



Regular article

Large-scale land acquisitions in Ethiopia: Impacts on agricultural productivity and deforestation[☆]Workineh Asmare Kassie^{a,*,}, Yeshwas Admasu^{a,b}, Dagim Belay^c, Solomon Zena Walelign^a, Jipeng Zhang^d^a University of Gondar, Gondar, Ethiopia^b FAO, Copenhagen, Denmark^c University of Copenhagen, Copenhagen, Denmark^d Shandong University, Shandong, China

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ABSTRACT

Large-scale land acquisitions (LSLAs) have expanded rapidly in developing countries and promoted as a pathway to accelerate agricultural transformation. Yet, credible evidence on their developmental and environmental impacts remains limited. This paper provides causal evidence on the effects of LSLAs on agricultural production and forest outcomes by exploiting spatial and temporal variation in the staggered implementation of LSLAs in Gambella, Ethiopia. We combine geo-referenced administrative records on land transactions (2000–2020) with high-resolution remote sensing data on crop production, forest cover, and land use. Using a heterogeneity robust difference-in-difference estimator, we find no evidence that LSLAs increase agricultural production or the share of crop land. In contrast, it leads to significant and persistent declines in tree cover and forest land share. This deforestation-production paradox suggests that, in settings characterized by weak oversight and insufficient infrastructure, poorly regulated large-scale investments can generate substantial environmental burden without delivering the anticipated structural transformation that justifies them.

1. Introduction

Food insecurity remains a major development challenge in low- and middle-income countries. In Africa, it has risen from 45 percent in 2015 to nearly 60 percent in 2024, affecting 893 million people (FAO et al., 2025). At the same time, smallholder agriculture which employs half of the workforce and contributes around 20 percent of the gross domestic product (GDP) of the continent (FAO et al., 2025; World Bank, 2025), continues to face persistent productivity constraints that limit its capacity to meet growing food demand (Suri and Udry, 2022). While expanding cultivated land has been one pathway to increase food production, it has come at substantial environmental cost, e.g., the loss of approximately 420 million hectares of forest globally since 1990, with particularly sharp declines in recent years (Branthomme et al., 2023). These trends underscore the central policy challenge of achieving agricultural growth while preserving natural ecosystems.

Against this backdrop, in the last two decades, many governments in the global South have promoted large-scale land acquisitions (LSLAs) as a policy instrument to facilitate structural transformation by attracting private capital and technology, improving agricultural productivity,

and greater market integration in areas that have previously been underutilized (Gollin et al., 2014b,a; Collier and Dercon, 2014). The surge in LSLAs accelerated after the 2007–2008 global food and financial crises, which sharply increased global demand for agricultural land and raw materials (Deininger, 2011; Rulli et al., 2019; Akalu et al., 2026). These transactions – typically involving transfers of areas greater than 200 hectares through sale, concession, or lease (Lay et al., 2021) – cover millions of hectares worldwide (Deininger, 2011; Arezki et al., 2015; Müller et al., 2021), with sub-Saharan Africa as a prominent target (Anseeuw et al., 2012; De Maria, 2019; Anti, 2021). Despite considerable policy attention, rigorous causal evidence on how large-scale agricultural investments affect agricultural productivity and the environment remains scarce. Thus, this study aims to estimate the causal effects of LSLAs on local agricultural productivity and forest conservation.

The existing literature provides conflicting accounts of LSLA effects, where proponents emphasize technology transfer, job creation, and market integration (Deininger and Byerlee, 2012; Deininger and Xia, 2016), while critics note displacement, environmental degradation,

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deforestation, loss of biodiversity, and food insecurity (Alamirew et al., 2015; Borras Jr. et al., 2022; Davis et al., 2023; Liu, 2014). These conflicting accounts share a common methodological limitation, i.e., most studies rely on descriptive analyses (e.g., Davis et al., 2020), correlations (e.g., Sullivan et al., 2023; Bezabih et al., 2024; Castet, 2024), case studies (e.g., Sändig, 2021), or simulations (Baumgartner et al., 2015) that cannot disentangle investment effects from pre-existing differences across locations. Without plausibly exogenous variation in where and when LSLAs occur, it remains impossible to determine whether observed outcomes reflect the causal impact of investments or simply the characteristics of places selected to receive them. We address this identification challenge by exploiting staggered implementation of Ethiopia's extensive LSLA program in the Gambella region, one of the largest in Africa, as a natural experiment (FDRE, Ethiopia, 2006, 2010).

Ethiopia has been a prominent case in debates over LSLAs. Since the early 2000s, the government has promoted agricultural investment through land access policies, tax incentives, concessional loans, and development plans (Ali et al., 2019). The Growth and Transformation Plan (GTP I, 2010–2015) set ambitious targets, designating 4.8 million hectares as potential investment land and aiming to transfer large areas to private investors (Rahmato, 2011; Ali et al., 2019; FDRE, Ethiopia, 2010). By 2016, about 2.47 million hectares had been allocated to private investors (Rahmato, 2011; Teklemariam et al., 2015), primarily in the lowland frontier regions of Gambella and Benishangul-Gumuz, where customary land uses overlap with high-biodiversity forested landscapes. In Gambella alone, about 0.664 million hectares were transferred to investors,¹ yet considerable institutional and operational challenges have impeded progress.

We leverage the staggered implementation of acquisitions as plausibly exogenous spatial and temporal variation in exposure to large-scale land acquisitions (LSLAs). Using this variation, we estimate the causal effects of LSLAs using an event study difference-in-differences (DID) framework designed for the adoption of staggered treatment (De Chaisemartin and d'Haultfoeuille, 2023, 2024; Roth, 2022). The analysis relies on a high-resolution panel that combines administrative data from large-scale agricultural investment projects with remote sensing information on deforestation, satellite-based indicators of agricultural production, and other spatial covariates, allowing a consistent assessment of the dynamic impacts of LSLAs on agricultural productivity and forest conservation.

Our main finding suggests that large-scale land acquisitions led to a significant increase in deforestation at the intensive margin (decline in percent tree cover and forest land shares). However, we find no significant effects on extensive-margin deforestation (forest loss) and no detectable gains in grid-level agricultural productivity. The results are robust to alternative specifications and data sources, with evidence suggesting that a reduction in the share of forest land between grids could be a potential primary mechanism driving changes in these outcomes.

This study contributes to the broader literature in the following ways. First, while previous research has examined the effects of LSLA on agricultural development (Lay and Nolte, 2018; Deininger and Xia, 2016; Davis et al., 2023; Anti, 2021), deforestation (Davis et al., 2023; Magliocca et al., 2020), water scarcity (Chiarelli et al., 2022; Dell'Angelo et al., 2017), and biodiversity (Davis et al., 2023; Dell'Angelo et al., 2017), most of these studies often lack credible causal identification or rely on case studies with limited generalizability. This study provides one of the first few causal evaluations of LSLA's impacts on agricultural and environmental outcomes, using plausibly exogenous variation. Second, it presents the first systematic, spatially

explicit analysis of LSLAs in Gambella, a region central to Ethiopia's land investment drive. Third, by integrating data from administrative agricultural investment projects with high-resolution satellite data, it provides empirical insights into the evaluation of development policies in data-scarce settings (Michler et al., 2026; Josephson et al., 2026). Finally, by distinguishing intensive and extensive margins of deforestation and documenting declines in the shares of forest land area, the study identifies mechanisms through which large-scale investments can exacerbate environmental degradation without improving productivity. Together, these contributions fill a critical empirical gap and provide robust evidence on the economic and environmental implications of large-scale agricultural investments in the global South.

2. Contextual background

2.1. Global land acquisitions

In the last two decades, LSLAs have expanded rapidly, driven by the growing demand for food, biofuels, and agricultural commodities (Deininger, 2011; Rulli et al., 2019). Figs. A.1 and A.2 provide a global overview of these investments, illustrating the spatial distribution of the LSLAs concluded (in hectares) by both the host and the investor countries. The maps also convey a distinct North-South pattern. The Global North is the main source of investment, while the Global South is the main destination. These cross-border flows occur mainly through foreign direct investment (FDI) or joint ventures with domestic firms. Several factors explain this pattern, including the relative abundance of arable land, weak land governance systems, and favorable investment policies in recipient countries (Müller et al., 2021). Together, these conditions have positioned Sub-Saharan Africa as a key destination for transnational farmland investment.

The surge in LSLAs following the 2007–2008 food price crisis generated an intense debate over their development consequences. This debate is shaped by two distinct perspectives. One perspective argues that large-scale investment can help address persistent constraints in capital, technology, and coordination by transforming underutilized land into commercial production and linking remote regions to national and global markets. In this context, large farms can drive rural development through direct gains in production, employment opportunities, and infrastructure improvements, as well as spillover effects on neighboring smallholders (Anti, 2021; Deininger and Xia, 2016). In contrast, a more critical view challenges the fact that many large-scale investments often fail to deliver the anticipated productivity gains or welfare improvements, instead functioning as forms of “land grabbing” aimed at speculative land and resource control, or rent extraction, rather than sustained productive investment (Rulli and D'Odorico, 2014; Pearce, 2012; Borras Jr. et al., 2011; Alamirew et al., 2015; Borras Jr. et al., 2022; Davis et al., 2023; Liu, 2014). From this perspective, the developmental benefits associated with large-scale land deals are often exaggerated, while their social and environmental impacts are often understated. This policy tension is particularly pronounced in settings where governments' administrative resources are insufficient to effectively screen investors, confirm capital adequacy, or monitor contractual compliance (Ali et al., 2019; Deininger and Byerlee, 2011).

This contradiction is central to the Ethiopian context. In its development strategy, the government identified and allocated large lowland areas in regions such as Gambella to investors, often disregarding local ecological systems and livelihoods (Rahmato, 2011; Lavers, 2012). Although this approach attracted investments, it suffered from poor oversight and poor execution. The available evidence suggests that around 55% of commercial farms in Ethiopia underutilized their allocated land, with this share rising to around 70% in Gambella (Ali et al., 2019). This issue is largely attributable to persistent challenges related to technology, labor, infrastructure, and investor capacity (Ali et al., 2019; Rahmato, 2011; Lavers, 2012; Keeley et al., 2019).

¹ According to administrative data from the Ministry of Agriculture and the Regional Bureau of Agriculture and Natural Resources, the government's potential investment land accounts for approximately 41 percent of the total regional area in Gambella region.

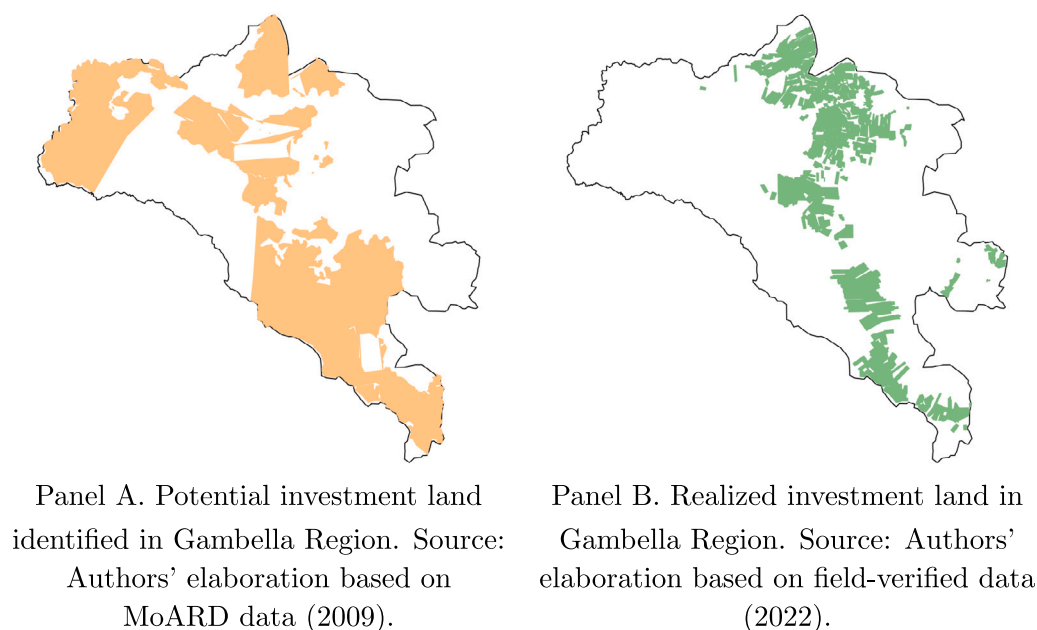


Fig. 1. Potential (Panel A) and realized (Panel B) large-scale agricultural investment land in Gambella Region.

2.2. Policy reform and land transaction in Ethiopia

Ethiopia's approach to large-scale agricultural investments has changed between political regimes (Ali et al., 2019). In the imperial era (pre-1974), private investors focused on cash crops. During the Derg regime (1974–1991), large commercial farms were nationalized and production was redirected to staple crops (Ali et al., 2017). After 1991, the EPRDF initially prioritized smallholder agriculture under the Agricultural Development-Led Industrialization (ADLI) strategy, but the policy emphasis moved toward large-scale commercial agriculture under the Plan for Accelerated and Sustained Development to End Poverty (PASDEP) (FDRE, Ethiopia, 2006). The first Growth and Transformation Plan (GTP, 2010–2015) consolidated this change by establishing the Ethiopian Agricultural Investment Land Administration Agency and setting a target of distributing approximately 3.3 million hectares to commercial investors (FDRE, Ethiopia, 2010).

The priority areas for these investments included Benishangul-Gumuz, Gambella, Oromia, and the SNNP regions, with the highest concentration in Benishangul-Gumuz and Gambella. Although these investments generated local economic shocks, studies found limited evidence of improved food security or reduced poverty (Hajjar et al., 2020; Moreda, 2017; Rulli and D'Odorico, 2014). Officially, the program aimed to: (i) increase foreign earnings through export crops, (ii) expand agro-industrial crops and employment, (iii) improve local infrastructure and social services, (iv) promote technology transfer, and (v) improve energy security through bio-fuels (Ali et al., 2019).

Before expanding these large-scale investments, the Ministry of Agriculture and regional governments identified potential investment areas, estimating available land at 1.7 million hectares in Oromia, 1.4 million hectares in Benishangul-Gumuz, 1.2 million hectares in Gambella and 0.5 million hectares in the regions of South Nations and Nationalities and People (Rahmato, 2011). Regional states subsequently transferred a portion of these lands to the federal “land bank”: totaling approximately 3.3 million hectares.

Within this framework, the Gambella region emerged as a central focus of agricultural land acquisitions. Fig. 1 panel A shows areas identified for large-scale agricultural investment, concentrated in Dima

district (64.7%), Itang (61.2%) and Lare districts (40.5%).² In 2009, approximately 40.9% of the total Gambella area had been designated for agricultural investments, compared to 23.8% for human settlement and 35.3% for forest and protected national parks.

Since 2007, the federal and regional governments have accelerated land allocation to domestic and foreign investors (Rahmato, 2011). Between 2005 and 2015, the government transferred approximately 2.47 million hectares of land Teklemariam et al. (2015). The regional distribution by area of the LSLA (2000–2016) is highly concentrated in the Gambella and Benishangul Gumuz regions (Fig. A.3).

2.2.1. Realized investment land in Gambella region

The Gambella regional state designated land for agricultural investment in ten districts. LSLAs occurred with varying intensity over time within these districts. Fig. 1 panel B shows the realized investment projects, with most of the investments concentrated in the northern, central, and southern parts of Gambella. Panel A in Fig. 2 shows the cumulative agricultural land (in hectares) contracted to private firms in each year, showing a sharp acceleration between 2007 and 2016. Panel B reports on the number of LSLAs projects, which closely mirrors the area dynamics over same period. The spatial spread of agricultural land contracted to private firms between 2000 and 2020 shows that LSLAs are highly concentrated in the Agnuak zone and in a few districts, particularly in Itang, where more than 40% of its area is under private agricultural investment during the reference period.

In many contexts, a substantial share of the land allocated is not immediately cultivated, and there are often significant delays in the execution of large-scale agricultural investment projects. In Gambella, there is a widespread failure to achieve productive use, as around 70% of commercial farms in the region report not effectively utilizing their allocated land (Ali et al., 2019). This underperformance is driven by significant execution delays and systemic supply-side constraints, including investor-specific constraints and institutional frictions. One of the significant challenges in Gambella is the delayed availability of machinery, often exacerbated by restrictive import regulations (Ali et al.,

² Similarly, Fig. A.4 in the Appendix show that the largest share of land identified for large-scale agricultural investment is concentrated in the western, southern, south central and northern Gambella.

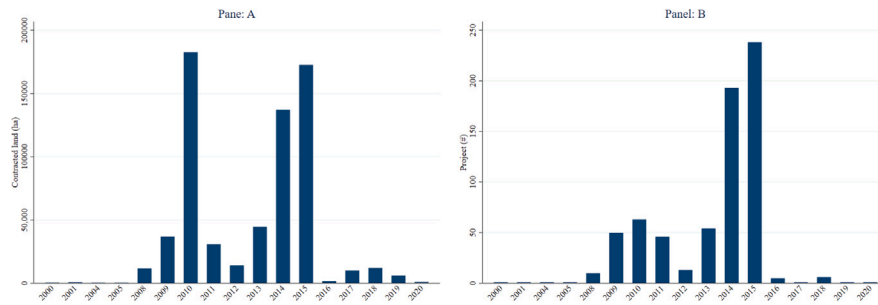


Fig. 2. Large-scale land transfers in Gambella by Year.
Source: own elaboration based on data from MoARD (2016), and Gambella Bureau of Agriculture and Natural Resources (2021).

