Differential Land Efficiency and the Environmental Consequences of Agricultural Productivity Growth*

Tiago Cavalcanti† Kilian Kamkar‡

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Abstract

Does improving agricultural productivity spare forests or accelerate their demise? We offer a new perspective on this debate by emphasizing the relative agricultural suitability of forest versus available vacant land for conversion. We develop a parsimonious framework in which land differs in agricultural efficiency across alternative expansion margins, showing that productivity gains translate into deforestation only when forests constitute the most cost-effective source of additional effective land. We test this prediction using a quasi-experimental design based on Tanzania's National Agricultural Input Voucher Scheme (NAIVS), which promoted modern seed and fertilizer adoption. Combining high-resolution satellite data on forest loss with spatial data on soil nitrogen to proxy relative suitability, we find that the program increased deforestation only in villages where vacant land was substantially less productive than forest land. Our results highlight the central role of land quality heterogeneity in shaping the environmental consequences of agricultural productivity growth, offer a complementary explanation for land-sparing versus expansionary outcomes, and point to a role for directed agricultural innovation in mitigating deforestation without constraining productivity growth.

Keywords: Agricultural Productivity, Deforestation, Land Use Change, Land Quality, Input Subsidies, Tanzania
JEL Codes: Q15, Q23, Q24, O13, O33

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†University of Cambridge, Sao Paulo School of Economics FGV-SP and CEPR. Email: tvdvc2@cam.ac.uk
‡University of Cambridge. Email: kk745@cam.ac.uk

1 Introduction

Increasing agricultural productivity is a cornerstone of development strategy, especially in sub-Saharan Africa, where higher farm yields are central to poverty reduction and structural transformation (Dercon & Gollin 2014; Gollin et al. 2021). At the same time, the environmental consequences of agricultural productivity growth remain contested. While higher yields can, in principle, reduce the amount of land required per unit of output, they also raise the profitability of farming, potentially strengthening incentives to expand cultivation. Reflecting these competing forces, the empirical literature documents both forest-sparing and forest-depleting effects of agricultural productivity growth, across and within countries. A prominent explanation for this heterogeneity emphasizes factor market constraints (e.g., Abman et al. 2024; Assunçao et al. 2017). When farmers face limited access to credit or labor, productivity gains may be absorbed through intensification on existing plots rather than expansion, thereby reducing pressure on forests.

This paper introduces and empirically validates an alternative, and complementary, mechanism to reconcile the conflicting evidence on the relationship between agricultural productivity and deforestation: *the role of relative land efficiency.* We argue that, even when agricultural expansion is profitable, the deforestation response to a productivity shock depends on the agricultural suitability of forest land targeted for conversion relative to that of alternative, non-forested land available for expansion (hereafter, "vacant" land). Vacant land is a common feature of developing landscapes, encompassing degraded or fallow areas, grasslands, and savannas. Yet standard models typically treat land as homogeneous, thereby abstracting from the discrete choice farmers face between converting forest and non-forest land. Our approach instead recognizes that, much like labor heterogeneity is captured through efficiency units reflecting skills, land varies substantially in its agricultural suitability, due to differences in soil fertility, water availability, and related characteristics.

We formalize this mechanism in a model of land-use choice in a small open economy (like a village) in which farmers own land and can expand agricultural production by converting either forest or vacant areas. A central feature of the model is that land is measured in *efficiency units* rather than physical area, so that the amount of effective agricultural land generated by conversion depends on both intrinsic land quality and conversion costs. In particular, converting forest land may yield more productive agricultural land per hectare than converting vacant land, while also entailing different clearing and preparation costs. This structure captures heterogeneity in land suitability and conversion costs that is typically abstracted from in standard models. The model implies that an increase in agricultural productivity raises the value of effective land and induces expansion, but that this expansion takes the form of deforestation if and only if forest conversion is more cost-effective, per efficiency unit, than conversion of vacant land.

We test this prediction using data from Tanzania's National Agricultural Input Voucher Scheme (NAIVS) between 2008 and 2012. We interpret NAIVS—which subsidized modern seeds and fertilizers for smallholder farmers—as a positive shock to agricultural productivity, corresponding to an increase in productivity in the model. Input subsidy programs of this type were widely implemented across sub-Saharan Africa during the 2000s and 2010s as central development strategies aimed at raising crop yields and ensuring national food security.[1]

In the empirical analysis, we combine high-resolution satellite data on forest loss and land use with nightlights and detailed climatic controls to estimate the environmental effects of the program. Crucially, we exploit spatial data on soil organic nitrogen to construct village-level measures of relative land productivity between forest areas and non-forested land not already under cultivation (hereafter, vacant land). This measure provides an empirical analogue to the model's relative land efficiency parameter, capturing variation in the productivity advantage of forest conversion relative to alternative expansion margins.

NAIVS initially targeted 11 high-potential growing regions and was later expanded nationwide in 2011, generating quasi-experimental variation in exposure to the productivity shock. Because treated regions were selected based on agricultural potential, treated and untreated areas would likely have followed different trajectories absent the policy. We therefore exploit the high spatial resolution of satellite data to implement a difference-in-discontinuities design, comparing villages located just inside treated district boundaries to nearby villages just outside.

Consistent with the model's prediction, we find that NAIVS-induced productivity gains led to increased deforestation only in villages where vacant land was relatively unproductive compared to forest land. In these locations, low nitrogen levels on vacant land imply a high relative efficiency advantage of forest conversion, making deforestation the cost-effective expansion margin. The productivity shock induced by NAIVS thus tipped land expansion toward the forest frontier precisely where the model predicts deforestation to occur.

Beyond providing a complementary explanation for the mixed empirical evidence, our results also have implications for the design of productivity-enhancing policies. In particular, they point to a role for *directed agricultural innovation*, whereby the direction of technological progress responds to economic incentives rather than being neutral across production environments (Acemoglu 2002). If technological change disproportionately raises the productivity of degraded or low-nutrient land—through seed varieties or fertilizer packages tailored to such conditions—it can alter the relative efficiency of alternative expansion margins. In this case, innovation reduces the productivity advantage of forest conversion and thereby weakens deforestation incentives without constraining agricultural growth. More broadly, this perspective echoes insights from the literature on environmental directed technical change, which emphasizes how the direction of innovation shapes the environmental consequences of economic growth (Acemoglu et al. 2012).

We investigate this mechanism in the context of sub-Saharan Africa, where more than half of the workforce is employed in agriculture, predominantly in subsistence-oriented smallholder farming, and where incomes remain close to or below international poverty thresholds. Despite the sector's central role in employment, agricultural value added per worker lags substantially behind that of other sectors and remains less than half of the global average. Crop yields are similarly far below international benchmarks, reflecting the continued use of low-input and low-technology production

[1] Twelve countries in sub-Saharan Africa implemented large-scale input subsidy programs, including the Agricultural Input Support Programme in Malawi (2005), the Fertilizer Support Programme in Zambia (2002), and the Fertilizer Subsidy Programme in Ghana (2008).

methods (Suri & Udry 2022). Approximately 80% of African farmers cultivate plots smaller than one hectare and rely primarily on rainfed agriculture, with limited access to improved seed varieties, chemical fertilizers, and irrigation. As a result, labor productivity in sub-Saharan African agriculture remains low even after accounting for differences in input quantities and quality (Gollin et al. 2014). At the same time, a large body of work highlights the central role of technology adoption and agricultural productivity growth in promoting inclusive growth and structural transformation in the region (Bustos et al. 2016, 2020; Dercon & Gollin 2014; Gollin et al. 2021).

2 Related Literature

A large literature examines how increases in agricultural productivity affect environmental outcomes, particularly deforestation. A central argument in this literature is the *Borlaug Hypothesis*, which posits that productivity gains lead to land-sparing intensification, allowing farmers to increase output while using less land (Borlaug, 2007). He argues that this mechanism prevented more than one billion hectares from being converted to agriculture during the second half of the twentieth century, a view supported by global-level evidence on the Green Revolution (Stevenson et al. 2013). Consistent with this hypothesis, numerous country- and sub-country studies across Asia, Africa, and Latin America link yield improvements from technologies such as improved seeds, irrigation, and fallows to reduced pressure on forests (e.g., Maertens et al. 2006; Pelletier et al. 2020; Shively & Pagiola 2004; Yanggen & Reardon 2001).

More recent causal evidence reinforces this land-sparing view. Szerman et al. (2022) show that rural electrification in Brazil reduced deforestation at a scale comparable to major conservation programs, while Abman et al. (2024) find that a large-scale agricultural extension program in Uganda lowered deforestation by promoting intensification on existing plots without expanding cultivated area. Importantly, both studies emphasize the role of factor market constraints—capital constraints in Brazil and labor constraints in Uganda—which limit farmers' ability to expand cultivation and thereby channel productivity gains toward intensification rather than land expansion.

However, a substantial body of research challenges this land-sparing view, providing evidence that productivity growth can lead to greater deforestation. This perspective argues that by making agriculture more profitable, efficiency gains create incentives for agricultural expansion (Rudel et al. 2009; Byerlee et al. 2014). Cross-country analyses often find no evidence that agricultural intensification is associated with decreases in total cropland area (Ewers et al. 2009). This expansionary outcome is documented in various contexts: for India, Foster & Rosenzweig (2003) show an adverse effect of agricultural productivity on local forest area, while Marchand (2012) find that for most farms in the Brazilian Amazon, higher efficiency implies more deforestation. Using a randomized trial in the Congo Basin, Bernard et al. (2023) show that modern seeds led farmers to clear more nutrient-rich primary forest. Similarly, Carreira et al. (2024) find that the introduction of genetically engineered soy seeds in Brazil was strongly associated with faster deforestation.

This conflicting evidence indicates that the relationship between agricultural productivity growth and deforestation is not uniform. While existing explanations often attribute these divergent outcomes to differences in factor market constraints, we contribute by identifying an additional and overlooked mechanism: the role of *relative land efficiency*. Even when agricultural expansion is profitable, deforestation is not an automatic outcome; it depends on where expansion occurs. In many developing landscapes, farmers can expand either into forests or into non-forested "vacant" land, and these alternatives differ markedly in agricultural suitability and conversion costs. When land quality is heterogeneous, the environmental response to a productivity shock is therefore governed by the relative cost per efficiency unit of converting forest versus vacant land. Our focus on differential land quality is motivated by evidence such as Bernard et al. (2023), who show that modern seed adoption can induce farmers to preferentially clear nutrient-rich primary forests, underscoring that not all land is equivalent at the expansion frontier. By providing causal evidence on how the relative quality of available land mediates the environmental effects of a widely used development policy, our paper offers a unified and granular explanation for the divergent land-sparing and expansionary outcomes documented in the literature.

Finally, our work connects to the broader literature on the drivers of deforestation. Deforestation is a complex outcome influenced by a range of factors, among others, including population growth (Cropper & Griffiths 1994), infrastructure (Araujo, Assunção & Bragança 2025, Asher et al. 2020, Chomitz & Gray 2017), land tenure (Deacon 1999), mining (Girard et al. 2022), epidemics (Sonno & Zufacchi 2022), credit constraints (Assunção et al. 2020), and administrative or policy changes (Costa et al. 2025, Hsiao 2021, Souza-Rodrigues 2019, Burgess et al. 2012). By providing causal evidence on the environmental trade-offs of a widely used development policy, we contribute to this field and offer insights for designing more sustainable agricultural interventions.

