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Assessing Forest Cover and Livelihood Dynamics in Central America from Household to Multi-National Scales

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Assessing Forest Cover and Livelihood Dynamics in Central America from Household to Multi-National Scales

By

Evan Patrick

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Committee in charge:

Professor Matthew D. Potts, Chair
Professor Iryna Dronova
Professor Van Butsic

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Abstract

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Professor Matthew D. Potts, Chair

Developing countries face the challenging and seemingly contradictory task of preserving or expanding their forests and natural ecosystems while lifting their populations out of poverty. Global change, or anthropogenic shifts in climate and ecosystems, is putting increasing strain on human and natural systems and threatens to dramatically undermine these efforts. Smallholder farms, which are the source of most food calories across many developing nations, are especially vulnerable to climate-related events like drought. These impacts can disrupt farmer livelihood strategies and land use arrangements in complex ways. Investigating how disruptors like drought affect land use and livelihoods, and how governments and local contexts mediate these impacts, is crucial to building adaptive capacity in smallholder systems in the face of global change.

In this dissertation, I explore global change dynamics in smallholder-dominated systems, focusing on drought and land use change. I investigate multinational changes in forest and crop cover due to livelihood shocks, the impact of national forestry payment programs, and farmers' relationships with drought in Zacapa Department, Guatemala. My analysis takes a land use systems approach, considering underlying drivers, dynamics, and scales in assessing change in smallholder-dominated regions. The three chapters that comprise the body of this dissertation address global change questions at increasingly smaller scales. Chapter 2 provides a multinational assessment of how livelihood shocks affect land use in the developing world. Chapter 3 examines the impact of Guatemala’s long-running national payment for ecosystem services on forest cover, considering different program contexts. Chapter 4 focuses on Zacapa Department, Guatemala, analyzing how households in this part of the Central American Dry Corridor experience droughts. This research stitches together the interplay of drought, conflict, and forestry on land cover and livelihoods to reveal key dynamics that are shaping these systems. My findings provide critical insights such as i) theoretically-backed links between livelihoods shocks and land use change; ii) improved understanding of how government-backed forestry incentives improve forest cover; and iii) regionally-specific measures of drought exposure and

drivers of vulnerability. Using a scaled approach that analyzes data at the multinational, national, and local levels allows for a comprehensive and a more nuanced understanding of global change in smallholder-dominated systems.

My research in Chapter 2 investigates the impact of food insecurity shocks on human land use. Existing literature largely describes the extent, patterns and drivers of food insecurity or land cover change separately, but the interplay between the two remains understudied. I use data from USAID to track food insecurity events and their resulting impacts on land use and population in 25 low- and middle-income countries. To isolate impacts on forest area, cropland, and population dynamics in the wake of food insecurity events, I use matching with difference-in-differences and two-stage least squares to disentangle the impacts of major food insecurity drivers. I find that spikes in regional food insecurity lead to forest recovery and a loss of cropland and population. When I parse the underlying drivers of food insecurity, I show that drought-driven shocks most impact land cover, whereas conflict-driven shocks most impact population, suggesting that changes to land productivity are most predictive of subsequent land use change.

Chapter 3 evaluates the effectiveness of two long-running forestry incentive programs in Guatemala which aim to expand forest cover and improve rural livelihoods. These programs underlie Guatemala's ambitious forest restoration goals, but have yet to be critically evaluated at a national scale. I use a synthetic control counterfactual to evaluate the impacts of over 16,000 individual Payment for Ecosystem Services projects on forest extent and loss. A program for smallholders resulted in lower rates of forest loss, while a program for industrial timber owners led to greater gains in forest cover. Across policies, I found dramatically higher forest cover increases from restoration projects compared to plantation and agroforestry projects. Overall, my analysis found forest cover increases to be under 10% of total enrolled area, although positive local spillovers suggest this is an underestimate.

In Chapter 4, I combine ethnographic research with remotely sensed data to characterize the climate vulnerability of smallholder farmers in Zacapa, Guatemala. This region of the Central American Dry Corridor has been one of the hardest hit by drought in recent decades, with the World Food Programme estimating that up to 70% of the corn crop was lost in recent years. I investigate the experiences of farmers through historic and recent droughts using ethnographic interviews across two smallholder communities. I further evaluate crop water stress within vegetation groups and agricultural fields using remotely sensed imagery. Integrating these datasets identified a socio-ecologically relevant measure of water stress that allows for better evaluation of drought exposure and also reveals how shifting land tenure may be driving drought vulnerability through limiting farmers' access to high-elevation forests.

These findings can inform policies aiding smallholder-dominated systems, targeting points of vulnerability and supporting interventions with the best socio-ecological outcomes. They also support future research via the application of findings across scales, to either zoom in on how important global drivers are mediated within local contexts or to apply a flexible but locally-relevant framework to multinational studies. I further suggest that better measurements of change drivers can improve our understanding of the mechanisms and impacts of global change, leading to more applicable and forward-thinking research findings in this field.

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Doing a PhD is a strange thing. When I started in the fall of 2019, I was staring down a long, 5-year road of soul-searching, reading, traveling, coding and writing, interrupted early on by a global pandemic and lockdown. My path was not particularly strange or notable other than the fact that it was mine, but after going through it I have a hard time pinning it down: an education, an apprenticeship, a right of passage. Whatever it was, I would not be here today without the direct support, mentorship and fellowship of my family, friends, professors and collaborators.

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Chapter 1: Introduction

1.1 Motivation

National governments in the developing world are faced with a seemingly-impossible task: to preserve or expand their forests and natural landscapes while also rapidly pulling their populations out of poverty. This challenge is only made harder in the face of global change, with pressures from climate, land use, and ecosystem change increasingly straining human and natural systems (6–8). Research has shown that smallholder-dominated systems produce a majority of food calories in many developing nations (9) but are highly vulnerable to climate impacts (8,10,11). Climate shocks like drought are increasingly straining smallholder farmers, leading to dramatic shifts in livelihood strategies and even land use (12–14). However, these systems also harbor a greater amount of biodiversity (15) and have a high potential for multi-benefit landscape management (16). This presents a challenge and opportunity for policymakers, as smallholder-dominated landscapes face increasing stressors but have a high capacity for resilience and sustainable resource management. Threading this needle has proved difficult. Long-standing programs that aim to promote conservation and support local populations, such as the REDD+ program, have been criticized as not living up to environmental (17–19) and economic promises (20,21). In recent years, nations have shifted to forest cover expansion programs to support ecosystems and sustainable development (22). These efforts have diverse program designs and are applied across wide-ranging environmental and cultural contexts, leading to dramatic uncertainty in potential results (23,24). Climate shocks like drought put further strain on smallholder-dominated landscapes, potentially eroding any benefits tree planting may provide these communities. In order to better understand how livelihoods and land use intersect, this dissertation explores how livelihood shocks operate at a regional and local scale, and how national governments and local contexts mediate changes.

I generally focus on Central America to ground this dissertation in a geography where I have particular expertise and can better contextualize global change dynamics, although Chapter 2 includes other smallholder-dominated regions. Central America is a focal point of global change, with high levels of vulnerability and need for adaptation to address climate impacts (25,26). Climate change has already dramatically impacted Central American smallholder farmers (27) and the region is likely to become a climate change hotspot under future warming scenarios (28). Recently, farmers across the region are reporting an increase in seasonal droughts and high agricultural losses associated with El Niño (29,30), and the frequency and intensity of these droughts are predicted to worsen in coming decades (31–33). There is some evidence that recent droughts increased human movement within the Northern Triangle. One recent article suggests that climate impacts could lead to greater rates of urbanization in the region (34). Understanding how climate change and policy are impacting households and land use dynamics necessitates a strong set of underlying theory and context that can point research to how and why changes are occurring. For example, payment for ecosystem services programs in Guatemala incentivize forest plantation establishment, but it is unclear if and how these programs are benefiting ecosystems and forests. Additionally, food insecurity can impact human productivity or land productivity based on its underlying drivers, and it is necessary to contextualize the drivers of food insecurity to identify the impacts on the landscape scale. Finally, drought impacts in Guatemala can occur across many time scales, but growing-season vegetation is most dramatically impacted by water deficits that occur over 3 or 4 months. This aligns with research showing family migration to the US from Central America is most correlated with 3-month water deficit increases (35).

This dissertation unpacks recent dynamics of global change in smallholder-dominated landscapes (9), with a specific focus on two drivers: a) climate warming and altered precipitation and b) land transformation (36). While many concomitant drivers affect these systems, these two are prominent in the scope and severity in which they affect smallholder-dominated landscapes. To understand overlapping and emergent trends in smallholder-dominated systems, this dissertation assesses change at the national and multinational scale as well as the regional and household scale. In this case, I investigate multinational changes in forest and crop cover resulting from livelihoods shocks, the large-scale importance and impacts of national payment for forestry programs, and farmer's relationship to drought in Zacapa Department, Guatemala. Using these contextual frameworks and methods allows for effective and informative analysis of land use systems. Across this dissertation, I keep these considerations of underlying drivers, dynamics, and scale in mind in identifying and assessing change.

This dissertation addresses these gaps by exploring the following questions:

- How do livelihood shocks impact subsequent forest and crop cover change in the developing world? What are the underlying drivers of these changes, and how do different drivers variably affect land cover outcomes?
- Are Guatemala's long-standing forestry payment programs delivering on their goals of expanding forest cover in Guatemala? Can scaling up these programs help meet Guatemala's Bonn Challenge goals of 1,200,000 ha of increased forest cover (around 11% of the country's land area) by 2030?
- How do droughts impact smallholder farmers in the Central American Dry Corridor? What creates vulnerability within a smallholder community and what kinds of water deficits are most impactful in these groups?

1.2 Structure

The three chapters that form the body of this dissertation focus on answering the above questions at increasingly smaller scales. Chapter 2 provides a multi-national assessment of how livelihood shocks impact land use change in the developing world. Chapter 3 investigates the impacts of a long-running, national payment for ecosystem services on Guatemala's forest cover, parsing the different types and contexts of program development that support variable outcomes. Chapter 4 dives into Zacapa Department, Guatemala, to understand how households in this region of the Central American Dry Corridor are affected by droughts. Taking this scaled approach allows for variability in the types of questions asked and the kinds of evidence and arguments presented, promoting a more full synthesis of global change within smallholder-dominated systems.

Chapter 2 examines the impact of food insecurity events between 2013 and 2020 in 25 low- and middle-income countries on land use change and demographics. By using propensity score matching, I created a counterfactual to compare changes in forest cover, crop cover, population, and nighttime luminosity between regions experiencing food insecurity and comparable food-secure regions. The analysis draws on Land Use Change theory, including agricultural intensification, land rent theory, and regime shifts, to explain the observed patterns. I found that food insecurity events lead to a 4% decline in population and a 3% decline in cropped areas, while forest cover increased by 4% in food-insecure regions compared to control regions. When breaking food insecurity events down by drivers, I found that drought-driven food insecurity had a more significant impact on land use, whereas conflict-driven food insecurity affected population and nighttime luminosity more. Additionally, urban areas experienced an increase in population and crop cover despite losses in neighboring rural areas, indicating a trend of local migration to cities. Finally, by assessing the impacts of discrete food insecurity events in three countries, I found that regional contexts mediate impacts, resulting in variable land use change trajectories.

Chapter 3 assesses the impacts of over 16,000 individual Payment for Ecosystem Services (PES) projects funded by Guatemala's forestry department. I created a synthetic control counterfactual to estimate the combined impact of programs aimed at expanding forest and conserving existing forest, and compared outcomes between the smallholder-focused PINPEP program and the more industry-focused PINFOR program. The findings reveal that a program for smallholders resulted in lower rates of forest loss, while a program for industrial timber owners led to greater gains in forest cover. Across policies, restoration projects demonstrated dramatically higher forest cover increases (15%) compared to plantation and agroforestry projects, which showed a 3%–6% increase. Additionally, projects that protected natural forest resulted in a 6% reduction in forest loss. Although forest cover increases were under 10% of the total enrolled area, positive local spillovers suggest this might be an underestimate.

Chapter 4 integrates an ethnographic analysis of smallholders' experiences of climate change in two adjacent communities in Zacapa with remotely sensed and modeled data on plant water stress, soil moisture, and land use. The findings indicate that water deficits early in the growing season are most detrimental to vegetation health across the landscape, though high-elevation pine-oak forests exhibit resilience to these seasonal droughts. Farmers often interpret these water deficits as delays in the rainy season and attribute the impacts to local environmental changes like deforestation rather than large-scale climate change. The surveyed communities perceive recent droughts as more frequent and harmful compared to historical events. Hydrological data reveals that droughts occur on a quasi-decadal cycle, with recent events appearing more severe when considering growing-season water deficits. In this study, I argue that focusing on socio-ecologically relevant drought metrics is crucial to identifying patterns of change that significantly impact farmer communities. Additionally, lower-resource farmers experienced less social network support and livelihood resilience, resulting in more severe individual drought impacts despite similar or lower signals of vegetation and crop water stress. These low-resource farmers historically had access to high-elevation pine-oak forests, which experienced delayed drought impacts during critical socioecological drought months. However, privatization and conservation efforts in recent decades have severely limited access to these drought-resistant forest resources, exacerbating the impacts on these communities.

The third chapter of my dissertation has been published in *Environmental Research Letters* with minor differences from the version presented here.

- Patrick E, Butsic V, Potts MD. Using payment for ecosystem services to meet national reforestation commitments: impacts of 20+ years of forestry incentives in Guatemala. Environmental Research Letters. 2023 Sep 26;18(10):104030.

I hope to publish the other two chapters shortly after the completion of this dissertation.

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Chapter 2: Assessing Land Use Change Trajectories following Food Insecurity Shocks in 25 Low- and Middle-Income Countries

Abstract

Food insecurity is a perennial problem in much of the developing world, with gains against hunger backsliding in recent years (1,2) and studies predicting climate change will accelerate this trend (2). Food insecurity is highly disruptive to rural livelihoods and can lead to dramatic shifts in food production strategies and resultant land use (3–6). However, studies to date have yet to outline the overarching patterns of land use change that can result from food insecurity. We elucidate the impact of food insecurity events between 2013 and 2020 in 25 low- and middle-income countries on resulting land use change and demographics. Using propensity score matching, we create a counterfactual and assess changes in forest cover, crop cover, population and nighttime luminosity between regions that experience food insecurity and comparable food-secure regions. Land Use Change theory, specifically the classical trajectories of agricultural intensification, land rent theory, and regime shifts help to explain observed land use trajectories. We find that food insecurity events lead to around a 4% decline in population and a 3% decline in cropped areas, alongside a 4% increase in forest cover compared to control regions. We found that drought-driven food insecurity showed greater impacts on land use and conflict-driven food insecurity showed greater impacts on population and nighttime luminosity. Food insecurity led to an increase in population and crop cover in urban areas despite losses in adjoining rural land, suggesting that food insecurity leads to an uptick in local migration to cities. Furthermore, by assessing the impacts of discrete food insecurity events in three countries, we find that regional contexts mediate impacts by producing variable land use change trajectories.

2.1 Introduction

2.1.1 Background

Land use change and food security are intricately linked, with numerous studies exploring the impacts of global and regional agricultural expansion on current and future food security (2,7). Tradeoffs between agricultural intensification and extensification are important considerations at the international scale and acknowledge growing demand for food calories as population increases in size and affluence (8). Global discussions of food security also highlight the influence of warming (9), natural hazards (10) and land degradation (11,12), with existing agricultural systems often requiring extensive management changes to support continued production. However, these studies often fail to address the impacts of food insecurity on land use and agriculture, especially the impact of short-term disruptions on livelihoods and land use practices. Understanding land use dynamics in the wake of short-term food insecurity events can provide insights into how shocks to agricultural livelihoods can change land use trajectories and support the development of realistic scenarios for the impacts of future food insecurity shocks. We investigate these dynamics by asking the following questions: 1) how do food insecurity events impact land cover change and demographics across the study region, 2) are these shocks having differential impact in rural areas, or more built-up, urban regions and 3) how do causal mechanisms of observed land use change vary across regional contexts?

2.1.2 Food Insecurity

Food insecurity is often defined as a lack of sufficient food quantity and quality available to people in each region. Many people across the world experience some baseline level of food insecurity in their day-to-day lives, but here we treat food insecurity as a discrete and disruptive event triggered by a confluence of human and natural factors (13). In this framework, many households in an area move from having sufficient access to food to having insufficient access. These types of food insecurity crises are often called 'complex emergencies' because they occur due to complex and interrelated factors such as natural disasters, climate disruption, war, and commodity price shocks (14).

Food insecurity often occurs in smallholder-dominated regions, which produce more than half of global food calories and are home to over 380 million farming households (15). Smallholder-dominated regions are also home to many of the world's poor who are vulnerable to food insecurity through climate, political, or economic disruptions. When considering smallholders' food security, it is common to use the entitlements framework to describe how resources are accessed and produced at the household level (16). In an entitlements framework, households work to obtain food via their access to resources, social networks, and capital. Food insecurity occurs when these entitlements are insufficient to gain sufficient food for many households (16). Notably, this can occur even when food availability or production is stable, so long as the ability for households to procure food is disrupted.

2.1.3 Land Use Change Theory

To study food insecurity in smallholder-dominated regions, we integrate a diverse set of land use change theories to explain potential mechanisms explaining the relationship between food insecurity events and land use and land cover change. Meiyfroidt et al. (17) pose that land use change theory has provided a useful and wide-ranging set of 'middle-range' theories that provide "chains of causal mechanisms" of land use phenomena, with clear explanations of the conditions needed to trigger or block these causal chains (18). We apply relevant middle-range theories to the context of food insecurity events, with a specific focus on general theories that can explain patterns of change at the regional scale we assess in this study. Overall, land use change is hard to predict and is very path-dependent (19), with non-linearities and long-term trends both dominating land use patterns. When integrating with food insecurity shocks, we posit causal mechanisms of land use change are constrained by the adaptation choices available to smallholders in each region. By looking at adaptation strategies, we can scale up from the household level to the regional level and contextualize the drivers and consequences of observed land use trends.

The classical trajectories of land use intensification (20) provide a helpful outline of agricultural change under varying regimes of land and labor productivity. These include Boserup's theory of agricultural intensification which states that, when land is limited, agricultural intensification will increase production as long as land productivity improvements outpace labor productivity losses associated with intensification (21). Geertz added the theory of agricultural involution, when land productivity levels off while labor inputs continue to rise (22) such that food production is maintained but at the cost of increasing labor. Further declines in land and labor productivity would trigger a Malthusian crisis, when per capita labor output and per area land output decline in tandem and crop production drops (20). These theories generally leave out off-farm employment opportunities and markets but provide a helpful framework for trends in agricultural productivity and land use.

We also consider land rent theories in the distribution of land use changes during food insecurity shocks, as these operate well in regional contexts. Land rent theory posits that land prices vary by biophysical characteristics, distance to market, and overall land scarcity (17). When land rent rises, agricultural intensification would be incentivized and we would expect land use shifts from forest, agroforestry, swidden agriculture or pasture to monoculture, specialty crops, or buildings. Alternately, when land rent falls, we would expect a movement towards agricultural extensification and forest regrowth.

Regime shifts provide another helpful theory with which to understand the impact of food insecurity events on land use change (23,24). Regime shifts in land use change are generally marked by rapid shifts in land use patterns, such as a dramatic expansion of plantation agriculture or swift recovery of secondary forest (23). They are often driven by an initial disrupting event, followed by positive feedback that leads to a long-term shift in land use trajectory (17). Regime shifts are inherently difficult to predict but Lade et al. (6) provide a model where food insecurity shocks might result in re-arrangement of agricultural regimes. In their model, long-term agricultural intensification leads to improved economic outcomes, but increases the vulnerability of the system to change. A shock, such as a drought or ill-timed rainfall event, then leads to land degradation and reversions in economic gains. This may be exacerbated if intensified agricultural practices coincide with declines in cultural knowledge, further limiting the adaptive capacity of the system. Lade et al. (6) refer to this pathway as an 'intensification trap.' Assuming agricultural intensification trends, we might expect food insecurity events to lead to land degradation and a disruption of rural livelihoods. Land use might, by necessity, expand or remain constant due to constant demands on agricultural production for food and income, but the ability to effectively gain a livelihood from this land would be depleted. Strongest impacts would be seen economically, with outmigration or declines in rural GDP likely in affected areas.

2.1.4 Observational Research

Because of measurement challenges and limited research activity, there is not a wide body of research linking food insecurity events to land use change outcomes. However, we do find case studies that link frequent drought, conflict, common drivers of food insecurity, to land use change. A typical pattern is rural-urban migration resulting from drought, potentially as an adaptive strategy employed by households when entitlements from agricultural production decline (3,25). Drought-prone regions in the Ethiopian Rift Valley have also been shown to have moved away from livestock raising in favor of cultivated agriculture (4), a pattern mirrored in Mali (5), suggesting this move is a risk-reduction strategy in the face of climate shocks. Additionally, studies have demonstrated high rates of cropland abandonment during intense periods of conflict (26–29). We often see state changes in the wake of these conflict events, where cropland may remain mostly abandoned (26) or abandoned cropland may be used by remaining households leading to agricultural extensification (29). However, this pattern is reversed in some cases. Elkund et al. (27) found evidence of cropland expansion, but not intensification, within Islamic State-controlled regions of Iraq and Syria, likely because militants forced farmers to expand agricultural production. Spikes in food prices may harm or help smallholders, depending on their reliance on purchased staple foods and market integration (30), and most studies suggest that smallholders are poorly positioned to take advantage of food price increases (30,31). Food price spikes are also correlated with disruptions in local production from climate or conflict shocks (13), when smallholders would be most exposed to commodity price risk and have the least ability to benefit via agricultural production.

2.1.4 Causal Mechanisms of Food Insecurity-Driven LUC

Building on these findings, we present sets of causal mechanisms for land use change specific to drought-induced and conflict-induced food insecurity shocks, incorporating some potential influences of commodity prices. This allows us to contextualize findings and empirically test relevant Land Use Change theories. In reality, these drivers are often interrelated, with droughts often increasing the likelihood of conflict (32–34) and commodity prices (35) and commodity price shocks driving conflict (36,37). However, we propose that these drivers variably influence land use outcomes, and therefore try to disentangle them here before assessing overall patterns. Below, drought-induced food insecurity and conflict-driven food insecurity are described through the classical trajectory of agricultural intensification, land rent theory, and regime shifts using observational studies to expand upon these theories.

Drought-induced food insecurity events are marked by a temporary decline in land productivity as water shortages lead to crop losses during drought years. In the classical trajectory of agricultural intensification, we would expect labor inputs to increase to offset these losses if land availability is limited. Depending on the severity of drought, we would either see agricultural involution where agricultural outputs remain stagnant because of increased labor inputs, or a Malthusian crisis where increased labor cannot offset land productivity declines (17). Resulting declines in labor productivity would make off-farm employment more desirable compared to on-farm work and shifts away from agriculture would be expected. Drought-induced food insecurity, when considered using land rent theory, would transiently reduce the biophysical suitability of land for agriculture, temporarily reducing land rent and incentivizing extensification of agriculture. Risk reduction is also an important factor in smallholder decision-making after climate-driven food insecurity shocks, with two studies showing a shift from pastoralism to agriculture from severe multi-year drought (4,5). This is likely because cattle represent a large percentage of household wealth and, under contemporary land arrangements, are highly vulnerable to drought. Initial vulnerability of the agricultural system and the severity and length of drought are important factors when considering regime shifts of smallholder land use. For example, degraded agricultural land or vulnerable ecosystems may not be able to recover from severe drought, leading to desertification and a permanent shift away from agriculture. Alternately, drought-resilient agricultural systems may experience temporary impacts but would regain productive capacity after impacts subsided.

Conflict-driven food insecurity events primarily impact human labor and livelihoods by making it unsafe to do agricultural work or to access necessary markets and capital for growth. When considering the trajectory of agricultural intensification, loss of human labor and capital inputs may lead to a stagnation in agricultural output, or agricultural involution, but would likely not produce a Malthusian crisis as land productivity would not be impacted except in the most extreme circumstances. Land rent could be impacted if access to markets is disrupted, incentivizing extensification or abandonment of agriculture. Land rent impacts could be differentially concentrated in peri-urban or rural areas, depending on where conflict is most intense. In cases when militants force farmers to continue agricultural production or when producers are not involved directly in conflict, high land availability and low labor availability would incentivize agriculture extensification over intensification (27). Regime shifts in the wake of conflict events are most likely when the underlying agricultural system is already precarious, such that disruption would drive rapid shifts in livelihoods away from agriculture. This was likely the case in the Caucuses in the 1990s (26), when only 17% of abandoned land was recultivated post-conflict because the Soviet-era agricultural collectives had disbanded.

Food insecurity shocks driven by crop price increases would likely increase intensification as prices would drive up land rents and increase the economic returns on human labor. However, we have seen that smallholders are often unable to take advantage of these price increases either because they are driven by conflict or drought or because smallholder systems are less adaptive to short-term market signals than industrial systems (31,38).

2.2. Methods

2.2.1 Methods Overview

To assess the impact of food insecurity shocks on land use and demography, we aggregated gridded datasets to second level administrative units (county or municipality political boundaries) for 25 countries in Africa, Latin America, and the Middle East. We include datasets covering food insecurity, demographics, land cover, connectivity, food prices, conflict, weather, and climate. Data were extracted from raster datasets and averaged to the administrative unit unless otherwise noted. We also pulled data for urban, semi-urban and rural land within each administrative unit using raster masks. Then we performed propensity score matching to produce a set of comparable administrative units that did not experience food insecurity shocks as a counterfactual. This matching was repeated for urban, semi-urban, and rural values to create four matched datasets with an equal number of treatment and counterfactual units. Finally, land use and demographic impacts were assessed using linear regressions and event studies on the matched datasets. We outline the datasets, matching, and analytical methods below.

2.2.2 Datasets

We used the Food Insecurity Hotspots Dataset (39) to quantify food insecurity. This data is rasterized from the Famine Early Warning System Network (FEWS NET), a program funded by USAID that tracks food insecurity level in low- and middle-income countries. FEWS NET uses a network of in-country workers and partners to measure direct signs of food insecurity, such as food consumption, livelihoods, malnutrition, and mortality (39). These factors are incorporated into a 5-tier scale of food insecurity, with 1 signifying generally food secure, 2 for moderately food insecure, 3 for acute food and livelihood crisis, 4 for humanitarian emergency and 5 for famine. Measurements are primarily made to target humanitarian relief through food aid and development interventions; however, data is made available to researchers to study the patterns of food insecurity. The dataset begins in July 2009 and is collected quarterly until 2015 and three times per year after 2016. We pulled gridded food insecurity estimates from July 2009 February 2020 for 25 countries with sufficient food insecurity data across the study period.

The FEWS NET food insecurity dataset generally tracks food insecurity level at the second administrative unit level–often a county or municipality, depending on the country–so we used the level 2 GADM administrative unit bounds (available at https://gadm.org/data.html) as our unit of analysis. The GADM administrative unit dataset provides up-to-date boundaries for global administrative units as of 2019. All data was extracted to this level across countries, which led to some country-level variation in administrative unit size and shape. We defined any administrative units that rose above a value of 2 at any point after 2012 as our treatment group. Food insecurity level 2 represents 'moderately / borderline food insecure' and 3 represents 'acute food and livelihood crisis', so we treat this cutoff as the point at which an area experiences a food insecurity event. In all, data was collected for 2829 administrative units across 25 countries, with

623 experiencing food insecurity and 2206 that are generally food secure across the study period. After matching, this dataset was filtered down to 1246 administrative units, with 623 in each group. Data was extracted from gridded data to administrative units using the Google Earth Engine python API (*ee* library), with cleaning, matching and analysis performed in R.

Land cover change is tracked using the Global Forest Watch forest loss dataset (40), which measures yearly global forest loss from 2001 to 2023, and the Global Land Cover and Land Use Change 2000-2020 dataset (41), which provides measures of crop cover and forest cover from 2000 to 2020. We assess population change using the Gridded Population of the World, Version 4 dataset (CIESIN), which gives gridded population estimates every 5 years between 2000 and 2020 at 30 arc-second resolution (42). To control for market connectivity, we included gridded estimates of the travel time to cities with a population larger than 20,000 in 2015 (43) and a measure of movement difficulty across the landscape (44). Drought and flooding susceptibility is measured using the baseline water risk layer from World Resource Institute's Aqueduct 4.0 dataset (45).

Nighttime luminosity was included as an estimate of economic growth over the study period. For the years 2000-2012 we used the Defense Meteorological Program Operational Linescan System Version 4's Consistent and Corrected Nighttime Lights Dataset (CCNL) (46), which provides corrected yearly measures of global nighttime luminosity at 1 kilometer resolution. For 2013-2020, we used NASA's BlackMarble yearly near-nadir cloudfree, snowfree Visible Infrared Imaging Radiometer Suite (VIIRS) images (47). We filtered very high luminosity values that likely contain snow and clouds (e.g. districts that contain Mt. Kilimanjaro) to remove outliers before analysis. We also included several climate variables from WorldClim BIO1 gridded global data, which averages climate over 1970-2000 at 1 km resolution (48). These were annual mean temperature, mean diurnal range, isothermality, temperature seasonality, max temperature of warmest month, min temperature of coldest month, annual precipitation, precipitation of wettest month, precipitation of the driest month, and precipitation seasonality. We estimated conflict level across the administrative units using conflict event data from the Armed Conflict Location & Event Data Project (49). This dataset tracks global conflict events using local partners, media, reports and 'new media' (i.e. quality controlled social media posts). Conflict events are recorded daily with an estimated coordinate point location. We used the 'Disorder Type' class to split conflict events into Political violence, Demonstrations, Political violence in Demonstrations, and Strategic Developments. We spatially joined conflict events with administrative units and sum event counts to food insecurity measurement periods in R.

Weather was tracked using the fifth generation European Reanalysis data (ERA5) (50). We extracted temperature, precipitation and potential evapotranspiration by administrative unit and calculated the anomaly for each of these across the 2000-2022 period. Additionally, we pulled global gridded estimates of Palmer Drought Severity index from the Terraclim dataset to provide another measure of drought stress (51). Prices of dominant staple foods in the nearest market were accessed from the FAO's Food Price Monitoring and Analysis tool (http://www.fao.org/giews/food-prices/tool/public/#/home) (52). Dominant staple foods for each country were determined using the FEWS NET food price country reports and are listed in SI Table 4. Price data are reported in USD per kilogram, and abnormally high price data (20x standard prices or more) was filtered out. Nearest market to administrative unit was calculated using the 'sf' package in R (53). In some cases, food prices were only available at the country level.

We also included a measure of degree of urbanization, which differentiates between urban, semi-urban and rural areas (54). The dataset classifies urban areas as 4 or more adjoining cells with at least 1500 people per square kilometer and a collective minimum population of 50,000. Semi-urban areas needed at least 300 people per square kilometer, 8 or more adjoining cells, and a combined population of at least 5000. Rural areas are all pixels not classified as urban or semi-urban. We controlled for the average degree of urbanization in 2000 and used degree of urbanization in 2015 and 2020 as an outcome indicator. Additionally, we subsetted our data by urbanization level by masking covariates and outcomes to rural, semi-urban, and urban regions to understand if land cover trajectories behaved differently based on human population density. This helped us understand whether impacts from food insecurity were more strongly impacting rural or urban livelihoods, and if land use patterns and populations were shifting between these areas in the wake of food insecurity events. Importantly, the degree of urbanization dataset was defined using the Gridded Population of the World version 4 dataset, which we use to measure population. Summary statistics for all data are available in SI Table 1, with SI Table 2 and SI Table 3 showing summary statistics for treated and untreated groups, respectively.

2.2.3 Matching & Analytical Method

To control for variation across the dataset, we used propensity score matching to produce comparable sets of treated and untreated administrative units. Control groups were matched with treatment using the MatchIt package in R (55,56) after filtering the data to administrative units with greater than 10% forest cover. All pre-treatment trends from 2000 to 2012 (food insecurity level, forest cover, crop cover, forest loss, nighttime luminosity, population density in 2000, 2005 and 2010, weather and built-up level) and covariates (worldclim, connectivity) were matched using the nearest neighbor method and a caliper of 0.5. In the unmatched data, treated units had lower population, lower connectivity, more conflict events and more forest cover than untreated units. Climate data did not vary dramatically between the two groups. We present the distribution of propensity scores and covariate alignment before and after matching in SI Appendix C.

We estimated the impact of food insecurity events on outcomes of interest by running event studies on outcomes that are measured yearly and running linear regressions on all other outcomes using the matched dataset. Building on the pre-regression matching, linear regressions control for all listed covariates in the pre-treatment period (2000-2012). Linear regressions were performed on the matched dataset for outputs with only one post-treatment time step, including urbanization level, 2019 crop cover, 2020 forest cover, and percent population change. Estimates were provided for each variable and for variables split by degree of urbanization (urban, semi-urban, and rural). When a specific land use outcome was split by urbanization classification, we controlled for pre-2013 trends for the outcome and covariates within the urbanization class. The equation for the linear model we used to estimate the treatment effects on percent population change from 2010 to 2020 is provided in SI Section F1.

Event studies control for pre-treatment variation and provide estimates of impacts at each timestep post-treatment (57,58). This allowed us to determine if treatment impacts were consistent across treatment years or if impacts increased or lessened during food insecurity events. For this study, we used event studies to estimate impacts of food insecurity event start on subsequent forest loss and nighttime luminosity. We graph post-treatment effects by time period and report average treatment coefficients for the post-treatment period, which approximates to traditional difference-in-differences effects. Our treatment period is defined as the time steps where the level of food insecurity rose above 2.0 for any given administrative unit.

We limited these events to 2013 or later to allow for matching on 2009-2012 food insecurity levels. However, we ran into an issue with the staggered treatment design, where food insecurity event starts were uncoordinated across the treatment units. This staggered treatment can introduce bias into a two-way fixed-effects event study model, so we used the estimator presented by Sun and Abraham (59) which addresses this potential bias. The event study equation used to estimate forest loss impacts is outlined in SI Section F2.

To better understand the relationship between food insecurity drivers and outcomes, we ran two-stage least squares regressions on our outcomes using conflict events and weather as instruments. Two-stage least squares is a type of instrumental variable analysis, where the variation in the explanatory variable is limited to an exogenous instrument. This allows for a better estimation of impact, because it can control for endogeneity that is otherwise difficult to separate from the analysis. In this case, we used the same technique to separate the impacts of food insecurity that are related to conflict versus the impacts of food insecurity that are related to drought. As discussed above, conflict can be driven by drought and therefore these two drivers are not fully independent. However, we found that drought and conflict level had a low level of covariance in our data, suggesting we could use them as separate instruments in this context. Prior time steps in the outcome variables were included as controls, but other covariates were not included to avoid under-identification of the models. For conflict event regressions, Palmer drought severity index was included as a control, and conversely political violence events were included as a control for weather regressions. This allowed for better identification between conflict-driven food insecurity and weather-driven food insecurity. These drivers are correlated and Two-stage least squares was performed using the ivreg() function from the AER package in R (60), and we provide the two-step equation for this analysis in SI Section F3.

2.2.4 Case Studies

In addition to tracking the overall impact of food insecurity events on land use and population outcomes, we pulled three case studies from the overall data to understand regional patterns and impacts from food insecurity events. These included southern Mozambique's drought in 2016 and 2017, a drought in Guatemala from 2015 to 2017, and prolonged conflict-induced food insecurity in northeastern Nigeria which began in 2013. To do this, we ran an event study analysis with a static event start cutoff based on when food insecurity rises above 2 in most affected administrative units. Country-level contexts and patterns of change in the case studies were compared with overall data to provide better insights into potential food insecurity-driven land use dynamics.

2.2.5 Robustness Checks

Our initial robustness check was to evaluate the goodness of fit of the matching process. Post-matching propensity scores and variable distributions were graphed and compared for fit (SI Appendix C). For the Mozambique data, we found that matching was insufficient in controlling for our variables of interest using only Mozambique data, so we adjusted the case study analysis to include administrative units from adjacent countries (Malawi, Tanzania, Zambia and Zimbabwe) that were generally food secure.

For each regression we checked the distribution of the residuals by graphing a quantile-quantile (q-q) plot. The plots take an S shape, suggesting that one of the groups has more outliers than the other. We determine outliers for each linear and two-stage least squares regression using leverage statistics, which were calculated using the hatvalues() function in R. The threshold was determined using the function where k is equal to the number of predictors, excluding the intercept. We then make a list of outlier values where the leverage statistic exceeds the threshold for each outcome variable. Finally, multicollinearity was checked using a variance inflation factor (VIF) analysis, and we found that only time-series data (population in 2000, 2005, 2010, etc.) or data across various urbanization classes (e.g. rural crop cover vs total crop cover) had high multicollinearity, which is accounted for in our empirical method.

Finally, we evaluated the trends in forest loss and nighttime luminosity to identify potential bias in the event study. For each event study, we graphed the mean yearly outcome variable for the treated and control groups to see if pre-treatment trends were parallel (SI Appendix B). While matching should create comparable groups, we found that most outcomes showed parallel trends pre-treatment, suggesting that the Sun and Abraham event study method was suitable to identify treatment impacts.

2.3 Results

2.3.1 Impacts of Food Insecurity on Land Use and Demographics

Overall, we find that food insecurity events lead to declines in crop cover, nighttime luminosity and population and increases in forest cover compared to administrative areas that did not have food insecurity events (Figure 1). We found that forest loss declined slightly during food insecurity events, although the degree of decline only partially accounts for the observed forest gain. For administrative units that experienced a food insecurity event, forest cover increased by 4% from 2000 to 2020 and crop cover decreased by 3% from 2011 to 2019. This represented a relative gain in forest cover of 2% of the total land area, and a crop cover decline of 0.3% of the total land area. Crop cover changes for all administrative units averaged to an increase of 0.17% of the total area per year, so the impact of a food insecurity event is equivalent to nearly two lost years of normal cropland expansion. Population declined by 4% from 2010 to 2020 and nighttime luminosity decreased by 2.5, a 7% change from the mean, over the food insecurity event dates. Two-stage least squares regression outputs are displayed in Figure 2 and show that weather events were more aligned with overall trends than conflict events. Conflict-related food insecurity events showed no significant impact to crop cover and forest loss but had a negative impact on population and nighttime luminosity. We also found that impacts to nighttime luminosity and forest loss increase or remain constant in the years following food insecurity events start (Figure 3).

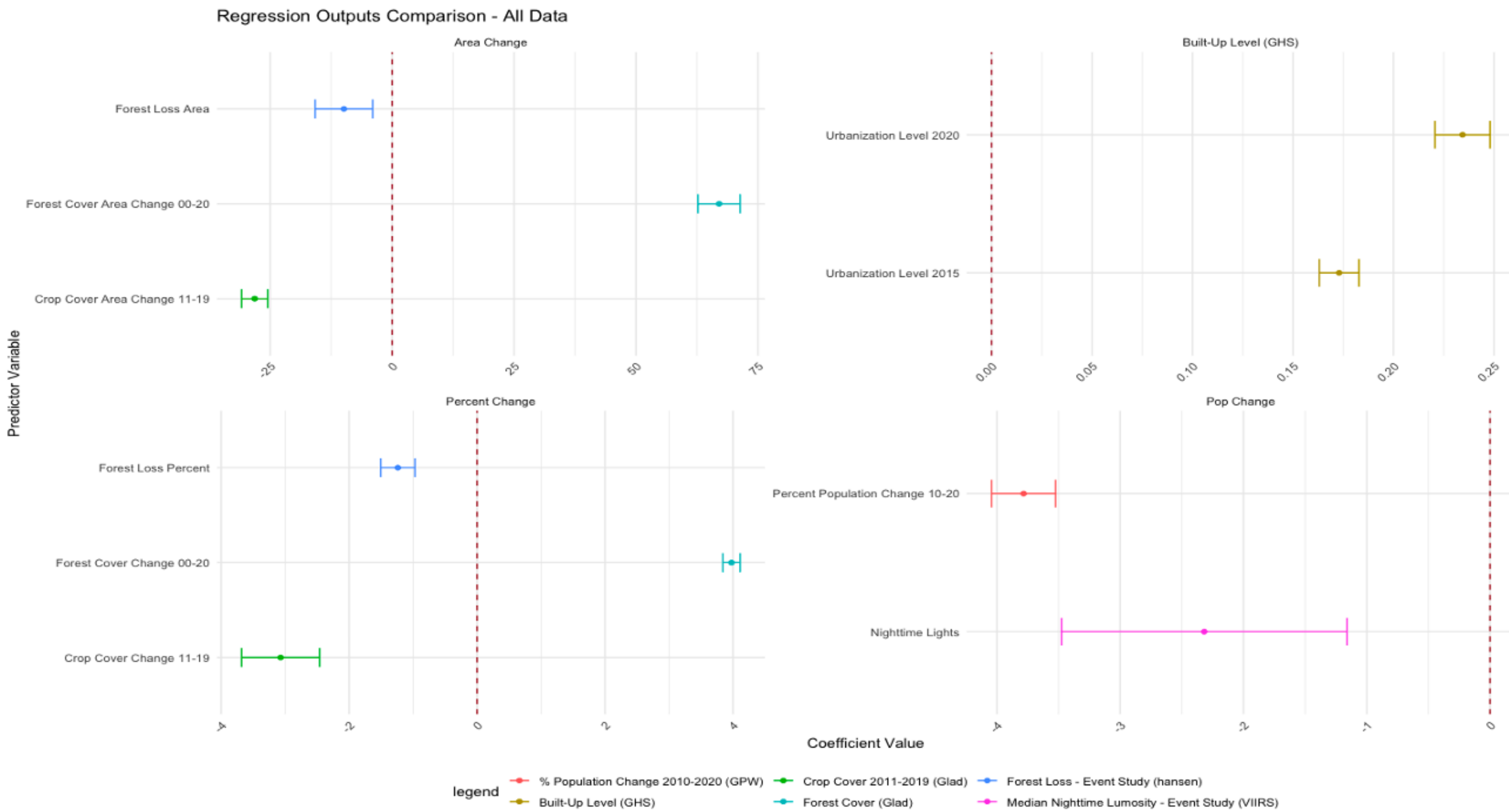

Figure 1: Event Study and Fixed Effect Regression Coefficient Chart

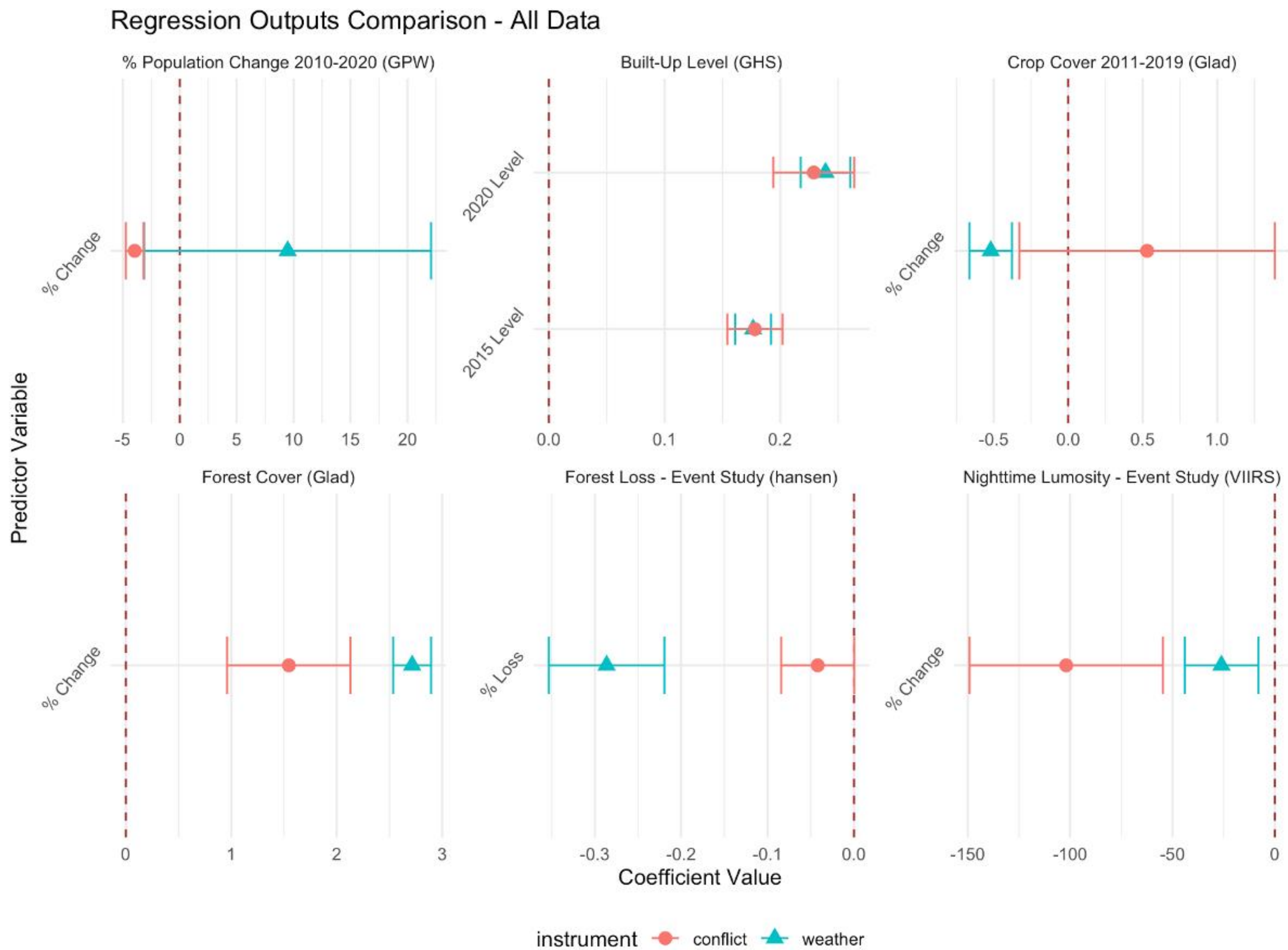

Figure 2: 2SLS Outputs when using Conflict and Weather as Instruments on Food Insecurity Events

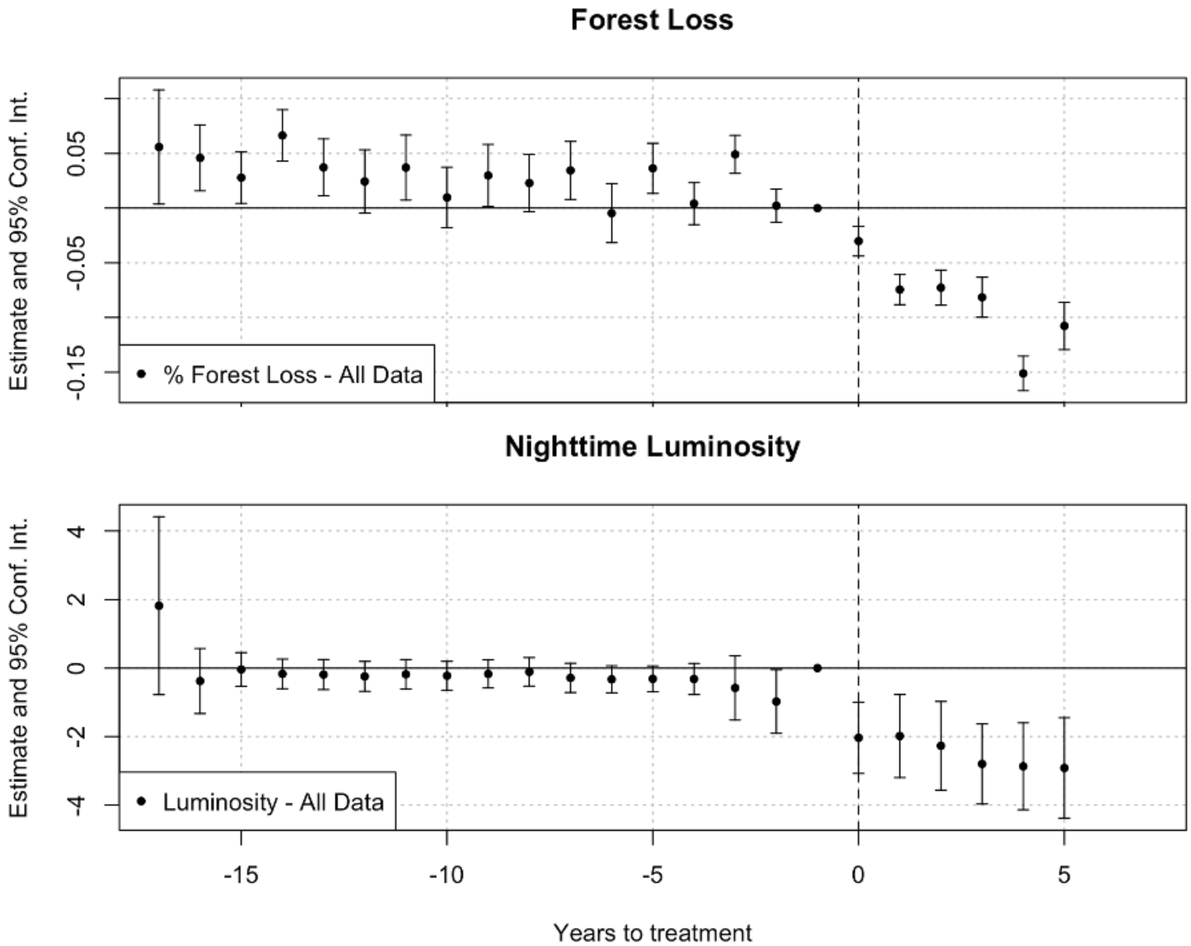

Figure 3: Yearly Event Study Coefficients for Forest Loss (top) and Nighttime Luminosity (bottom)

2.3.2 Outcomes by Urbanization Level

When splitting outcomes by urbanization level we find that impacts on land cover and population diverge between rural areas and more built-up semi-urban and urban regions. Rural areas saw essentially the same trend as the overall regressions for land cover, with forest cover increasing from 2000 to 2020 and crop cover declining. Rural areas also saw the highest population declines out of the urbanization levels but did not show significant declines in nighttime luminosity (Figure 5). Rural areas showed the most significant drops in forest loss, with drops in urban and semi-urban forest loss being less significant and consistent over the treatment period (Figure 6). Semi-urban areas showed increases in crop coverage from 2011 to 2019 and experienced slight declines in forest cover and forest loss. Semi-urban population and nighttime luminosity declined significantly. Urban areas showed a similar trend in land cover, with slight declines in forest cover from 2000 to 2020, declines in forest loss during food insecurity events, and increases in crop cover from 2011 to 2019. Urban nighttime luminosity declines were the largest out of the urbanization classes (Figure 7), but population significantly increased in these regions.

