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Abstract: Agriculture and forests are often viewed as competing land uses, and stronger land tenure is expected to sharpen that competition by making land easier to clear and cultivate. We revisit this trade-off using the Digital India Land Records Modernization Programme, which digitized over 380 million land records across more than 630,000 villages while leaving property rights unchanged. Exploiting its staggered rollout in a difference-in-differences framework, we find that agricultural and forest cover both increased, in spatially separate areas. This pattern fits India's dry-forest ecology, where cultivation and forest are interspersed, unlike rainforest frontiers. Reduced transaction costs for citizens and the state appear to drive the results. Land conflict declined, agriculture expanded where credit access had been limited, and forest cover improved in state-protected areas. These results indicate that digital land administration can have biophysical consequences without reallocating rights.

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1 Introduction

As societies ramp up agricultural production to meet rising demand for food and income, forests pay the price through deforestation and land conversion (1–4). This apparent trade-off between expanding agriculture and protecting forests is widely recognized by scholars and policymakers (5, 6), and shapes debates over both food production (7, 8) and conservation (9). Most prior work on this trade-off centers on tropical rainforests, which span the Amazon Basin, Central Africa, and Southeast Asia, and store roughly half of the world’s terrestrial carbon while covering less than one-third of global tree-cover (7, 10, 11). These areas are also home to some of the most aggressive frontiers of agricultural expansion (6).¹

In this paper we examine if the trade-off between agriculture and forest conservation is a general feature of policy, or of the frontier settings where they have been studied. To do so, we study tropical dry forest regions, which represent another important, yet relatively understudied forest type that account for roughly 40–45 percent of tropical and subtropical forest area worldwide and store an estimated 15–20 percent of tropical forest carbon (11, 16, 17). These areas are found across countries with prolonged droughts like India, Mexico, Madagascar, and parts of East Africa, where rainfall is highly seasonal (18, 19). Dry-forest areas are characterized by two sets of conditions. First, agricultural systems in these regions are typically smallholder-dominated, rain-fed, and labor-intensive (20). Second, agriculture and forests are relatively spatially interwoven in dry-forest areas and not organized along an expanding frontier as in the rainforest (21, 22). Because of these conditions, interventions that raise the value of land need not generate the zero-sum trade-offs between agricultural productivity and forests.

We examine these potential trade-offs by evaluating a land record digitization reform implemented across India. The Digital India Land Records Modernization Programme (DILRMP) has digitized over 380 million land records, making it the world’s largest experiment in land record modernization.² The reform aimed to bring transparency, accessibility, and administrative coherence to India’s complex system of property documentation. Succinctly, the program converted existing paper titles to digital titles, which potentially reduced transaction costs for both citizens and administrators. For instance, citizens no longer needed to travel long distances to carry out property transactions, while administrators became less dependent on local intermediaries for planning and verification.

Unclear, fragmented, and difficult-to-access land records weaken de facto property

¹In Latin America, mechanized soybean cultivation and cattle ranching have advanced deep into the Amazon (12, 13) and in Southeast Asia, oil-palm plantations have replaced extensive lowland forests (14). Together, beef, soy, and palm oil account for over half of tropical agricultural deforestation (15). This model of export-oriented, capital-intensive expansion delivers short-term economic returns but erodes long-term ecological stability, pitting farms and forests directly against each other (1).

²Based on India’s Digital India Land Records Modernization Programme MIS, which reports about 380 million Records of Rights and 630,000 villages as of November 2025 (23). This scale exceeds the publicly reported figures for Indonesia’s Pendaftaran Tanah Sistematis Lengkap (PTSL) ($\approx$ 117 million plots registered by September 2024 (24)) and Turkey’s Tapu ve Kadastro Genel Müdürlüğü (TKGM) cadastral register ($\approx$ 59 million parcels (25)). Comparable global rankings are not available, but to the best of our knowledge no other national land-records digitization program documents a larger record count.

rights and reduce landholders' incentives to invest through a number of channels. First, when owners are uncertain about their ability to reap returns from their land, they underinvest in long-term improvements (26–28). Insecure titles lower expected returns of productive investments by heightening fear of expropriation or encroachment (29). They also impede access to credit as banks rely on clear documentation to collateralize loans (30–32). Second, unclear titles also raise the risk of dispute over land diverting resources toward protection rather than investment. Together, these channels imply that improvements in the clarity and accessibility of land records should raise agricultural investment.

For state administrators, unclear or inconsistent records similarly undermine the ability to monitor land use and protect government property. Enforcement agencies face higher costs of detecting encroachment or illegal extraction with unclear boundaries, and jurisdictional disputes weaken their ability to intervene effectively (33–35). Reforms that digitize records and cadastral maps, therefore, can reduce informational frictions and increase the state's capacity to detect, deter, and sanction unauthorized forest clearance (36, 37). These improvements should enhance forest protection, especially in areas where government agencies have clear authority, such as protected areas.

We use a difference-in-differences design to study if the implication of these household and administrative about the potential co-benefits for agriculture and forests bear out the data. We use the staggered implementation of DILRMP to estimate the effects of land record digitization on agriculture and forest cover in a primarily dry-forest setting, India. Understanding the effects of such reforms is important both for their country-wide scale and also because the impact of reforms that build government land administration capacity have been less well-researched than reforms that provide titles to landowners (38).

We begin our analysis by showing that, contrary to prior work on property-rights reforms, digitization resulted in improvements in agriculture without forest cover loss. In fact, we show that in DILRMP subdistricts both agricultural and forest cover increased, relative to non-adopting subdistricts. We observe no differences in subdistricts before the implementation of the program, allowing us to attribute these gains to the timing of digitization. DILRMP therefore provides at-scale evidence that improving the legibility of existing land records, without altering ownership, can be beneficial for both ecological and economic outcomes.

Because prior work notes that competition between agriculture and forest can be localized, the second part of our analysis investigates whether such trade-offs are present despite the average positive effects. We show that improvements in both agriculture and forests arise from different parts of India. First, we demonstrate that at baseline agricultural and forest cover are already largely spatially separate, suggesting that different mechanisms might be at play for the two outcomes. Second, we show responsiveness to DILRMP also varied spatially: agriculture increased primarily in zones with low baseline agriculture and low forest cover, while forest gains occurred where baseline forest share was high and agricultural cover low. Taken together, this set of results suggests, unlike a frontier dynamic between agriculture and forest, the reform allowed both agricultural and forest systems to strengthen along different margins of the landscape.

In the final set of analyses we provide evidence on the mechanisms undergirding these

impacts on agriculture and forests. First, we show that the program reduced the incidence of reported land conflicts, consistent with improved dispute resolution and tenure clarity, which we broadly interpret under the umbrella of reduced transaction costs. Second, agricultural gains concentrated in subdistricts with weaker prior bank coverage. One interpretation is that these are locations where prior to digitization banks rationed credit due to the lack of information on potential borrowers. Third, turning towards forests, we show that improvements are concentrated in protected areas, where digitization likely enhanced boundary enforcement and reduced administrative ambiguity. Finally, since land is a finite resource, improvements in agriculture and forest cover must come at the cost of other land uses. We document that trade-offs arise in savannas and grasslands. Both of these land covers are often classified as “wastelands,” an administrative category for ecologically “degraded” or “unproductive” land that is suitable for reclamation by the state.³ Together, these results suggest that enhanced property-records legibility can operate through separate channels: by enabling agricultural expansion through credit access and secure use rights, and by strengthening forest protection through clearer jurisdictions.