3 The Model

We motivate our empirical analysis with a model where agents choose their occupation and land-use. The economy consists of a continuum of agents of mass one, each endowed with a farming talent or idiosyncratic productivity z drawn from a Pareto distribution, $G(z) = 1 - z^{-\zeta}$. Agents can work in a non-agricultural sector with productivity A_n, which provides the wage $w = A_n$. Alternatively, an agent can leverage their talent z to become a farmer. The agricultural sector produces goods sold at a constant exogenous world price p_a.

Efficient agricultural land, $\tilde{l}$, which is the input used in production, is generated through the conversion of physical forest or vacant land. We assume that the efficiency and cost of this conversion process may differ by land type. Specifically, converting one physical unit of forest, denoted by d, yields ϕ units of efficient land $\tilde{l}$. Converting one physical unit of vacant land, denoted by u, yields one unit of efficient land $\tilde{l}$. The parameter $\phi > 0$ thus represents the *relative efficiency* of forest conversion compared to vacant land conversion. When $\phi > 1$, forest land is inherently more suitable, yielding more effective agricultural land per physical unit converted. Based on our empirical approach, we associate $\phi > 1$ with conditions where forest soils (e.g., higher nitrogen) are superior to vacant land soils. A farmer's decision is how to expand their stock of quality-adjusted agricultural land, $\tilde{l}$, by converting their endowment of forest and vacant land. We assume that land is owned by the farmer and cannot be sold or rented out. The farmer's objective is to maximize profits:

$$\pi(z) = \max_{d,u\geq 0} \left\{ p_a A_a z^{1-\gamma} \tilde{l}^{\gamma} - \kappa_v u - \kappa_f d - \frac{\theta_e}{2} \frac{d^2}{f} \right\}, \tag{1}$$

subject to the total effective land generated:

$$\tilde{l} = \phi d + u, \tag{2}$$

and the constraints $u \leq v$ and $d \leq f$, where v is the available vacant land and f is the forest cover. The parameter $\gamma \in (0, 1)$ governs the curvature of the production function, and A_a denotes agricultural productivity.

The cost of converting each land type $i \in \{f, v\}$ includes a linear component κ_i, representing direct input costs.[2] Deforestation also generates an additional enforcement cost, represented by $\frac{\theta_e}{2} \frac{d^2}{f}$, where $\theta_e > 0$.

The convex enforcement cost $\frac{\theta_e}{2} \frac{d^2}{f}$ with $\theta_e > 0$ captures the idea that the marginal cost of deforestation increases with the scale of clearing. As farmers deforest more land, detection becomes more likely, enforcement actions intensify, and the physical effort required to clear additional forest rises. The term's dependence on f reflects that deforestation is more costly when forest cover is scarce, as regulators and local communities react more strongly to further losses. This term provides therefore a reduced-form way to capture rising legal, environmental, and logistical costs as deforestation expands.

3.1 Land Conversion and Efficiency

Let's assume that vacant land and forest are abundant such that $u < v$ and $d < f$. The farmer's problem can be solved by comparing the marginal costs of land expansion. The decision to convert land is governed by the cost of acquiring an additional unit of effective land, $\tilde{l}$.

The farmer compares the marginal cost per efficiency unit of forest land,

$$\frac{\kappa_f}{\phi} + \frac{\theta_e}{\phi} \frac{d}{f},$$

against the cost per efficiency unit of vacant land, κ_v.

Farmers will deforest as long as

$$\frac{\kappa_f}{\phi} + \frac{\theta_e}{\phi} \frac{d}{f} \leq \kappa_v. \tag{3}$$

When there is equality, the marginal product of converting vacant land and forest into efficient land units is the same, and the farmer is indifferent between the two sources of land. Therefore,

$$d = \max \left\{ 0, \ \frac{f\,(\kappa_v \phi - \kappa_f)}{\theta_e} \right\}. \tag{4}$$

Assumption 1. Let $\kappa_v \phi < \kappa_f + \theta_e$.

[2] This can be interpreted as the cost of converting the two types of land into units of efficient land, as well as the opportunity cost of using vacant land and forests.

Under Assumption 1, either there will be no deforestation, or, if deforestation is positive, it will always remain below total forest cover.

This decision rule reveals that land conversion requires the relative efficiency of expansion to overcome a hurdle. A farmer only begins to deforest when the productive efficiency of forest (ϕ) is sufficiently high to justify the direct input cost, $\kappa_f + \theta_e d/f$, relative to the alternative. This creates an extensive margin condition for deforestation, which occurs only if $\phi > \kappa_f/\kappa_v$.

Consider two regions facing the same productivity shock (A_a). In a region where forests are highly fertile (high ϕ), the hurdle κ_f/ϕ is low. Farmers there will readily clear forests to expand production. In another region with less productive forests (low ϕ), the hurdle is high. Farmers may find it unprofitable to clear forests and will instead use more vacant land, where the hurdle is simply κ_v, as long as $u < v$. Thus, ϕ acts as the key parameter that can mediate the environmental impact of aggregate economic shocks.

Once farmers begin to deforest, a lower enforcement cost θ_e and a larger forest stock f both increase deforestation per hectare.

3.2 Equilibrium

An increase in agricultural productivity A_a pushes the economy toward a new equilibrium with a larger agricultural sector. The transition involves a wave of land conversion driven by two channels: an extensive margin (entry) and an intensive margin (farm size).

First, the intensive margin works through existing farmers, who expand their operations. A positive shock to A_a increases the optimal farm size for a farmer with talent z:

$$\tilde{l}^*(z) = \left(\frac{p_a A_a \gamma}{\kappa_v}\right)^{\frac{1}{1-\gamma}} \cdot z, \tag{5}$$

$$u^*(z) = \tilde{l}^*(z) - \phi \max\left\{0,\ \frac{f\left(\kappa_v \phi - \kappa_f\right)}{\theta_e}\right\}, \tag{6}$$

and

$$d^*(z) = \max\left\{0,\ \frac{f\left(\kappa_v \phi - \kappa_f\right)}{\theta_e}\right\}. \tag{7}$$

Second, on the extensive margin, an increase in agricultural productivity (A_a) makes farming a more attractive occupation. This lowers the entry threshold, $\bar{z}$, which is the specific talent level of the marginal farmer who is indifferent between farming and working in the non-agricultural sector. As this threshold falls, it induces new agents to enter farming. The total mass of farmers in the economy, N_F, is therefore determined by the fraction of the population with talent above this threshold. The mass of workers is the remainder of the population or $N_W = 1 - N_F$.

Profits are given by:

$$\pi^*(z) = (1-\gamma)\left(p_a A_a \left(\frac{\gamma}{\kappa_v}\right)^{\gamma}\right)^{\frac{1}{1-\gamma}} z + \mathbf{1}_{\{\kappa_v \phi > \kappa_f\}} \left(\frac{f(\kappa_v \phi - \kappa_f)^2}{2\theta_e}\right), \tag{8}$$

where $\mathbf{1}_{\{\kappa_v\phi>\kappa_f\}}$ is an indicator function that takes value of 1 when $\kappa_v\phi > \kappa_f$ (i.e., deforestation is positive) and zero otherwise. Agents become a farmer if and only if $\pi^*(z) \geq A_n$. Therefore, the mass of farmers is

$$N_F = \left\{ \frac{1}{1-\gamma} \left[A_n - \mathbf{1}_{\{\kappa_v\phi>\kappa_f\}} \left(\frac{f(\kappa_v\phi - \kappa_f)^2}{2\theta_e} \right) \right] \left(\frac{\kappa_v^\gamma}{p_a A_a \gamma^\gamma} \right)^{\frac{1}{1-\gamma}} \right\}^{-\zeta}. \tag{9}$$

3.3 Aggregate Deforestation

The demand for new agricultural land, created by the expansion of existing farms and the entry of new ones, can be met in two ways: by converting vacant land or/and by clearing forests. Our model shows that the choice is determined by the relative cost-effectiveness of conversion. Deforestation occurs only when the cost per efficiency unit of forest land is lower than that of vacant land. Proposition 1 defines the conditions and magnitude of aggregate deforestation in our model economy.

Proposition 1. *The effect of an agricultural productivity shock A_a on total deforestation $\mathcal{D}$ depends on the relative cost-efficiency of land conversion.*

1. *If vacant land is more cost-effective ($\kappa_f/\phi \geq \kappa_v$), the productivity shock causes no deforestation. The expansion occurs entirely on vacant land, hence $\mathcal{D} = 0$.*
2. *If forest land is more cost-effective ($\kappa_f/\phi < \kappa_v$), the productivity shock causes a wave of deforestation. The total amount of forest cleared is given by:*

$$\mathcal{D} = \frac{f\left(\kappa_v\phi - \kappa_f\right)}{\theta_e} \times \left\{ \frac{1}{1-\gamma} \left[A_n - \left(\frac{f(\kappa_v\phi - \kappa_f)^2}{2\theta_e} \right) \right] \left(\frac{\kappa_v^\gamma}{p_a A_a \gamma^\gamma} \right)^{\frac{1}{1-\gamma}} \right\}^{-\zeta},$$

and

$$\frac{\partial \ln(\mathcal{D})}{\partial \ln(A_a)} = \frac{\zeta}{1-\gamma} > 0.$$

Proof in Appendix.

A positive shock to agricultural productivity increases farming profitability, creating incentives for land expansion through both intensive and extensive margins. The land efficiency parameter ϕ first determines whether this expansion occurs at the expense of forests, which happens only if forest conversion becomes the more cost-effective option.

3.4 Alternative Mechanisms

Beyond a general shock to agricultural productivity A_a, agricultural policies may influence land-use decisions through different channels. In our model there are two possible scenarios: changes to the relative land efficiency ϕ and changes to the costs of land conversion κ_i for each land type $i \in \{f, v\}$.

The Role of Relative Land Efficiency (ϕ). Modern agricultural inputs may not be neutral with respect to land type. If new seeds or fertilizers are disproportionately more effective on forest soils—perhaps due to higher initial nutrient content—then a policy promoting their use could effectively increase the relative efficiency parameter ϕ. This possibility is suggested by Bernard et al. (2023) who argue that modern seeds' higher nutrient demands led farmers to preferentially clear nutrient-rich primary forest. Within our framework an increase in ϕ incentivizes expansion on forest land. This may be a complementary channel through which an input subsidy program could spur deforestation by enhancing the perceived quality advantage of forest soils, independent of the general productivity shock.

The Role of Conversion Costs (κ_i). Agricultural input programs may also alter the cost structure of land conversion. If vacant land is initially less fertile and requires more preparation (e.g., clearing stubborn grasses, significant initial fertilization), the provision of modern inputs might reduce the effective cost of bringing it into production. In our framework, this corresponds to a reduction in the cost of converting vacant land, κ_v. This cost-reduction mechanism works in the opposite direction by making vacant land conversion cheaper. The net environmental outcome of a policy like an input subsidy therefore depends on the relative strength of these competing effects. Our empirical finding that deforestation increased most in areas with a high ϕ suggests that the productivity-enhancing effects (on A_a and possibly ϕ itself) dominated any cost-reducing effects on vacant land conversion.