2019). Combined with a lack of technology and manpower shortages, this leaves a substantial share of the transferred land uncultivated.

Existing evidence further suggests that heterogeneity among investors, especially disparities in financial resources, is a critical factor, and many domestic investors were unable to develop land immediately after acquisition due to insufficient capital (Rahmato, 2011; Lavers, 2012). A key barrier is the high cost and complexity of land development, particularly in frontier regions such as Gambella, where clearing land and preparing it for cultivation requires substantial capital and time. In addition, administrative obstacles, such as difficulties in obtaining credit and machinery, contributed to further delays. Infrastructure limitations, particularly in remote parts of Gambella, often resulted in projects dependent on state-led investments in transportation and electrification (Keeley et al., 2019). Institutional weaknesses also play a critical role: limited investor screening, weak monitoring and enforcement capacity, and the misuse of investment licenses, often to access credit or import duty-free equipment, have resulted in many projects being underdeveloped or diverted to alternative uses (Keeley et al., 2019). Finally, policy interventions, especially the federal and regional monitoring reviews of large-scale agricultural investment projects introduced in the mid-2010s, also created abrupt externally imposed incentives for land clearing based on contract timelines rather than land attributes (Moreda, 2017). Collectively, these elements produce significant variability in the implementation timing that appears to be largely independent of previous land use.

The cumulative effect of these institutional and operational constraints suggests that Gambella represents a critical case in examining the gap between land allocation and economic outcomes. Although the federal government has demonstrated considerable capacity to quickly allocate large-scale concessions, evidence also reveals comparatively weaker institutional capacity to effectively screen investors and enforce requirements for productive land use. This imbalance suggests an environment where environmental costs associated with commercialization, such as substantial loss of tree cover, may materialize soon after land transfer, while the anticipated agrarian transformation remains largely unrealized. Consequently, the Gambella case offers a valuable empirical context for assessing whether LSLAs in regions marked by weak implementation capacity and inadequate monitoring foster a pattern of clearing without transformation.

3. Empirical strategy

3.1. Impact of LSLAs on crop production and deforestation

We estimate the causal impact of large-scale land transactions on agricultural productivity and forest cover by exploiting the staggered rollout of acquisitions across Kebeles in the Gambela region as a quasi-natural experiment. Identification rests on the assumption that, absent the program, treated spatial grids would have followed parallel trends

in outcomes relative to comparable untreated grids within the same region. We estimate dynamic treatment effects using an event-study specification rather than a static DID for two reasons. First, the effects of large-scale investments are unlikely to be immediate, i.e., land clearing, cultivation, and deforestation unfold over multiple years following initial allocation, and a static estimator would obscure this heterogeneity. Second, the event-study framework allows us to formally test the parallel trends assumption by examining pre-treatment placebo estimates. The event-study specification takes the following form:

$$Y_{gt} = \beta_{-9} \text{LSLT}_{g,\tau \leq -9} + \sum_{\tau=-8}^{\tau \leq 11} \beta_{\tau} \text{LSLT}_{g\tau} + X'_{it} \gamma + \delta_i + \phi_t + \psi_{kt} + \varepsilon_{gt} \quad (1)$$

where Y_{gt} represents our measures of crop growth, forest loss, and tree cover for a 1 km × 1 km grid area g and in year t .³ $\text{LSLT}_{g\tau}$ is a binary variable equal to 1 for grid area g if it intersects the geometry of a Kebele where LSLAs occurs in year $\tau \leq t$, where τ is the year when the first LSLAs implemented in Kebele k . The index τ represents the relative year to the first large-scale land acquisition event in a Kebele, which varies from −17 to 19. In estimation of Eq. (1), the time periods from −17 to −9 are grouped into a single category due to the limited number of observations; so are the time periods from 19 to 11. The reference period is $\tau = -1$. Our coefficients of interest, β_{τ} , represent the average change in the outcome variables, Y_{gt} , between time τ and the previous year relative to the change in the outcome variables during the same time period for the unaffected grid areas. The coefficients β_{-8} to β_{-2} , represent nonparametric trends in the outcome variables Y_{gt} , before the first event of large-scale land transactions. The vector X_{gt} includes grid-level time-varying controls that include demographic (population density), climate variables (precipitation and temperature). The δ_g are grid level fixed effects that control for time-invariant characteristics of grids that may be correlated with crop production, forest loss, and tree cover; ϕ_t are year fixed effects that capture time shocks common to all grid areas; ψ_{kt} are Kebele interacted year fixed effects that control for Kebele level specific time trends which controls for any Kebele level time varying unobservable such as changes in institutions, infrastructure, investment, population size, etc. ε_{gt} is the random error term. Standard errors are clustered at the grid level to allow for correlation of errors over time within spatial grids.

Our empirical setting departs from the canonical single-treated group event study framework for two reasons. First, LSLAs exhibit staggered rollout across space and time throughout the 2001–2020 period (see Section 2.2). Second, there is substantial heterogeneity in treatment timing and cohort size across grid areas, as documented in Fig. 3 and Table 1. Under staggered rollout with heterogeneous treatment effects, the standard TWFE estimator can produce biased

³ Grid area of 1 km × 1 km is the unit of analysis we defined to construct our geospatial panel dataset.

Table 1
Sample composition.

	Obs. number	Group share	Treatment coverage
Never treated	19,217	0.62	0.00
Treated since 2001	555	0.02	1.00
Treated since 2005	51	0.00	0.80
Treated since 2008	982	0.03	0.65
Treated since 2009	4242	0.14	0.60
Treated since 2010	1739	0.06	0.55
Treated since 2011	1817	0.06	0.50
Treated since 2012	350	0.01	0.45
Treated since 2013	367	0.01	0.40
Treated since 2014	793	0.03	0.35
Treated since 2015	92	0.00	0.30
Treated since 2016	30	0.00	0.25
Treated since 2018	194	0.01	0.15

Notes: The table reports the number and share of spatial grids first affected by LSLTs for each year since 2001, and the treatment coverage which represents the percentage of time periods (years) each group is considered treated over the whole estimation period (2001–2020).

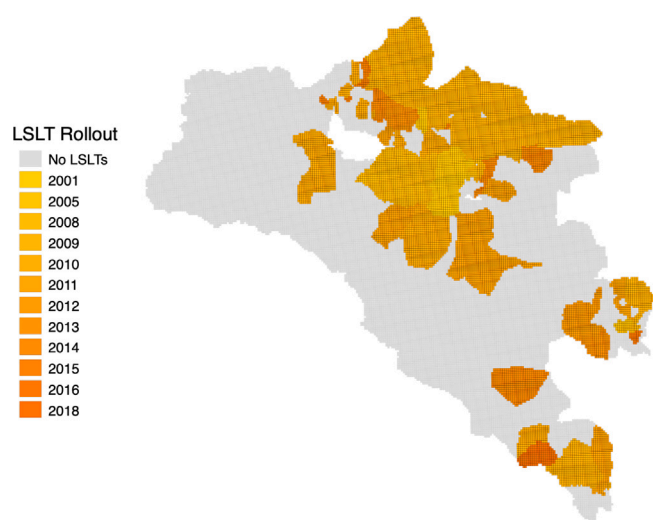


Fig. 3. Rollout of Large-scale Land Transactions over the study period.

estimates because it implicitly uses already-treated units as controls for later-treated units, potentially assigning negative weights to some treatment effects (Callaway and Sant’Anna, 2021; De Chaisemartin and d’Haultfoeuille, 2020; Goodman-Bacon, 2021; Sun and Abraham, 2021; Roth et al., 2023; Athey and Imbens, 2022). To address this, we adopt the estimator of De Chaisemartin and d’Haultfoeuille (2020, 2023, 2024), hereafter DCDH, as our preferred specification, retaining TWFE as a conventional benchmark. In selecting among available staggered DID estimators, we also evaluated Callaway and Sant’Anna (2021) (CS) and Borusyak et al. (2021) (BJS), but do not report these for reasons specific to our setting. The BJS imputation estimator requires predicting counterfactual outcomes from pre-treatment data, but with 13 cohorts spanning 2001–2018, several of which are very small, and the earliest of which has no pre-treatment observations. The imputation model fails to converge, producing monotonically growing pre-trends that invalidate its identifying assumption. The CS estimator is feasible but assigns cohort-size weights when aggregating group-time average treatment effects, giving disproportionate influence to the 2009 cohort, which accounts for approximately 60 percent of treated observations. This produces visibly unstable pre-treatment placebo estimates that reflect cohort imbalance rather than genuine violations of parallel trends.

We prefer the DCDH estimator for three reasons specific to our setting. First, it is robust to heterogeneous treatment effects across cohorts and time periods without relying on cohort-size weighting (Gardner

et al., 2024; Henningsen et al., 2025). Second, it directly accommodates the Kebele by year fixed effects central to our identification strategy through the *trends_nonparam()* option, allowing flexible control for Kebele-specific time-varying unobservables, which include changes in local institutions, infrastructure, and investment climate that neither CS nor BJS can support. Third, pre-treatment placebo tests under DCDH pass cleanly across all main outcomes, providing direct support for the parallel trends assumption (Roth, 2022). TWFE estimates are therefore presented throughout to facilitate comparison with the conventional approach and to illustrate the direction and magnitude of heterogeneity bias that motivates our preferred estimator (Henningsen et al., 2025).

The event-study plots (Figs. 7–11) and raw trends graphs (Figs. A.5–A.7), together with the joint significance tests reported in Table B.10, support this assessment. Observed volatility in some of the pre-treatment coefficients largely reflects limited pre-period observations and sampling variation rather than systematic violations of the parallel-trends assumption. Joint significance tests on the pre-trend coefficients of our main outcomes, reported in Table B.10, confirm that pre-trend coefficients are not jointly different from zero at conventional significance levels for NDVI-MODIS, NDVI-Landsat, and Forest Cover (VCF), supporting the identifying assumptions of our preferred specification. For Forest Loss (GFC), the joint test is marginally significant at the 10% level; however, this is driven entirely by a single spike at $t = -2$, all remaining pre-treatment coefficients are individually indistinguishable from zero and visual inspection of the event-study graph confirms flat and parallel pre-treatment trends for both estimators across the full pre-treatment window. The marginal joint rejection therefore reflects an isolated one-period anticipation effect consistent with pre-announcement land clearance prior to formal treatment registration, rather than a systematic violation of the parallel trends assumption. Roth (2022). We therefore interpret the dynamic coefficients as reflecting heterogeneous temporal responses to aggregate policy realization while exercising caution against over-interpreting noisy pre-treatment fluctuations (Roth, 2022).

3.2. Identification

The nonrandom transfer of agricultural land poses a significant challenge in assessing the impact of policy reforms that have promoted large-scale land transactions in Ethiopia. First, the leasee, private agricultural companies – as a profit-maximizing business entity – choose a land where the net present value of future profits is the greatest possible. Second, the government identified areas with agricultural potential and targeted them for investment. The profitability and investment potential of land vary between locations in an agricultural region based on factors that define the local context, including physical and institutional infrastructure, the availability of farm labor and water, the productive potential, reliable security and other unobserved characteristics. These factors are correlated with local development outcomes, including farm productivity and environmental degradation, and the effect of large-scale land acquisitions is likely to be confounded by differences in factors that determine the investment potential and profitability of farm projects in the chosen locality. Hence, comparing agricultural and environmental outcomes for areas in a locality with direct exposure to large-scale land acquisitions to those without exposure may yield biased estimates.

To credibly estimate the causal effect of large-scale land acquisitions, the localities where we compare agricultural and environmental outcomes are required to be similar. Inspired by Greenstone et al. (2010), our research design is based on the availability of designated potential investment land (‘Potential Investment’) and inventory of land transactions (‘Realized Investment’) to identify a valid counterfactual for what would have happened to areas in affected localities in the absence of large-scale land acquisitions. We acquired spatial data for potential investments areas and realized investments transpired during the 2000–2020 period. Based on these data presented in Figs. 1 and A.8,

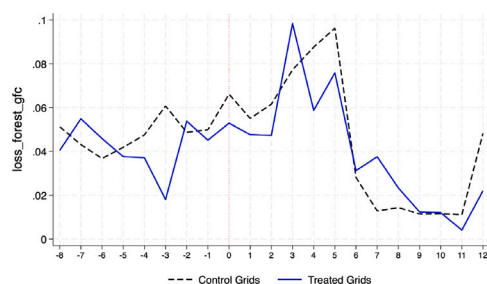


Fig. 4. Forest loss (Panel A) and percent tree loss (Panel B),2000–2020.

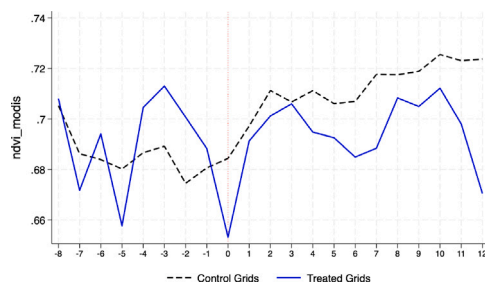
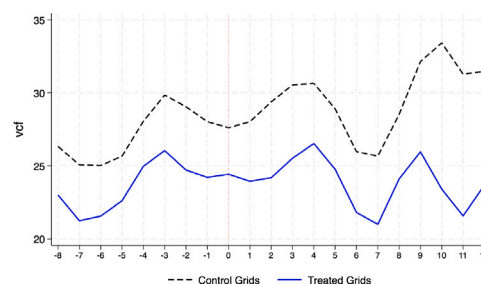


Fig. 5. Crop production,2000–2020.

we identified Kebeles that are exposed to large-scale land acquisitions ('grabbed') and those that do not host large-scale land acquisitions ('saved'). Consequently, we selected grids in the grabbed Kebeles that are not directly affected by LSLAs to identify what would have happened to the outcomes of grids that overlap contracted areas for LSLAs in the absence of large-scale land acquisitions.

Fig. 3 shows the grid map (1 km $\times$ 1 km) of Gambella, reflecting the staggered rollout of LSLAs over the 2001–2018 period.

It is self evident from Fig. 3 and Table 1 that the initial phase of large-scale land acquisition was not uniformly distributed in rural Kebeles in the Gambella region. Some Kebeles experienced their first large-scale agricultural investments earlier, while others encountered such investments within the study period of 2000–2020. The second column of Table 1 shows the proportion of grid within rural Kebeles that have been exposed to LSLAs projects over time: approximately 62 percent of grids remained unaffected, while the remaining half of the total grids turned to LSLAs area between 2008 and 2014.

Our identification assumption is that grid-level outcomes would have trended identically in the absence of large-scale land acquisitions in grabbed and saved localities. This requires that the occurrence of large-scale land acquisitions in a specific rural Kebele in a particular year be uncorrelated with other determinants of the change in our measures of agricultural productivity and environmental degradation over time. This assumption seems to hold reasonably. Figs. 4 and 5 show a similar trend in our main outcome variables between the treatment and control grid areas for the years before the year of large-scale land investment despite minor aberrations in a few years (see Section 3.3 for details on the variable definition and measurement). In cases where the identification assumption might not fully hold, we still contend that our identification strategy is more reliable than plausible alternatives that one can think about: (i) a naïve comparison of localities that exhibit large-scale land acquisitions to all other localities in the Gambella regional state; and (ii) a matching approach that solely depends on observable attributes. Our approach allows us to overcome the challenges associated with unobserved heterogeneity and confounding factors, typical econometric challenges in the absence of randomized assignment in the implementation of large-scale agricultural land acquisitions.

In our estimation, we further exploit two features of our data. First, we control for observable grid-level characteristics that might account for some source of bias in the regression analyses. Second, we use our panel data to control for unit, time, and Kebele-year fixed effects in our regression analysis. Including grid fixed effects not only controls for time-invariant unit-specific (grid-level) sources of unobserved heterogeneity but also controls for time-invariant grid-level factors that could cause bias in our estimates of land acquisition effects.

3.3. Data and descriptive statistics

We combine several sources to create a unique panel dataset on large-scale land acquisitions, crop growth, forest loss, percent tree cover, land use, population density, luminosity, precipitation, and temperature. Specifically, we rely on two types of data: (1) georeferenced administrative data on large-scale land investment projects; and (2) high-resolution satellite data on forest cover change, crop growth, night time lights, and other geographic and climate variables. Based on a 1 km $\times$ 1 km resolution grid, we assembled an original geospatial dataset that covers the Gambella regional state over the 2000–2020 period. Fig. 6 shows the grid that we drop for Gambella to process and analyze remote sensing data, in which the information about the potential and the reallocation of the investment land is embedded.

We use the 1 km $\times$ 1 km grid as our spatial unit of analysis because agricultural investment projects involve the cultivation of land that directly affects land use and land cover at a lower resolution than the 30 m pixels, which is the resolution of our main measure of environmental outcome. We restrict our sample to the 2000–2020 period to capture both pre- and post-reform years such that we can examine the evolution of our outcomes of interest and the estimated treatment effects at least five years before and after the agricultural investment reform program we study and the intensification of large-scale land investments. We proxy environmental degradation by a measure of deforestation both at the intensive and extensive margins, measured with a change from non-zero forest cover to zero forest cover of a given cell in a given year and with a gradual reduction in the area's percent forest cover over time, respectively.