India’s DILRMP breaks new ground on both scale and substance. First, on scale, few property rights reforms have achieved such national reach, offering a rare opportunity to examine how large-scale administrative capacity-building can shape agricultural and environmental outcomes. Other prominent programs, while implemented nation-wide, are substantially smaller than DILRMP, with only Indonesia’s Pendaftaran Tanah Sistematis Lengkap closest in size as described in footnote 2.

Second, on substance, most prior research examines the important impacts of titling and formalization reforms, both of which entail *de jure* changes in land rights (31, 34, 35, 38, 41–45). DILRMP is neither a titling nor a formalization program. It does not issue new land titles, change ownership, legalize informal cultivation, or redistribute property. Instead, DILRMP is a systemic effort to improve the capacity of land administration in India, by digitizing textual land records, computerizing cadastral maps, linking ownership and spatial data, and integrating them into unified, state-level platforms.

These features of DILRMP fill a crucial gap in the study of property rights reforms building on prior work on titling and formalization programs in the literature. In a recent review of land tenure interventions across the world, Tseng et al. (2021) highlight a striking gap (38): among the 117 studies they analyze, of which less than half had a research design with a counterfactual and more than one time period, only seven evaluate capacity-building reforms usually at a much smaller scale, leaving room for at-scale causal evidence. To our knowledge, no existing study demonstrates that capacity-building reforms can generate joint agricultural and ecological gains, what we call the double dividend of property rights.

³Researchers argue that the wasteland classification is a political construction rather than an environmental one (39). Grasslands and savannas are ecologically distinct biomes that are important for biodiversity and as a common pool resource to those who rely on these lands for foraging, fuel, and grazing (40).

2 Land Administration in India

India's land administration system imposes high transaction costs on both landholders and the state because the responsibility for documenting property rights is split across three partially disconnected arms: registration, revenue, and survey. Registration offices record transactions; revenue departments maintain property ownership documents known as Records of Rights (RoRs) and mutation entries; and survey departments manage cadastral maps and boundary demarcations. Because of improper coordination across the three meant that records tended to be out of date (46–48).

Various field audits outline these frictions. For instance, in tehsil-level surveys conducted by the National Council of Applied Economic Research (NCAER), ownership-record discrepancies between paper RoRs and on-ground holdings reached 34% in Shimla Rural and 6% in Baddi (Himachal Pradesh), and 78% of parcels in Shimla Rural and 52% in Baddi showed area variation greater than 5% between RoR and ground measurement (49). Beyond unreliability, paper-based records are also costly to access. Landowners often need to visit subdistrict offices in person, and are sometimes asked to make informal payments to obtain certified documents. Taken together, these frictions raise the cost of proving ownership creating impediments to accessing credit, government agricultural schemes, and other programs that require documentation of rights (50).

These documentation gaps also create governance problems in forested regions where inconsistent records blur the boundary between agricultural and legally protected land. Cadastral maps often do not align with forest department maps or reflect decades of settlement (51, 52), so farmers may cultivate land that official records classify as forest, while forest departments may assert authority over land villagers consider privately held. Land Conflict Watch records that an estimated 0.5 million people in India are affected by conservation and forest-related land conflict over 2 million hectares (53, 54). Paper-based systems compound the problem. State-level forest departments cannot access local records and rely on manual inspections, local memory, or outdated maps, so gradual encroachment and illegal extraction often go unnoticed.

2.1 DILRMP Implementation

India experimented with land administration modernization as early as the late 1980s. The Strengthening of Revenue Administration and Updating of Land Records scheme was launched in 1987-88 and the Computerization of Land Records scheme in 1988-89, but both were limited in scope and uneven across states (46, 55). The two were merged into the National Land Records Modernisation Programme in 2008 and renamed the Digital India Land Records Modernisation Programme in 2016, when the program was folded into the Digital India initiative and central funding was raised to 100% (46). Because land policy is governed by India's federal states, DILRMP is fully funded by the central government but implemented by states, and program funds support a tehsil-level infrastructure layer. The original guidelines budgeted approximately Rs. 1,220 crore for modern record rooms across roughly 4,880 tehsils and Rs. 3,200 crore for cadastral survey and resurvey (56, pp. 40-43).

DILRMP was designed to target administrative frictions directly. Rather than altering

property rights or redistributing land, DILRMP modernizes the informational infrastructure of land governance through three components: (i) digitizing textual RoRs, (ii) updating and rescanning cadastral maps, and (iii) integrating spatial and ownership records through computerization of registration (56, 57).⁴ Overall, the program is built around four design principles articulated in the original 2008 guidelines: a single window for handling land records; a “mirror” principle in which cadastral records reflect ground reality; a “curtain” principle in which the digital record is taken as definitive; and eventual title insurance (56, p. 8).

DILRMP’s institutional architecture distributes responsibilities across four nested administrative tiers: state, district, subdistrict/tehsil/block, and village. Three features of DILRMP’s institutional design make the subdistricts a key unit for the program’s success.

First, the citizen-facing infrastructure of the reform is at the subdistrict level. The subdistrict tier includes modern record rooms, computer centers, and the local-revenue-office connectivity that issues certified RoRs and processes mutations (58, 59). The 2008 program guidelines designate the modern record room as the physical locus of citizen-service delivery, envisioning a storage area for records, an operational area with computers and printers, and a public-service area for reception at each subdistrict location (56, p. 43).

Second, the subdistrict review committee is perhaps the most operationally consequential. DILRMP’s Monitoring and Review architecture comprises four committees whose meeting frequency intensifies at lower tiers. The state committee meets twice a year, division every quarter, district every month, and the subdistrict committee meets fortnightly (58, pp. 58-59). In addition, unlike the higher committees whose Forest Department coordination occurs at the level of senior administrators, the subdistrict committee seats the State Forest Department representative alongside the line revenue functionaries (Tehsildar, Naib Tehsildar, Patwari, and Village Development Officer) who demarcate revenue-forest boundaries in the field (58, pp. 58-59), enabling on-the-ground coordination.

Third, the subdistrict is the lowest tier at which independent state verification of the digitized records occurs. Village-level 100% checking by the Patwari is tightly coupled with the data-entry process itself, whereas the Tehsildar is asked to randomly check 10% of the data at the subdistrict, which is the first check performed at arm’s length from the data-entry process (58, p. 37).

The subdistrict, therefore, serves as the primary citizen interface for land administration under DILRMP aiming to reduce the time, uncertainty, and coordination problems associated with obtaining certified RoRs, filing mutations, resolving disputes, and linking maps to textual records.