4 Background

4.1 Deforestation and Land Ownership in Tanzania

Tanzania is among the world's poorest economies with over 80% of the population living in rural areas. The country's landscape encompasses forests across approximately 36% of its expanse (URT 2017), serving as a vital source of wood-derived energy, primarily in the form of charcoal and timber, which caters to the energy needs of over 90% of the population. Forests also provide construction materials and various non-wood products such as plant-based medicines and food. The economic worth attributed to the services offered by these forests is considerable, amounting to an estimated 20% of the nation's GDP (FAO 2000, Milledge et al. 2007, Kideghesho 2015 and Commission 2014). The agricultural sector, which employs 75% of the population merely accounts for a quarter of the annual GDP. Yet, agricultural relies on forests as an input to production: either for land expansion or land replacement. The latter is commonly known as shifting cultivation and is practiced because virgin forest soils are more productive and less labor intensive (see e.g., Kideghesho 2015). The relative factors of deforestation are still poorly understood. This is exemplified in Tanzania's conservation policies that primarily aim to reduce the demand for charcoal. However, recent research provides stark evidence that the main driver of deforestation is not charcoal consumption, but rather the activities of subsistence agriculture and smallholder farming (see Doggart et al. 2020, Willcock et al. 2016, Curtis et al. 2018, De Sy et al. 2019). Tanzania, similar to other countries in sub-Saharan Africa, has experienced ongoing tree loss and forest degradation with a mean annual deforestation rate of around 1.47% between 2002 and 2013 (URT 2017). Deforestation contributes to soil erosion and land degradation. Exacerbated by improper land use practices (deforestation, over-grazing, and over-cultivation), tree loss compromises soil integrity, leading to the degradation of arable land and, hence, directly impacts agricultural productivity. Tree loss also results in reduced precipitation and an increase in temperatures, which may further reduce productivity (e.g., Smith et al. 2023). Moreover, deforestation raises significant environmental and ecological implications for the region. That is by posing a threat to Tanzania's diverse ecosystems, wildlife habitats, and the overall balance of its natural resources. Beyond Protected Areas (PAs), there are currently no effective policies limiting agricultural land expansion or replacement. However, PAs are protected de facto by being inaccessible and not *de jure* i.e., by law (see e.g., Joppa et al. 2008). According to the Land Act of 1999, all land in Tanzania is public and categorized into three types:

I **Reserved Land** is land in Protected Areas (e.g., national parks, government forest reserves, etc.). Around 38% of Tanzania is under protection (World Bank as of 2018). However, areas are only protected *de facto* by being inaccessible.

II **Village Land** is managed by communities as a communal resource or with a "right of occupancy" for an individual or group. Most land outside of PAs falls into the village land category.

III **General Land** is a residual category, usually located in urban and peri-urban centers or in privately owned agricultural estates.

Most of Tanzania's forests ($\sim$ 50%) fall under village lands where land is allocated by the village council. When farmers decide to clear an area for agricultural land, they may need a permit from the village council, or not, depending on context and the area involved. Cutting trees on existing small-scale farms like household shambas also requires a permit (The Forest Act, Section 15 of GN 417). However, enforcement of this regulation is notably lenient, except when individuals intend to trade wood products, such as charcoal or timber, for which permits are obligatory.

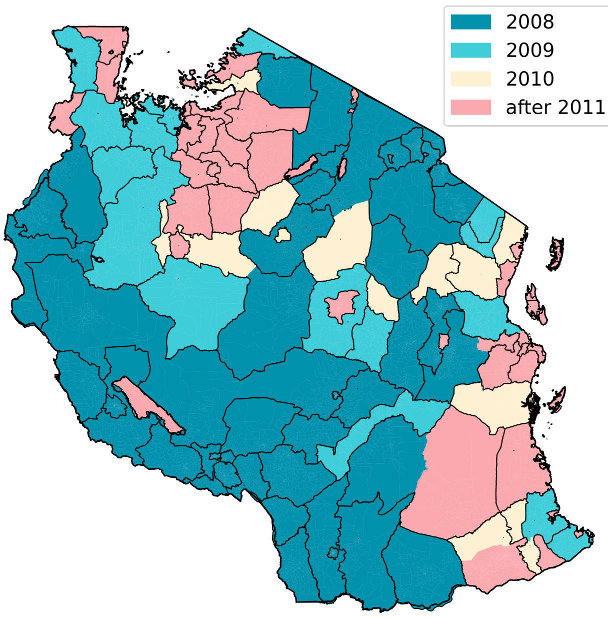
4.2 The National Agricultural Input Voucher Scheme (NAIVS)

The National Agricultural Input Voucher Scheme (NAIVS) was launched in 2008 as a strategic response to a sharp rise in global grain and fertilizer prices. Collaboratively undertaken by the Tanzanian Government and the World Bank, the subsidy program was endowed with an investment of approximately US$ 300 million. Its primary objective was to bolster the production of maize and rice, thereby preserving national food security. NAIVS introduced a 50% discount voucher system for new seed varieties and chemical fertilizers to aid around 2.5 million smallholder farmers. The policy was largely considered to be a success by helping smallholder farmers to harvest more than 2.5 million tons of additional maize and rice grains.

The allocation of vouchers started in 11 "high potential" maize-growing regions (58 districts) in 2008 and gradually expanded to nationwide coverage by 2012 (see Figure 1). The dominant share of input subsidy vouchers continued the be allocated in the originally selected 58 districts for which the government estimated the highest productivity gains. However, due to political pressure to make the program more universal, by 2012 roughly 40% of vouchers were distributed elsewhere in the country.

The voucher program specifically targeted first-time adopters of improved seeds and fertilizers with a cultivation area of less than one hectare. Priority was given to female-headed households and farmers with limited input purchases in the preceding five years. Eligible farmers were then selected by a Village Voucher Committee.[3] Chosen farmers were provided with three vouchers, each applicable for seed, basal fertilizer, and top dress fertilizer. Approximately 80% of the vouchers were allocated to maize farmers, entitling them to a 50% cash top-up for 10kg of either an enhanced open-pollinated maize variety or a maize hybrid, both suited for cultivating an area of approximately one acre.[4] The remaining 20% of seed vouchers were allocated to rice farmers, granting them access to a 15kg package of paddy seeds suitable for approximately one acre of irrigated cultivation. The second and third vouchers were for either one 50kg bag of diammonium phosphate basal fertilizer or two 50kg bags of Minjingu Rock Phosphate, and a 50kg package of top dress fertilizer (urea), respectively.[5] The three vouchers could be redeemed at a local agro-dealer who were specifically trained prior to the start of the program. Following a span of three years benefiting from this support, farmers were expected to purchase their own seeds and fertilizers (World Bank 2014).

Figure 1: First-time treated districts



Note. The map depicts first-time treated districts that received vouchers from the NAIVS program in Tanzania during each policy wave in 2008 (dark blue), 2009 (light blue), 2010 (yellow), and 2011 onwards (red).

[3]The Committee included three men and three women.

[4]Whether a village would receive vouchers for an enhanced open-pollinated maize variety or a maize hybrid was decided by District extension officers in advance.

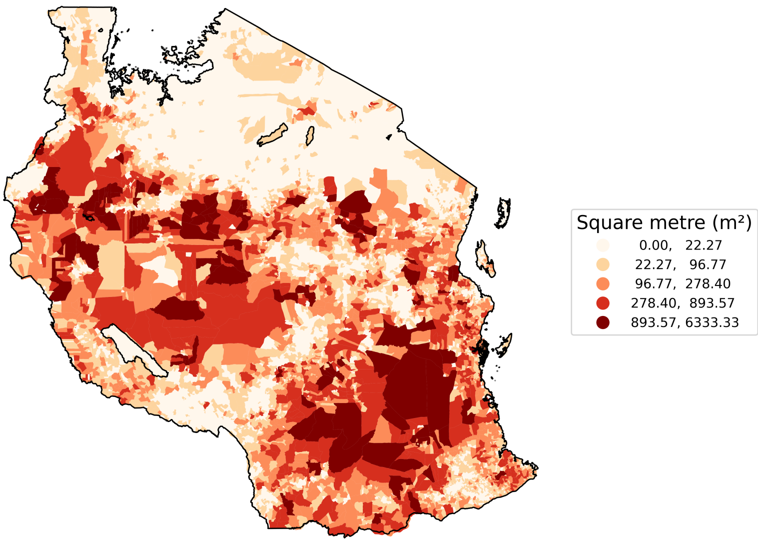
[5]Due to dissatisfaction with the Minjingu Rock Phosphate, the fertilizer was later replaced with a similar product called Minjingu Mazao granulated with nitrogen.

5 Empirical Analysis

5.1 Data

For our empirical research design, we aggregate high-resolution satellite data on the village (ward) level, which is the lowest administrative level. We treat villages as the unit of observation since the village council allocates land at the village level. Hence, the decision to deforest is made at the village level. The resulting dataset consists of more than 130,000 observations with annual information on forest loss, cropland cover, burned area, GDP, nightlight intensity, total precipitation, and mean surface temperature between 2001 and 2011. We also obtain information on the pre-policy crop yields of maize and rice in the year 2000 from the FAO Global Agro-Ecological Zones database (FAO-GAEZ).

Figure 2: Total forest loss between 2001 and 2011



Note. The map shows total aggregated tree loss in all Tanzanian villages between 2001 and 2011 (in square meters) from the Hansen et al. (2013) Global Forest Change dataset. Tree loss is defined as the complete removal of vegetation above a height of 5 meters.

Tree Loss. For our main variable of interest, we calculate the total forest loss (in square meter) within each village boundary for each year between 2001 and 2011 with data from the Hansen et al. (2013) Global Forest Change dataset. The dataset provides annual tree cover loss data between 2001 and 2020 with a 30x30m resolution across all global land (except Antarctica and other Arctic islands). The data was generated with multi-spectral satellite imagery from Landsat 5. Tree cover loss is defined as "stand replacement disturbance," or the complete removal of vegetation above a height of 5 meters at each pixel. Furthermore, we observe tree cover (for all vegetation taller than 5m) in the year 2000 as a percentage per pixel (0-100). For our robustness exercise, we additionally obtain data on the yearly percentage of tree cover with a 250x250m resolution from MODIS Vegetation Continuous Fields (VCF) (DiMiceli et al. 2017). The main advantage of the Hansen et al. (2013) dataset over MODIS VCF is its unprecedented high resolution that allows us to map the data onto the village level. On the other hand, MODIS VCF may be less suitable for analyzing changes in tree cover, particularly in sparsely vegetated areas (Adzhar et al. 2021). The data on total forest loss in each village (in square meters) between 2001 and 2011 is shown in Figure 2. There is considerable variation in the data which is useful for identification. While some villages experienced forest loss of up to 80.000 square meters, other villages only experienced moderate to no deforestation. This is due to Tanzania's stark geospatial variation in terrain and economic activity.

Cropland. We obtain data on the extent of cropland from the MODIS Land Cover Product (Friedl et al. 2010) annually between 2001 and 2011 and aggregate the total cropland area on the village level. The raw data has a spatial resolution of 500x500m and classifies each pixel into one of 17 classes e.g., urban and built-up lands, savannas, or water bodies.[6] For each pixel and in each year, the dataset has information on whether at least 60% of the area is cultivated by cropland. To the best of our knowledge, the MODIS Land Cover Product is the most comprehensive dataset on yearly changes in cropland area that covers regions in sub-Saharan Africa. The relatively low spatial resolution is the main data limitation for our empirical analysis. Furthermore, to investigate the heterogeneous policy effect depending on the relative land productivity between forests and vacant land, we exploit cropland data at a 30-m spatial resolution between the interval interval 2004/2007 from Potapov et al. (2022). Unfortunately, the data is not available at a yearly frequency but it nevertheless allows us to calculate land productivity within non-cropland and non-forest areas (i.e, vacant land) before the introduction of NAIVS.

Fires. We are also interested in the policy implications on fires. Therefore we collect monthly data of the total burned area between 2001 and 2011 on a 500x500m grid for Tanzania and aggregate it to the yearly total burned area in each village. The data is from the MODIS Burned Area data product (Giglio et al. 2018) and is constructed by using surface reflectance data, active fire observations, and a hybrid algorithm with a dynamic threshold to determine the occurrence of a fire (or burned area). The data gives information about which day of the year the fire was detected. This means, for each pixel, we observe if there was a fire event during each month or not.