3.3.1. Investment data

The investment data covers both the potential and the realized investment land for agricultural production. The potential investment area is identified and banked by the government based on a study conducted by a national task force in collaboration with regional state authorities, following the shift in the national development strategy from promoting small-holder productivity to large-scale agricultural investments (Rahmato, 2011; Hajjar et al., 2020). We acquired spatial data for potential investment land from the Ministry of Agriculture and Rural Development (MoARD). However, the land used for the investment is agricultural land that the government has transferred to private agricultural investors to promote agricultural transformation through mechanized commercial farming. Data on potential land investment areas and large-scale land investments are obtained from the Ministry of Agriculture and the Bureau of Agriculture and Natural Resources

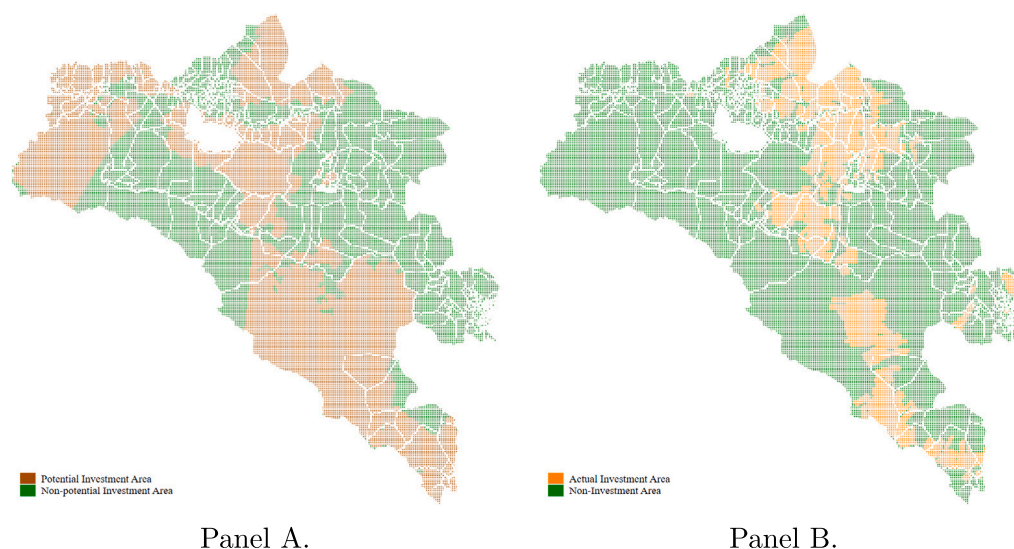


Fig. 6. 1 km $\times$ 1 km Grid of Gambella Region. Source: own elaboration based on the potential (Panel A) and realized (Panel B) investment land data from MoA (2009) and Agriculture and Natural Resource Management Bureau of Gambella Region.

Management in the Gambella regional state, respectively. We first obtained the record of agricultural investment projects and associated spatial information at the federal and regional state levels and compiled a census of agricultural investment projects for the Gambella region. Then we conduct a validation study of randomly selected projects (20%) from our inventory of investment projects. Finally, we produce geospatial data of large-scale agricultural acquisitions with information on, *inter alia*, the size of the contracted land, the year of the contract, and the lowest administrative unit (*Kebelle*) where the acquisition took place.

3.3.2. Deforestation data

To analyze deforestation at the extensive margin, we use the Global Forest Change (GFC) data for the years 2000–2020. The dataset, based on a time series analysis of Landsat images, describes different aspects of global forest change (Hansen et al., 2008). The data have a high resolution (30 m), classifying forest cover as vegetation growth of at least 5 m in height. In other words, trees are defined as vegetation taller than 5 m in height and are expressed as a percentage per 30-meter grid cell. The GFC data has four main bands. First, the tree cover band provides information on the percent tree cover (forest cover) by 2000 for each 30-meter grid cell. Second, the loss band provides information on the forest cover loss, which is an aggregate sum of the 30-meter grid cells that transition from forest to non-forest state. Third, the gain band provides information on the forest cover gain, which is an aggregate sum of the 30-meter grid cells that change entirely from a non-forest to forest state during the relevant period. Fourth, the loss year band disaggregates the total forest loss on annual time scales, *calendar year*.

The GFC data have been widely used in economic studies, for example, ethnic fractionalization and deforestation in Indonesia (Alesina et al., 2019); refugee camps and deforestation in Sub-Saharan Africa (Salemi, 2021), the rule of law and deforestation of protected areas in the world (Abman, 2018), payment for ecosystem services and deforestation in Mexico (Alix-Garcia et al., 2013), political jurisdiction and tropical deforestation in Indonesia (Burgess et al., 2012). Although the GFC is the most comprehensive and consistent dataset available for the study of deforestation, it has limitations related to high thresholds for change and misclassification of plantations for products such as oil palm and rubber as natural forests (Burivalova et al., 2015; Tropek et al., 2014). However, such plantations are not common in our study area, and we use the GFC data to measure deforestation at an extensive margin.

To analyze deforestation at the intensive margin, we use data from the Terra MODIS Vegetation Continuous Field (VCF) product. The VCF product is produced using monthly composites of Terra MODIS 250- and 500-meter Land Surface Reflectance data. It provides a gradation of three components of surface cover: percent tree cover, percent nontree cover, and percent bare (DiMiceli et al., 2021). Unlike the GFC, the VCF product provides estimates of percent tree cover, percent nontree cover, and percent bare ground for each pixel — a yearly representation of surface vegetation from 2000 to the present at 250 m spatial resolution. The data is derived from a machine learning model that uses Moderate Resolution Imaging Spectroradiometer (MODIS) data and other high-resolution data from NASA and Google Earth. As a continuous measure of forest cover, the VCF data can capture marginal reductions in percent forest cover that do not result in the grid cell transitioning to zero forest cover. For example, if the percentage of forest cover in a grid cell decreases from 90% to 80%, the VCF data will still record this as a change in forest cover, even though the grid cell has not yet reached zero forest cover. Thus, it allows us to track the gradual loss of forests except for its lack of sufficient variation between years (Hirvonen et al., 2022).

Similarly, the VCF product is widely used in several applications, including forest change assessments over time and space (Gao et al., 2018; Ryan et al., 2017), biomass and carbon emissions estimates (Anaya et al., 2009; Rodríguez-Veiga et al., 2016; Tang et al., 2021; Zomer et al., 2016), biodiversity and conservation (Miles et al., 2006; Vijay et al., 2016), payment for ecosystem services (Phan et al., 2018), parameterization of environmental and climate models (Forrest et al., 2020), and as input or integrated use with Landsat data for forest cover mapping (Hansen et al., 2008; Sexton et al., 2013).

3.3.3. Crop production data

To examine the effect of large-scale agricultural land acquisitions on agricultural production, we construct an indicator of crop growth by combining the Normalized Difference Vegetation Index (NDVI) with highly disaggregated land use, crop type, and crop calendar data. We use the NDVI data from the MODIS VI products that are available bi-monthly at a 250-meter spatial resolution. NDVI is widely used as a proxy for vegetation health and crop productivity (Asher and Novosad, 2020; Gazeaud and Stephane, 2023; Ali et al., 2020). Specifically, Gazeaud and Stephane (2023) showed that the NDVI-based measure of crop production is well correlated with survey-based measures of total production and average land productivity.

Table 2
Summary statistics: Mean values at grid-year level for entire Gambella.

	(1) Treatment	(2) Control	(3) Total
Percent forest loss (GFC)	0.042 (0.167)	0.047 (0.177)	0.045 (0.173)
Percent tree cover (VCF)	0.236 (0.162)	0.279 (0.198)	0.263 (0.187)
NDVI (Landsat)	0.623 (0.095)	0.634 (0.101)	0.627 (0.097)
NDVI (MODIS)	0.691 (0.045)	0.699 (0.056)	0.694 (0.049)
Share of crop land (MODIS)	0.031 (0.139)	0.007 (0.055)	0.016 (0.096)
Share of forestland (MODIS)	0.199 (0.377)	0.242 (0.417)	0.226 (0.404)
Share of urbanland (MODIS)	0.000 (0.007)	0.000 (0.008)	0.000 (0.008)
Share of savannaland (MODIS)	0.769 (0.386)	0.751 (0.417)	0.758 (0.406)
Baseline percent forest loss (GFC)	0.056 (0.196)	0.053 (0.192)	0.054 (0.194)
Baseline percent tree cover (VCF)	0.286 (0.153)	0.313 (0.181)	0.303 (0.172)
Baseline NDVI (Landsat)	0.581 (0.064)	0.618 (0.083)	0.601 (0.077)
Baseline NDVI (MODIS)	0.714 (0.035)	0.727 (0.044)	0.720 (0.040)
Baseline forest land share	0.205 (0.374)	0.232 (0.410)	0.222 (0.397)
Baseline crop land share	0.048 (0.165)	0.023 (0.103)	0.032 (0.129)
Baseline savannaland share	0.746 (0.384)	0.744 (0.410)	0.745 (0.401)
Observations	214,301	373,468	587,769

Notes: The table reports summary of outcome and selected other variables by the treatment group. Standard deviations in parentheses. Acronyms in bracket (e.g., GFC) refers to the satellite data product (Hansen [2013] Global Forest Change) used to construct the variable. Baseline moments are generated for 2000/2001.

Based on the spatial unit of analysis that we defined, we aggregated the NDVI data at the grid-year level. The grid-year level aggregation might be susceptible to the aggregate-out problem if the impact of large-scale land acquisition is spatially localized and/or unevenly spread over the calendar year. With the view that the effect of large-scale agricultural acquisitions is spatially localized and seasonally concentrated to the main growing season for agricultural outcomes, we constrain the aggregation of NDVI by spatial and time constraints, as in Gazeaud and Stephane (2023).

Our spatial constraint limits the grid-year level aggregation of NDVI for only cultivated land in the Gambella region. To this end, we use the MODIS land cover dynamics data product, which provides global land surface phenology metrics at yearly intervals in which land use and land cover information is made available at a resolution of 500 m. We particularly consider cultivated land by 2001, about five years earlier than the major shift in government policy toward mechanized commercial farms that involved an influx of large-scale agricultural investors. This improves our proxy measure of crop production by addressing concerns about structural differences in productivity between cultivated land before such a change in policy and after its implementation on a scale. Similarly, we restrict our aggregation of NDVI to the main growing season of the main crops cultivated in Gambella using crop calendar data from MIRCA 2000. Hence, we computed the average NDVI using pixels that covered cultivated land in 2001 and the months corresponding to the main growing season at the grid year level for the 2000–2020 period.

Table 2 presents a summary of key variables, revealing notable differences between eventually treated grids and never treated grids. In the last group of rows, it highlights the baseline characteristics of grids for the baseline (2000/2001) year in which treated and control

grids exhibit differences in land use and vegetation cover. Specifically, forest land share in eventually treated grids is lower (20.5%) than control grids (23.2%) while the share of cropland is twice as high (4.8%). However, the share of savannah land is almost similar in both treated (74.6%) and control grids (74.4%). In line with the baseline forest land share, treated grids show considerably lower baseline tree cover density (28.6%) compared to control grids (31.3%), while the difference in percent forest loss is negligible. Similarly, treated grids exhibit lower baseline vegetation indices (NDVI) across both Landsat and MODIS satellite products.

Looking at the averages across the entire study period, baseline differences largely persist. Treated grids maintain a noticeably higher average share of cropland compared to control grids (3.1% versus 0.7%), but a lower average share of forestland (19.9% versus 24.2%). Both areas remain heavily dominated by savannaland, with treated grids at 76.9% and control grids at 75.1%. Furthermore, average rates of overall forest loss remain relatively comparable over time (4.2% for treated versus 4.7% for control), while mean percent tree cover is somewhat lower in the treated group (23.6% versus 27.9%). Consistent with these land-use patterns, overall vegetation indices (NDVI) are marginally lower in treated grids across both Landsat and MODIS satellite products (see also Tables B.1 and B.2). The pre-existing differences in initial land-use and vegetation health underscore the importance of controlling for fixed effects and robust dynamic estimators to properly isolate the causal impact of the land transfers from time-invariant spatial heterogeneity.

4. Results

This section presents estimates of the effects of large-scale land acquisitions on key agricultural and environmental outcomes. We focus on three main dimensions: crop production, forest loss, and percent tree cover. These indicators capture both the productivity and environmental consequences of promoting large-scale commercial agriculture, reflecting how land acquisitions influence agricultural productivity and environmental change.

To address concerns about the validity of the counterfactual and the robustness of our estimates, we run all specifications across three alternative sample definitions. First, we estimate the models using the full sample. Second, we restrict the analysis exclusively to ever-treated LSLTs Kebeles (that experience at least one large-scale land acquisition). This within-treated-area comparison excludes never-treated kebeles, particularly the northwestern part of Gambella, whose distinct pastoralist livelihood and remote geography may not provide a valid counterfactual, thereby enhancing baseline comparability between treated and control units. Third, we re-estimate the models excluding the Karuturi concession, the largest single LSLAs in the country, to confirm that our results are not driven by the scale or outcome of a single mega-project.

4.1. Effect of large-scale land acquisitions on crop production

Our analysis begins by examining the effect of LSLA's on the main objective of the underlying land policy, improving commercial agricultural production. Table 3 presents the estimated average effects of LSLA on crop production, using NDVI as a proxy for crop yield. The findings in all models reveal null effects, suggesting that land transfers to large-scale investors improve agricultural output in the full sample. These null results remain robust under alternative sample restrictions. Focusing exclusively on ever-treated LSLA kebeles or excluding the extensive Karuturi concessions produces similarly consistent and statistically insignificant point estimates. The magnitudes are modest in NDVI units, suggesting that LSLAs do not deliver significant broad-based gains in crop production at the grid level.

To ensure that these null effects are not obscuring a delayed agricultural boom, we estimate an event-study specification that presents

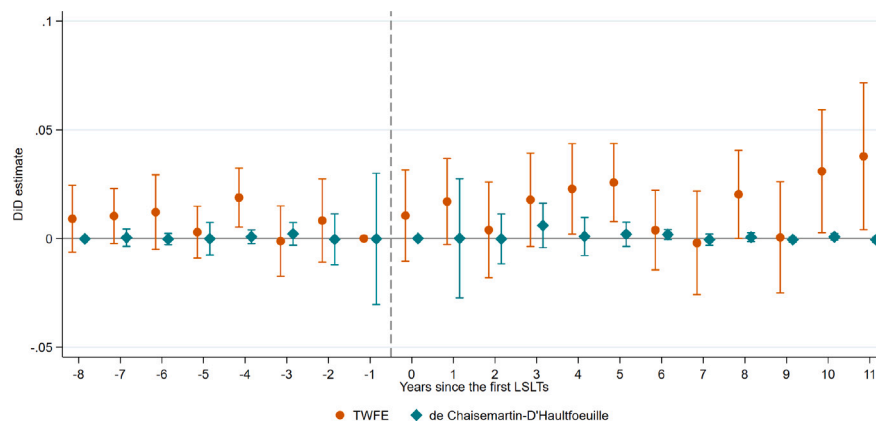


Fig. 7. Event Study — dynamic effect of LSLAs on crop production.

Table 3

LSLAs impact on agricultural output (NDVI-MODIS).

	(1) TWFE	(2) DCDH
<i>Entire Gambella</i>		
ATT	-0.001 (-0.15)	0.006 (0.53)
Observations	17,105	17,105
<i>LSLAs Kebele</i>		
ATT	-0.001 (-0.15)	0.006 (0.53)
Observations	13,728	13,728
<i>Excluding Karaturi</i>		
ATT	-0.001 (-0.15)	0.006 (0.53)
Observations	17,086	17,086
Controls	Yes	Yes
Grid FE	Yes	Yes
Year FE	Yes	Yes
Kebele × Year FE	Yes	Yes

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parentheses are clustered by spatial grid. Units of observation are grid-year for 2001–2020. TWFE = two-way fixed effects; DCDH = de Chaisemartin-D'Haultfoeuille. All specifications include controls for precipitation, temperature, and population density.

Table 4

LSLAs impact on deforestation (Loss - GFC).

	(1) TWFE	(2) DCDH
<i>Entire Gambella</i>		
ATT	0.003 (0.75)	0.021 (1.50)
Observations	270,660	270,660
<i>LSLAs Kebele</i>		
ATT	0.003 (0.79)	0.021 (1.50)
Observations	199,240	199,240
<i>Excluding Karaturi</i>		
ATT	0.003 (0.67)	0.021 (1.49)
Observations	269,820	269,820
Controls	Yes	Yes
Grid FE	Yes	Yes
Year FE	Yes	Yes
Kebele × Year FE	Yes	Yes

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parentheses are clustered by spatial grid. Units of observation are grid-year for 2001–2020. TWFE = two-way fixed effects; DCDH = de Chaisemartin-D'Haultfoeuille. All specifications include controls for precipitation, temperature, and population density.

evidence consistent with the average effect estimates. The dynamic estimates presented in Fig. 7 suggest that there are no differential pre-treatment trends in NDVI between treated and control grids (except for a few aberrations in the TWFE estimator), validating our parallel trend assumption. In addition, the post-treatment trajectory reveals a persistent, precise null effect across most of the post treatment years. Following the first LSLAs ($t > 0$), the estimated effects remain small and center around zero. In the short run, the DCDH estimators show a positive effect (in $t = 2$ and $t = 3$), while the TWFE estimator shows small positive effects (in $t = 10$ and $t = 11$). In general, we found no robust evidence that LSLAs affect crop production during the study period. The complete estimates of the event study are presented in Table B.3 in the annex.