2.2 Key Changes Introduced by Digitization

After digitization, records become available online or through Common Service Centres (CSCs), which are privately operated kiosks authorized to issue certified copies at

⁴A revenue official in Kerala explained the process for digitizing RoRs, which was the first component of the program: “In the village offices, they took the registers and scanned them in the village office. Then the revenue department conducted a massive data entry exercise... After verification, the record was approved.” (Author’s interview with an official in the Kerala Survey and Land Records Directorate, 2025.08.18., Ernakulam district.)

government-fixed fees.⁵ Citizen access was eased in terms of time and effort costs through the standardization of fees, setting specific timelines for processing, and by the reduction of discretionary control by bureaucrats. Under the new system, RoRs and cadastral maps can be retrieved within a day, and in some cases within minutes, compared to multi-day waits in subdistricts where paper records remained in use (49, 60).

On the state side, digitization improved the legibility and accessibility of land records for government agencies, which historically faced longstanding mismatches between Revenue Department records and those maintained by Forest Departments that relied on separate maps and notifications (52, 61). A Forest Department official in Kochi described the change directly: “As we have different departments, when the Revenue Department assigns the land [to a person], the Forest Department [records] might not get updated. . . . However, by the digitization of [land records], further changes in the forest land can be monitored properly.”⁶ While digitization is unlikely to automatically resolve underlying disputes, it lowers the costs of identifying them by consolidating textual records into centralized, searchable databases, making inconsistencies across departments visible and easier to flag.

2.3 How DILRMP Shapes Agriculture and Forest Protection

India’s tropical dry forests differ ecologically from the tropical rain forest frontiers that dominate the existing literature on property rights and land use. In rain forest ecologies, cultivation and forest cover are typically arrayed along an active frontier, where agricultural expansion advances into previously forested land (62, 63). Contrast this with dry-forest settings where agriculture and forest are spatially interspersed such that cultivation concentrates on historically settled, irrigable, or more fertile zones, while forests persist on marginal or less arable terrain (64, 65). This ecological structure reshapes the theoretical question around the role of property rights.

We argue that digitization’s effect on both agriculture and forest cover operates through reducing transaction costs for both landowners and the state. On the agriculture side, we expect that digitization, first, should make it easier for landowners to access their landownership documents by reducing waiting times and rent-seeking. Second, faster and more transparent documentation strengthens tenure security and reduces uncertainty about the ability to prove ownership in the event of dispute or state action (66–68). Third, easier access to land documents should reduce the costs of using land as collateral, expanding access to credit (28). Banks ration credit when they cannot easily verify who will reliably repay (69), and this problem is most severe where local branches and the relationships and local knowledge they produce are sparse (70). Digitized land records make ownership verifiable even when bank presence is sparse, so their effect on agricultural investment should be largest in subdistricts with fewer bank branches. Together, these imply that improved access to credit and lower likelihood of land disputes should enable landowners to invest more into expanding cultivation (28, 41, 66, 71–73).

On the state side, digitization should strengthen forest protection by lowering the transaction costs of monitoring and enforcement through two main pathways. First,

⁵The local names of CSCs vary by state: Akshaya Centre (Kerala), e-Seva (Tamil Nadu), MeeSeva (Andhra Pradesh), Jan Seva Kendra (Gujarat) etc.

⁶Author’s interview with Forest Department official in Kochi, 2026.03.03, Ernakulam district.

consolidating records into a centralized and searchable database should reduce the informational cost of detecting encroachment and verifying claims on government land.⁷ Second, improved records management should also reduce the cost of resolving boundary disputes that have historically impeded forest department officials. These pathways are most likely to be effective where the state has clear jurisdictional authority, such as protected areas.

3 Materials and Methods

We construct a balanced panel dataset at the subdistrict (tehsil) level for India spanning the period 2001–2022. The dataset combines information on the timing of DILRMP adoption, land use outcomes derived from satellite imagery, measures of land conflict, indicators of financial access, and administrative and geographic covariates. Summary statistics are reported in Supp. Mat. Table A3. All spatial data are harmonized to 2011 Census subdistrict boundaries, which serve as the reference geography throughout the analysis.

3.1 Rollout of DILRMP

Information on the implementation of DILRMP is obtained from the official Management Information System maintained by the Department of Land Resources, Government of India.⁸ While the MIS reports the completion status of multiple components of the reform at the village level, we focus on the core component which is the digitization of textual property titles known as Records of Rights. Digitization of RoRs directly improves the legibility and accessibility of property documentation for both landholders and the state.⁹ Other components include cadastral map digitization, integration of textual and spatial records, establishment of tehsil-level modern record rooms, training of revenue and survey officials, etc (56, 59). RoR digitization is listed as the first component in enumeration of DILRMP activities (46, 56, 59, 77).¹⁰

We code a subdistrict as having adopted the program (treated) in the year when any village in that subdistrict reports the completion of RoR digitization. We scraped the MIS data at three points in time (July 2020, August 2023, and May 2024) in order to recover the earliest reported completion date for this component. Because the MIS does not include Census identifiers, we manually harmonize village and subdistrict names to 2011 Census boundaries.

We match MIS villages to 2011 Census villages using a hierarchical name-matching procedure that proceeds from finer to coarser geographic levels. We first retain exact matches on state, district, subdistrict, and village names (433,124 villages). For unmatched

⁷Weak forest governance often reflects not only political resistance or limited coercive capacity, but also fragmented and opaque information systems (61, 74–76).

⁸<https://dilrmp.gov.in/>

⁹Across Indian states, different terms are used for RoRs: Record of Rights, Tenancy and Crops (Karnataka), 7/12 extract (Gujarat and Maharashtra), Khasra (Uttar Pradesh, Madhya Pradesh, Chhattisgarh, Rajasthan).

¹⁰In practice, states have completed RoR digitization far ahead of other components: nationally, 90 percent of RoRs had been digitized by January 2021 compared to 53 percent of cadastral maps (78).

cases, we then apply fuzzy matching on village names, where we break ties with household counts within units that are exactly matched on state-district-subdistrict levels (71,468 villages at an 80% similarity threshold). Together, these tiers, all of which are exact at the subdistrict level, account for 504,592 villages. The remaining matches relax the geographic requirement: 18,983 villages are matched by fuzzy village-name matching within units exact only at the state–district level (90% threshold), and 1,294 within units exact only at the state level (95% threshold). In total we match 524,869 villages, or 82.5% of the village universe. The vast majority of matches (504,592, or 96.1% of matched villages) are exact at the subdistrict level and are thus correctly assigned to their treatment unit; only 20,277 villages (3.9% of matches) are assigned to a subdistrict on the basis of a coarser match.