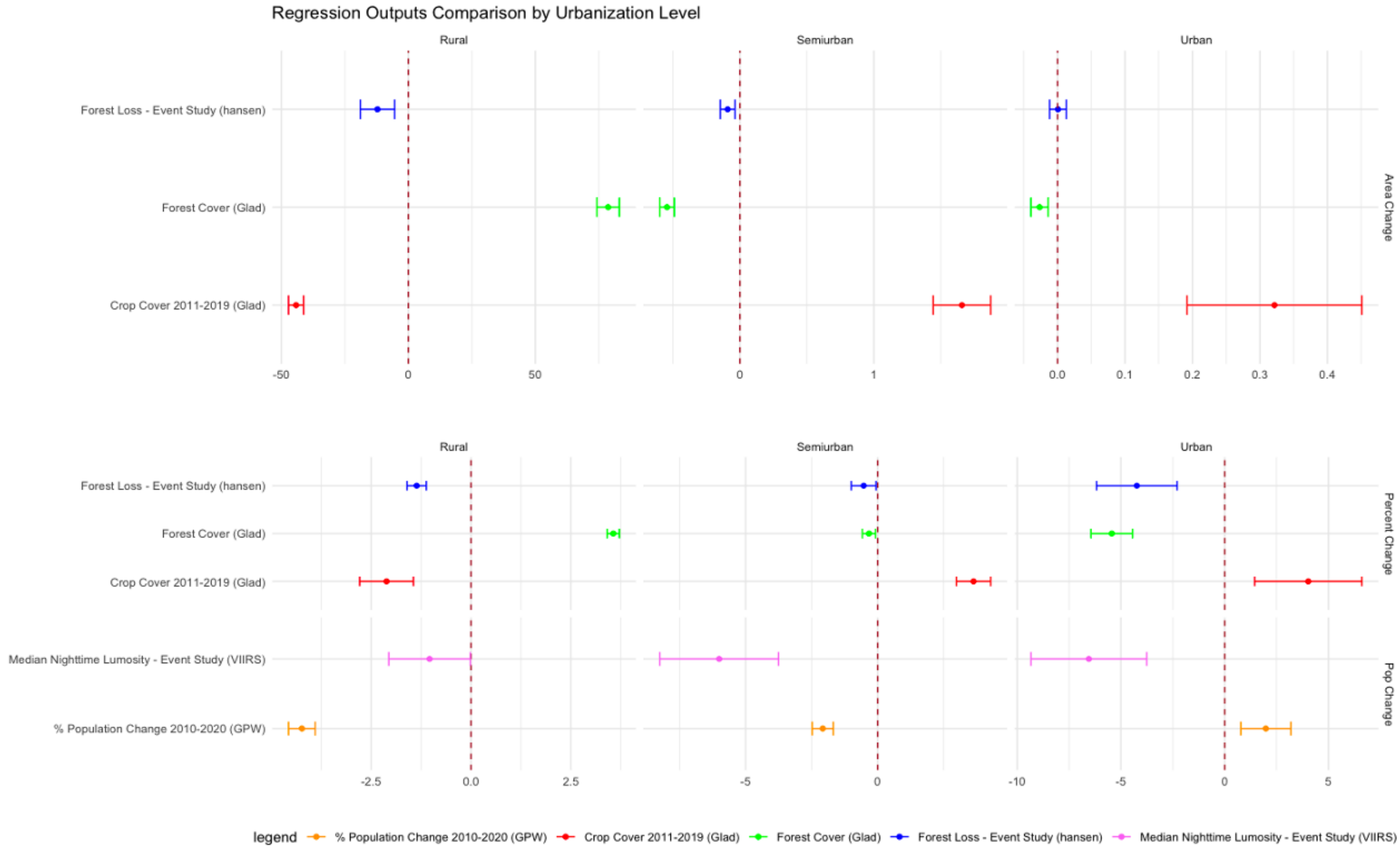

Figure 4: Event Study and Regression Outputs by Urbanization Level

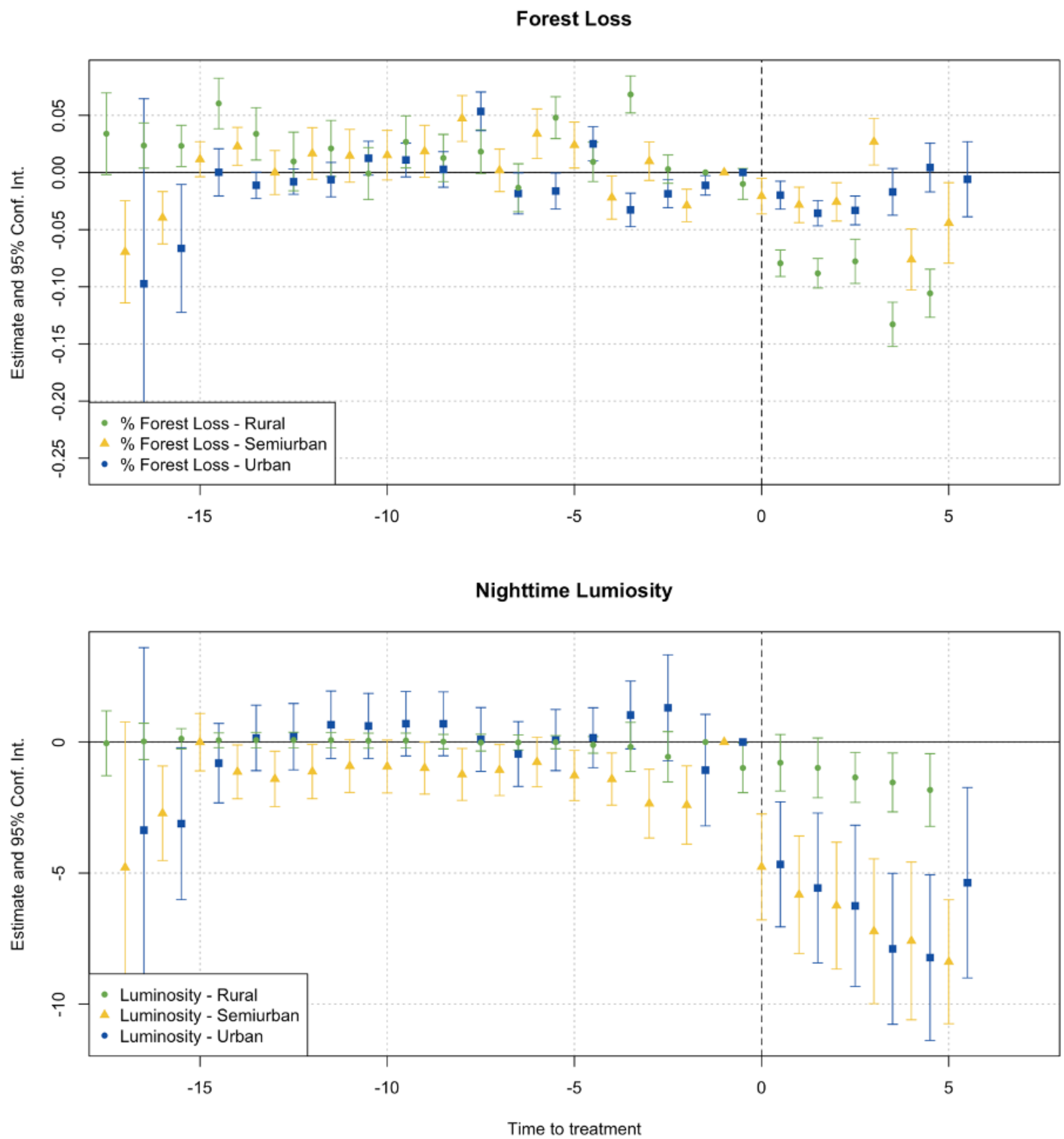

Figure 5: Yearly Event Study Coefficients for Forest Loss (top) and Nighttime Luminosity (bottom) by Built-up Level

2.3.3 Case Studies

Prior to Mozambique's 2016 food insecurity event, we see a prolonged spike in temperature and a dip in precipitation, with the Palmer drought severity index dipping to its lowest level right at the beginning of the food insecurity event in affected regions (SI Figure C6). We do not observe a spike in conflict events before the onset of the food insecurity event, although there is a moderate increase in staple food prices. Food insecurity levels continue to increase over the next year even as drought conditions improved, then fall dramatically in June 2017 such that the whole country becomes generally food secure (SI Figure C7). In Guatemala, a similar spike in temperatures and drop in Palmer drought severity index is observed, with the lowest drought index value coinciding with the onset of the food insecurity event. Food insecurity in Guatemala declined after June 2017 such that most of the country was generally food secure, although one or two regions still experienced an elevated level of food insecurity. Nigeria's trend diverged from this, with some signal of high temperatures before the onset of food insecurity but no concurrent drop in Palmer drought severity index. However, conflict events in the treated area of northeastern Nigeria rose sharply just before food insecurity increases and remained high through 2020. Additionally, food insecurity in the treated region remained high from 2013 through the end of the study period.

Land use changes in Mozambique following the food insecurity event showed increases in forest cover and crop cover, with crop cover gains being the most dramatic (Figure 6). Demographic impacts were more limited, with no observed change in nighttime luminosity, population, or urbanization level (Figure 7). When splitting results by rural, semi-urban, and urban change, we find that forest cover increased in rural areas but declined in semi-urban areas, whereas crop cover gains were seen across urbanization levels (Figure 8). Population and nighttime luminosity also diverge, with declines seen in rural areas but increases in urban areas. In semi-urban areas, population increased while nighttime luminosity declined over the study period.

Guatemala's food insecurity event was also correlated with some increases in forest cover and crop cover. Population increased slightly and nighttime luminosity and urbanization level declined (Figure 7). When splitting by urbanization level, we see that crop and forest cover changes occur almost entirely within rural areas, with small or no significant changes in semi-urban and urban regions. Nighttime luminosity consistently declines across urbanization levels. However, the population of rural areas increases while urban populations decline slightly (Figure 8).

In Nigeria, food insecurity led to increases in crop cover and declines in forest cover. Population went slightly up overall and nighttime luminosity declined compared to the control (Figure 7). Crop cover increases were limited to rural areas with semi-urban, and to a lesser extent urban areas, seeing declines in crop cover from 2011 to 2019. Nighttime luminosity increased in semi-urban areas but declined in urban areas, while population ticked up slightly in rural and urban areas (Figure 8).

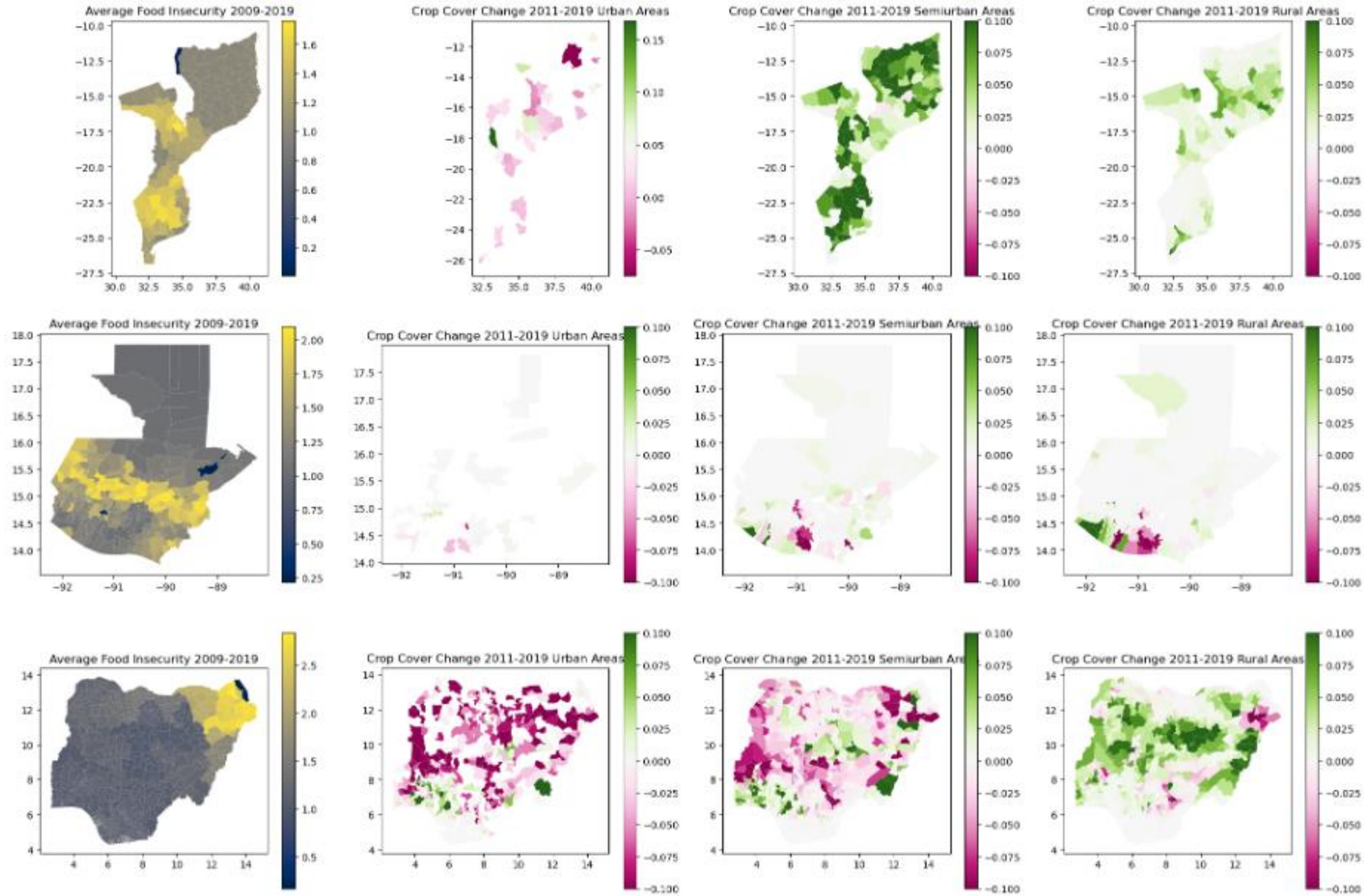

Figure 6: Mean Food Insecurity 2009-2019 and Crop Cover Percent Change 2011-2019 for Case Studies

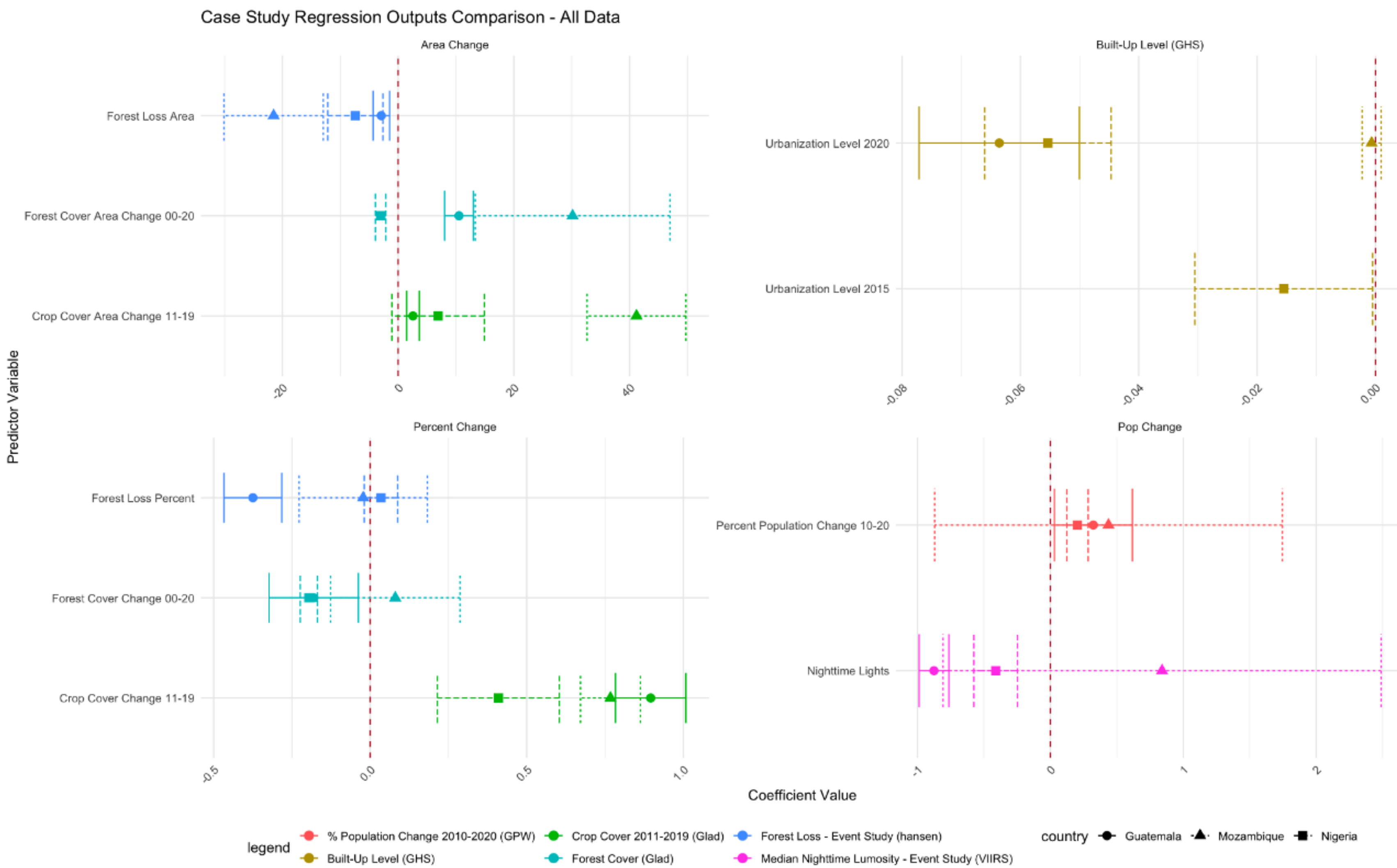

Figure 7: Coefficients of Case Study Regressions, by Country

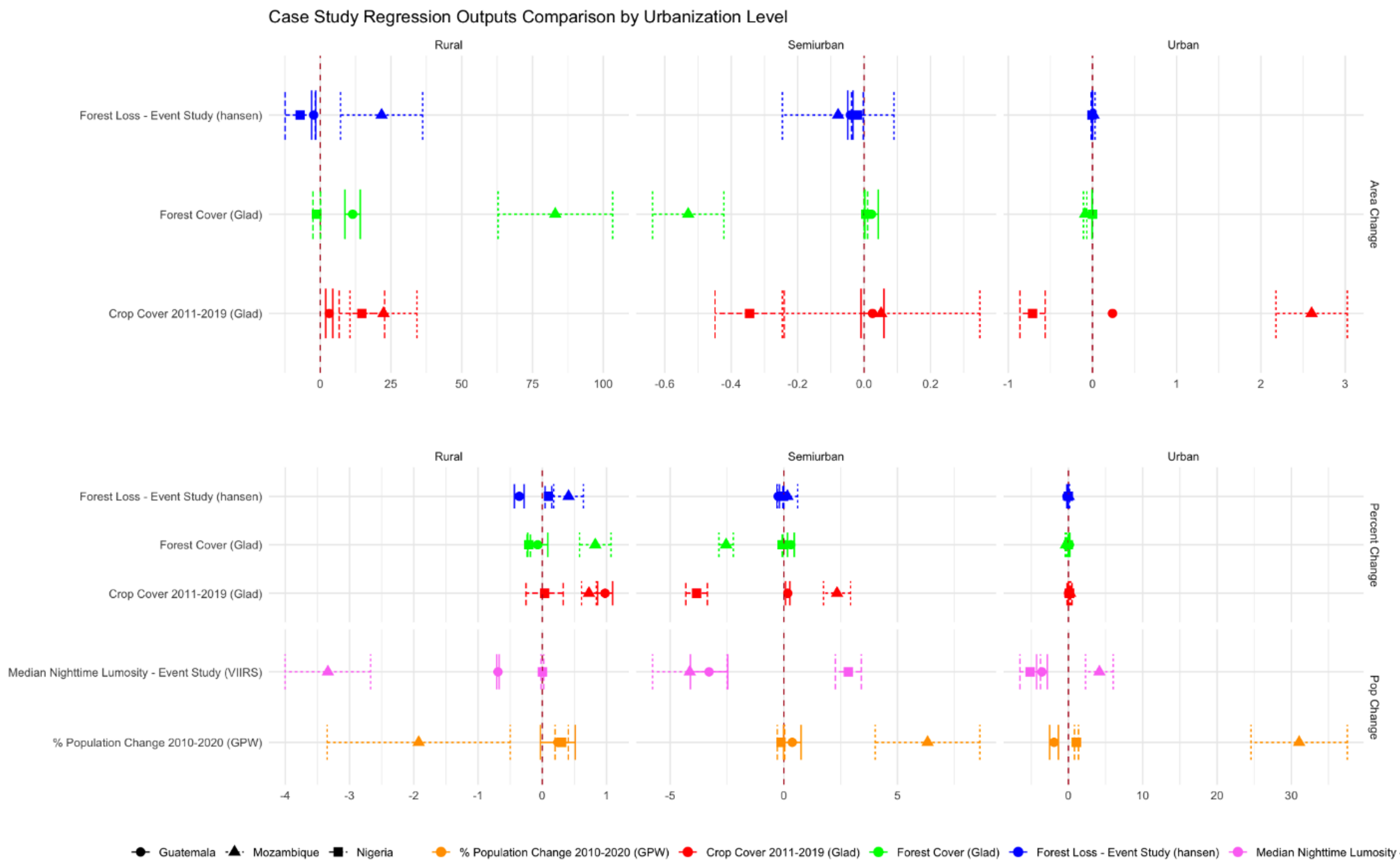

Figure 8: Coefficients of Case Study Regressions, by Country and Urbanization Level

2.4. Discussion

2.4.1 Drivers of LUC Trends

We find that food insecurity leads to overall drops in forest clearing, population, nighttime luminosity and crop cover and increases in forest cover in our study countries. These results suggest that food insecurity leads to less pressure on land for agriculture, either through outmigration of farming households or from households switching to off-farm employment. Observed population declines across each administrative unit and population increases in urban areas suggest that either of these pathways are plausible. This aligns with land rent theory and the classical trajectories of agricultural intensification, if we assume land scarcity across the study region. However, the degree of change detected in this study does not show widespread evidence of regime shifts, with only 3-4% changes in crop area and forest cover. Local land degradation may be occurring and leading to declines in crop cover, but if most cropland loss was due to land degradation, we would likely not see a concurrent rise in forest cover. These results suggest that food insecurity events disrupt rural livelihoods to a degree that impacts land cover at a regional scale. Smallholder farmers are highly vulnerable to shocks, and the countries assessed here are some of the more vulnerable regions in the world (61).

Land cover and population changes across urbanization levels point to significant differentiation in food insecurity impacts based on the economic contexts of a given location. Additionally, differential impacts suggest local movement of people and agricultural production from rural to semi-urban and urban areas. Rural areas see population declines, crop cover declines, and forest gains while urban areas see population growth, crop cover increases and forest loss, with semi-urban areas seeing similar but less pronounced trends to urban areas (Figure 5). Most of the smallholder-dominated landscapes in this study are within rural areas (15). These regions are generally far from markets and have lower access to labor and inputs, so a disruption to food production such as drought may be more likely to undermine the agricultural system and cause out-migration. Semi-urban and urban areas, even if they are smallholder-dominated, have more access to labor and technology like irrigation and fertilizers that can allow for the maintenance of some agricultural productivity during drought. Semi-urban and urban areas may be experiencing temporary ‘agricultural involution’ where food insecurity events cause increases in cropped area, labor, and inputs even while food production stagnates, whereas rural areas may be experiencing some amount of temporary agricultural crisis, where food production drops dramatically and households must result to adaptive strategies like migration or off-farm employment to maintain food access.

2.4.2 Contextual LUC Drivers in Case Studies

Across case studies, we see that regional contexts drive varying patterns of land use and demographic change. Mozambique showed large population growth in urban and semi-urban areas that experienced food insecurity alongside a decline in rural populations. This suggests that Mozambique's drought-induced food insecurity event is causing rural to urban migration within food insecure regions. At the same time, crop cover increased or remained constant across all urbanization levels compared to the control. This might be related to the duration of the food insecurity event. Two years of drought would cause temporary declines in land productivity, but a resulting drop in land rents may lead to extensification of agriculture after land productivity increases post-drought. Additionally, Mozambique is experiencing agricultural expansion overall (62), with increasing scrutiny of international agribusiness land-grabs across the country (63). The 2016/2017 drought may have increased smallholder displacement, facilitating the expansion of middle- to large-scale farming operations, but more grounded research on local agricultural systems and land tenure is needed to make any definitive claims.

Guatemala's food insecurity event was also driven by a temporary drought, which mostly resolved after a couple of years. Like Mozambique, Guatemala also showed slight increases in crop cover, generally concentrated in rural areas. We did not find reports of extensive land grabs or agribusiness expansion within the food insecure regions of Guatemala, suggesting that crop changes are primarily driven by smallholder activities. Guatemala and Mozambique's cases indicate that transitory disruptions to smallholder livelihoods from drought may not lead to the declines in crop cover seen in the overall results. It is possible that longer-term impacts may be necessary to see regional shifts in land use. The event studies on forest loss (Figure 3 and Figure 6) show that, when food insecurity events do reduce forest loss, impacts are primarily seen after the first year. Additionally, Guatemalan urban areas showed a small decline in population (approx. 2%) from 2010 to 2020 compared to the control. This suggests that drought is not driving large amounts of rural to urban movement in Guatemala, as is seen in Mozambique.

In Nigeria, conflict-driven food insecurity does not see resultant dramatic changes on land cover and even increases crop cover in some cases. We propose that the prolonged conflict experienced in northeastern Nigeria may lead to adaptation in place. There may not be suitable outmigration pathways for people to seek non-rural livelihoods, so expansion of food cropping could continue. Additionally, conflict would not reduce the productive capacity of the land in the way that drought would, meaning agricultural productivity would be maintained or could even increase if human labor inputs are not reduced. Under this scenario, there is no economic incentive for smallholders to reduce food production, so fields would likely only be abandoned if it is unsafe to do so. Smallholders or agribusiness have been shown to return or expand in post-conflict areas (64), suggesting that only the most prolonged and violent conflicts lead to lasting changes in the agricultural landscape.

Case study results diverged significantly from overall findings, likely because we chose cases where food insecurity is transitory or where regional contexts lead to specific land use outcomes. Many food insecure regions outside of the case studies are chronically food insecure, with the degree of insecurity increasing or declining at points through the study period due to climate or conflict drivers. These regions are more likely to experience regime shifts due to prolonged pressures on agricultural systems (6), leading to livelihood shifts away from agriculture and into urban and semi-urban areas, which we see in the overall results.

2.4.3 Limitations

The food insecurity data we use in this study is recorded at administrative unit level, so we cannot distinguish food insecurity differences at sub-administrative unit scales. It is likely that food insecurity is experienced to a different degree in urban, semi-urban and rural areas, making direct comparisons between these regions difficult. Additionally, the time steps of our forest cover, crop cover and population data often did not line up well with food insecurity events, meaning that impacts before and after food insecurity events may be driving some of the observed changes. Propensity score matching should remove some of this variability, but as we see in the Mozambique case study it may not account for trends in international agricultural investment and expansion. Finally, nighttime luminosity data covers two different datasets, with matching performed on CCNL data from 2000 to 2012, and analysis performed on VIIRS data from 2013 to 2020. This shift in datasets can produce bias because matching does not fully control for differences in the datasets. However, the event study analysis controls for pre-treatment level in the outcome variable, meaning that potential bias would mainly be introduced if trends varied across the datasets, which is unlikely in the overall data but may cause issues in the semi-urban and urban regions where there is more variability between the datasets.

2.5. Conclusion

We find that food insecurity events are important drivers of land use and demographic change, with food insecurity generally leading to shifts away from agriculture and resultant land use impacts. However, the specific mechanisms through which these occur are important, with long-term drought likely causing most of the observed land use shifts and conflict more predictive of demographic shifts. Theory on the stages of agricultural intensification suggest this is because drought leads to drops in land productivity, reducing the relative outputs of agriculture compared to other livelihood strategies. On the other hand, conflict reduces available labor inputs without impacting land productivity, incentivizing the extensification of agriculture, which allows for higher output per unit labor. The variability of impacts across urbanization levels provides evidence for land rent mechanisms of change as well, with agricultural losses in rural areas coinciding with gains in semi-urban and urban areas. This reallocation of agricultural labor indicate that food insecurity events push smallholder systems to become more aligned with markets, increasing the value and use of cropland near markets and decreasing the value and use of more remote cropland. The observation that multi-year food insecurity events lead to greater land-use change impacts also provides evidence for regime shifts in land use systems across this study. Regime shift impacts indicate that many smallholder-dominated systems are highly vulnerable to food insecurity events, especially those driven by long-term drought. While these impacts are hard to avoid, investments in natural and cultural capital through practices like soil conservation and agroforestry can support long-term resilience of agricultural systems to change (6,65). Since this study looks at food insecurity rather than the underlying causes of drought and conflict, we implicitly filter out smallholder-dominated regions that are resilient to these disruptions from our treatment group.

Overall, we find that land productivity and abundance of labor explain much of the changes to land use due to food insecurity events. The underlying vulnerability of agricultural systems mediates whether severe or prolonged disturbance leads to regime shifts in land use practices, and underlying changes may emerge in the reorientation of agriculture to export markets and shifts towards more resilient, lower labor farming practices. We show that these theories can be applied generally across the study, with regional or national dynamics leading to context-dependent outcomes. Applying and testing the efficacy of these Land Use Change theories empirically is necessary if researchers are going to understand and forecast how climate, demographics, and economic forces continue to shape the terrestrial system and the people that rely on it into the future.

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Ch2 Appendix A - Descriptive Statistics

Source	Variable	Mean	Sd	Min	Max	Se
(44)	Movement Difficulty	0.013	0.009	0.0001	0.080	0.013
(42)	pop00	163160	266838.8	33.652	4064403.9	163160
	pop05	187070	308666.2	36.078	4789357.9	187070
	pop10	215054	357590.3	40.392	5615502.3	215054
	pop15	246828	414931.6	46.335	6478505	246828
	pop20	281878	483370.5	53.538	7341734.8	281878
(48)	Annual Mean Temp.	237.077	38.339	103.528	303.794	237.077
	Mean Diurnal Range	121.275	22.067	63.976	193.400	121.275
	isothermality	65.654	9.016	44.877	90.984	65.654
	Temp. Seasonality	1879.77	959.615	207.437	6705.554	1879.77
	Max Temp. Warmest Mo	329.64	46.835	179.341	459.893	329.64
	Min Temp. Coldest Mo	141.28	47.277	1.161	227.335	141.28
	Annual Precipitation	1083.14	707.341	5.079	4250.028	1083.14
	Precip. Wettest Mo	220.80	114.482	3.160	711.426	220.80
	Precip. Driest Mo	9.141	15.085	0	123.452	9.141
	Precip. Seasonality	91.423	29.314	25.939	207.025	91.423
(41)	crp03	0.146	0.223	0	0.957	0.146
	crp07	0.151	0.230	0	0.960	0.151
	crp11	0.158	0.234	0	0.962	0.158
	crp15	0.166	0.237	0	0.964	0.166
	crp19	0.174	0.238	0	0.967	0.174
	glad00	0.294	0.310	0	0.989	0.294
	fc20	0.283	0.305	0	0.985	0.283
	gladfh00	3.131	3.891	0	21.1866	3.131
	fh20	3.028	3.795	0	20.313	3.028
(54)	ghs_2000	12.774	3.466	10.008	30	12.774
	ghs_2015	13.346	3.839	10.009	30	13.346
	ghs_2020	13.596	3.980	10.009	30	13.596
(43)	ttc20k	105.636	244.230	0	4718.972	105.636
(40)	gfw_forestcover00	18.348	19.768	0	91.752	18.348
	hansenLoss_total	0.013	0.043	0	1.011	0.013
(66)	Baseline water risk	3.0416	0.757	0	4	3.0416
(46)	CCNL_nighttimeLights	1.906	8.021	-0.112	132.370	1.906
(67)	VIIRS_nighttimeLights	14.182	475.5	0	37033.3	1.364
(39)	food_insecurity_level	0.992	0.862	0	5.000	0.992
(49)	Political.violence	1.8236	13.978	0	913	1.8236
	Demonstrations	0.4560	3.212	0	205	0.4560
	StrategicDevel	0.168	1.393	0	95	0.168
(52)	Food_usd/kg	0.375	0.167	0	1.068	0.0005
(51)	pdsi	-7.491	113.766	-1384.6	1076.3	-7.491
(50)	temperature_2m	44.257	105.813	0	308.690	44.257
	total_precip_sum	0.067	0.260	0	5.081	0.067

SI Table A1: Summary Statistics - All Administrative Units

Source	Variable	Mean	Sd	Min	Max	Se
(44)	Movement Difficulty	0.0	0.0	0.0	0.1	0.0
(42)	pop00	131303.8	300101.0	1576.7	4064403.8	1289.3
	pop05	151366.1	349747.1	1824.8	4789357.9	1502.6
	pop10	174904.8	407707.0	2107.8	5615502.3	1751.6
	pop15	201821.3	475649.3	2406.7	6478505.0	2043.5
	pop20	231504.9	557309.2	2702.8	7341734.8	2394.3
(48)	Annual Mean Temp.	226.3	41.2	103.5	303.8	0.2
	Mean Diurnal Range	125.6	19.8	70.4	193.4	0.1
	isothermality	64.2	7.9	45.2	89.7	0.0
	Temp. Seasonality	2136.0	958.0	298.6	6606.4	4.1
	Max Temp. Warmest Mo	322.0	47.8	179.3	459.9	0.2
	Min Temp. Coldest Mo	124.3	47.9	1.2	224.8	0.2
	Annual Precipitation	847.3	735.0	21.2	4250.0	3.2
	Precip. Wettest Mo	180.2	127.8	6.2	711.4	0.5
	Precip. Driest Mo	8.0	15.5	0.0	120.4	0.1
	Precip. Seasonality	93.5	26.3	25.9	180.8	0.1
(41)	crp03	0.1	0.1	0.0	0.9	0.0
	crp07	0.1	0.2	0.0	0.9	0.0
	crp11	0.1	0.2	0.0	0.9	0.0
	crp15	0.1	0.2	0.0	0.9	0.0
	crp19	0.1	0.2	0.0	0.9	0.0
	glad00	0.2	0.3	0.0	1.0	0.0
	fc20	0.2	0.3	0.0	1.0	0.0
	gladfh00	2.9	4.4	0.0	21.2	0.0
	fh20	2.8	4.3	0.0	20.3	0.0
(54)	ghs_2000	12.1	2.2	10.1	30.0	0.0
	ghs_2015	12.5	2.5	10.1	30.0	0.0
	ghs_2020	12.7	2.7	10.2	30.0	0.0
(43)	ttc20k	130.0	249.6	0.0	3465.6	1.1
(40)	gfw_forestcover00	16.6	22.5	0.0	90.9	0.1
	hansenLoss_total	0.02	0.4	0.0	0.79	0.0
(66)	Baseline water risk	3.1	0.9	0.0	4.0	0.0
(46)	CCNL_nighttimeLights	1.2	6.2	0.0	130.2	0.0
(67)	VIIRS_nighttimeLights	2.199	23.97	0	927.95	0.11
(39)	food_insecurity_level	1.2	1.1	0.0	5.0	0.0
(49)	Political.violence	3.1	20.5	0.0	913.0	0.1
	Demonstrations	0.4	2.9	0.0	169.0	0.0
	StrategicDevel	0.3	2.0	0.0	95.0	0.0
(52)	Food_usd/kg	0.41	0.19	0	1.033	0.0009
(51)	pdsi	-8.7	124.5	-1384.6	1076.3	0.5
(50)	temperature_2m	53.4	114.2	0.0	308.7	0.5
	total_precip_sum	0.1	0.3	0.0	4.7	0.0

SI Table A2: Summary Statistics - Treated (unmatched)

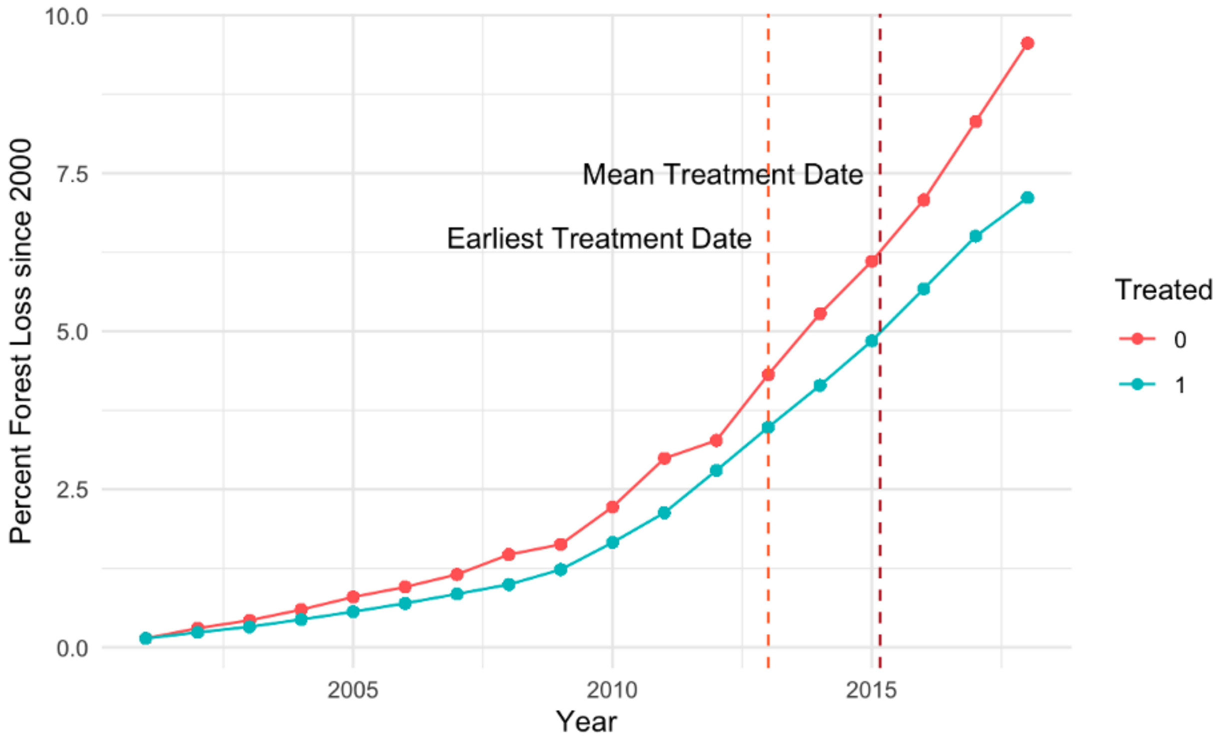
Source	Variable	Mean	Sd	Min	Max	Se
(44)	Movement Difficulty	0.0	0.0	0.0	0.1	0.0
(42)	pop00	187041.8	236084.1	33.7	2944096.5	878.2
	pop05	213835.9	270788.9	36.1	3450899.9	1007.3
	pop10	245153.6	311456.2	40.4	4008175.6	1158.6
	pop15	280567.8	359132.0	46.3	4621390.1	1335.9
	pop20	319641.6	415496.0	53.5	5286211.5	1545.6
(48)	Annual Mean Temp.	245.1	33.9	108.6	297.6	0.1
	Mean Diurnal Range	118.0	23.1	64.0	184.8	0.1
	isothermality	66.8	9.6	44.9	91.0	0.0
	Temp. Seasonality	1687.7	914.9	207.4	6705.6	3.4
	Max Temp. Warmest Mo	335.4	45.3	183.9	446.2	0.2
	Min Temp. Coldest Mo	154.1	42.5	12.4	227.3	0.2
	Annual Precipitation	1260.0	630.4	5.1	3740.3	2.3
	Precip. Wettest Mo	251.3	92.3	3.2	648.6	0.3
	Precip. Driest Mo	10.0	14.7	0.0	123.5	0.1
	Precip. Seasonality	89.8	31.3	30.1	207.0	0.1
(41)	crp03	0.2	0.3	0.0	1.0	0.0
	crp07	0.2	0.3	0.0	1.0	0.0
	crp11	0.2	0.3	0.0	1.0	0.0
	crp15	0.2	0.3	0.0	1.0	0.0
	crp19	0.2	0.3	0.0	1.0	0.0
	glad00	0.3	0.3	0.0	1.0	0.0
	fc20	0.3	0.3	0.0	1.0	0.0
	gladfh00	3.3	3.5	0.0	18.9	0.0
	fh20	3.2	3.4	0.0	18.3	0.0
(54)	ghs_2000	13.3	4.1	10.0	30.0	0.0
	ghs_2015	14.0	4.5	10.0	30.0	0.0
	ghs_2020	14.3	4.6	10.0	30.0	0.0
(43)	ttc20k	87.3	238.5	0.0	4719.0	0.9
(40)	gfw_forestcover00	19.6	17.3	0.0	91.8	0.1
	hansenLoss_total	0.02	0.05	0.0	1.0	0.0
(66)	Baseline water risk	3.0	0.7	1.6	4.0	0.0
(46)	CCNL_nighttimeLights	2.4	9.1	-0.1	132.4	0.0
(67)	VIIRS_nighttimeLights	21.668	605.7	0	37033.3	2.21
(39)	food_insecurity_level	0.8	0.6	0.0	4.0	0.0
(49)	Political.violence	0.8	5.0	0.0	318.0	0.0
	Demonstrations	0.5	3.4	0.0	205.0	0.0
	StrategicDevel	0.1	0.7	0.0	38.0	0.0
(52)	Food_usd/kg	0.357	0.145	0	1.068	0.0005
(51)	pdsi	-6.6	105.0	-1130.8	908.4	0.4
(50)	temperature_2m	37.4	98.6	0.0	308.4	0.4
	total_precip_sum	0.1	0.3	0.0	5.1	0.0