The absence of a detectable change in NDVI may provide quantitative support for the implementation gap hypothesized in the literature on global land acquisitions. The null findings are consistent with the remote-sensing based evaluation of Ali et al. (2019), which documents that a vast majority of the land transferred for commercial agriculture (about 55%) in Ethiopia remains underutilized years after acquisition. This is compounded by the fact that most commercial farms are owned by local investors who face severe capital constraints, prohibiting the massive upfront investment required to clear land, technology, manpower, import machinery, and establish irrigation in

remote areas (Rahmato, 2011; Lavers, 2012; Ali et al., 2019). Additionally, infrastructure bottlenecks may contribute to prolonged inactivity or speculative holding of concessions (Keeley et al., 2019), resulting in a disconnect between administrative transfers of land and actual agricultural production.

4.2. Effect of large-scale land acquisitions on forest loss

In the main specification, we find no evidence that formal land allocation to large-scale commercial investors leads to deforestation (see Table 4). Estimates from the conventional TWFE and the robust DCDH estimators are statistically insignificant and close to zero. The magnitudes rule out economically significant increases in forest-to-non-forest conversion in treated grid areas. This finding is consistent with regional evidence that, in many sub-Saharan Africa, forest loss is dominated by smallholder agriculture shifting rather than commodity-driven conversion (Tyukavina et al., 2018), compared to cases in Southeast Asia and Latin America, where land concessions accelerated deforestation (Davis et al., 2020).

To ensure that these baseline findings are not driven by unobserved spatial heterogeneity or outlier investments, we estimate the same models on two restrictive sub-samples (reported alongside the baseline in Table 4). First, we estimate the sample exclusively to Kebeles that eventually received LSLAs. By dropping never-treated

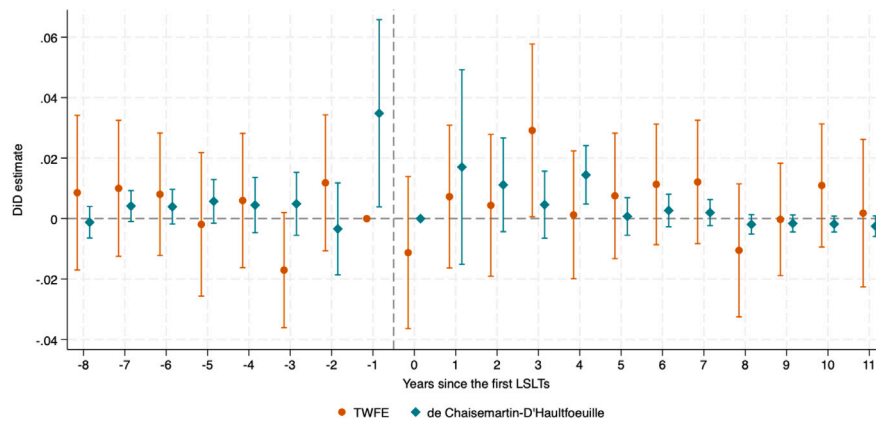


Fig. 8. Event Study — dynamic effect of LSLAs on forest loss.

Kebeles, we compare areas with highly homogeneous baseline characteristics and agro-ecological suitability. Second, we re-estimate the models excluding large investments (the Karuturi concession) to rule out the possibility of a disproportionate effect from the scale of a single mega-project. Across both robustness exercises, the pattern remains consistently stable; we do not find statistically significant evidence of forest loss in either the TWFE or DCDH models. The robustness of these estimates indicates that the muted average effect is an inherent characteristic of the implementation of LSLAs in Gambella, rather than a result of sampling bias.

The absence of immediate and general forest loss effects suggests the need for a more detailed investigation of the temporal patterns of land conversion. If LSLAs operate through gradual, cumulative processes rather than abrupt, isolated events, conventional average treatment will underestimate their true effects. Our event-study specification formally tests this hypothesis (Fig. 8). The analysis provides two key insights. First, we find no evidence of differential pre-treatment trends in forest loss between treated and control areas, thereby supporting the primary identification assumption. Second, the dynamic treatment effects remain insignificant and close to zero (see the full result in Table B.5). This observation may indicate a significant temporal delay, as forest loss generally occurs several years after the initial allocation of land. These lagged dynamics are consistent with the well-documented implementation gap in global land investments (Messerli et al., 2014; Ali et al., 2019). In the Ethiopian context, the transition from land allocation to active agricultural production is significantly constrained by institutional and infrastructure challenges. Frequent obstacles, such as credit constraints, infrastructure bottlenecks, and administrative delays, hinder both capital investment and land development (Rahmato, 2011; Keeley et al., 2019). In addition, weak oversight encourages the speculative use of investment licenses for imports rather than agriculture (Keeley et al., 2019), and even with policy reviews, development is often delayed (Moreda, 2017). These financial and institutional obstacles lead to considerable variation in the development timeline, as shown by our findings from the event-study on environmental impacts.

The combined evidence points to a precise null effect on extensive-margin deforestation: LSLAs are not associated with a broad conversion of forest to non-forest land within the study window. Any environmental impact, if present, is more consistent with localized intensive margin adjustments (e.g., edge effects or selective clearing) than with large-scale clearing detectable in annual forest loss measures.

4.3. Effect of large-scale land acquisitions on percent tree cover

In the preceding section, we assessed the effects of LSLAs on forest loss using our measure of forest loss derived from the GFC data and found no evidence that formal allocation to investors results in immediate deforestation. The absence of a widespread deforestation

Table 5

LSLAs impact on deforestation (Tree Cover - VCF).

	(1) TWFE	(2) DCDH
<i>Entire Gambella</i>		
ATT	−0.398*** (−4.08)	−0.422*** (−3.52)
Observations	608,920	608,920
<i>LSLAs Kebele</i>		
ATT	−0.388*** (−3.98)	−0.422*** (−3.52)
Observations	442,580	442,580
<i>Excluding Karuturi</i>		
ATT	−0.378*** (−3.84)	−0.422*** (−3.52)
Observations	606,100	606,100
Controls	Yes	Yes
Grid FE	Yes	Yes
Year FE	Yes	Yes
Kebele × Year FE	Yes	Yes

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parentheses are clustered by spatial grid. Units of observation are grid-year for 2001–2020. TWFE = two-way fixed effects; DCDH = de Chaisemartin–D’Haultfoeuille. All specifications include controls for precipitation, temperature, and population density.

event indicates that LSLAs do not directly trigger rapid, large-scale clearing upon land allocation in Gambella. However, the analysis using the continuous measure of forest cover (VCF percent tree cover) reveals a markedly different, yet theoretically consistent, evidence on deforestation on the intensive margin. As detailed in Table 5, the results suggest a modest, consistent decline in tree density following LSLTs. In the full sample, both TWFE and DCDH indicate reductions of approximately half a percentage point in percent tree cover per treated grid-year, with both estimates statistically significant at the 1 percent level. The estimates remain robust in alternative sample restrictions. Restricting the estimation to ever-treated LSLA kebeles or excluding the massive Karuturi concession yields nearly identical point estimates. These, combined with the consistent point estimates between the TWFE and DCDH estimates, strengthen the credibility of these findings, indicating that the negative effect on tree cover is a robust result evident in the data.

Economically, the pattern indicates intensive-margin thinning, selective clearing, site preparation, edge effects around fields, or increased fuel wood extraction, rather than complete forest conversion to a cropped area. Taken together, the evidence suggests that LSLTs are associated with declines in percent tree cover, consistent with localized thinning rather than large forest losses.

The estimates of the dynamic event study presented in Fig. 9 support the above interpretation, which plots the estimates for percentage tree

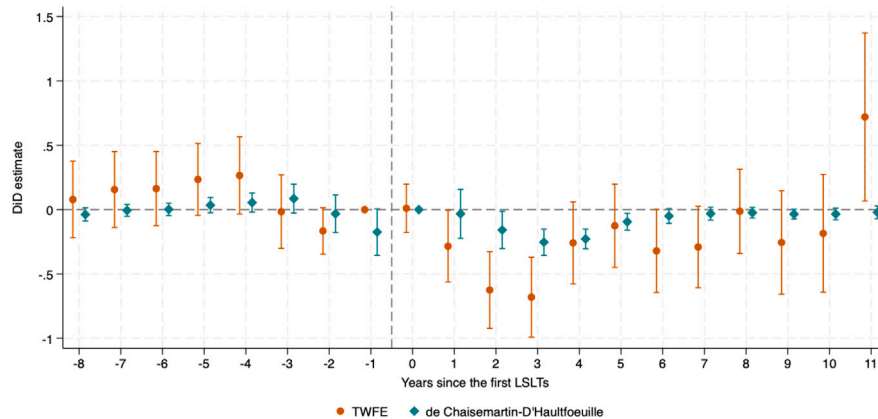


Fig. 9. Event Study — dynamic effect of LSLAs on percent tree cover.

cover using the TWFE and DCDH estimators (see the full result in Table B.6). The result reveals no sharp post-treatment break; instead, the treatment effect initially remains close to zero before exhibiting persistent negative dips in the medium run (between $t = 1$ to $t = 4$), the pattern summarized in Table 5, where both estimators deliver modest average declines in tree cover. Taken together, both the average and dynamic estimates confirm that LSLAs in the Gambella region do not trigger rapid, large-scale clearing, but rather catalyze a localized, progressive thinning of forest density.

The difference in statistical significance between the percent tree cover and forest loss analyses suggests that the environmental effect of LSLAs in frontier contexts is mainly characterized by progressive degradation of the land cover rather than immediate, abrupt deforestation events. This observation is consistent with theoretical expectations of agricultural expansion in regions facing capital constraints. Increased land value, driven by greater commercialization and improved infrastructure access, incentivizes early-stage land clearing (Angelsen, 2010). Even when financial and infrastructure frictions delay full-scale cultivation, investors often engage in selective clearing, the construction of access routes, and the development of base camps (Ali et al., 2019). Therefore, land conversion in Gambella tends to occur in distinct stages, with gradual change.

5. Potential channels

In this section, we explore potential mechanisms underlying our main findings, namely, the null effects on crop production and forest loss, alongside a decline in tree cover, using measures of crop and forest land shares derived from MODIS land use and land cover data. Changes in these land shares may constitute important channels through which LSLAs affect agricultural productivity and forest outcomes.

A key plausible channel is changes in cropland shares, which represent a necessary first step prior to any increase in agricultural production in response to LSLAs. Estimates reported in Table 6 indicate that, on average, LSLAs have little effect on cultivated land under both TWFE and DCDH specifications. While DCDH estimates suggest marginally positive changes in cropland shares, these effects are economically negligible and statistically indistinguishable from zero. Overall, the results provide no evidence of meaningful expansion in cultivated land following LSLAs. This is consistent with our main findings, which show no significant impact on agricultural productivity.

The event study in Fig. 10 further supports this finding (see the full result in Table B.7). TWFE estimates exhibit considerable uncertainty, whereas DCDH estimates remain largely insignificant throughout, aside from a few pre-treatment fluctuations. The dynamic pattern aligns with

Table 6

LSLAs impact on Land Use (Crop Land - MODIS).

	(1) TWFE	(2) DCDH
<i>Entire Gambella</i>		
ATT	−0.002 (−1.11)	0.002* (1.69)
Observations	609,880	609,880
<i>LSLAs Kebele</i>		
ATT	−0.002 (−1.05)	0.002* (1.69)
Observations	443,000	443,000
<i>Excluding Karaturi</i>		
ATT	−0.002 (−1.13)	0.002* (1.69)
Observations	607,060	607,060
Controls	Yes	Yes
Grid FE	Yes	Yes
Year FE	Yes	Yes
Kebele × Year FE	Yes	Yes

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parentheses are clustered by spatial grid. Units of observation are grid-year for 2001–2020. TWFE = two-way fixed effects; DCDH = de Chaisemartin-D'Haultfoeuille. All specifications include controls for precipitation, temperature, and population density.

the average treatment effects, suggesting that any changes in cultivated land are modest, cohort-specific, and gradual rather than reflecting a sharp expansion at the onset of the LSLAs project.

The absence of significant changes in cultivated land is consistent with field evidence indicating that many allocated parcels remained idle for several years. Several factors may explain this pattern: (i) many investors did not develop acquired land despite benefiting from tax incentives and credit access; (ii) the identification of investment land prioritized non-forest areas, limiting extensive-margin expansion; and (iii) where projects were implemented, land preparation often involved selective tree extraction than full land clearing, resulting in canopy thinning without increasing cultivated area.

Next, we examine whether changes in forest outcomes are driven by changes in forest land shares. Using MODIS land use and land cover data, we assess whether LSLAs lead to shifts in forest land shares. This mechanism is relevant for interpreting the effects on environmental outcomes. To this end, we conduct the analysis using a more conservative comparison within grids that have a non-zero share of forest cover throughout.

Table 7 presents the estimated impacts on forest cover using both the TWFE and DCDH estimators. The results reveal a consistent and

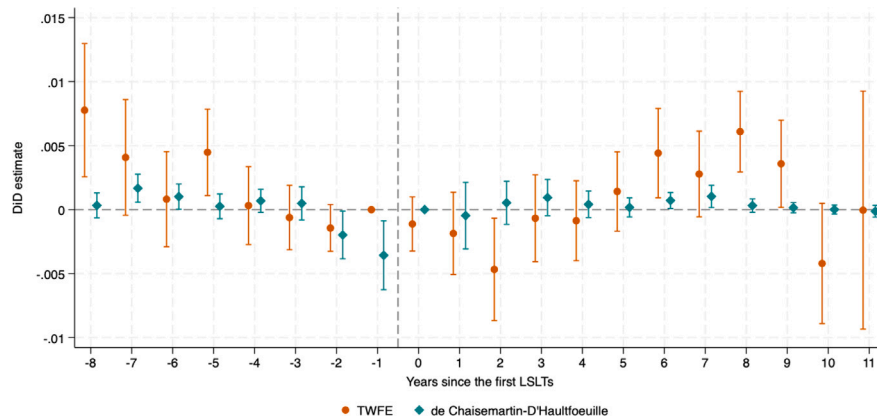


Fig. 10. Event Study — dynamic effect of LSLAs on crop land shares.

Table 7

LSLAs impact on Land Use (Forest Land - MODIS).

	(1) TWFE	(2) DCDH
<i>Entire Gambella</i>		
ATT	−0.039*** (−3.99)	−0.029*** (−3.76)
Observations	160,703	160,703
<i>LSLAs Kebele</i>		
ATT	−0.040*** (−4.02)	−0.029*** (−3.76)
Observations	107,109	107,109
<i>Excluding Karaturi</i>		
ATT	−0.041*** (−4.05)	−0.029*** (−3.76)
Observations	160,328	160,328
Controls	Yes	Yes
Grid FE	Yes	Yes
Year FE	Yes	Yes
Kebele × Year FE	Yes	Yes

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parentheses are clustered by spatial grid. Units of observation are grid-year for 2001–2020. TWFE = two-way fixed effects; DCDH = de Chaisemartin–D’Haultfoeuille. All specifications include controls for precipitation, temperature, and population density.

statistically significant reduction in forest cover. These results are robust when we limit the data to directly affected Kebeles or exclude the Karaturi concessions, indicating that LSLAs consistently contribute to deforestation at the intensive margins.

The dynamic estimate presented in Fig. 11 reinforces this interpretation. The DCDH event study indicates a negative effect on land use in the early periods ($t + 1$ to $t + 5$). Although the conventional TWFE estimate shows localized volatility in specific post-treatment periods (see the full result in Table B.8), the presence of these effects in the corrected DCDH model confirms that they are likely driven by the negative weighting biases inherent to staggered treatment timing.

The statistically meaningful changes in land cover is consistent with the broader pattern emerging from our environmental results. Land cover and land use measures register changes when landscapes undergo sufficiently large and discrete transformations, such as from forest to agriculture. However, in the context of Ethiopia, severe financial and institutional challenges prevent investors from moving from formal land acquisitions to full-scale cultivation. Combined with the GFC and VCF results, this evidence points to a coherent mechanism: the environmental effects of LSLAs in Gambella operate primarily through gradual canopy degradation and partial clearing along the intensive margin, rather than through immediate and complete conversion into a new land-use class.

Table 8

LSLAs impact on Agricultural Output (NDVI-LANDSAT).

	(1) TWFE	(2) DCDH
<i>Entire Gambella</i>		
ATT	−0.015 (−1.38)	−0.010 (−0.79)
Observations	27,532	27,532
<i>LSLAs Kebele</i>		
ATT	−0.015 (−1.40)	−0.010 (−0.79)
Observations	20,933	20,933
<i>Excluding Karaturi</i>		
ATT	−0.015 (−1.40)	−0.011 (−0.82)
Observations	27,401	27,401
Controls	Yes	Yes
Grid FE	Yes	Yes
Year FE	Yes	Yes
Kebele × Year FE	Yes	Yes

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parentheses are clustered by spatial grid. Units of observation are grid-year for 2001–2020. TWFE = two-way fixed effects; DCDH = de Chaisemartin–D’Haultfoeuille. All specifications include controls for precipitation, temperature, and population density.

5.1. Robustness checks

In this section, we conduct a series of robustness checks to assess the sensitivity of our baseline estimates to alternative data sources and potential measurement errors. Our primary concern is whether the absence of a significant effect on crop production is a robust result or attributable to limitations in remote sensing or changes in underlying crop composition.