3.2 Treatment Definition

We code treatment as the timing of the Computerization of Records of Rights (Figure 1 (a)). Within DILRMP, RoR digitization is the program’s first component and a logical prerequisite for all subsequent steps: the digitization and integration of cadastral maps, the linkage of registration with land records, and the voluntary integration of Aadhaar all presuppose a digitized textual record of rights. Figure 1 illustrates the digitization process: panel (b) shows a record room where paper records are kept; panel (c) a paper record from a tax register; and panel (d) a final digitized form. Coding treatment at this first step therefore captures the onset of a subdistrict’s entry into the program, with later components layered on afterward.

Implementation has been highly heterogeneous. By 2012 only Karnataka had completed RoR digitization, but by 2020 most states had begun or completed this step, with rollout staggered across subdistricts between 2012 and 2022 (Supp. Mat. Fig. A2). A subdistrict is classified as treated in the first year in which any village within its jurisdiction completes RoR digitization, and zero otherwise. This is a conservative definition that minimizes measurement error from staggered village-level implementation and potential spillovers among villages within the same subdistrict. The comparison group includes both subdistricts that never adopt DILRMP during the sample period and not-yet-treated subdistricts in periods prior to their adoption (79). For details on treatment data construction, see Supp. Mat. A.

Figure 1: DILRMP Timing across Subdistricts



Notes: Panel a) shows the number of subdistricts by year of first treatment adoption. Panel b) shows the image of a land record room which stores paper-based cadastral maps for a district; Panel c) shows an image of a Basic Tax Register (BTR) in Kerala, which is used by the Revenue Department to establish property ownership and assess taxes on land, while panel d) shows a digitized version of a BTR.

3.3 Land Use Outcomes

To measure our land cover outcomes, we use annual land use data from the MODIS Collection 6 Land Cover Type product at 500-meter pixel resolution for the years 2001–2022 (80). This database offers advantages when classifying land cover due to its calculation methodology, which accounts for potential biases and errors caused by atmospheric pollution in images, as well as specific effects of brightness and cloud cover (further description in Supp. Mat. B). Land use classes are defined following the International Geosphere–Biosphere

Programme (IGBP) classification scheme. Supp. Mat. Table A1 provides the description of each land cover type.

We begin by spatially intersecting land use pixels with subdistrict boundaries. To construct our forest measure, we compute for each subdistrict the share of its area falling into each of the five forest sub-categories: evergreen needleleaf forest (layer 1), evergreen broadleaf forest (layer 2), deciduous needleleaf forest (layer 3), deciduous broadleaf forest (layer 4), and mixed forest (layer 5), where each layer defines a pixel as a one in the data if there is tree coverage greater than 60 percent of the relevant category, and zero otherwise. We sum these shares into a single forest category. Agricultural cover is similarly measured using the cropland category, where a pixel is classified as agricultural if croplands cover at least 60 percent of its area.¹¹

We aggregate pixel-level classifications to subdistrict to mitigate concerns about classification noise in satellite data. The median subdistrict in our sample covers approximately 340 square kilometers, which is equivalent to over 1,360 MODIS pixels (Supp. Mat. Fig. A1). This process ensures that our outcomes capture meaningful changes in land use rather than idiosyncratic pixel-level variation. For further discussion on minimizing measurement error, see the Supp. Mat. B.

3.4 Mechanisms

To examine whether forest outcomes differ on state-owned land, we compile protected area boundaries from OpenStreetMap (81), which classifies areas according to the International Union for Conservation of Nature (IUCN) management categories. We retain the seven categories that designate protected nature areas, spanning IUCN categories Ia through VI which refer to areas from strictly protected reserves to areas managed for sustainable resource use and exclude areas protected for social, cultural, or resource-specific purposes.¹² See Supp. Mat. Table A2 for a description of the different categories. We georeference protected areas as points and polygons. Additionally, we draw a 10-km buffer around these protected areas and code subdistricts as exposed if they have either a protected area or a buffer intersecting them. The 10-km buffers represent Environmentally Sensitive Zones (ESZ) defined by the Environment Protection Act, 1986. Within ESZs, cutting down trees remains regulated by the government. We code each subdistrict based on whether or not they intersect with a protected area and its buffer.

Data on land-related conflict are drawn from the Land Conflict Watch database, which documents ongoing conflicts across India and classifies them by sector, including conservation, infrastructure, and land use (53). Conflict locations are geocoded using the Google Maps API and spatially matched to subdistricts. For each subdistrict-year, we count the number of ongoing conflicts as the cumulative number of conflicts that have started up to

¹¹For further analyses, we repeat these procedures for other layers. Shrubland cover is constructed by aggregating closed shrublands (layer 6) and open shrublands (layer 7). Grassland cover uses the grasslands category (layer 10). Savanna cover combines woody savannas (layer 8) and savannas (layer 9). We also construct a measure of cropland/natural vegetation mosaics (layer 14).

¹²Specifically, we code as protected nature areas: Strict Nature Reserve (`protect_class=1a`), Wilderness Area (1b), National Park (2), Natural Monument (3), Habitat/Species Management Area (4), Protected Landscape/Seascape (5), and Protected Area with Sustainable Use of Natural Resources (6).

that year, minus the cumulative number of conflicts that have reached a legal resolution. A conflict enters the count in the year it begins and exits in the year its legal resolution takes effect. The series starts in the year of the first recorded conflict in the database.

To capture variation in access to formal credit, we calculate the number of branches per thousand residents based on data of bank branches and 2011 census data (82, 83) and we classify subdistricts into under- and highly-banked subdistricts. Under-banked subdistricts are situated in districts with a lower than national median ratio of bank branches to population and highly-banked subdistricts are situated in districts with higher than median branches per capita ratio. We estimate treatment effects in both of these categories.

Qualitative Evidence To trace the mechanisms linking the reform to outcomes on the ground and to understand how landowners and the state interact in the land administration system, we conducted fieldwork in 2025 in Ernakulam and Thiruvananthapuram districts (Kerala) and Madurai district (Tamil Nadu). Qualitative fieldwork was approved by the London School of Economics and Political Science in Research Ethics Protocol 580731. Local civil-society organizations working with farming communities helped facilitate site access in each location. At every site we held semi-structured interviews with smallholder and large farmers, village council presidents, and officials from the land administration apparatus, including revenue officers, forest officers, and survey staff. We conducted interviews in local languages with the help of translators where needed. These interviews covered respondents’ experiences obtaining and using ownership documents, accessing records before and after digitization, and the day-to-day consequences of the reform. The resulting accounts, that we provide throughout the manuscript, illuminate how citizens and officials perceive and adapt to institutional change in land administration, and together they offer the on-the-ground texture that complements our study’s quantitative findings.

