. Both indicators ensure the objectivity and reliability of these weather shocks.

To strengthen the empirical analysis, self-reported drought indicators—capturing household perceptions of rainfall deficits—are included as robustness checks alongside satellite-based measures. Additionally, low-temperature thresholds are incorporated to contrast their effects with high-temperature extremes. This approach enables a more comprehensive assessment of weather shocks by integrating subjective and objective measures and accounting for the full range of temperature variability.

However, identification challenges emerge when land cover dynamics are non-random. Specifically, villages exhibiting better changes in vegetation greenness may simultaneously experience higher agricultural productivity, suggesting potential endogeneity between land cover dynamics and productivity outcomes. This endogeneity implies that the interaction coefficient, β_3, in Equation 4.1, may be biased. The average change in greenness reflects the interplay between natural and societal factors. Conversely, it is shaped by natural conditions, especially prevailing weather patterns, while human activities may either enhance or degrade land cover dynamics within rural economies.

A high correlation between the dependent variable and land cover dynamics may introduce endogeneity bias. To address this issue, a high-dimensional MWFE specification by Correia (2017) controls for time-invariant unobserved heterogeneity. The within transformation removes the unobserved term in Equation 4.1, yielding consistent estimates.

Moreover, this identification strategy effectively mitigates endogeneity concerns associated with the interaction between an exogenous variable, such as satellite-based weather shocks (e.g., annual mean temperature), and a potentially endogenous variable, such as EVI, which reflects land cover dynamics. In addition to employing the efficient high-dimensional fixed effects framework estimator, Nizalova and Murtazashvili (2016) demonstrates that, assuming the exogeneity of the weather shocks, the coefficient on the interaction term can be consistently estimated. This approach allows for a credible interpretation of the moderating role of land cover dynamics on the relationship between weather shocks and agricultural productivity.

An identification challenge arises when villages with high land cover dynamics may be more vulnerable to weather shocks. However, this is mitigated by the negative correlation between land cover dynamics and weather shocks, allowing for a consistent estimate by comparing villages based on long-term average greenness.

4.5 Results and discussion

This section examines the impact of weather shocks on agricultural productivity and the role of land cover dynamics in mitigating these effects. Section 4.5.1 presents the main results, Section 4.5.2 explores the heterogeneous effects across agroecological zones, Section 4.5.3 discusses the results, Section 4.5.4 assesses the robustness of the results, and Section 4.5.5 outlines the study's limitations and offers directions for future research.

4.5.1 Main Results

4.5.1.1 Satellite-based drought shock measure

Table 4.2 displays the impact estimates of past season weather shocks, measured using satellite-based drought, on agricultural productivity and the mediating role of land cover change. The first two columns present agricultural productivity in logarithmic form, while the last six columns report alternative metrics, categorizing agricultural productivity into three thresholds: bottom 25%, middle 50%, and top 25%.

The primary explanatory variable in Table 4.2 is the objective weather shock indicator derived from EVI anomalies, which quantifies the drought shock experienced in the previous season. EVI anomalies assess vegetation stress by identifying deviations from typical seasonal patterns, providing an objective measure of drought impacts on agricultural productivity.

Specifically, columns (1) and (2) in Table 4.2 present the impact of drought shock on agricultural productivity, with column (1) displaying the results from the baseline linear MWFE estimator, which does not include additional control variables. Column (2), on the other hand, presents the results from the full specifications, which incorporate a comprehensive set of control variables. This comparison allows for an assessment of how long-term average changes in greenness mitigate the adverse effects of drought, highlighting the role of land cover dynamics in moderating the impacts of climatic shocks under different model specifications.

The final six columns (columns 3 to 8) of Table 4.2 provide estimates of agricultural productivity, segmented into three distinct thresholds: the bottom 25%, middle 50%, and top 25% of productivity levels. These columns analyze the heterogeneous effects of past drought shocks across different productivity groups. Similar to columns (1) and (2), estimators under a given threshold present the linear MWFE estimator with baseline regression and the full specification with additional controls; these columns also assess the moderating role of land cover dynamics in alleviating the negative impacts of drought. By examining these thresholds, the analysis offers a nuanced understanding of how agricultural productivity at different levels responds to climatic shocks and how variations in land cover dynamics can enhance resilience, depending on the productivity profile of the households.

Columns (1) and (2) of Table 4.2 assess the mitigating role of land cover dynamics on drought shock, with column (1) representing the baseline model and column (2) incorporating additional controls. The results consistently show negative and statistically significant coefficients for drought shock, indicating a decrease in agricultural productivity due to drought events. However, the interaction term between drought shock and average change in greenness is positive and statistically significant at the 1% level with coefficients of 0.028 and 0.023 in columns (1) and (2), respectively. These estimates remain stable with the inclusion of additional controls, suggesting that improved land cover dynamics significantly mitigate the adverse effects of drought on agricultural productivity. In other words, the estimated impacts derived from the

Table 4.2 Satellite-based drought and agricultural productivity: the role of land cover change

	Dependent Variable: ln(Agricultural productivity)$_{i,t}$		Dependent Variable:Productivity$_{i,t}$(dummy)					
			Bottom 25%		Middle 50%		Top 25%	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$DroughtShock_{v,t-1}$(1=yes; ref: no shock)	-1.424***	-1.177***	-0.265***	-0.205***	-0.515***	-0.407***	-0.486***	-0.386***
	(0.224)	(0.234)	(0.063)	(0.067)	(0.079)	(0.083)	(0.069)	(0.071)
$LandCoverChange_{v,t}$	0.001	-0.004*	0.000	-0.001	-0.000	-0.002***	-0.001	-0.002***
	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
$DroughtShock_{v,t-1} \times LandCoverChange_{v,t}$	0.028***	0.023***	0.005***	0.004***	0.010***	0.008***	0.010***	0.008***
	(0.005)	(0.005)	(0.001)	(0.001)	(0.002)	(0.002)	(0.001)	(0.002)
Constant	7.948***	8.016***	0.738***	0.745***	0.526***	0.546***	0.292***	0.440***
	(0.097)	(0.156)	(0.028)	(0.045)	(0.030)	(0.054)	(0.025)	(0.048)
Household Fixed Effects	✓	✓	✓	✓	✓	✓	✓	✓
Year Fixed Effects	✓	✓	✓	✓	✓	✓	✓	✓
Controls	—	✓	—	✓	—	✓	—	✓
Number of observations (no shock)	4875	4875	4875	4875	4875	4875	4875	4875
Observations	5941	5760	5941	5760	5941	5760	5941	5760
R^2	0.259	0.294	0.209	0.238	0.172	0.204	0.100	0.129

All model specifications are estimated using the MWFE estimator developed by Correia (2017). The dependent variable measures agricultural productivity, expressed as the natural logarithm in columns (1) and (2) and as a binary indicator in columns (3) through (8), corresponding to three defined productivity thresholds. Columns (3) to (8) report coefficients estimated at each threshold. Control variables include the household head's age (years), household size (adult equivalents), tenure security (binary), use of improved seed (binary), use of chemical fertilizer (binary), access to credit (binary), access to irrigation (binary), food security status (dummy), non-farm income (index), and distance to the nearest market (kilometers). Robust standard errors are reported in parentheses. Asterisks show significance at the * 10%, ** 5%, and *** 1% levels.

full specifications are presented in column (2), with a focus on drought impact and the magnitude of the coefficient estimate for the core variable of interest, and the interaction term remains robust despite the inclusion of additional control variables. Hence, this indicates that enhanced land cover, such as increased vegetation, helps to reduce productivity losses in drought-affected areas, thereby increasing resilience to climate-induced shocks.

Furthermore, these findings underscore the critical role of land cover dynamics in mitigating the adverse effects of weather shocks on agricultural productivity. Specifically, the positive and statistically significant interaction terms in the third row of 4.2 demonstrate that farm households exposed to drought shocks experience higher productivity as long-term average greenness improves. These results confirm that improved land cover dynamics boost agricultural productivity and serve as informal insurance, enhancing farmers' resilience to weather shocks. By fostering sustainable farming practices that enhance land cover dynamics, farmers are better equipped to adapt to recurring harvest disruptions, improving agricultural productivity.

In columns (3) through (8) of 4.2, the drought shock variable consistently shows negative and statistically significant coefficients. These results highlight that droughts reduce agricultural productivity, particularly in higher-productivity households, emphasizing the vulnerability of rainfed agricultural production to weather-induced disruptions like drought. Columns (3), (5), and (7) of 4.2 present the impact of drought shocks and their interaction with average land cover dynamics from the previous growing season for the baseline MWFE estimator linear regressions, corresponding to the specified productivity thresholds. Columns (4), (6), and (8) present similar results incorporating full control variables. The findings indicate that drought significantly reduces agricultural productivity across all thresholds. The coefficient on the interaction term, $DroughtShock_{v,t-1} \times LandCoverChange_{v,t}$, in the third row is positive and statistically significant in all cases. Therefore, this suggests that an increase in long-term average greenness helps mitigate the adverse effects of drought, enhancing productivity for farm households, particularly in drought-prone areas growing cereal crops.

4.5.1.2 Relative threshold for extreme temperature

Another key weather shock indicator is the relative extreme temperature threshold of $\geq 23°C$, shown in the highest category in Figure 4.3. Studies indicate that temperatures above this threshold adversely affect crop growth, leading to lower agricultural productivity. These extreme temperatures cause heat stress, reduce photosynthesis, and disrupt growth cycles. Table 4.3 presents the results for this threshold using the MWFE estimator, providing a robust assessment of extreme temperature shocks on agricultural productivity while controlling for unobserved heterogeneity.

In all cases, columns (1) through (8) in Table 4.3, regardless of the dependent variable units or control specifications, extreme temperatures consistently negatively affect agricultural productivity. As temperatures rise, productivity declines, indicating that heat stress disrupts

Table 4.3 Extreme temperature and agricultural productivity: Role of land cover change

	Dependent Variable: ln(Agricultural productivity)$_{i,t}$		Dependent Variable:Productivity$_{i,t}$(dummy)					
			Bottom 25%		Middle 50%		Top 25%	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$MeanTemperature \geq 23°C_{v,t-1}$	-0.702***	-0.858***	-0.154**	-0.193***	-0.109	-0.153*	-0.164**	-0.232***
	(0.271)	(0.279)	(0.071)	(0.072)	(0.079)	(0.081)	(0.066)	(0.068)
$LandCoverChange_{v,t}$	0.001	-0.005***	0.000	-0.001*	-0.000	-0.002***	-0.000	-0.002***
	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
$MeanTemperature \geq 23°C_{v,t-1} \times LandCoverChange_{v,t}$	0.018***	0.026***	0.004***	0.006***	0.004**	0.006***	0.005***	0.007***
	(0.005)	(0.005)	(0.001)	(0.001)	(0.002)	(0.002)	(0.001)	(0.001)
Constant	7.897***	8.107***	0.736***	0.774***	0.496***	0.568***	0.256***	0.453***
	(0.088)	(0.152)	(0.026)	(0.045)	(0.029)	(0.053)	(0.024)	(0.047)
Household Fixed Effects	✓	✓	✓	✓	✓	✓	✓	✓
Year Fixed Effects	✓	✓	✓	✓	✓	✓	✓	✓
Controls	—	✓	—	✓	—	✓	—	✓
Number of observations (no shock)	5615	5615	5615	5615	5615	5615	5615	5615
Observations	6153	5970	6153	5970	6153	5970	6153	5970
R^2	0.255	0.296	0.209	0.241	0.162	0.202	0.093	0.128

All model specifications are estimated using the MWFE estimator developed by Correia (2017). The dependent variable measures agricultural productivity, expressed as the natural logarithm in columns (1) and (2) and as a binary indicator in columns (3) through (8), corresponding to three defined productivity thresholds. Columns (3) to (8) report coefficients estimated at each threshold. Control variables include the household head's age (years), household size (adult equivalents), tenure security (binary), use of improved seed (binary), use of chemical fertilizer (binary), access to credit (binary), access to irrigation (binary), food security status (dummy), non-farm income (index), and distance to the nearest market (kilometers). Robust standard errors are reported in parentheses. Asterisks show significance at the * 10%, ** 5%, and *** 1% levels.

crop growth and reduces yields. This finding is robust across different model specifications, highlighting the significant impact of extreme temperature events on agricultural output.