Table 1: Summary statistics 2001 to 2011

Variable in log Δ	Obs.	Mean	Std. dev.	Min	Max
Tree Loss	87,324	0.03	1.72	-8.54	7.68
Cropland	36,415	0.02	0.31	-4.51	3.09
Burned Area	52,182	-0.21	1.34	-7.76	6.62

Note. The table shows the annual summary statistics for the three outcome variables of interest: total forest loss, cropland area, and burned area. Data is aggregated yearly on the village level and taken from Hansen et al. (2013), Friedl et al. 2010 and Giglio et al. 2018, respectively.

Land Productivity. We use nitrogen as a proxy for land productivity since nitrogen is commonly argued one of the most important nutrient for plants and plays a crucial role in their developmental processes (see e.g, Yang et al. 2022). Therefore we obtain soil total organic Nitrogen levels (log-

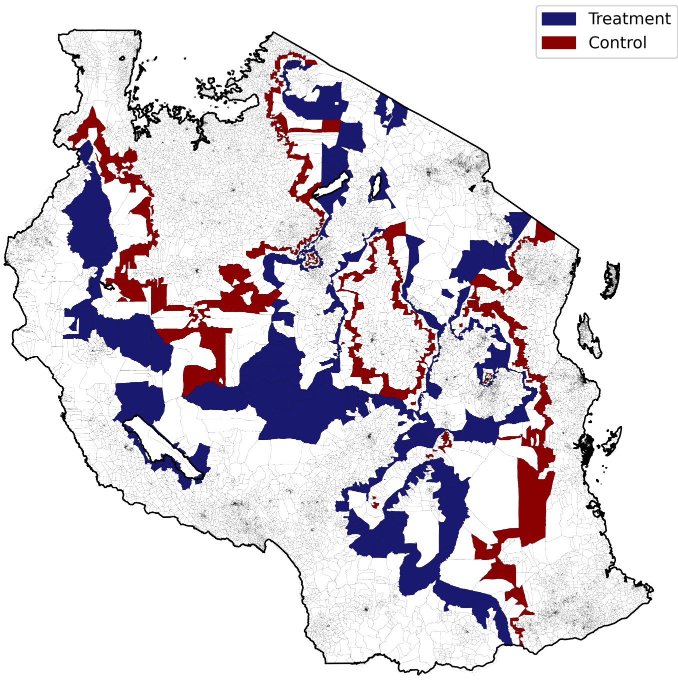
[6]MODIS Land Cover Product also classifies pixels into forest cover (e.g., Evergreen Broadleaf Forests or Mixed Forests). However, for our analysis, we use the Hansen et al. (2013) dataset as it is the most granular data obtainable.

transformed) at a depth of 0–20cm from the iSDAsoil dataset (Hengl et al. 2021) at a 30x30m resolution. Hengl et al. (2021) estimate soil nutrients within the African continent using a comprehensive compilation of soil samples and earth Observation data.

Controls. As controls we create variables on the mean annual Gross Domestic Product (GDP), nightlight intensity, total precipitation, and mean temperature between 2001 and 2011 on the village level. We also consider lagged climatic variation in our baseline specification as well as monthly standard deviations of rainfall. Data on GDP is from Kummu et al. (2018) who construct gridded data at 5 arcmin resolution on annual GDP (PPP) by interpolating existing national, regional, and sub-national data sources. We use corrected nightlights data from Bluhm & Krause (2022) at a 30 by 30 arc seconds resolution as well as monthly precipitation and land surface temperatures from Chen et al. (2002) and Fan & Van den Dool (2008), respectively.

5.2 Identification & Empirical Specification

Figure 3: Treatment and 2nd neighbor controls in 2008



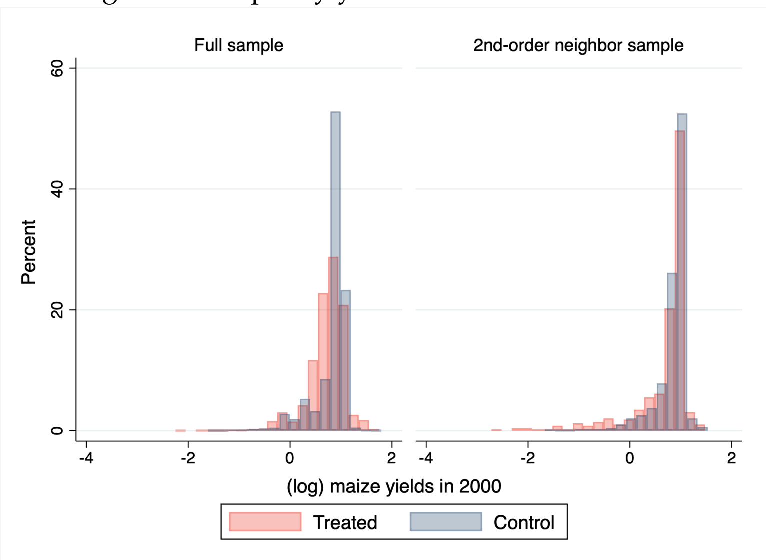
Note. The map depicts our choice of treatment (blue) and control (red) group in 2008, namely villages that are adjacent to treated districts with their 2nd order neighbors located outside treated districts.

Our empirical research strategy is to compare changes in forest loss, cropland, and fires over time between villages that are located in districts that received farming vouchers and villages that did not meet the targeting criteria of the policy program. The key to this identification strategy is to restrict our sample to villages that are located *just inside* and *just outside* treated district borders. Recall that Tanzania's voucher scheme specifically targeted "high potential" maize and rice-growing regions. Hence, the spatial allocation of vouchers was not random but conditional on potentially time-varying variables such as previous harvests, economic and political factors, as well as climatic and other topographical variables. This means that village-fixed effects alone would not help to adequately control for this selection bias.

We further restrict our choice of the control group to the 2nd order neighbors of treated villages. We do this for two reasons: First, we want to account for potential spillovers of the policy. Since corruption is omnipresent in Tanzania, vouchers redeemed in one village could easily be used in another. The second reason is that village borders might be very loosely enforced in the first place rendering 1st order neighbors a poor control choice. Hence, in our final sample, we exclusively include villages that are adjacent to treated districts with their 2nd order neighbors located outside treated districts. Given the proximity of our treatment and control group choices, we argue that they are likely to be very similar without inducing noise from potential spillovers. The sample choice is illustrated in Figure 3 which shows the treatment and control group during the first policy wave in 2008. The sample restriction leaves us with 18,502 observations of which 4,147 villages were never treated. The sample size is shown in Table 2 (Appendix) which lists the number of villages that were treated during each policy wave.

We motivate our sample choice by comparing pre-policy (in 2000) distributions of maize and rice yields between treated and control villages in the full sample with the restricted 2nd order sample. The respective distributions are presented in Figure 4 and 10 (Appendix). Indeed we find the 2nd order neighbor sample appears to have sufficiently similar treatment and control group in terms of mean and variance in pre-policy maize and rice yields.

Figure 4: Pre-policy yield distributions of maize



Note. The figure shows the distribution of village-level total (log) maize yields in 2000 of the treatment and control group in the full sample (all Tanzanian villages) and the restricted 2nd-order sample. The data is from the FAO Global Agro-Ecological Zones database (FAO-GAEZ) and aggregated on the village level.

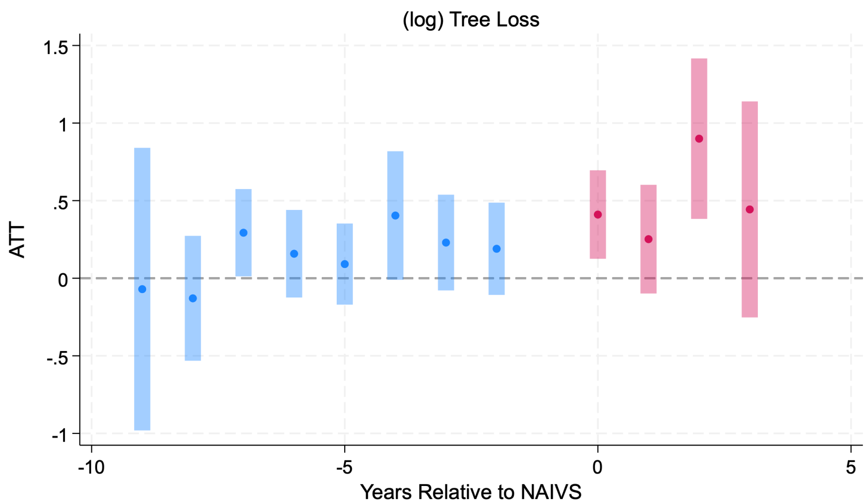
Formally, we are interested in the following two-way fixed-effects (TWFE) regression:

$$y_{it} = \alpha_i + \gamma_t + \beta \text{D(Policy)}_{dt} + \rho X_{it} + \varepsilon_{it} \tag{10}$$

where y_{it} is the (log) outcome variable of interest for village i at time t. D(Policy)$_{dt}$ is a treatment dummy for district d at time t. α_i and γ_t are village and time-fixed effects and X_{it} is a set of time-varying controls, namely average (log) GDP as well as climatic variables (total precipitation and mean surface temperature). The results of these regressions are presented in Figure 3 of the Appendix. However, in the context of staggered treatments, the TWFE may be severely biased. Recent research points out that β is not guaranteed to recover a reliable causal estimator of the Average Treatment Effects of Treated (ATT) (Borusyak et al. 2021; Goodman-Bacon 2021; De Chaisemartin & d'Haultfoeuille 2020). In light of these findings, our baseline empirical approach is to use the state of the art robust difference-in-difference estimator from Callaway & Sant'Anna (2021).[7] A visual representation of the results is in Figures 5, 6, 11 which shows the difference-in-difference estimates of NAIVS on (log) forest loss, cropland, and fires with the restricted 2nd order neighbor sample using the estimation method by Callaway & Sant'Anna (2021).

5.3 Empirical Results

Figure 5: Staggered treatment effect on Tree Loss



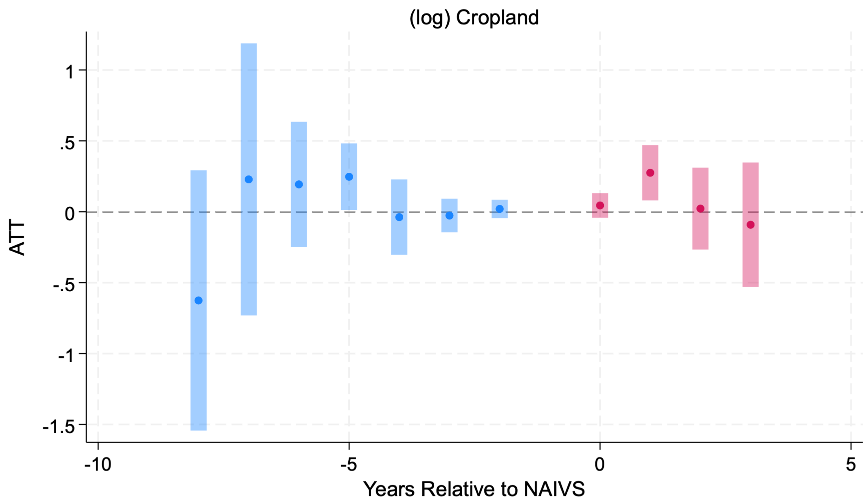
Note. The figure shows the estimated average treatment effect on the treated of the policy on (log) tree loss with the difference-in-difference estimation method by Callaway & Sant'Anna (2021) on the restricted 2nd order neighbor sample. Point estimates represent dynamic effects relative to the reference period (long differences). Controls include village-level average GDP, rainfall standard deviations, as well as total rainfall and mean surface temperature variation. Standard errors on the 1% level.