A common critique of NDVI-based analysis using satellite data in development research is whether the spatial resolution of satellite products is adequate to detect changes. To address these limitations, we supplement our results with Landsat-based NDVI measurements. We re-estimate our primary specification, both the TWFE and DHCD estimators, using the Landsat-based NDVI measures. As reported in Table 8, the point estimates remain small in magnitude and statistically insignificant in all samples. This indicates that LSLTs have no significant effect on crop cultivation when assessed using MODIS or Landsat-based measures, suggesting that our results are not driven by sensor-specific measurement error or lack of spatial granularity. The complete event-study estimates are presented in Table B.4 in the Appendix.

A second concern is that the NDVI signal may be confounded by changes in the crop mix rather than by changes in cultivation intensity. If LSLAs induced a shift from staple crops to cash crops

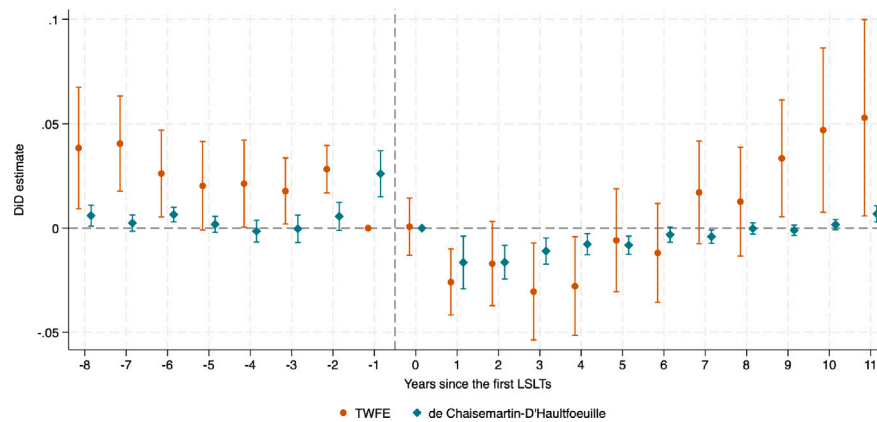


Fig. 11. Event Study — dynamic effect of LSLAs on forest land shares.

without reducing total cultivated area, the aggregate vegetation index may appear stable, even as substantial changes occur within the local production system. To address this, we use the Ethiopian Agricultural Sample Survey (AgSS) data to construct district-level crop area shares over 2004–2022 period. We present results that compare cultivated land area trends by crop and districts (see Fig. A.9). In so doing, we group all administrative districts in Gambella into two, i.e., districts with high and low exposure to LSLTs. High-intensity districts (Gambela Zuriya, Abobo, Gog, Dima, Lare, Itang, and Godere) are defined as those with at least 20 percent of land allocated to LSLA, while low-intensity districts (Jikawo, Makoy, Jor, and Mengeshi) have less than 20 percent allocated.

The evidence points to a clear and economically meaningful contrast in crop structure. In high-LSLT districts, cultivation is highly concentrated and becomes more so after the 2009 investment wave. Maize is already dominant prior to LSLA expansion and rises further thereafter, stabilizing at roughly 65–80 percent of cultivated area. Sorghum declines sharply and remains at low levels, while all other crops account for only marginal shares. *Quantitatively*, the top 10 crops account for over 92 percent of cultivated area, and residual categories such as “other fruits”, “other vegetables”, and “other cereals” together represent only about 5–6 percent. This indicates that crop composition is both highly concentrated and well captured by the observed data, with little scope for large unobserved shifts into alternative crops.

In contrast, low-LSLT districts exhibit a more diversified but stable crop structure. Maize and sorghum co-exist throughout the period, and several additional crops (including Moringa, sugarcane, coriander, rice, and enset) maintain non-trivial shares. While the top 10 crops also account for a large fraction of cultivated area (approximately 94 percent), the distribution is more even and no sharp structural break is observed around either the 2009 investment wave. Importantly, residual “other crop” categories remain small in this group as well, again indicating limited reallocation outside the main crops.

These patterns are directly informative for interpreting the NDVI results. In high-LSLT districts, the observed change in crop mix is toward maize-dominated cultivation. Because maize produces higher canopy density and peak NDVI values than the sorghum-based systems it replaces, any substantial expansion or intensification of cultivation would be expected to generate a detectable increase in NDVI. However, we find no such response. At the same time, the small share of residual crop categories implies that there is no large-scale reallocation into alternative crops that could mask vegetation changes in aggregate NDVI measures. If anything, the observed shift toward maize in high-LSLT districts would be expected to increase NDVI, which suggests that our estimated effects, if biased, are more likely to overstate rather than understate any positive crop production response.

Taken together, this evidence allows us to rule out crop substitution toward lower-NDVI crops as an explanation for the null results.

The absence of detectable NDVI effects is therefore unlikely to reflect measurement error or compositional shifts in cultivation. Instead, it is most consistent with limited on-the-ground agricultural development on land allocated to large-scale investments. While maize remains the dominant crop according to AgSS data, this persistence is not accompanied by measurable gains in vegetation productivity, suggesting that commercially designated land was not cultivated at sufficient scale or intensity to register in satellite-based indicators. This interpretation aligns with broader evidence from the Gambella program, indicating that substantial shares of allocated land remained uncultivated or only partially developed, a pattern that may also have contributed to the subsequent suspension of new LSLAs.

6. Discussions

The study aims to estimate whether LSLAs have truly driven agricultural transformation or mainly caused territorial shifts with limited productive outcomes. We leverage Earth Observation (EO) data to construct panel data at grid level from Gambella region in Ethiopia, one of the leading nations in hosting LSLAs. We find that LSLAs lead to declines in tree cover and forest land share within grids, but have no effect on agricultural production.

Although LSLAs were intended to boost productivity and local development through commercial agriculture, our empirical findings reveal a significant gap between the formal transfer of land and its subsequent productive use. This distinction is fundamental to the ongoing discussion on large-scale land investments in the global south. The policy arguments supporting LSLTs in Gambella have largely been based on the assumption that granting extensive concessions would transform supposedly underutilized land into productive commercial agriculture, address limitations in capital and technology, and generate benefits for neighboring communities. However, our analysis does not clearly support this proposed sequence. Rather, the data indicate that land transfers are associated with ecological disruption, primarily reductions in tree cover, without a corresponding transition to sustained productive use.

This paradox can be understood as a mismatch between state capacity for allocating land and regular oversight. Investors in Gambella face significant supply-side constraints, including administrative and institutional constraints, machine availability, labor shortages, and access to credit (Ali et al., 2019; Rahmato, 2011; Keeley et al., 2019), which could hinder progress beyond preliminary land preparation. In contrast, while the state can quickly allocate territory, it is ineffective in evaluating investor quality or enforcing productive-use covenants. As a result, many concessions remain only partially realized. In such cases, the land can be prepared to establish physical supervision or satisfy administrative lease obligations. However, the integration, investment, and supervision required for ongoing productivity are not implemented.

This trend suggests that in frontier settings with limited execution capacity, LSLAs can contribute to the 'enclosure of the commons', which leads to immediate environmental effects without achieving the expected long-term productivity gains associated with agricultural transformation.

While our results provide consistent estimates of the direct average effects of LSLAs designation and realization, several limitations warrant discussion. First, potential measurement error in remotely sensed indicators remains a concern. We use NDVI to proxy crop productivity, and GFC and VCF to measure forest loss and percent tree cover, respectively. These measures are standard but may introduce noise due to resolution constraints, crop heterogeneity, and aggregation across mixed land uses (Lu et al., 2025). Although these data provide consistent coverage over two decades, higher-resolution imagery and complementary ground- or survey-based validation would strengthen inference. Future work could build on this by combining satellite data with administrative and household-level agricultural statistics to refine productivity estimates and reduce potential measurement bias.

Second, our analysis focuses on LSLA designations and their realization, but it does not fully capture the share of land actually brought into production. Evidence from administrative sources suggests that many allocated parcels were only partially cultivated or remained unused. As a result, our estimates likely capture the effects of policy implementation rather than the impacts of operational farms. Differentiating between 'designated', 'acquired', and 'actively cultivated' parcels would sharpen the interpretation of both direct and indirect effects. This could be another avenue for future work.

Third, the current estimates do not isolate the potential spillover effects from direct effects. Although spillover effects are plausible, the average treatment effects we estimate are small, which could leave limited power to detect externalities in the current empirical setup. In theory, we could consider several potential spillover channels. For instance, displacement represents a particularly relevant channel. Smallholders dispossessed of land allocated to LSLA, even when that land subsequently goes uncultivated, may clear and cultivate neighboring areas, including forested land, as an outside option. Deforestation spillovers of this kind could, in principle, exceed the direct treatment effect in magnitude. More broadly, several other channels, including local labor and input market disruptions and indirect effects on tenure security, could bias our estimates in either direction across the outcomes we examine.

However, due to data and design feasibility issues, we rely on nighttime light intensity (luminosity) as a proxy for local economic activity, to estimate potential spillover effects of LSLAs in areas neighboring LSLA locations. We compare grids adjacent to LSLA locations against comparable unexposed grids within Gambella. We additionally conduct within-LSLA kebele comparisons and robustness checks excluding Karaturi grids. The results, reported in [Appendix Fig. A.10](#) and [Table B.9](#), show broadly parallel pre-implementation trends between treated and control grids. Following implementation, treated grids display lower luminosity relative to controls, with more prolonged exposure associated with significantly lower luminosity levels. These findings provide no evidence of positive economic spillovers in neighboring areas; if anything, the estimates suggest small but statistically significant negative spillovers, consistent with the broader pattern of limited agricultural realization under LSLA. We acknowledge, however, that luminosity does not directly capture forest loss or agricultural displacement.

A more complete assessment of displacement-driven deforestation spillovers, for instance, through distance-based or exposure-weighted analysis in surrounding areas (see e.g., [Belay and Ayalew, 2020](#)) would require reformulating the identification strategy into a continuous treatment framework ([Callaway et al., 2024a,b](#)), which is beyond the scope of the present paper. Moreover, such approaches may inadequately capture nonlinear spatial effects and introduce additional uncertainty. We therefore interpret our estimates as identifying the

average direct effects of LSLAs, rather than as ruling out general equilibrium or spatial spillover effects.

Fourth, the observed fluctuations in pre-treatment trends in our event study estimates could be driven by spikes in Earth Observation (EO) data ([Michler et al., 2026](#); [Josephson et al., 2026](#)) but they could also highlight the sensitivity of dynamic specifications to cohort size given substantial heterogeneity in the distribution of new LSLA pixels across the years. Future work could investigate whether these variations reflect data limitations or genuine heterogeneity in policy impacts across local contexts ([Gardner et al., 2024](#); [Henningsen et al., 2025](#)). In sum, extending this research using finer spatial data, validated productivity measures, and explicit modeling of spatial interactions would deepen understanding of how large-scale land allocation policies shape agricultural and environmental outcomes in developing settings.

A final key issue relates to external validity. Gambella represents a unique peripheral frontier characterized by a lowland region with low population density, vast tracts of uncultivated land, severe infrastructure deficits, limited market integration, and a politically complex ethnic and administrative environment. These attributes are integral to understanding the implications of the findings. Specifically, the lack of production effects may be attributable to a setting where land allocation is relatively straightforward, yet the supporting factors essential for sustained commercial agriculture, such as infrastructure, machinery availability, access to labor, service provision, and local market connectivity, remain underdeveloped. In this regard, the dynamics observed here are highly representative of other lowland investment target regions in Ethiopia (such as Benishangul-Gumuz) and vast areas of Sub-Saharan Africa. However, it is not recommended to directly generalize these results to other LSLA contexts in Ethiopia or internationally. In areas with higher population density, stronger infrastructure, and vibrant land and output markets, the outcomes of large-scale investments may differ considerably. Such regions tend to experience increased land competition, clearer market signals, and stronger incentives for efficient land use. Therefore, the Gambella case should be viewed as illustrating specific frontier conditions under which LSLAs may produce ecological changes without commensurate increases in production, rather than as representing a universal model.

7. Conclusions

Large-scale land investments have been a major development policy in most developing countries since the turn of the millennium. Governments in the global south have transferred large areas of agricultural land to private agricultural investors to achieve their national growth and transformation objectives. These investments inevitably have a substantial effect on both agricultural production and the environment. Despite existing empirical evidence on the effect of large-scale land transactions, rigorous causal studies remain scarce.

This paper examines the impacts of LSLAs on agricultural productivity and deforestation in the Gambella region of Ethiopia, using geo-referenced data on land transactions, information on annual forest cover and loss, and Normalized Difference Vegetation Index (NDVI). Specifically, we created a panel dataset based on the administrative inventory of commercial agricultural investments and high-resolution satellite data on forest loss, percent tree cover, and NDVI adjusted for land use type and crop calendar. Leveraging the spatial and temporal variation in the staggered rollout of LSLAs, we employ a quasi-experimental design to estimate the impact of the policy reform that promoted large-scale land acquisitions. Our identification strategy exploits the presence of land areas (grids) within rural Kebeles that receive large-scale land acquisition for commercial farming, which is not eventually allocated for investor farmers or agricultural companies. It compares those eventually saved to ever-grabbed grids during the sample period.

The results demonstrate that LSLAs have a negative effect on percent tree cover, or a positive effect on deforestation at the intensive margin.

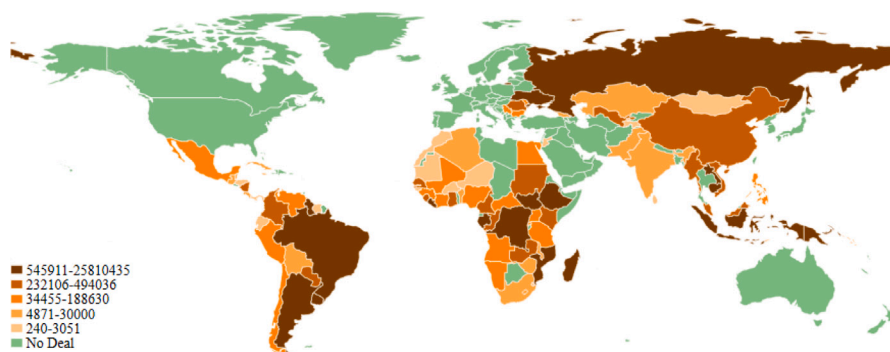


Fig. A.1. Hectares of large-scale land acquisitions by country.
Source: Own elaboration based on Land Matrix Global Observatory database (2020–2022).

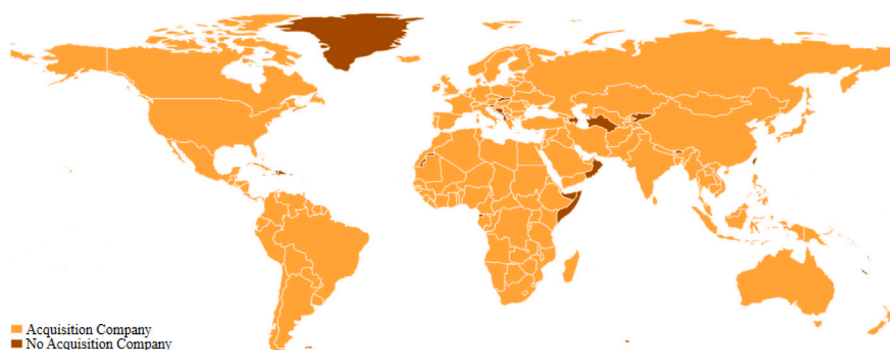


Fig. A.2. Large-scale land acquisitions: company registration by country.
Source: Own elaboration based on Land Matrix Global Observatory database (2020–2022).

However, large-scale land acquisitions do not affect our measure of crop production and forest loss, i.e., deforestation at the extensive margin. Decline in land share of forests within grids emerges as a potential channel for the effects of large-scale land acquisitions that we observed. Our finding supports the view that LSLAs exacerbate environmental degradation that threatens natural forests. Unlike (Davis et al., 2020), this study finds that the negative environmental impact does not operate through forest loss (extensive-margin effects), but rather through a reduction in tree cover within existing forests (intensive-margin effects). This finding opens doors for national and local policies that can effectively integrate economic and environmental goals in their development policies, strategies, and interventions.

CRediT authorship contribution statement

Workineh Asmare Kassie: Writing – review & editing, Writing – original draft, Visualization, Software, Project administration, Methodology, Investigation, Formal analysis, Data curation, Funding acquisition, Conceptualization. **Yeshwas Admasu:** Writing – review & editing, Writing – original draft, Supervision, Project administration, Methodology, Investigation, Formal analysis, Funding acquisition, Conceptualization. **Dagim Belay:** Writing – review & editing, Visualization, Software, Methodology, Investigation, Formal analysis, Funding acquisition, Conceptualization. **Solomon Zena Walelign:** Writing – original draft, Supervision, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Conceptualization. **Jipeng Zhang:** Writing – review & editing, Writing – original draft, Supervision, Methodology, Conceptualization.

Declaration of Generative AI and AI-assisted technologies in the writing process

During the preparation of this work, the author(s) used Copilot and GPT-5 to improve the clarity of some sections of the article and to verify spelling. After using this tool/service, the author(s) reviewed and edited the content as needed and take(s) full responsibility for the content of the published article.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A

See Figs. A.1–A.10.

Appendix B

See Tables B.1–B.10.

Data availability

The replication data and code supporting the findings of this study are available via Mendeley Data at the following link: <https://data.mendeley.com/datasets/wwkpn7pj7w/1>.