The coefficient on the interaction term, $MeanTemperature \geq 23°C_{v,t-1} \times LandCoverChange_{v,t}$, in the third row of Table 4.3 is consistently positive and statistically significant at the 1% level across all cases. Hence, this indicates that an increase in land cover dynamics, reflected in the average change in greenness, significantly mitigates the detrimental effects of extreme temperatures on agricultural productivity. In other words, higher land cover dynamics enhance productivity in areas experiencing extreme temperatures, suggesting that improved vegetation cover can buffer the adverse impacts of temperature extremes. This finding underscores the role of sustainable land management in increasing resilience, as increased greenness can help protect agricultural output from the detrimental effects of heat stress, particularly in regions prone to high temperatures and drought.

Appendix Table C.2 presents a falsification test for the impacts of extreme temperatures, as shown in Table 4.3. This test investigates the effects of lower temperature thresholds, specifically $Temperature_{v,t-1} < 17°C$, to determine whether these low-temperature conditions negatively affect agricultural productivity like extremely high temperatures. The results indicate that lower temperature thresholds have a minimal impact on agricultural productivity, with no significant effects observed across the various productivity metrics except for continuous productivity measures under full control specifications. Furthermore, the interaction terms between these low-temperature thresholds and land cover dynamics, $Temperature_{v,t-1} < 17°C \times LandCoverChange_{v,t}$, are generally not statistically significant. These findings suggest that while land cover dynamics can effectively mitigate the adverse impacts of extreme temperatures, their effect is less pronounced under low-temperature conditions.

4.5.2 Agroecological heterogeneity: Tropical cool vs. Tropical warm

Drought impacts vary across agroecological zones, with arid and semi-arid regions experiencing the most severe effects due to limited water availability and heavy reliance on rainfall. These areas are more vulnerable as natural water systems cannot support crops during dry spells. Sub-humid and humid regions typically have more resilient ecosystems and better irrigation access, making them generally more capable of withstanding droughts. However, severe events can still lead to significant crop losses, particularly during critical growing periods. Therefore, drought impacts are most severe in arid and semi-arid regions (Naylor et al., 2007; Parry et al., 2005).

Table 4.4 examines the impact of drought shocks on agricultural productivity across the tropical cool and tropical warm zones. The results show that drought significantly reduces productivity in both zones, particularly in the tropical cool zone, and affects the middle and top productivity thresholds. However, its impact on the bottom threshold is limited, likely due to the lower capacity of these systems to adapt. Additionally, the interaction between drought and land cover dynamics indicates that improved land cover significantly mitigates drought effects, especially for tropical cool climates and higher productivity levels, enhancing resilience in more productive agricultural systems.

Table 4.4 Agroecological heterogeneity, satellite-based drought, and agricultural productivity: Role of land cover

	Tropical Cool Climates				Tropical Warm Climates			
		Agricultural productivity$_{i,t}$(dummy)				Agricultural productivity$_{i,t}$(dummy)		
	ln(Agrl prodty)$_{i,t}$	Bottom 25%	Middle 50%	Top 25%	ln(Agrl prodty)$_{i,t}$	Bottom 25%	Middle 50%	Top 25%
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$DroughtShock_{v,t-1}$(1=yes; ref: no shock)	-1.000***	-0.176	-0.349***	-0.363***	-2.594	-0.152	-0.916*	-1.347***
	(0.246)	(0.116)	(0.088)	(0.075)	(2.763)	(0.670)	(0.538)	(0.518)
$LandCoverChange_{v,t}$	-0.007***	-0.001	-0.003***	-0.003***	0.029	0.004	0.004	-0.003
	(0.002)	(0.001)	(0.001)	(0.001)	(0.020)	(0.003)	(0.004)	(0.004)
$DroughtShock_{v,t-1} \times LandCoverChange_{v,t}$	0.019***	0.003	0.006***	0.007***	0.038	0.003	0.012	0.020**
	(0.005)	(0.002)	(0.002)	(0.002)	(0.045)	(0.011)	(0.009)	(0.009)
Constant	8.135***	0.767***	0.565***	0.473***	6.569***	0.480*	0.575*	0.758**
	(0.160)	(0.052)	(0.056)	(0.050)	(1.268)	(0.269)	(0.334)	(0.304)
Household Fixed Effects	✓	✓	✓	✓	✓	✓	✓	✓
Year Fixed Effects	✓	✓	✓	✓	✓	✓	✓	✓
Controls	✓	✓	✓	✓	✓	✓	✓	✓
Number of observations (no shock)	4564	4564	4564	4564	311	311	311	311
Observations	5376	5376	5376	5376	354	354	354	354
R^2	0.304	0.245	0.213	0.134	0.461	0.400	0.408	0.471

All model specifications are estimated using the MWFE estimator developed by Correia (2017). The dependent variable measures agricultural productivity, expressed as the natural logarithm in columns (1) and (5) and as a binary indicator in columns (2)-(4) and (6)-(8), corresponding to three defined productivity thresholds that report coefficients estimated at each threshold. Control variables include the household head's age (years), household size (adult equivalents), tenure security (binary), use of improved seed (binary), use of chemical fertilizer (binary), access to credit (binary), access to irrigation (binary), food security status (dummy), non-farm income (index), and distance to the nearest market (kilometers). Robust standard errors are reported in parentheses. Asterisks show significance at the * 10%, ** 5%, and *** 1% levels.

4.5.3 Discussion

The findings of this study demonstrate that extreme weather shocks, regardless of the metrics or methodologies used in the analysis, represent a substantial threat to agricultural productivity in villages that are particularly vulnerable to climate variability. The results suggest that, despite the challenges posed by such extreme weather events, farmers have the potential to adapt through targeted interventions. Specifically, adopting improved land-use practices or implementing conservation agriculture techniques that enhance land cover change improves the resilience of agriculture-based livelihoods. These adaptive strategies lead to increased productivity in cereal production, offering a means for farmers to mitigate the negative impacts of climate shocks.

This conclusion aligns with the findings of several studies that emphasize the positive effects of enhanced land cover on agricultural productivity. Enhanced land cover, including the restoration of degraded areas and improved vegetation management, is vital for boosting soil fertility, water retention, and overall agricultural productivity. In rural areas of developing economies, where agriculture remains central to livelihoods, such improvements are essential for boosting productivity and ensuring food security.

The study's findings are consistent with a growing body of research in developing countries (e.g., (Leng and Hall, 2019; Vogel et al., 2019; Matiu et al., 2017; Lesk et al., 2016)), which underscores the intensifying impact of climate change on agricultural productivity. These studies highlight the acute vulnerability of rural communities, where livelihoods depend heavily on climate-sensitive, resource-dependent farming systems. Increasingly frequent and intense droughts and temperature extremes disrupt crop development, depress yields, and threaten food security, particularly in rainfed, cereal-producing regions. The effects are most pronounced when farmers lack access to critical adaptive resources, including irrigation infrastructure, agricultural credit, weather-indexed insurance, and modern technologies. Furthermore, the findings illustrate the interlinked consequences of climate shocks, as reduced productivity in agriculture cascades into lower crop yields, diminished farm incomes, and heightened food insecurity.

Droughts deplete vital water resources, reduce cultivated areas, and diminish crop productivity. Moreover, extreme heat intensifies plant stress during key growth stages, leading to significant yield losses and supply chain disruptions (Leng and Hall, 2019; Matiu et al., 2017). These shocks compromise household food access, lower incomes, raise food prices, and heightened food insecurity, especially in vulnerable rural areas. In response to these findings, the study underscores the urgent need for adaptive strategies and policies to mitigate the impacts of extreme weather shocks, particularly recurrent droughts and rising temperatures. Key priorities include promoting climate-resilient farming, investing in sustainable land management, enhancing early warning systems and risk transfer mechanisms, and improving farmers' access to adaptive tools and knowledge. Strengthening institutional support and local adaptive capacity is critical to ensuring agricultural sustainability, food security, and resilient rural livelihoods under increasing climate stress.

To complement national initiatives such as Arengwade Zemacha, watershed development, and the Green Legacy, this study recommends more locally adaptive and ecologically grounded strategies. These include integrated landscape planning that combines agroforestry, soil conservation, and grassland restoration; promotion of farmer-managed natural regeneration (FMNR) as a cost-effective approach to vegetation recovery; and payment for ecosystem services (PES) to incentivize on-farm conservation. Strengthening community forest management and implementing climate-smart village platforms—with drought-resilient crops, water harvesting, and early warning systems—can further enhance land cover, agricultural productivity, and resilience in drought-prone areas.

4.5.4 Robustness checks

This section evaluates the robustness of the main findings by employing an alternative measure of climate shock—self-reported drought experiences. Table 4.5 presents the estimated impacts of these self-reported drought shocks on agricultural productivity, using the MWFE estimator consistent with the main specification. The analysis maintains the same productivity metrics to ensure comparability. The results confirm that drought shocks, as reported by households, significantly reduce agricultural productivity across all specifications, reinforcing the reliability of the primary findings.

Moreover, the interaction between self-reported drought shocks and the average change in land cover dynamics yields a positive and statistically significant coefficient. Hence, this indicates that improvements in vegetation cover—reflecting enhanced land management or natural regrowth—play a critical role in buffering the negative impacts of drought on productivity. The comparable magnitude of these estimates to those in the primary analysis further substantiates the consistency and robustness of the core results, demonstrating that enhanced land cover functions as an effective adaptive mechanism in the face of climate variability.

Specifically, the analysis in Table 4.5 provides a comprehensive evaluation of the impact of drought shocks on agricultural productivity, emphasizing the interaction between these shocks and long-term changes in land cover or greenness. Columns (1) and (2) present continuous agricultural productivity measures in logged value terms, reflecting the overall impact of drought shocks on productivity. Columns (3) through (8) extend this analysis by examining the effects of drought shocks across various productivity thresholds, offering a detailed understanding of how different levels of agricultural output respond to climate shocks.

The findings in Table 4.5 evaluate whether long-term changes in land cover can help mitigate the impacts of drought, particularly in rural areas of developing economies vulnerable to climate variability. The results emphasize that increased vegetation cover and effective land management enhance resilience and adaptive capacity. Therefore, this can alleviate the immediate effects of drought and support long-term agricultural sustainability, allowing rural communities to better cope with future environmental challenges.

4.5.5 Limitations and directions for future research

This study is subject to two primary limitations, which offer essential directions for future research. The first limitation concerns the nature of the relationship examined between land cover dynamics and agricultural productivity. This analysis focuses on identifying statistical associations rather than determining causal relationships. However, drawing robust causal inferences necessitates that the key explanatory variables be strictly exogenous or, at a minimum, instrumented to account for endogeneity concerns. One of the central constraints of this study is the inability to confirm that changes in land cover occur randomly across space and time. In the absence of well-established random variation, it is

Table 4.5 Self-reported drought and agricultural productivity: the role of land cover change

	Dependent Variable: ln(Agricultural productivity)$_{i,t}$		Dependent Variable:Productivity$_{i,t}$(dummy)					
			Bottom 25%		Middle 50%		Top 25%	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$DroughtShock_{v,t-1}$(1=yes; ref: no shock)	-1.231***	-1.085***	-0.255***	-0.208***	-0.357***	-0.302***	-0.233***	-0.225***
	(0.218)	(0.222)	(0.058)	(0.059)	(0.065)	(0.066)	(0.054)	(0.055)
$LandCoverChange_{v,t}$	-0.003	-0.006***	-0.001	-0.001*	-0.002**	-0.003***	-0.001	-0.002***
	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
$DroughtShock_{v,t-1} \times LandCoverChange_{v,t}$	0.025***	0.022***	0.005***	0.004***	0.007***	0.005***	0.004***	0.004***
	(0.005)	(0.005)	(0.001)	(0.001)	(0.002)	(0.002)	(0.001)	(0.001)
Constant	8.164***	8.363***	0.791***	0.814***	0.601***	0.670***	0.311***	0.529***
	(0.096)	(0.169)	(0.030)	(0.049)	(0.034)	(0.059)	(0.030)	(0.054)
Household Fixed Effects	✓	✓	✓	✓	✓	✓	✓	✓
Year Fixed Effects	✓	✓	✓	✓	✓	✓	✓	✓
Controls	—	✓	—	✓	—	✓	—	✓
Number of observations (no shock)	4842	4842	4842	4842	4842	4842	4842	4842
Observations	5868	5700	5868	5700	5868	5700	5868	5700
R^2	0.270	0.303	0.222	0.248	0.175	0.206	0.098	0.128

All model specifications are estimated using the MWFE estimator developed by Correia (2017). The dependent variable measures agricultural productivity, expressed as the natural logarithm in columns (1) and (2) and as a binary indicator in columns (3) through (8), corresponding to three defined productivity thresholds. Columns (3) to (8) report coefficients estimated at each threshold. Control variables include the household head's age (years), household size (adult equivalents), tenure security (binary), use of improved seed (binary), use of chemical fertilizer (binary), access to credit (binary), access to irrigation (binary), food security status (dummy), non-farm income (index), and distance to the nearest market (kilometers). Robust standard errors are reported in parentheses. Asterisks show significance at the * 10%, ** 5%, and *** 1% levels.

difficult to rule out the influence of unobserved confounding factors that may simultaneously affect both land cover and agricultural productivity, thus undermining causal interpretation.