SI Table A2: Summary Statistics - Untreated (unmatched)

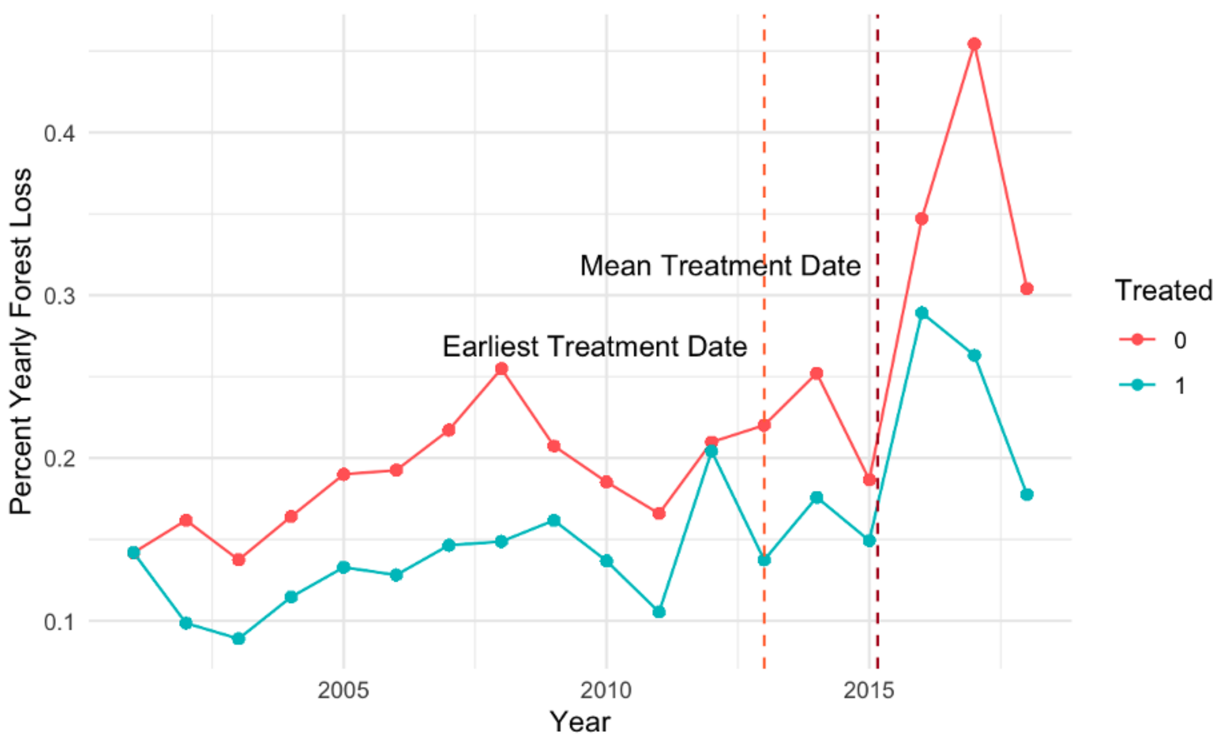
Country	Dominant Staple Food	Date Range of Data	Mean Value usd/kg
Burundi	Maize	2009-2023	0.38
Burkina Faso	Sorghum	2006-2023	0.30
Central African Republic	Cassava	2004-2023	0.38
Democratic Republic of the Congo	Cassava	2009-2022	0.51
Ethiopia	Teff	2000-2022	0.59
Guinea	Rice	2022-2023	0.70
Guatemala	Maize	2000-2023	0.36
Haiti	Rice	2023	0.83
Kenya	Maize	2006-2023	0.29
Malawi	Maize	2007-2023	0.23
Mozambique	Maize	2000-2023	0.28
Mauritania	Wheat	2003-2023	0.55
Niger	Sorghum	2000-2023	0.38
Nigeria	Millet	2004-2023	0.40
Rwanda	Beans	2008-2023	0.57
South Sudan	Sorghum	2011-2023	0.50
Somalia	Maize	2000-2023	0.37
Sudan	Sorghum	2003-2023	0.51
Chad	Sorghum	2002-2023	0.32
Tanzania	Maize	2006-2023	0.27
Uganda	Maize	2006-2023	0.27
Yemen	Wheat	2015-2023	0.49
Zambia	Maize	2004-2023	0.21
Zimbabwe	Maize	2004-2023	0.23

SI Table A4: Dominant Staple Foods by Country

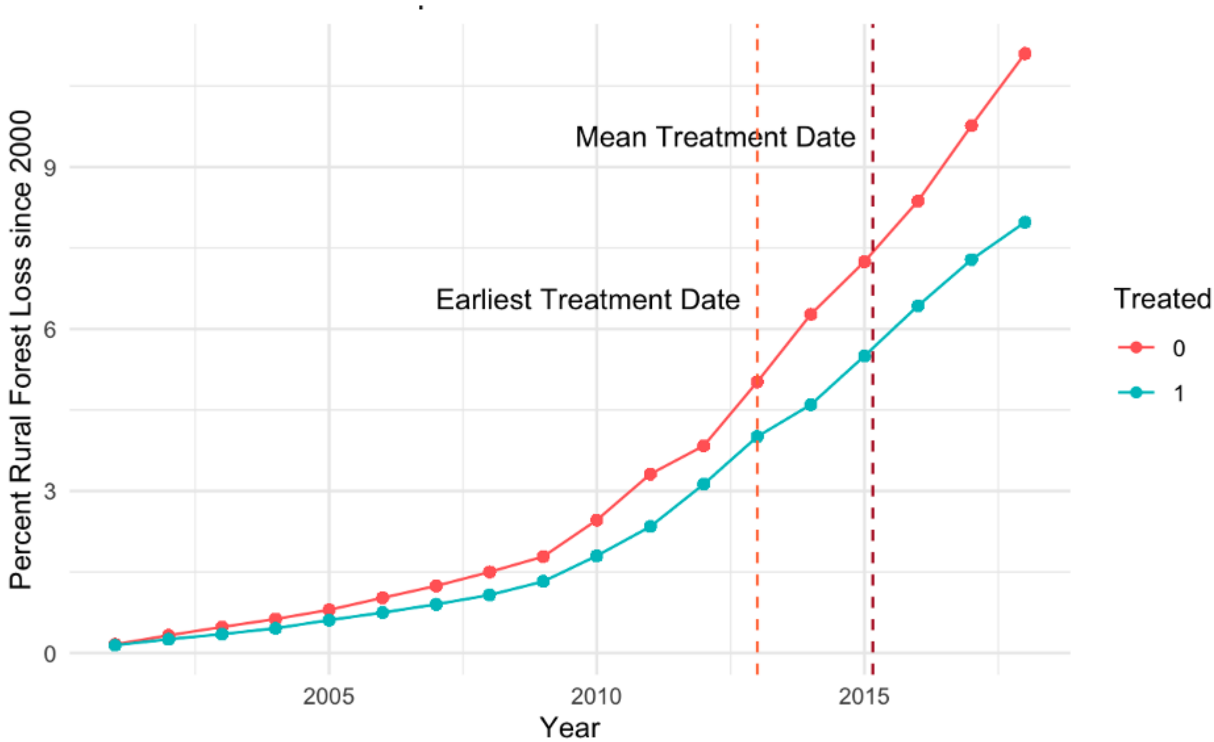
CH2 Appendix B - Parallel Trends Visualizations



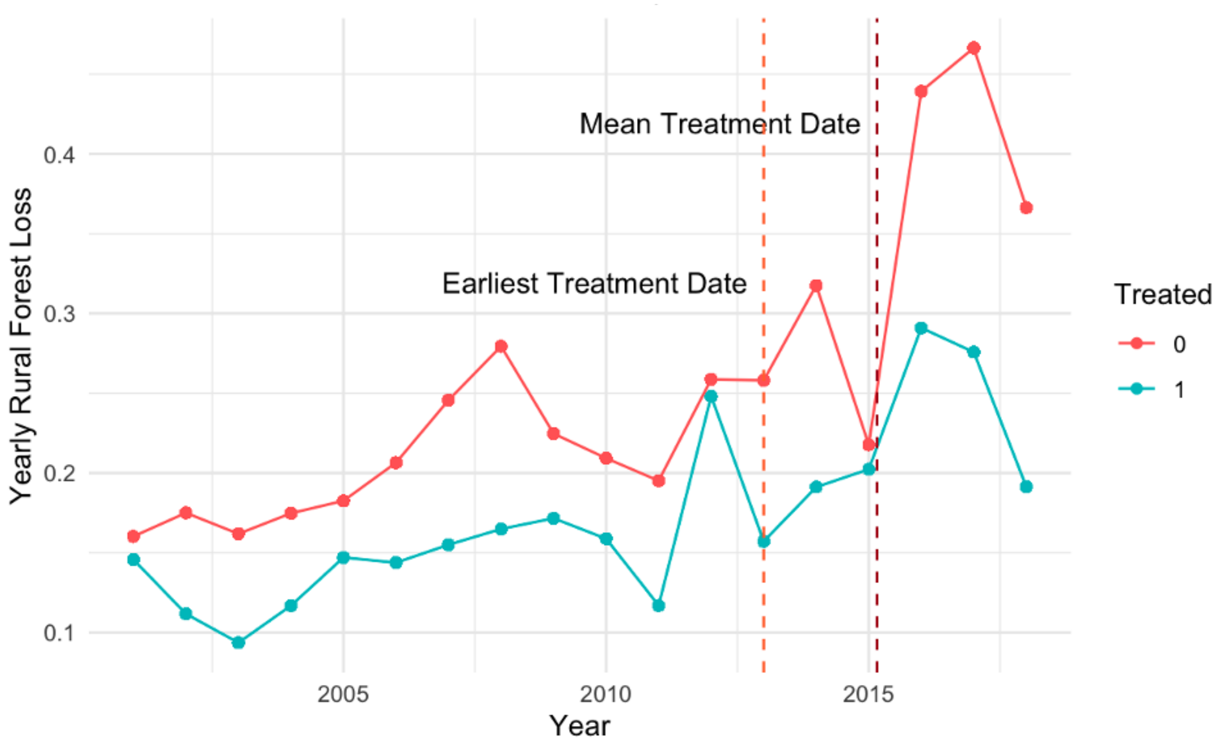
SI Figure B1: Parallel Trends Visualization for Cumulative Forest Loss



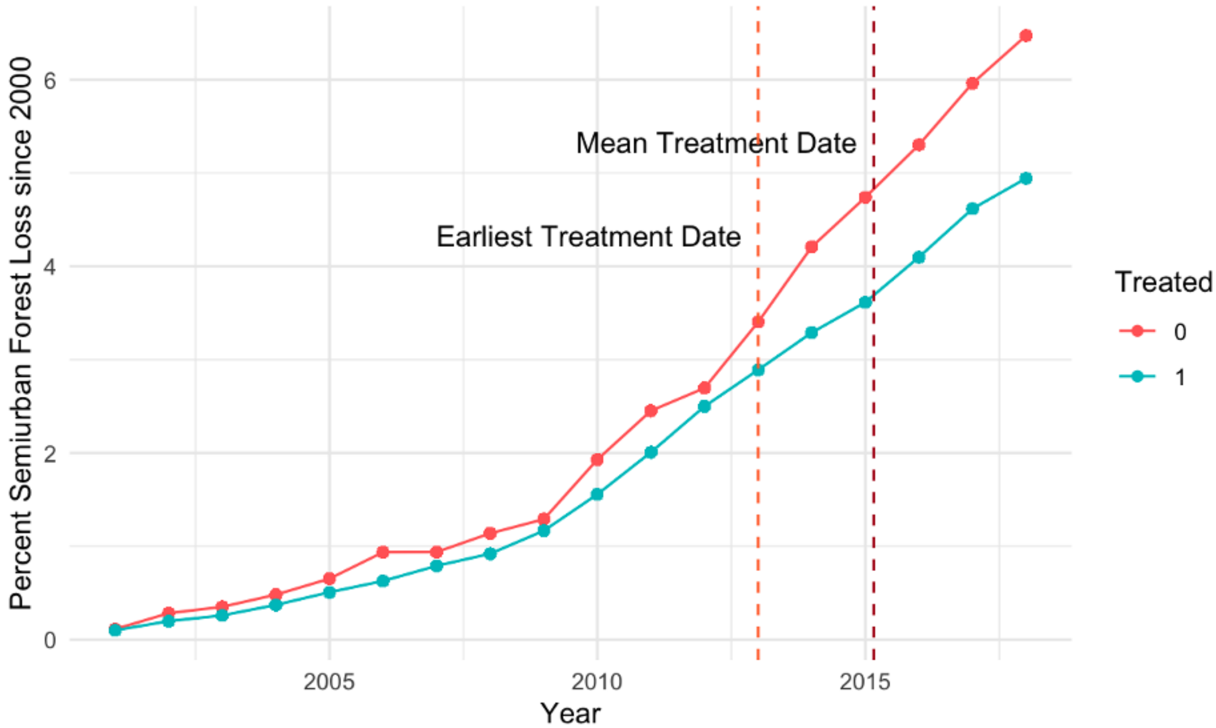
SI Figure B2: Parallel Trends Visualization for Yearly Forest Loss



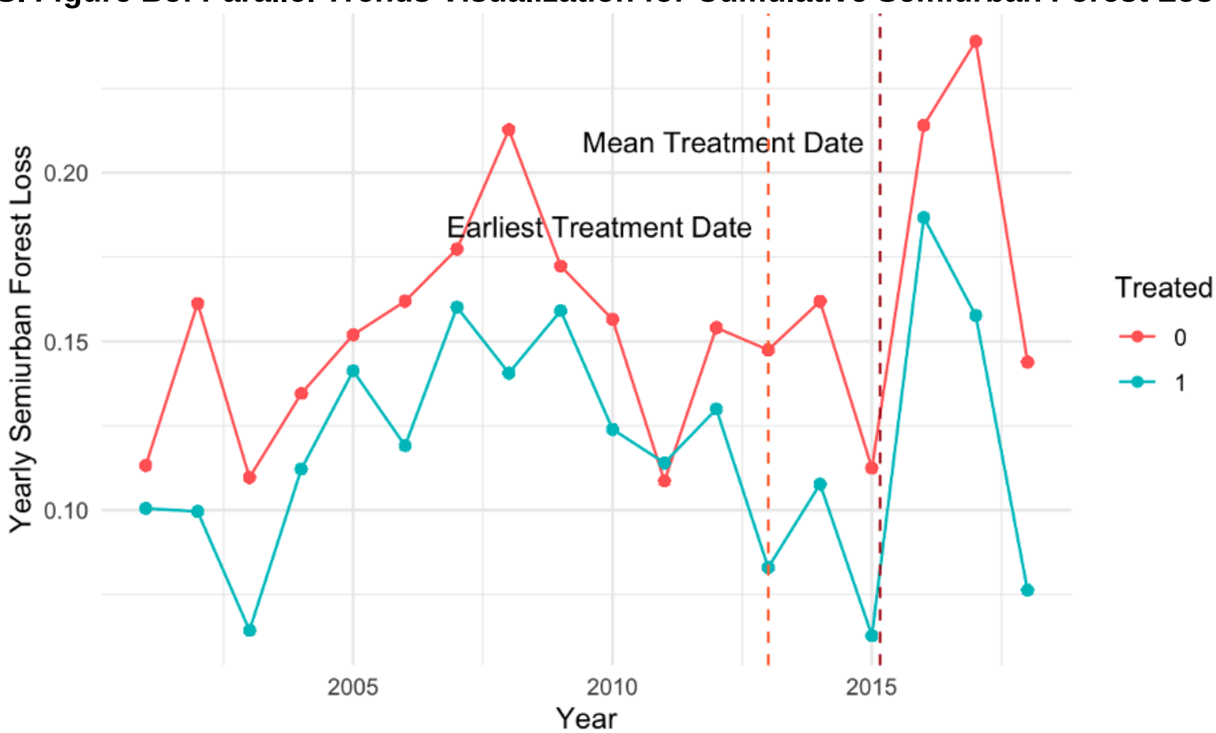
SI Figure B3: Parallel Trends Visualization for Cumulative Rural Forest Loss



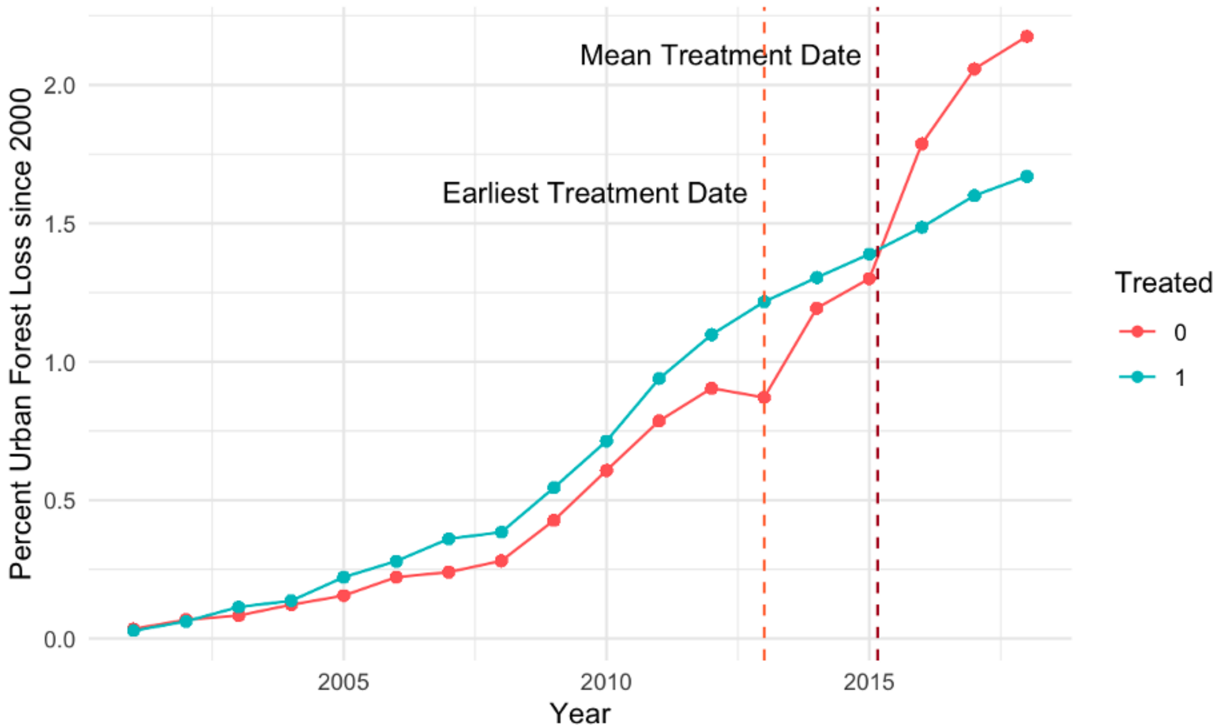
SI Figure B4: Parallel Trends Visualization for Yearly Rural Forest Loss



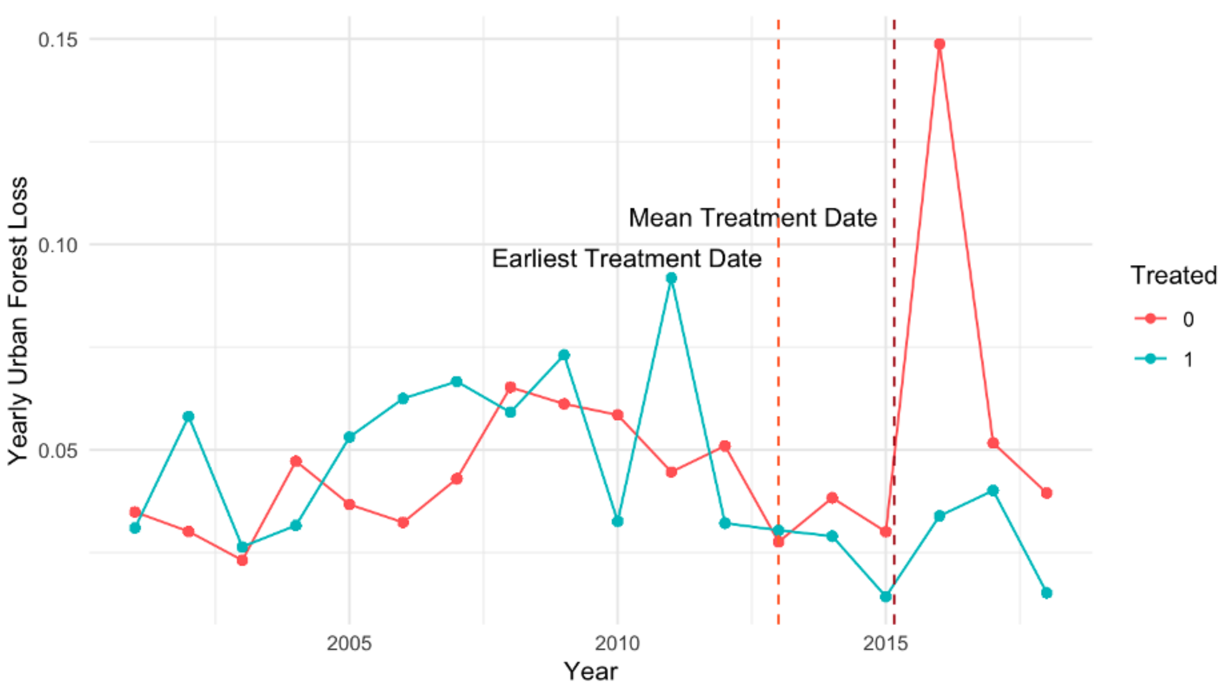
SI Figure B5: Parallel Trends Visualization for Cumulative Semiurban Forest Loss



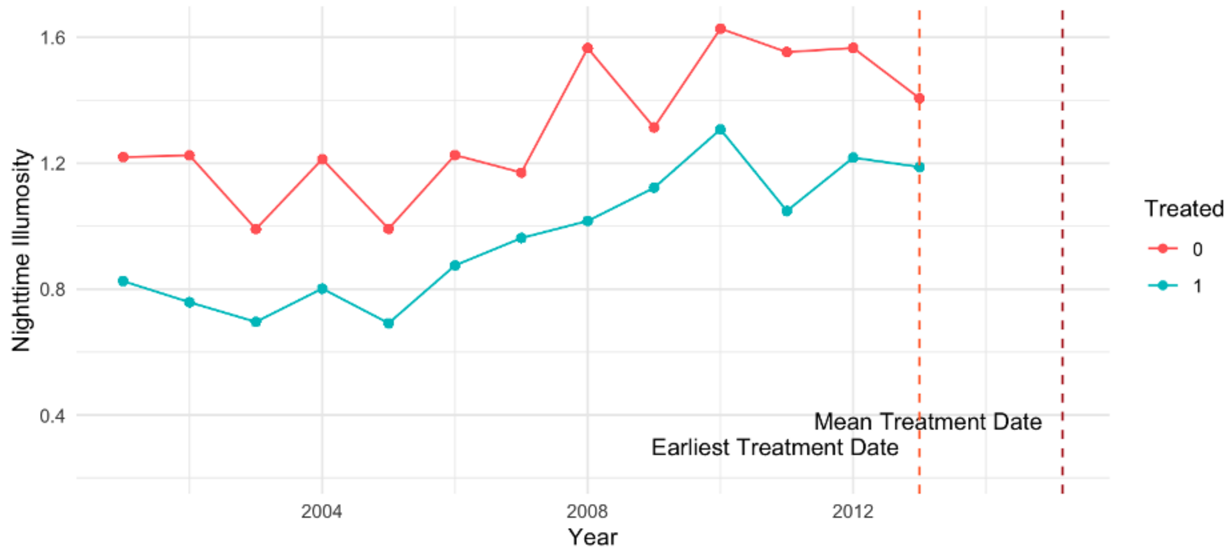
SI Figure B6: Parallel Trends Visualization for Yearly Semiurban Forest Loss



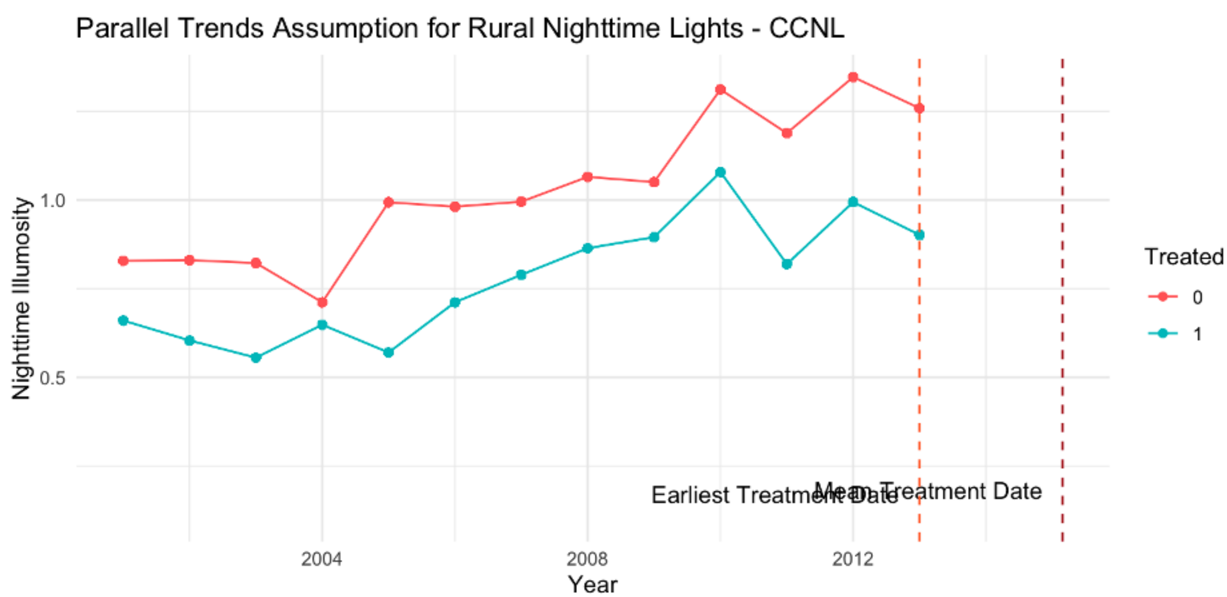
SI Figure B7: Parallel Trends Visualization for Cumulative Urban Forest Loss



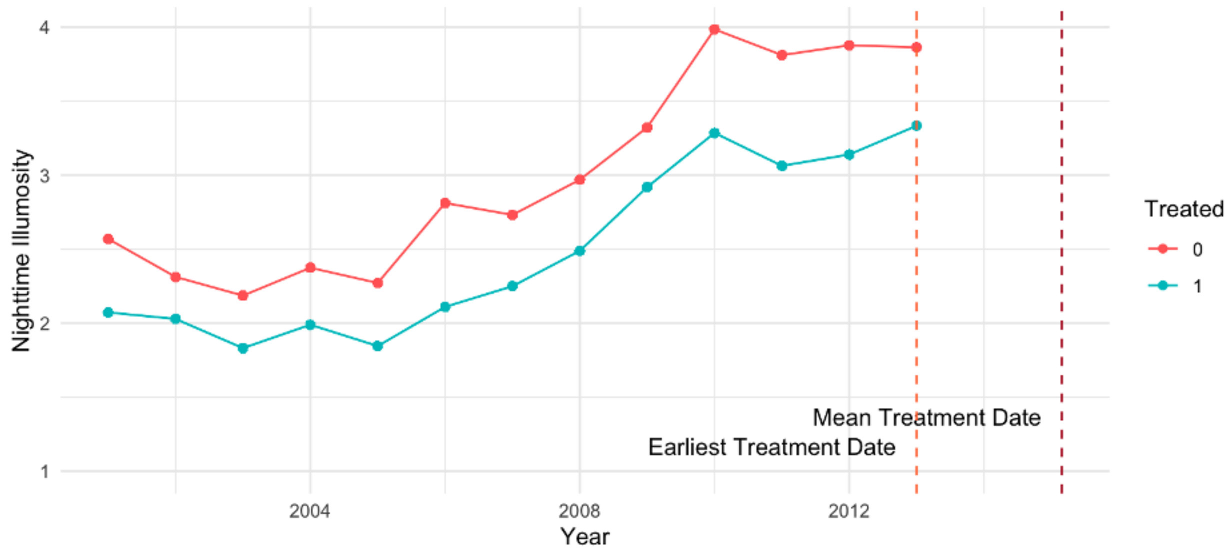
SI Figure B8: Parallel Trends Visualization for Yearly Urban Forest Loss



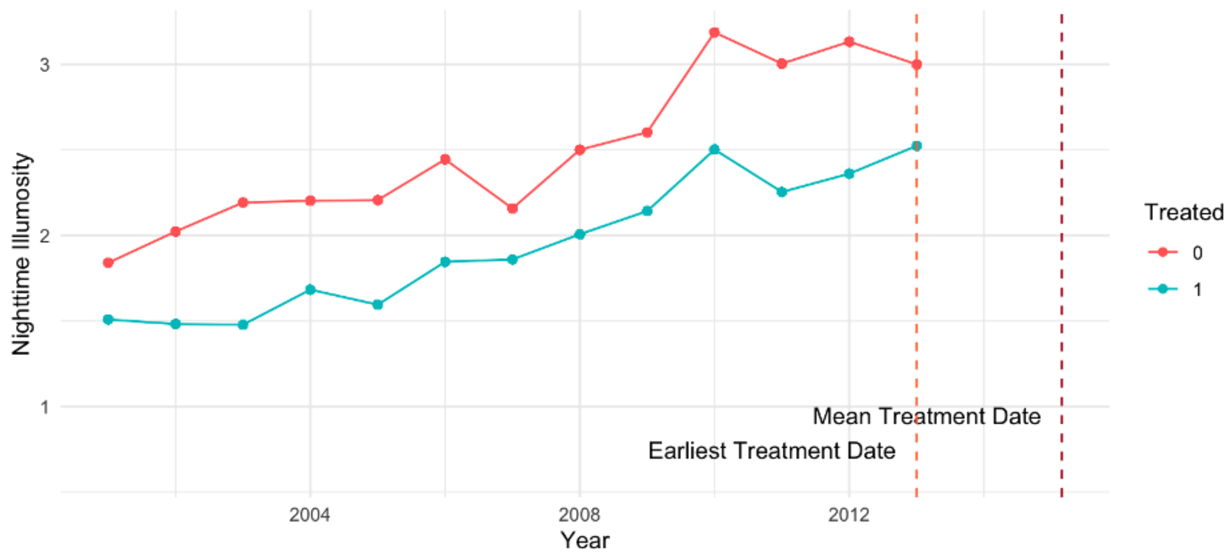
SI Figure B9: Parallel Trends Visualization for Yearly Nighttime Lights (CCNL)



SI Figure B10: Parallel Trends Visualization for Yearly Rural Nighttime Lights (CCNL)

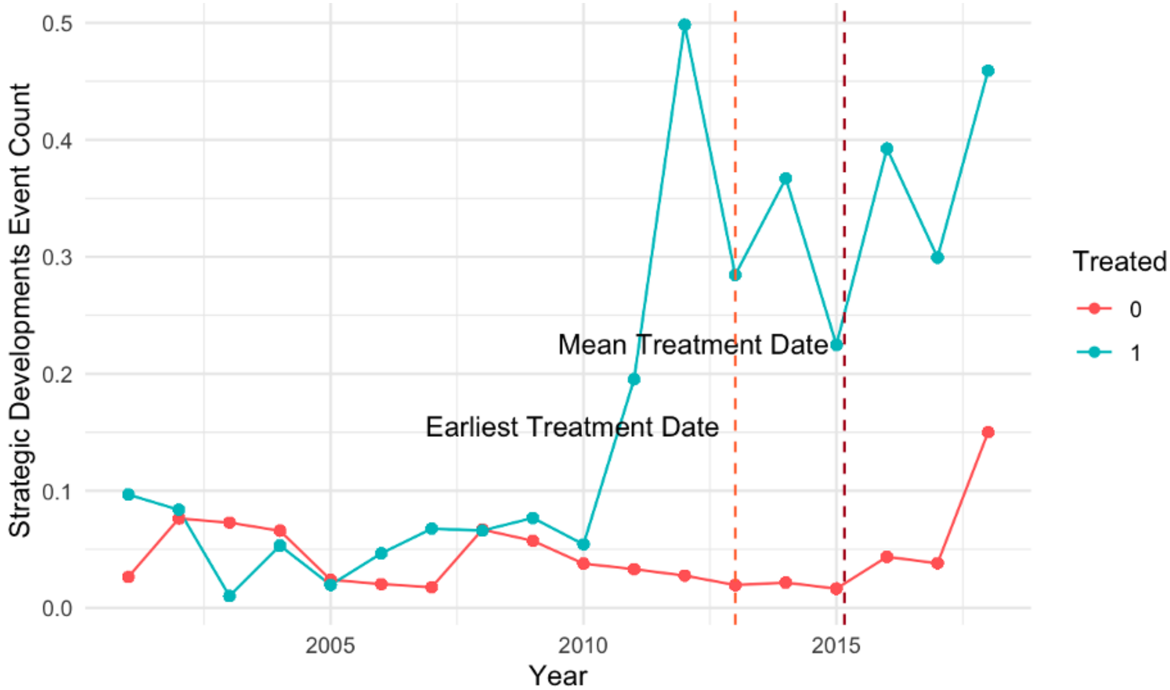


SI Figure B11: Parallel Trends Visualization for Yearly Semiurban Nighttime Lights (CCNL)

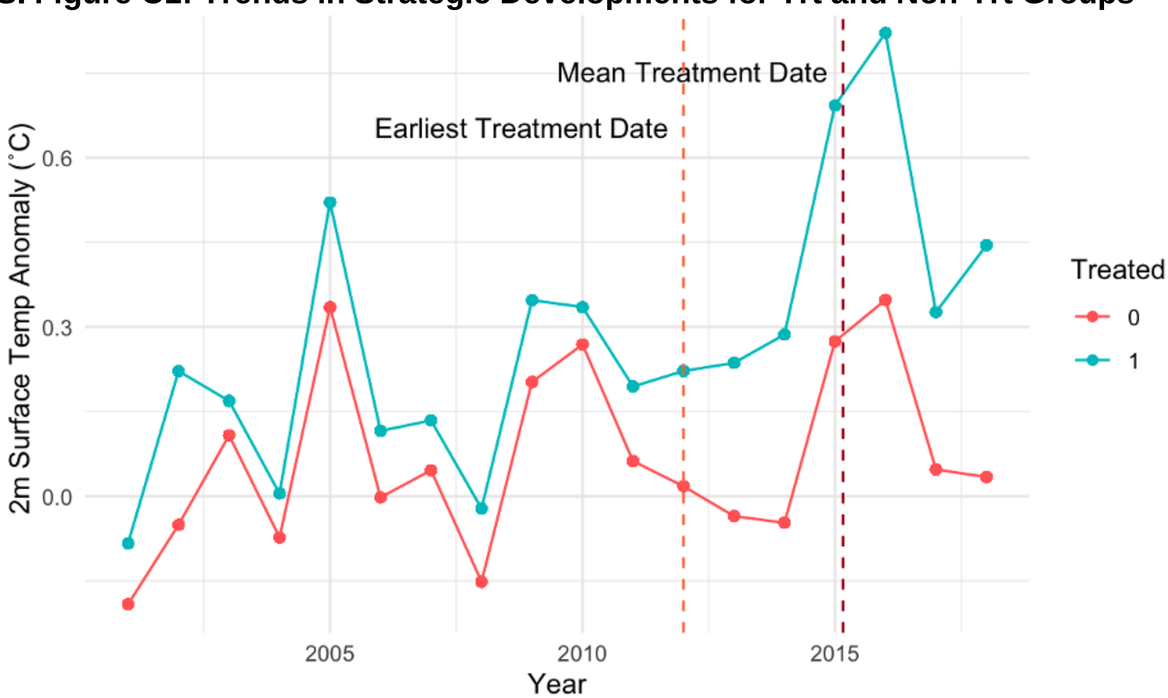


SI Figure B12: Parallel Trends Visualization for Yearly Urban Nighttime Lights (CCNL)

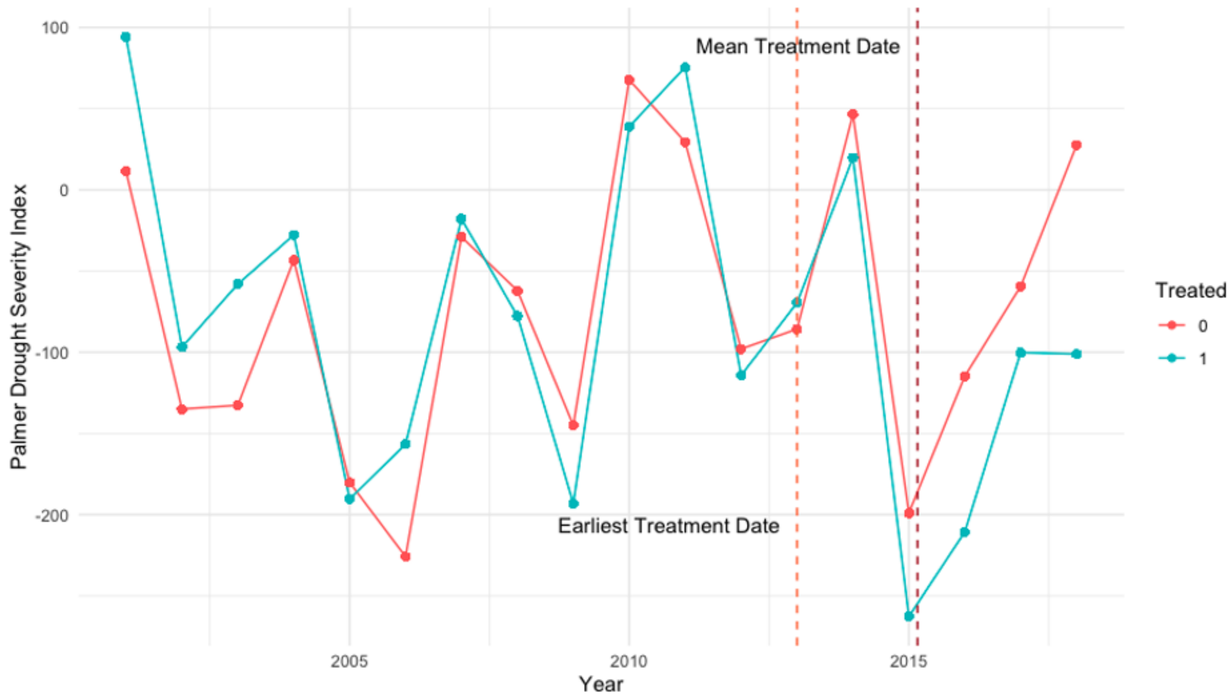
CH2 Appendix C: Exploring Drivers of Food Insecurity (All Data)



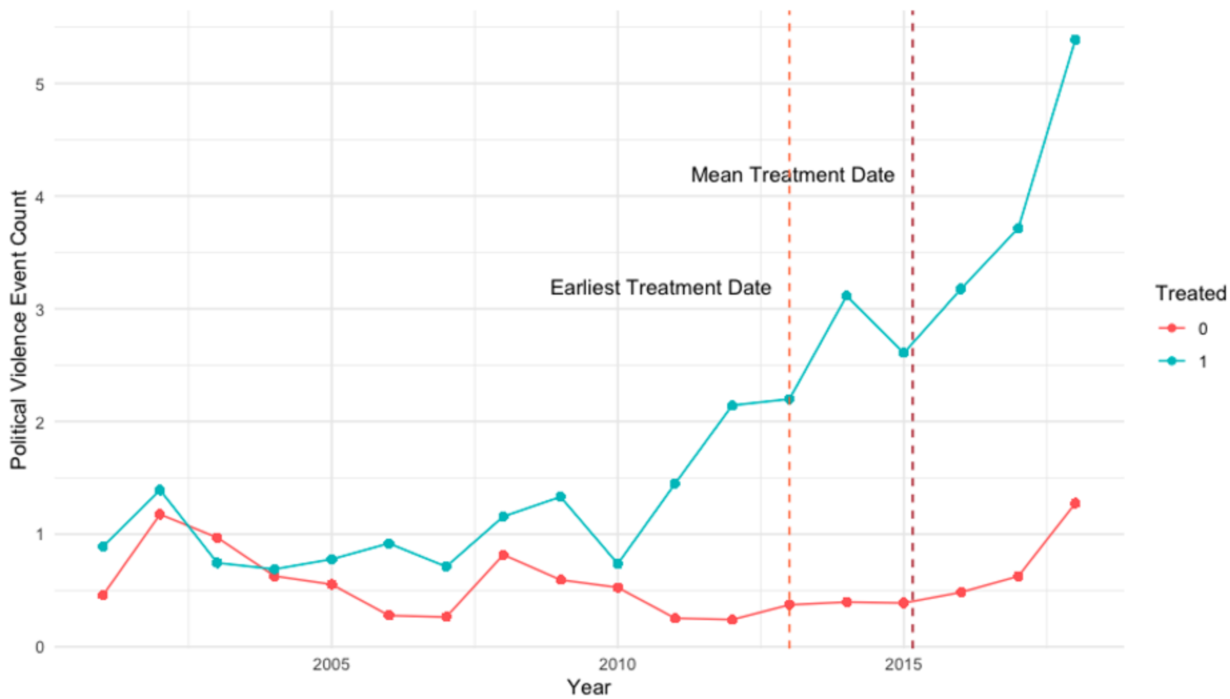
SI Figure C1: Trends in Strategic Developments for Trt and Non-Trt Groups