A visual representation of the results is shown in Figures 5, 6, and 11 for (log) tree loss, (log) cropland, and (log) fires, respectively. The figures show the difference-in-difference estimates using the estimation method by Callaway & Sant'Anna (2021) with the restricted 2nd-order neighbor sample, a not-yet treated control group. We estimate dynamic effects using long-differences relative to the period immediately prior to treatment, rather than year-on-year changes. This specification allows us to explicitly test for pre-existing trends in levels relative to the baseline (Roth 2024). We control for village-level average (log) GDP, rainfall standard deviations, as well as total rainfall and mean surface temperature variation. For the effect on cropland, we additionally control for lagged rainfall.

[7]The estimator is based on stabilized inverse probability weighting and ordinary least squares. Standard errors.

The results suggest a sizable and persistent effect on deforestation after vouchers were allocated (see Figure 5). Treated villages experience an immediate statistically significant increase in tree loss of around 40 to 50 percent. We also do not observe a significant differential effect between treated villages and controls before the policy was implemented. This finding suggests that redeemed vouchers were used to either expand or shift cultivation to land previously covered by trees resulting in deforestation. Analogously, we also observe a rise in the cropland area. The point estimate lies between 10 and 20 percent increases in cropland, which is less than the corresponding observed rise in tree loss (see Figure 6).

Figure 6: Staggered treatment effect on Cropland



Note. The figure shows the estimated average treatment effect on the treated of the policy on (log) cropland with the difference-in-difference estimation method by Callaway & Sant'Anna (2021) on the restricted 2nd order neighbor sample. Point estimates represent dynamic effects relative to the reference period (long differences). Controls include village-level average GDP, rainfall standard deviations, as well as total rainfall and mean surface temperature variation and lagged total rainfall. Standard errors on the 5% level.

The results on cropland are reported with 95% significance bands and only weakly statistically significant, which likely stems from the coarse resolution of the MODIS Land Cover data that classifies land use in 25-hectare (500x500m) pixels. Since the NAIVS program specifically targeted farmers with a cultivation area of less than one hectare, any resulting increase in cropland occurs at a scale that is likely far below the satellite's 25-hectare detection threshold. The difference in magnitude of the estimates between forest loss cropland estimates can be interpreted in several ways. One possibility is that it reflects shifting cultivation whereby farmers translate agricultural productivity gains into moving cultivation to a new plot previously covered by trees. An alternative explanation is that farmers may clear land to claim property rights. Unfortunately, we don't have the data to distinguish between possible explanations. However, we think that the coarse MODIS data is simply not well-suited to capture the changes in cultivation area of smallholder farmers with less than one hectare of cultivated area.

Lastly, we do not find a significant effect on the villages' burned area (see Figure 11, Appendix). This finding is consistent with anecdotal evidence for Tanzania that trees are mostly processed into wood products like timber or charcoal for energy use or trade. This is because farmers exploit the value of forests in addition to the land gains for cultivation. Our findings are in contrast to Garg et al. (2024), who suggest that farmers adopt fire as a labor-saving technology on existing cropland in the context of India and other findings connection agriculture to forest fires (e.g, Balboni et al. 2021). The absence of fire-related effects in our setting shows that the role of fire in land-use change can differ and depends on the economic context, particularly the value of timber (Barbier & Burgess 1997). We demonstrate the robustness of these results in section 5.5.

5.4 Land Productivity on Forest vs. Vacant Land

To test the main prediction of our framework, we investigate how the program's effect on deforestation varies with the relative agricultural suitability of forest versus vacant land. Therefore, we calculate village-level measures of relative land productivity between forests and vacant land by utilizing 30x30m resolution spatial data on forest, cropland and soil nitrogen (log) levels. We define the set of pixels j within vacant land $\mathcal{V}(i)$ in village i as pixels that are not classified as cropland, have a forest cover of less than 100% or have been deforested by 2007 and not replaced by cropland. Conversely, we define the set of pixels within forest land $\mathcal{F}(i)$ as observations that are not classified as cropland, have a forest cover of more than 0% as observed in the year 2000 and have not been deforested until 2007. We show an example of the spatial distribution of land usage and nitrogen levels in Figure 7. For each village i, we then estimate the relative land productivity of forest vs. vacant land denoted by ϕ_i as follows:

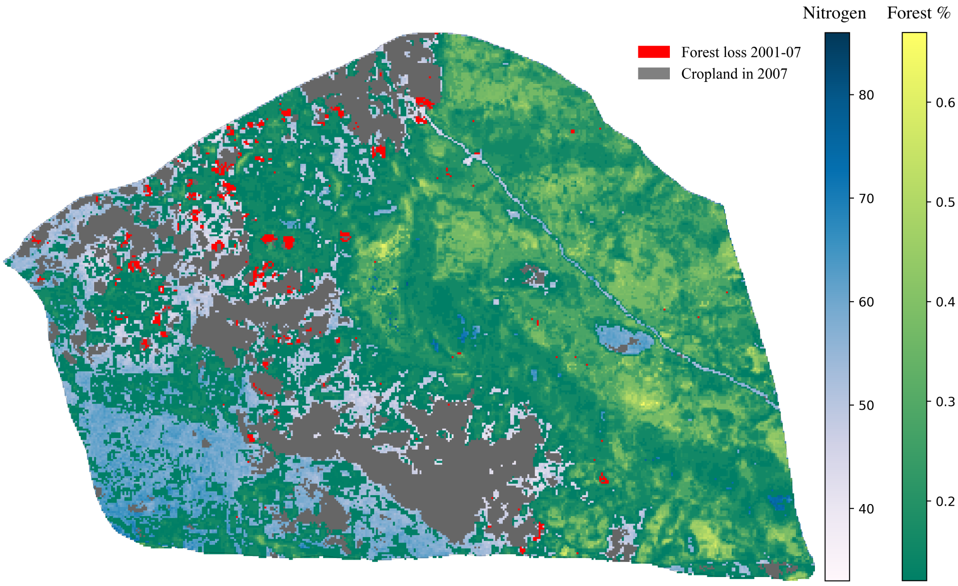
$$\phi_i = \frac{\frac{1}{F_i}\sum_{j\in\mathcal{F}(i)} N_j \text{ Forest}_j}{\frac{1}{V_i}\sum_{j\in\mathcal{V}(i)} N_j \left(1 - \text{Forest}_j(1 - \text{Forest Loss}_j)\right) + N_j\text{Forest Loss}_j} \tag{11}$$

where V_i and F_i denote the total number of pixels within vacant land and forest, respectively. N_j is the observed nitrogen level in pixel j, Forest_j is the observed percent of forest cover and Forest Loss_j is a dummy variable that takes the value of one if pixel j experienced forest between 2001 and 2007. Hence, the denominator of equation 11 measures the average nitrogen level within vacant land that is on non-cropland and is either weighted by the percentage of non-forest as of the year 2000 or has been deforested up until 2007. The nominator measures the average nitrogen level within forests, weighted by the percent of forest cover.

We acknowledge that our estimated measure ϕ_i is an imperfect proxy for the complex concept of relative land efficiency. For instance, it relies on soil nitrogen as the primary indicator of quality, abstracting from other important factors like soil composition, water availability, or topography. Furthermore, our definition of vacant land as a residual category may group together areas with heterogeneous characteristics. Despite these limitations, we argue this measure is well-suited for our analysis. First, soil nitrogen is widely considered a key limiting nutrient for staple crop production in sub-Saharan Africa, making it a highly relevant indicator of agricultural suitability in the context of the NAIVS program. Second, the 30x30m spatial resolution of our data allows for a highly granular and localized measure. This minimizes aggregation bias and enables us to capture the trade-offs between adjacent land parcels, a scale that can accurately reflect the actual land-use decisions made by smallholder farmers. While potentially noisy, we believe that ϕ_i reflects its theoretical counterpart from our model.

Given our measure of relative land productivity ϕ_i, we run our baseline difference-in-difference regression from Section 5.3 for villages above/below the median value of ϕ_i. That is, a difference-in-difference estimates using the estimation method by Callaway & Sant'Anna (2021) with the restricted 2nd-order neighbor sample, a not-yet treated control group, and 95% significance bands. Again, we control for village-level average (log) GDP, rainfall standard deviations, as well as total rainfall and mean surface temperature variation. A visual representation of the results is shown in Figure 8 with the left panel showing the effect on villages below the median of ϕ_i and on the right above.

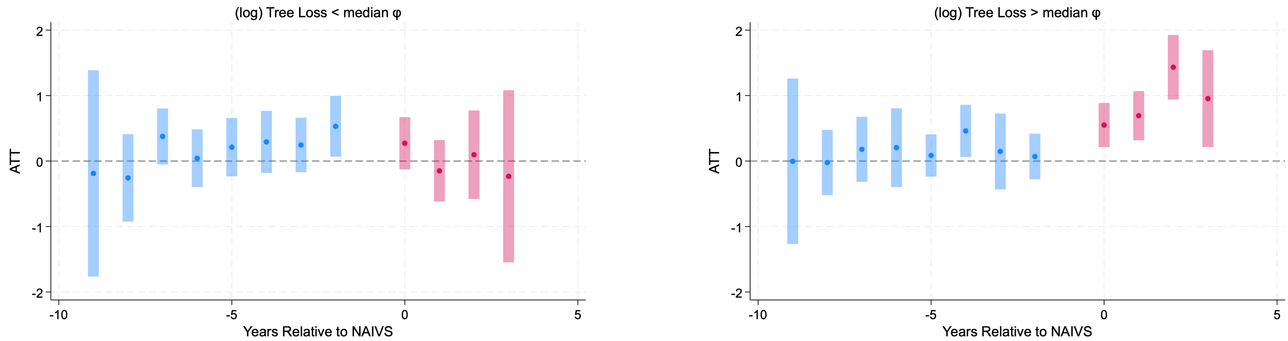
Figure 7: Nitrogen on Vacant Land



Note. The figure shows pixels classified as cropland in 2007 (grey), pixels that have been deforested until 2007 (red), the percent of forest cover as of the year 2000 and the nitrogen levels for a random village selected in Tanzania.

The findings suggest that in villages where vacant land contains higher nitrogen levels than forest areas, the allocation of vouchers does not significantly affect deforestation rates. However, in villages where forest soil is relatively more productive, there is a substantial and sustained increase in deforestation rates. This outcome is consistent with the relative land efficiency mechanism outlined in our theoretical framework. The model predicts that a positive shock to agricultural productivity (A_a) incentivizes expansion, with the choice of which land to convert depending on the relative cost per efficiency unit. While we lack direct data on the linear costs of conversion, κ_f and κ_v, our empirical test relies on the variation in land quality ϕ to explain the deforestation outcome. This implicitly assumes that, within a village, the direct costs of clearing forest versus vacant land are comparable, or at least do not vary in a way that would systematically counteract the quality differential. Under this assumption, the results align with the model's predictions. In villages where vacant land is relatively nitrogen-rich (our proxy for a low ϕ), the cost per efficiency unit of converting forest, κ_f/ϕ, remains high. Here, our framework suggests expansion would favor the more cost-effective vacant land, resulting in no significant increase in deforestation, which is what we observe. Conversely, in villages where forest soils are significantly more productive (high ϕ), the effective cost per efficiency unit of converting forest is lower, making it the more attractive option ($\kappa_f/\phi < \kappa_v$). In this context, the NAIVS-induced shock to productivity tipped the balance in favor of expanding cultivation onto the more productive forest frontier. The observed increase in deforestation is therefore concentrated precisely where our model predicts the condition for forest conversion is most likely to be met: where the efficiency advantage of forest land is highest.