Establishing causality is essential for guiding targeted interventions and policy decisions. Future research should adopt experimental or quasi-experimental designs, such as RCTs, natural experiments, or instrumental variables, to rigorously identify causal effects. Clearly defined treatment and control groups will allow for better quantification of the economic and ecological benefits of land cover changes, aiding in uncovering the mechanisms that link ecosystem services to agricultural outcomes.

The second limitation relates to the scope of the analysis, which is confined to agricultural productivity in rural areas and limited to the production of major cereal crops. While this focus provides valuable insights into staple food systems, it limits the applicability of the findings to other agricultural contexts. Agricultural systems are diverse, and land cover changes may have varying implications depending on the crop type, production system, and agroecological conditions. To broaden the applicability and relevance of future research, subsequent studies should consider expanding the scope of analysis to include a wider variety of crops, such as legumes, horticultural products, and high-value commercial crops, as well as different farming systems, including peri-urban and mixed crop-livestock systems.

In sum, future research should prioritize methodological rigor to establish causal relationships and expand the empirical scope to reflect the diversity of agricultural landscapes and production systems. Understanding how land cover changes affect agricultural outcomes can enhance policy relevance and comprehensiveness.

4.6 Conclusions

In developing countries, agriculture is predominantly rainfed and characterized by small-scale subsistence farming, rendering households highly vulnerable to weather shocks that adversely impact productivity. Extreme weather events can undermine farmers' financial resilience, limiting their capacity to adapt and adopt improved technologies. Consequently, risk-averse households may opt for low-cost, less effective inputs over more productive alternatives. Efficient weather index insurance, credit, and labor markets are critical for mitigating these risks; however, such markets are often underdeveloped or inaccessible in rural areas, underscoring the need for greater inclusion and institutional strengthening.

This paper investigates the impact of weather shocks on agricultural productivity in rural Ethiopia, focusing on the potential role of land cover changes in mitigating these effects. Utilizing satellite-derived drought indicators and extreme temperature data from climatological sources, the study investigates how variations in vegetation cover, measured by average changes in greenness, can buffer the negative impacts of weather shocks, particularly on cereal crop production. The analysis draws on data from three waves of the Ethiopian LSMS-ISA surveys conducted in 2011/12, 2013/14, and 2015/16, which cover rural areas and small towns across the country. This study provides important insights into how land cover changes enhance agricultural resilience and productivity in response to climate variability.

The study utilizes a linear regression approach with a MWFE estimator to account for unobserved differences across time, location, and households. The results emphasize the importance of land cover changes in mitigating the adverse effects of climate extremes on agricultural production. Hence, this highlights the critical role of ecosystem services in strengthening the resilience of smallholder farmers.

The findings reveal that weather shocks, particularly droughts and extreme temperatures, substantially reduce cereal crop productivity, with consistent effects across different agroecological zones and a self-reported drought. Lower temperature thresholds do not show a significant impact. The adverse effects are more pronounced for households directly exposed to these shocks, with enhanced land cover mediating role, particularly pronounced in tropical cool and high-productivity tropical warm zones. Notably, increased vegetation greenness helps mitigate these impacts, sustaining productivity under climate stress.

The findings emphasize that improving land cover is essential for mitigating the adverse effects of weather-related shocks, thereby enhancing agricultural productivity and the resilience of subsistence farming communities. However, realizing these benefits requires not only coordinated efforts among stakeholders—such as policymakers, local communities, and development partners—but also a critical assessment of existing policy frameworks and institutional arrangements. Current strategies often fall short due to fragmented implementation, limited local ownership, and weak inter-sectoral coordination, which undermine the effectiveness and sustainability of land restoration efforts. Therefore, strengthening local support networks must go hand-in-hand with institutional reforms that address these structural limitations. Advancing inclusive multi-stakeholder engagement and investing in sustainable land management practices—anchored in policy coherence, long-term monitoring, and capacity building—are vital for enhancing climate resilience and ensuring durable improvements in rural livelihoods.

Investing in and collaborating on land cover enhancement is critical for ensuring sustainable agriculture and food security, particularly in the face of climate variability. These initiatives bolster agricultural resilience, reduce the impacts of climate change, and contribute to rural development. Although the study focuses on rural Ethiopia, it provides broader insights into the significance of land cover for food security, climate adaptation, and long-term sustainability. The findings highlight the need for integrated land management approaches that utilize ecosystem services to strengthen resilience. Future research should broaden its scope to other regions, evaluating the effectiveness of such strategies in fostering climate-resilient agriculture, particularly in areas prone to drought.

CRediT authorship contribution statement:

Gemeda Olani Akuma: Conceptualization, Methodology, Formal analysis, Data curation, Visualization, Writing – original draft, Writing – review & editing.

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References

Abd El-Hamid, Hazem T., Wei Caiyong, Mohammed A. Hafiz, and Elhadi K. Mustafa (2020). “Effects of land use/land cover and climatic change on the ecosystem of North Ningxia, China”. *Arabian Journal of Geosciences* 13, pp. 1–13.

AbdelRahman, Mohamed A. E. (2023). “An overview of land degradation, desertification and sustainable land management using GIS and remote sensing applications”. *Rendiconti Lincei. Scienze Fisiche e Naturali*, pp. 1–42.

Abtew, Wossenu, Assefa M. Melesse, and Tibebe Dessalegne (2009). “El Niño southern oscillation link to the Blue Nile River basin hydrology”. *Hydrological Processes: An International Journal* 23.26, pp. 3653–3660.

Adamseged, Muluken Elias (2019). “Dynamics of rural livelihoods and rainfall variability in Northern Ethiopian Highlands”. *Climate Risk Management* 25, pp. 1–14.

Adom, Philip Kofi (2024). “The socioeconomic impact of climate change in developing countries over the next decades: A literature survey”. *Heliyon*.

Affoh, Raïfatou, Haixia Zheng, Kokou Dangui, and Badoubatoba Mathieu Dissani (2022). “The impact of climate variability and change on food security in sub-saharan africa: Perspective from panel data analysis”. *Sustainability* 14.2, p. 759.

Ahmad, Adnan, Q. I.-Jing Liu, S. M. Nizami, Abdul Mannan, and Sajjad Saeed (2018). “Carbon emission from deforestation, forest degradation and wood harvest in the temperate region of Hindukush Himalaya, Pakistan between 1994 and 2016”. *Land use policy* 78, pp. 781–790.

Ahmed, Nafiu, Taherul Islam Khan, and Aboh Augustine (2018). “Climate change and environmental degradation: a serious threat to global security”. *European Journal of Social Sciences Studies*.

Akuma, Gemeda Olani, Gunnar Köhlin, and Fantu Guta (2025). “Adapting to drought: how do public works affect conservation and labor engagement in rural Ethiopia?” *Discover Sustainability* 6.1, p. 172.

Alemu, Mulugeta, Bikila Warkineh, Ermias Lulekal, and Zemede Asfaw (2024). “Analysis of land use land cover change dynamics in Habru District, Amhara Region, Ethiopia”. *Heliyon* 10.19.

Amare, Abayineh and Belay Simane (2017). “Climate change induced vulnerability of smallholder farmers: agroecology-based analysis in the Muger sub-basin of the upper Blue-Nile basin of Ethiopia”. *American Journal of Climate Change* 6.4, pp. 668–693.

Amare, Mulubrhan, Nathaniel D. Jensen, Bekele Shiferaw, and Jennifer Denno Cissé (2018). “Rainfall shocks and agricultural productivity: Implication for rural household consumption”. *Agricultural systems* 166, pp. 79–89.

Amare, Mulubrhan, Bekele Shiferaw, Hiroyuki Takeshima, and George Mavrotas (2021). “Variability in agricultural productivity and rural household consumption inequality: Evidence from Nigeria and Uganda”. *Agricultural Economics* 52.1, pp. 19–36.

Amfo, Bismark, Ernest Baba Ali, and David Atinga (2021). “Climate change, soil water conservation, and productivity: Evidence from cocoa farmers in Ghana”. *Agricultural Systems* 191, p. 103172.

Ananda, Jayanath and Gamini Herath (2003). "Soil erosion in developing countries: a socio-economic appraisal". *Journal of environmental management* 68.4, pp. 343–353.

Anteneh, Mesfin (2022). "Analysis of land use/land cover change and its implication on natural resources of the Dedo watershed, Southwest Ethiopia". *The Scientific World Journal* 2022.

Appiah, Mark and Ari Pappinen (2010). "Farm forestry prospects among some local communities in Rachuonyo District, Kenya". *Small-scale Forestry* 9, pp. 297–316.

Ariti, Adenew Taffa, Jasper van Vliet, and Peter H. Verburg (2015). "Land-use and land-cover changes in the Central Rift Valley of Ethiopia: Assessment of perception and adaptation of stakeholders". *Applied Geography* 65, pp. 28–37.

Asfaw, Solomon, Giacomo Pallante, and Alessandro Palma (2020). "Distributional impacts of soil erosion on agricultural productivity and welfare in Malawi". *Ecological Economics* 177, p. 106764.

Babulo, Bedru, Bart Muys, Fredu Nega, Eric Tollens, Jan Nyssen, Jozef Deckers, and Erik Mathijs (2008). "Household livelihood strategies and forest dependence in the highlands of Tigray, Northern Ethiopia". *Agricultural systems* 98.2, pp. 147–155.

Bai, Zhanguo G., David L. Dent, Lennart Olsson, and Michael E. Schaepman (2008). "Proxy global assessment of land degradation". *Soil use and management* 24.3, pp. 223–234.

Barakat, Ahmed, Zainabe Ouargaf, Rida Khellouk, Aafaf El Jazouli, and Fatima Touhami (2019). "Land use/land cover change and environmental impact assessment in béni-mellal district (morocco) using remote sensing and gis". *Earth Systems and Environment* 3.1, pp. 113–125.

Barati, Ali Akbar, Milad Zhoolideh, Hossein Azadi, Ju-Hyoung Lee, and Jürgen Scheffran (2023). "Interactions of land-use cover and climate change at global level: How to mitigate the environmental risks and warming effects". *Ecological Indicators* 146, p. 109829.

Barbier, Edward B. and Jacob P. Hochard (2018). "Land degradation and poverty". *Nature Sustainability* 1.11, pp. 623–631.

Barrett, Christopher B. and Leah E. M. Bevis (2015). "The self-reinforcing feedback between low soil fertility and chronic poverty". *Nature Geoscience* 8.12, pp. 907–912.

Bedeke, Sisay B., Wouter Vanhove, Muluken G. Wordofa, Kolandavel Natarajan, and Patrick Van Damme (2020). "Vulnerability to climate change among maize-dependent smallholders in three districts of Ethiopia". *Environment, Development and Sustainability* 22, pp. 693–718.

Belete, Fikire, Melesse Maryo, and Alemtshay Teka (2023). "Land use/land cover dynamics and perception of the local communities in Bita district, south western Ethiopia". *International Journal of River Basin Management* 21.2, pp. 211–222.

Bewket, Woldeamlak (2003). "Household level tree planting and its implications for environmental management in the northwestern highlands of Ethiopia: A case study in the Chemoga watershed, Blue Nile basin". *Land Degradation & Development* 14.4, pp. 377–388. DOI: 10.1002/ldr.570.

Bouteska, Ahmed, Taimur Sharif, Faruk Bhuiyan, and Mohammad Zoynul Abedin (2024). "Impacts of the changing climate on agricultural productivity and food security: Evidence from Ethiopia". *Journal of Cleaner Production* 449, p. 141793.

Braun, Joachim von, Bezawit Beyene Chichaibelu, Maximo Torero Cullen, David Laborde, and Carin Smaller (2021). "Ending hunger by 2030–policy actions and costs".

Canton, Helen (2021). "Food and agriculture organization of the United Nations—FAO". *The Europa directory of international organizations 2021*. Routledge, pp. 297–305.

Correia, Sergio (2015). “Singletons, cluster-robust standard errors and fixed effects: A bad mix”. *Technical Note, Duke University* 7.