3.5 Empirical Strategy

We estimate the effect of land record digitization on land use outcomes using a difference-in-differences framework. Recent work shows that conventional two-way fixed effects estimators can produce biased estimates when treatment effects are heterogeneous across cohorts or over time (84–86). We therefore estimate the average treatment effect on the treated using the doubly robust estimator of Callaway & Sant’Anna (79), designed for staggered adoption. We first estimate the cohort-period treatment effects:

$$ATT(g, t) = \mathbb{E}[Y_t(g) - Y_t(0) | G_g = 1] \quad (1)$$

where $Y_t(g)$ and $Y_t(0)$ denote potential outcomes in year t under digitization beginning in year g and under no digitization, and G_g indicates subdistricts first digitized in year g . We then aggregate the cohort-period effects into event-study and overall summaries. We condition on a binary indicator for whether a subdistrict’s baseline land cover, such as agricultural (or forest) cover, in 2010 two years before the first wave of adoption, was above the median. This means that each newly digitized subdistrict is compared to not-

yet-digitized or never-digitized subdistricts with a similar baseline land cover, so that our estimates are not driven by, for instance, heavily forested areas being digitized earlier or later than sparsely forested ones.¹³ Because the cohort-period estimator compares changes in outcomes between newly digitized and not-yet-digitized subdistricts over the same period, time-invariant subdistrict characteristics and common annual shocks are differenced out, serving the role of subdistrict and year fixed effects. Standard errors are clustered at the subdistrict level.

For each of our analyses, we examine the dynamics of treatment effects using an event-study design that estimates differences in control and treatment trends relative to the year of adoption. Identification does not require early and late adopters to be comparable in levels, only that they follow parallel trends. This matters because early adopters and pilot sites were, according to government sources and press coverage, disproportionately large districts or those with stronger pre-existing state capacity.¹⁴ Because we condition on baseline characteristics, our key identification assumption is that subdistricts with similar baseline land cover would have evolved similarly absent digitization. We expect that if selection into digitization adoption is driven by pre-existing trends that also affect agricultural and forest cover, this would show up in pre-treatment trends. We present event-study estimates to assess the parallel trends assumption, test for pre-treatment trends, and to trace the temporal pattern of post-treatment impacts.

4 Results

4.1 Improvements in Both Agriculture and Forests

Without legible property rights, landowners face high transaction costs of investing in agriculture and the state faces high transaction costs of protecting forested areas. Digitizing land records should reduce transaction costs for both sides, allowing for both greater investment in agriculture and improvements in forest protection, especially when the two are not spatially trading off at a frontier.

In interviews, landowners consistently emphasized that digitization reduces both wait times and rent-seeking associated with accessing their land documents. 28 out of 36 respondents we interviewed expressed that digitization facilitated access to documents and reduced rent-seeking. A further 7 expressed that digitization improved the accuracy and trustworthiness of their documents and likely reduced disputes over land.

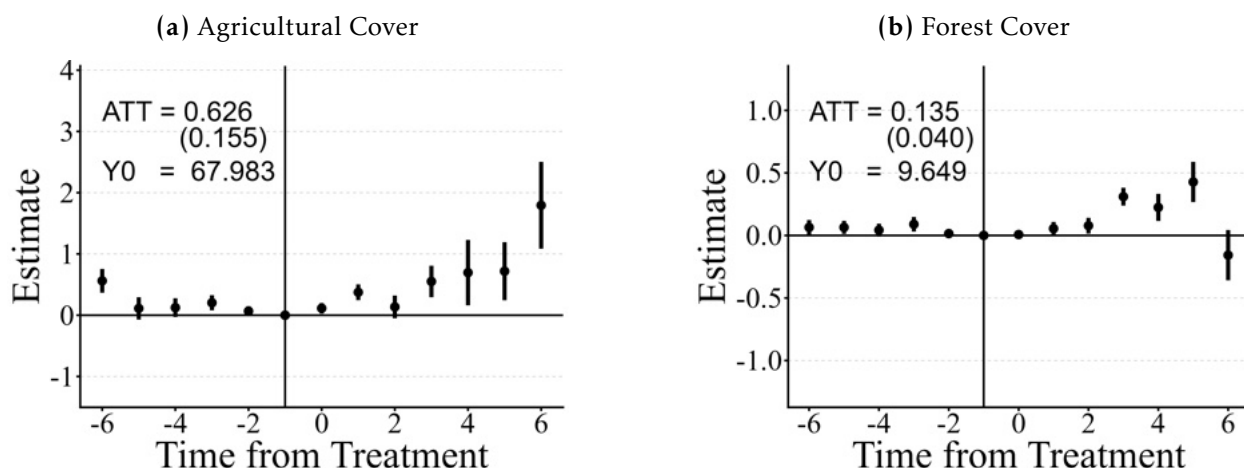
We quantitatively assess these insights from fieldwork interviews using the difference-in-differences models discussed above. We find positive effects of land record digitization on both forest and agriculture cover. Following digitization, the proportion of the subdistrict under agricultural cultivation increases by 0.626 percentage points (SE = 0.149; Tab. A4). This represents an increase of about 1% compared to a pre-digitization baseline of 67.98 percent of agricultural cover. For forest cover, the pre-digitization baseline is 9.649 percent of the average subdistrict. After digitization, this increases by 0.135 percentage

¹³In Supp. Mat. E, we also present results without conditioning on binary baseline land use characteristics and with using alternative conditioning such as terciles, quintiles, and deciles of the baseline outcome.

¹⁴See Government of Mizoram (2024) (87); Bhosale (2012) (88).

points ($SE = 0.044$) or by about 1.4%. Given that these results represent averages across all of India, they indicate significant improvements both in agricultural and forest cover. More specifically, these effects imply an additional 2 million hectares of agricultural area and an additional 0.44 million hectares of forest cover.¹⁵ Another way of interpreting these increases is to look at yearly average changes in agriculture and forest cover. For agriculture, the impact of digitization represents a reversal of 12 years of decline in agricultural areas and, for forests, it is equivalent to 6 years of net forest growth, from one administrative reform.¹⁶ These results are robust to using alternative conditioning variables and to not conditioning on baseline characteristics (Supp. Mat. Tab. A5).

Figure 2: DILRMP Effect on Agricultural and Forest Cover



Notes: Estimates come from the doubly robust staggered difference-in-differences estimator. Cohort-period treatment effects are aggregated into event-study estimates by relative time, measured in years before and after DILRMP adoption, with zero indicating the adoption year. Outcomes are the share of subdistrict area with agriculture cover (Panel a) and forest cover (Panel b). Comparisons are made conditional on a binary indicator for whether a subdistrict's baseline agricultural (or forest) cover in 2010 was above or below the median. The comparison group consists of not-yet-treated and never-treated subdistricts. Estimates are normalized relative to the period immediately before adoption; 95% confidence intervals are shown. Standard errors are clustered at the subdistrict level.

The key assumption to isolate the effect of land record digitization is that of parallel trends: treated and control units would have trended the same way if the treatment group did not receive the treatment. We report event-study estimates of the dynamic impact of digitization on land use outcomes as a diagnostic test for this assumption (Fig. 2). Relative time 0 corresponds to the adoption year. Pre-adoption (negative) coefficients capture differences between treated and control units before treatment. The estimated

¹⁵We compute these absolute area changes by applying the average treatment effects on the share of subdistrict area (Tab. A4) to India's total geographical area of approximately 328.7 million hectares: $0.626\% \times 328.7 \text{ M ha} \approx 2.06 \text{ M ha}$ for agriculture and $0.135\% \times 328.7 \text{ M ha} \approx 0.44 \text{ M ha}$ for forest cover.