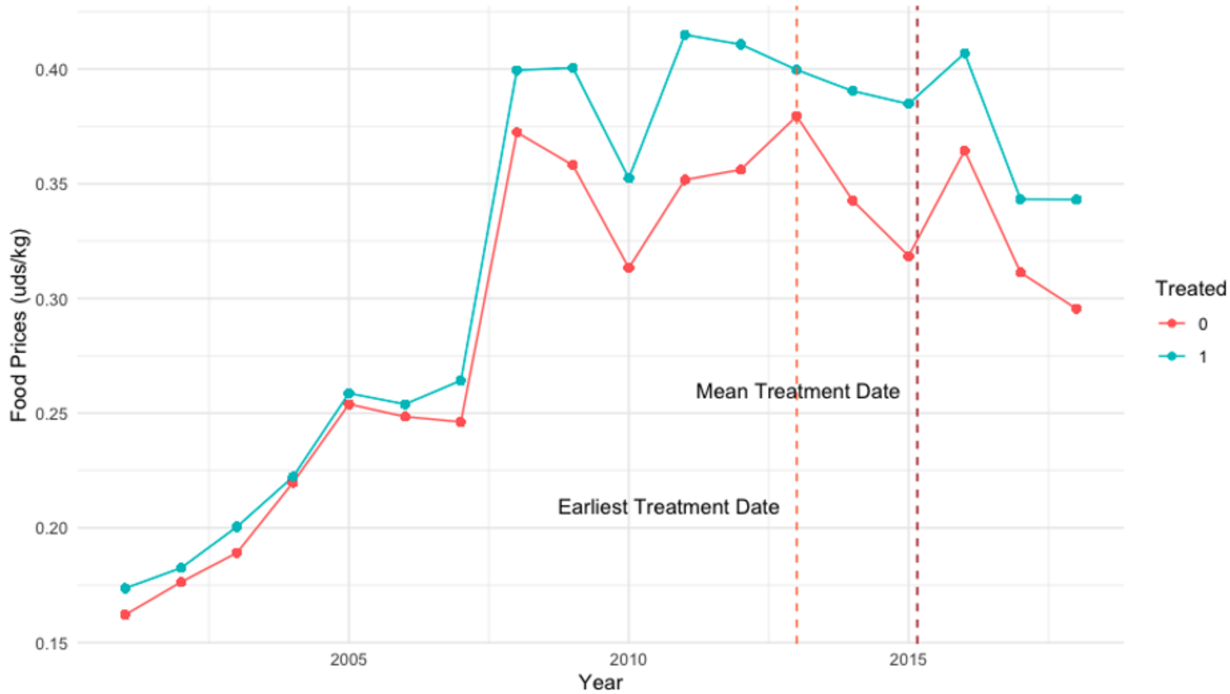
SI Table C2: Surface Temperature Trends for Trt and Non-Trt Groups



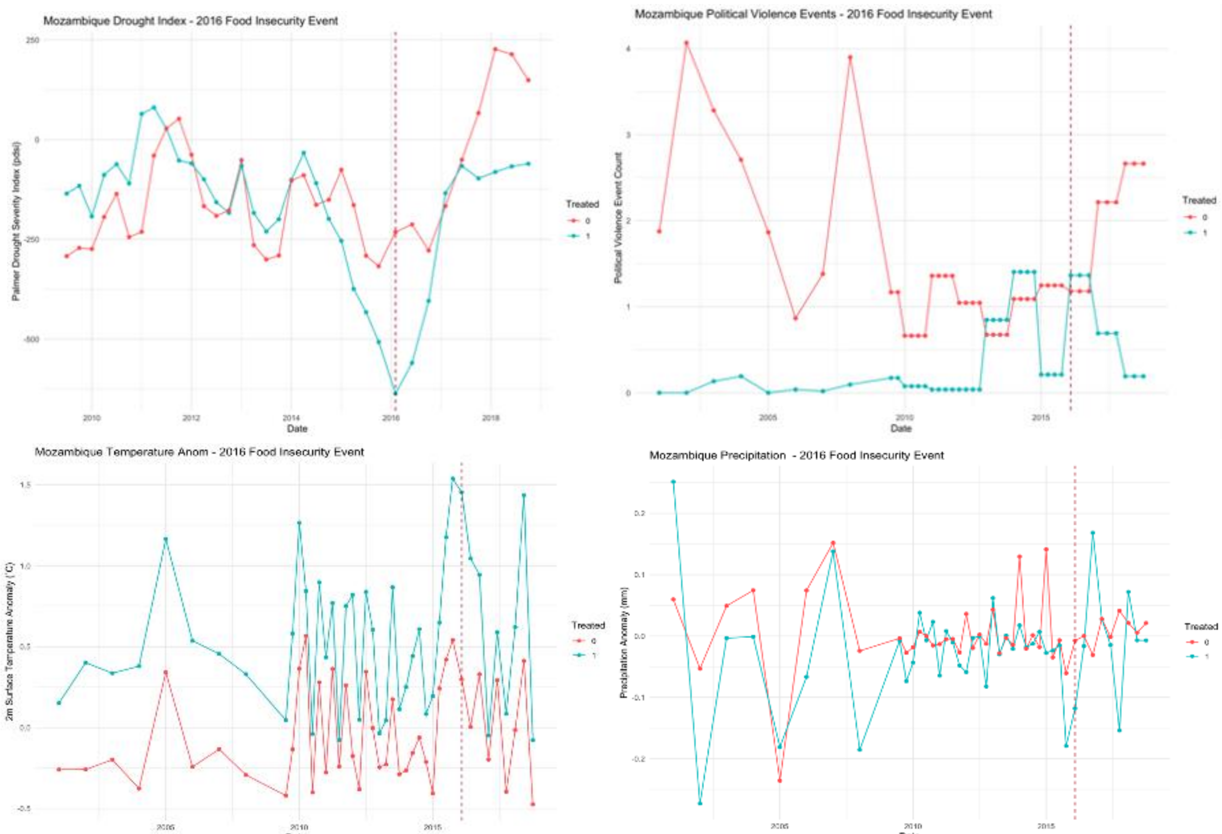
SI Table C3: Drought Index (PDSI) Trends for Trt and Non-Trt Groups



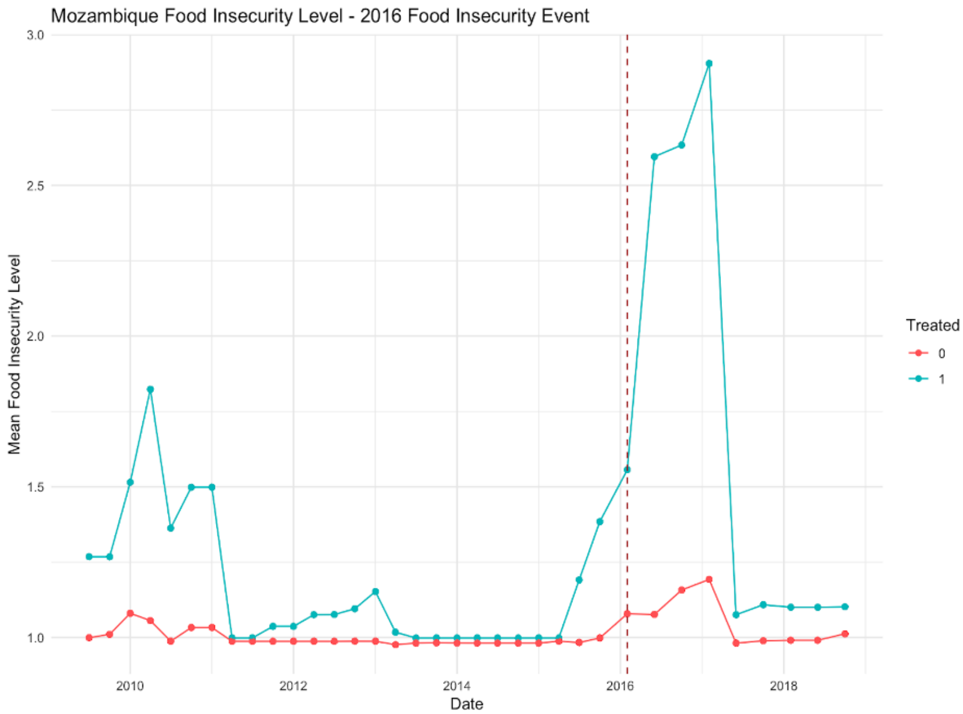
SI Table C4: Political Violence Trends for Treatment and Non-Treatment Groups



SI Figure C5: Staple Food Price Trends for Treatment and Non-Treatment Groups

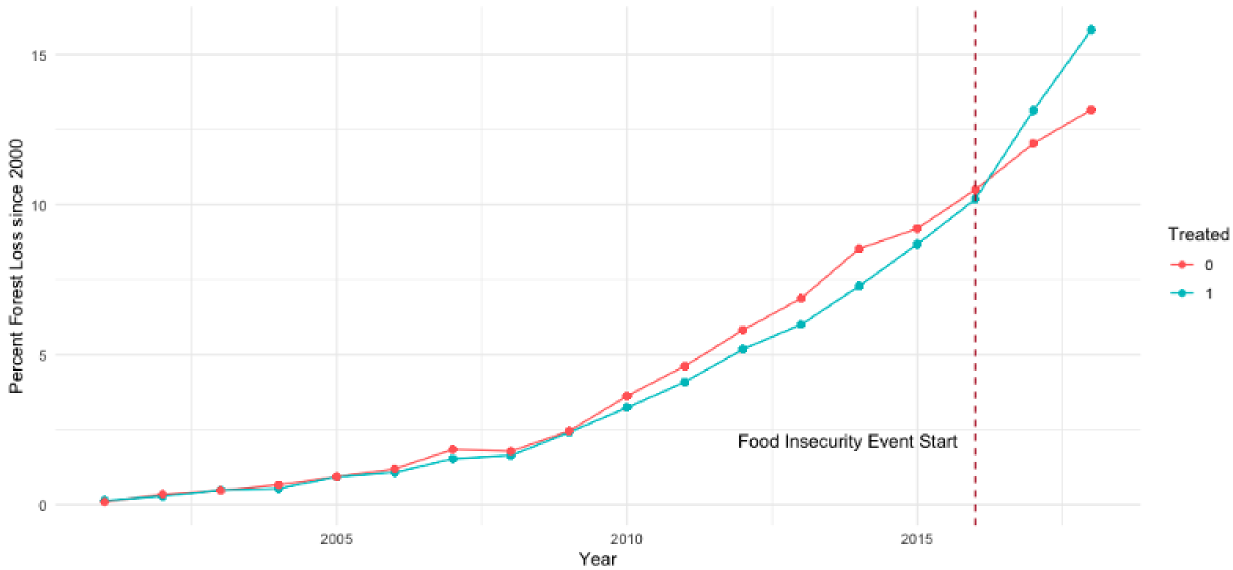


SI Figure C6: Visualizing Potential Drivers of 2016 Mozambique Food Insecurity Event

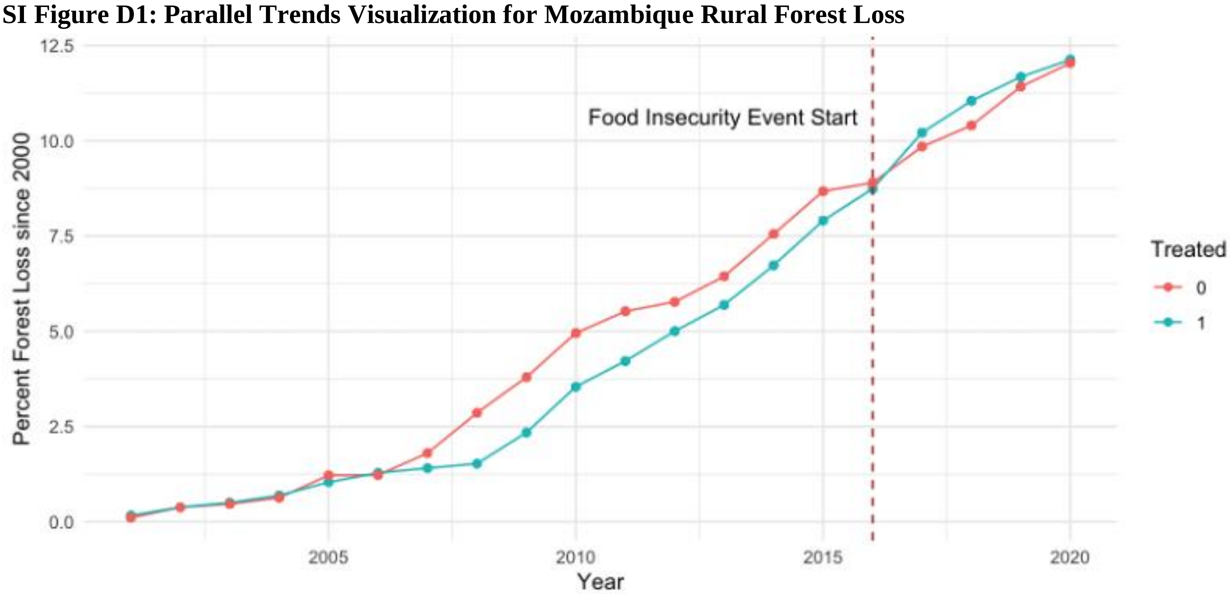


SI Figure C7: Mozambique food insecurity levels, comparing districts experiencing food insecurity in 2016 and 2017 with those that did not. Dotted red line represents food insecurity event onset.

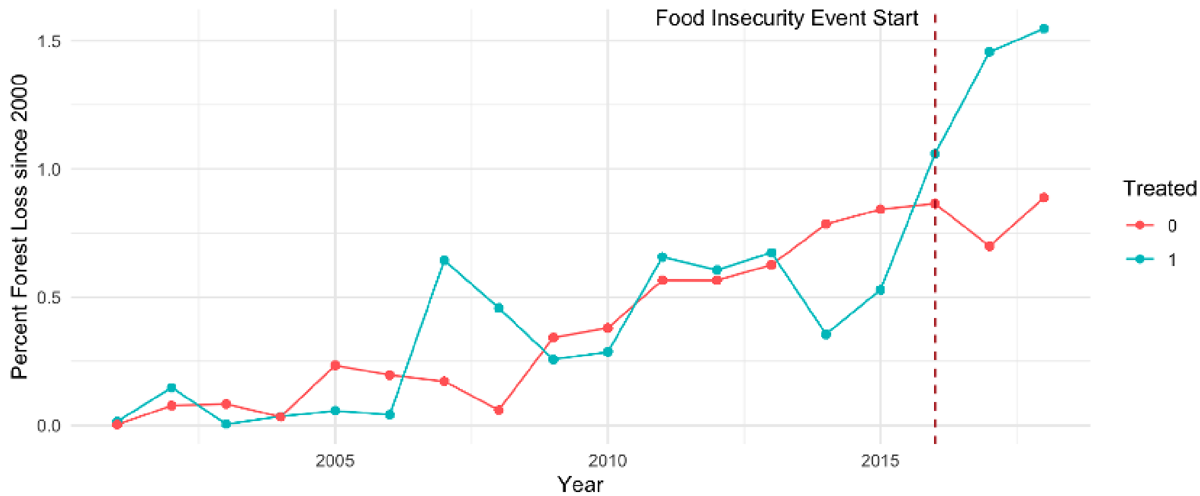
CH2 Appendix D: Parallel Trends Visualization for Case Studies



SI Figure D1: Parallel Trends Visualization for Mozambique Rural Forest Loss



SI Figure D2: Parallel Trends Visualization for Mozambique Semiurban Forest Loss



SI Figure D3: Parallel Trends Visualization for Mozambique Urban Forest Loss

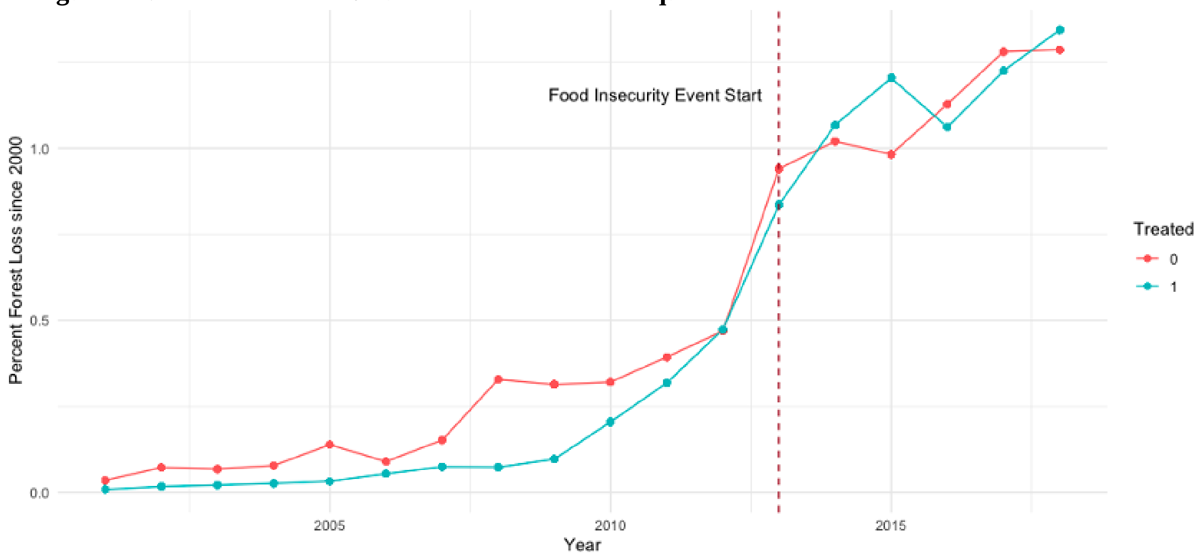


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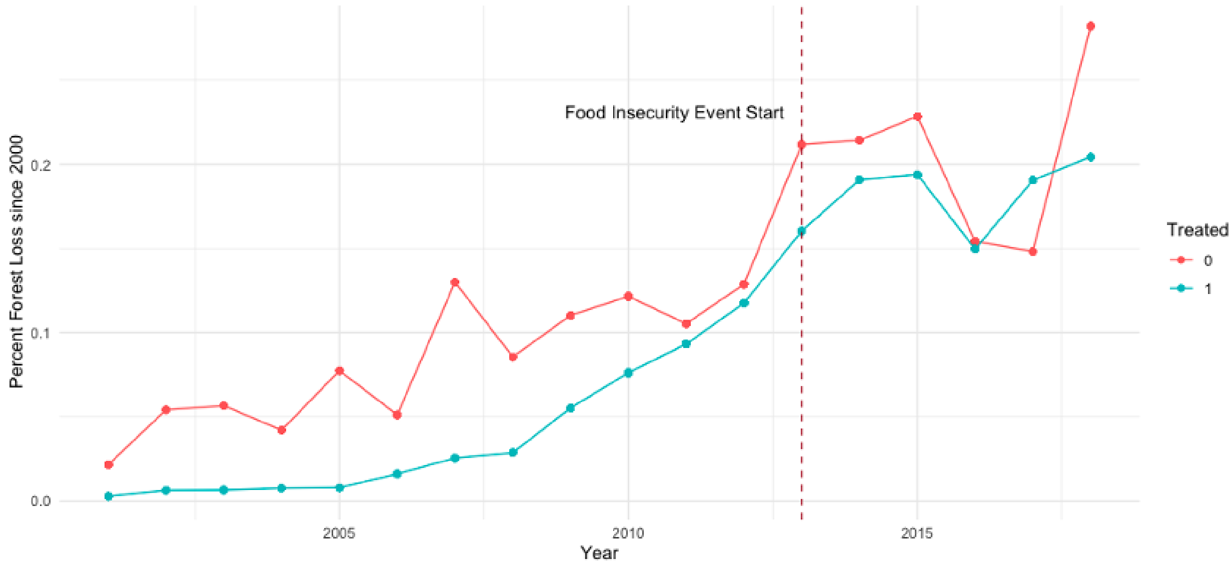
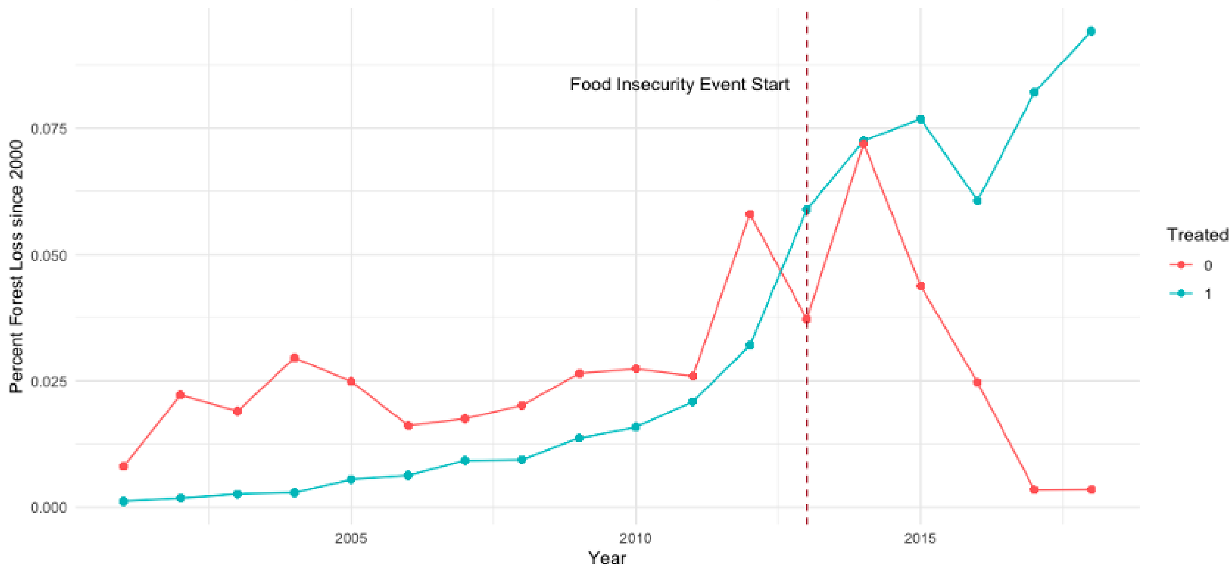
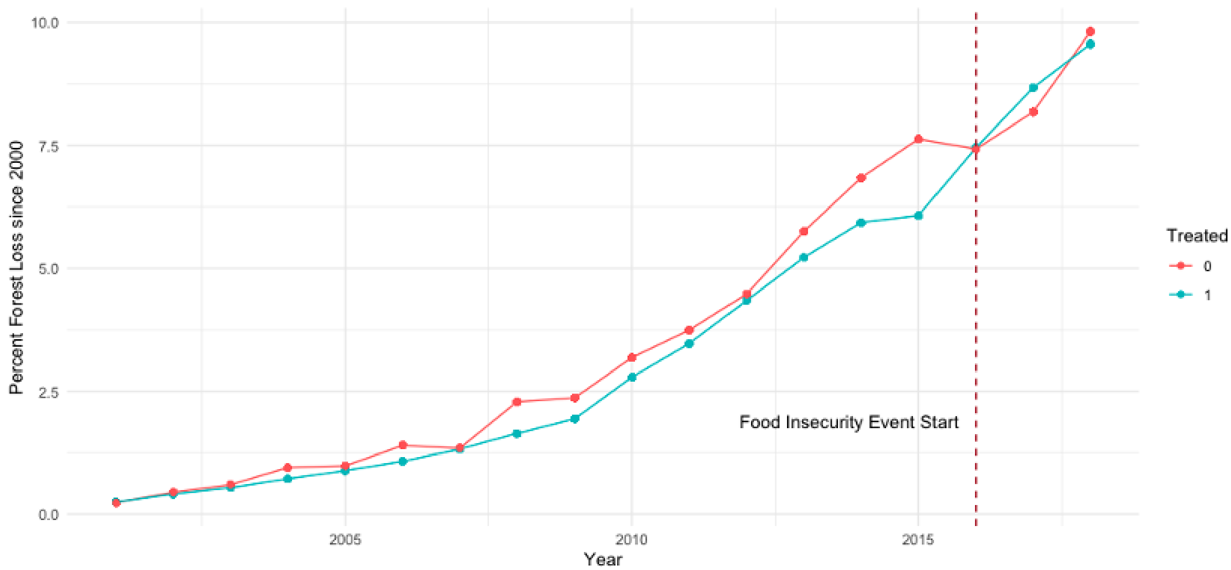
Figure D4: Parallel Trends Visualization for Nigeria Rural Forest Loss



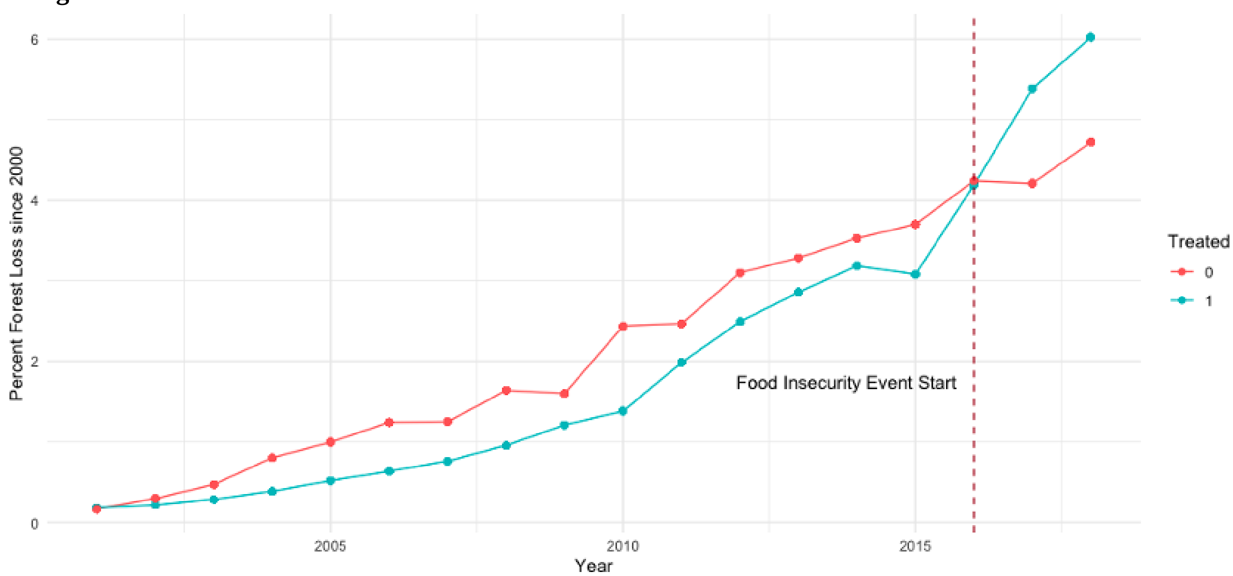
SI Figure D5: Parallel Trends Visualization for Nigeria Semiurban Forest Loss



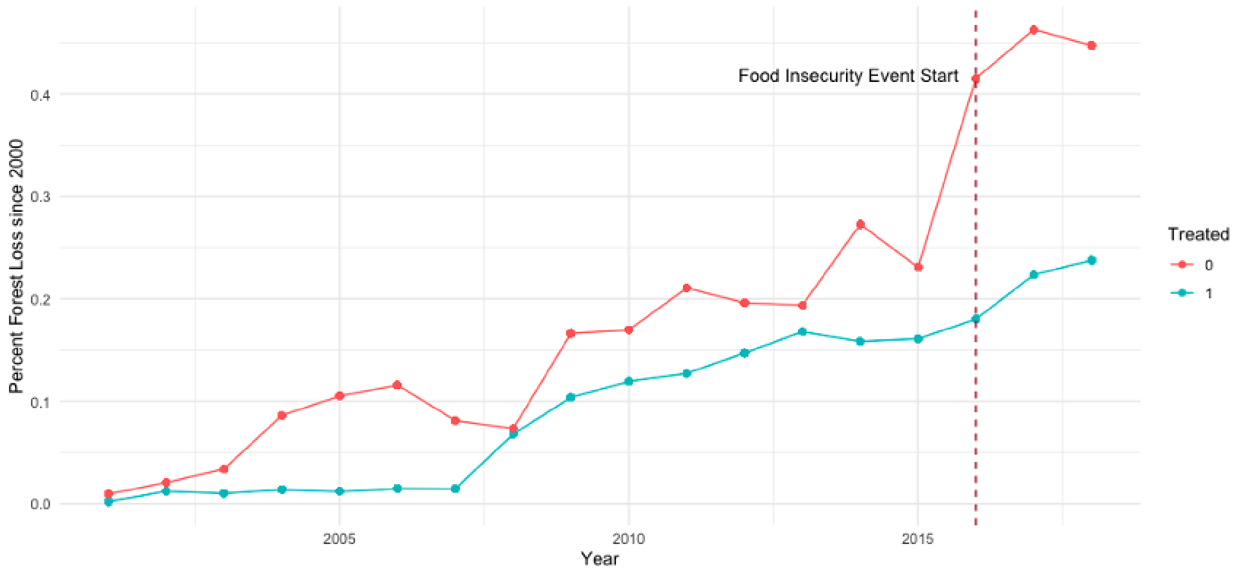
SI Figure D6: Parallel Trends Visualization for Nigeria Urban Forest Loss



SI Figure D7: Parallel Trends for Guatemalan Rural Forest Loss

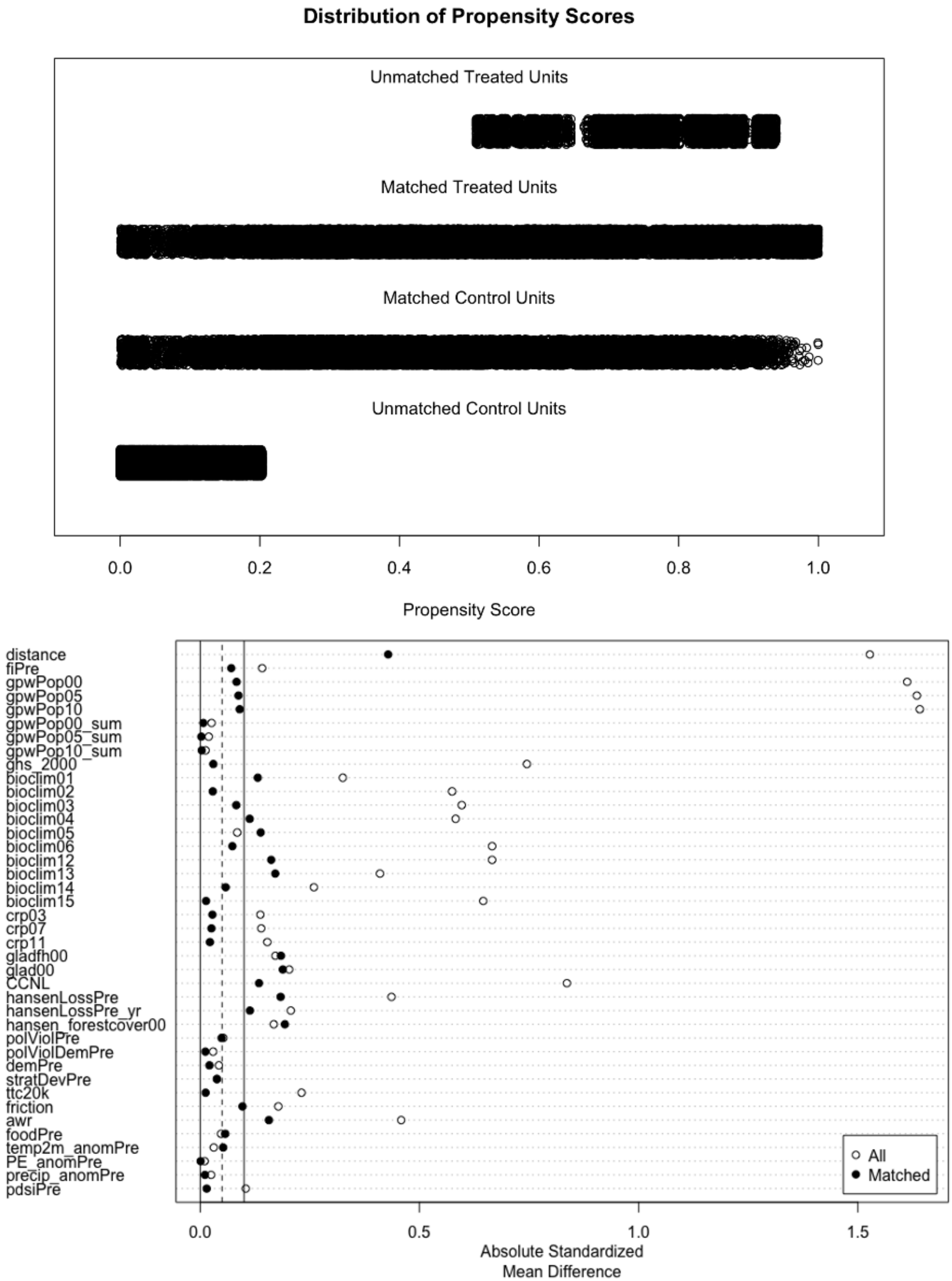


SI Figure D8: Parallel Trends for Guatemalan Semiurban Forest Loss

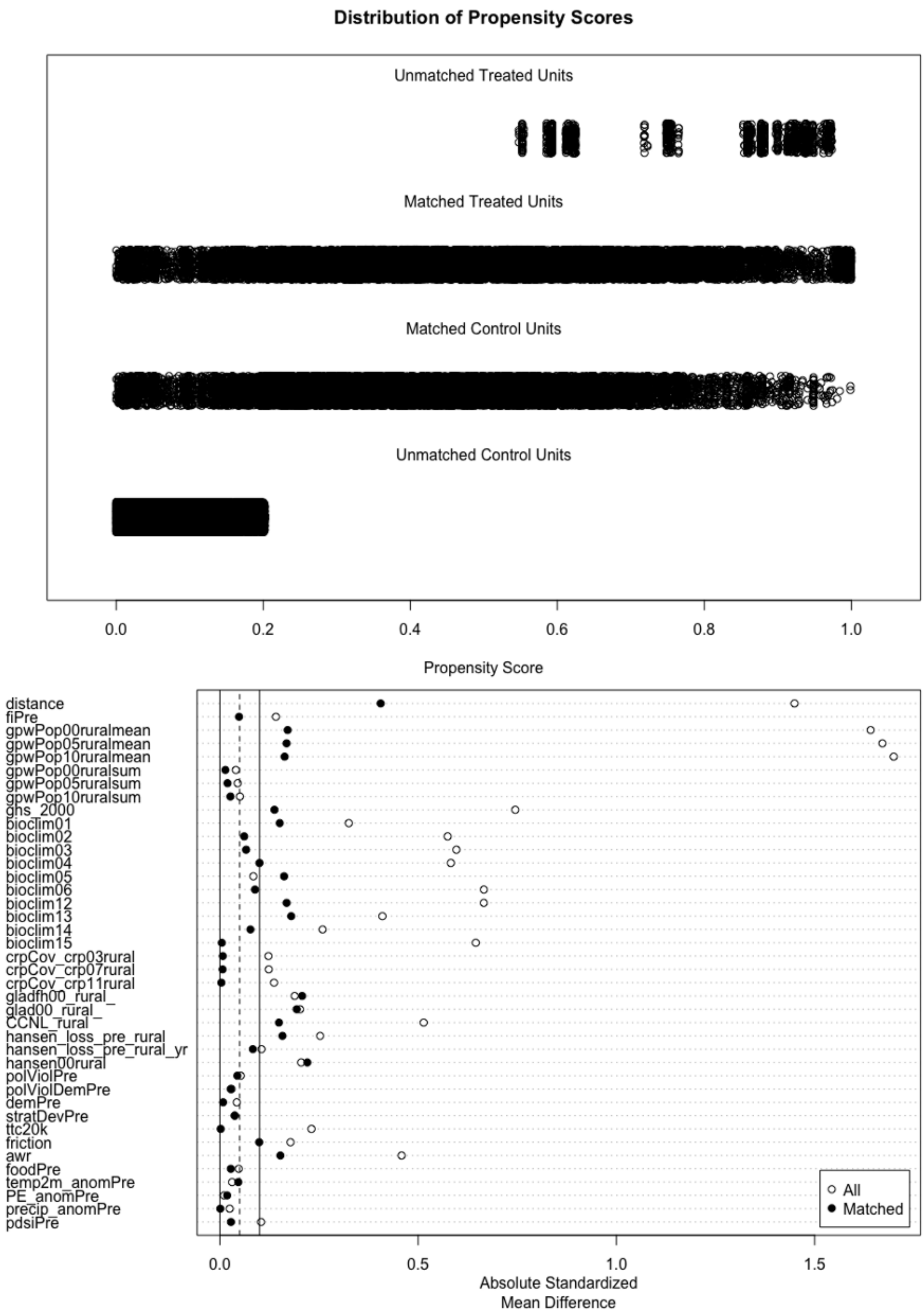


SI Figure D9: Parallel Trends for Guatemalan Urban Forest Loss

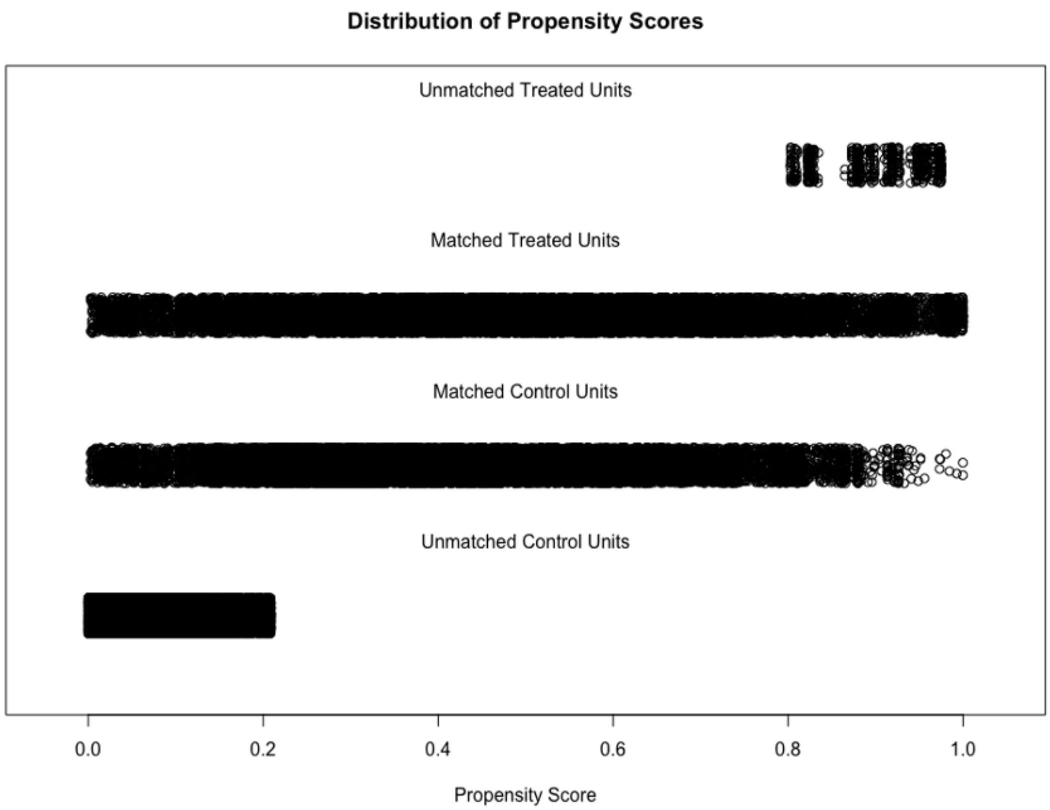
CH2 Appendix E: Matching Results

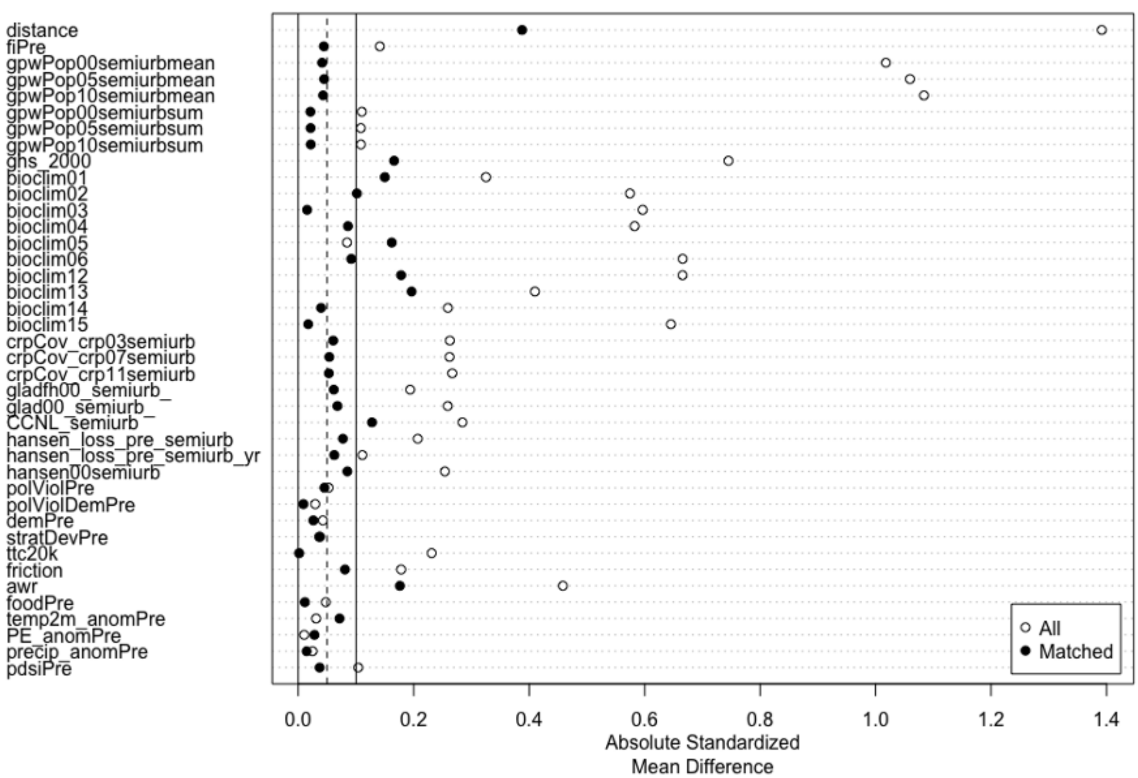


SI Figure E1: Matching Fit with Propensity Score and Variable Breakdown - All Data

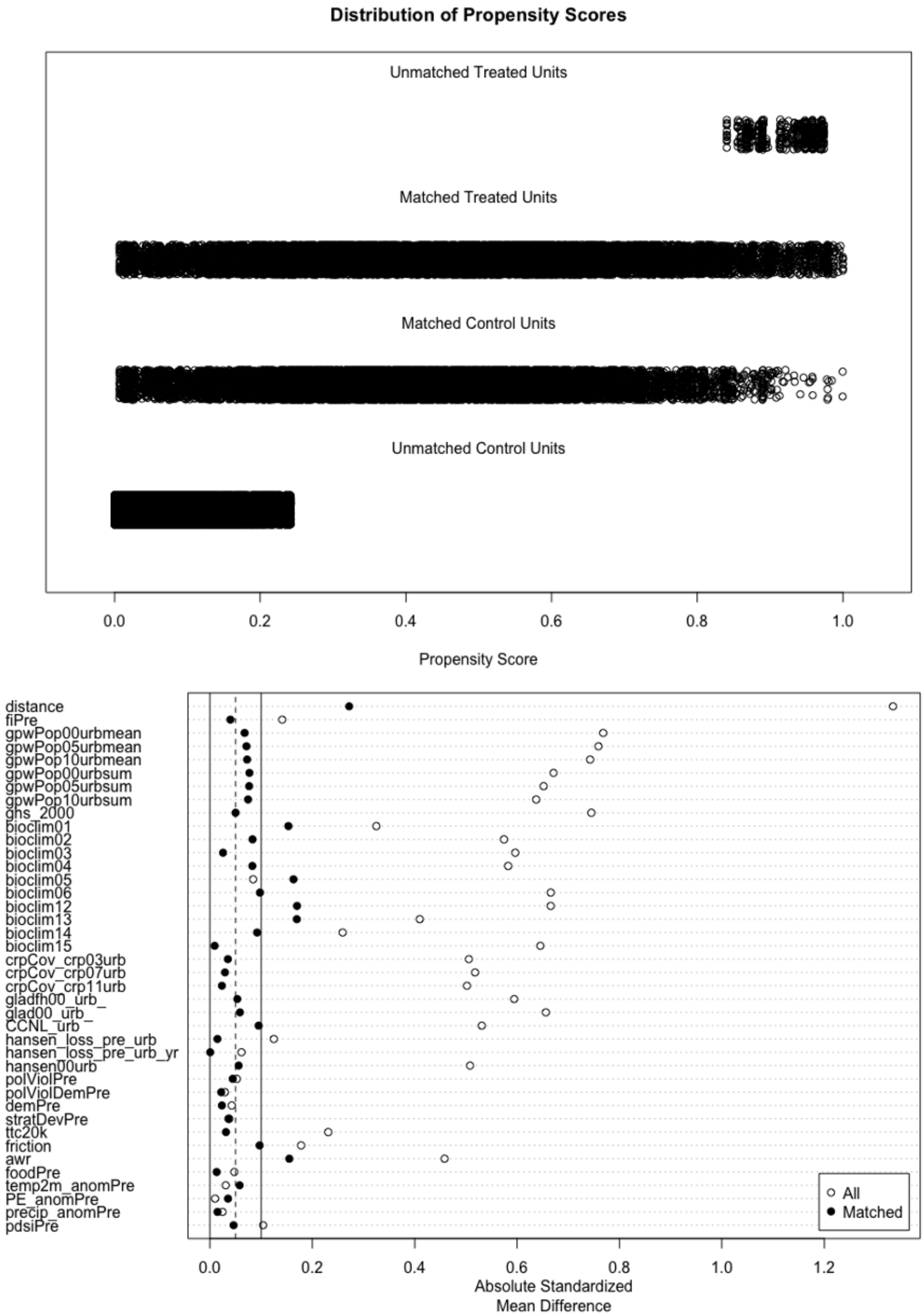


SI Figure E2: Matching Fit with Propensity Score and Variable Breakdown - Rural Data