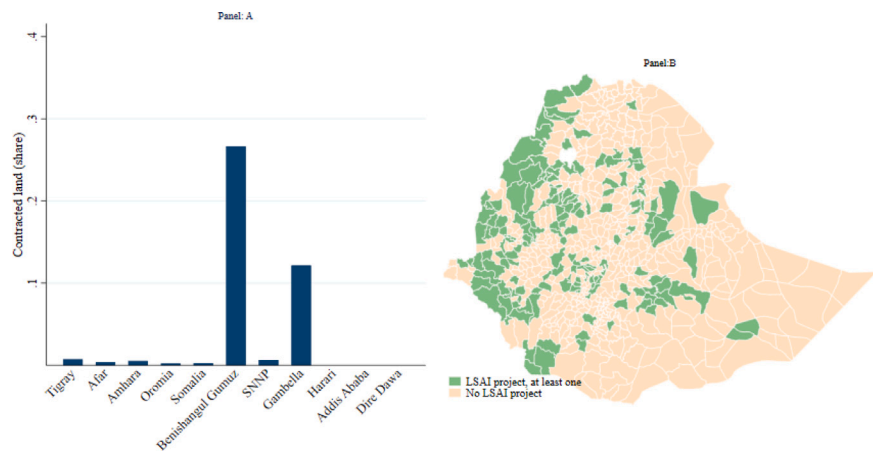


Fig. A.3. Large-scale land transfers by the Regional State and districts.
Source: Own elaboration based on MoARD data (2000–2022).

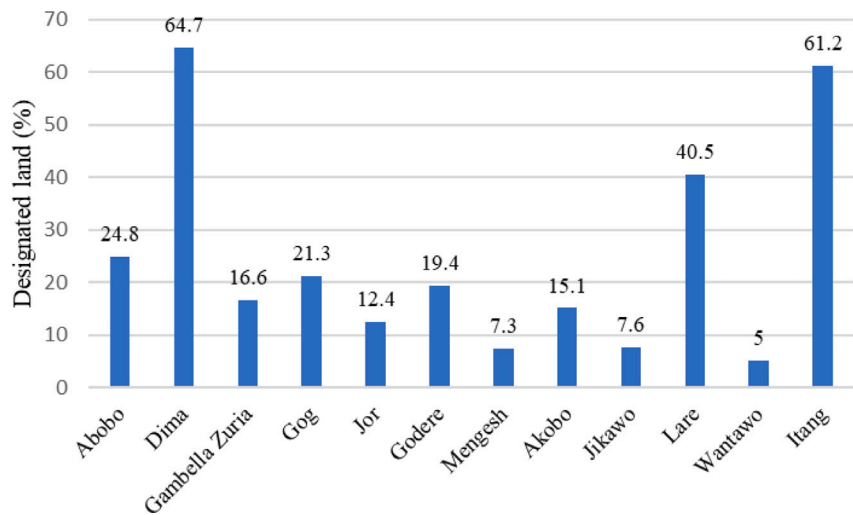


Fig. A.4. Share of potential investment land by district.
Source: Own elaboration based on MoARD data (2009).

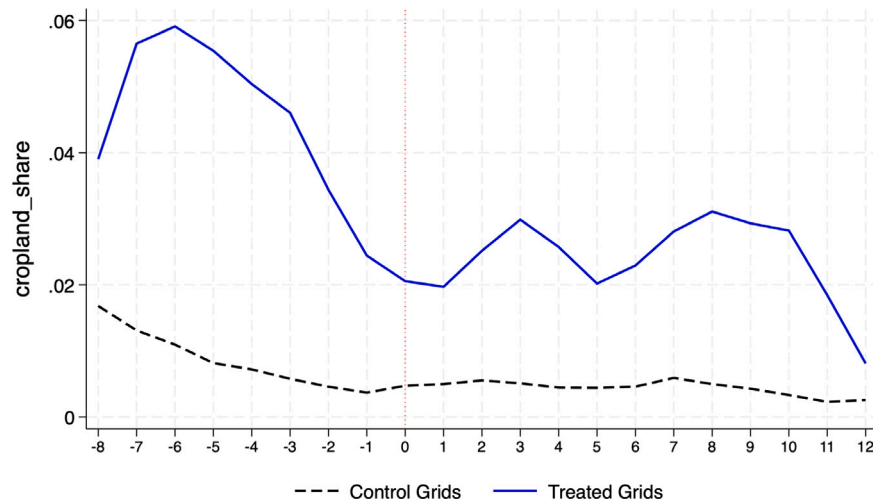


Fig. A.5. Trends in crop land shares.

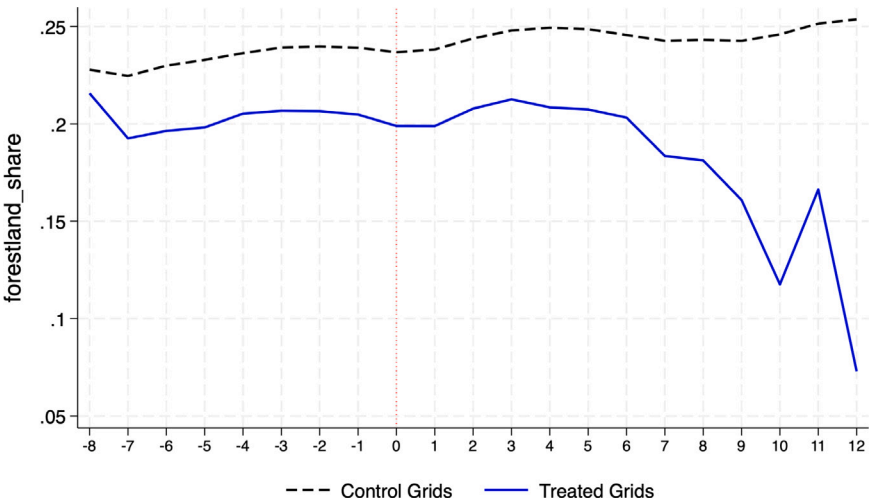


Fig. A.6. Trends in forest land shares.

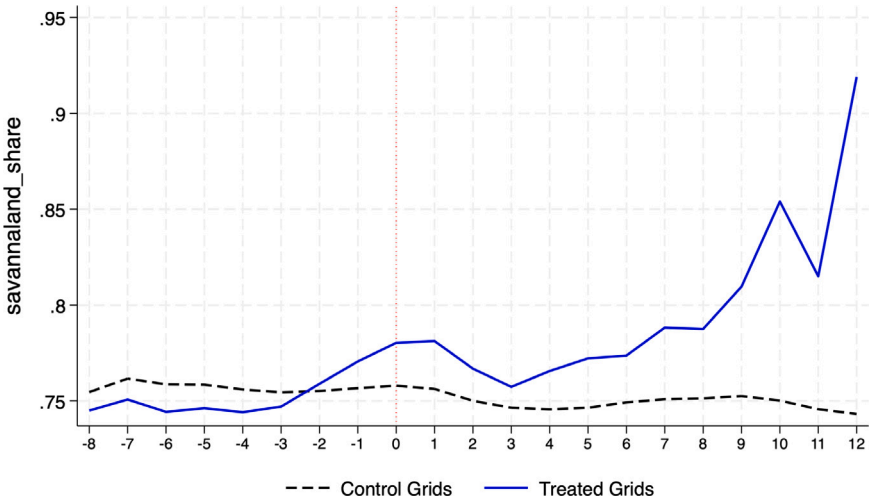


Fig. A.7. Trends in savanna land shares.

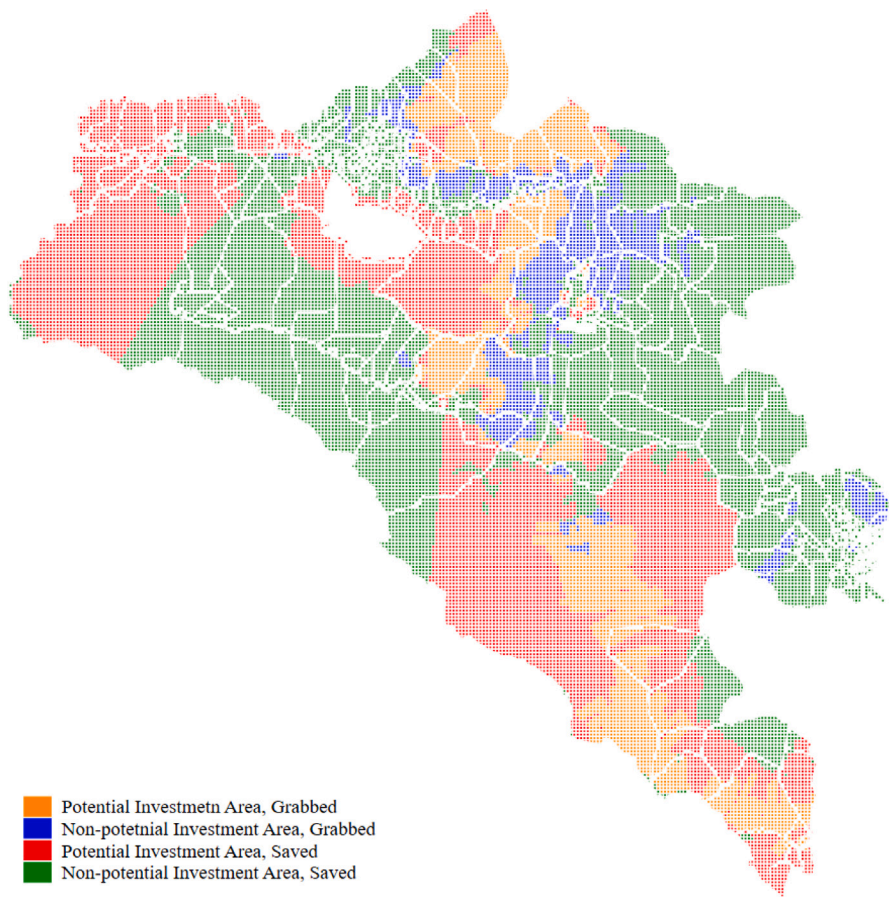
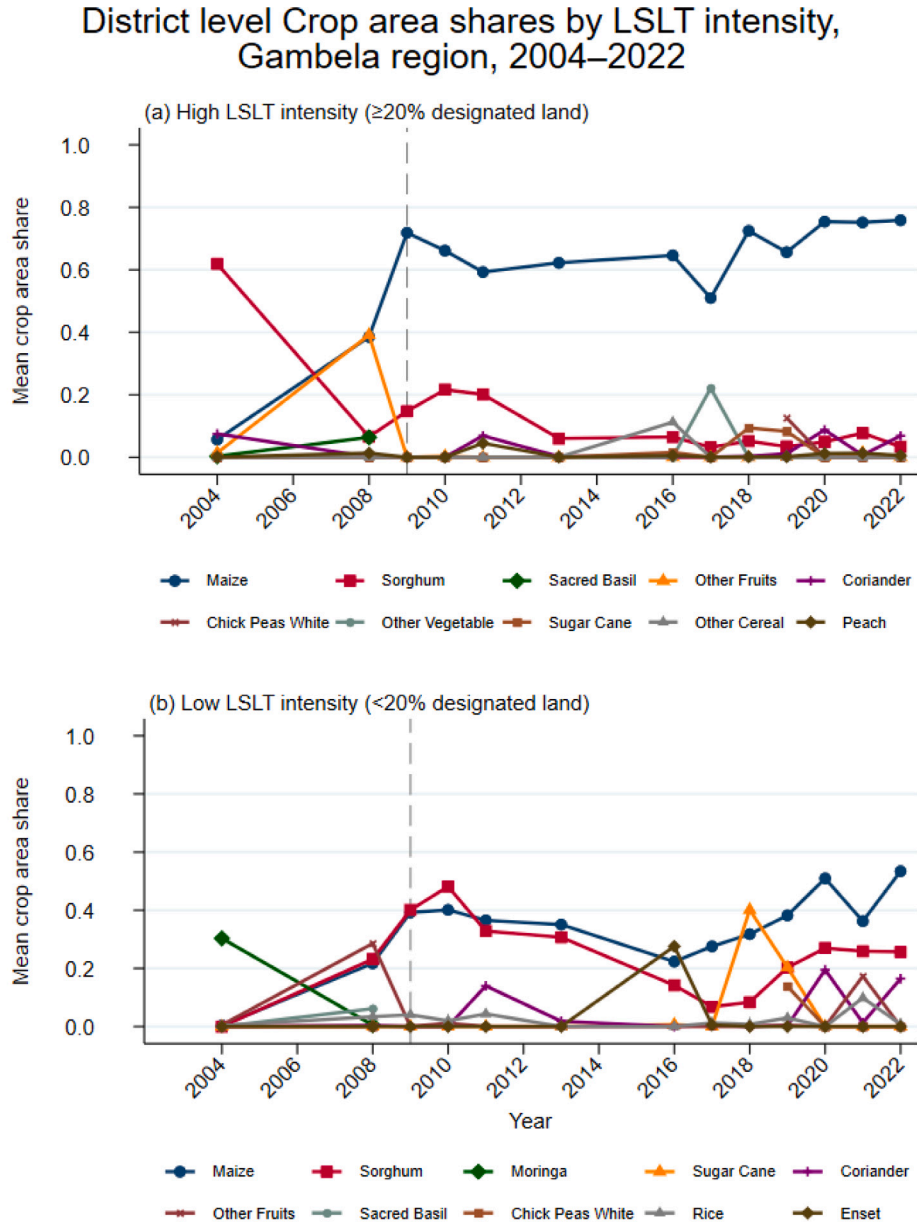


Fig. A.8. Spatial context of LSLTs in Gambella.



Notes: Vertical dashed line = 2009 peak LSLT investment wave.
High-intensity districts: Gambela Zuriya, Abobo, Gog, Dima, Lare, Itang, Godere ($\geq 20\%$ land designated).
Low-intensity districts: Jikawo, Makoy, Jor, Mengeshi ($< 20\%$ land designated).
Top 10 crops ranked by mean area share within each group. Source: Agricultural Sample Survey (AgSS), 2004–2022.

Fig. A.9. District level land shares of major crops (AgSS).

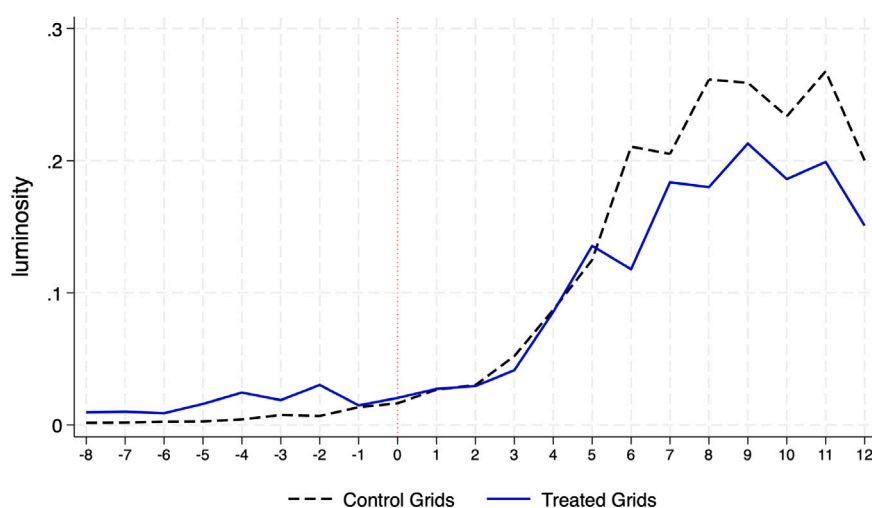


Fig. A.10. Trends in night light intensity (luminosity).

Table B.1

Summary statistics: Mean values at grid-year level for entire Gambella.

	(1) Treatment	(2) Control	(3) Total
Percent forest loss (GFC)	0.042 (0.167)	0.047 (0.177)	0.045 (0.173)
Percent tree cover (VCF)	0.236 (0.162)	0.279 (0.198)	0.263 (0.187)
NDVI (LandSat)	0.623 (0.095)	0.634 (0.101)	0.627 (0.097)
NDVI (MODIS)	0.691 (0.045)	0.699 (0.056)	0.694 (0.049)
Share of crop land (MODIS)	0.031 (0.139)	0.007 (0.055)	0.016 (0.096)
Share of forestland (MODIS)	0.199 (0.377)	0.242 (0.417)	0.226 (0.404)
Share of urbanland (MODIS)	0.000 (0.007)	0.000 (0.008)	0.000 (0.008)
Share of savannaland (MODIS)	0.769 (0.386)	0.751 (0.417)	0.758 (0.406)
Share of waterland (MODIS)	0.000 (0.005)	0.000 (0.017)	0.000 (0.014)
Share of barrenland (MODIS)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)
Percent tree cover 2000 (GFC)	35.256 (19.892)	34.983 (23.096)	35.083 (21.982)
Precipitation (CHIRPS)	1.376 (0.384)	1.397 (0.460)	1.389 (0.434)
Temperature (MODIS)	27.188 (2.384)	27.580 (2.624)	27.437 (2.546)
Population density (WorldPop)	12.820 (83.875)	9.996 (70.499)	11.026 (75.663)
Night time light (DMSP-VIIRS)	0.073 (0.340)	0.084 (0.446)	0.080 (0.411)
Baseline percent forest loss (GFC)	0.056 (0.196)	0.053 (0.192)	0.054 (0.194)
Baseline percent tree cover (VCF)	0.286 (0.153)	0.313 (0.181)	0.303 (0.172)
Baseline NDVI (Landsat)	0.581 (0.064)	0.618 (0.083)	0.601 (0.077)
Baseline NDVI (MODIS)	0.714	0.727	0.720

(continued on next page)

Table B.1 (continued).