— (2017). “Linear models with high-dimensional fixed effects: An efficient and feasible estimator”. *Unpublished manuscript, http://scorreia. com/research/hdfe. pdf (last accessed 25 October 2019)* 4.2.

Crook, David R., Brian E. Robinson, and Ping Li (2020). “The impact of snowstorms, droughts and locust outbreaks on livestock production in Inner Mongolia: anticipation and adaptation to environmental shocks”. *Ecological Economics* 177, p. 106761.

CSA (2017). “Agricultural sample survey report on area and production of major crops”. *Private peasant holdings, Meher season 2016/2017 (2009 EC)*.

Dagnaw, Yezihalem Tesfa (2007). “Critical factors hampering agricultural productivity in ethiopia: the case of northern ethiopian farmers”.

De Janvry, Alain, Elizabeth Ramirez Ritchie, and Elisabeth Sadoulet (2016). “Weather index insurance and shock coping: evidence from Mexico’s CADENA Program”. *World Bank Policy Research Working paper* 7715.

Degife, Arega, Hailu Worku, and Shumete Gizaw (2021). “Environmental implications of soil erosion and sediment yield in Lake Hawassa watershed, south-central Ethiopia”. *Environmental Systems Research* 10.1, p. 28. DOI: 10.1186/s40068-021-00232-6.

Degife, Azeb W., Florian Zabel, and Wolfram Mauser (2021). “Climate change impacts on potential maize yields in Gambella Region, Ethiopia”. *Regional Environmental Change* 21.2, p. 60.

Delgado, Jorge A., Victor H. Barrera Mosquera, Jeffrey R. Alwang, Alexis Villacis-Aveiga, Yamil E. Cartagena Ayala, Donna Neer, Carlos Monar, and Luis O. Escudero López (2021). “Potential use of cover crops for soil and water conservation, nutrient management, and climate change adaptation across the tropics”. *Advances in Agronomy* 165, pp. 175–247.

Dercon, Stefan (2004). “Growth and shocks: evidence from rural Ethiopia”. *Journal of Development Economics* 74.2, pp. 309–329.

Deressa, Temesgen Tadesse, Rashid M Hassan, Claudia Ringler, Tekie Alemu, and Mahmud Yesuf (2009). “Determinants of farmers’ choice of adaptation methods to climate change in the Nile Basin of Ethiopia”. *Global environmental change* 19.2, pp. 248–255.

Di Falco, Salvatore, Marcella Veronesi, and Mahmud Yesuf (2011). “Does adaptation to climate change provide food security? A micro-perspective from Ethiopia”. *American journal of agricultural economics* 93.3, pp. 829–846.

Endalamaw, Nega T., Mamaru A. Moges, Yadeta S. Kebede, Bekalu M. Alehegn, and Berhanu G. Sinshaw (2021). “Potential soil loss estimation for conservation planning, upper Blue Nile Basin, Ethiopia”. *Environmental Challenges* 5, p. 100224.

FAO (2011). *The state of the world’s land and water resources for food and agriculture: Managing systems at risk*. Earthscan.

FDRE, Federal Democratic Republic of Ethiopia (2011). *Ethiopia’s Climate-Resilient Green Economy: Green Economy Strategy*. Federal Democratic Republic of Ethiopia.

Fentie, Amare and Abebe D. Beyene (2019). “Climate-smart agricultural practices and welfare of rural smallholders in Ethiopia: Does planting method matter?” *Land use policy* 85, pp. 387–396.

Gashaw, Temesgen et al. (2022). “Evaluating InVEST model for simulating annual and seasonal water yield in data-scarce regions of the Abbay (Upper Blue Nile) Basin: implications for water resource planners and managers”. *Sustainable Water Resources Management* 8.5, p. 170. DOI: 10.1007/s40899-022-00757-3.

Gautier, Denis, David Denis, and Bruno Locatelli (2016). “Impacts of drought and responses of rural populations in West Africa: a systematic review”. *Wiley Interdisciplinary Reviews: Climate Change* 7.5, pp. 666–681.

Gazeaud, Jules and Victor Stephane (2023). “Productive Workfare? Evidence from Ethiopia’s Productive Safety Net Program”. *American Journal of Agricultural Economics* 105.1, pp. 265–290.

Gebeyehu, Adane K., Denyse Snelder, and Ben Sonneveld (2023). “Land use-land cover dynamics, and local perceptions of change drivers among Nyangatom agro-pastoralists, Southwest Ethiopia”. *Land Use Policy* 131, p. 106745.

Gebreegziabher, Zenebe and G. Cornelis van Kooten (2013). “Does community and household tree planting imply increased use of wood for fuel? Evidence from Ethiopia”. *Forest Policy and Economics* 34, pp. 30–40. DOI: 10.1016/j.forpol.2013.03.003.

Gebreselassie, Samuel, Oliver K. Kirui, and Alisher Mirzabaev (2016). “Economics of land degradation and improvement in Ethiopia”. *Economics of Land Degradation and Improvement–A Global Assessment for Sustainable Development*. Ed. by Ephraim Nkonya, Alisher Mirzabaev, and Joachim von Braun. Springer, pp. 401–430. DOI: 10.1007/978-3-319-19168-3_15.

Geremu, Tadele (2019). “Review on role of soil and water conservation measures on Soil Physico chemical properties and its implication to climate change mitigation and adaptation”. *Journal of Natural Sciences Research* 9.11, pp. 27–41.

Girard, Julia, Philippe Delacote, and Antoine Leblois (2021). “Agricultural households’ adaptation to weather shocks in Sub-Saharan Africa: implications for land-use change and deforestation”. *Environment and Development Economics* 26.5-6, pp. 538–560.

Gitima, Ginjo, Menberu Teshome, Meseret Kassie, and Monika Jakubus (2023). “Quantifying the impacts of spatiotemporal land use and land cover changes on soil loss across agroecologies and slope categories using GIS and RUSLE model in Zoa watershed, southwest Ethiopia”. *Ecological Processes* 12.1, p. 24.

Gizaw, Mesgana Seyoum and Thian Yew Gan (2017). “Impact of climate change and El Niño episodes on droughts in sub-Saharan Africa”. *Climate Dynamics* 49.1-2, pp. 665–682.

Gollin, Douglas (2010). “Chapter 73 agricultural productivity and economic growth. Handbook of agricultural economics”.

Haile, Bereket Tesfaye, Tadesse Terefe Zeleke, Kassahun Ture Beketie, Desalegn Yayeh Ayal, and Gudina Legese Feyisa (2021). “Analysis of El Niño Southern Oscillation and its impact on rainfall distribution and productivity of selected cereal crops in Kembata Alaba Tembaro zone”. *Climate Services* 23, p. 100254.

Haile, Kaleab K., Eleonora Nillesen, and Nyasha Tirivayi (2020). “Impact of formal climate risk transfer mechanisms on risk-aversion: Empirical evidence from rural Ethiopia”. *World Development* 130, p. 104930.

Hansen, James et al. (2019). “Climate risk management and rural poverty reduction”. *Agricultural Systems* 172, pp. 28–46.

Harvey, Celia A., Zo Lalaina Rakotobe, Nalini S. Rao, Radhika Dave, Hery Razafimahatratra, Rivo Hasinandrianina Rabarijohn, Haingo Rajaofara, and James L. MacKinnon (2014). “Extreme vulnerability of smallholder farmers to agricultural risks and climate change in Madagascar”. *Philosophical Transactions of the Royal Society B: Biological Sciences* 369.1639, p. 20130089.

He, Xi and Zhenshan Chen (2022). “Weather, cropland expansion, and deforestation in Ethiopia”. *Journal of Environmental Economics and Management* 111, p. 102586.

Hishe, Hadgu et al. (2021). “Analysis of land use land cover dynamics and driving factors in Desa’a forest in Northern Ethiopia”. *Land use policy* 101, p. 105039.
Holden, Stein T. and Keijiro Otsuka (2014). “The roles of land tenure reforms and land markets in the context of population growth and land use intensification in Africa”. *Food Policy* 48, pp. 88–97.
Hossain, Mohammad Mobarak, Sharif Ahmed, Mohammad Saiful Alam, and Akbar Hossain (2024). “Adverse effects of heat shock in rice (Oryza sativa L.) and approaches to mitigate it for sustainable rice production under the changing climate: A comprehensive review”. *Heliyon*.
Huete, Alfredo, Kamel Didan, Tomoaki Miura, E. Patricia Rodriguez, Xiang Gao, and Laerte G. Ferreira (2002). “Overview of the radiometric and biophysical performance of the MODIS vegetation indices”. *Remote sensing of environment* 83.1-2, pp. 195–213.
Hurni, Hans, Solomon Abate, Amare Bantider, Berhanu Debele, Eva Ludi, Brigitte Portner, Birru Yitaferu, and Gete Zeleke (2010). “Land degradation and sustainable land management in the highlands of Ethiopia”.
Hussain, Anwar, Junaid Alam Memon, and Sadia Hanif (2020). “Weather shocks, coping strategies and farmers’ income: A case of rural areas of district Multan, Punjab”. *Weather and Climate Extremes* 30, p. 100288.
Jayachandran, Seema, Joost De Laat, Eric F. Lambin, Charlotte Y. Stanton, Robin Audy, and Nancy E. Thomas (2017). “Cash for carbon: A randomized trial of payments for ecosystem services to reduce deforestation”. *Science* 357.6348, pp. 267–273.
Kakpo, Ange, Bradford F. Mills, and Stéphanie Brunelin (2022). “Weather shocks and food price seasonality in Sub-Saharan Africa: Evidence from Niger”. *Food Policy* 112, p. 102347.
Kassie, Geremew Worku (2018). “Agroforestry and farm income diversification: synergy or trade-off? The case of Ethiopia”. *Environmental Systems Research* 6, pp. 1–14.
Kassie, Menale, John Pender, Mahmud Yesuf, Gunnar Kohlin, Randall Bluffstone, and Eshetu Mulugeta (2008). “Estimating returns to soil conservation adoption in the northern Ethiopian highlands”. *Agricultural Economics*. Published online 2008. DOI: 10.1111/j.1574-0862.2008.00362.x.
Koo, Jawoo, James Thurlow, Hagar ElDidi, Claudia Ringler, Alessandro De Pinto, et al. (2019). *Building resilience to climate shocks in Ethiopia*. Tech. rep. International Food Policy Research Institute (IFPRI).
Kosmowski, Frédéric, Antoine Leblois, and Benjamin Sultan (2016). “Perceptions of recent rainfall changes in Niger: a comparison between climate-sensitive and non-climate sensitive households”. *Climatic change* 135, pp. 227–241.
Kumar, Shalander, Ashok K. Mishra, Soumitra Pramanik, Sravya Mamidanna, and Anthony Whitbread (2020). “Climate risk, vulnerability and resilience: Supporting livelihood of smallholders in semiarid India”. *Land Use Policy* 97, p. 104729.
Lambin, Eric F and Patrick Meyfroidt (2011). “Global land use change, economic globalization, and the looming land scarcity”. *Proceedings of the national academy of sciences* 108.9, pp. 3465–3472.
Lambin, Eric F., Helmut J. Geist, and Erika Lepers (2003). “Dynamics of land-use and land-cover change in tropical regions”. *Annual review of environment and resources* 28.1, pp. 205–241.
Lankford, Bruce A. and Catherine F. Grasham (2021). “Agri-vector water: boosting rainfed agriculture with urban water allocation to support urban–rural linkages”. *Water International* 46.3, pp. 432–450.

Lasco, Rodel D., Rafaela Jane P. Delfino, and Marya Laya O. Espaldon (2014). "Agroforestry systems: helping smallholders adapt to climate risks while mitigating climate change". *Wiley Interdisciplinary Reviews: Climate Change* 5.6, pp. 825–833.

Lemenih, Mulugeta and Fikadu Itanna (2005). "Soil carbon stocks and turnovers in various vegetation types and arable lands along an elevation gradient in southern Ethiopia". *Tropical Ecology* 46.2, pp. 179–188.

Leng, Guoyong and Jim Hall (2019). "Crop yield sensitivity of global major agricultural countries to droughts and the projected changes in the future". *Science of the Total Environment* 654, pp. 811–821.

Lesk, Corey, Pedram Rowhani, and Navin Ramankutty (2016). "Influence of extreme weather disasters on global crop production". *Nature* 529.7584, pp. 84–87.

Lewis, Kirsty (2017). "Understanding climate as a driver of food insecurity in Ethiopia". *Climatic Change* 144, pp. 317–328.