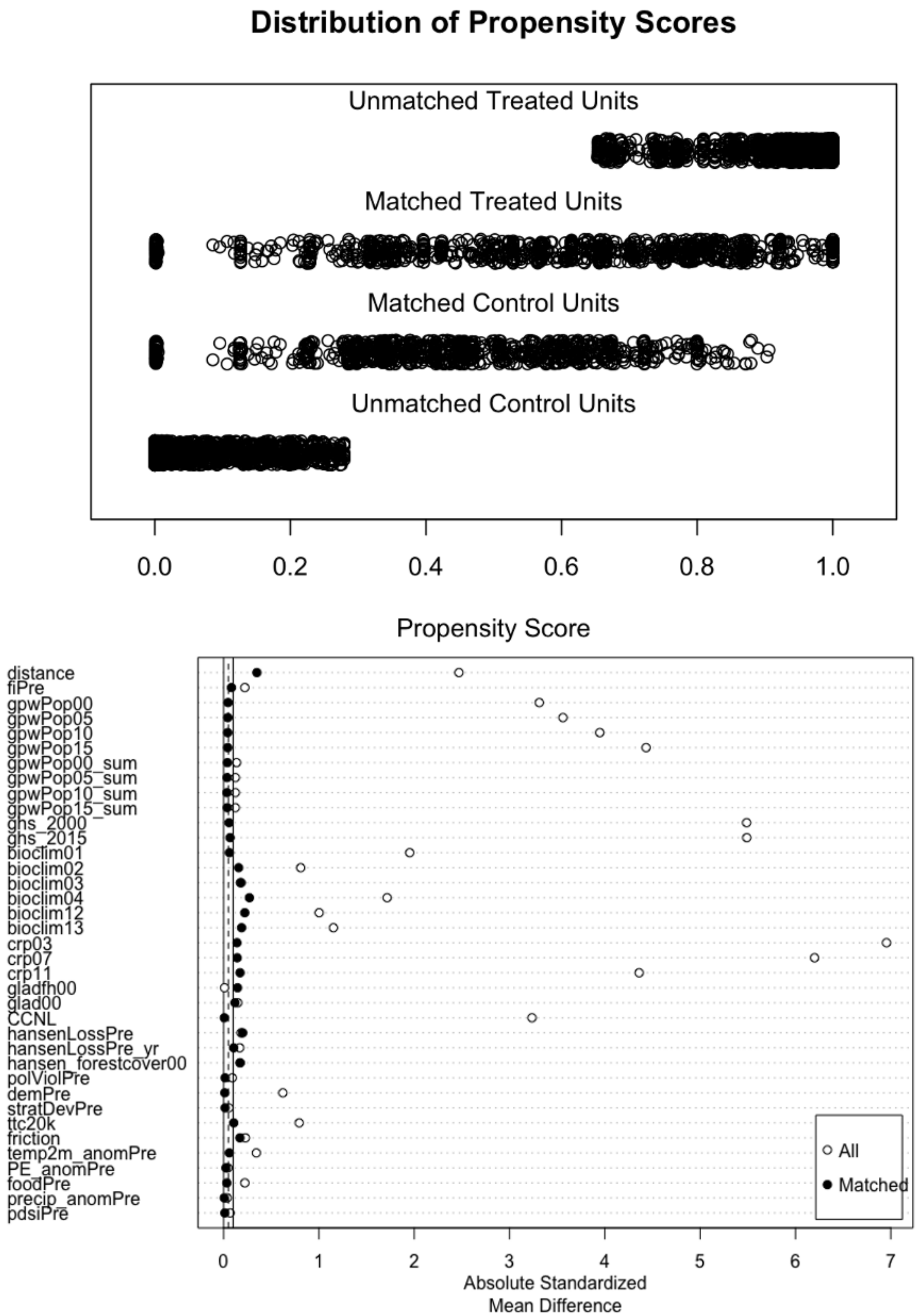




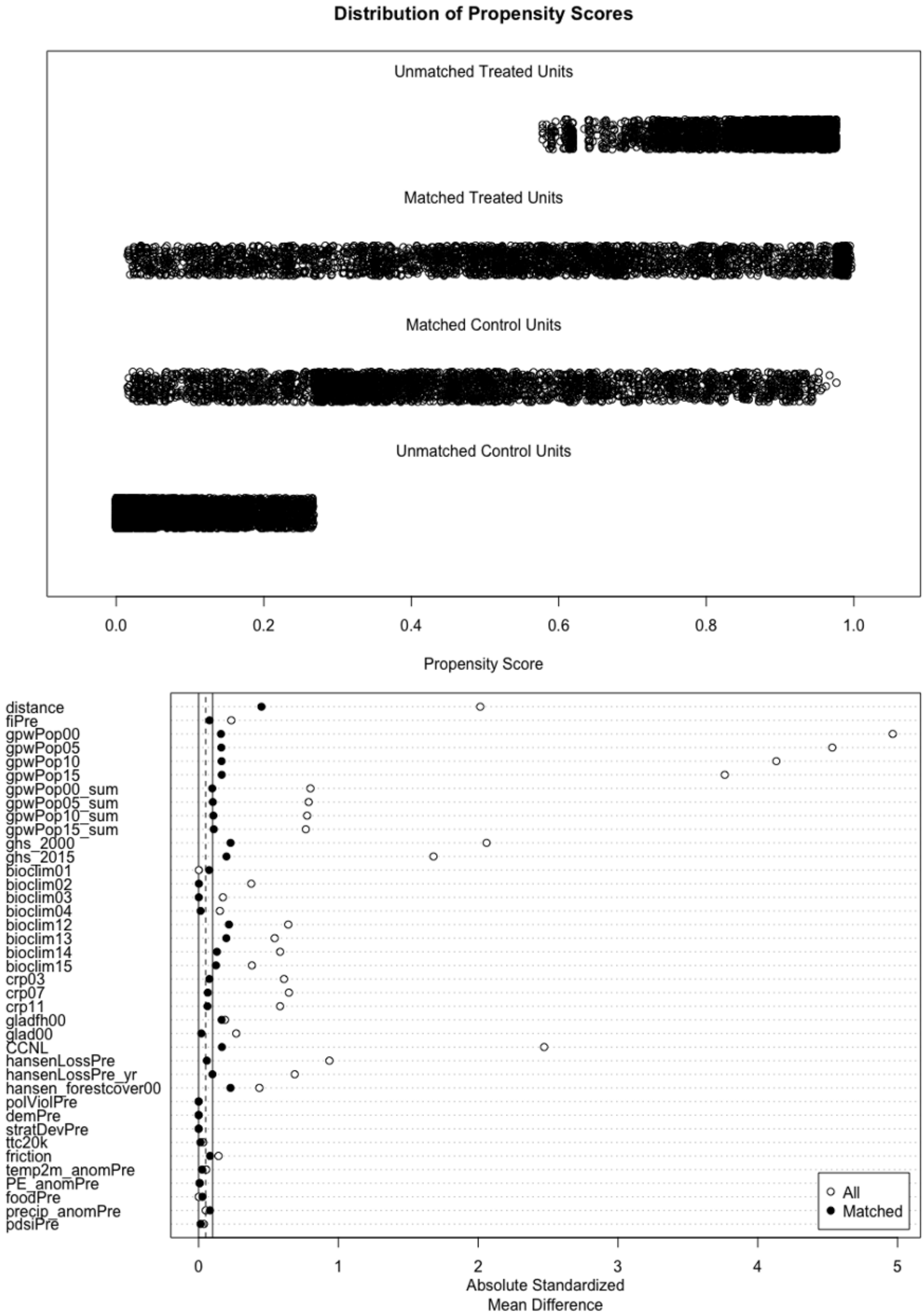
SI Figure E3: Matching Fit with Propensity Score and Variable Breakdown - Semiurban Data



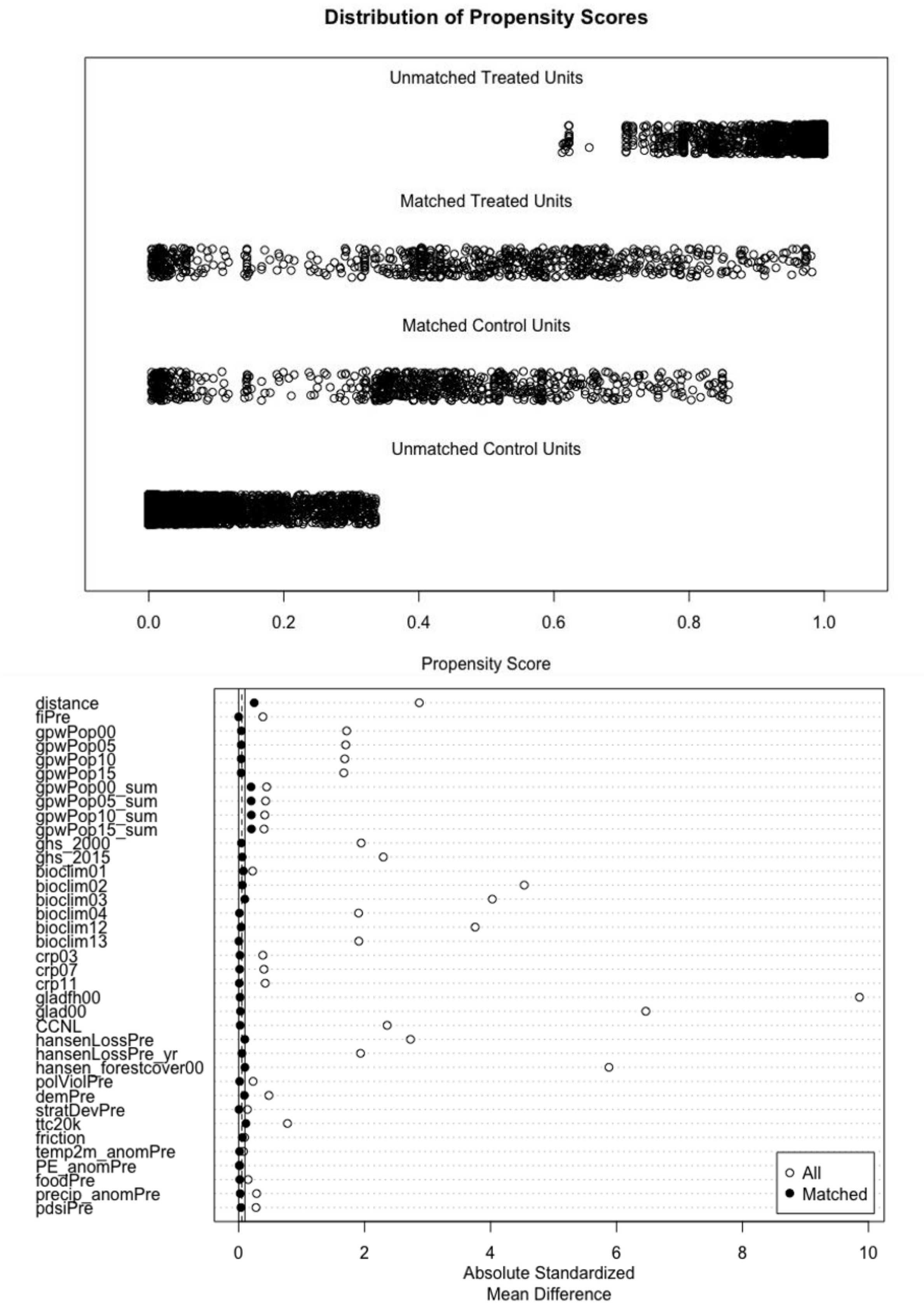
SI Figure E3: Matching Fit with Propensity Score and Variable Breakdown - Urban Data



SI Figure E4: Distribution of Propensity Scores before and after Matching - Mozambique



SI Figure E5: Distribution of Propensity Scores before and after Matching - Guatemala



SI Figure E6: Distribution of Propensity Scores before and after Matching - Nigeria

CH 2 Appendix F: Equations for Analytical Methods

SI Section F1: Linear Model Equation

Where:

- i indexes the unit of observation (administrative unit within a country).
- *Population2020*$_i$ is the outcome variable, representing the population in the year 2020 for unit i.
- Treat$_i$ is a binary variable indicating the presence (1) or absence (0) of a specific treatment or intervention.
- Population2010$_i$, Population2005i and Population2000$_i$ are variables representing the population in the years 2010, 2005, and 2000, respectively, for unit i.
- DemogCovars$_i$, LandUseCovars$_i$ and ClimateCovars$_i$ represent vectors of other relevant demographic, land use, and climate variables for unit i.
- β_0 is the intercept.
- β_1 to β_7 are the coefficients for the treatment variable, the population variables from previous years, and the vectors of other covariates, respectively.
- ϵ_i the error term for unit i.

SI Section F2: Event Study Model Equation (SUNAB)

Where:

- i indexes the unit of observation (e.g., a specific geographic region within a country).
- t indexes the time (year).
- *ForestLoss*$_{it}$ is the yearly outcome variable, representing the forest loss in year t for unit i.
- α_i represents the fixed effects for each unit i, capturing unobserved characteristics that are constant over time within each unit but vary across units.
- δ_t represents fixed effects for each time period t, capturing factors that are common to all units in a particular year but vary across years.
- is a series of indicator (dummy) variables for each period relative to the treatment start date, where k ranges from $-K$ to K, representing the number of years before and after the treatment start date. For example, $k=-1$represents the

year before the treatment, $k=0$ represents the treatment start year, and $k=1$ represents the year after the treatment starts.

- β_k are the coefficients for each period relative to the treatment, measuring the impact of the treatment on forest loss in the years before, during, and after the treatment start date.
- γ_1, γ_2, and γ_3 are vectors of coefficients for demographic, land use, and climate covariates, respectively.
- $DemogrCovars_{it}$, $LandUseCovars_{it}$ and $ClimateCovars_{it}$ represent vectors of other relevant demographic, land use, and climate variables for year *t* and unit *i*.
- ϵ_{it} is the error term for unit *i* in year *t*

SI Section F3: Two-Stage Least Squares Model Equation

First Stage:

In the first stage, you predict the potentially endogenous treatment variable using the instrumental variables and any other exogenous covariates.

Where:

- *i* indexes the unit of observation.
- $TempAnom_i$ and $PDSI_i$ are the instrumental variables.
- $Population2010_i$, $Population2005_i$, and $Population2000_i$, represent population in the years 2010, 2005, and 2000 respectively, for unit i
- $DemCovars_i$, $LandUseCovars_i$ *and* $ClimCovars_i$ are vectors of demographic, land use, and climate covariates.
- is the error term.

Second Stage:

In the second stage, you regress the outcome variable on the predicted treatment variable from the first stage, along with the other covariates.

Where

- is the predicted treatment variable from the first stage.
- is the error term in the second stage.

Chapter 3: Using Payment for Ecosystem Services to Meet National Reforestation Commitments: Impacts of 20+ Years of Forestry Incentives in Guatemala

Abstract

International environmental initiatives, such as the Bonn Challenge and the UN Decade on Restoration, have prompted countries to put the management and restoration of forest landscapes at the center of their land use and climate policies. To support these goals, many governments are promoting forest landscape restoration and management through financial forestry incentives, a form of payment for ecosystem services. Since 1996, Guatemala has implemented a series of forestry incentives that promote active forest landscape restoration and management on private and communal lands. These programs have been widely hailed as a success with nearly 600,000 hectares enrolled since 1998. However, there has been no systematic assessment of the effectiveness of these programs on preserving and restoring Guatemalan forests. This study evaluates the impacts of over 16,000 individual PES projects funded through two incentive programs using a synthetic control counterfactual. Overall, a program for smallholders resulted in lower rates of forest loss, while a program for industrial timber owners led to greater gains in forest cover. Across policies, we found dramatically higher forest cover increases from restoration projects (15% forest cover increase) compared to plantation and agroforestry projects (3-6% increase in forest cover). Projects that protected natural forest also showed a 6% reduction in forest loss. We found forest cover increases to be under 10% of total enrolled area, although positive local spillovers suggest this is an underestimate. Restoration projects show the most promise at promoting forest landscape restoration, but these benefits need to be weighed against priorities like resilience and rural development, which may be better served by other projects.

Keywords: Payment for Ecosystem Services, Synthetic Controls, Reforestation, Forest Landscape Restoration, Smallholders, Plantations, Forest Management

3.1 Introduction

For at least the past decade, forest restoration has been portrayed as an essential part of climate change mitigation efforts (1), as it could provide enormous near-term benefits in carbon sequestration (2) and numerous benefits to ecosystems and local communities. Guatemala, like many countries around the world, has set ambitious targets for reducing deforestation and restoring forest cover. Under the Bonn Challenge, Guatemala has comitted to restore 1,200,000 hectares of forest, around 11% of its total land area, by 2030. Guatemala has experienced rapid deforestation in recent decades (3) leading some to call into question the efficacy of many Bonn Challenge commitments (4), but forest restoration remains a key priority for Guatemala.

3.1.1 Guatemala’s Forestry Incentives

To meet these ambitious goals, sound landscape governance is needed to engage stakeholders and to provide the infrastructure as well as capacity to effectively restore and sustainably manage forests (5). Guatemala’s long-standing forestry incentive programs, which have operated since the 1990s, have provided critical infrastructure and expertise to implement forest landscape restoration. PINFOR (Programa de Incentivos Forestales) was instated by the 1996 forestry law and incentivized landowners to improve forest cover and kickstart the nascent timber industry in Guatemala (6). PINFOR primarily focused on productive systems, promoting planting and management of high-value trees. It proved highly popular, with enrolled acrage and projects increasing tenfold between 1998 and 2016 (7). However, nearly all smallholders were ineligible for the PINFOR program due to minimum size and land tenure requirements, so a parallel program called PINPEP (Programa de Incentivos Forestales para Poseedores de Pequeñas) was launched by the Dutch development bank in 2006 and funded by the Guatemalan Government in 2010, propelled by the grassroots organization of indigenous and smallholder groups (8). Smallholder priorities were built into PINPEP’s design, with significant funding allocated to agroforestry and fire prevention, which were priorities for many of the indigenous and smallholder groups who championed it (8, 9). Alongside these programs, the Guatemalan National Institute of Forests (INAB) created a national forest governance apparatus that introducted strict forest regulations, developed a network of forestry technicians, and built systems to track and disburse funds to participating landowners (6). Together, the PINPEP and PINFOR programs enrolled 588,276 ha between 1998 and 2019, approximately half of the area committed to forest restoration through the Bonn Challenge, and almost all of the restored forest area in Guatemala’s national commitment comes from their forest incentive programs (7). Furthermore, Guatemala’s Nationally Determined Contributions from the UNFCCC Paris Climate Agreement rely on these same programs for carbon sequestration via forest expansion (10).

Guatemala’s forestry incentives have been hailed by politicians and policymakers as a success (8), and some studies have mentioned localized successes for PINFOR (11,12). However, there has not been a systematic analysis of how these programs have impacted forest cover in Guatemala. Meanwhile, several high-profile studies have questioned the efficacy of popular forest incentive programs. Just to the north, Mexico’s billion-dollar Sembrando Vida may be accelerating forest loss (13). REDD+ continues to face challenges, with several recent studies finding mixed project success and overstated benefits (14-16). Without a greater understanding of impacts and trade-offs across projects that support forest landscape restoration and management, maintaining the momentum and funding needed to achieve Bonn Challenge and the UN Decade on Restoration goals will be challenging.

In this study, we investigate the outcomes and trade-offs of forestry incentive program approaches in Guatemala. We addressed the following questions: 1) to what degree did PINPEP and PINFOR contribute to forest cover changes in Guatemala; 2) how do different project types (e.g., natural forest management, plantations, restoration) impact forest cover; 3) do project impacts persist after unenrolment; and 4) are there any local spillovers, or effects of enrolment on surrounding areas?

3.2 Methods

3.2.1 Study Area

Guatemala has a diverse range of ecosystems, with wet tropical lowlands in the north and along the coasts, pine-oak forests and a cooler, wet climate across the country's central highlands, and dry tropical regions in the Pacific Coast and Motagua Valley (17). As referenced earlier, Guatemala has experienced rapid deforestation in recent years, primarily due to agricultural expansion (18). Guatemala's deforestation rate hovered around 2% in the 1990s (19) but declined to around 1% in the late-2000s (20). Rapid deforestation in the 1990s was attributed to ranching and smallholder farming (19) but recent scholarship suggest narcotrafficking (21) and expansion of export crops (22) are driving much of the current forest loss. Some research also suggests that migration is driving agricultural expansion through the reinvestment of remittances into smallholder farming (23, 24) and that Guatemala's forestry incentive programs might be responsible for the declining rates of forest loss (24).

We analyzed forest cover trends for Guatemalan sites enrolled in PINFOR and PINPEP programs between 1999 and 2018 (Figure 1). Data on enrolled sites was gathered via the INAB's GIS portal, which provided data for over 50,000 PINPEP and PINFOR projects. Sites were filtered to exclude uninitiated projects, duplicates, and those lacking project type information. Project area was estimated based on available metadata, which varied between PINPEP and PINFOR projects (SI Appendix 1). Ownership types for assessed PINFOR is quite diverse, with projects spread across individuals, businesses, cooperatives, municipalities, NGOs, and government organizations (SI Figure 1). PINPEP property owners were primarily individuals (SI Figure 2).

PINPEP and PINFOR allow landowners to enroll in one of five types of projects, each with different goals, management, and payment schemes. PINPEP supports tree planting through agroforestry or plantations, and natural forest management for protection of natural resources (NFM Protection) or timber production (NFM Production). PINFOR offers the same projects with the exception of agroforestry, instead paying for forest restoration. Each project requires that a certified forestry technician design a management plan that is then approved by INAB. NFM Production projects were the least common (less than 200 projects for PINPEP or PINFOR), but we included over a thousand sites for every other project type in the analysis. On average, PINPEP projects in the analysis lasted 1.8 years and PINFOR projects lasted 4.7 years, although this underestimates the actual enrolled period (Table 1). PINPEP and PINFOR sites were on average wetter, at higher elevation, and initially had more forest cover than unenrolled areas (SI Table 1).

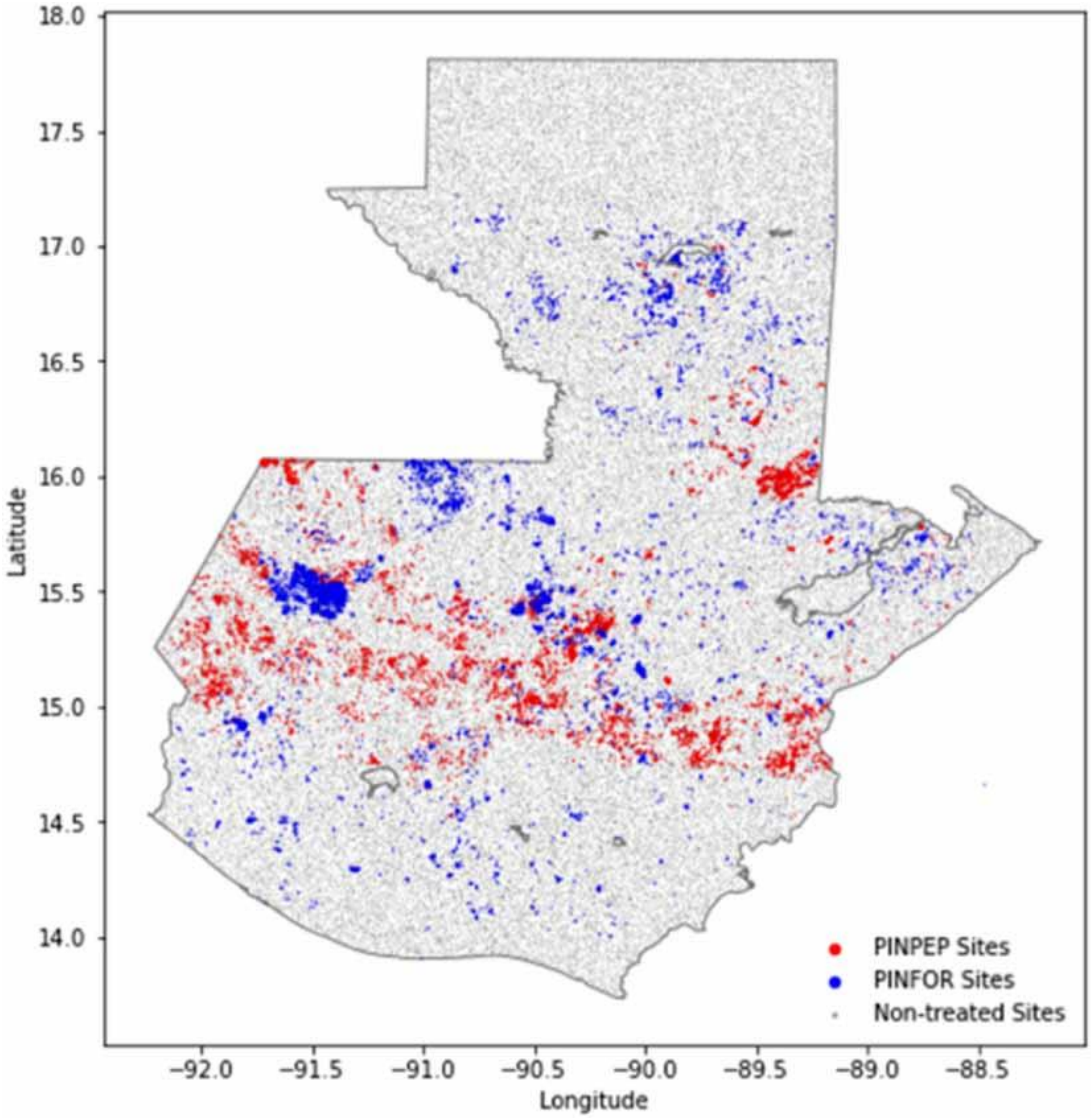


Figure 1. Guatemalan forestry incentive locations.The distribution of PINPEP (red) and PINFOR (blue) projects across Guatemala. Non-treated sites used to calculate the counterfactual are shown in gray.

3.2.2 Data Description

In order to account for factors relevant to forest landscape restoration success, we identified gridded datasets to track terrain, climate, and human influence. Terrain features comprising slope, elevation, and aspect, were derived from SRTM v4 elevation data (25), with slope and aspect calculated using a 3x3 moving window with bilinear resampling. We included yearly population density from WorldPop, which provides population estimates at approximately 100-meter resolution (26) and travel time to cities with a population larger than 20,000 (27) to estimate human influence. We used distance to rivers and streams, derived from the HydroSHEDS dataset (28), as a proxy for water availability and accessibility. To control for climate, we included historical measures of yearly precipitation, precipitation of the driest month, and mean annual temperature from WorldClim (29). Coordinate location was also recorded for each site to measure geographic spread of projects.

Additionally, we gathered data on forest extent, loss and structure to estimate project impacts on forest extent and density. To calculate a pre-treatment baseline, we used above and belowground biomass in the year 2010 (30), 30-m resolution forest cover maps for 2001, 2006 and 2010 provided by partners at Universidad del Valle de Guatemala (UVG) (20), percent forest cover in 2000, yearly forest loss events from 2001-2010 and cumulative forest gain from 2000-2012 from Global Forest Watch (GFW) (31), and forest extent and height in 2000 from the Global Land Analysis and Discovery lab (GLAD) (32). We also included distance to intact forest using the 2010 UVG forest cover data, with intact forest defined as 6 or more contiguous pixels of forest. To measure outcomes, we used yearly forest loss events from 2011-2020 from GFW (31) and forest height and extent change between 2000 and 2020 from GLAD (32). We used GFW forest loss events to better isolate the impacts of natural forest projects, which work to conserve and manage existing forests, and used GLAD forest extent and height to evaluate planted forest projects that may experience periodic harvesting.

Table 1. Program statistics for PINPEP and PINFOR project types.

Program	Project type	Study count	Mean project area	Mean years enrolled (*pre-2010*)	Total area (1998–2019)	Total USD spent (1998–2019) [1]
PINPEP	Agro-forestry	1078	1.8 ha	1.7 (*5.3*)	5899 ha	$9374 150
PINPEP	NFM Production	195	3.1 ha	3.3 (*8.1*)	2971 ha	$5015 666
PINPEP	NFM Protection	5810	4.4 ha	1.8 (*7.8*)	118 813 ha	$158 471 926
PINPEP	Plantation	1387	1.6 ha	1.8 (*3.5*)	12 048 ha	$7956 884
PINFOR	NFM Production	147	31.0 ha	3.6 (*4.1*)	22 450 ha	$4388 727
PINFOR	NFM Protection	2601	31.2 ha	5.0 (*4.5*)	221 203 ha	$55 422 041
PINFOR	Plantation	3595	3.7 ha	4.6 (*6.1*)	139 915 ha	$188 004 582
PINFOR	Restoration	1520	2.9 ha	4.8 (*7.5*)	Reported with PINFOR Plantation	

3.2.3 Program Impact Estimation

We estimated the impact of PINPEP and PINFOR on forest cover and forest loss using synthetic controls. For a valid impact analysis, we need to isolate the effect of enrollment from other factors that could influence forest cover. Accurately estimating impact can be complicated, as programs are rarely unbiased in their assignment of treatments, unless they are randomized. There are a few standard methods to retrospectively isolate the impacts of treatment on outcomes like forest cover, but counterfactuals are generally seen as more accurate and conservative than traditional analyses (33). We estimate impacts by generating a counterfactual using the synthetic controls methodology developed by Robbins et al. (34). Synthetic controls were first introduced by Abadie & Gardeazabal (35) and Abadie et al. (36), and have rapidly grown in popularity in the intervening decades because of their transparency and interpretability. Robbins et al. (34)

extend the synthetic control methodology to interventions with many treatment units by creating a single pooled synthetic control for a large treatment group. This provides a flexible framework for impact evaluation that can be easily applied to large programs like PINPEP and PINFOR. There are alternative specifications for this estimation, including matching with difference-in-differences, which we compare with the synthetic control results in SI Appendix 2.

Using synthetic controls requires a large group of untreated sites which should be generally comparable to the treated sites. In this case, treated sites were projects that were enrolled in either PINPEP or PINFOR. Untreated sites were created by randomly generating 100,000 3.1 ha areas across Guatemala and filtering for overlap with enrolled sites (Figure 1). PINPEP and PINFOR projects that began before 2010 were removed so that all projects began between 2010 and 2018. We then created the synthetic control by assigning a weight to each untreated unit, such that the weighted untreated units matched the treated units in all covariates and baseline variables. This allowed us to measure the effect as the percent difference between the treated group and synthetic control. Standard errors were calculated using survey methods to account for the weights of the synthetic controls (34).

3.2.4 Project Type Impact Estimation

We estimated the impact of the five project types within PINPEP or PINFOR using the microsynth R package provided by Robbins et al. (37) to replicate their method for applying synthetic controls to multiple treatment units. In this case, a separate synthetic control was generated for each program and project type combination, for eight synthetic control runs in all. For PINFOR sites enrolled in Restoration projects, we included additional control sites within a high plateau region in Western Guatemala called the Sierra de los Chuchumatanes, where many of the projects were located, to get a more representative set of untreated sites (SI Appendix 2). Importantly, the relevant outcomes vary across project types. We used forest cover loss as an outcome for projects that manage natural forest, as these projects should be maintaining existing forest relative to the control. Alternately, we use changes in forest cover and canopy height as outcomes for tree planting projects, as these seek to expand forest extent.

3.2.5 Durability Analysis

We evaluated the persistence of forest outcomes after project completion by conducting event study and simple regression analyses on project unenrolment. Program impacts can be short-lived if landowners clear the forest or stop beneficial practices after the project ends. Testing the impact of unenrollment allowed us to determine if clearing is occurring soon after payments stop. We used an event study analysis, which estimates the impact of a treatment on a time-variant outcome (38), to determine if clearing occurs shortly after payments stop. Event studies provide a good estimation of treatment effects on outcome trends in short time windows, with increasingly difficult assumptions over longer timespans. The model specification is described in SI Appendix 3. We also regressed project end date on forest outcomes to see if there is an impact of unenrollment date on forest outcomes. This allowed us to test if projects that ended earlier are seeing less improvements in forest cover than projects that ended later. Both analyses control for baseline forest conditions, climate, and population and included year, region, and project type fixed effects.

3.2.6 Spillover Analysis

We investigated local spillovers by examining changes in forest outcomes in the areas surrounding projects over the study period. Spillovers are effects that are seen outside of a project's boundaries due to project-induced changes in markets, landowner behavior, or other factors, and often lead to unaccounted benefits or harms (39). We estimated the impacts of enrollment on forest extent and height in areas directly adjacent to enrolled sites (local land use spillovers). Adjacent areas were generated by taking a buffer around each treated site equal to that site's radius. To estimate the impact of treatment on the non-treated buffer area, we regressed forest cover change and forest height change on site type (PINPEP, PINFOR, or respective buffers) controlling for initial forest conditions, climate, and 2010 population. This approach allowed us to identify spillovers at the local level, amongst landowners and neighbors, but program spillovers that occur at a larger scale, such as changes in wood product markets or the creation of a national forestry technician network, were not assessed in this analysis.

3.2.7 Robustness Checks

We assessed the robustness of the synthetic control results with untreated 'placebo' synthetic control runs to assess the variation in potential non-treated forest trajectories and provide a confidence interval for our data. Placebos were generated using random selections of non-treated units. Each of the randomly selected groups was weighted to match the treated group using the same method that created the initial synthetic control. Then, the outcomes were compared across the treatment period to get a measure of the variation in non-treated outcomes. Because of the number of sites included in this analysis, we limited the number of placebo runs to 200, but we were still able to find near-perfect fits for all placebo runs. We used the placebo runs to generate 95% confidence intervals, which we compared to the synthetic control standard errors.

3.3 Results

3.3.1 Program-wide Results and Comparison

Using synthetic control methods, we estimated the impact of enrollment in either the PINPEP or PINFOR program on percent change in GLAD forest cover and forest height from 2000 to 2020 and GFW forest loss in the years after enrollment. Forest cover increased at both PINFOR and PINPEP sites relative to the control, with 8.7% and 3.2% increases, respectively (Table 2). PINFOR sites saw a 5.7% increase in forest height relative to the control, while PINPEP had no significant effect. Forest loss showed diverging trends, with PINFOR sites experiencing a 1.6% increase in percent forest cover loss and PINPEP sites seeing a 3.4% decline.

Table 2. Percent change between treated and counterfactual by program and project type.

Program	Project type	GFW forest loss	GLAD forest cover change 2000–2020	GLAD forest height change 2000–2020
PINPEP	All Sites	**−3.4% (0.001)*** **	**3.2% (0.000)*** **	2.0% (0.095)
PINPEP	Agroforestry	**0.9%ǂ (0.001)*** **	**2.8% (0.000)*** **	0.1% (0.956)
PINPEP	NFM Production	**2.3%ǂ (0.002)** **	**2.8% (0.018)* **	**7.5% (0.000)*** **
PINPEP	NFM Protection	**−6.2% (0.000)*** **	**3.4% (0.000)*** **	1.9% (0.125)
PINPEP	Plantation	−4.2% (0.406)	**2.8% (0.001)*** **	2.0% (0.484)
PINFOR	All Sites	**1.6 (0.003)** **	**8.3 (0.001)*** **	**5.7 (0.022)* **
PINFOR	NFM Production	**8.6% (0.000)*** **	2.0%ǂ (0.080)	**−6.2% (0.035)* **
PINFOR	NFM Protection	−6.0% (0.145)	1.7% (0.074)	**5.5% (0.022)* **
PINFOR	Plantation	**3.8 (0.000)*** **	**5.7 (0.000)*** **	5.3 (0.072)
PINFOR	Restoration	0.1%ǂ (0.663)	**15.0% (0.000)*** **	**12.5% (0.000)*** **

Outputs of the counterfactual analysis are displayed as the percent difference between the treatment and control, followed by the *p*-value in parentheses. Values in bold have a *p*-value of less than 0.05. Forest loss is measured as cumulative yearly difference from the control after treatment begins, whereas forest cover and forest height change are measured as the difference between 2000-2020 controlling for all forest covariates between 2000 and 2010. Values found insignificant using the confidence interval generated via the placebo runs are marked with ǂ.

3.3.2 Impacts by Project Type

We evaluated the impacts of the five different project types under PINPEP and PINFOR on forest cover, height and loss using the same counterfactual approach. PINFOR Restoration projects showed the largest gains in forest cover, with forest cover increasing 15% as compared to the control (Table 2). Tree planting projects (Agroforestry, Plantation and Restoration) all experienced increases in forest cover relative to the control, with PINFOR outperforming PINPEP. The only tree planting project type to see a change in forest height was PINFOR Restoration, which increased in height 12.5%. We found diverging trends for natural forest management projects, with projects focused on forest protection seeing decreases in forest loss and projects focused on production experiencing increases in forest loss relative to the control, although this trend was not significant for PINFOR NFM Protection when using standard errors (Figure 2).

3.3.3 Durability

When investigating the impact of project unenrollment on forest loss events to determine whether project benefits last past a project's end date, we found that forest loss events decreased in the years following unenrollment for PINPEP sites but that unenrollment otherwise had no effect on forest loss (SI Figures 3 and 4). Our results also show that longer-running PINFOR projects saw greater gains in forest height from 2000 to 2020 (SI Table 3) than PINPEP projects and that PINFOR and PINPEP projects that ended more recently showed less change in forest height by 2020. PINFOR projects that ended more recently also had less change in forest cover by 2020 (SI Table 4).

3.3.4 Local Spillovers

To investigate local spillovers from projects, we compared forest outcomes for enrolled sites, buffer areas, and the untreated Guatemalan average. The buffer areas of PINPEP and PINFOR sites experienced much higher forest cover and forest height change than the Guatemalan average, but slightly lower change than the treated sites. We observed increases in forest cover in both project and buffer areas, but forest height increases were only detected in PINFOR sites and buffer areas. In a regression analysis, areas around PINPEP sites showed higher gains in forest cover and height compared to those around PINFOR sites, which experienced significant but more modest increases (SI table 5).

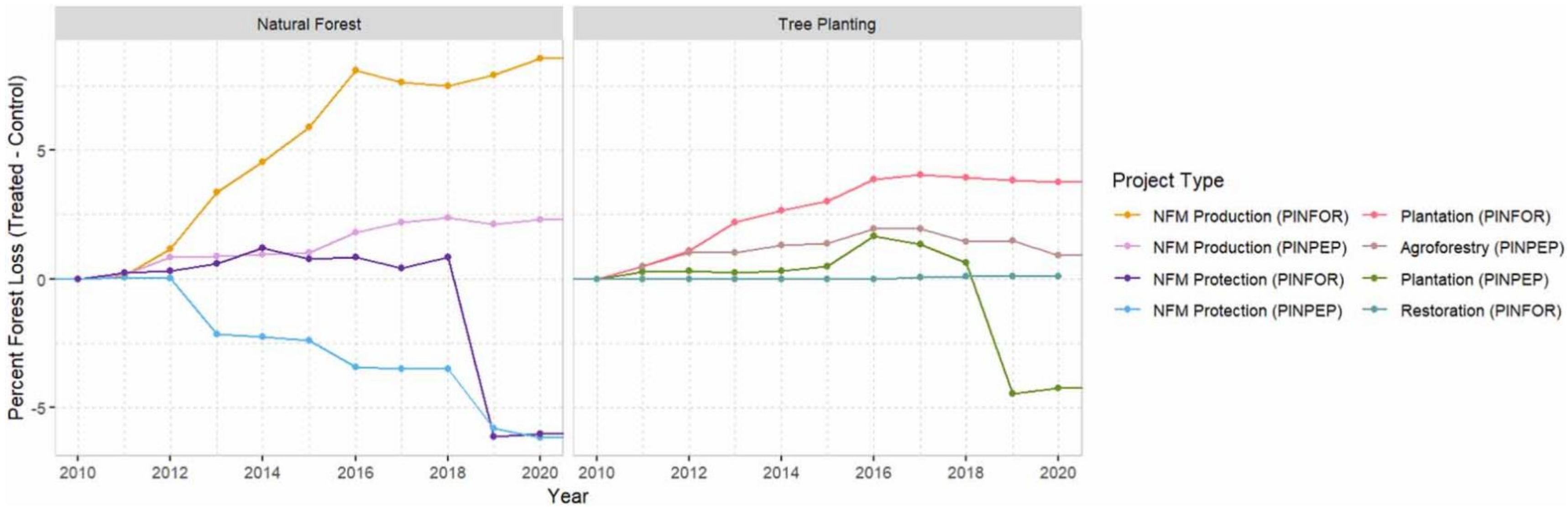


Figure 2. The impact of natural forest management vs tree planting projects on GFW forest loss.Cumulative percentage of project area forest loss (5% means forest loss was recorded across an area equivalent to 5% of all sites) relative to the control from 2010–2020 for all project types. Graphs are broken up by natural forest management projects and tree planting projects. NFM Protection and PINPEP Plantation sites saw the greatest reductions in forest loss, while NFM Production and PINFOR plantation sites experienced increases in forest loss, relative to the control.

3.4 Discussion

3.4.1 Overall Program Effectiveness

The evaluated incentive programs consistently increased forest cover, though absolute changes have been modest. The size of these impacts is comparable to other studies of financial forest incentive programs that have used similar counterfactual approaches (40-43). Additionally, we found substantial local spillover effects that had large, positive impacts on forest height and forest cover (SI Table 5), suggesting that our synthetic control estimates underestimate total project benefits.

We also found that, while PINPEP led to smaller forest cover gains, enrollment in the smallholder-aligned program showed a decline in forest loss while forest loss increased in PINFOR sites. PINFOR generally supported productive forests, so while overall forest extent may have increased these areas are likely experiencing harvest cycles that produce a signal in the yearly forest loss data. PINPEP aligned heavily on smallholder priorities, meaning that many of the projects have a mix of useful trees which may be left longer than plantation rotaitons, and would be harvested on different cycles, leading to little to no deforestation signal.

3.4.2 Project Type Effectiveness

When we compared the outcomes of project types across programs, restoration projects, which were restricted to PINFOR sites, were clearly the most effective at increasing forest cover and forest height. Restoration had a far greater impact on forest cover than plantations and agroforestry, which also seek to increase forest cover through tree planting. Incentives that promote agroforestry or plantation projects may not be creating as much additional forest cover because the sites were already mostly forested before enrollment (46% for Restoration vs 78% for PINFOR Plantation), suggesting that restoration projects resulted in substantial additional forest cover by targeting non-forested areas and successfully restoring forest cover in these areas.

NFM Protection sites showed declines in forest loss of around 6%, although this change was only shown to be significant for PINPEP projects. These reductions in forest loss suggest that PINPEP's smallholder projects are better at increasing the stability of natural forest cover. Additionally, PINFOR and PINPEP NFM Production sites experienced increases in forest loss after enrollment, likely because these projects are supporting the active management (i.e., harvests) in natural forests.

3.4.3 Project Durability

When analyzing the durability of project benefits, we found no sign that programs were losing forest cover after unenrollment. Our event study results show that PINPEP sites experience less forest loss events after unenrollment, while our analysis of post-project impacts suggested that

PINFOR sites continue to grow in forest cover after unenrollment. These results indicate that projects benefits are generally maintained for at least a few years after payments end.
While these results suggest that tree cover benefits continue for the first few years after unenrollment, durability is an ongoing concern for forests in Central America. Reid et al. (44) studied long-term forest change in an area of southern Costa Rica and found that 50% of secondary forests were re-cleared in 20 years and 85% were re-cleared in 54 years. Rates of forest re-clearance in Guatemala have not been estimated, but clearance and regrowth has been a longstanding feature of forest landscapes in the country (45, 46). Promoting projects that align with landowner objectives, such as planting productive tree species, improving water quality, and reducing fire risk could help improve the long-term stability of forests restored or managed through PES programs.

3.4.4 Data Limitations and Program Challenges

Data for this analysis were collated from many sources, and it is important to keep in mind the limitations of these data in estimating program impacts. Project areas were estimated using the best available metadata, but direct comparison of this dataset with publicly visible polygon data showed that these area estimations were inaccurate for irregularly shaped projects (SI Figure 1). PINFOR estimated areas are overall less accurate and therefore may muddle treatment signals with spillover signals, based on the variations of size, shape and location of projects. Additionally, two of our major outcome variables only have measurements for 2000 and 2020. We used a number of datasets to control for baseline forest change from 2000 to 2010, and found that forest cover in 2010 correlated well with GLAD forest cover data. However, this may not have controlled for all changes in this data across the pre-treatement period. If our counterfactual had a bias in low-canopy forest cover change between 2000 and 2010 compared to the treatment, our forest cover and height results may be biased, as we were not able to account for this in our baseline data.