	(1) Treatment	(2) Control	(3) Total
Baseline forest land share	0.035 (0.205) (0.374)	0.044 (0.232) (0.410)	0.040 (0.222) (0.397)
Baseline crop land share	0.048 (0.165)	0.023 (0.103)	0.032 (0.129)
Baseline savannaland share	0.746 (0.384)	0.744 (0.410)	0.745 (0.401)
Baseline urbanland share	0.000 (0.007)	0.000 (0.008)	0.000 (0.008)
Baseline waterland share	0.000 (0.009)	0.001 (0.023)	0.001 (0.019)
Baseline barrenland share	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)
Observations	214,301	373,468	587,769

Notes: The table reports summary of outcome and selected other variables by the treatment group. Standard deviations in parentheses. Acronyms in bracket (e.g., GFC) refers to the satellite data product (Hansen [2013] Global Forest Change) used to construct the variable. Baseline moments are generated for 2000/2001.

Table B.2

Summary statistics: Mean values at grid-year level for LSLAs Kebele.

	(1) Treatment	(2) Control	(3) Total
Percent forest loss (GFC)	0.042 (0.167)	0.046 (0.178)	0.044 (0.172)
Percent tree cover (VCF)	0.236 (0.162)	0.242 (0.168)	0.239 (0.165)
NDVI (LandSat)	0.623 (0.095)	0.635 (0.110)	0.624 (0.097)
NDVI (MODIS)	0.691 (0.045)	0.677 (0.060)	0.690 (0.047)
Share of crop land (MODIS)	0.031 (0.139)	0.004 (0.042)	0.018 (0.104)
Share of forestland (MODIS)	0.199 (0.377)	0.185 (0.372)	0.192 (0.374)
Share of urbanland (MODIS)	0.000	0.000	0.000

(continued on next page)

Table B.2 (continued).

	(1)	(2)	(3)
	Treatment	Control	Total
	(0.007)	(0.000)	(0.005)
Share of savannaland (MODIS)	0.769 (0.386)	0.811 (0.373)	0.790 (0.380)
Share of waterland (MODIS)	0.000 (0.005)	0.001 (0.019)	0.000 (0.014)
Share of barrenland (MODIS)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)
Percent tree cover 2000 (GFC)	35.256 (19.892)	34.718 (20.371)	34.992 (20.130)
Precipitation (CHIRPS)	1.376 (0.384)	1.486 (0.394)	1.430 (0.393)
Temperature (MODIS)	27.188 (2.384)	27.803 (2.102)	27.490 (2.271)
Population density (WorldPop)	12.820 (83.875)	5.209 (14.038)	9.085 (60.773)
Night time light (DMSP-VIIRS)	0.073 (0.340)	0.096 (0.524)	0.084 (0.440)
Baseline percent forest loss (GFC)	0.056 (0.196)	0.067 (0.215)	0.061 (0.205)
Baseline percent tree cover (VCF)	0.286 (0.153)	0.292 (0.150)	0.289 (0.152)
Baseline NDVI (Landsat)	0.581 (0.064)	0.606 (0.096)	0.587 (0.074)
Baseline NDVI (MODIS)	0.714 (0.035)	0.732 (0.037)	0.718 (0.036)
Baseline forest land share	0.205 (0.374)	0.166 (0.353)	0.186 (0.365)
Baseline crop land share	0.048 (0.165)	0.012 (0.074)	0.030 (0.130)
Baseline savannaland share	0.746 (0.384)	0.821 (0.356)	0.783 (0.372)
Baseline urbanland share	0.000 (0.007)	0.000 (0.000)	0.000 (0.005)
Baseline waterland share	0.000 (0.009)	0.001 (0.026)	0.001 (0.019)
Baseline barrenland share	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)
Observations	214,301	206,568	420,869

Notes: The table reports summary of outcome and selected other variables by the treatment group. Standard deviations in parentheses. Acronyms in bracket (e.g., GFC) refers to the satellite data product (Hansen [2013] Global Forest Change) used to construct the variable. Baseline moments are generated for 2000/2001.

Table B.3

TWFE and DCDH dynamic estimates, parallel trend and anticipation tests: NDVI-MODIS.

	Entire Gambella		LSLAs Kebele		No Karaturi	
	(1)	(2)	(3)	(4)	(5)	(6)
	TWFE	DCDH	TWFE	DCDH	TWFE	DCDH
−9	0.008 (0.006)	0.004* (0.002)	0.008 (0.006)	0.004* (0.002)	0.008 (0.006)	0.004* (0.002)
−8	0.009 (0.008)	0.002** (0.001)	0.009 (0.008)	0.002** (0.001)	0.009 (0.008)	0.002** (0.001)
−7	0.010 (0.006)	0.005 (0.004)	0.010 (0.006)	0.005 (0.004)	0.010 (0.006)	0.005 (0.004)
−6	0.012 (0.009)	0.008 (0.005)	0.012 (0.009)	0.008 (0.005)	0.012 (0.009)	0.008 (0.005)
−5	0.003 (0.006)	0.003 (0.003)	0.003 (0.006)	0.003 (0.003)	0.003 (0.006)	0.003 (0.003)
−4	0.019*** (0.007)	0.006 (0.009)	0.019*** (0.007)	0.006 (0.009)	0.019*** (0.007)	0.006 (0.009)
−3	−0.001 (0.008)	−0.001 (0.002)	−0.001 (0.008)	−0.001 (0.002)	−0.001 (0.008)	−0.001 (0.002)
−2	0.008 (0.010)	0.014* (0.008)	0.008 (0.010)	0.014* (0.008)	0.008 (0.010)	0.014* (0.008)
−1 (baseline)	0.000 [ref.]	0.000 [ref.]	0.000 [ref.]	0.000 [ref.]	0.000 [ref.]	0.000 [ref.]
0	0.011 (0.011)	0.006 (0.011)	0.010 (0.011)	0.006 (0.011)	0.011 (0.011)	0.006 (0.011)
+1	0.017* (0.010)	0.011*** (0.003)	0.017* (0.010)	0.011*** (0.003)	0.017* (0.010)	0.011*** (0.003)
+2	0.004 (0.011)	0.012*** (0.004)	0.004 (0.011)	0.012*** (0.004)	0.004 (0.011)	0.012*** (0.004)
+3	0.018 (0.011)	0.002 (0.002)	0.018 (0.011)	0.002 (0.002)	0.018 (0.011)	0.002 (0.002)
+4	0.023** (0.011)	0.004* (0.002)	0.023** (0.011)	0.004* (0.002)	0.023** (0.011)	0.004* (0.002)
+5	0.026*** (0.009)	0.007 (0.005)	0.026*** (0.009)	0.007 (0.005)	0.026*** (0.009)	0.007 (0.005)
+6	0.004 (0.009)	0.008 (0.007)	0.004 (0.009)	0.008 (0.007)	0.004 (0.009)	0.008 (0.007)
+7	−0.002 (0.012)	0.006 (0.005)	−0.002 (0.012)	0.006 (0.005)	−0.002 (0.012)	0.006 (0.005)
+8	0.020** (0.010)	0.006 (0.006)	0.020** (0.010)	0.006 (0.006)	0.020** (0.010)	0.006 (0.006)
+9	0.000 (0.013)	0.008 (0.007)	0.000 (0.013)	0.008 (0.007)	0.000 (0.013)	0.008 (0.007)
+10	0.031** (0.014)	0.005 (0.005)	0.031** (0.014)	0.005 (0.005)	0.031** (0.014)	0.005 (0.005)
+11	0.038** (0.017)		0.038** (0.017)		0.038** (0.017)	
Overall ATT		0.036 (0.028)		0.036 (0.028)		0.036 (0.028)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Grid FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Kebele × Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	17,105	17,105	13,728	13,728	17,086	17,086

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parentheses are clustered by spatial grid. Coefficients are event-time effects relative to the year immediately preceding treatment (event time −1), normalized to zero. All specifications control for precipitation, temperature, and population density, and include grid, year, and kebele × year fixed effects. “Overall ATT” is the average treatment effect on the treated across post-treatment periods.

Table B.4

TWFE and DCDH dynamic estimates parallel trend and anticipation tests: NDVI - LANDSAT.

	Entire Gambella		LSLAs Kebele		No Karaturi	
	(1)	(2)	(3)	(4)	(5)	(6)
	TWFE	DCDH	TWFE	DCDH	TWFE	DCDH
−9	−0.002 (0.021)	0.023 (0.022)	−0.003 (0.021)	0.023 (0.022)	−0.004 (0.021)	0.023 (0.022)
−8	0.002 (0.016)	−0.008 (0.007)	0.002 (0.016)	−0.008 (0.007)	−0.001 (0.016)	−0.008 (0.007)
−7	0.032 (0.020)	0.027 (0.027)	0.032 (0.020)	0.027 (0.027)	0.031 (0.020)	0.027 (0.027)
−6	0.008 (0.023)	0.048 (0.044)	0.008 (0.023)	0.048 (0.044)	0.006 (0.023)	0.048 (0.044)
−5	−0.020 (0.019)	0.001 (0.006)	−0.020 (0.018)	0.001 (0.006)	−0.022 (0.019)	0.001 (0.006)
−4	0.018 (0.019)	−0.002 (0.012)	0.017 (0.019)	−0.002 (0.012)	0.020 (0.019)	−0.002 (0.012)
−3	0.001 (0.014)	−0.009 (0.009)	0.000 (0.014)	−0.009 (0.009)	−0.005 (0.014)	−0.008 (0.009)
−2	−0.019* (0.010)	−0.009 (0.018)	−0.019* (0.010)	−0.009 (0.018)	−0.022** (0.011)	−0.009 (0.018)
−1 (baseline)	0.000 [ref.]	0.000 [ref.]	0.000 [ref.]	0.000 [ref.]	0.000 [ref.]	0.000 [ref.]
0	0.008 (0.014)	−0.006 (0.014)	0.008 (0.014)	−0.006 (0.014)	0.005 (0.015)	−0.011 (0.014)
+1	−0.002 (0.015)	−0.003 (0.008)	−0.002 (0.015)	−0.003 (0.008)	−0.004 (0.015)	−0.003 (0.008)
+2	−0.039*** (0.014)	0.005 (0.006)	−0.039*** (0.014)	0.005 (0.006)	−0.040*** (0.015)	0.005 (0.006)
+3	−0.029** (0.014)	−0.001 (0.004)	−0.029** (0.014)	−0.001 (0.004)	−0.031** (0.014)	−0.001 (0.004)
+4	0.011 (0.014)	−0.002 (0.005)	0.011 (0.014)	−0.002 (0.005)	0.010 (0.015)	−0.002 (0.005)
+5	−0.012 (0.015)	−0.002 (0.002)	−0.012 (0.015)	−0.002 (0.002)	−0.012 (0.016)	−0.002 (0.002)
+6	−0.019 (0.017)	−0.012*** (0.004)	−0.019 (0.017)	−0.012*** (0.004)	−0.022 (0.017)	−0.012*** (0.004)
+7	−0.023 (0.019)	−0.005 (0.006)	−0.023 (0.019)	−0.005 (0.006)	−0.027 (0.019)	−0.005 (0.006)
+8	−0.004 (0.022)	0.007 (0.007)	−0.004 (0.022)	0.007 (0.007)	−0.003 (0.023)	0.007 (0.007)
+9	−0.034 (0.022)	−0.017* (0.009)	−0.034 (0.022)	−0.017* (0.009)	−0.036 (0.022)	−0.017* (0.009)
+10	−0.017 (0.021)	−0.006 (0.006)	−0.017 (0.021)	−0.006 (0.006)	−0.021 (0.021)	−0.006 (0.007)
+11	−0.027 (0.025)		−0.027 (0.024)		−0.028 (0.025)	
Overall ATT		−0.016 (0.018)		−0.016 (0.018)		−0.017 (0.018)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Grid FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Kebele × Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	27,532	27,532	20,933	20,933	27,401	27,401

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parentheses are clustered by spatial grid. Coefficients are event-time effects relative to the year immediately preceding treatment (event time −1), normalized to zero. All specifications control for precipitation, temperature, and population density, and include grid, year, and kebele × year fixed effects. “Overall ATT” is the average treatment effect on the treated across post-treatment periods.

Table B.5

TWFE and DCDH dynamic estimates, parallel trend and anticipation tests: Forest Loss - GFC.

	Entire Gambella		LSLAs Kebele		No Karaturi	
	(1)	(2)	(3)	(4)	(5)	(6)
	TWFE	DCDH	TWFE	DCDH	TWFE	DCDH
−9	0.002 (0.010)	−0.001 (0.003)	0.002 (0.010)	−0.001 (0.003)	0.000 (0.010)	−0.001 (0.003)
−8	0.009 (0.013)	0.004 (0.003)	0.009 (0.013)	0.004 (0.003)	0.007 (0.013)	0.004 (0.003)
−7	0.010 (0.011)	0.004 (0.003)	0.010 (0.011)	0.004 (0.003)	0.009 (0.011)	0.004 (0.003)
−6	0.008 (0.010)	0.006 (0.004)	0.008 (0.010)	0.006 (0.004)	0.007 (0.010)	0.006 (0.004)
−5	−0.002 (0.012)	0.004 (0.005)	−0.002 (0.012)	0.004 (0.005)	−0.003 (0.012)	0.004 (0.005)
−4	0.006 (0.011)	0.005 (0.005)	0.006 (0.011)	0.005 (0.005)	0.005 (0.011)	0.005 (0.005)
−3	−0.017* (0.010)	−0.003 (0.008)	−0.017* (0.010)	−0.003 (0.008)	−0.019* (0.010)	−0.003 (0.008)
−2	0.012 (0.011)	0.035** (0.016)	0.012 (0.011)	0.035** (0.016)	0.011 (0.012)	0.035** (0.016)
−1 (baseline)	0.000 [ref.]	0.000 [ref.]	0.000 [ref.]	0.000 [ref.]	0.000 [ref.]	0.000 [ref.]
0	−0.011 (0.013)	0.017 (0.016)	−0.011 (0.013)	0.017 (0.016)	−0.014 (0.013)	0.016 (0.016)
+1	0.007 (0.012)	0.011 (0.008)	0.008 (0.012)	0.011 (0.008)	0.006 (0.012)	0.011 (0.008)
+2	0.004 (0.012)	0.005 (0.006)	0.004 (0.012)	0.005 (0.006)	0.003 (0.012)	0.005 (0.006)
+3	0.029** (0.015)	0.014*** (0.005)	0.029** (0.015)	0.014*** (0.005)	0.030** (0.014)	0.014*** (0.005)
+4	0.001 (0.011)	0.001 (0.003)	0.002 (0.011)	0.001 (0.003)	−0.001 (0.011)	0.001 (0.003)
+5	0.008 (0.011)	0.003 (0.003)	0.008 (0.011)	0.003 (0.003)	0.006 (0.011)	0.003 (0.003)
+6	0.011 (0.010)	0.002 (0.002)	0.012 (0.010)	0.002 (0.002)	0.010 (0.010)	0.002 (0.002)
+7	0.012 (0.010)	−0.002 (0.002)	0.012 (0.010)	−0.002 (0.002)	0.011 (0.010)	−0.002 (0.002)
+8	−0.010 (0.011)	−0.002 (0.001)	−0.010 (0.011)	−0.002 (0.001)	−0.012 (0.011)	−0.002 (0.001)
+9	−0.000 (0.009)	−0.002 (0.001)	−0.000 (0.009)	−0.002 (0.001)	−0.001 (0.009)	−0.002 (0.001)
+10	0.011 (0.010)	−0.003 (0.002)	0.011 (0.010)	−0.003 (0.002)	0.010 (0.010)	−0.003 (0.002)
+11	0.002 (0.012)		0.002 (0.012)		0.001 (0.012)	
Overall ATT		0.010 (0.013)		0.010 (0.013)		0.010 (0.013)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Grid FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Kebele × Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	270,660	270,660	199,240	199,240	269,820	269,820

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parentheses are clustered by spatial grid. Coefficients are event-time effects relative to the year immediately preceding treatment (event time −1), normalized to zero. All specifications control for precipitation, temperature, and population density, and include grid, year, and kebele × year fixed effects. “Overall ATT” is the average treatment effect on the treated across post-treatment periods.

Table B.6

TWFE and DCDH Dynamic Estimates, Parallel Trend and Anticipation Tests:
% Forest Cover - VCF.