Makate, Clifton, Arild Angelsen, Stein Terje Holden, and Ola Tveitereid Westengen (2022). "Crops in crises: Shocks shape smallholders' diversification in rural Ethiopia". *World Development* 159, p. 106054.

Massrie, Kelemu Dessie (2024). "Contribution of Ethiopian Green Legacy on Fruit Crop Production: A Review". *Frontiers in Sustainable Food Systems* 8, p. 1488303. DOI: 10.3389/fsufs.2024.1488303.

Matiu, Michael, Donna P Ankerst, and Annette Menzel (2017). "Interactions between temperature and drought in global and regional crop yield variability during 1961-2014". *PloS one* 12.5, e0178339.

Mbow, Cheikh, Pete Smith, David Skole, Lalisa Duguma, and Mercedes Bustamante (2014). "Achieving mitigation and adaptation to climate change through sustainable agroforestry practices in Africa". *Current opinion in Environmental sustainability* 6, pp. 8–14.

Mehra, Nishant and Janaki Ballav Swain (2023). "Use of enhanced vegetation index (EVI) as a land cover classification tool and its suitability in urban development studies". *AIP Conference Proceedings*. Vol. 2852. 1. AIP Publishing.

Mekonnen, Esubalew Nebebe, Shimeles Damene, Ephrem Gebremariam, and Alemu Nebebe (2023). "Geospatially-Based Land Use/Land Cover Dynamics Detection, Central Ethiopian Rift Valley". *GeoJournal* 88.3, pp. 3399–3417.

Mekonnen, Z., H. Kassa, M. Lemenih, and B. M. Campbell (2007). "The role and management of Eucalyptus in Lode Hetosa District, Central Ethiopia". *Forest Trees and Livelihoods* 17.4, pp. 309–323. DOI: 10.1080/14728028.2007.9752606.

Mendoza-Ponce, Alma et al. (2021). "Impacts of land management and climate change in a developing and socioenvironmental challenging transboundary region". *Journal of Environmental Management* 300, p. 113748.

Meyer, Jessica (2023). "How do forests contribute to food security following a weather shock? Evidence from Malawi". *World Development* 169, p. 106307.

Mirzabaev, Alisher, Anton Strokov, and Pavel Krasilnikov (2023). "The impact of land degradation on agricultural profits and implications for poverty reduction in Central Asia". *Land Use Policy* 126, p. 106530.

MoFED (2011). *Growth and Transformation Plan I (2010/11–2014/15)*. Technical Report. Addis Ababa, Ethiopia: Government of Ethiopia. URL: https://www.ethiopia.gov.et/road-map-growth-and-transformation-plan-gtp-ii/.

Mohammed, Yimer, Fantaw Yimer, Menfese Tadesse, and Kindie Tesfaye (2018). "Meteorological drought assessment in north east highlands of Ethiopia". *International Journal of Climate Change Strategies and Management* 10.1, pp. 142–160.

Naylor, Rosamond L, David S Battisti, Daniel J Vimont, Walter P Falcon, and Marshall B Burke (2007). "Assessing risks of climate variability and climate change for Indonesian rice agriculture". *Proceedings of the National Academy of Sciences* 104.19, pp. 7752–7757.

Nguyen, Thanh-Tung, Trung Thanh Nguyen, Manh Hung Do, Duy Linh Nguyen, and Ulrike Grote (2022). "Shocks, agricultural productivity, and natural resource extraction in rural Southeast Asia". *World Development* 159, p. 106043.

Nizalova, Olena Y. and Irina Murtazashvili (2016). "Exogenous treatment and endogenous factors: Vanishing of omitted variable bias on the interaction term". *Journal of Econometric Methods* 5.1, pp. 71–77.

Oeba, Vincent Onguso and Salamatou Abdourahamane Illiassou (2020). "Role of tree-based systems in enhancing food security and nutrition". *Zero hunger*, pp. 712–723.

Otieno, Mark (2024). "Climate Change and Its Consequences on Future Agriculture in Sub-Saharan Africa". *Sustainable Agroecological Practices in Sub-Saharan Africa in the Face of Climate Change.* Springer, pp. 235–243.

Parry, Martin, Cynthia Rosenzweig, and Matthew Livermore (2005). "Climate change, global food supply and risk of hunger". *Philosophical Transactions of the Royal Society B: Biological Sciences* 360.1463, pp. 2125–2138.

Partey, Samuel T., Robert B. Zougmoré, Mathieu Ouédraogo, and Bruce M. Campbell (2018). "Developing climate-smart agriculture to face climate variability in West Africa: Challenges and lessons learnt". *Journal of cleaner Production* 187, pp. 285–295.

Patel, Sanoj Kumar, Pramit Verma, and Gopal Shankar Singh (2019). "Agricultural growth and land use land cover change in peri-urban India". *Environmental monitoring and assessment* 191, pp. 1–17.

Pellikka, Petri K. E., Barnaby J. F. Clark, Alemu Gonsamo Gosa, Nina Himberg, Pekka Hurskainen, Eduardo Maeda, James Mwang'ombe, Loice M. A. Omoro, and Mika Siljander (2013). "Agricultural expansion and its consequences in the Taita Hills, Kenya". *Developments in earth surface processes.* Vol. 16. Elsevier, pp. 165–179.

Quan, Julian and Nat Dyer (2008). "Climate change and land tenure: The implications of climate change for land tenure and land policy (Land Tenure Working Paper 2)".

Reid, Walter V et al. (2005). *Ecosystems and human well-being-Synthesis: A report of the Millennium Ecosystem Assessment.* Island Press.

Sayyadi, Fatemeh, Reza Moghaddasi, and Saeed Yazdani (2019). "How climate change affects land use pattern: an iranian provincial experience". *International Journal of Environmental Research* 13, pp. 67–75.

Shikur, Zewdie Habte (2020). "Agricultural policies, agricultural production and rural households' welfare in Ethiopia". *Journal of Economic Structures* 9.1, pp. 1–21.

Shukla, Priyadarshi R. et al. (2019). "IPCC, 2019: Climate Change and Land: an IPCC special report on climate change, desertification, land degradation, sustainable land management, food security, and greenhouse gas fluxes in terrestrial ecosystems".

Singh, Roop, Mulugeta Worku, Solomon Bogale, Adrian Cullis, Alebachew Adem, Ben Irwin, Sheri Lim, Lorenzo Bosi, and Courtenay Cabot Venton (2016). "Reality of resilience: Perspectives of the 2015-16 drought in Ethiopia". *BRACED Resilience Intel* 6, pp. 1–28.

Sinore, Tamrat and Fei Wang (2024). "Impact of climate change on agriculture and adaptation strategies in Ethiopia: A meta-analysis". *Heliyon* 10.4.

Sinore, Tamrat and Fei Wang (2025). “Climate change impact and adaptation options in Sub-Saharan Africa: a systematic review”. *Environment, Development and Sustainability*, pp. 1–29.

Sleeter, B. M., T. Loveland, G. Domke, N. Herold, J. Wickham, and N. Wood (2018). “Land Cover and Land-Use Change. In Impacts, Risks, and Adaptation in the United States: Fourth National Climate Assessment, Volume II”. *Washington, DC: US Global Change Research Program.*

Szerman, Dmitri, Juliano J. Assunção, Molly Lipscomb, and Ahmed Mushfiq Mobarak (2022). *Agricultural productivity and deforestation: Evidence from Brazil.* Tech. rep. Center Discussion Paper.

Taddese, Girma (2001). “Land degradation: a challenge to Ethiopia”. *Environmental management* 27, pp. 815–824.

Tadesse, Lemlem, K. V. Suryabhagavan, G. Sridhar, and Gizachew Legesse (2017). “Land use and land cover changes and Soil erosion in Yezat Watershed, North Western Ethiopia”. *International soil and water conservation research* 5.2, pp. 85–94.

Tambet, Heleene and Yaniv Stopnitzky (2021). “Climate adaptation and conservation agriculture among Peruvian farmers”. *American Journal of Agricultural Economics* 103.3, pp. 900–922.

Tarfasa, Solomon, Bedru B. Balana, Tewodros Tefera, Teshale Woldeamanuel, Awdenegest Moges, Mengistu Dinato, and Helaina Black (2018). “Modeling smallholder farmers’ preferences for soil management measures: a case study from South Ethiopia”. *Ecological Economics* 145, pp. 410–419.

Tebkew, Mekuanent, Zebene Asfaw, and Adefires Worku (2024). “The role of agroforestry systems for addressing climate change livelihood vulnerability of farmers of Northwestern Ethiopia”. *Heliyon* 10.17.

Teketay, Demel (2000). *Facts and experiences on eucalyptus in Ethiopia and elsewhere: Ground for making wise and informed decision.* Proceedings of a Workshop, Addis Ababa, Ethiopia.

Teshome, Debela Sorsa, Mengistu Benti Moisa, Daba Oljira Gemeda, and Shuang You (2022). “Effect of Land Use-Land Cover Change on Soil Erosion and Sediment Yield in Muger Sub-Basin, Upper Blue Nile Basin, Ethiopia”. *Land* 11.6, p. 856. DOI: 10.3390/land11060856. URL: https://www.mdpi.com/2073-445X/11/6/856.

Tessema, Israel and Belay Simane (2019). “Vulnerability analysis of smallholder farmers to climate variability and change: an agro-ecological system-based approach in the Fincha’a sub-basin of the upper Blue Nile Basin of Ethiopia”. *Ecological Processes* 8, pp. 1–18.

Thapa, Pawan (2021). “The relationship between land use and climate change: A case study of Nepal”. *The Nature, Causes, Effects and Mitigation of Climate Change on the Environment.*

Tigabu, Anbaw and Agenagnew A. Gessesse (2025). “Mapping forest cover change and estimating carbon stock using satellite-derived vegetation indices in Alemsaga forest, Ethiopia”. *PloS one* 20.2, e0310780.

Tofu, Daniel Assefa, Teshale Woldeamanuel, and Firafis Haile (2022). “Smallholder farmers’ vulnerability and adaptation to climate change induced shocks: The case of Northern Ethiopia highlands”. *Journal of Agriculture and Food Research* 8, p. 100312.

Tofu, Daniel Assefa and Kebede Wolka (2023). “Transforming food insecure farmers from climate variability and land degradation susceptibility to resilient livelihoods”. *Research in Globalization* 7, p. 100168.

Tolossa, AA, RUFORUM Books, R OER, R SCARDA, and R Tenders (2015). “Seasonal climate prediction for rain-fed crop production planning in the upper Awash basin”. *Central highland of Ethiopia*.

Vogel, Elisabeth, Markus G. Donat, Lisa V. Alexander, Malte Meinshausen, Deepak K. Ray, David Karoly, Nicolai Meinshausen, and Katja Frieler (2019). “The effects of climate extremes on global agricultural yields”. *Environmental Research Letters* 14.5, p. 054010.

Wassie, Simachew Bantigegn (2020). “Natural resource degradation tendencies in Ethiopia: a review”. *Environmental systems research* 9.1, pp. 1–29.

Woldesenbet, Tekalegn Ayele (2022). “Impact of land use and land cover dynamics on ecologically-relevant flows and blue-green water resources”. *Ecohydrology & Hydrobiology* 22.3, pp. 420–434.

Wolka, Kebede, Birhanu Biazin, Fikadu Getachew, Firehiywot Girma, and Gizaw Desta (2023). “Towards sustainable watershed-based landscape restoration in degraded drylands: Perceived benefits and innovative pathways learnt from project-based interventions in Ethiopia”. *Journal of Environmental Management* 335, p. 117499.

Wooldridge, Jeffrey M. (2010). *Econometric analysis of cross section and panel data*. MIT press.

Wubie, Mesfin Anteneh, Mohammed Assen, and Melanie D. Nicolau (2016). “Patterns, causes and consequences of land use/cover dynamics in the Gumara watershed of lake Tana basin, Northwestern Ethiopia”. *Environmental Systems Research* 5.1, pp. 1–12.

Yang, Shengjie, Shuai Song, Fadong Li, Mingzhao Yu, Guangming Yu, Qiuying Zhang, Haotian Cui, Rui Wang, and Yanqi Wu (2022). “Vegetation coverage changes driven by a combination of climate change and human activities in Ethiopia, 2003–2018”. *Ecological Informatics* 71, p. 101776.

Yang, Siqi, Wenwu Zhao, and Paulo Pereira (2022). “Land-use modelling by CLUMondo under contrasting scenarios: a case study in the Yanhe watershed (China)”. *Mapping and Forecasting Land Use*. Elsevier, pp. 173–192.