Researchers have noted the difficulty of running large incentive programs at a national scale. Political turnover, ongoing financial obligations, and administrative overhead all challenge program longevity (47, 48), and these programs are no exception. Over the years, several issues in program management and administration have emerged. For example, PINPEP, which funds many small projects, has struggled to develop a robust infrastructure for project and landowner tracking. Many program participants report not receiving payments from the government, and many have had to travel to the capital to protest before receiving their payments (8). Additionally, PINFOR was designed primarily for forest production, focusing on high-value tree species and less on ecological services (8). Another program called PROBOSQUE that focuses more explicitly on ecosystem services replaced PINFOR in 2016 after an updated version of the forestry law was passed, although many PINFOR participants have continued receiving benefits under the new program.

3.5 Conclusion

Forest incentive programs underlie ambitious goals of large-scale landscape transformation but require clear evaluation to understand whether these goals can be met. While PINPEP and PINFOR combined have treated nearly 600,000 hectares, the realistic additional forest cover these programs delivered is a small fraction of that amount. However, these programs still demonstrate clear success when compared to similar financial forest incentives. Restoration projects showed by far the most success at adding additional forest cover to the landscape, in part because these projects best targeted areas without existing forest cover. Ensuring that projects are sited on previously deforested or degraded lands is critical to ensuring the success of programs in providing additional forest cover. However, incentive programs aimed at achieving multiple benefits need to weigh the trade-offs between forest cover expansion and other projects that support local economies and ecosystems with more modest forest cover benefits. Overall, this analysis shows that large-scale forest incentives provide real benefits to forest cover, but that governments need to better target projects, dramatically increase their acreage, and more seriously consider land management trade-offs if they are to reach the ambitious goals they have set for forest landscape restoration.

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CH3 Appendix 1: Project Area Estimation

Project location data was downloaded from the INAB GIS portal (https://sig.inab.gob.gt/portal/home/gallery.html) in September 2021. The portal has since been updated to display polygons with no access to the underlying dataset, but we provide the data with this article. Projects are estimated using perimeter length metadata provided with the dataset, approximating project area through a circle. The majority of PINPEP projects have this metadata, and the subset for which this wasn't available is filtered out. For around half of PINFOR projects, no perimeter length metadata is provided. The area for these projects is estimated based on the summary of projects provided elsewhere by INAB (Custodio de Leon, 2019), and site areas are drawn as circles. For projects where shape length is provided, we can expet an overestimation of size for strangely shaped projects. Additionally, the size of PINFOR projects that do not have a shape length was generally underestimated, many projects without metadata appear to larger than average. Overlap with project area is also not exact, with point locations providing a poor estimation of irregularly shaped projects. This can be seen in Supplementary Figure 3. Irregularly shaped projects were uncommon (no more than 10%), and most projects were generally rectangular. Many projects were enrolled in grids, with coverage across a larger combined parcel of private or communal lands. Area estimation is generally much more successful at capturing the spatial area of these projects (Supplementary Figure 4). Finally, some point locations are recorded at the edges of projects instead of at the center, leading to further area estimation error. Overall, imperfect location data proved adequate for determining the direction and relative size of project impacts but may lead to some treatment effects being included in the local spillover estimates.

CH3 Appendix 2: Comparison of Synthetic Controls to Matching with Difference-in-Differences

We compare our approach, which uses synthetic controls, to propensity score matching with difference-in-differences to better understand how the choice of method influences our results. To do this we use the MatchIt package in R, nearest neighbor matching, a caliper of 1, and a glm propensity score to match treated with control units, then run a difference-in-differences analysis on Hansen GFW forest loss, and regressions on GLAD forest height and forest cover in 2020. In the matching and regression analyses we included the same covariates used in our synthetic control analysis, and included year fixed effects. The results of these regressions are displayed here in Supplementary Table 2. Broadly, the results between the models are similar, with more variation in forest loss and forest height results and more alignment in forest cover results.

While conducting this robustness check we discovered that there were very few viable matches for PINFOR Restoration sites (3% of sites). This is because these sites are primarily found in a high mountainous region of Guatemala called the Sierra de los Cuchumatanes, which is higher and colder than most of the country. To produce more viable matches for PINFOR Restoration, we generated random sites for the region of Sierra de los Cuchumatanes exclusively instead of trying to finding comparisons from the whole country. We defined this region as two adjacent areas entirely above 3000m where the majority of PINFOR Restoration sites are located. Untreated sites were spaced at least 200m apart so that they dp not overlap. Untreated sites that overlapped with PINFOR and PINPEP sites were filtered out, and the remaining 7297 new untreated areas were added to the original set of approximately 100,000 untreated sites. We re-ran the matching and difference-in-differences analyses with the new set of untreated sites as well as our synthetic control analysis. Our results are shown in Table 2 below, with runs that included additional control data from Sierra de los Cuchumatanes abbreviated with SDLC.

From a practical perspective, there are some trade-offs between the modelling techniques. Synthetic controls allow for easy interpretation and clear matching across the treatments and controls. Difference-in-differences with matching works well in this situation, but synthetic controls should theoretically work equally well. Synthetic controls generally have similar limitations to diff-in-diff with matching, where a long pretreatment time series is needed for effective measurement of the outcome variable. However, it is more commonly applied in settings with a low number of control and treated units. Abadie (2021) discusses common approaches and considerations for using synthetic controls for multiple treatment units. One issue that arises is the inability to create a valid synthetic control. Robbins et al. (2017) address this by creating a single pooled synthetic control for the treatment group, which in our case allowed for nearly exact matching for all of our synthetic control runs. Abadie (2021) also points out that

> "Large interpolation biases may also arise in settings where the predictor values for treated units fall outside the convex hull of the predictor values for the units in the donor [untreated] pool, especially when the units contributing to synthetic controls are far away from the treated units in the space of predictors."

In other words, if the untreated pool is not sufficiently representative of the treated units, it can introduce bias. This is unlikely to be an issue for most of our data given the high rates of matching, but could be an issue for PINFOR Restoration, which had very few suitable matches when we re-ran the analysis using propensity score matching (3% of total sites had viable matches). Because of the low matching of PINFOR Restoration, we replace the initial synthetic control results with the synthetic control results where we include the additional untreated sites from the Sierra de los Cuchumatanes.

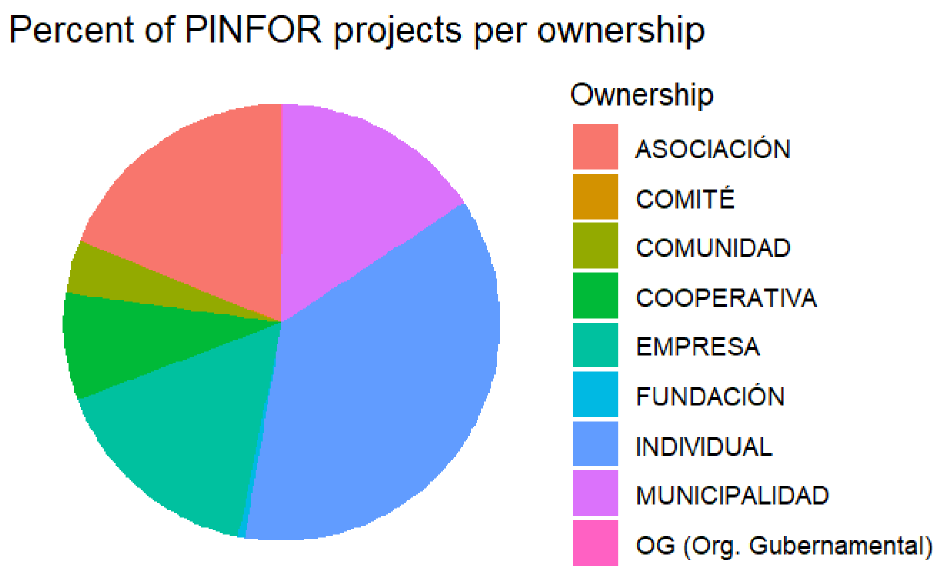
CH3 Appendix 3: Estimating the durability of project impacts using an Event Study

We ran an event study on unenrollment for PINPEP and PINFOR sites to determine whether forest loss rates changed after projects ended (Figure 3 and Figure 4). We include data from the untreated sites as a control, which allows us to better test for deviations from the general trend of forest loss in Guatemala. We show our model specification below:

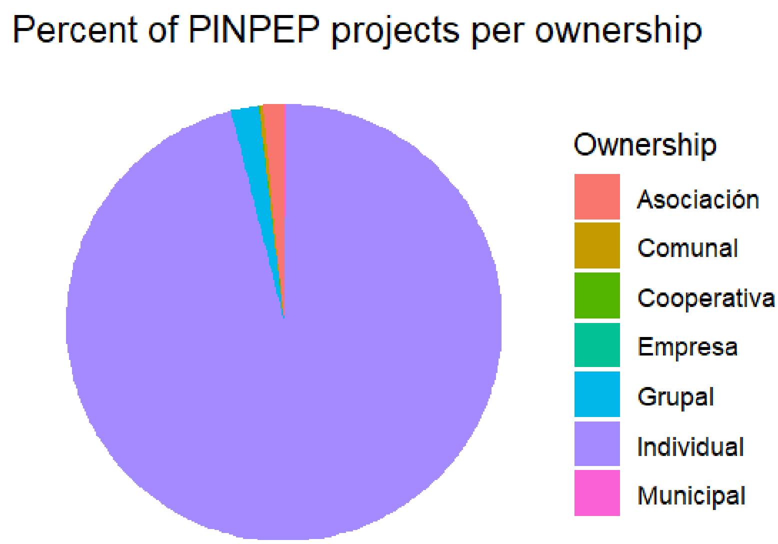
$$\text{hansenForestLoss} = \beta_0 + \beta_1 \cdot \text{i(endyear, ended)} + \beta_2 \cdot \text{elevation} + \beta_3 \cdot \text{travelTimeToCities} + \beta_4 \cdot \text{slope} + \beta_5 \cdot \text{aspect} + \beta_6 \cdot \text{distToRivers} + \beta_7 \cdot \text{biomass2010} + \beta_8 \cdot \text{distToForest} + \beta_9 \cdot \text{hansenForestGain00-12} + \beta_{10} \cdot \text{uvgForestCov2001} + \beta_{11} \cdot \text{uvgForestCov2006} + \beta_{12} \cdot \text{uvgForestCov2010} + \beta_{13} \cdot \text{annualMeanTemp} + \beta_{14} \cdot \text{hansenForestCov2000} + \beta_{15} \cdot \text{precipDriestMonth} + \beta_{16} \cdot \text{annualPrecip} + \beta_{17} \cdot \text{gladForestHeight2000} + \beta_{18} \cdot \text{gladForestCov2000} + \gamma_i + \epsilon$$

These variables are equivalent to those included in our synthetic control runs, with an indicator of post-unenrolment included for the event study estimation. Our results found that there was no immediate clearing of forest cover on PINPEP and PINFOR sites. The event studies also found that PINFOR no strong trends in forest loss after programs ended, while PINPEP saw decreases in forest loss.

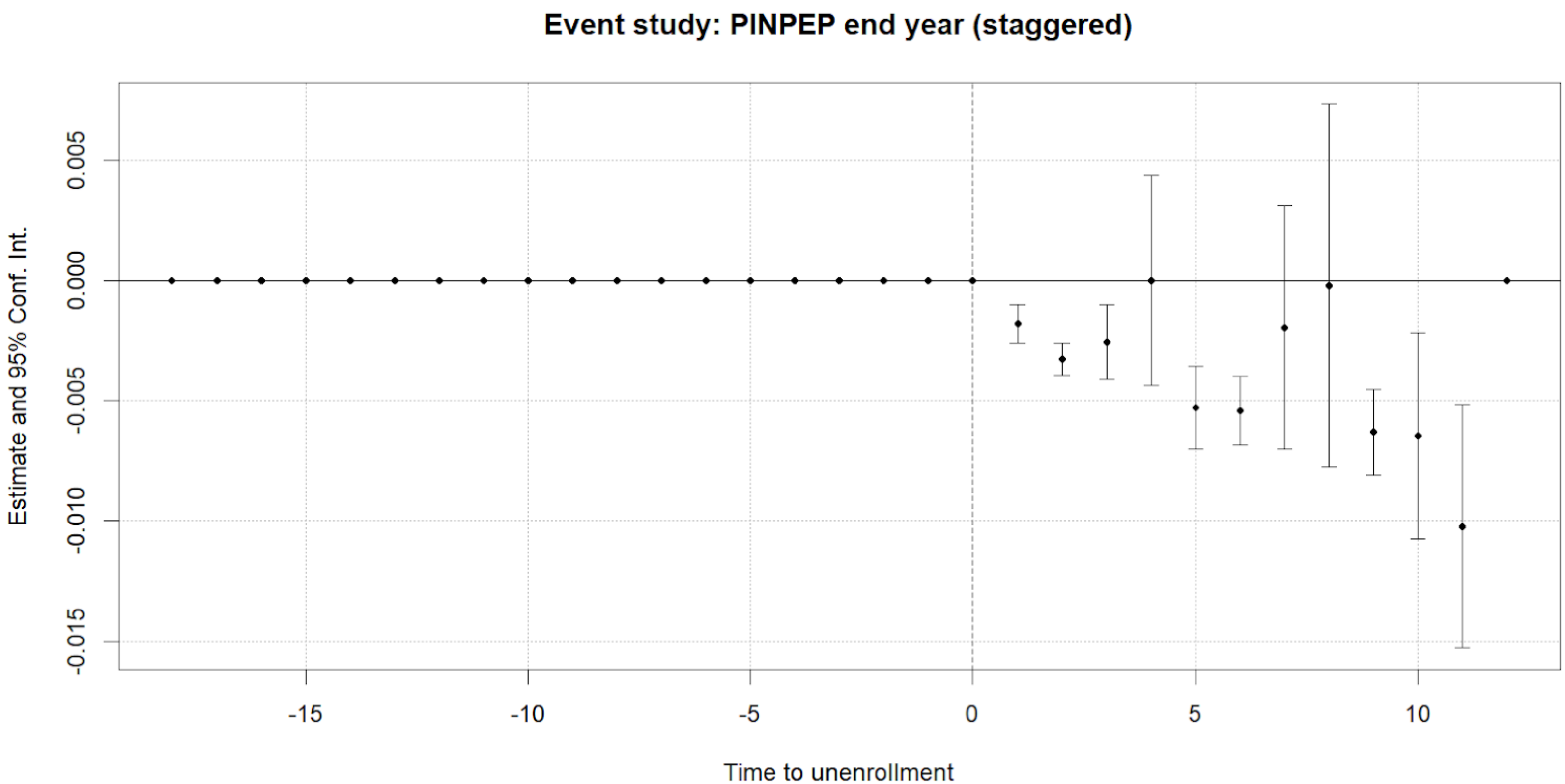
CH3 Supplementary Figure 1: Breakdown of ownership type for PINFOR sites included in the study.



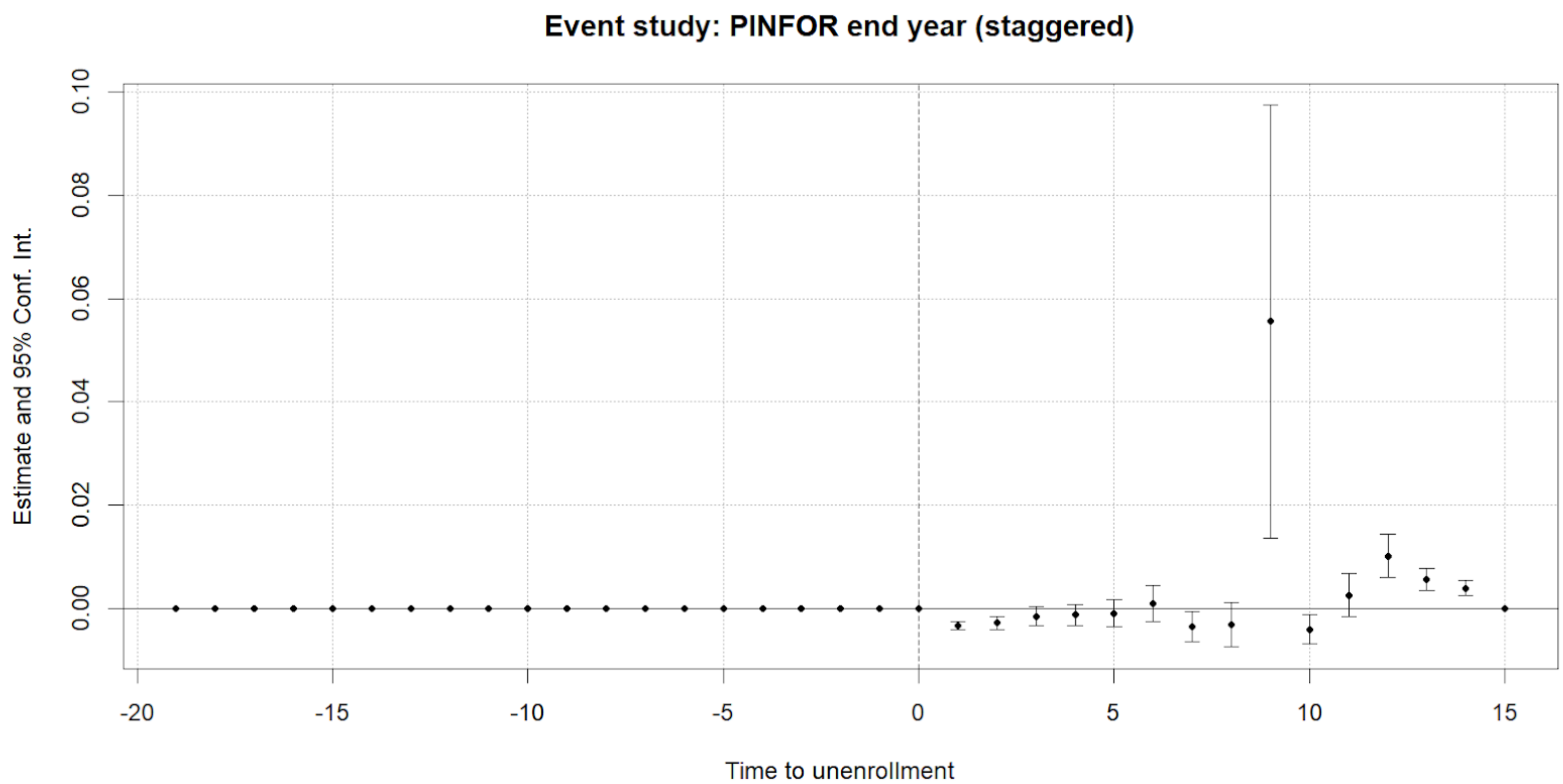
CH3 Supplementary Figure 2: Breakdown of ownership type for PINPEP sites included in the study.



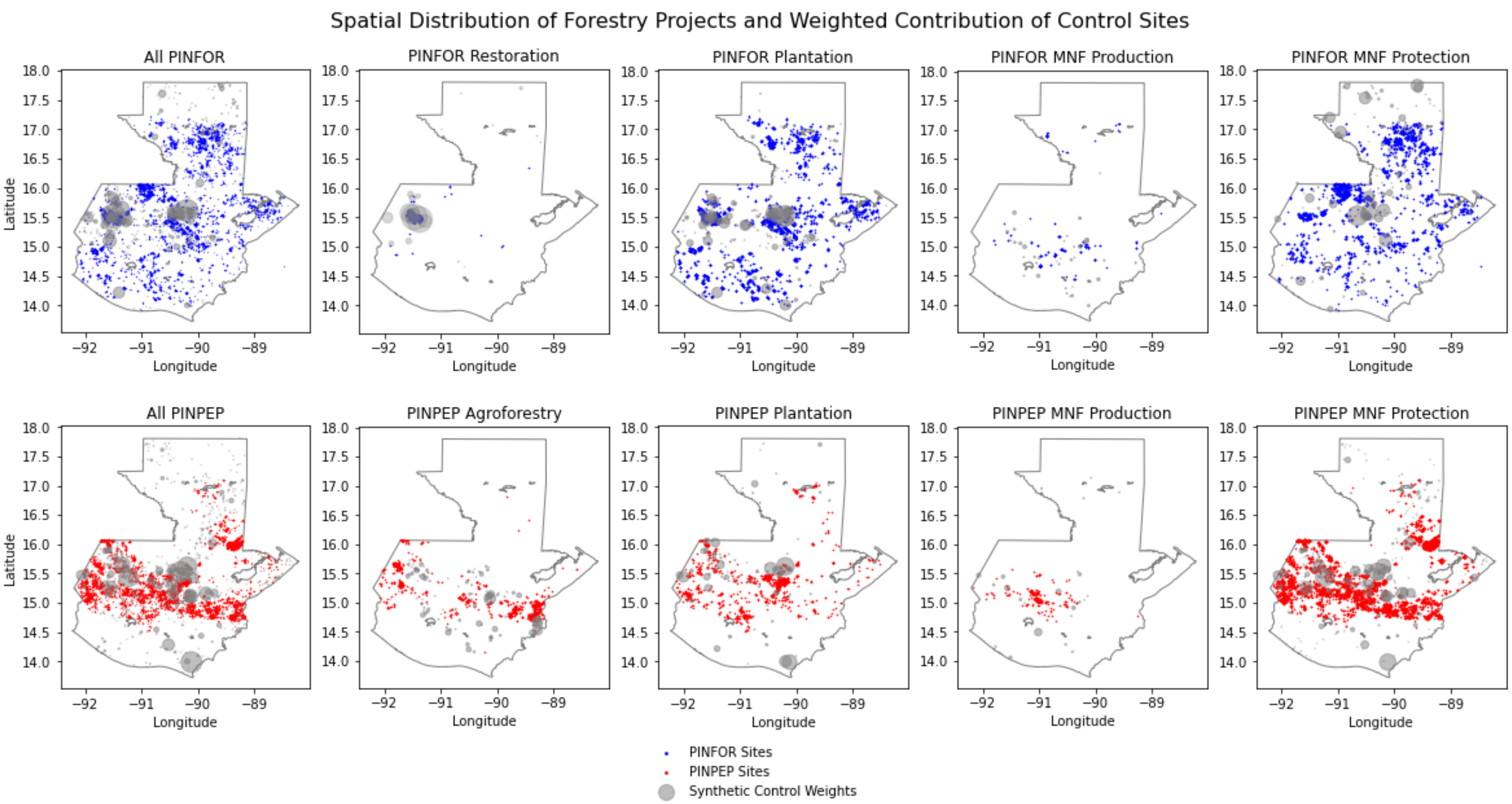
CH3 Supplementary Figure 3: Results from the event study on PINPEP end year on yearly GFW forest loss.



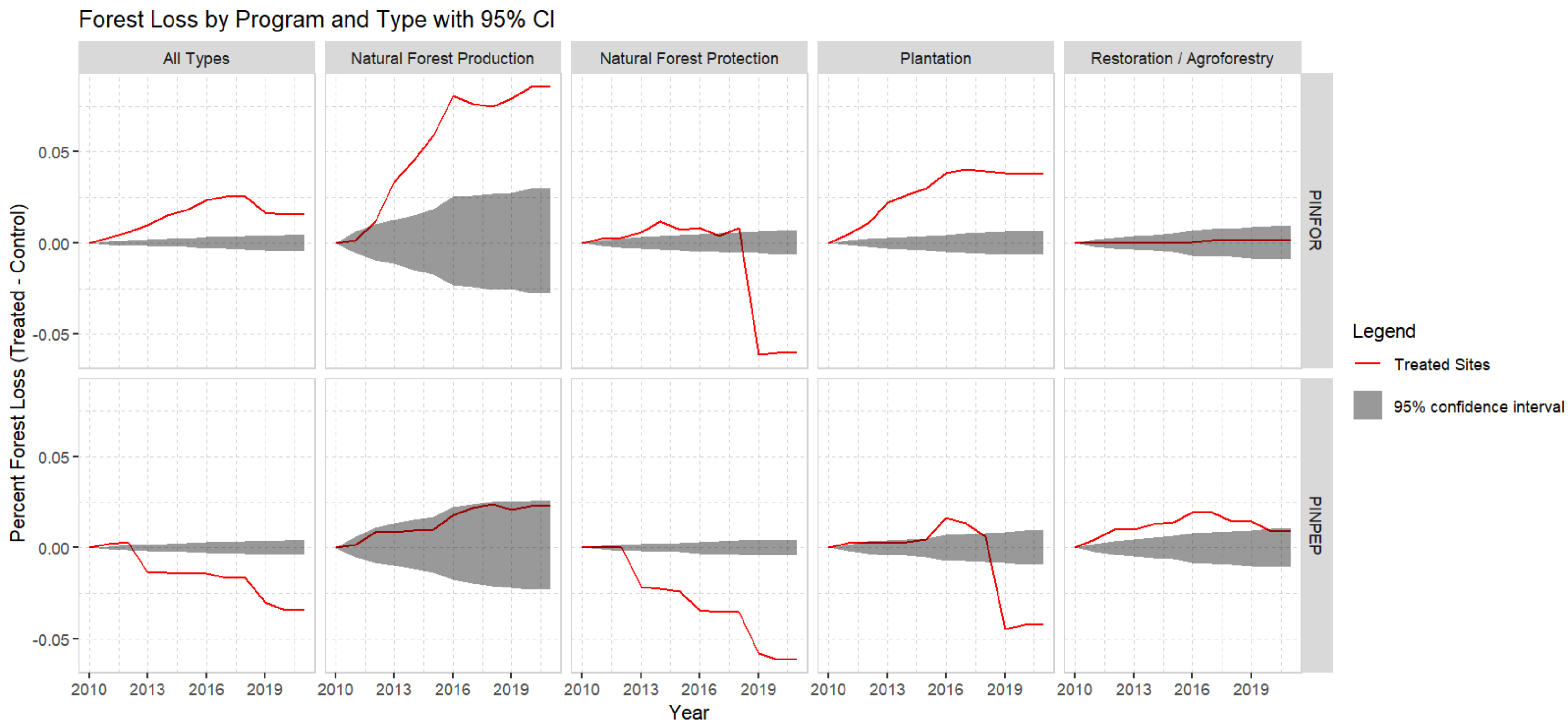
CH3 Supplementary Figure 4: Results from the event study on PINFOR end year on yearly GFW forest loss.



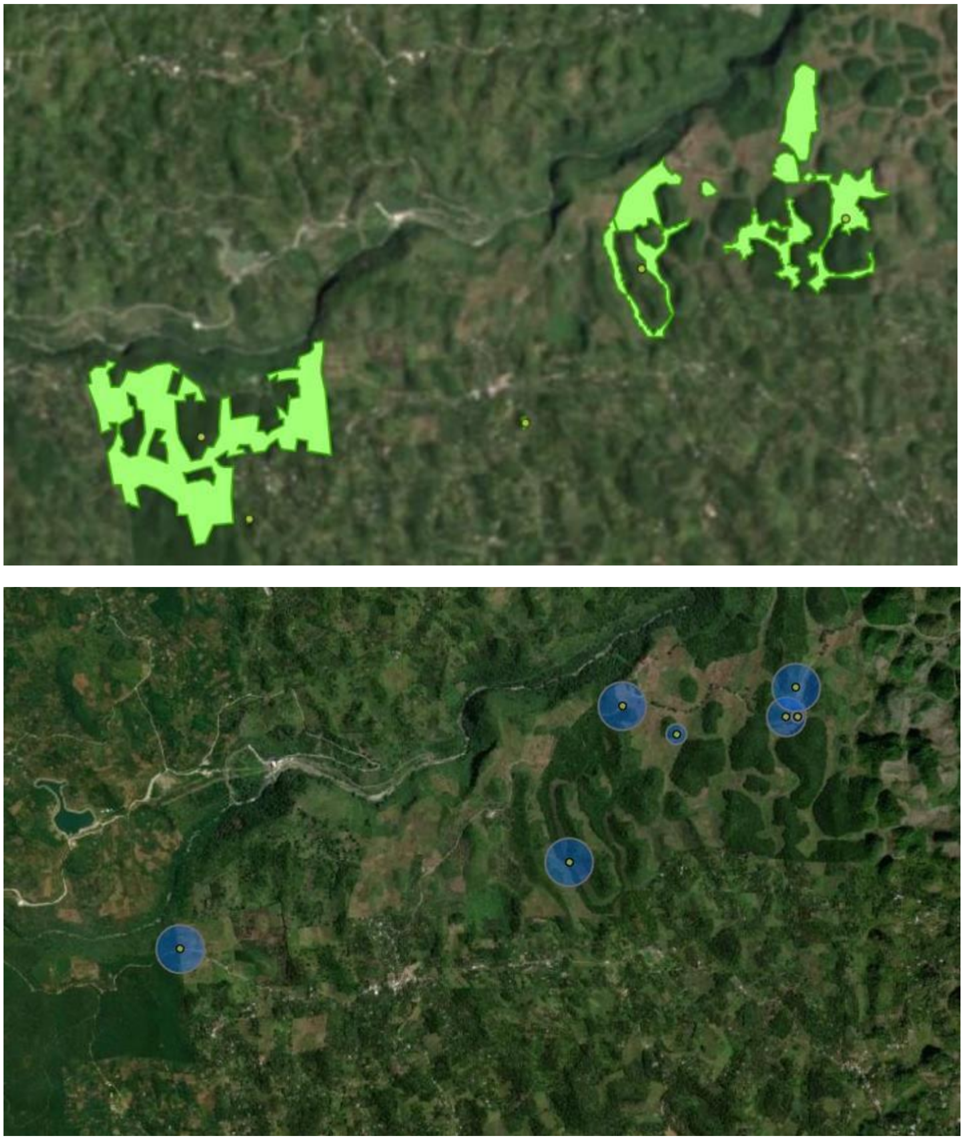
Supplementary Figure 5: Spatial Distribution of Forestry Projects and Weighted Contributions of Control sites



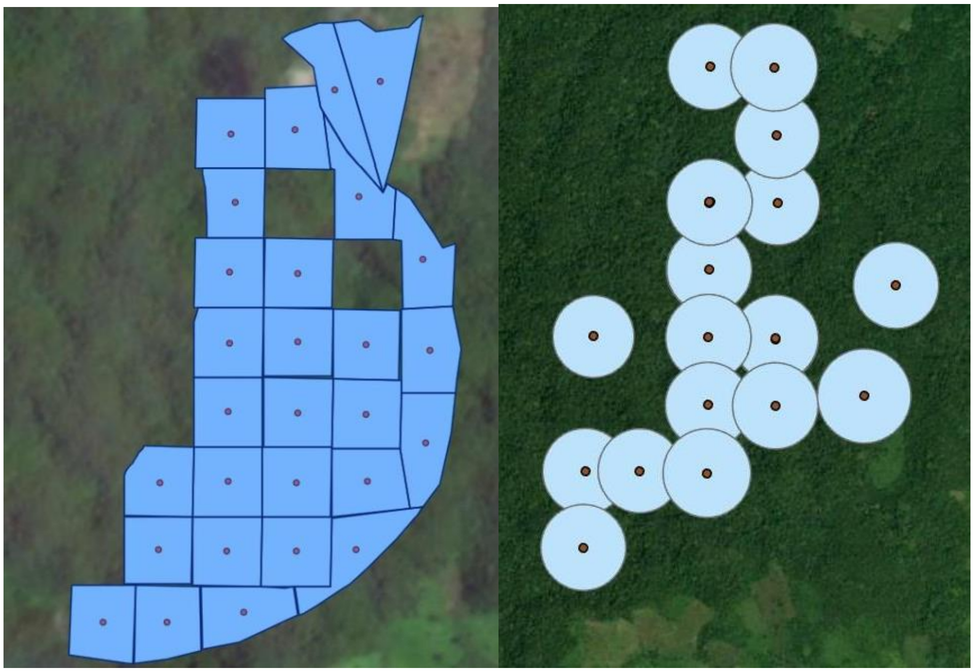
Supplementary Figure 6: Cumulative Forest Loss with 95% Confidence Interval, Derived from Synthetic Control Permutation Runs



Supplementary Figure 7: Poor Area Estimation of Abnormally Shaped PINFOR Projects



Supplementary Figure 8: Area Estimation of Gridded PINPEP Projects



Supplementary Table 1: Descriptive Statistics of Program Sites and Untreated Sample

Variable	Untreated Mean (Sd)	PINPEP Mean (Sd)	PINFOR Mean (Sd)	Data Source
Slope Aspect Elevation (m)	9.4 (9.0) 175.9 (78.0) 738.2 (789.5)	16.6 (8.1) 178.4 (94.1) 1347.3 (794.9)	11.5 (8.8) 171.1 (80.8) 1568.0 (1276.6)	Jarvis et al., 2008
Population Density (pop/km^2) 2001-2020	1.1 (4.1)	0.9 (1.0)	1.0 (1.0)	Sorichetta et al., 2015
Travel time to cities (>20k pop) 2015	43.3 (52.3)	88.0 (101.6)	81.4 (93.3)	Nelson et al., 2020
X-coordinate Y-coordinate	516411 (88941) 1736624 (117097)	499178 (95828) 1699016 (49607)	484294 (83560) 1727339 (70114)	ICN Guatemala, 2013
Biomass 2010	25.2 (25.1)	46.4 (25.2)	40.8 (28.1)	Spawn et al., 2020
Distance to Rivers	929.9 (692.8)	1027.0 (654.3)	942.7 (620.9)	Lehner & Grill, 2013
Forest Cover 2001 Forest Cover 2006 Forest Cover 2010 Forest Cover 2016	0.38 (0.42) 0.36 (0.42) 0.34 (0.41) 0.33 (0.41)	0.44 (0.41) 0.42 (0.42) 0.41 (0.42) 0.38 (0.41)	0.33 (0.38) 0.31 (0.37) 0.31 (0.37) 0.28 (0.36)	Universidad del Valle de Guatemala, OES
Forest Cover 2000 Forest Gain 12-20 Forest Loss 01-20	60.3 (35.5) 0.01 (0.06) 0.007 (0.05)	75.2 (28.7) 0.005 (0.03) 0.004 (0.03)	58.7 (35.7) 0.013 (0.05) 0.007 (0.04)	GFW (Hansen et al., 2014)
Annual Temp (°C) Precip Driest Mo Annual Precip	25.8 (25.4) 5.7 (11.3) 2036.4 (691.5)	19.4 (4.2) 33.5 (29.1) 1798.7 (737.5)	18.3 (6.8) 42.2 (30.5) 2056.9 (749.1)	Hijmans et al., 2005
Forest Height 2000 Forest Cover 2000 Forest Cover 00-20 Forest Height 00-20	10.0 (7.4) 0.72 (0.37) -0.04 (0.23) -0.58 (3.6)	13.4 (7.2) 0.88 (0.22) 0.01 (0.09) -0.01 (2.4)	10.6 (7.1) 0.77 (0.33) 0.03 (0.19) 0.44 (3.2)	GLAD (Potapov et al., 2022)

SI Table 1: Data description for covariates and outcome variables used in the analysis. We used data from 2000 to 2010 and GFW forest gain (total 2000-2012) for matching and data that extend to 2020 for outcomes. X- and Y-coordinates are meters from the origin, using the Guatemalan Transverse Mercator projection (ICN Guatemala, 2013).

Supplementary Table 2: Comparison of reported synthetic control results to propensity score matching combined with difference-in-differences

Program / Project Type	Run	Percent Matched	GFW Forest Loss	GLAD Forest Extent 00-20	GLAD Forest Height 00-20
PINPEP / All Sites	Match + did	52%	-0.3 (0.000)***	3.9 (0.000)***	3.1 (0.000)***
	Synth Ctrl	N/A	-3.4 (0.001)***	3.2 (0.000)***	2.0 (0.095)
	Match + did SDLC	86%	-0.1 (0.003) **	4.9 (0.000)***	2.8 (0.559)
	Synth Ctrl SDLC	N/A	-2.3 (0.635)	3 (0.000)***	2.7 (0.117)
PINPEP / Agroforestry	Match + did	100%	0 (0.976)	3.2 (0.000)***	3.7 (0.000)***
	Synth Ctrl	N/A	0.9 (0.001)***	2.8 (0.000)***	0.1 (0.956)
	Match + did SDLC	100%	0 (0.156)	5.1 (0.000)***	5.1 (0.000)***
	Synth Ctrl SDLC	N/A	2 (0.000)***	2.6 (0.000)***	1.3 (0.645)
PINPEP / Plantation	Match + did	73%	-0.2 (0.244)	3.1 (0.000)***	0.8 (0.199)
	Synth Ctrl	N/A	-4.2 (0.407)	2.8 (0.001)***	2.0 (0.484)
	Match + did SDLC	78%	0 (0.472)	5.9 (0.000)***	1.8 (0.000)***
	Synth Ctrl SDLC	N/A	-5.8 (0.487)	4.9 (0.001)***	3.4 (0.268)
PINPEP / NFM Protection	Match + did	60%	-0.4 (0.000)***	4.0 (0.000)***	3.0 (0.000)***
	Synth Ctrl	N/A	-6.2 (0.000)***	3.4 (0.000)***	1.9 (0.125)
	Match + did SDLC	88%	-0.3 (0.000)***	5.0 (0.000)***	2.8 (0.000) ***
	Synth Ctrl SDLC	N/A	-5.1 (0.369)	3.7 (0.000)***	2 (0.230)
PINPEP / NFM Production	Match + did	93%	-0.5 (0.097)	4.8 (0.001)***	5.5 (0.004)**
	Synth Ctrl	N/A	2.3 (0.013)*	2.8 (0.018)*	7.5 (0.000)***
	Match + did SDLC	83%	-0.1 (0.249)	5.4 (0.003)**	7.2 (0.002) **

Program / Project Type	Run	Percent Matched	GFW Forest Loss	GLAD Forest Extent 00-20	GLAD Forest Height 00-20
	Synth Ctrl SDLC	N/A	1.2 (0.147)	1.9 (0.032)*	7.2 (0.037)*
PINFOR / All Sites	Match + did	57%	1.4 (0.009)**	3.6 (0.000)***	3.5 (0.000)***
	Synth Ctrl	N/A	1.6 (0.003)**	8.3 (0.001)***	5.7 (0.022)*
	Match + did SDLC	93%	-0.1 (0.001)***	6.4% (0.000)***	3.2 (0.000)***
	Synth Ctrl SDLC	N/A	0 (0.192)	6.7 (0.000)***	3.2 (0.282)
PINFOR / Plantation	Match + did	65%	0.24 (0.002)**	4.4 (0.000)***	8.0 (0.000)***
	Synth Ctrl	N/A	3.8 (0.000)***	5.7 (0.000)***	5.3 (0.072)
	Match + did SDLC	88%	0.0 (0.492)	6.5 (0.000)***	8.9 (0.000)***
	Synth Ctrl SDLC	N/A	4.9 (0.000)***	4.1 (0.000)***	6.1 (0.000)***
PINFOR / Restoration	Match + did	3%	0.0 (0.831)	7.1 (0.043)*	8.1 (0.158)
	Synth Ctrl	N/A	0.2 (0.032)*	28.2 (0.000)***	24.4 (0.008)**
	Match + did SDLC	100%	0.0 (0.443)	9.8 (0.000)***	6.8 (0.000)***
	Synth Ctrl SDLC	N/A	0.1 (0.663)	15 (0.000)***	12.5 (0.000)***
PINFOR / NFM Protection	Match + did	92%	0 (0.735)	0.6 (0.172)	0.0 (0.783)
	Synth Ctrl	N/A	-6.0 (0.145)	1.7 (0.074)	5.5 (0.022)*
	Match + did SDLC	92%	-0.1 (0.004)**	2.5 (0.000)***	1.1 (0.003)**
	Synth Ctrl SDLC	N/A	-5.5 (0.249)	0.7 (0.607)	3.5 (0.106)
PINFOR / NFM Production	Match + did	100%	-0.3 (0.246)	0.009 (0.487)	-10.0 (0.000)***
	Synth Ctrl	N/A	8.6 (0.000)***	2.0 (0.080)	-6.2 (0.035)*
	Match + did SDLC	100%	-0.3 (0.003)**	3.8 (0.011) *	-7.4 (0.001)***
	Synth Ctrl SDLC	N/A	9.4 (0.000)***	-0.3 (0.770)	-9.6 (0.000)***

Supplementary Table 3: Outputs of Regressing Forest Outcomes on Project Duration

	GLAD Forest Cover Change 00-20	GLAD Forest Height Change 00-20
PINPEP Sites (No Controls)	**0.0011 (0.037)***	**0.0375 (0.012)***
PINFOR Sites (No Controls)	**0.0048 (0.000)*****	**0.1265 (0.000)*****
PINPEP Sites	0.0007 (0.168)	0.0194 (0.194)
PINFOR Sites	0.0006 (0.543)	**0.1081 (0.000)*****
PINPEP Sites (Project Type + Region FEs)	0.0007 (0.156)	0.0168 (0.263)
PINFOR Sites (Project Type + Region FEs)	0.0009 (0.352)	**0.0992 (0.000)*****

SI Table 3: Forest outcomes regressed on project duration. For the third through sixth rows, we control for annual precipitation, annual mean temperature, precipitation of the driest month, forest cover and height in 2000, and 2010 population. The fifth and sixth rows also include regional fixed effects.

Supplementary Table 4: Outputs of regressing forest outcomes on project end date

	GLAD Forest Cover Change 00-20	GLAD Forest Height Change 00-20
PINPEP Sites (No Controls)	-0.0009 (0.363)	**-0.0690 (0.010)****
PINFOR Sites (No Controls)	0.0007 (0.497)	**-0.0569 (0.001)*****
PINPEP Sites	-0.0010 (0.290)	**-0.0637 (0.016)***
PINFOR Sites	**-0.0030 (0.001)*****	**-0.0666 (0.000)*****
PINPEP Sites (Project Type + Region FEs)	-0.0010 (0.290)	**-0.0655 (0.015)***
PINFOR Sites (Project Type + Region FEs)	**-0.0029 (0.001)****	**-0.0677 (0.000)*****

SI Table 4: Forest outcomes regressed on project end date. For the third through sixth row, we control for annual precipitation, annual mean temperature, precipitation of the driest month, forest cover and height in 2000, and 2010 population. We also include region fixed effects in the fifth and sixth rows. An earlier project end date led to higher forest height for PINPEP and PINFOR, and higher forest cover for PINFOR when controls were included.

Supplementary Table 5: Regressing Forest Cover and Height Change on Program or Program Buffer

	PINPEP	PINPEP Buffer	PINFOR	PINFOR Buffer
Forest Cover Change 00-20	**0.0774 (0.000)*****	**0.0653 (0.000)*****	**0.0869 (0.000)*****	**0.0260 (0.000)*****
Forest Height Change 00-20	**0.9218 (0.000)*****	**0.7800 (0.000)*****	**1.1430 (0.000)*****	**0.2147 (0.005)****

SI Table 5: Outputs of spillover analysis, where we regress inclusion in incentive programs or incentive buffer areas on forest cover and forest height change from 2000 to 2020. When controlling for initial forest conditions, climate, terrain, distance to cities and 2010 population, we found that sites in PINPEP, PINPEP buffers, PINFOR and PINFOR buffers experienced an increase in forest cover and forest height relative to the Guatemalan average.

Chapter 4: Integrating Farmer Ethnography with Vegetation Drought Responses in Zacapa, Guatemala to Assess Dynamics of Drought and Vulnerability in the Central American Dry Corridor

Abstract

Zacapa Department, Guatemala, has seen dramatic impacts from El Niño-driven seasonal drought on smallholder agricultural systems, with reports of up to 80% crop losses in recent years. Zacapa is part of the Central American Dry Corridor, a region stretching from Mexico to Costa Rica faced with increasing climate change induced drought stressors and home to vulnerable populations that rely on rainfed agriculture for their livelihoods. We investigate these stressors by integrating an ethnographic analysis of smallholders' experiences of climate change in two adjacent communities in Zacapa, Guatemala with remotely sensed and modeled data on plant water stress, soil moisture, and land use. We find that water deficits in the early growing season are most detrimental to vegetation health across the landscape, but that high-elevation pine-oak forests are resilient to these seasonal droughts. Farmers often frame these deficits as 'delays' in the rainy season and connect the impacts to local environmental change, such as deforestation rather than large-scale climate change. Farmers in our surveyed communities perceive recent droughts to be more frequent and harmful than historic events. Hydrological data show droughts occuring on a quasi-decadal cycle, with recent events only appearing more detrimental when looking at growing-season water deficit. We argue that focusing on socio-ecologically relevant drought metrics is critical to identifying patterns of change that are most impactful to farmer communities. Additionally, lower-resource farmers experienced lower social network support and livelihood resilience, leading to much more severe individual drought impacts despite similar or lower signals of vegetation & crop water stress. These low-resource farmers were more likely to have had historic access to high-elevation pine-oak forests, which see delayed drought impacts during the most socioecologically impactful drought months but have been privatized or set aside for conservation in recent decades, severely limiting drought-resistant forest resource access in these communities.