	Entire Gambella		LSLAs Kebele		No Karaturi	
	(1)	(2)	(3)	(4)	(5)	(6)
	TWFE	DCDH	TWFE	DCDH	TWFE	DCDH
−9	−0.175 (0.179)	−0.038 (0.026)	−0.169 (0.179)	−0.038 (0.026)	−0.204 (0.180)	−0.038 (0.026)
−8	0.079 (0.152)	−0.006 (0.023)	0.076 (0.152)	−0.006 (0.023)	0.081 (0.153)	−0.006 (0.023)
−7	0.156 (0.150)	0.002 (0.025)	0.155 (0.150)	0.002 (0.025)	0.135 (0.152)	0.002 (0.025)
−6	0.163 (0.147)	0.035 (0.030)	0.153 (0.147)	0.035 (0.030)	0.135 (0.148)	0.035 (0.030)
−5	0.235* (0.143)	0.055 (0.038)	0.230 (0.143)	0.055 (0.038)	0.224 (0.144)	0.055 (0.038)
−4	0.266* (0.153)	0.086 (0.057)	0.258* (0.153)	0.086 (0.057)	0.247 (0.155)	0.086 (0.057)
−3	−0.016 (0.146)	−0.032 (0.075)	−0.020 (0.146)	−0.032 (0.075)	−0.048 (0.147)	−0.032 (0.075)
−2	−0.166* (0.092)	−0.175* (0.092)	−0.177* (0.092)	−0.175* (0.092)	−0.167* (0.093)	−0.167* (0.092)
−1 (baseline)	0.000 [ref.]	0.000 [ref.]	0.000 [ref.]	0.000 [ref.]	0.000 [ref.]	0.000 [ref.]
0	0.010 (0.096)	−0.032 (0.097)	0.005 (0.096)	−0.032 (0.097)	0.001 (0.097)	−0.032 (0.097)
+1	−0.285** (0.142)	−0.158** (0.074)	−0.286** (0.142)	−0.158** (0.074)	−0.284** (0.144)	−0.159** (0.074)
+2	−0.625*** (0.152)	−0.253*** (0.052)	−0.611*** (0.152)	−0.253*** (0.052)	−0.622*** (0.154)	−0.253*** (0.052)
+3	−0.681*** (0.158)	−0.228*** (0.039)	−0.672*** (0.158)	−0.228*** (0.039)	−0.684*** (0.160)	−0.228*** (0.039)
+4	−0.258 (0.163)	−0.095*** (0.034)	−0.242 (0.162)	−0.095*** (0.034)	−0.280* (0.164)	−0.095*** (0.034)
+5	−0.126 (0.165)	−0.050* (0.029)	−0.119 (0.165)	−0.050* (0.029)	−0.160 (0.166)	−0.050* (0.029)
+6	−0.321* (0.165)	−0.031 (0.026)	−0.301* (0.165)	−0.031 (0.026)	−0.321* (0.167)	−0.031 (0.026)
+7	−0.290* (0.161)	−0.024 (0.021)	−0.280* (0.161)	−0.024 (0.021)	−0.312* (0.164)	−0.024 (0.021)
+8	−0.013 (0.167)	−0.035* (0.019)	−0.006 (0.167)	−0.035* (0.019)	−0.005 (0.170)	−0.035* (0.019)
+9	−0.255 (0.205)	−0.035 (0.023)	−0.252 (0.206)	−0.035 (0.023)	−0.235 (0.209)	−0.035 (0.023)
+10	−0.185 (0.233)	−0.021 (0.025)	−0.165 (0.234)	−0.021 (0.025)	−0.257 (0.237)	−0.021 (0.025)
+11	0.721** (0.333)		0.758** (0.333)		0.643* (0.348)	
Overall ATT		−0.385*** (0.119)		−0.385*** (0.119)		−0.386*** (0.119)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Grid FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Kebele × Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	608,920	608,920	442,580	442,580	606,100	606,100

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parentheses are clustered by spatial grid. Coefficients are event-time effects relative to the year immediately preceding treatment (event time −1), normalized to zero. All specifications control for precipitation, temperature, and population density, and include grid, year, and kebele × year fixed effects. “Overall ATT” is the average treatment effect on the treated across post-treatment periods.

Table B.7

TWFE and DCDH dynamic estimates, parallel trends and anticipation tests:
Crop land share - MODIS.

	Entire Gambella		LSLAs Kebele		No Karaturi	
	(1)	(2)	(3)	(4)	(5)	(6)
	TWFE	DCDH	TWFE	DCDH	TWFE	DCDH
−9	0.004 (0.003)	0.000 (0.000)	0.004 (0.003)	0.000 (0.000)	0.004 (0.003)	0.000 (0.000)
−8	0.008*** (0.003)	0.002*** (0.001)	0.008*** (0.003)	0.002*** (0.001)	0.008*** (0.003)	0.002*** (0.001)
−7	0.004* (0.002)	0.001** (0.001)	0.004* (0.002)	0.001** (0.001)	0.004* (0.002)	0.001** (0.001)
−6	0.001 (0.002)	0.000 (0.000)	0.001 (0.002)	0.000 (0.000)	0.001 (0.002)	0.000 (0.000)
−5	0.004*** (0.002)	0.001 (0.000)	0.004*** (0.002)	0.001 (0.000)	0.005*** (0.002)	0.001 (0.000)
−4	0.000 (0.002)	0.000 (0.001)	0.000 (0.002)	0.000 (0.001)	0.000 (0.002)	0.000 (0.001)
−3	−0.001 (0.001)	−0.002** (0.001)	−0.001 (0.001)	−0.002** (0.001)	−0.001 (0.001)	−0.002** (0.001)
−2	−0.001 (0.001)	−0.004*** (0.001)	−0.001 (0.001)	−0.004*** (0.001)	−0.001 (0.001)	−0.003** (0.001)
−1 (baseline)	0.000 [ref.]	0.000 [ref.]	0.000 [ref.]	0.000 [ref.]	0.000 [ref.]	0.000 [ref.]
0	−0.001 (0.001)	−0.000 (0.001)	−0.001 (0.001)	−0.000 (0.001)	−0.001 (0.001)	−0.000 (0.001)
+1	−0.002 (0.002)	0.001 (0.001)	−0.002 (0.002)	0.001 (0.001)	−0.002 (0.002)	0.001 (0.001)
+2	−0.005** (0.002)	0.001 (0.001)	−0.005** (0.002)	0.001 (0.001)	−0.005** (0.002)	0.001 (0.001)
+3	−0.001 (0.002)	0.000 (0.001)	−0.001 (0.002)	0.000 (0.001)	−0.001 (0.002)	0.000 (0.001)
+4	−0.001 (0.002)	0.000 (0.000)	−0.001 (0.002)	0.000 (0.000)	−0.001 (0.002)	0.000 (0.000)
+5	0.001 (0.002)	0.001** (0.000)	0.002 (0.002)	0.001** (0.000)	0.002 (0.002)	0.001** (0.000)
+6	0.004** (0.002)	0.001** (0.000)	0.005*** (0.002)	0.001** (0.000)	0.004** (0.002)	0.001** (0.000)
+7	0.003 (0.002)	0.000 (0.000)	0.003* (0.002)	0.000 (0.000)	0.003 (0.002)	0.000 (0.000)
+8	0.006*** (0.002)	0.000 (0.000)	0.006*** (0.002)	0.000 (0.000)	0.006*** (0.002)	0.000 (0.000)
+9	0.004** (0.002)	0.000 (0.000)	0.004** (0.002)	0.000 (0.000)	0.004** (0.002)	0.000 (0.000)
+10	−0.004* (0.002)	−0.000 (0.000)	−0.004* (0.002)	−0.000 (0.000)	−0.004* (0.002)	−0.000 (0.000)
+11	−0.000 (0.005)		0.000 (0.005)		0.000 (0.005)	
Overall ATT		0.002* (0.001)		0.002* (0.001)		0.002* (0.001)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Grid FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Kebele × Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	609,880	609,880	443,000	443,000	607,060	607,060

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parentheses are clustered by spatial grid. Coefficients are event-time effects relative to the year immediately preceding treatment (event time −1), normalized to zero. All specifications control for precipitation, temperature, and population density, and include grid, year, and kebele × year fixed effects. “Overall ATT” is the average treatment effect on the treated across post-treatment periods.

Table B.8

TWFE and DCDH dynamic estimates, parallel trend and anticipation tests:
Forest land share - MODIS.

	Entire Gambella		LSLAs Kebele		No Karaturi	
	(1)	(2)	(3)	(4)	(5)	(6)
	TWFE	DCDH	TWFE	DCDH	TWFE	DCDH
−9	0.071*** (0.022)	0.006** (0.003)	0.071*** (0.022)	0.006** (0.003)	0.071*** (0.022)	0.006** (0.003)
−8	0.038*** (0.015)	0.002 (0.002)	0.038** (0.015)	0.002 (0.002)	0.038*** (0.015)	0.002 (0.002)
−7	0.041*** (0.012)	0.007*** (0.002)	0.040*** (0.012)	0.007*** (0.002)	0.040*** (0.012)	0.007*** (0.002)
−6	0.026** (0.011)	0.002 (0.002)	0.027** (0.011)	0.002 (0.002)	0.027** (0.011)	0.002 (0.002)
−5	0.020* (0.011)	−0.001 (0.003)	0.019* (0.011)	−0.001 (0.003)	0.021* (0.011)	−0.001 (0.003)
−4	0.021** (0.011)	−0.000 (0.003)	0.021* (0.011)	−0.000 (0.003)	0.021** (0.011)	−0.000 (0.003)
−3	0.018** (0.008)	0.006* (0.003)	0.017** (0.008)	0.006* (0.003)	0.018** (0.008)	0.006* (0.003)
−2	0.028*** (0.006)	0.026*** (0.006)	0.029*** (0.006)	0.026*** (0.006)	0.027*** (0.006)	0.026*** (0.006)
−1 (baseline)	0.000 [ref.]	0.000 [ref.]	0.000 [ref.]	0.000 [ref.]	0.000 [ref.]	0.000 [ref.]
0	0.001 (0.007)	−0.016** (0.006)	0.001 (0.007)	−0.016** (0.006)	−0.001 (0.007)	−0.016** (0.006)
+1	−0.026*** (0.008)	−0.016*** (0.004)	−0.026*** (0.008)	−0.016*** (0.004)	−0.028*** (0.008)	−0.016*** (0.004)
+2	−0.017* (0.010)	−0.011*** (0.003)	−0.019* (0.010)	−0.011*** (0.003)	−0.019* (0.010)	−0.011*** (0.003)
+3	−0.030** (0.012)	−0.008*** (0.003)	−0.030** (0.012)	−0.008*** (0.003)	−0.034*** (0.012)	−0.008*** (0.003)
+4	−0.028** (0.012)	−0.008*** (0.002)	−0.029** (0.012)	−0.008*** (0.002)	−0.031*** (0.012)	−0.008*** (0.002)
+5	−0.006 (0.013)	−0.003* (0.002)	−0.006 (0.013)	−0.003* (0.002)	−0.008 (0.013)	−0.003* (0.002)
+6	−0.012 (0.012)	−0.004** (0.002)	−0.013 (0.012)	−0.004** (0.002)	−0.013 (0.012)	−0.004** (0.002)
+7	0.017 (0.013)	−0.000 (0.001)	0.018 (0.013)	−0.000 (0.001)	0.017 (0.013)	−0.000 (0.001)
+8	0.013 (0.013)	−0.001 (0.001)	0.014 (0.013)	−0.001 (0.001)	0.011 (0.014)	−0.001 (0.001)
+9	0.033** (0.014)	0.002 (0.001)	0.033** (0.014)	0.002 (0.001)	0.033** (0.014)	0.002 (0.001)
+10	0.047** (0.020)	0.007*** (0.002)	0.046** (0.020)	0.007*** (0.002)	0.046** (0.021)	0.007*** (0.002)
+11	0.053** (0.024)	0.051** (0.024)	0.051** (0.024)	0.061** (0.025)	0.061** (0.025)	
Overall ATT		−0.018** (0.008)		−0.018** (0.008)		−0.018** (0.008)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Grid FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Kebele × Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	160,703	160,703	107,109	107,109	160,328	160,328

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parentheses are clustered by spatial grid. Coefficients are event-time effects relative to the year immediately preceding treatment (event time −1), normalized to zero. All specifications control for precipitation, temperature, and population density, and include grid, year, and kebele × year fixed effects. “Overall ATT” is the average treatment effect on the treated across post-treatment periods.

Table B.9

TWFE and DCDH dynamic estimates and parallel trend and anticipation tests:
Luminosity.

	Entire Gambella		LSLAs Kebele		No Karaturi	
	(1)	(2)	(3)	(4)	(5)	(6)
	TWFE	DCDH	TWFE	DCDH	TWFE	DCDH
−9	0.009*** (0.002)	0.001*** (0.000)	0.009*** (0.002)	0.001*** (0.000)	0.009*** (0.002)	0.001*** (0.000)
−8	0.004** (0.002)	0.001*** (0.000)	0.004** (0.002)	0.001*** (0.000)	0.004** (0.002)	0.001*** (0.000)
−7	0.005*** (0.002)	0.001*** (0.000)	0.005*** (0.002)	0.001*** (0.000)	0.005*** (0.002)	0.001*** (0.000)
−6	0.006** (0.002)	0.002*** (0.001)	0.006** (0.002)	0.002*** (0.001)	0.006** (0.002)	0.002*** (0.001)
−5	0.005*** (0.002)	0.002*** (0.000)	0.004*** (0.002)	0.002*** (0.000)	0.004** (0.002)	0.002*** (0.000)
−4	0.004** (0.002)	0.002*** (0.001)	0.004** (0.002)	0.002*** (0.001)	0.004** (0.002)	0.003*** (0.001)
−3	0.004** (0.002)	0.004*** (0.001)	0.004** (0.002)	0.004*** (0.001)	0.004** (0.002)	0.004*** (0.001)
−2	0.003* (0.002)	0.006*** (0.001)	0.003 (0.002)	0.006*** (0.001)	0.003* (0.002)	0.006*** (0.001)
−1 (baseline)	0.000 [ref.]	0.000 [ref.]	0.000 [ref.]	0.000 [ref.]	0.000 [ref.]	0.000 [ref.]
0	0.001 (0.002)	0.001 (0.002)	0.002 (0.002)	0.001 (0.002)	0.001 (0.002)	0.001 (0.002)
+1	0.001 (0.002)	−0.000 (0.001)	0.001 (0.002)	−0.000 (0.001)	0.000 (0.002)	−0.000 (0.001)
+2	−0.004 (0.003)	−0.004*** (0.001)	−0.003 (0.003)	−0.004*** (0.001)	−0.004 (0.003)	−0.004*** (0.001)
+3	0.008 (0.006)	0.002 (0.002)	0.008 (0.006)	0.002 (0.002)	0.008 (0.006)	0.002 (0.002)
+4	−0.004 (0.004)	−0.002** (0.001)	−0.003 (0.004)	−0.002** (0.001)	−0.007* (0.004)	−0.003** (0.001)
+5	−0.014** (0.007)	−0.003** (0.001)	−0.013** (0.007)	−0.003** (0.001)	−0.013* (0.007)	−0.003** (0.001)
+6	−0.038*** (0.005)	−0.007*** (0.001)	−0.037*** (0.005)	−0.007*** (0.001)	−0.037*** (0.005)	−0.007*** (0.001)
+7	−0.013** (0.005)	−0.003*** (0.001)	−0.013** (0.005)	−0.003*** (0.001)	−0.014*** (0.005)	−0.003*** (0.001)
+8	−0.028*** (0.004)	−0.004*** (0.001)	−0.027*** (0.004)	−0.004*** (0.001)	−0.028*** (0.004)	−0.004*** (0.001)
+9	−0.017*** (0.005)	−0.003*** (0.001)	−0.017*** (0.005)	−0.003*** (0.001)	−0.018*** (0.005)	−0.003*** (0.001)
+10	−0.014*** (0.005)	−0.002*** (0.001)	−0.013** (0.005)	−0.002*** (0.001)	−0.016*** (0.005)	−0.002*** (0.001)
+11	−0.015*** (0.005)	−0.014** (0.005)	−0.014** (0.005)	−0.012** (0.005)	−0.012** (0.005)	
Overall ATT		−0.015*** (0.003)		−0.015*** (0.003)		−0.015*** (0.003)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Grid FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Kebele × Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	609,880	609,880	443,000	443,000	607,060	607,060

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parentheses are clustered by spatial grid. Coefficients are event-time effects relative to the year immediately preceding treatment (event time −1), normalized to zero. All specifications control for precipitation, temperature, and population density, and include grid, year, and kebele × year fixed effects. “Overall ATT” is the average treatment effect on the treated across post-treatment periods.

Table B.10
Joint pre-trends test (*p*-value).

Outcome	Sample	Pre-trend window (−8 to −2, <i>K</i> = 7)	
		<i>F</i> -stat	<i>p</i> -value
NDVI – MODIS	Entire Gambella	0.134	0.996
	LSLAs Kebele	0.134	0.996
	Excluding Karaturi	0.134	0.996
	Entire Gambella	0.656	0.710
NDVI – Landsat	LSLAs Kebele	0.656	0.710
	Excluding Karaturi	0.651	0.714
	Entire Gambella	1.947	0.058*
	LSLAs Kebele	1.947	0.058*
Forest Loss – GFC	Excluding Karaturi	1.953	0.058 [†]
	Entire Gambella	1.360	0.218
	LSLAs Kebele	1.360	0.218
	Excluding Karaturi	1.313	0.240

* *p* < 0.10, ** *p* < 0.05, *** *p* < 0.01. *H*₀: all pre-treatment DCDH coefficients are jointly equal to zero (parallel trends). The test statistic is $F = \frac{1}{K} \sum_{k=1}^K (\hat{\delta}_k / \hat{se}_k)^2$, where *K* = 7 covers event times −8 through −2 and *t* = −1 is the omitted baseline. NDVI-MODIS, NDVI-Landsat, and Forest Cover (VCF) fail to reject *H*₀ at conventional significance levels across all samples, supporting the parallel trends assumption. For Forest Loss (GFC), the joint test is marginally significant at 10%, but visual inspection of the event-study graph confirms pre-treatment trends that are flat and parallel for both the TWFE and DCDH estimators across the full pre-treatment window. The marginal rejection is driven entirely by a single spike at *t* = −2, consistent with pre-announcement land clearance in anticipation of formal treatment registration rather than a systematic violation of the parallel trends assumption.

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