Yigezu Wendimu, Gebissa (2021). “The challenges and prospects of Ethiopian agriculture”. *Cogent Food & Agriculture* 7.1, p. 1923619.

Zaroug, Modathir A. H., Elfatih A. B. Eltahir, and Filippo Giorgi (2014). “Droughts and floods over the upper catchment of the Blue Nile and their connections to the timing of El Niño and La Niña events”. *Hydrology and Earth System Sciences* 18.3, pp. 1239–1249.

Zewdu, Shegena, K. V. Suryabhagavan, and M. Balakrishnan (2016). “Land-use/land-cover dynamics in Sego Irrigation Farm, southern Ethiopia: A comparison of temporal soil salinization using geospatial tools”. *Journal of the Saudi Society of Agricultural Sciences* 15.1, pp. 91–97.

Chapter 5

Concluding Remarks

This dissertation investigates the dynamic interrelationships among climate adaptation strategies, agricultural productivity, conservation practices, and household labor allocation in rural Ethiopia, focusing on three thematically interlinked studies. The first paper highlights the effectiveness of tailored, plot-specific CA practice information in improving farmers' adoption of sustainable practices to enhance agricultural productivity. By aligning research-based CA practices to local agroecological conditions and farm-specific characteristics, this study demonstrates that context-specific information interventions significantly boost the adoption of conservation practices while concurrently increasing agricultural productivity. This finding underscores the importance of personalized and targeted extension services that account for variations in soil type, topography, and other environmental factors to promote area-specific conservation practices.

The second paper examines the impact of public works programs on strengthening SWC efforts while shaping household labor allocation between on-farm and off-farm activities, ultimately enhancing resilience to drought in rural Ethiopia. The findings underscore the dual role of social protection programs in fostering environmental sustainability through conservation practices while shaping household labor allocation. In other words, these programs can effectively incentivize households to reallocate labor toward their farm plots. Despite concerns in the literature regarding the potential for public works to crowd out participants' private soil and water conservation efforts, the findings suggest that such programs may reinforce these practices. By supporting on-farm conservation, diversifying income sources, and reducing vulnerability to droughts and climate shocks, public works contribute positively to household resilience and sustainable agricultural development. Therefore, the study underscores the need to integrate conservation efforts with local livelihood strategies to enhance climate resilience in drought-prone regions.

The third paper explores the impact of land cover dynamics, assessing how vegetation shifts, which imply how spatial and temporal greenness changes, deforestation, and afforestation enhance agricultural productivity by mitigating climate variability's adverse effects. The findings show that land cover changes mitigate climate variability's adverse effects, increasing agricultural productivity. Thus, the findings emphasize that land cover changes are key indicators of environmental health and drivers of agricultural sustainability and resilience. The paper advocates for policies supporting sustainable land management and ecosystem restoration to preserve productivity and long-term climate resilience, urging the integration of land restoration into climate adaptation frameworks to enhance food security in rural areas.

To this end, these three papers demonstrate how customized conservation information, public works programs, and land cover changes can improve agricultural productivity, conservation practices, and climate resilience in rural Ethiopia. They highlight the importance of context-specific, integrated approaches that tackle environmental and socio-economic factors to promote long-term climate resilience.

The findings of this dissertation offer key policy implications for enhancing climate resilience and agricultural productivity in rural Ethiopia. First, the positive impact of tailored conservation information suggests that agricultural extension services should incorporate context-specific, plot-level recommendations to optimize the adoption of sustainable practices. Policymakers should focus on strengthening extension services to deliver targeted information that reflects diverse agroecological conditions and farm characteristics.

Second, public works programs, which promote conservation and influence household labor allocation, should be further integrated into broader rural development strategies. Policymakers should enhance these programs' design and implementation to support environmental sustainability while boosting household labor participation in agricultural and non-agricultural sectors, thereby strengthening climate resilience.

Lastly, land cover dynamics can sustain agricultural productivity amid climate variability and extreme weather. Land use policies should prioritize sustainable practices like afforestation, soil conservation, and landscape rehabilitation to enhance ecosystem resilience and agricultural sustainability. Integrating land cover monitoring into climate resilience strategies is crucial for tracking environmental changes, informing adaptive decisions, and guiding interventions. Well-designed and proactive land management can enhance the resilience of rural communities to climate shocks, thereby supporting sustained agricultural productivity and long-term food security.

In summary, this dissertation emphasizes the critical need for tailored, integrated policies that address conservation, labor dynamics, and land cover management to strengthen climate resilience and agricultural productivity in rural Ethiopia. Future research and policy efforts should prioritize adapting and extending these strategies to other regions facing comparable challenges.

Dissertation Appendices

Appendix A

Enhancing Agricultural Productivity through Tailored Information on Conservation Practices: Evidence from Ethiopia

A.1 Additional Tables

Table A.1 Tailored information and CA adoption for all cereals

	T=1 (2015)		T=2 (2015 & 2016)		T=3 (2015-2017)		T=5 (2015-2021)	
Dept var: CA uptake (1=yes)	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Treatment	0.030	0.066	0.423***	0.424***	0.569***	0.566***	0.622***	0.616***
	(0.052)	(0.053)	(0.028)	(0.028)	(0.020)	(0.020)	(0.014)	(0.014)
HH head gender		0.105*		0.029		0.034		0.032
		(0.055)		(0.039)		(0.029)		(0.023)
Household size		-0.023**		-0.011		-0.010*		-0.016***
		(0.011)		(0.007)		(0.006)		(0.004)
HH highest education		0.007		0.007		0.004		0.003
		(0.006)		(0.004)		(0.003)		(0.002)
HH average age		-0.002		-0.001		-0.001		-0.002***
		(0.002)		(0.002)		(0.001)		(0.001)
Off-farm income		-0.081*		-0.037		-0.024		0.026*
		(0.044)		(0.029)		(0.023)		(0.015)
Credit access		0.042		0.054**		0.041**		0.048***
		(0.036)		(0.025)		(0.019)		(0.014)
Tenure security		-0.093**		-0.062*		-0.060**		-0.078***
		(0.045)		(0.032)		(0.025)		(0.022)
Migration		0.052		-0.000		0.000		-0.013
		(0.038)		(0.025)		(0.020)		(0.014)
Average rainfall (all seasons)		-0.004***		-0.000		0.000		0.001**
		(0.001)		(0.000)		(0.000)		(0.000)
Year (reference year=2015)								
2016			0.216***	0.224***	0.169***	0.178***	0.153***	0.166***
			(0.026)	(0.026)	(0.023)	(0.023)	(0.021)	(0.021)
2017					0.096***	0.110***	0.073***	0.092***
					(0.024)	(0.025)	(0.022)	(0.022)
2019							0.165***	0.105***
							(0.021)	(0.027)
2021							0.072***	0.074***
							(0.022)	(0.023)
Constant	0.315***	0.792***	0.258***	0.360***	0.236***	0.274***	0.229***	0.315***
	(0.020)	(0.131)	(0.017)	(0.091)	(0.016)	(0.069)	(0.015)	(0.052)
Additional controls	—	✓	—	✓	—	✓	—	✓
Number of observations	643	643	1297	1292	1916	1909	3188	3181
F-value	0.319	6.275	223.493	41.568	387.522	97.663	488.335	180.045
Prob > F	0.573	0.000	0.000	0.000	0.000	0.000	0.000	0.000
R-squared	0.000	0.090	0.257	0.263	0.378	0.382	0.434	0.443

In all cases, pooled OLS (POLS) is used for regression. Standard errors in parentheses. * 10%, ** 5%, & *** 1%.

A.2 Additional Figures

Fig. A.1 Tailored CA Practices Written Information

Tailored CA Practices Information for Farmer Demonstration

Introduction

In Ethiopia, the following are some of the main attributes that can lead to a reduction in yield and productivity:

- Tilling a field frequently for many years to produce crops
- Less minimum tillage practice
- Less crop rotation practice
- Less moisture holding capacity of the soil
- Flood soil erosion
- Overgrazing
- Reduction in soil fertility over time

Currently, conservation agriculture is one of the widely employed modern agricultural practices in different countries that help to reduce the adverse effects of the agricultural sector on the environment, conserve natural resources, and improve productivity. It is a globally accepted agricultural practice that improves crop production and productivity by reducing the effects of climate change, which many developed and developing countries broadly implement to ensure sustainability by building an agricultural sector resilient to climate variability.

What is conservation agriculture?

Conservation agriculture is an agricultural production system that involves no-tilling of the arable land or use of minimum tillage practice in crop production. This type of agricultural practice mainly includes the implementation of three basic activities. These are:

➢ avoiding frequent tilling of farm plots,

➢ using minimum tillage practice and any other similar practices to improve the soil fertility of a field, and

➢ employing crop rotation practice.

The use of improved seed varieties in combination with the above-mentioned conservation agriculture practices improves the benefits of conservation agriculture practices that enhance ensuring farmers' food security.

➢ It is known that some farmers do not use the conservation agriculture package at all, and others employ only a few practices among the conservation agriculture package.

➢ However, different studies confirm that variation in net farm return depends on coordinated efforts of conservation agriculture practice, soil fertility, and agricultural landscapes.

➢ Accordingly, the estimated percentage increase in net return from agricultural production due to the use of the conservation agriculture package (i.e., minimum tillage practice and avoided frequent tilling of farm plots, and crop rotation practice complemented with the use of improved seed) in comparison with the use of only crop rotation and improved seed variety (without the use of minimum tillage practice and avoided frequent tilling of farm plots) subject to farm plots landscapes and soil fertility presented using posters.

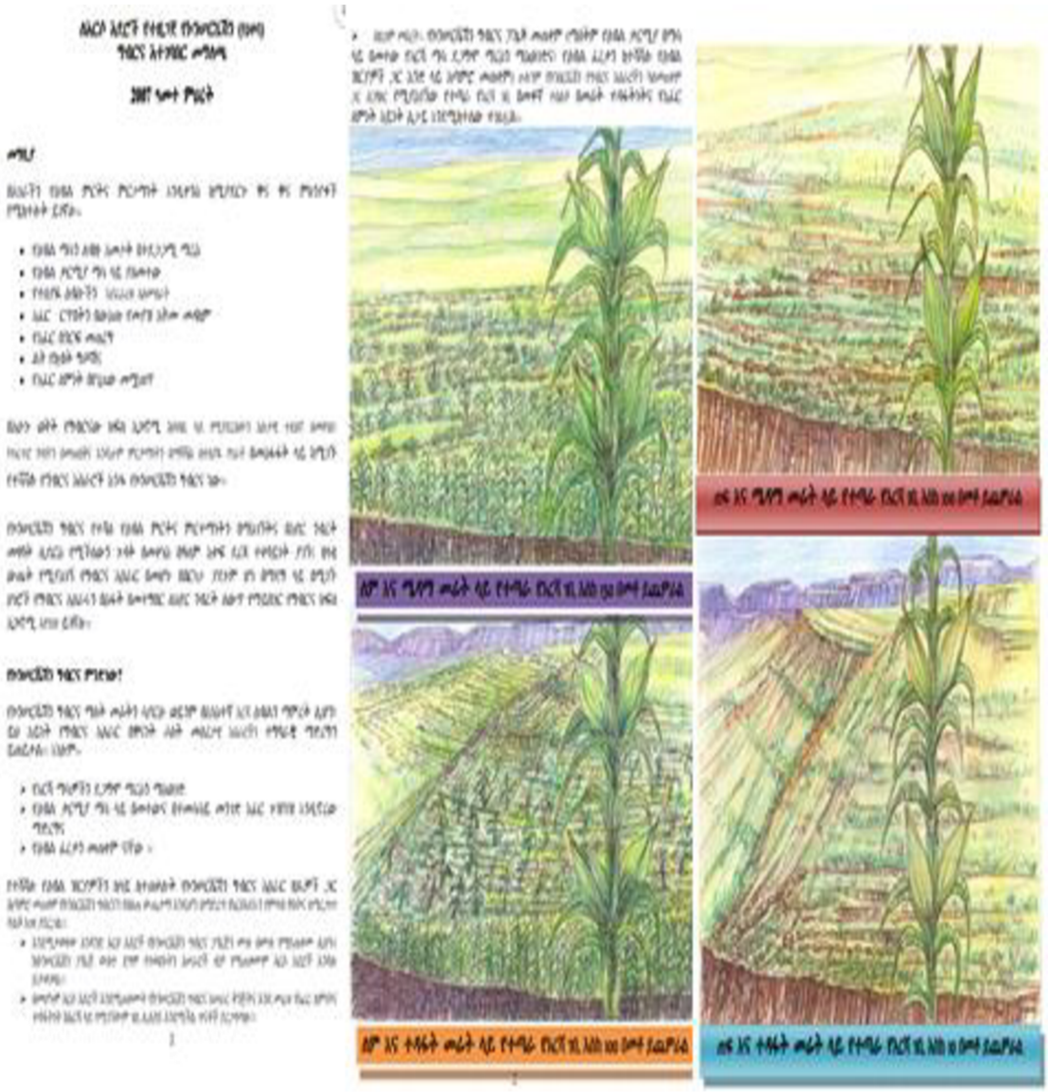
Recommendation

In addition, avoiding overgrazing, timely weed management, etc., measures improve the effectiveness of the conservation agriculture practice. Moreover, even though the use of conservation agriculture practices reduces labor and animal use on farm plots, it could increase weeds during the early few years of production. Therefore, timely weed management enhances a greater extent of increment in productivity.