Figure 8: Staggered treatment effect on Tree Loss



Note. The figure shows the estimated average treatment effect on the treated of the policy on (log) tree loss with the difference-in-difference estimation method by Callaway & Sant'Anna (2021) on the restricted 2nd order neighbor sample. Point estimates represent dynamic effects relative to the reference period (long differences). On the left panel we further restrict the sample to villages below the median of ϕ_i and on the right panel above the median of ϕ_i. Controls include village-level average GDP, rainfall standard deviations, as well as total rainfall and mean surface temperature variation. Standard errors on the 1% level.

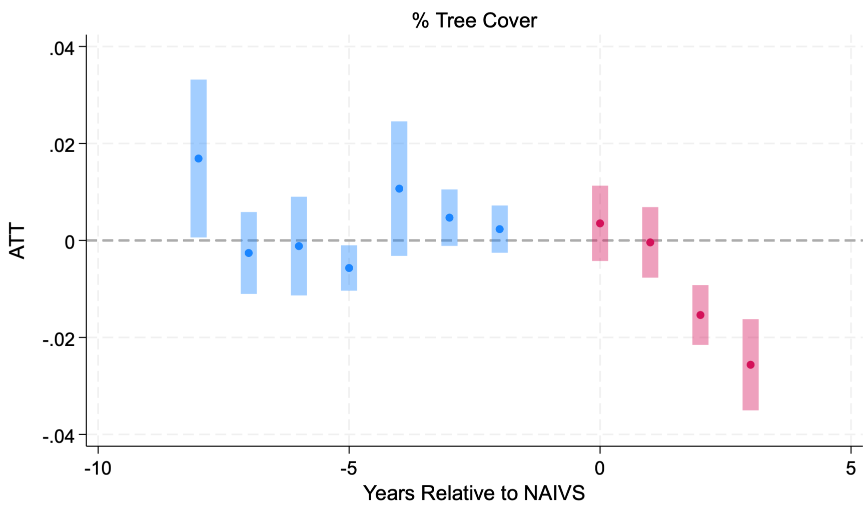
We acknowledge that conversion costs, the cost to clear a physical unit of forest κ_f and prepare vacant land κ_v, are likely heterogeneous (see e.g, Araujo, Costa & Sant'Anna 2025). A potential issue for our interpretation is how these heterogeneous costs might correlate with land quality. However, we believe a correlation between nitrogen levels and land conversion costs would create a bias against our findings. First, high-nitrogen forest soils typically indicate more mature and denser biomass, which implies higher clearing costs κ_f. This makes the choice to deforest less attractive by increasing the cost term in the cost-efficiency ratio (κ_f/ϕ). Second, we expect higher nitrogen levels correlate with more suitable vacant land which is cheaper to bring into production. This implies that the low-nitrogen vacant land found in areas where forests are of high relative quality would likely have higher preparation costs κ_v. Both of these factors would discourage deforestation.

A concern for our interpretation would only arise if the opposite were true, for example, if high-nitrogen forests were systematically cheaper to clear. In that scenario, heterogeneous costs, rather than efficiency, could explain our results. The fact that we observe increased deforestation precisely where clearing costs are likely higher and the vacant land alternative is likely more expensive suggests that the efficiency gain from higher quality soil ϕ is large enough to outweigh these cost considerations. Therefore, our results show that deforestation occurred despite plausible heterogeneous costs that may correlate systematically with nitrogen levels and would otherwise be expected to discourage it.

5.5 Robustness

The main concern for our analysis is that our measure of relative land efficiency ϕ_i may be correlated with a village's pre-policy land endowment. When splitting the sample, the high-ϕ_i group may systematically differ from the low-ϕ_i group in its land composition. Specifically, villages with high ϕ_i might also be those that were endowed with a larger stock of both forest and cropland before the policy 2007. A stronger treatment effect in this group could therefore be driven by a greater capacity for agricultural expansion, rather than by relative land efficiency. We address this concern by isolating the component of ϕ_i that is orthogonal to the a village's 2007 forest stock and cropland area.[8] Splitting the sample on this adjusted measure that is statistically independent of a village's land composition allows us to isolate the effect of relative land efficiency from the influence of the pre-policy land endowment. We find that our main result is robust to this procedure: splitting the sample by the median of the orthogonalized residuals $\hat{\phi}_i$ yields results consistent with our main findings (Figure 12, Appendix). This suggests that the relative quality of land, independent of its quantity, is the mechanism driving the heterogeneous treatment effect.

Figure 9: Staggered treatment effect on % Tree Cover



Note. The figure shows the estimated average treatment effect on the treated of the policy on the average percentage tree cover with the difference-in-difference estimation method by Callaway & Sant'Anna (2021) on the restricted 2nd-order neighbor sample. Point estimates represent dynamic effects relative to the reference period (long differences). Controls include village-level average GDP, average nightlight intensity, rainfall standard deviations, as well as total rainfall and mean surface temperature variation and lagged total rainfall. Standard errors on the 1% level.

Our results are also robust towards the deforestation measure, the sample choice, and the empirical specification. First, we verify our results with alternative deforestation data. Therefore we aggregate the yearly percentage tree cover data from MODIS VCF with a 250x250m resolution on the village level by averaging (see Section 5.1). The estimation results of using this alternative measure of deforestation are presented in Figure 9. The ATT is highly significant, but less in magnitude compared to our baseline measure. However, this is expected, as the coarser spatial resolution of the MODIS

[8]The orthogonal measure $\hat{\phi}_i$ is the residual of regressing ϕ_i on the pre-treatment forest and cropland area.

data is less sensitive to the small-scale forest clearing. Deforestation peaks after four years after the implementation of the policy with a point estimate of around 0.3 percentage points loss. We also do not observe a significant differential effect between treated and non-treated before the policy change in period 0. Second, we choose a different control group to verify our results, namely by adding non-treated villages that share a *direct* border with treated villages. The estimation results on tree loss, cropland, and fires with the sample that includes the 1st order neighbors are presented in Figures 13, 14, and 15 in the Appendix, respectively. The results generally support our baseline findings and suggest a point estimate of approximately 20-30 percent loss in forest loss, a 10-40 percent increase in cropland, and no statistically significant effect on fires.

Third, in our baseline estimation, our 2nd order neighbor control group includes villages that up until 2011 never participated in the policy program as well as, for a particular policy wave, villages that have not been treated yet (though will eventually receive vouchers). However, the results are robust towards further restricting the control group to villages that never received vouchers (Figure 16, Appendix). The empirical results also hold when, additionally, controlling for nightlight intensity (Figure 17, Appendix).

Lastly, we show the results of the TWFE estimator in regression 5.2 in Table 3 of the Appendix. Again, the point estimate suggests a statistically significant annual forest loss of around 30 percent which is consistent with our baseline findings.

6 Conclusion

Does improving agricultural productivity spare forests or accelerate their demise? This paper shows that the answer depends critically on the quality of available, non-forested land. Using a quasi-experimental design based on Tanzania's national input subsidy program (NAIVS), we find that productivity gains led to significant deforestation—but only in villages where vacant land was relatively unproductive compared to existing forests. These results indicate that differential land efficiency helps reconcile the conflicting land-sparing and expansionary effects documented in the literature.

The central mechanism we identify operates independently of factor market frictions. Even when agricultural expansion is profitable, deforestation is not an inevitable outcome; it depends on where expansion occurs. We formalize this logic in a stylized model of land-use choice in which land is measured in efficiency units rather than physical area. In this framework, productivity shocks increase the value of effective land and induce expansion, but whether that expansion takes the form of deforestation is governed by the relative cost-effectiveness of converting forest versus vacant land. Our empirical results, using spatial variation in soil nitrogen as a proxy for land suitability, provide causal evidence consistent with this mechanism.

These findings have important policy implications for sub-Saharan Africa and other developing regions. They show that broad-based agricultural subsidy programs—while potentially central to food security and poverty reduction—are not environmentally neutral. Their land-use impacts are heterogeneous and depend on the characteristics of the local land frontier. Designing sustainable agricultural intensification strategies therefore requires a more nuanced approach, either by explicitly accounting for land quality in policy design or by pairing productivity-enhancing interventions with complementary land-use planning and conservation policies that steer expansion away from ecologically valuable areas.

Our results also suggest a role for directed agricultural innovation. If technological change disproportionately raises the productivity of degraded or low-nitrogen land—through seed varieties or fertilizer packages tailored to such conditions—it can alter the relative efficiency of expansion margins. In the language of our framework, such innovations reduce the productivity advantage of forest conversion and thereby weaken deforestation incentives without constraining agricultural growth.

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A Derivations and Proofs

The farmer's objective is to maximize profits:

$$\pi(z) = \max_{d,u\geq 0} \left\{ p_a A_a z^{1-\gamma} \tilde{l}^{\gamma} - \kappa_v u - \kappa_f d - \frac{\theta_e}{2} \frac{d^2}{f} \right\} \quad \text{s.t.} \quad \tilde{l} = \phi d + u, \;\; u \leq v, \;\; d \leq f.$$

Let $\lambda_v \geq 0$ and $\lambda_f \geq 0$ denote the Lagrange multipliers on the constraints $u \leq v$ and $d \leq f$, respectively. The Kuhn–Tucker conditions are:

$$\begin{aligned}
&\frac{\partial \pi(z)}{\partial u} = \gamma p_a A_a z^{1-\gamma} \tilde{l}^{\gamma-1} - \kappa_v - \lambda_v \leq 0, && u \geq 0, && u\,\frac{\partial \pi(z)}{\partial u} = 0,\\
&\frac{\partial \pi(z)}{\partial d} = \gamma p_a A_a z^{1-\gamma} \tilde{l}^{\gamma-1} \phi - \kappa_f - \theta_e \frac{d}{f} - \lambda_f \leq 0, && d \geq 0, && d\,\frac{\partial \pi(z)}{\partial d} = 0,\\
&\lambda_v \geq 0, && v - u \geq 0, && \lambda_v (v-u) = 0,\\
&\lambda_f \geq 0, && f - d \geq 0, && \lambda_f (f-d) = 0.
\end{aligned}$$