¹⁶Between 2019 and 2021, agricultural area declined in India by approximately 170,000 ha and forest cover grew by approximately 77,000 ha. Forest cover figures are computed from the difference between successive India State of Forest Reports (52, 89); agricultural-area changes are computed from the Land Use Statistics at a Glance series published by India's Directorate of Economics and Statistics (90).

pre-trends are statistically indistinguishable from zero and remain stable up until the adoption year, offering evidence that the treatment and control groups had parallel trends prior to digitization. For agriculture, we see almost immediate treatment effects, whereas for forested areas digitization has a delayed impact of 1-2 years. Given the parallel trends assumption, the post-adoption coefficients can be interpreted as the causal effects of land record digitization. In the supplementary materials, we show that the event study estimates are robust to the set of baseline characteristics on which we condition parallel trends: we replace the linear baseline measure with indicators for terciles, quintiles, and deciles of the 2010 outcome, and we also report estimates with no conditioning at all (Supp. Mat. Fig. A3).

These results stand in contrast with prior work that finds in tropical rainforest settings that stronger property rights raise the value of land and, thus, contribute to increased forest clearing (3, 4, 91–93). The theoretical case for a trade-off is laid out by Angelsen (94): stronger tenure raises the net present value of clearing forests, therefore, improvements in tenure can produce a “race to the frontier” in which landowners and squatters clear preventively to secure ownership. However, Angelsen also warns that the impact of tenure security on deforestation may be context specific. The next section probes if such patterns might be localized despite net positive effects overall that we document thus far.

4.2 Minimal Evidence for Trade-offs

Our results so far offer evidence for the double dividend of land record digitization. However, in the prior section we have presented average effects, which might mask trade-offs between agriculture and forests in specific zones. For example, agricultural expansion may drive deforestation in places where pre-reform agricultural cover is low but forest cover is high.

To study the possibility of trade-offs by pre-reform forest and agricultural cover, first, we inspect the distribution of agricultural areas and forests pre-reform. Figure 3a shows that agricultural areas and forests are spatially distinct in India. Highly forested subdistricts typically have very low share of agricultural area and vice versa (Supp. Mat. Fig. A4). The fact that agriculture and forests are positioned spatially distinctly may suggest that agricultural expansion is unlikely to come at the cost of increased deforestation.

Second, we estimate the effect of digitization on agricultural and forest cover in three zones: subdistricts with lower than median pre-digitization share of agricultural and forest cover, subdistricts with higher than median pre-digitization share of agricultural area and lower than median share of forested areas, and subdistricts with lower than median share of agricultural area and higher than median share of forested area.¹⁷

We find that the effect of digitization dominates in different zones for agriculture and forests respectively. Agriculture expands most in places with low levels of pre-existing agricultural and forest cover (Fig. 3b; Tab. A6). In these subdistricts, the share of the subdistrict under agricultural cultivation expands by 1.799 percentage points (SE = 0.461) or by about 3.2%. Forest cover, meanwhile, improves in subdistricts of low pre-reform

¹⁷There are no subdistricts with higher than median share of pre-digitization agricultural and forested area.

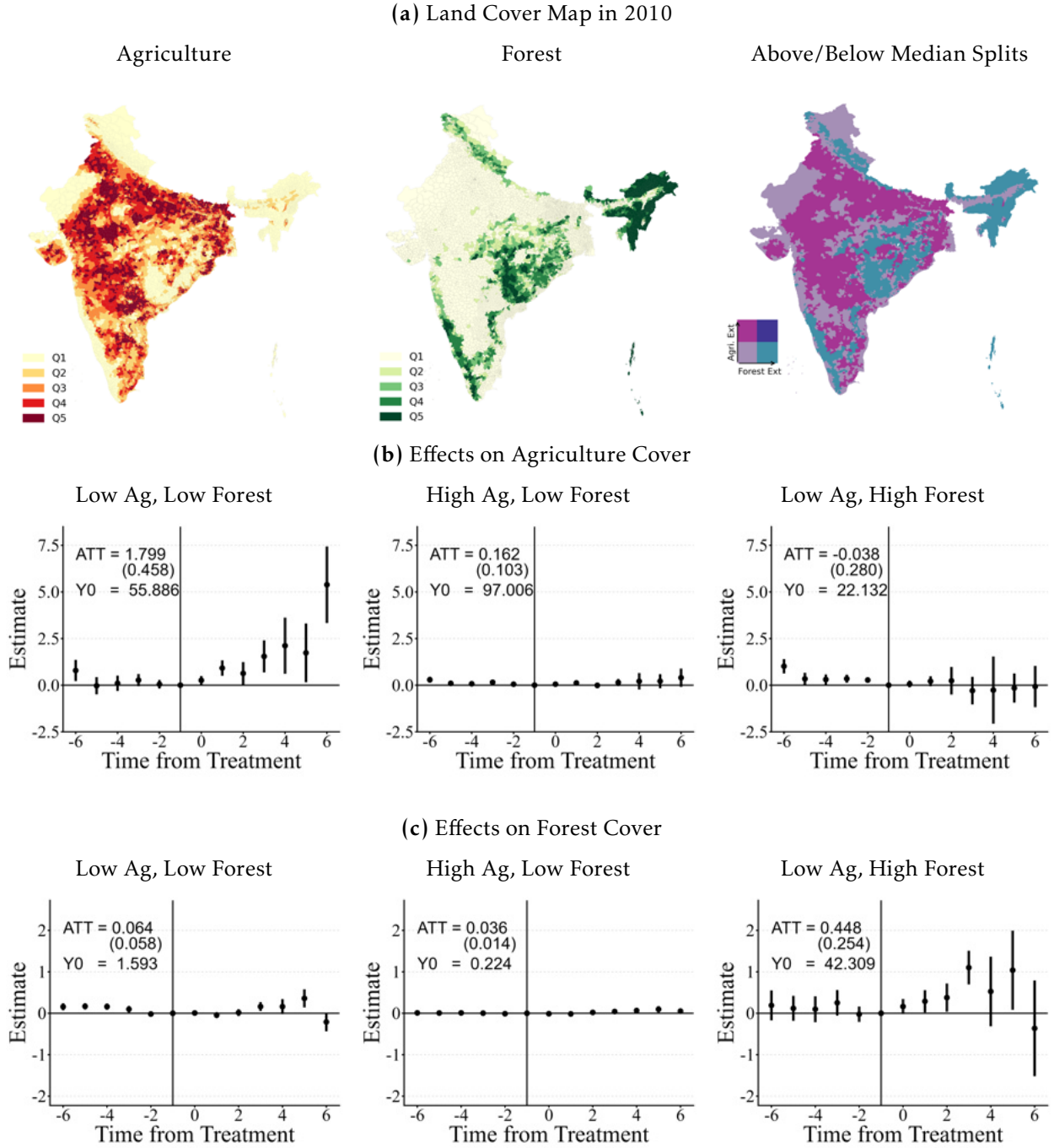
agricultural area, but high forest cover. There, we detect an increase of 0.448 percentage points ($SE = 0.254$) or 1.06% in forest cover, with close to zero change in forested areas in other zones (Fig. 3c; Tab. A6, Cols. 4-6).¹⁸

Although these results offer evidence of a double dividend in agriculture and forest cover, we may miss agriculture-driven deforestation where it is most likely to occur: at areas neighboring dense forests. We zoom into these areas by subsetting our dataset to only those subdistricts that have low-low pre-digitization shares of agricultural and forest cover with neighboring subdistricts with low-high pre-digitization share of agricultural and forested areas. We analyze the effects of digitization reform only within this subset.