The main benefits of conservation agriculture

- Reduces land degradation,
- Improves soil moisture,
- Increase soil fertility and amount of decomposition in the soil,
- Increase productivity, and
- Reduce environmental pollution

Fig. A.2 Tailored CA Practices Visual Information

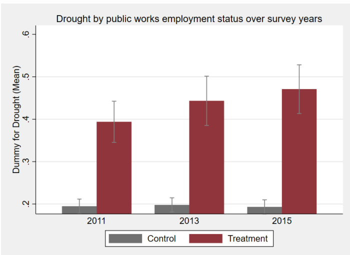


Appendix B

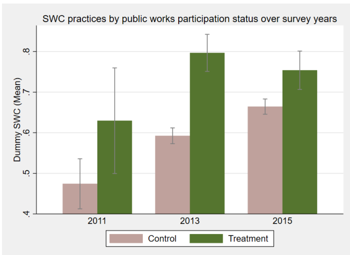
Adapting to drought: how do public works affect conservation and labor engagement in rural Ethiopia?

B.1 Additional Figures

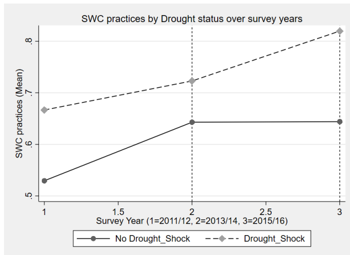
Fig. B.1 Drought and SWC practices by public works employment over survey years



(a) Drought (dummy) by participation



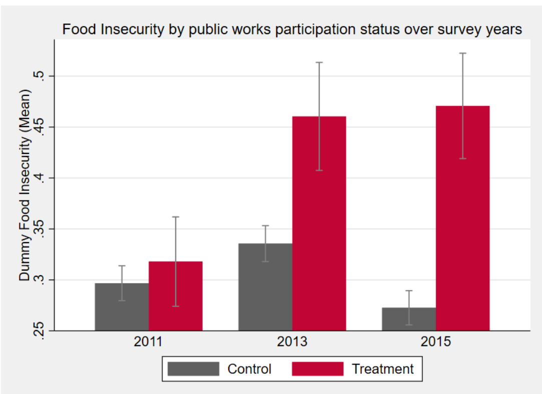
(b) SWC practices (1=yes) by public works employment



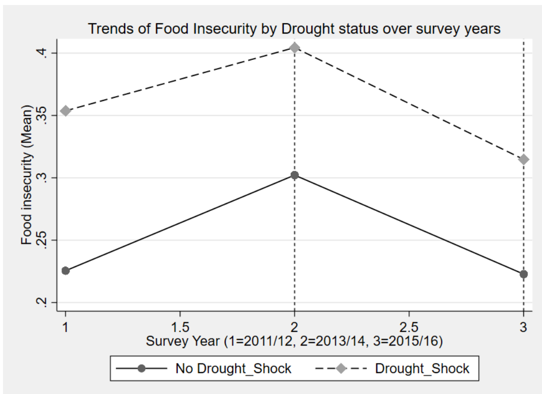
(c) SWC practices (1=yes) by drought status

Appendix B Figure B.1 shows Drought status by participation (panel a), SWC practices by participation (panel b), and SWC practices by drought status (panel c).

Fig. B.2 Food insecurity by public works employment and drought status over survey years



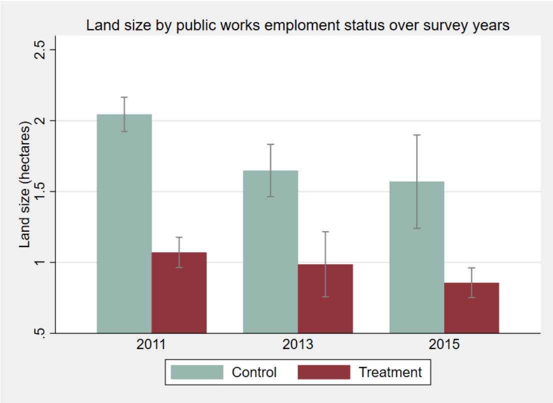
(a) Food insecurity by participation status



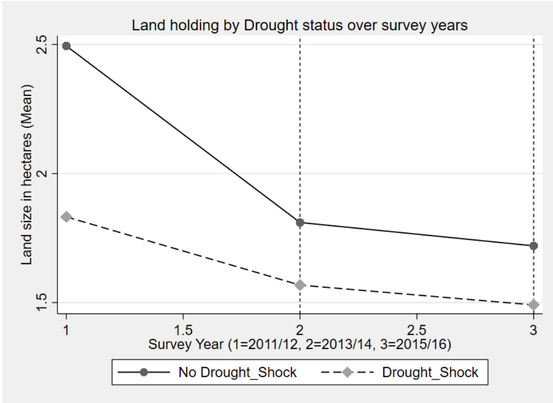
(b) Food insecurity (1=food insecure) by drought status

Appendix B Figure B.2 Food insecurity by participation (panel a), Food insecurity by drought (panel b).

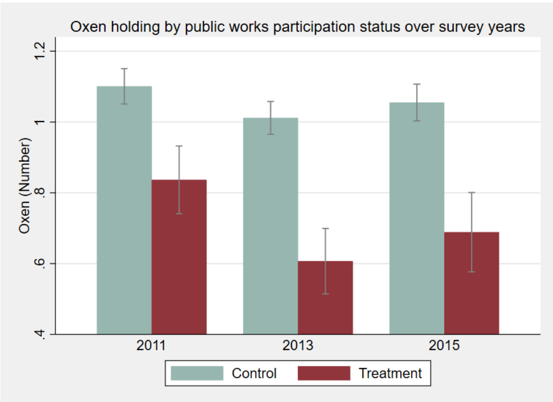
Fig. B.3 Resource Endowment and Asset Holdings by public works employment and drought status over the years



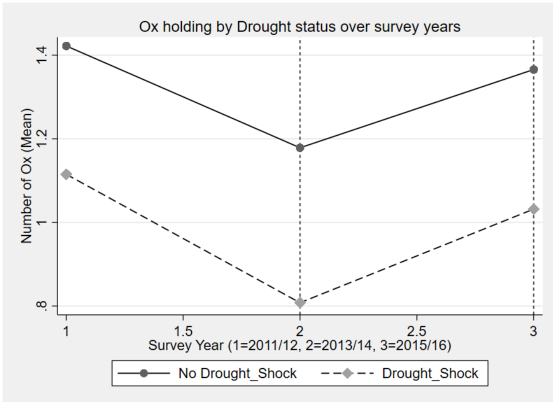
(a) Land size (hectares) by participation



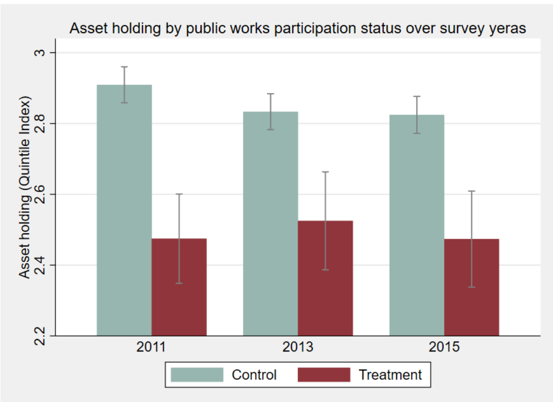
(b) Land size (hectares) by drought status



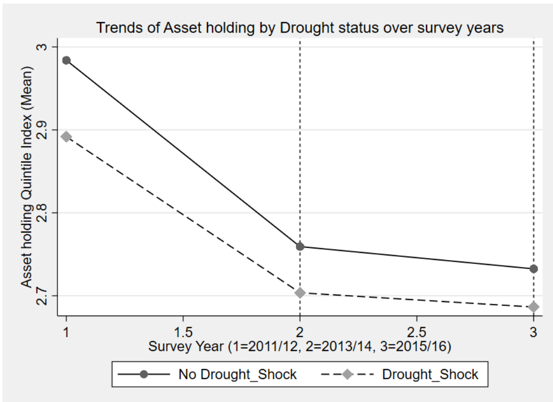
(c) Oxen holding (number) by participation



(d) Oxen holding (number) by drought status



(e) Asset holding (Quintile Indices) by participation



(f) Asset holding (Quintile Indices) by drought status

Appendix B Figure B.3 shows resource endowment in terms of land size (panels a & b), oxen (panels c & d), and asset holding (panels e & f) by participation and drought status over the years.

B.2 Additional Tables

Table B.1 Correlates of public works employment and SWC practices using self-reported drought measure

	Public works employment(1=treated)			SWC practices (1=yes)		
	(1)	(2)	(3)	(4)	(5)	(6)
Drought (dummy self-reported)	0.096***	0.081***	0.072***	0.072***	0.067***	0.084***
	(0.009)	(0.009)	(0.010)	(0.015)	(0.015)	(0.016)
ln(Distance to central admin)	-0.015***	-0.007	-0.008*	-0.021**	-0.016*	-0.012
	(0.004)	(0.004)	(0.004)	(0.009)	(0.009)	(0.009)
Household size			0.005***			0.011***
			(0.002)			(0.003)
Land size			-0.001*			0.000
			(0.001)			(0.001)
Irrigation access			0.070***			0.138***
			(0.012)			(0.018)
Tenure security			-0.017**			0.044***
			(0.007)			(0.014)
Credit access			0.025***			0.054***
			(0.008)			(0.016)
Asset holding			-0.005***			-0.013**
			(0.001)			(0.005)
Food security			-0.041***			0.031**
			(0.008)			(0.014)
Elevation			-0.000**			0.000
			(0.000)			(0.000)
Constant	0.027*	-0.013	0.031	0.609***	0.589***	0.411***
	(0.014)	(0.015)	(0.026)	(0.042)	(0.044)	(0.059)
Time Fixed Effects	✓	✓	✓	✓	✓	✓
District Fixed Effects (21)	—	✓	✓	—	✓	✓
Additional controls	—	—	✓	—	—	✓
R^2	0.075	0.093	0.109	0.014	0.037	0.055
$F-stat$	197.470	36.318	26.747	19.256	9.607	11.520
$Prob > F$	0.000	0.000	0.000	0.000	0.000	0.000
Observations	7414	7414	7164	5077	5077	5076

The coefficient estimates represent the probabilities of (a) public works employment in columns (1)–(3) and (b) SWC practices in columns (4)–(6). The standard errors in parentheses are robust. Asterisks indicate significance at * 10%, ** 5%, and *** 1% levels.