4.1 Background

4.1.1.Drought in Central America

The Central American Dry Corridor is a region stretching from Mexico to Panama where rainfall variability can produce severe impacts for rainfed agriculturalists (1–3). In recent years, high-profile droughts have drawn attention from international aid organizations who have called for aid after dramatic crop losses (4,5). While these recent droughts have been highly disruptive to farmers in the region, Central America has for decades experienced cycles of drought on quasi-decadal timescales (2) and recent events were not outside of the historic range of probability of occurrence (3). The quasi-decadal cadence of drought is mirrored in tree ring data (6) and is generally driven by deviations in wet-season precipitation, as dry season precipitation is quite small and much less variable (2). The region experiences a dry season between November and April, with the rainy season running from May to October. During the rainy season, the region can experience a Mid-Summer Drought (MSD), where rainfall declines slightly during July and August (7). Research shows that increasing temperatures will make the MSD more likely (3,8), which would likely put additional strain on agriculturally-dependent people in the region.

Drought is known to impact a number of important socioeconomic outcomes, including food and livelihood security and likelihood of displacement (4,9,10). Studies on livelihoods and food security demonstrate incredible variability across communities, due to a variety of income sources, cultural backgrounds, and agricultural practices across the region (11–13). Systems theory posits that small shifts in any number of factors can dramatically influence downstream outcomes. Determining non-linearities and feedback loops in the system could help to identify potential tipping points and emergent vulnerabilities for farming systems in the region. In addition, as agricultural practices and cultural perceptions of nature are intricately linked to the past experience including climate. Thus to study the impacts of droughts in Central America, we propose treating climate regimes and farmers' ongoing experiences, practices and perceptions of climate as an integrated part of this system, with slow-onset drought 'shocks' being a driver of change in these systems.

Broadly, households' perceptions on climate and nature are culturally mediated and socially constructed. Climate shocks like droughts or storms shape human perceptions and social knowledge on nature and also condition decision-making in the face of extreme climate events. Wens et al. (14) found that smallholder farmers' adaptation decisions during droughts went beyond common decision-making frameworks, with religion, social networks, financial capital, extension services, and weather forecasts all influencing the risk evaluation and decision-making processes. Therefore, taking a simple, cost-benefit analysis approach that assumes decisions are made simply to maximize individual utility, as is often assumed in decision-making models, is insufficient to predict final outcomes given these additional socioeconomic and cultural factors assessed at the household level (15). In addition, human actions in response to climate and nature might also vary across cultures and societies. For this work, we used cultural models to identify how nature is represented and understood at the level of discourse and practice and how this, in turn, informs decision-making.

4.1.2 Quantifying Biophysical and Socio-Economic Responses to Drought

Droughts are classified variably based on the level at which impacts are measured. Meteorological drought refers to precipitation deficits, Hydrological droughts occur when there is a lack of sufficient surface or subsurface water for water management needs, Agricultural drought considers declining soil moisture and resulting crop losses, and socio-economic droughts assess the relative supply and demand of water resources as an economic good (16). While Zacapa department has a large amount of irrigated industrial agriculture, the households that are generally considered vulnerable to drought rely on rainfed agriculture. Therefore, we focused on meteorological and agricultural droughts in this study. Meteorological droughts are often measured through water deficit models, generally using some kind of gridded reanalysis dataset.

Plant biophysical responses to drought vary with timing and intensity of drought. During early water deficit stages, plants will close their stomata to reduce water loss, impacting leaf temperature, photosynthetic activity, and leaf water content. Long-term drought may lead to leaf die-back and tree mortality in severe cases (17–19). Vegetation-level responses to drought vary regionally and by vegetation types (20), with impacts from droughts often follow diverging patterns based on the type of drought and the specific biology of a land cover type. For example, in Coastal California most land cover types see the greatest vegetation impacts in the summer and fall, however annual grasslands generally see the greatest impacts in the winter and spring (21). Tropical dry forests, one of the dominant vegetation covers in Zacapa Department, are known to respond to water scarcity by adjusting the timing of budding and leaf fall (22), which may give these forests tolerance to water stressors. In fact, research suggests that seasonal drought exposure may lead to existing plant community distributions across the neotropics (23). In Zacapa, these plant communities may match the biophysical boundaries of seasonal drought stress, with tropical dry forest having high exposure to seasonal drought and higher elevation pine-oak forests not experiencing such dramatic seasonal impacts. Across tropical biomes, tropical dry forests are known to be highly responsive to drought (24), suggesting Zacapa's tropical dry forests likely are bounded by and impacted by seasonal water deficits. These changes can be tracked using Normalized Difference Vegetation Index (NDVI), a common index used to track vegetation health through droughts (25,26), although changes in vegetation water content often precede measurable changes in greenness (27,28).

Previous research has shown that dry growing seasons have a strong impact on family migration from Guatemala, El Salvador and Honduras (29), with a one standard deviation drop in Standardized Precipitation-Evapotranspiration Index (SPEI) measured over the preceding 3 months leading to 70% more family migrant apprehensions at the US border. This effect dropped dramatically when using 12-month SPEI, suggesting that short-term drought impacts are most impactful to households. Drought is often measured by long-term water deficits, but households experience drought impacts which can occur over much shorter time periods (30). This disconnect emphasizes the need to focus drought measurements on socio-ecologically important time-scales and seasons. We identify and compare standard and regionally-informed measures of drought to understand how these various measurements shift the impacts and understanding of drought across the Dry Corridor.

In this paper, we explore the impacts of drought on vegetation health and livelihoods in Guatemala by integrating remote sensing and ethnographic evidence. As outlined above, we consider drought as a process that is mediated by local ecological and social factors, with ecological factors likely impacting communities differently based on their location across ecosystem gradients and farming practices. We ask and answer the following questions: (1) how do the magnitude and timing of drought responses compare across land cover types in Zacapa based on NDVI; (2) Which time spans (seasonal, interannual) was vegetation NDVI most correlated to drought, and how did this vary by cover type and season; (3) how do observed changes in vegetation health translate to lived experiences and understandings of drought in households across an environmental/cultural gradient? Drought impacts are likely most important at specific timeframes (e.g. growing season), such that hydrological drought during this time period is much more relevant to socio-ecological systems than cumulative water deficit across a year or in less relevant seasons (29). Similar to other contexts (21), we expected deciduous or annual vegetation types (tropical dry forest or *Milpa* agriculture) to be most impacted by drought in the wet season, whereas evergreen pine-oak forests would see the greatest drought impacts during the dry season. Additionally, we posited that community-level characteristics, such as social support networks (31,32) and livelihood diversification (33), should strongly mediate the overall exposure of farmers to drought impacts. Finally, within the study region, we expected farmers in La Trementina who are more integrated with national economies to have more options in the face of drought impacts than farmers in Los Achotes who may not be able to shift their labor activities in the face of crop losses.

4.2 Methods

4.2.1 Study Area

Zacapa Department is located in the Eastern Guatemala region close to the Atlantic coast and contains a large portion of Guatemala's tropical dry forest. The department has around 250,000 inhabitants, with 55% of the population residing in rural areas. Around 97% of the population identifies as mestizo or ladino, with the remaining three percent being mixed indigenous groups or Creole (34). The Motagua river, the second largest river in the country, splits Zacapa Department down the middle and marks a historically important route connecting Guatemala City to the Atlantic. Tropical dry forests are the primary natural vegetation cover from the valley floor (200 m in elevation in Zacapa) to about 800 m along the mountains that rim the valley. To the north, the Sierra de las Minas mountains produce a strong orographic effect on rainfall from the Atlantic, resulting in semi-arid conditions across the lower reaches of the Motagua Valley. To the south there are the foothills of the Eastern Highlands and the Granadillas Mountains.

These mountain ranges are dominated by tropical montane pine-oak forests, and the Sierra de las Minas is protected by the second largest biosphere reserve in Guatemala. Agriculture has shaped much of the landscape, with industrial irrigated agriculture dominating the Motagua valley floor, and smallholder rainfed agriculture common at the rim of the valley and in the mountainous regions.

Vegetation and drought analyses were performed for all of Zacapa Department, but a focused analysis on household experiences of and vulnerabilities to drought was performed in La Trementina and Los Achiotes, two villages located near the department's capital in Zacapa municipality. La Trementina is situated at the base of the Granadillas mountains at 350 meters, and Los Achiotes at around 1000 meters above sea level, around halfway up the Granadillas. La Trementina is surrounded by tropical dry forest and Los Achiotes is bounded by dry forest at lower elevations and pine-oak forest at higher elevations (Figure 1).

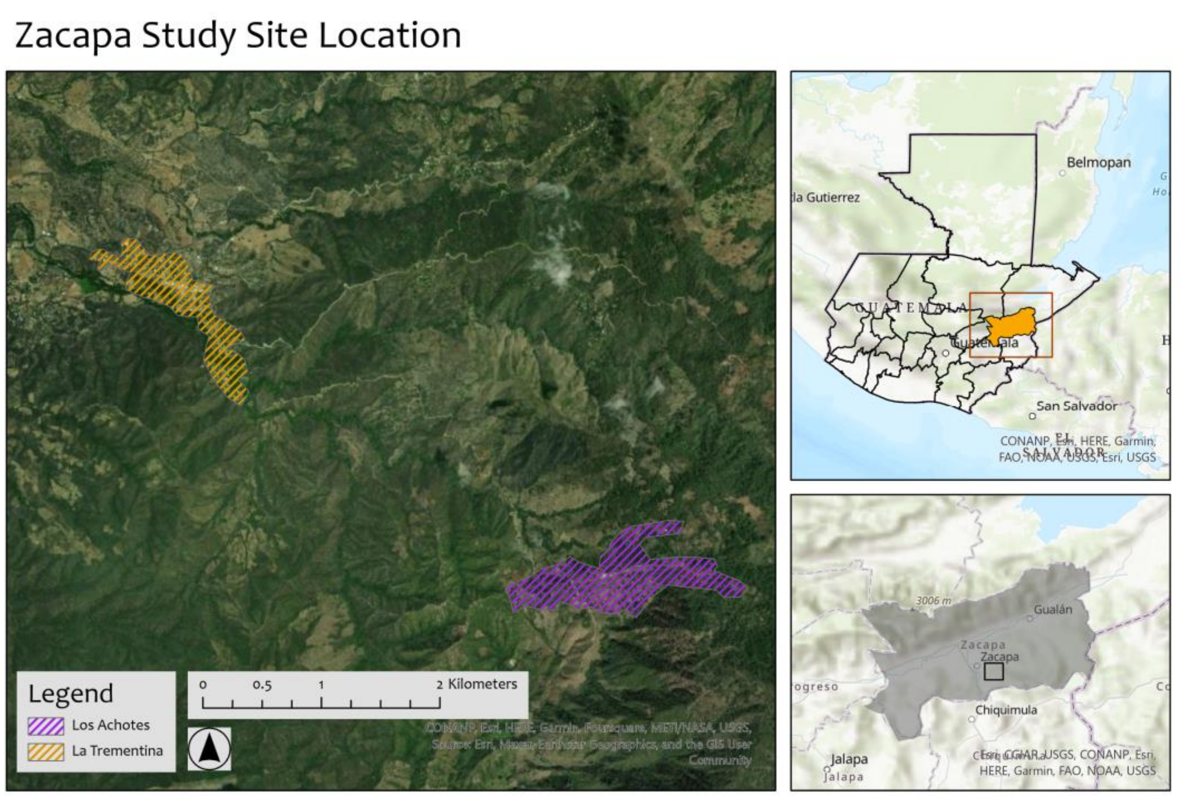


Figure 1: Study site location, showing Zacapa Department and the two towns, La Trementina and Los Achotes, in Guatemala. Figure produced in ArcPro 3.2.

4.2.3 Remote Sensing

We used a variety of remote sensing analyses to explore the context and impacts of droughts in La Trementina and Los Achotes. First, we looked at long-term economic trajectories of the communities using nighttime luminosity data from 1991-2020. Then, we assessed vegetation sensitivity to drought by extracting seasonal vegetation NDVI patterns by land cover type, and comparing these patterns with drought indices. This method detects spatial and temporal patterns in plant water stress, looking at seasonal shifts in vegetation greenness and rainfall alongside variable measurements of drought. Finally, we pulled NDVI time series at the field level to assess impacts experienced by interviewed farmers in La Trementina and Los Achotes.

4.2.4 Nighttime Luminosity

Due to limitations in traditional data sources across much of the developing world, nighttime luminosity is often used as a proxy for economic development or growth (35,36). In Guatemala, census data is available in 2002 and 2018, but data below the municipality level or at more frequent time intervals is unavailable. The wide spatial reach of nighttime luminosity data, as well as its time series going back to 1992, allows us to compare changes over a long time period for the two sites. However, care should be taken to ensure that non-economic activities are not being detected. However, averaging values by year and looking at overall, decadal trends generally allows for clearer comparisons between sites.

To assess economic trajectories via nighttime luminosity, we used the annual Defense Meteorological Program Operational Linescan System Version 4's Consistent and Corrected Nighttime Lights Dataset (CCNL) from 1992 to 2012 (37), and monthly average radiance from 2013 to 2022 via the Visible Infrared Imaging Radiometer Suite (VIIRS) Day/Night Band (DNB) (38). Average values for village boundaries were extracted for all years from 1992 to 2012 and all months from 2013 to 2022 to estimate change in nighttime luminosity from an early-1990s baseline. Because of calibration issues between the two datasets, we compared them separately and compared trends between the villages across the two separate times-scales (1992-2012 and 2013-2022).

4.2.5 Land Cover Classification

We used multispectral Landsat imagery to classify the department's land cover into seven distinct types: tropical dry forest, pine-oak forest, industrial agricultural systems (dominated by melon farms), smallholder agricultural fields or *Milpa* systems, bare soil, water, and built-up/urban areas. We compared classifications using random forests and dynamic time warping across a couple different datasets to determine our best classification. This allowed us to split the data by land cover type and understand vegetation dynamics by cover. This land cover classification was then used to extract the median NDVI values for each vegetation type for recent (2016-2023) and historic (1986-2023) multispectral imagery.

Mapping dry tropical forest ecosystems is a persistent problem, with widespread disagreement among estimates of dry forest extent (39). The most up-to-date map of tropical dry forests across Latin America does not include any of the forests in the Motagua Valley (40) although other mapping efforts, such as the WWF Ecoregions, do identify these regions broadly without providing cover estimates (41,42). Additionally, forest cover mapping efforts in Guatemala do not include these forests in their estimation of total forest cover in the country, despite their wide extent below 800m in Zacapa (23). These inconsistencies arise, in part, because forest cover maps generally use cloud-free image composites for classification, which are almost entirely restricted to the dry season in Guatemala. In images taken between December and April, tropical dry forest trees in Guatemala will generally be leafless, making the forests difficult to distinguish from non-forest vegetation using standard methods. Because of this, most existing maps of tropical dry forest rely on MODIS sensors to provide sufficient spectral specificity for differentiating dry forest from other forest cover types (40,42). For this analysis, we needed to distinguish between forest and rainfed agriculture at moderate- to high-resolution scales to identify patterns at the field level, meaning these maps and methods were too coarse for our application.

To get around the limitations of dry season-based classifications, we used median composite Landsat 8 and Landsat 9 OLI images for the wet and dry seasons to identify deciduous dry forests in the region. Images composites were created for the wet season (June through November) and dry season (December through May) by filtering within each season and removing images with more than 25% cloud cover to get a wet-season and dry-season cloud-free image from 2019-2023. Wet and dry season images were then combined, creating a wet-season and dry-season value for each Landsat band. Querying and mosaicing of images was performed in the Google Earth Engine code editor. Creating a seasonal composite allowed us to pick up properties of the dormant forest vegetation during the dry season (for example, SWIR reflectance) and create more consistent measures of wet season vegetation greenness.

After the image composite was created, we created a classification of land cover for Zacapa Department with seven land cover classes encompassing important cover types seen in the region. Land cover classes were chosen to identify important vegetation covers in the region and after exploratory unsupervised classifications. We chose to classify tropical dry forest, pine-oak forest, rainfed *Milpa* agriculture, irrigated agriculture (dominated by plastic-lined melon fields), bare soil, built-up/urban areas, and water. Fifty training polygons were generated for each land cover classification based on high-resolution Google Earth imagery. An additional 100 testing points were generated based on the same high-resolution imagery for classification accuracy assessments. Classification was performed using the ee.Classifier.smileRandomForests() function in Google Earth Engine. In order to increase the accuracy of the classification, especially in distinguishing between regrowing rainfed agriculture (*Milpas*) and tropical dry forest, we added a forest height band to the composite image. Forest height was pulled from Potapov et al (2021) (44), which estimates 2019 forest height at 30m resolution by integrating GEDI LIDAR data with Landsat spectral imagery. Finally, 30 additional training polygons were added for tropical dry forest and soil, and 50 additional training polygons were added for rainfed agriculture plots to better distinguish land cover classes that had lower accuracy in initial classifications.

4.2.6 Assessing Drought and Greenness

To explore the ways that drought impacts vegetation health within Zacapa department, we looked at how vegetation cover greenness was impacted by water deficits across varying timeframes. Vegetation cover greenness, as measured by the NDVI, is a good proxy for plant health, especially when considering deviations from the norm. We extracted NDVI time series from 2016 to 2023 from the HLS dataset, which aligns Landsat 8 and 9 OLI data with Sentinel-2 MSI data to provide medium resolution imagery with a very high revisit rate. This allowed us to get wide-coverage NDVI measurements throughout the growing season and compare it with Standardized Precipitation Evapotranspiration Index (SPEI), calculated across 1-48 month intervals (45).

Additional NDVI values were extracted across the Landsat archive, from 1988 to 2023, to better identify historic patterns of drought across vegetation types. Data was extracted from Google Earth Engine's Python API to cloud, then aligned and masked to vegetation type in R. Images with greater than 50% cloud cover were filtered out, and median NDVI was extracted for each date and land cover type.

We also calculated historic 3-month SPEI for Zacapa Department from 1979 to 2024 by combining ERA5 Reanalysis 2m Surface Temperature (46) with CHIRPS precipitation data (47). Using the methodology laid out by Linke et al. (29), we defined Zacapa's growing season using the ASAP phenology data (48). On average, Zacapa's growing season starts on May 1, and ends on October 2, although this varies across elevation and temperature gradients (SI Figure 2). We compared 3-month SPEI trends for all months compared to trends in growing season months to assess trends in overall and farmer-relevant drought.

4.2.7 Field Assessments

Field-level assessments were performed to identify patterns specific to interviewed households. During field visits and interviews, we walked with farmers to their milpas and identified the boundaries of fields cultivated by informant farmers. We also identified adjacent forest areas for comparisons between cultivated fields and forest vegetation. These bounds were then used to identify vegetation dynamics via NDVI values and drought indices. This gives us specific insights into the patterns of vegetation health in the households we interviewed and allows for direct comparison between Los Achiotes and La Trementina agricultural impacts. Data is reported and assessed at the village level to reduce statistical noise and preserve farmer anonymity.

First, we considered the monthly NDVI anomaly at the field level using the Landsat archive, regressing it on El Niño 3.4 index to determine how predictive ENSO is of NDVI variation from norm. Then we charted median NDVI across fields and adjacent forest types to determine how drought impacts greenness at the vegetation level.

4.2.8 Ethnographic Methods

Fieldwork was conducted during visits that lasted from 2 weeks to 1 month between 2013 to 2024. During field visits, we talked with community members and developed relationships with people before conducting structured interviews. Before structured interviews, we would walk with farmers to their fields to see the landscape and discuss issues of agriculture and water. Field locations and bounds were identified using GPS and later converted to polygons in GIS software. Over the course of the study, we were able to talk with 16 agricultural households, conducting structured interviews with male heads of households, the primary agricultural workers in each family. 14 of these interviews were conducted in La Trementina, and 2 of these interviews were in Los Achiotes. Additional fieldwork to create a more balanced sample of farmer interviews will be conducted in August, 2024.

Structured interviews focused on the history and experience of farming, identifying area and productivity of land and moving towards drought impacts and understandings of drought. Interviews ranged between 30 and 60 minutes. Transcriptions of interviews were created using Google Pinpoint and interviews were analyzed by identifying and comparing themes of agricultural production, drought impacts, livelihoods and history. As further interviews will be conducted in August 2024, we provide an initial assessment of broad, emergent themes in the current interview set.

4.3 Results

We find evidence of a quasi-decadal cycle of droughts in Zacapa that mirrors trends found across Central America, with a decline in frequency and severity of droughts between 1998 and 2009 (Figure 2). Across this time period, we observe an upward trend in precipitation, but the risk of drought appears to be increasing because of precipitation variability and increases in average temperature (SI Figures 1 & 2). Drought impacts during the dry season are increasing much faster than drought impacts across the whole year (Figure 2), suggesting a climate signal that is particularly impactful to agriculture and deciduous vegetation.

We also find a strong divergence in nighttime luminosity data between La Trementina and Los Achiotes. While nighttime luminosity was approximately equivalent in the 1990s, luminosity in La Trementina began increasing rapidly in the 2000s and continues to increase more rapidly than Los Achiotes in recent years (SI Figure 3). Despite this trend, both communities have seen increases in luminosity, with overall trends suggesting increasing development and electrification infrastructure over recent decades.

4.3.1 Timing of Drought Responses

When looking at NDVI for fields and adjacent forest plots in La Trementina and Los Achotes, we found that fields and forest plots in La Trementina were more variable during the wet season

(May - October), with the 2018/2019 drought most visible in the early wet season and in 2018. Three-month SPEI, on the other hand, peaks in 2019, suggesting that vegetation might be responsive to shorter or more inopportunely-timed water deficit signals. In this case, 2016 SPEI dropped at the beginning of the wet season, while 2018 and 2019 SPEI dropped in the middle of the wet season (July and August) suggesting a mid-summer drought mechanism. Pine-oak forests adjacent to fields in Los Achotes have the most variable NDVI during the dry season (Figure 3). Additionally, when assessing the correlation between NDVI anomaly and Niño 3.4, fields and forests in La Trementina decline in greenness during El Niño events, whereas fields and forests in Los Achotes are not significantly affected (Table 3).

Our land cover classification defined 7 different land cover types across Zacapa: tropical dry forest, pine-oak forest, industrial agricultural systems (dominated by melon farms), smallholder agricultural fields or *Milpa* systems, bare soil, water, and built-up/urban areas. Natural vegetation cover consists primarily of tropical dry forest below about 800m and pine-oak forest above 800m, with some riparian systems interspersed with the dry forest in low elevations. User's and Producers' accuracies are shown in Table 3, and the final land cover classification is shown in Figure 4.

Figure 5 indicates that HLS-derived NDVI, when extracted across land cover from 2016 to 2023, is highly variable across land cover types (Figure 5). Drops in NDVI due to the 2018/19 drought were most prominent in the early dry season (July and August) for most land cover classes. The exception was pine-oak forests, which had much more consistently high NDVI across all seasons. When comparing the correlation between NDVI and SPEI across different SPEI time spans, we see that tropical dry forests and *Milpa* plots showed the highest correlation between NDVI and SPEI across 2-3 month periods during the early wet season, and ~12 month periods in the late wet season (Figure 6). Industrial agriculture and urban areas see a similar relationship between NDVI and SPEI for the early wet season, but a stronger relationship in the 5-10 month range for NDVI and SPEI in the late wet season. Pine-oak forests, on the other hand, showed the largest relationship between SPEI and NDVI in the late dry season across an SPEI range of 18 months, suggesting that annual precipitation deficits are more impactful to these forests.

Finally, we found that El Niño 3.4 was negatively correlated with NDVI during the wet season, but not consistently correlated with NDVI during the dry season (Figure 7). This suggests that ENSO is driving some of the relevant vegetation impacts, but that these are concentrated in the rainy season. When looking across the landsat archive, we see that SPEI of 8-12 months is strongly correlated with NDVI in the early rainy season (SI Figure 4). This correlation occurs during La Niña conditions (SI Figure 5), but not during El Niño conditions (SI Figure 6).

4.3.2 Ethnographic Results

Farmers in both communities report drought impacts but identify divergent experiences of drought. In La Trementina, farmers are financially stressed by drought and have started delaying planting in the early rainy season to reduce the chance of losses. However, farmers in Los Achiotes are often much more reliant on these crops and see much more dramatic impacts from drought. One Los Achiotes farmer reported only having a tortilla to eat a day during the 2016 wet season, with reports of hunger consistent across interviewed households. Further analysis identified underlying drivers of this divergence. First, clear differences in livelihood opportunities exist between the communities. Farmers in La Trementina often were choosing between working the fields and getting a wage labor or salaried job. Many farmers in the community are older, and some returned to agriculture after receiving their pensions from salaried jobs. These farmers also reported greater social support, with trusted friends and family members in the community who they would go to in times of financial trouble. Farmers in Los Achiotes did not have these opportunities, with agriculture being a key component of their economic well-being. Many farmers in Los Achiotes would work on plantations outside of the normal growing season, for example to pick coffee, but still relied on their crops as a key source of food and income during the wet season. Additionally, farmers in Los Achiotes reported much lower levels of social support, with fewer friends and family members who they would go to in times of financial stress. This socioeconomic context is likely a driver of the observed difference between communities, as ecological and hydrological measurements were relatively consistent between the sites.

We also identified some historical patterns of drought experience and livelihood strategies across the interviewed households. Most importantly, farmers from both communities report drought occurring during their lifetimes and their parents' lifetimes, but that recent droughts have been more impactful to their crops than historic events. Households in Los Achiotes also identified the forest above the village, which covers the higher reaches of the Granadillas Mountains, as formerly being communal lands for towns and communities ringing the mountains. These lands have, in recent decades, been privatized and are now owned by wealthy individuals who grow shade coffee and harvest timber from the region. This change in access to highland forests that are less affected by drought in wet season months, alongside socioeconomic factors, may have further eroded the resilience of Los Achiotes farmers to drought impacts.

Among the respondents we found farmers had at least two ways of explaining the perceived increases in drought. One explanation links water scarcity to human activity through the deforestation of forests in the mountains above the communities. The other ties changing rainfall patterns with passages from the Bible, prophecy or Divine intervention. These explanations are not mutually exclusive, and farmers often had overlapping conceptions of divine and human change causing drought. The following two responses from two different participants show how some farmers understand drought as driven through human activity.

> *"Puede ser que sea por el cambio climático que le dicen, porque yo me recuerdo que años atrás quizás llovía más, quizás unos 15 ó 20 años atrás… Algunos dicen que quizás*

sea la maldad del hombre, por eso es que ya no llueve … Yo me imagino [las montañas] que tiene que mucho que ver, pues mientras más árboles se talen y menos árboles hay, la tierra está menos protegida, calienta más entonces, cuando se tala una montaña me imagino yo que eso hace que se caliente más la tierra y llueva menos tal vez".

"It may be because of climate change, as they say, because I remember that years ago it may have rained more, perhaps 15 or 20 years ago… Some say that perhaps it is the evil of man, that is why it no longer rains... I imagine [the mountains] have a lot to do with it, because the more trees are cut down and the fewer trees there are, the earth is less protected, it heats up more so, when a mountain is cleared, I imagine that this makes the earth warmer more and it rains less perhaps."

"Ya a veces las nubes no son constantes como eran antes, ya con tanto calor. Lo que a veces no me explico yo es que, si el sol pasará un poco más bajo o si podría ser que pase un poco más cerca, eso es lo que yo me pongo a pensar. Si no fuera así, las nubes cuando se levantan permanecerían en el lugar que corresponde, pero con ese calentamiento pasa como que si nos ponemos una marqueta de hielo al sol, eso con el calor se va derritiendo, se va desapareciendo, y no lo vimos ni a qué horas. Yo me imagino así, es posible que así sea."

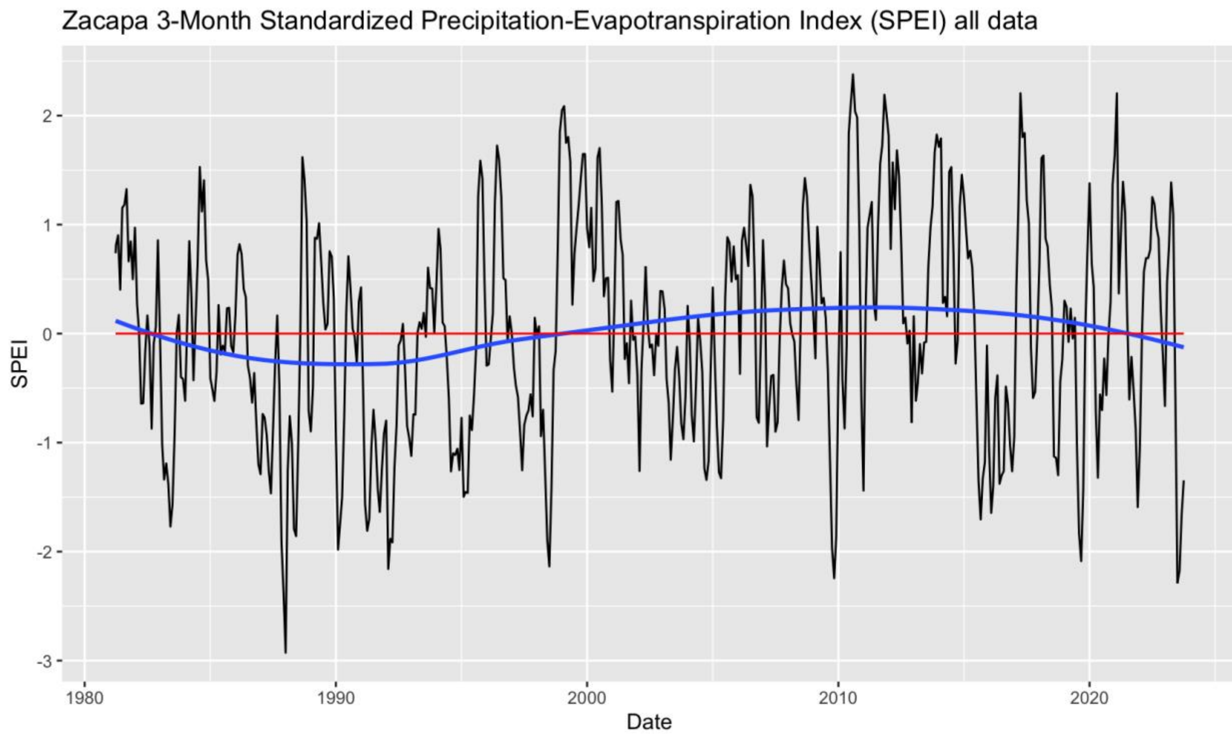
"And sometimes the clouds are not as constant as they used to be, with all this heat. What I sometimes can't explain is whether the sun might be passing a bit lower or if it could be passing a bit closer, that's what I start to think about. If it weren't like that, the clouds when they rise would stay in their proper place, but with this warming, it's like putting a block of ice in the sun, with the heat it melts, it disappears, and we didn't even see when it happened. That's how I imagine it, it might be like that."

An example of the second explanatory model is shown in the following quote:

"Bueno mire, algunos dicen que es por la deforestación, pero según las escrituras desde el tiempo cuando el primer hombre mató, Caín mató a Abel, Dios dijo 'maldita será la tierra por tu causa y nunca más te dará el fruto. Cuando labres la tierra, espinos y cardos te producirá y comerás hierbas del campo'." Entonces, de ahí viene ya toda la situación que se está viviendo porque el año pasado, a pesar de que hay deforestación, nos pegó un asotón de invierno y no, no afectó la deforestación pero, como realmente, el caso es todo lo que se ve, usted pone las noticias en tele y todo lo que se ve".

"Well look, some say it's due to deforestation, but according to the scriptures from the time when the first man killed, Cain killed Abel, God said 'cursed is the ground because of you, and it will never again yield its crops. When you till the ground, it will produce thorns and thistles for you, and you will eat the plants of the field.' So, from there comes all the situation that is being experienced because last year, despite deforestation, we had a heavy winter and no, it wasn't affected by deforestation but, as really, the case is everything that is seen, you turn on the news on TV and all that is seen."

(a)



(b)

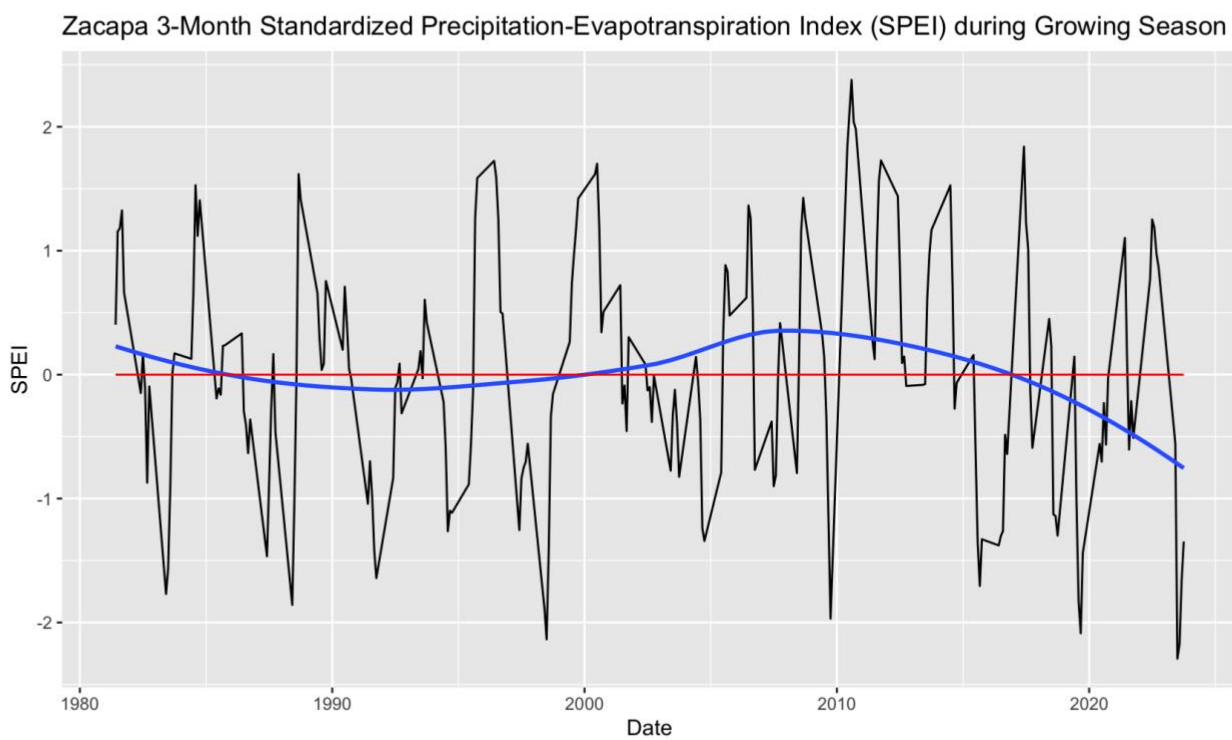
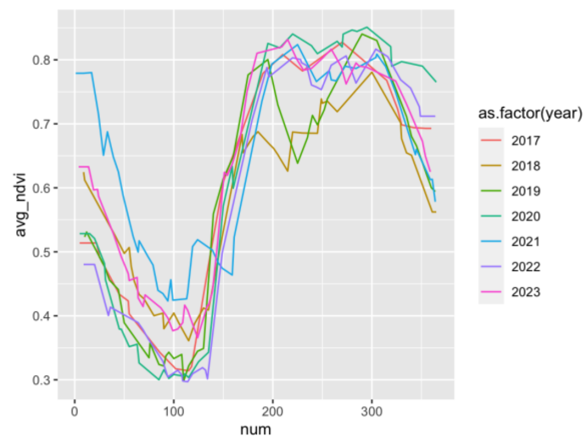


Figure 2: When considering only growing season dates, as defined by the ASAP phenology dataset (48), average SPEI in Zacapa has declined dramatically since the mid-2010s. This trend is less pronounced when considering all data, including non-growing season months.

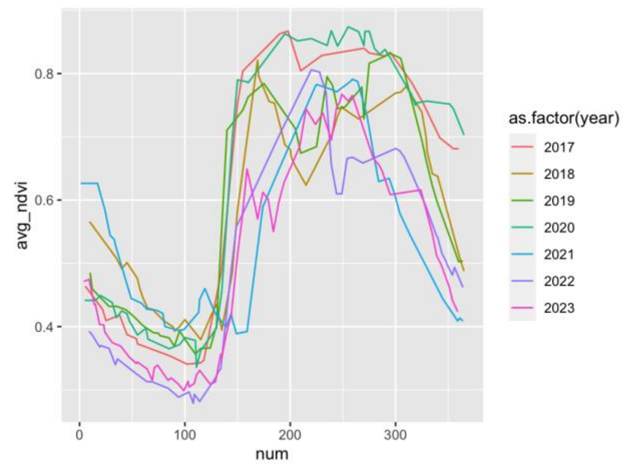
Group	Coefficient	Pr(>|t|)	Variable
La Trementina fields	-0.264	0.000 ***	Niño 3.4
Adjacent Tropical Dry Forest	-0.277	0.002 **	Niño 3.4
Los Achotes fields	-0.084	0.388	Niño 3.4
Adjacent Pine-Oak Forest	-0.086	0.311	Niño 3.4

Table 2: Coefficients and P-values when regressing NDVI anomaly on Niño 3.4 in fields in La Trementina and Los Achotes, as well as in adjacent forest plots. We see that El Niño seems to be driving declines in vegetation and field greenness in La Trementina, but not in Los Achotes

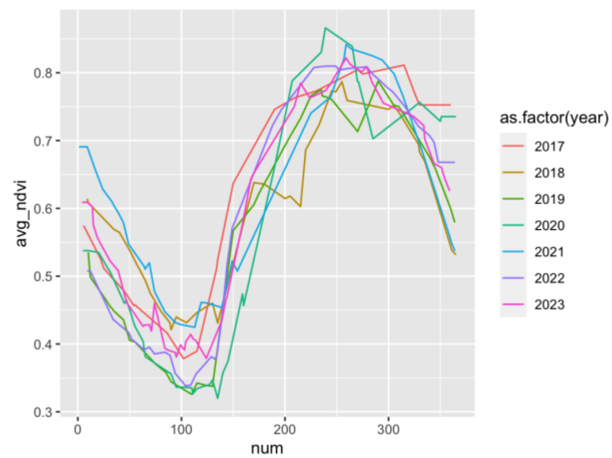
(a) Upper Milpa Plots la Trem



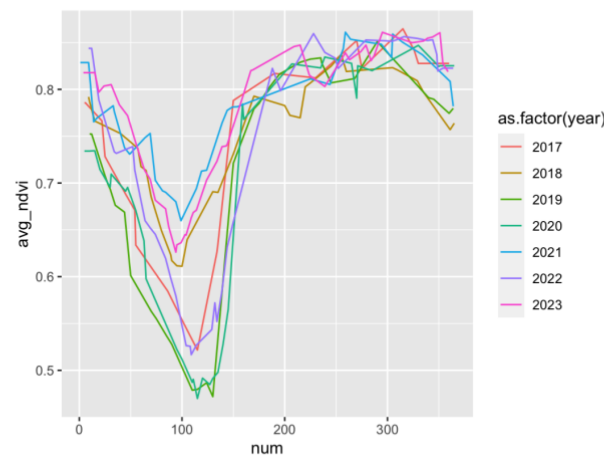
(b) La Trementina Lower Milps NDVI



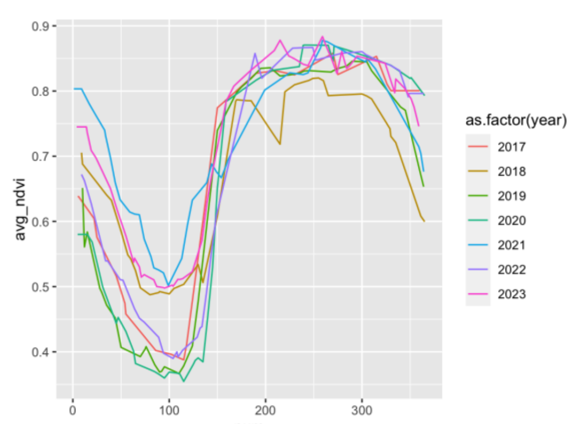
(c) Los Achotes Milps NDVI



(d) Los Achotes Pine-Oak Forest



(e) Los Achotes tropical dry forest



(f) Zacapa tropical dry forest

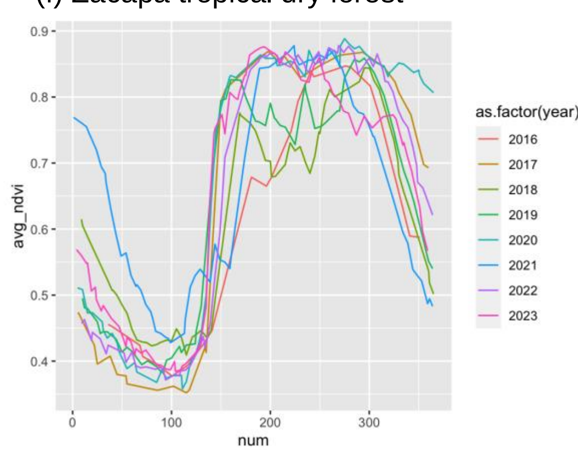


Figure 3: Yearly NDVI patterns (2017-2023) for field and forest plots in La Trementina and Los Achotes. (d) shows that impacts to Pine-Oak forest are delayed to the subsequent dry season.

Land Cover	User’s Accuracy	Producer’s Accuracy
Tropical Dry Forest	0.8	0.99
Pine-oak Forest	0.87	0.99
Rainfed Fields/Milpa Systems	0.78	0.81
Irrigated Agriculture	0.84	0.9
Water	0.88	0.96
Bare Soil	0.82	0.66
Urban	0.95	0.83

Table 3: Accuracy of Zacapa Land Cover Classification

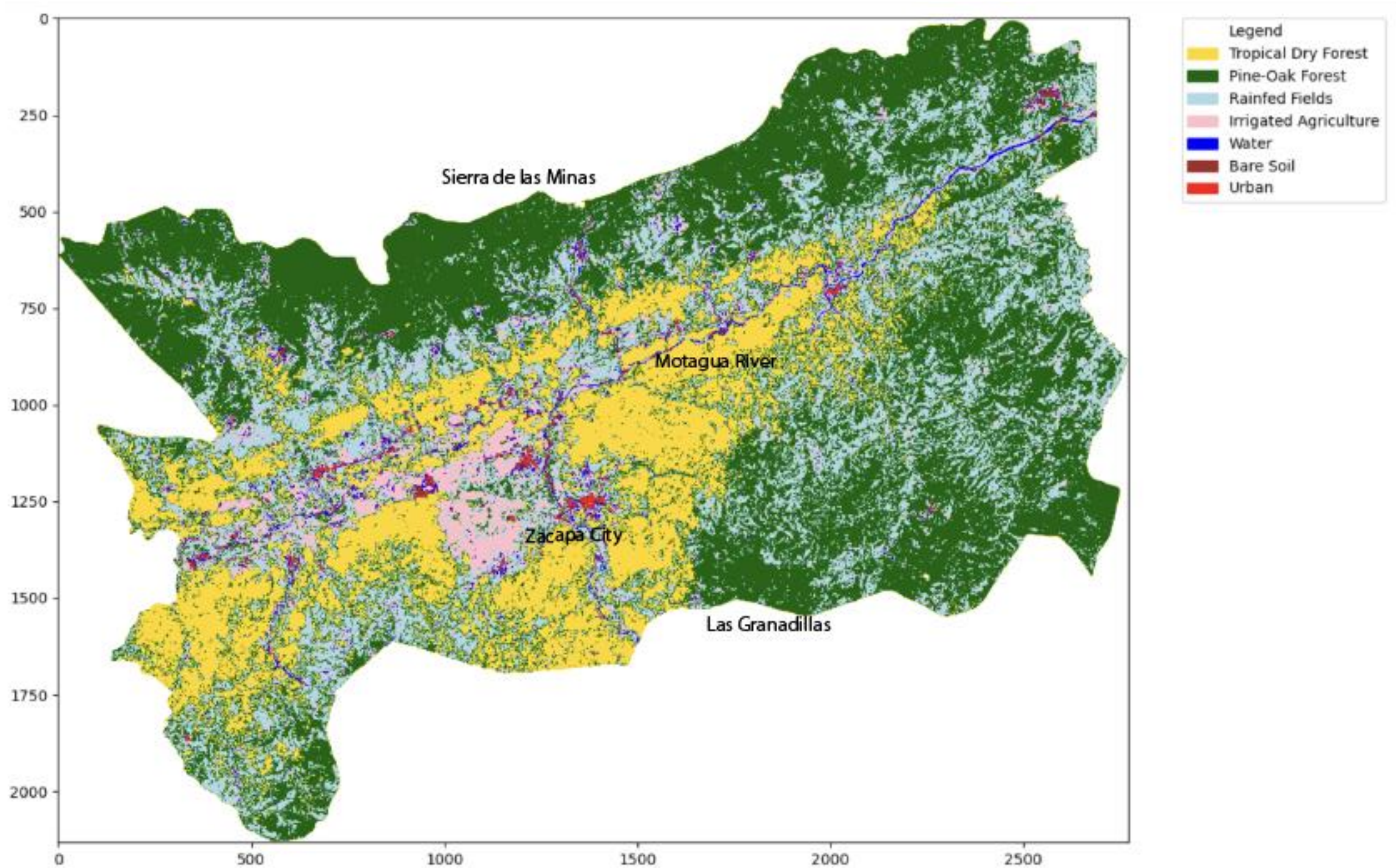


Figure 4: Land Cover Classification for Zacapa, Guatemala. Visible prominent features include the Motagua valley, which is home to all of the department's irrigated agriculture, and flows Northeast through Zacapa, Sierra las Minas, a protected, forested mountain range bounding to the north, and Las Granadillas, which are a smaller forested range in the Southeast.