When vacant land and forest are abundant, so that $u < v$ and $d < f$, we have $\lambda_v = 0$ and $\lambda_f = 0$. Under the assumption $\kappa_v \phi < \kappa_f + \theta_e$, we have $u > 0$ and $\gamma p_a A_a z^{1-\gamma} \tilde{l}^{\gamma-1} = \kappa_v$. Hence,

$$\tilde{l}^*(z) = \left(\frac{p_a A_a \gamma}{\kappa_v} \right)^{\frac{1}{1-\gamma}} z, \tag{12}$$

$$d^*(z) = \max \left\{ 0, \; \frac{f(\kappa_v \phi - \kappa_f)}{\theta_e} \right\}, \quad \text{and} \tag{13}$$

$$u^*(z) = \tilde{l}^*(z) - \phi\, d^*(z). \tag{14}$$

Profits are

$$\pi^*(z) = (1-\gamma) \left(p_a A_a \left(\frac{\gamma}{\kappa_v} \right)^{\gamma} \right)^{\frac{1}{1-\gamma}} z + \mathbf{1}_{\{\kappa_v \phi > \kappa_f\}} \left(\frac{f(\kappa_v \phi - \kappa_f)^2}{2\theta_e} \right), \tag{15}$$

where $\mathbf{1}_{\{\kappa_v \phi > \kappa_f\}}$ is an indicator function that equals 1 if $\kappa_v \phi > \kappa_f$ and 0 otherwise. Agents become farmers if and only if $\pi^*(z) \geq A_n$. This defines a threshold value for farm productivity, $\bar{z}$, given by

$$\bar{z} = \frac{1}{1-\gamma} \left[A_n - \mathbf{1}_{\{\kappa_v \phi > \kappa_f\}} \left(\frac{f(\kappa_v \phi - \kappa_f)^2}{2\theta_e} \right) \right] \left(\frac{\kappa_v^{\gamma}}{p_a A_a \gamma^{\gamma}} \right)^{\frac{1}{1-\gamma}}, \tag{16}$$

such that if $z \geq \bar{z}$ the agent is a farmer, and if $z < \bar{z}$ the agent works in the non-farming sector. The mass of farmers is

$$N_F = \int_{\bar{z}}^{\infty} \zeta z^{-\zeta-1}\, dz = \Big[-z^{-\zeta} \Big]_{z=\bar{z}}^{z=\infty} = \bar{z}^{-\zeta}.$$

Using (16) yields

$$N_F = \left\{ \frac{1}{1-\gamma} \left[A_n - \mathbf{1}_{\{\kappa_v \phi > \kappa_f\}} \left(\frac{f(\kappa_v \phi - \kappa_f)^2}{2\theta_e} \right) \right] \left(\frac{\kappa_v^{\gamma}}{p_a A_a \gamma^{\gamma}} \right)^{\frac{1}{1-\gamma}} \right\}^{-\zeta}. \tag{17}$$

For the proof o Proposition 1, notice that if $\kappa_f/\phi > \kappa_v$, then $d^*(z) = 0$ and aggregate deforestation is zero, $\mathcal{D} = 0$. In this case, improvements in agricultural productivity A_a have no effect on deforestation.

If $\kappa_f/\phi < \kappa_v$, then

$$d^*(z) = \frac{f\left(\kappa_v \phi - \kappa_f\right)}{\theta_e} > 0,$$

and aggregate deforestation is given by

$$\begin{aligned}\mathcal{D} &= \int_{\bar{z}}^{\infty} \zeta \, \frac{f\left(\kappa_v \phi - \kappa_f\right)}{\theta_e} \, z^{-\zeta-1} \, dz \\ &= \left[- \frac{f\left(\kappa_v \phi - \kappa_f\right)}{\theta_e} z^{-\zeta} \right]_{z=\bar{z}}^{z=\infty} = \frac{f\left(\kappa_v \phi - \kappa_f\right)}{\theta_e} \, \bar{z}^{-\zeta}.\end{aligned}$$

Substituting for the productivity threshold $\bar{z}$ yields

$$\mathcal{D} = \frac{f\left(\kappa_v \phi - \kappa_f\right)}{\theta_e} \left\{ \frac{1}{1-\gamma} \left[A_n - \left(\frac{f(\kappa_v \phi - \kappa_f)^2}{2\theta_e} \right) \right] \left(\frac{\kappa_v^{\gamma}}{p_a A_a \gamma^{\gamma}} \right)^{\frac{1}{1-\gamma}} \right\}^{-\zeta}. \tag{18}$$

Taking logs of both sides,

$$\ln \mathcal{D} = \text{const} + \frac{\zeta}{1-\gamma} \ln A_a.$$

Differentiating with respect to $\ln A_a$ yields

$$\frac{\partial \ln \mathcal{D}}{\partial \ln A_a} = \frac{\zeta}{1-\gamma} > 0. \tag{19}$$

This completes the proof.

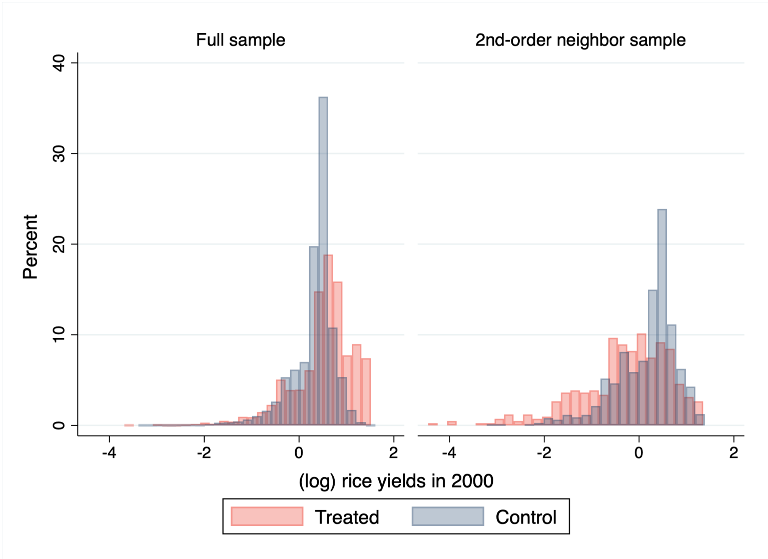
B Empirics

Table 2: # Observations in 2nd neighbor sample

First Treated	Freq.	Percent (%)
Never	4,147	22.41
2008	5,434	29.37
2009	5,071	27.41
2010	3,850	20.81
Total Obs.	18,502	100

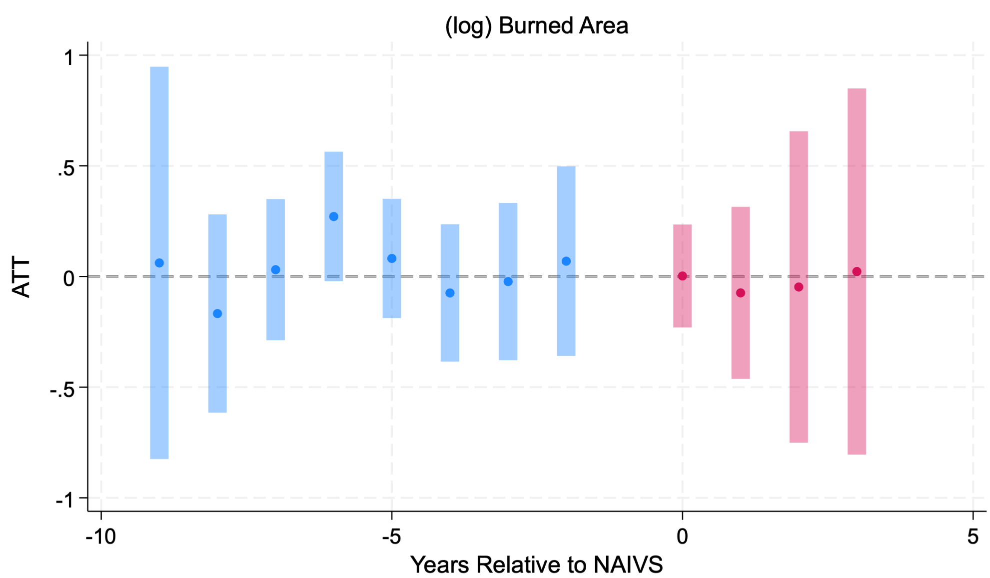
Note. The table shows the number of observations (and % of the sample) in the restricted 2nd order neighbor sample for villages that got first treated in each policy wave.

Figure 10: Pre-policy yield distributions of rice



Note. The figure shows the distribution of village-level total (log) rice yields in 2000 of the treatment and control group in the full sample (all Tanzanian villages) and the restricted 2nd order sample. The data is from the FAO Global Agro-Ecological Zones database (FAO-GAEZ) and aggregated on the village level.

Figure 11: Staggered treatment effect on Fires



Note. The figure shows the estimated average treatment effect on the treated of the policy on (log) burned area with the difference-in-difference estimation method by Callaway & Sant'Anna (2021) on the restricted 2nd order neighbor sample. Point estimates represent dynamic effects relative to the reference period (long differences). Controls include village-level average GDP, rainfall standard deviations, as well as total rainfall and mean surface temperature variation. Standard errors on the 1% level.

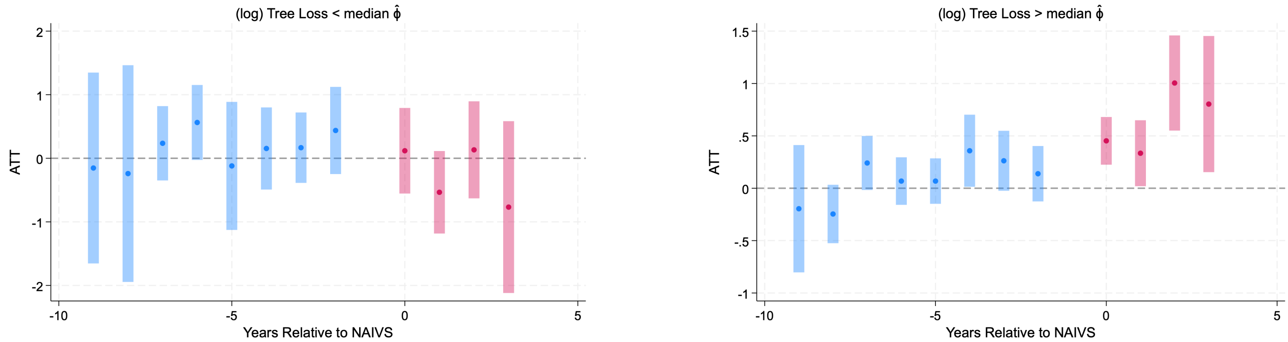
Table 3: Two-way Fixed Effects Regressions

	(1)	(2)	(3)
	Log Forest Loss	Log Cropland	Log Burned Area
D(Policy)	0.206***	-0.0182	0.0174
	(0.0439)	(0.0442)	(0.0458)
(log) GDP	-0.609***	-0.0649	-0.0917
	(0.155)	(0.197)	(0.189)
Precipitation$_t$	0.544***	0.0223	0.839***
	(0.140)	(0.0968)	(0.156)
Temperature$_t$	73.36***	9.606	30.15
	(26.92)	(21.90)	(27.63)
Temperature$_{t-1}$	-12.63	-1.749	118.9***
	(26.97)	(21.58)	(26.61)
Precipitation$_{t-1}$	-2.412***	0.114	0.877***
	(0.135)	(0.0916)	(0.140)
Precipitation std.$_t$	-0.0582***	0.0431***	-0.00481
	(0.0185)	(0.0108)	(0.0191)
Constant	yes	yes	yes
Fixed effects	yes	yes	yes
Time FE	yes	yes	yes
Observations	12,985	4,851	7,951
R-squared	0.729	0.935	0.812