Even in these most likely subdistricts, we find no evidence of a trade-off between agriculture and forest cover. If agricultural expansion comes at the cost of deforestation, we would expect agriculture to expand in subdistricts with low prior share of agricultural area and high forest cover. Furthermore, we would expect the share of forested areas to decline in these subdistricts post-digitization. We do not find evidence of such a dynamic. Instead, we find that agricultural cover expands in low-low areas (Supp. Mat. Fig. A5a, Tab. A7), but without any change in forest cover on either side of the boundary (Supp. Mat. Fig. A5b, Tab. A7).

¹⁸We detect a 0.036 percentage-point ($SE = 0.013$) change in forest cover in subdistricts with high levels of pre-reform agriculture and low forest. Although, this result is statistically significant, substantively it results in a small amount of forest cover change given the low baseline value.

Figure 3: No Evidence of Trade-offs Between Agriculture and Forest Areas



Notes: Panel (a) maps agriculture and forest cover, each the share of subdistrict area under that land use, and the above/below-median interaction classification. Panels (b) and (c) show the effect of digitization on agriculture and forest cover, estimated separately for subdistricts with low agriculture and low forest, high agriculture and low forest, and low agriculture and high forest cover. Points are event-study aggregations of the cohort-period effects from the doubly robust difference-in-differences estimator, normalized to the year before adoption, with 95% confidence intervals. Relative time zero denotes the adoption year. Each panel reports the overall ATT, its standard error in parentheses, and the 2010 outcome mean. Comparisons condition on above/below-median baseline cover in 2010, with not-yet-treated and never-treated subdistricts as controls. Standard errors are clustered at the subdistrict level.

5 Mechanisms

We have shown that digitization creates a double dividend of agricultural expansion alongside forest cover increase, which is not anticipated by explanations focused on a trade-off between these land use types. Hence, we turn to three observable implications of our proposed mechanism: reduction in the transaction costs of accessing ownership documents for landowners and of monitoring and enforcement for the state. If digitization's effect operates through lower transaction costs, we expect to see a reduction in land-related disputes, a more prominent increase in agricultural cover in subdistricts with previously lower coverage of bank branches, and a larger increase in forest cover in places where the state already has jurisdiction to enforce environmental outcomes.

Program reduced conflict around land on average We test the first of these observable implications by estimating the impact of digitization on land conflict. Before digitization, many disputes stemmed from landowners' inability to prove ownership, so we expect digitization to improve dispute resolution through two mechanisms: greater accessibility and greater tamper-resistance. Qualitative interviews support both channels. Landowners in Kerala, a state with high rates of outmigration, emphasized the accessibility channel. As one interviewee put it: "It's possible that some people have encroached on others' land, because those have gone abroad and once they are back their land is gone. After digitization, all of these issues will be cleared up."¹⁹ Others stressed that digital records are harder to manipulate. One response exemplified this view: "If I need to get a position certificate, my land record has already been scanned, so there's no possibility of cheating or altering the record. It has become easier for the ordinary people to access the record. With digitization, there won't be any room for malpractices or cheating."²⁰

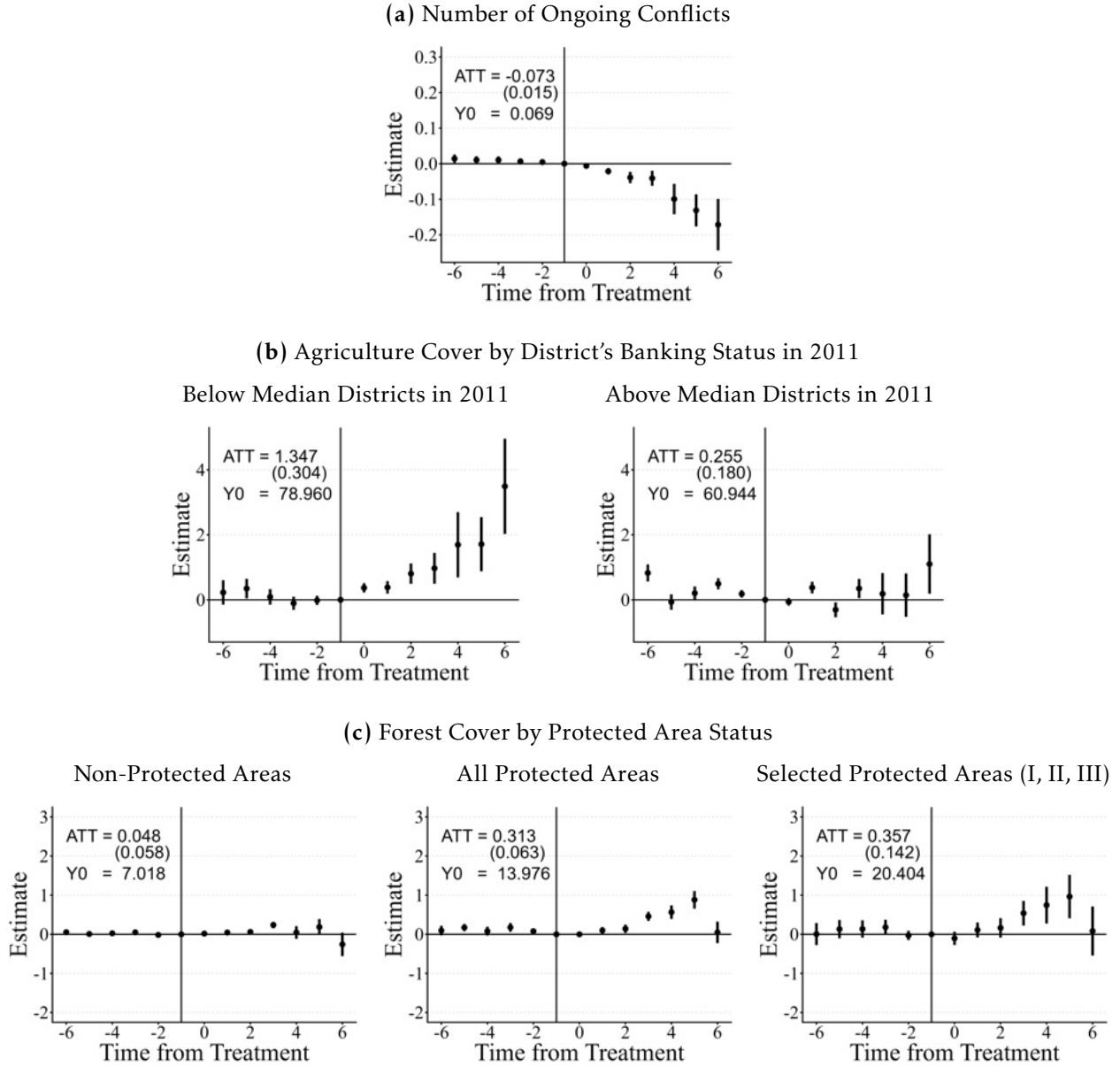
We more formally test digitization's impact on the number of ongoing land conflicts using data from the Land Conflict Watch database. Figure 4a shows that following digitization, there is a decline of 0.073 (SE = 0.015) in the number of ongoing conflicts. The effect is zero at adoption and grows over time, which indicates digitization prevents new conflicts rather than resolves existing ones. Because conflicts are rare in absolute terms, these are small changes in levels; but relative to the rate at which disputes accumulate absent the reform, they are substantial. Furthermore, when we break down these results by conflict type, we see that the largest reductions are in categories that our mechanisms directly imply: conflicts related to conservation and forestry and land use (Supp. Mat. Fig. A6 and Tab. A9). In contrast, we see no decline in conflicts linked to industry or energy projects.