Table B.2 Effects of public works employment on different measures of SWC practices: Pooled Ordinary Least Squares (POLS) Estimations

	Aggregate SWC practices			Physical SWC measures			Biological SWC measures		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Public works: ATE	0.119***	0.108***	0.114***	0.181***	0.157***	0.163***	-0.020	-0.012	-0.010
	(0.023)	(0.023)	(0.023)	(0.027)	(0.027)	(0.026)	(0.028)	(0.028)	(0.028)
ln(Distance to central admin)	-0.030***	-0.023***	-0.013	-0.032***	-0.026***	-0.014	0.020**	0.025***	0.030***
	(0.009)	(0.009)	(0.009)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
Household size		0.010***	0.011***		0.007**	0.009***		0.014***	0.015***
		(0.003)	(0.003)		(0.003)	(0.003)		(0.003)	(0.003)
Land size		0.000	0.001		-0.002**	-0.002**		0.002***	0.003***
		(0.001)	(0.001)		(0.001)	(0.001)		(0.001)	(0.001)
Irrigation access		0.131***	0.148***		0.259***	0.278***		-0.085***	-0.077***
		(0.018)	(0.018)		(0.020)	(0.020)		(0.018)	(0.019)
Tenure security		0.080***	0.059***		0.073***	0.049***		0.069***	0.058***
		(0.013)	(0.013)		(0.013)	(0.014)		(0.013)	(0.013)
Credit access		0.077***	0.065***		0.047***	0.034**		0.090***	0.084***
		(0.015)	(0.015)		(0.016)	(0.016)		(0.016)	(0.016)
Elevation			0.000***			0.000***			0.000***
			(0.000)			(0.000)			(0.000)
Constant	0.610***	0.482***	0.278***	0.498***	0.381***	0.155***	0.147***	0.029	-0.074
	(0.041)	(0.043)	(0.052)	(0.040)	(0.043)	(0.053)	(0.036)	(0.038)	(0.049)
Time Fixed Effects	✓	✓	✓	✓	✓	✓	✓	✓	✓
District Fixed Effects (21)	✓	✓	✓	✓	✓	✓	✓	✓	✓
Dependent variable control mean		0.621			0.414			0.347	
R^2	0.036	0.058	0.065	0.040	0.075	0.083	0.021	0.042	0.044
$F-stat$	11.857	15.643	17.285	148.469	94.068	69.758	47.055	17.250	17.922
$Prob > F$	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Observations	5801	5800	5800	5801	5800	5800	5801	5800	5800

In all cases, estimations demonstrate the impact of public works employment on a binary measure aggregate SWC practices indicator (consisting of terracing, check dams, afforestation, and contour farming) in columns (1)-(3), structural/physical SWC measures (terracing and check dams) in columns (4)-(6), and biological measures (afforestation and contour farming) in column (7)-(9). The LPM estimates correspond to ATE measures under different specifications. Columns (1), (4), and (7) present baseline estimates without additional controls, while columns (2), (5), and (8) include additional controls such as household size (in adult equivalent), land size (in hectares), irrigation access (dummy), tenure security (dummy), and credit access (dummy). Columns (3), (6), and (9) are full specifications by incorporating the farm plot's elevation (in meters) in addition to earlier controls in columns (2), (5), and (8) for respective outcome variables. All estimations report robust standard errors in parentheses, and asterisks show significance at the * 10%, ** 5%, and *** 1% levels.

Table B.3 Public works employment and SWC practices: Lewbel instrumental variable approach

Lewbel instrumental variable approach:[a]	GenInst	GenExtInst	GenInst	GenExtInst	GenInst	GenExtInst
Dept variable: Aggregate SWC practice (1=yes)	(1)	(2)	(3)	(4)	(5)	(6)
Public works: ATE	0.125***	0.135***	0.147***	0.153***	0.173***	0.175***
	(0.034)	(0.034)	(0.032)	(0.031)	(0.030)	(0.030)
Household size			0.009***	0.009***	0.011***	0.011***
			(0.003)	(0.003)	(0.003)	(0.003)
Land size			0.000	0.000	0.000	0.000
			(0.001)	(0.001)	(0.000)	(0.000)
Irrigation access			0.149***	0.152***	0.167***	0.168***
			(0.018)	(0.018)	(0.018)	(0.018)
Tenure security			0.074***	0.073***	0.049***	0.049***
			(0.013)	(0.013)	(0.013)	(0.013)
Credit access			0.080***	0.080***	0.069***	0.069***
			(0.015)	(0.015)	(0.015)	(0.015)
Elevation					0.000***	0.000***
					(0.000)	(0.000)
Year dummy (1=2015/16)	0.060***	0.059***	0.057***	0.057***	0.057***	0.057***
	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)
Constant	0.602***	0.602***	0.491***	0.491***	0.328***	0.328***
	(0.009)	(0.009)	(0.018)	(0.018)	(0.030)	(0.030)
Instrument	✓	✓	✓	✓	✓	✓
Dependent variable control mean	0.621					
Under identification test	199.260***	221.607***	263.245***	271.53***	251.726***	264.208***
Hansen J statistic (over-identification test of all instruments): χ^2(p−value)		8.364 (0.004)	2.476 (0.7801)	7.300 (0.294)	8.236 (0.221)	9.152 (0.242)
Hansen J statistic (eqn. excluding suspect orthog. conditions): χ^2(p−value)				2.472 (0.7808)		8.216 (0.2227)
Observations	5801	5801	5800	5800	5800	5800

In all cases, estimations demonstrate the impact of public works employment, instrumented by distance to central administration, on a binary measure aggregate SWC practices indicator, including terracing, check dams, afforestation, and contour farming. The Lewbel instrumental variable approach assumes the two-step generalized method of moments (IV-GMM) and provides efficient estimates for arbitrary heteroskedasticity (statistics robust to heteroskedasticity). It simultaneously provides the Generated Instruments only (GenInst) and Generated Instruments and External Instruments (GenExtInst) in a single step. The coefficient estimates on public works correspond to ATE under different specifications. Columns (1) and (2) present baseline estimates without additional controls, while columns (3) and (4) include additional controls such as household size (in adult equivalent), land size (in hectares), irrigation access (dummy), tenure security (dummy), and credit access (dummy). Columns (5) and (6) are full specifications by incorporating the farm plot's elevation (in meters) in addition to earlier controls in columns (3) and (4). All estimations report robust standard errors in parentheses, and asterisks show significance at the * 10%, ** 5%, and *** 1% levels.

[a] The Lewbel method provides three alternative estimation outputs, namely the Standard IV Results (StdIV), IV with Generated Instruments only (GenInst), and IV with Generated Instruments and External Instruments (GenExtInst) simultaneously in a single step. Appendix B Table B.3 reports the latter two estimation results.

Appendix C

Weather shocks and agricultural productivity in rural Ethiopia: Role of land cover dynamics

C.1 Additional Tables

Table C.1 Description of variables

Variable	Description
Ln[a](Productivity)	Agricultural productivity measured as the ratio of cereal crop income to land size (ETB/ha)[b]
Bottom 25%	A dummy for productivity threshold greater than the bottom 25% (1 if productivity $\geq$ Bottom 25%; 0=otherwise)
Middle 50%	A dummy for productivity threshold greater than 50% (1 if productivity $\geq$ 50%; 0=otherwise)
Top 25%	Dummy for productivity threshold greater than the top 25% (1 if productivity $\geq$ Top 25%; 0=otherwise)
Food security	Refers to a dummy measure of whether a household was food secure during the last 12 months (1 if food secure; 0=food insecure
Non-farm income	Non-farm income Quintile [nq(5)] indices[c] of the first principal component (PC1)[d] from 13 different sources that a household member received during the last 12 months
Age	Household head's age in years
Household size	Number of household members in adult equivalent[e]
Land area	Total land area holdings in hectares for cereal crops growing
Improved seed	The type of seed used (1=improved; 0=local)
Chemical fertilizer use	Household chemical fertilizers use on any crop field (1=yes; 0=no)
Tenure security	A status if a household received a certificate for any of the parcels (1 if certified; 0=not certified)
Credit access	Did anyone in your household have access to credit within the last 12 months? (1=yes; 0=no)
Irrigation access	An answer to a question if a household had access to small-scale irrigation practices (1=yes; 0=no)
Distance to market	Distance in kilometers from the nearest market
Agroecological zone (1=Tropical Cool; 0=Tropical Warm)	Eight traditional agro-ecological zone classifications are categorized into two as: Tropical cool climates includes Tropic-cool/arid, Tropic-cool/semiarid, Tropic-cool/subhumid, Tropic-cool/humid; and Tropical warm climates includes Tropic-warm/arid, Tropic-warm/semiarid, Tropic-warm/subhumid, Tropic-warm/humid
$LandCoverChange_{v,t}$	The long-term average total change in greenness (integral of daily EVI values), averaged by zone, within the main (Meher) in the current growing season (reference periods: 2001-2011, 2001-2013 & 2001-2015)
$DroughtShock_{v,t-1}$	The satellite-based drought measure is derived from EVI anomalies and identifies drought conditions as values below -0.025, indicating limited rainfall during the preceding season (1=yes; 0=no)
$AverageTemperature_{v,t-1}$	It shows the Mean overall annual temperature calculated from monthly climatology for the main (Meher) previous growing season ($^\circ C$)
$< 17^\circ C$	It refers to a relatively cool and Low Mean annual temperature threshold calculated from monthly climatology for the previous main growing season (Dummy: 1 if mean temperature $< 17^\circ$C; 0=otherwise)
$17^\circ C \leq$Temp$< 23^\circ C$	This indicates a Moderate average annual temperature threshold calculated from monthly climatology for the previous main growing season (dummy: 1 if $\geq 17^\circ C$ & $< 23^\circ C$; 0=otherwise)
$\geq 23^\circ C$	This is a relatively hot average annual temperature threshold calculated from monthly climatology for the previous main growing season (Dummy: 1 if $\geq 23^\circ C$; 0=otherwise)
$DroughtShock_{v,t-1}$	The self-reported drought measure is based on reported crop damage attributed to insufficient rainfall during the preceding season (1=yes; 0=otherwise)

Source: Ethiopian LSMS-ISA survey of three waves conducted in 2011/12, 2013/14, and 2015/16.

[a] "Ln" denotes natural logarithm.

[b] ETB denotes to Ethiopian Birr. On average, 1 USD equaled 16.9747 ETB in 2011, 18.7144 ETB in 2013, and 20.6862 ETB in 2015.

[c] nq(5) describes quintile indices of non-farm income ranging from 1 to 5; where "1" refers to the lower 20% (an index category in 1-20%), "2" shows an index category in 21-40%, "3" signifies an index category in 41-60%, "4" is an index category in 61-80%, and "5" indicates the upper 20% (an index category in 81-100%).

[d] PC1 is the line that best accounts for the shape of the point swarm in the principal component analysis. It shows the maximum variance direction in the data. This component logically refers to the line in K-dimensional space that best approximates the data in the least squares. This line goes through an average point and a projection of each observation onto this line to get a coordinate value along the PC line. This value refers to a score (Eriksson et al., 2013).

[e] Generating adult equivalent household size uses weights used in Krishnan et al. (1998).

Table C.2 Effects of low and moderate temperature thresholds on land productivity: Role of land cover change

	Dependent Variable: ln(Agricultural productivity)$_{i,t}$		Dependent Variable:Productivity (dummy)$_t$					
			Bottom 25%		Middle 50%		Top 25%	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$Temperature_{v,t-1} < 17°C$ (dummy)	0.197	0.443**	0.036	0.103	0.039	0.094	-0.057	0.024
	(0.188)	(0.194)	(0.063)	(0.065)	(0.080)	(0.082)	(0.070)	(0.072)
$LandCoverChange_{v,t}$	0.004**	0.001	0.001	0.000	0.000	-0.001	0.000	-0.001
	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
$Temperature_{v,t-1} < 17°C \times LandCoverChange_{v,t}$	-0.001	-0.008*	0.000	-0.001	0.000	-0.001	0.001	-0.001
	(0.004)	(0.004)	(0.001)	(0.001)	(0.002)	(0.002)	(0.001)	(0.002)
Constant	7.750***	7.922***	0.706***	0.737***	0.469***	0.532***	0.233***	0.401***
	(0.093)	(0.153)	(0.026)	(0.044)	(0.029)	(0.053)	(0.024)	(0.047)
Household Fixed Effects	✓	✓	✓	✓	✓	✓	✓	✓
Year Fixed Effects	✓	✓	✓	✓	✓	✓	✓	✓
Controls	—	✓	—	✓	—	✓	—	✓
Number of observations (no shock)	4815	4815	4815	4815	4815	4815	4815	4815
Observations	6153	5970	6153	5970	6153	5970	6153	5970
R^2	0.254	0.289	0.210	0.238	0.163	0.196	0.090	0.121

All model specifications are estimated using the MWFE estimator developed by Correia (2017). The dependent variable measures agricultural productivity, expressed as the natural logarithm in columns (1) and (2) and as a binary indicator in columns (3) through (8), corresponding to three defined productivity thresholds. Columns (3) to (8) report coefficients estimated at each threshold. Control variables include the household head's age (years), household size (adult equivalents), tenure security (binary), use of improved seed (binary), use of chemical fertilizer (binary), access to credit (binary), access to irrigation (binary), food security status (dummy), non-farm income (index), and distance to the nearest market (kilometers). Robust standard errors are reported in parentheses. Asterisks show significance at the * 10%, ** 5%, and *** 1% levels.