Robust standard errors in parentheses

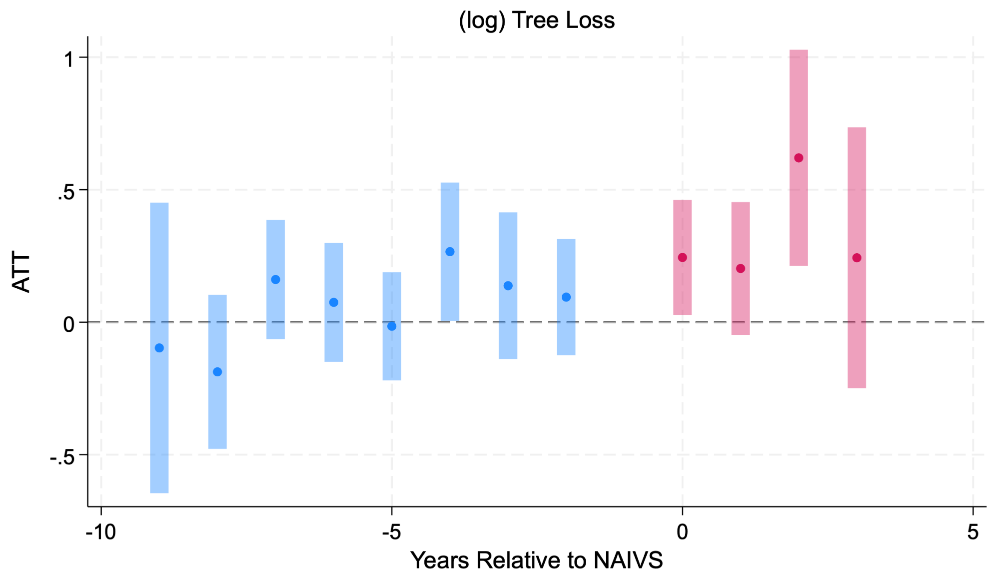
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Figure 12: Staggered treatment effect on Tree Loss - orthogonalized ϕ



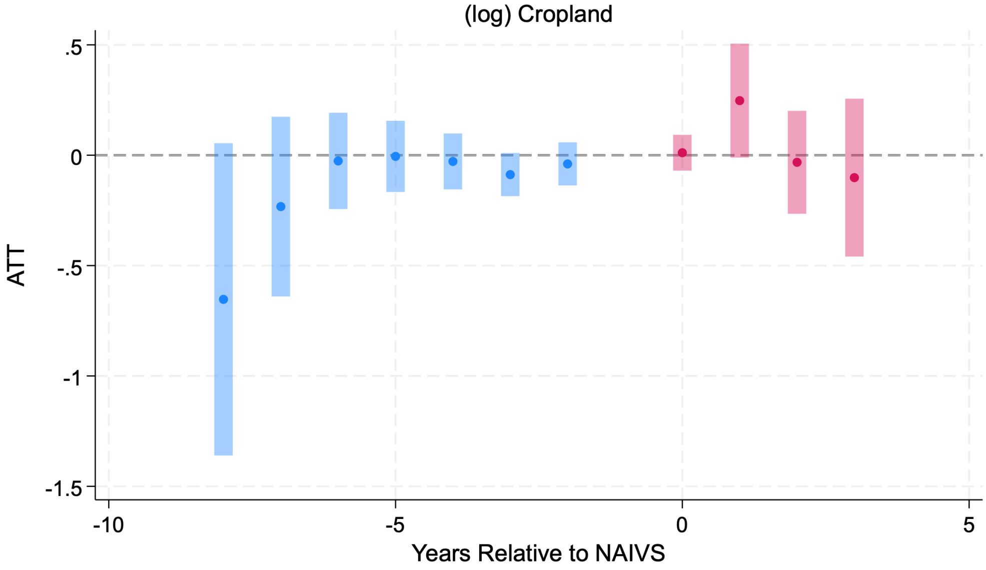
Note. The figure shows the estimated average treatment effect on the treated of the policy on (log) tree loss with the difference-in-difference estimation method by Callaway & Sant'Anna (2021) on the restricted 2nd order neighbor sample. On the left panel we further restrict the sample to villages below the median of the orthogonalized threshold $\hat{\phi}_i$ and on the right panel above the median of $\hat{\phi}_i$. Point estimates represent dynamic effects relative to the reference period (long differences). Controls include village-level average GDP, rainfall standard deviations, as well as total rainfall and mean surface temperature variation. Standard errors on the 1% level.

Figure 13: Staggered treatment effect on tree loss - including 1st order neighbor sample



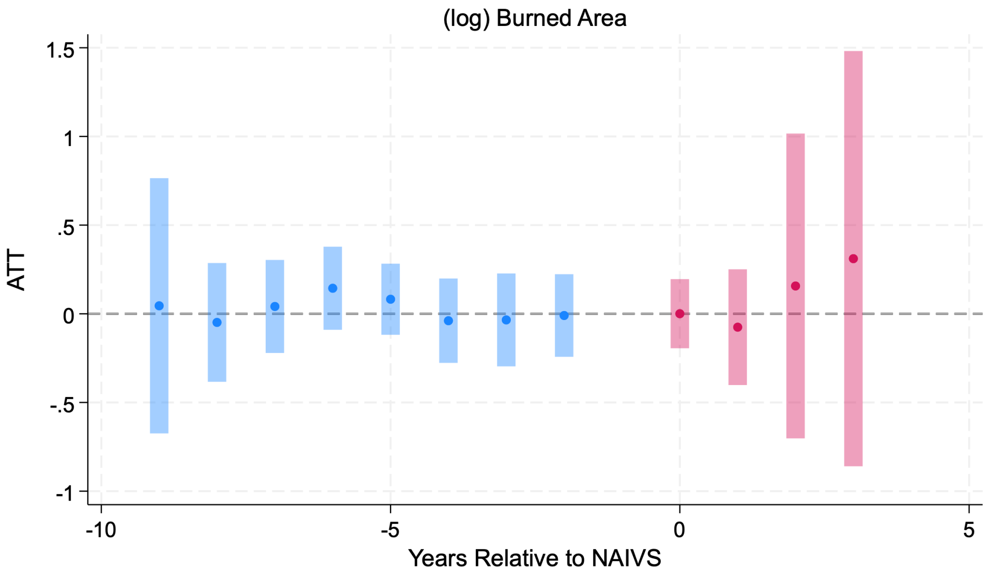
Note. The figure shows the estimated average treatment effect on the treated of the policy on (log) tree loss with the difference-in-difference estimation method by Callaway & Sant'Anna (2021) on the restricted 1st and 2nd neighbor sample. Point estimates represent dynamic effects relative to the reference period (long differences). Controls include village-level average GDP, rainfall standard deviations, as well as total rainfall and mean surface temperature variation. Standard errors on the 1% level.

Figure 14: Staggered treatment effect on cropland - including 1st order neighbor sample



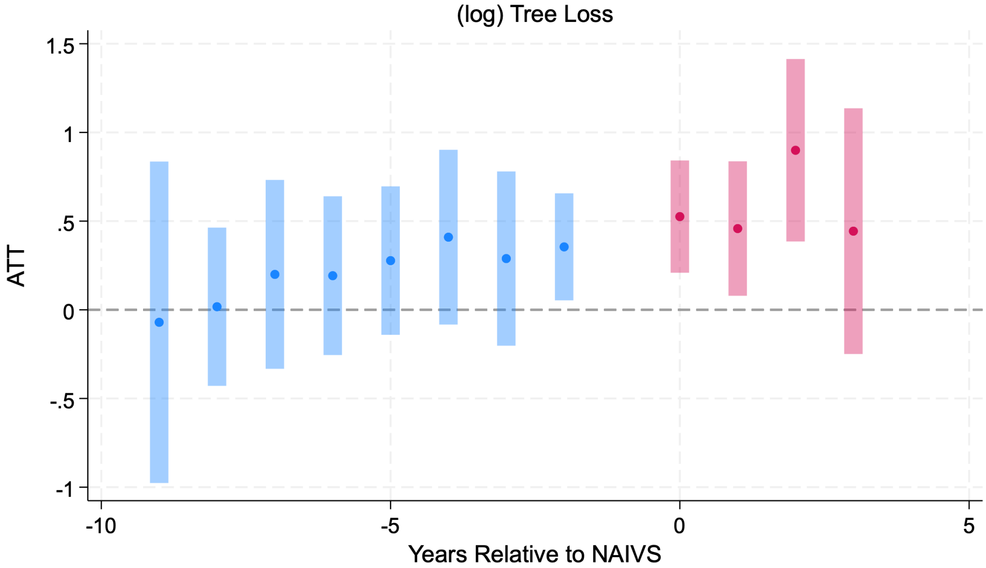
Note. The figure shows the estimated average treatment effect on the treated of the policy on (log) cropland with the difference-in-difference estimation method by Callaway & Sant'Anna (2021) on the restricted 1st and 2nd order neighbor sample. Point estimates represent dynamic effects relative to the reference period (long differences). Controls include village-level average GDP, rainfall standard deviations, as well as total rainfall and mean surface temperature variation and lagged total rainfall. Standard errors on the 5% level.

Figure 15: Staggered treatment effect on fires - including 1st order neighbor sample



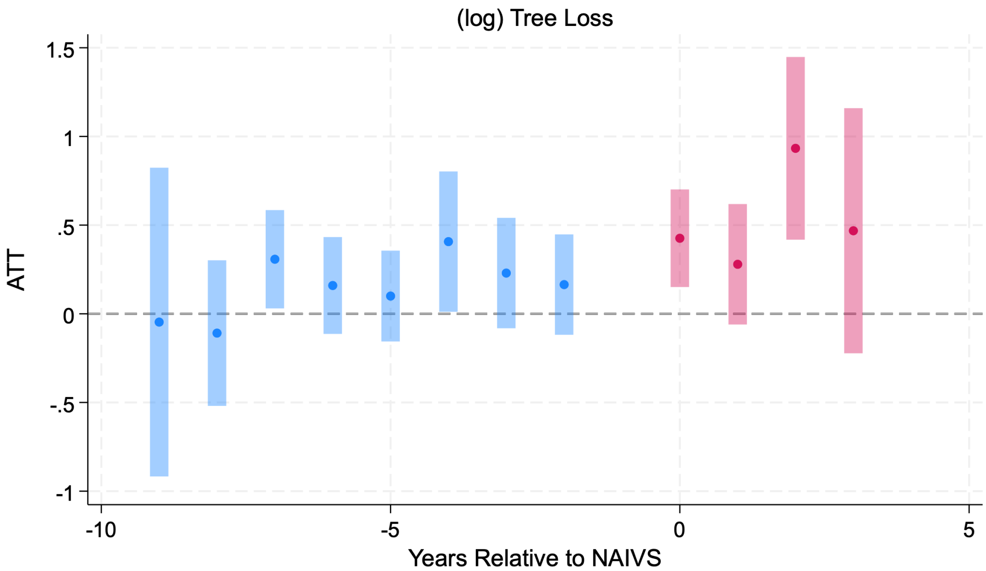
Note. The figure shows the estimated average treatment effect on the treated of the policy on (log) burned area with the difference-in-difference estimation method by Callaway & Sant'Anna (2021) on the restricted 1st and 2nd order neighbor sample. Point estimates represent dynamic effects relative to the reference period (long differences). Controls include village-level average GDP, rainfall standard deviations, as well as total rainfall and mean surface temperature variation. Standard errors on the 1% level.

Figure 16: Staggered treatment effect on Tree Loss - never treated control



Note. The figure shows the estimated average treatment effect on the treated of the policy on (log) burned area with the difference-in-difference estimation method by Callaway & Sant'Anna (2021) on the restricted 2nd order neighbor sample with a never treated control group. Point estimates represent dynamic effects relative to the reference period (long differences). Controls include village-level average GDP, rainfall standard deviations, as well as total rainfall and mean surface temperature variation. Standard errors on the 1% level.

Figure 17: Staggered treatment effect on fires - nightlight control



Note. The figure shows the estimated average treatment effect on the treated of the policy on (log) burned area with the difference-in-difference estimation method by Callaway & Sant'Anna (2021) on the restricted 2nd order neighbor sample. Point estimates represent dynamic effects relative to the reference period (long differences). Controls include village-level average GDP, average nightlight intensity, rainfall standard deviations, as well as total rainfall and mean surface temperature variation. Standard errors on the 1% level.