Figure 5: Median NDVI by month from 2016-2023 by land cover class in Zacapa. Blank values represent no observations. A relative drop in NDVI during the 2018/2019 drought is visible here in July and August for many of the land cover classes, but not pine-oak forests.

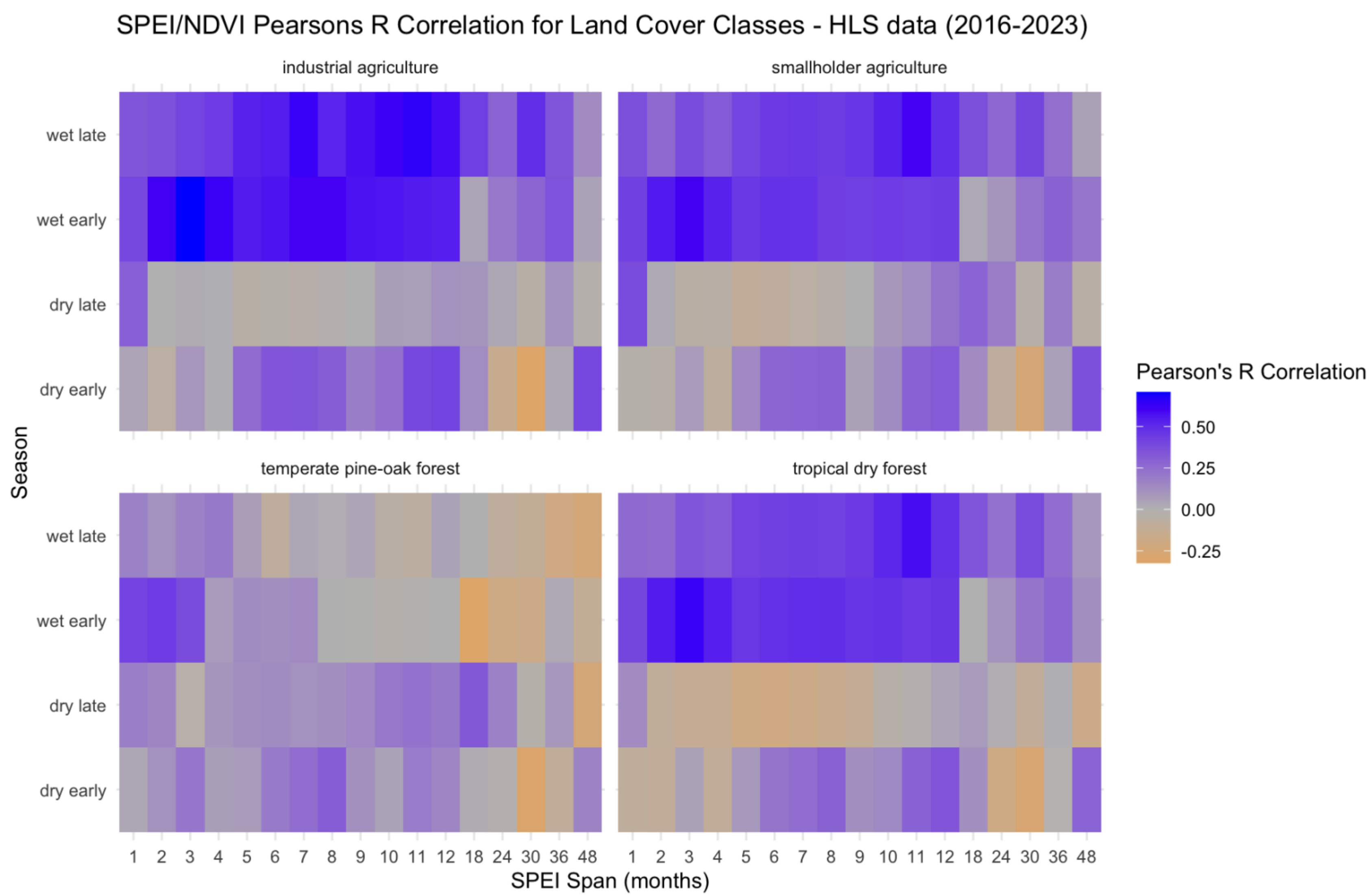


Figure 6: This shows the correlation between NDVI (greenness) and SPEI (drought index) using different time spans for calculating drought. We see that NDVI in the early wet season (June-August) is most correlated with short-term drought indices. For some cover types, NDVI in the late wet season is most correlated with longer-running (10-12 month) SPEI measures.

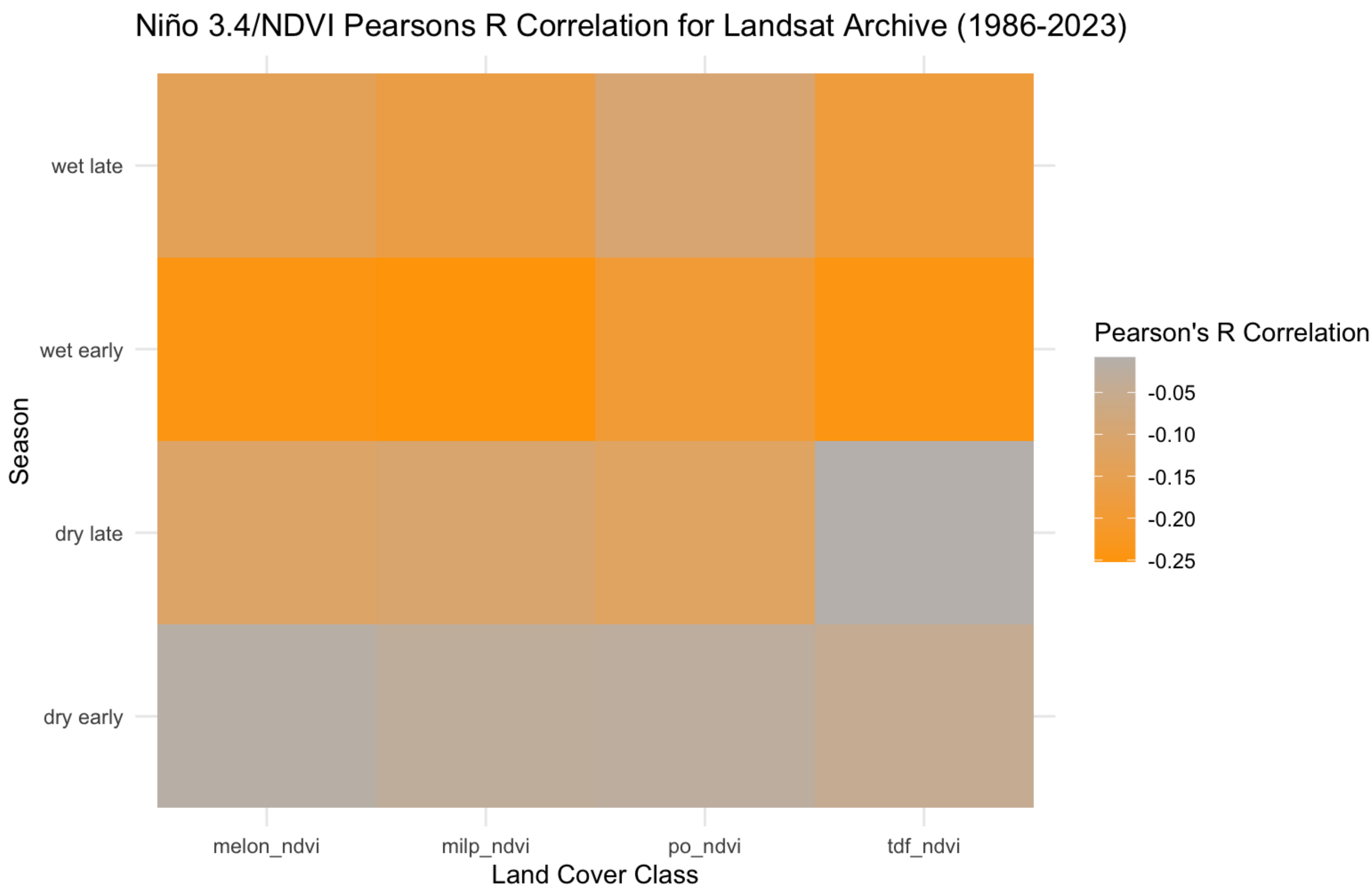


Figure 7: Correlation between NDVI and El Niño 3.4 across each season. In this case, the El Niño signal was negatively correlated with NDVI in the early wet season, suggesting that vegetation effects of El Niño are concentrated there.

4.4 Discussion

We see a strong relationship between socio-ecologically relevant seasonal droughts and impacts to farming households in Zacapa, Guatemala. While recent droughts in Zacapa appear to fall within historical climate variability (3), we find that wet season impacts are stronger and increasing in severity in recent decades, mirroring farmer perceptions of drought impacts. Additionally, we see local factors such as livelihood diversification and social networks to mediate experienced drought impacts. These factors suggest that socio-ecologically informed climate vulnerability assessments are needed to target the people and landscapes affected by climate shocks such as drought.

While recent Central American droughts are not outside of the range of historic variability, we show that Zacapa has experienced increasing water stress during the growing season (Figure 2). These increasing impacts are observed by farmers in La Trementina and Los Achotes, who consistently report recent droughts being more impactful than historic droughts. Recent studies on drought and border apprehensions highlight the importance of drought timing on potential livelihood disruption (29), and point to similar windows of impact in the growing season that we identify here. Drought impacts are generally aligned in tropical dry forest and *Milpa* agricultural systems, with greatest impacts from short to medium-term water deficits in the rainy season. Out of all the vegetation coverage in Zacapa, only the pine-oak forest regions showed drought impacts during the dry season. These patterns mirror other regions where vegetation cover goes dormant during drought (21). It is also possible that impacts like drought may produce the current spatial arrangements of plant communities (24), and that increasing exposure to drought might be a primary driver of vegetation community change into the future.

Lagging drought impacts in high-altitude pine-oak forests suggest that these regions may continue to provide resources for households during crop failure events. Households in the Western Highlands of Guatemala have shown relatively high levels of forest reliance (49), and although we did not assess forest reliance in this study, interviewees reported heavy reliance on forests for fuelwood and timber. However, access to high altitude pine-oak forests in Los Achotes is limited. Older interviewees indicated that the pine-oak forests in Las Granadillas used to be managed and accessed communally by the small towns that ring the mountains. However, these lands were gifted to private individuals by the government and now only a small section of forest adjacent to Los Achotes is communally managed. The town has enrolled this remaining communal land in a national program which generates revenue for the community for conservation actions, but bars community members from felling trees for timber or firewood. Limited access to pine-oak forest resources likely increases the vulnerability of households in Los Achotes, who have less social support to rely on during drought years. Cultural perceptions that identify deforestation as a cause or driver of drought may reflect lived experience, insofar as that forests are a socio-ecological refuge against immediate drought impacts, with drought-vegetation signal delayed 6+ months compared to agricultural regions. Therefore, logging, plantation establishment, and property right restrictions limit community access to forest resources that may otherwise have offset crop losses during drought events.

4.4.1 Limitations

While we consider the human impacts of drought, we do not specifically measure crop losses or economic impacts. Our ethnographic methods are focused on the experiences of drought. This approach can limit comparisons, where one drought can be seen as some percent more impactful than another, but it does allow us to understand what is important from the perspective of the farmer and how they have been affected along these relevant axes. The number of interviewed households in Los Achotes is still relatively small because fieldwork is not complete yet, leading to potential overapplication of a small sample size in our analysis. We will be revisiting this after fieldwork is finalized in August 2024.

Additionally, we used two different datasets to assess drought impacts: the Harmonized Landsat-Sentinel Dataset (OLI and MSI sensors) and the Landsat Archive (OLI and ETM+ sensors). In our analysis, the HLS dataset was able to better pick up differences in vegetation across seasons and land cover classes, whereas the Landsat Archive showed a much longer time series of changes. Finally, the land cover classification was made from imagery between 2019 and 2023, meaning any land cover change prior to 2019 would lead to error in the vegetation estimates of NDVI, especially in the historic landsat imagery. This may lead to an underestimation of historic vegetation impacts and lower precision in determining seasonal vegetation greenness patterns pre-2016. Because of this, we treat Landsat Archive NDVI data more as a description of past trends, rather than providing a clear comparison of between historic drought impacts and recent events.

4.5 Conclusions

In analyzing the impacts of drought in Zacapa, we see great benefits in integrating farmer interviews with drought assessments to provide a better understanding of the vulnerability of communities to climate impacts in the region. Farmer perceptions of drought mirror measured drought impacts only when measurements are shifted to reflect socio-ecologically relevant drought metrics, in this case water deficit during the wet season. Investigating the ecological patterns of drought allowed us to identify that water stress signals were most pronounced during the wet season in tropical dry forest and in agriculture but were delayed until the dry season in temperate pine-oak forest. When considering the social context, we see that these high-elevation pine-oak forests are increasingly inaccessible to smallholder farmers due to privatization and conservation, and that farmers in Los Achotes, who are closest and would be most likely to utilize these resources, are most impacted by drought. While we do not have a clear counterfactual, it seems likely that new arrangements of land are decreasing the resilience of these communities and pushing them to align closer to markets and labor for support during drought rather than utilizing natural drought buffers and resources. These findings indicate the importance of multi-disciplinary analysis in identifying and untangling the drivers and changing relationships of drought and vulnerability in Central America, and suggest that climate impacts should not be seen as simply a shift in weather patterns but an actor in a complex socio-ecological system that can disrupt complex and dynamic arrangements of land, labor and resources.

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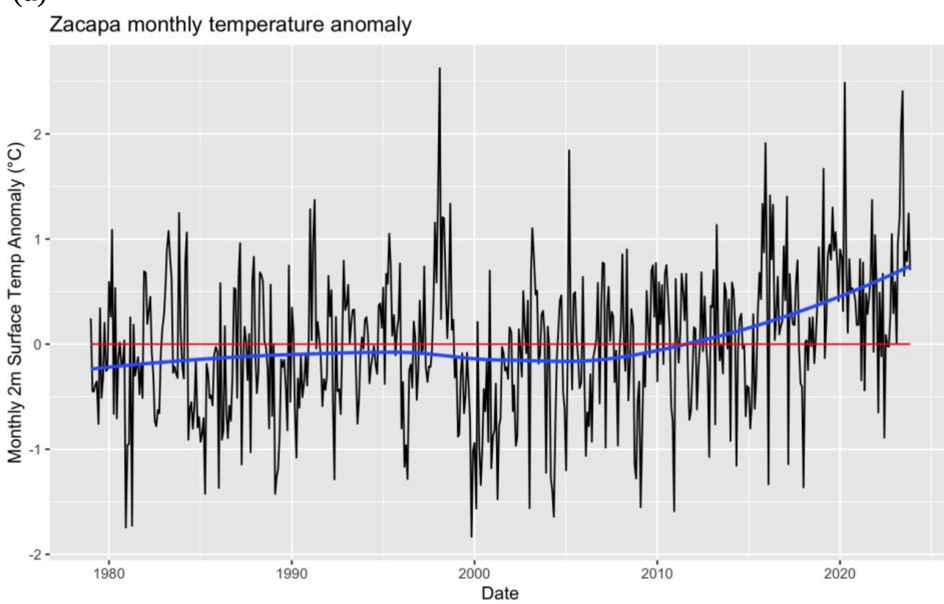
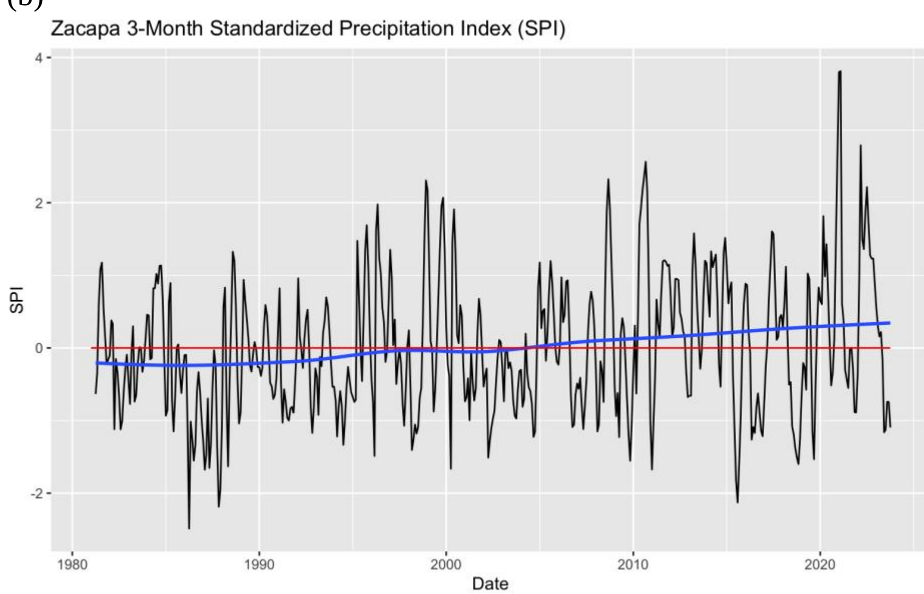
Chapter 4 Appendix A: Additional Hydrological and Vegetation Figures

(a)

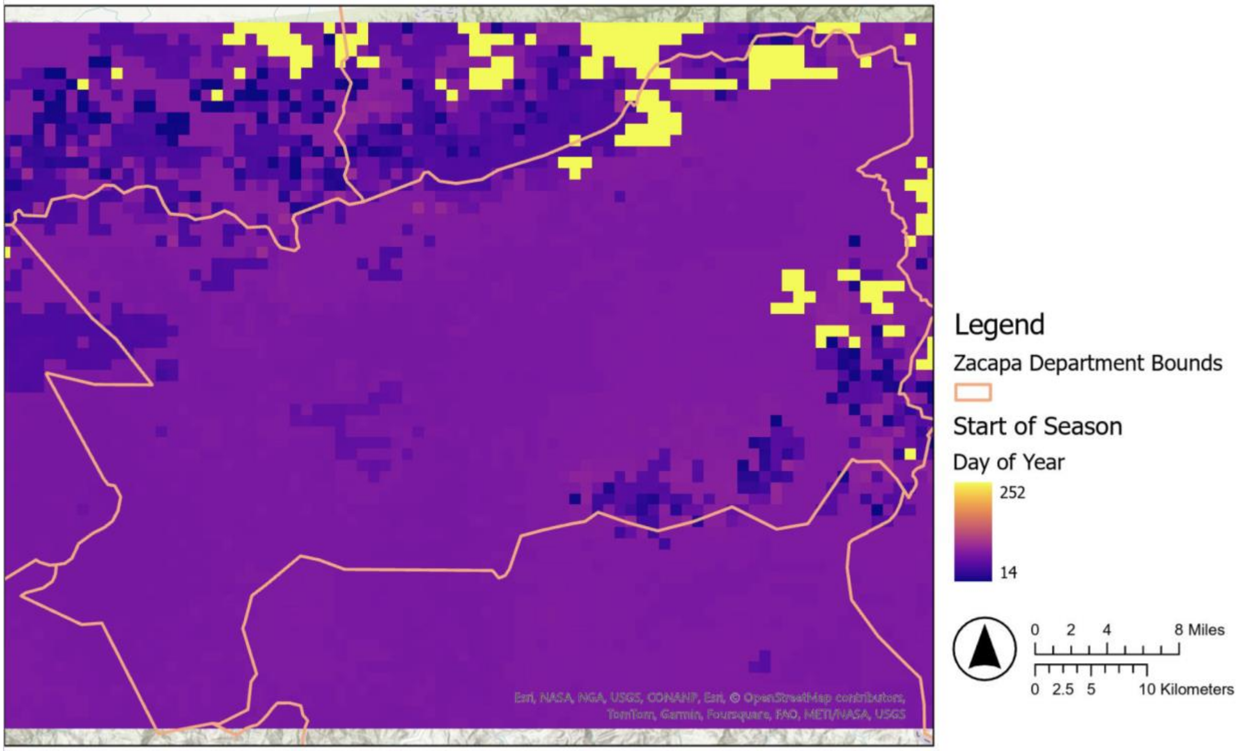


(b)

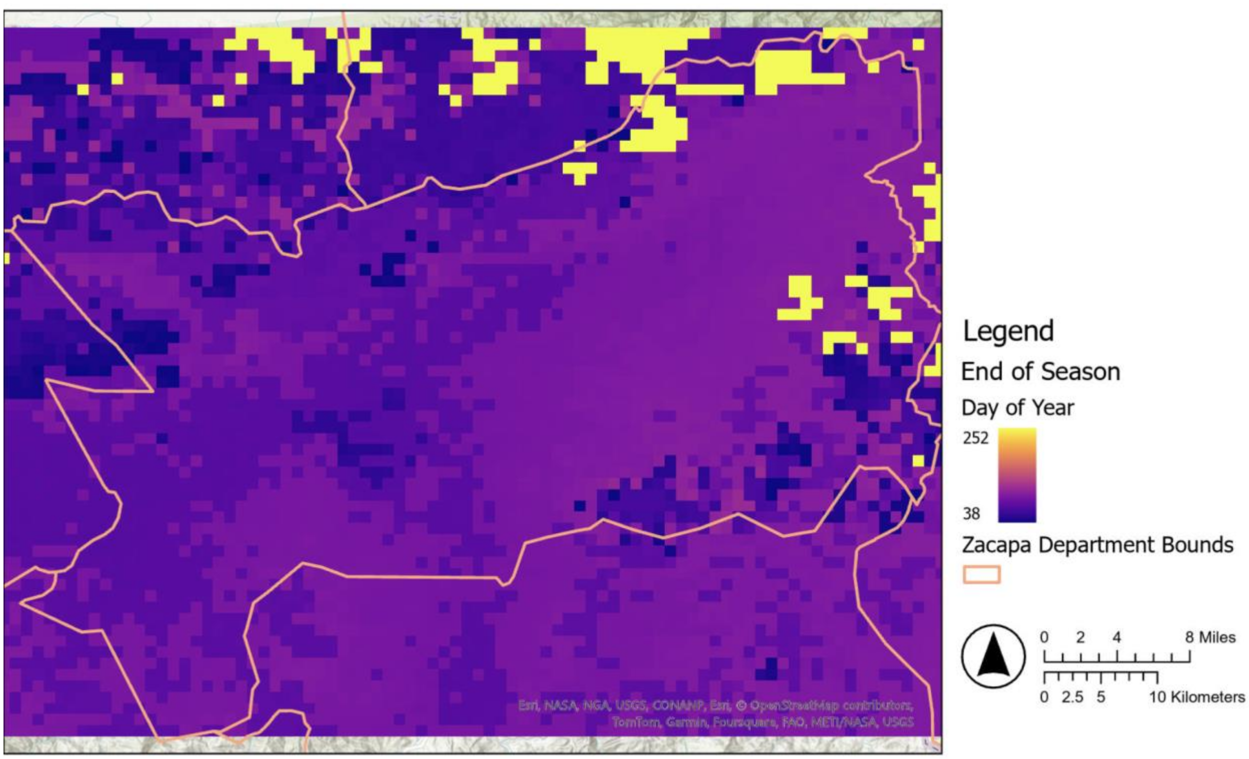


SI Figure 1: Input data for the SPEI dataset displayed in Figure 2. (a) Represents Zacapa's Monthly Temperature Anomaly, calculated from ERA5 Reanalysis (46) and (b) represents Zacapa's 3-Month Standardized Precipitation Index (SPI), from the CHIRPS dataset (47)

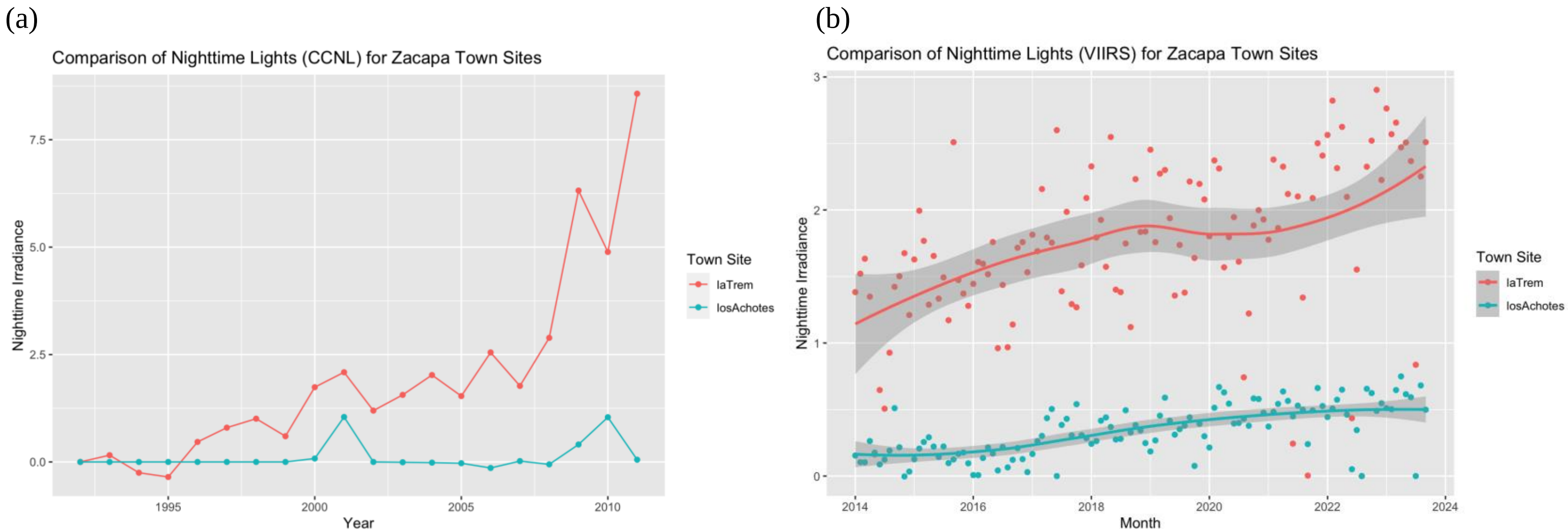
(a)



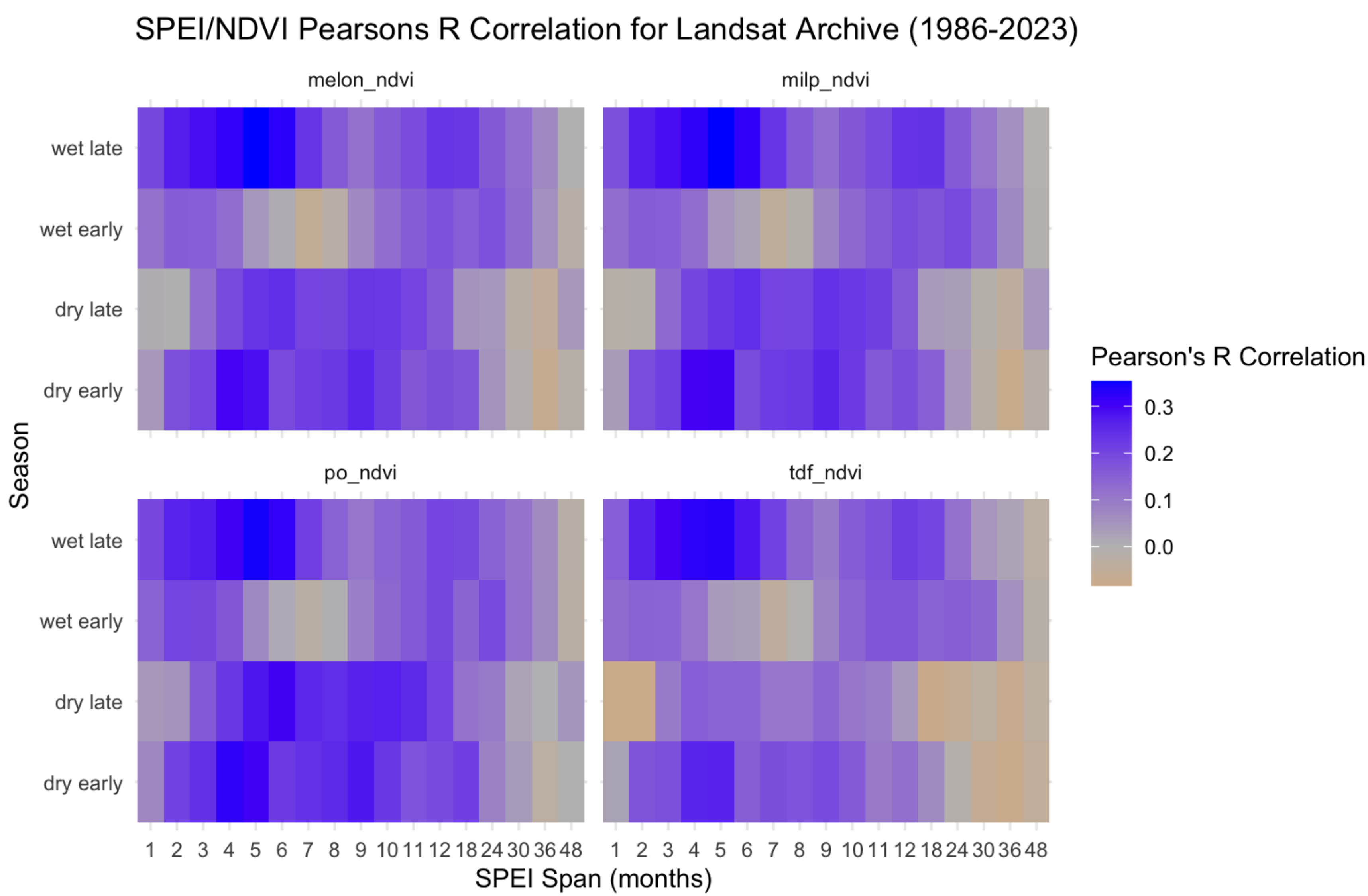
(b)



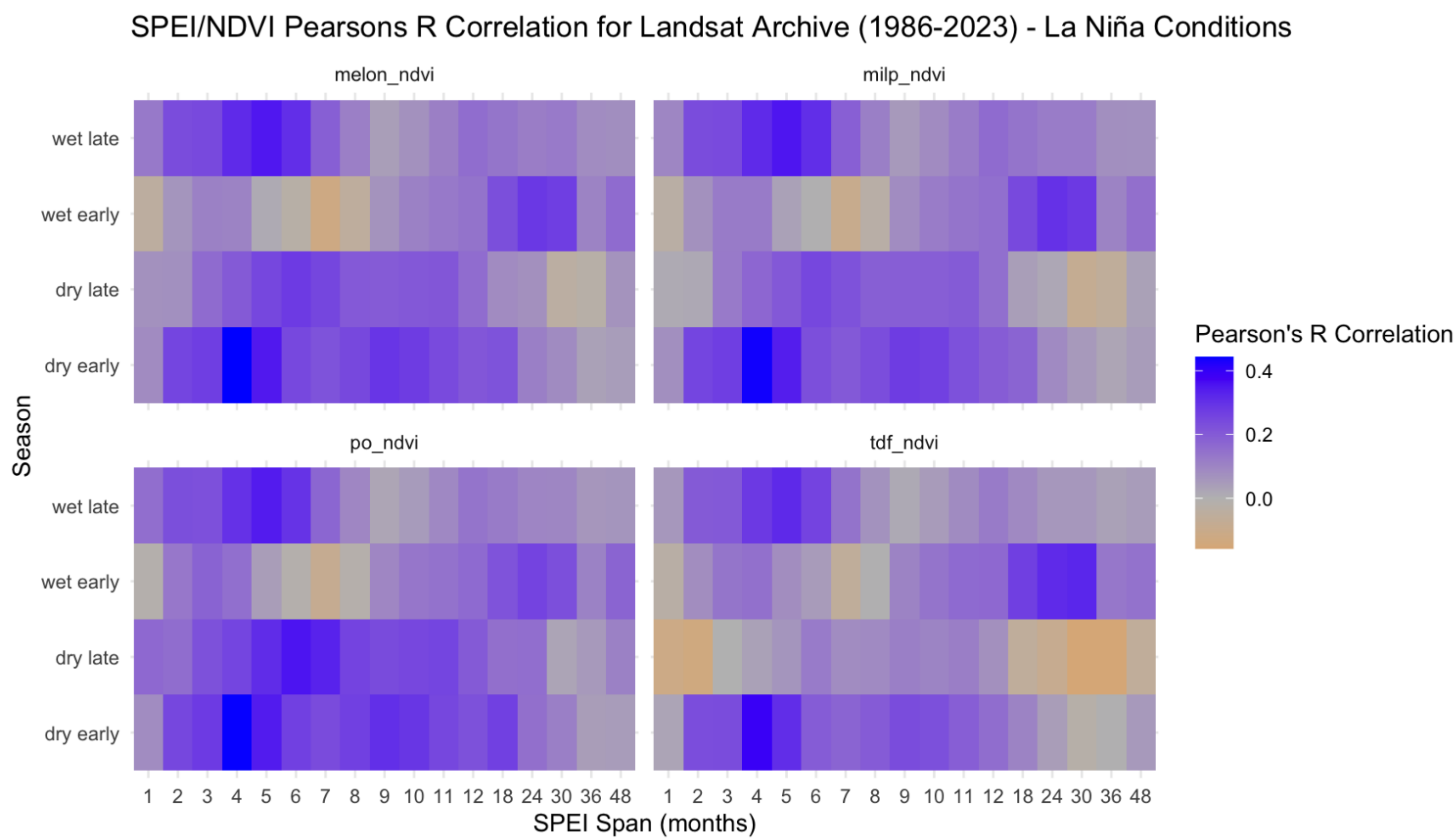
SI Figure 2: Estimated Start of Season (a) and End of Season (b) for Zacapa Department from the ASAP phenology dataset (48)



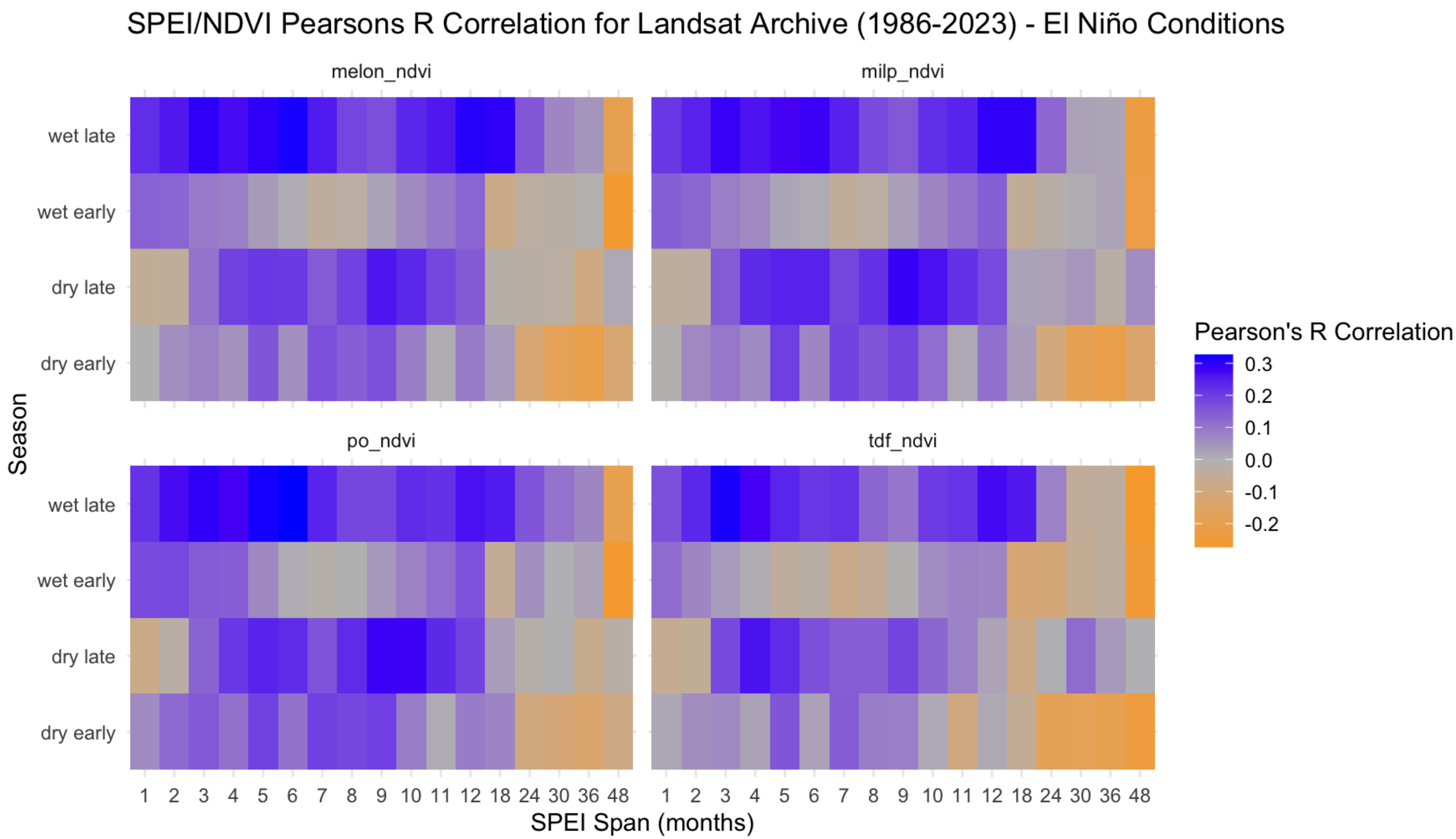
SI Figure 3: Nighttime Luminosity in La Trementina and Los Achotes, measured using the CCNL (a) and VIIRS (b) sensors. Luminosity was approximately the same in the early 1990s but rapidly diverged at the end of the 2000s, with recent data showing that La Trementina continues to increase its luminosity more rapidly than Los Achotes. Note that y-axis luminosity values are not comparable between the datasets because of differences in the collection and digital representation of luminosity.



SI Figure 4: SPEI / NDVI Pearson’s R Correlation from the landsat archive.



SI Figure 5: SPEI / NDVI Pearson’s R correlation for La Niña conditions (El Niño 3.4 Index < 0).



SI Figure 6: SPEI / NDVI Pearson's R Correlation for El Niño conditions (El Niño 3.4 > 0).

SI Figure 7: NDVI heatmap for the landsat archive across the vegetation classes.

Chapter 5: Conclusion

5.1 Overview

Today's smallholder-dominated systems are facing several contemporaneous pressures from global change drivers such as climate shocks, land degradation and economic instability. At the same time, large-scale conservation initiatives are trying to increase the resilience of these systems while also promoting forest cover and ecosystem health. Supporting both smallholder livelihoods and sustainability requires understanding the ways these change drivers interact with each other and change the landscapes they are operating within. In this thesis, I explored these dynamics across scales to gain insights into the ways that livelihoods shocks and forest cover initiatives are producing new and ongoing arrangements of land use. Using this cross-cutting approach provides new insights into smallholder-dominated systems and opens up novel research opportunities for synthesis across scales.

In Chapter 2, I tested core land use change theories by tracking change after food insecurity-based livelihood shocks. I showed that theories of agricultural intensification, rent theory, and regime shifts all explain different observations across the multi-country dataset. Additionally, I explored how impacts to human capital can lead to extensification of agriculture because of limited land use change observations even while population drops, while impacts to land productivity may lead to agricultural abandonment and forest regrowth, as seen in regions experiencing drought. Overall, the study finds that land productivity and the abundance of labor are significant factors explaining changes in land use due to food insecurity events. The vulnerability of agricultural systems influences whether severe or prolonged disturbances cause regime shifts in land use practices. These changes may lead to a reorientation of agriculture towards export markets of more drought-resistant farming practices. Empirically applying and testing these Land Use Change theories is essential for understanding and predicting how climate, demographics, and economic forces will continue to shape terrestrial systems and the people dependent on them in the future.

Chapter 3 demonstrated that, while Guatemala's payment for ecosystem services programs are restoring and conserving forest cover across the country, the impact of these programs is variable and overstated. Bonn Challenge reporting appears to count every treated hectare from PINPEP, PINFOR, and the new PROBOSQUE programs as restored forest, but remotely sensed data on tree cover shows more modest gains, with projects often sited in areas with moderate or high initial forest cover. This means the government is counting forests that previously existed on a site as additional. Forest incentive programs aim for large-scale landscape transformation but require thorough evaluation to determine if these goals are achievable. While programs like PINPEP and PINFOR have treated nearly 600,000 hectares, the actual increase in forest cover is likely a fraction of this area. Nonetheless, these programs are successful compared to similar financial forest incentives, with restoration projects being the most effective in adding forest cover. This success is partly because restoration projects targeted areas without existing forest cover. Ensuring that projects are implemented on previously deforested or degraded lands is crucial for maximizing forest cover. Overall, the analysis showed that large-scale forest incentives can significantly benefit forest cover, but governments need to better target projects, increase their scale, and consider land management trade-offs to achieve their ambitious forest restoration goals.

In Chapter 4, I drilled into the impacts and experiences of droughts in Zacapa Department, Guatemala. By integrating ethnographic and ecological data on droughts, my collaborator and I found a socio-ecologically relevant measure of drought in the region that better tracks the reported drought experiences of farmers and the measured impacts to vegetation. Combining these streams of evidence also highlights the importance of previous communal access to high altitude pine-oak forests, which have delayed drought responses compared to lower elevation dry forest and agricultural fields. These forests likely provided some ecological buffer from droughts, but with increasing privatization, social support networks and diversified livelihoods have become the main methods smallholders use to reduce their vulnerability to drought,
The study emphasizes the importance of using socio-ecologically relevant drought metrics to identify impactful patterns and notes that lower-resource farmers face more severe drought impacts due to reduced social network support and limited access to drought-resistant forest resources.

5.2 Future Research Directions

This research only addresses a small set of change drivers in smallholder-dominated systems and focuses on a relatively specific geographic context. While there are clear applications of using this framework to explore other change drivers, such as the extirpation of species that provide key ecosystem services, the overexploitation of freshwater resources, and CO_2 enrichment of plant communities, my research findings provide new avenues for research on land use and precipitation change drivers. Chapter 4 creates a measure of 'socio-ecologically relevant drought' for Zacapa Department, that does a better job of picking up drought impacts that are most impactful to agriculture and natural vegetation. The same approach can be used in a broader context, where growing season windows can be defined at scale to i) test whether this provides a more 'relevant' measure of drought and ii) apply this measure to better detect patterns of drought exposure and impacts in smallholder-dominated landscapes. This could be an update of Chapter 2, where instead of measuring livelihood shocks through food insecurity events, socio-ecologically relevant measures of drought could be used instead to better isolate water stress as a driver of land use change. Additionally, interviews conducted as part of Chapter 4 suggested that the forestry initiatives evaluated in Chapter 3 may have limited drought resilience by reducing smallholder access to the remaining community lands, as these had been enrolled in a conservation program. Guatemala's forestry programs can also support more active use of forest resources through silvopastoralism and other agroforestry, suggesting that the specific project types can have variable impacts on resource access and vulnerability. Further identifying the ways in which these programs limit access and impact livelihood vulnerability can help hone payment for ecosystem services programs to better support livelihoods alongside ecosystems and better achieve stated goals of supporting sustainable livelihoods.

The use of 'global change' analysis in human-natural systems is an important conceptual addition to this field. Currently, global change research is mostly centered in biology, but there is a growing consensus that multiple, interacting change drivers are acting on human-managed systems. Additional work is needed to understand how changes like reductions in water availability intersect with increasing CO_2 fertilization, land use change, and population dynamics. In this research, I take a retrospective approach to explore global change drivers, which I believe helps to develop the understanding of how change drivers can shift production and livelihoods. For example, identifying better measures of change drivers and distinguishing important drivers within a system can support better measurement of impacts and chart clearer pathways of change in smallholder-dominated systems. I also argue for a better application of theory in these systems. Currently, land use change theory is underdeveloped, with studies often showing observational shifts without putting them in the context of previous research or providing careful analyses of underlying drivers. This means that research takes an applied and piecemeal approach, with specific programs or regions being evaluated post-hoc. I argue for researchers to use more theoretically-embedded global change analyses, which I believe can be better contextualized and more widely applied in policy settings.