Agriculture improves in under-banked areas Second, we investigate whether digitization led to higher agricultural expansion in subdistricts where scarce information prior to reform led to credit rationing. Stiglitz and Weiss argue that when banks have imperfect information about borrowers, they may choose to ration credit as opposed to simply raising

¹⁹Author's interview with landowner, 2025.08.08, Ernakulam district.

²⁰Author's interview with landowner, 2025.08.09., Ernakulam district.

Figure 4: Mechanism Tests for Digitization's Effects



Notes: Event time is measured in years before and after DILRMP adoption, with zero denoting the adoption year. Points are event-study aggregations of the cohort-period effects from the doubly robust difference-in-differences estimator, normalized to the year before adoption, with 95% confidence intervals. Comparisons condition on above/below-median baseline cover in 2010, with not-yet-treated and never-treated subdistricts as controls. Each panel reports the overall ATT, its standard error in parentheses, and the 2010 outcome mean. Standard errors are clustered at the subdistrict level. Panels (a), (b), and (c) show effects on, respectively: the number of ongoing land conflicts; agricultural cover, by districts with above- vs. below-median bank branches per capita; and forest cover, by non-protected, all protected areas and selected protected areas (categories I, II and III based on the International Union for Conservation of Nature) which have all been created before 2012. The conflict measure includes all types without distinction, the district classification is based on the 2011 Census of India, and the protected-area boundaries come from OpenStreetMap. See Supp. Mat. Table A8 for further details.

interest rates (69).²¹ Such information problems are likely to be worse in places where bank networks are scarcer because banks have fewer relationships and less knowledge about borrowers, leading to lower access to credit (70).

Our fieldwork indicates that access to documents, a key component of proving ownership for credit as well as government subsidies, has become much easier following digitization. Most landowners access their land documents through Common Service Centres, which are kiosks that process government-related services such as passport applications, land document applications, caste certificates, etc. Once land records have been digitized, CSCs have been able to provide access to land documents as a service. Younger farmers are also able to apply for these documents using their phones. As one respondent explained during our fieldwork, “For revenue-related matters, we go to the Common Service Centers. There are not many problems, because there’s a stipulated time in which things need to be completed. For getting a loan in the bank, I needed to get a possession certificate, and I could just go to the CSC now to get it. For both the government and the common man, this saves a lot of time.”²² Similarly, a landowner felt that access to documents has vastly improved since digitization: “Dealing with the government has become much easier and speedier. Beforehand, we would have to go to the village office, wait there, then they might send us home, and we would have to come back the next day. We would also have to carry so many documents. It would take 2-3 working days to get something started.”²³ Another farmer highlighted how digitization curtailed the need to rely on informal intermediaries: “Earlier, we had to meet the middlemen when we went to the village office. [...] For the government service, we now pay a small fee, but at least we don’t have to engage the services of the middlemen. Whatever money we have to pay to the government, now at least is reaching the government.”²⁴

To test if greater document access translates to better access to credit and, consequently, increased investment in agriculture, we classify subdistricts based on their bank coverage prior to digitization. We code a district as under-banked if the number of branches per capita was below the national median in 2011 and highly-banked otherwise. Figure 4b) shows that digitization expanded the share of the subdistrict under agriculture by 1.347 percentage points (SE = 0.291) or 1.7% in under-banked districts, but had no effect in highly-banked districts. This suggests that digitization might have improved access to information for banks and expanded access to credit to landowners, leading to expanded cultivation.

Forests improved in protected areas We next turn to investigating whether digitization has reduced the state’s transaction costs of monitoring forested areas, enforcing boundaries, reducing conflict, and improving forest cover in turn. We first look at the impact of

²¹The reasoning is that when the bank cannot distinguish low and high-risk borrowers observationally, increasing the interest rate may not maximize the bank’s profit margins. This is both because of adverse selection (safe borrowers drop out as they cannot afford the interest rate) and moral hazard (high interest rates motivate borrowers to invest in high-risk higher-reward projects to pay back the loan). When raising the interest rate does not maximize bank profits, banks will turn to rationing credit.

²²Author’s interview with landowner, 2025.08.09., Ernakulam district.

²³Author’s interview with landowner, 2025.08.13., Ernakulam district.

²⁴Author’s interview with landowners, 2025.08.09., Ernakulam district.

digitization on different types of land conflict: conservation and forestry, industry, land use, mining, infrastructure, and power-related conflict. We find that the largest decline in conflict takes place for conservation and forestry conflicts, followed by land use and mining-related conflicts (Supp. Mat. Fig. A6). This implies that following digitization conflict over forestry becomes easier to settle or less likely to break out.

If digitization primarily improves the state's ability to monitor forests, we should mostly see improvements in forested areas that are overseen by the state. This mechanism is echoed in interviews we have conducted with officials in both the Forest and Land Records Departments. One forest department official told us that inter-departmental coordination is the primary challenge they face: "As we have different departments, when the revenue department assigns the land [to a person], the forest department [records] might not get updated...However, by the digitization of [land records], further changes in the forest land can be monitored properly."²⁵

To further investigate how digitization changes monitoring by the state, we divide subdistricts into those that have a protected nature area, those that do not, and those with selected protected areas that were created before 2012. Our results show that forested areas have primarily improved in protected areas (Figure 4c). This holds both for all protected areas and for those selected areas that were created prior to 2012. In subdistricts without protected areas, we find no change in forested areas. This supports our suggested mechanism: forest cover improves where digitization reduces the government's costs of monitoring forest areas.

Savanna & Grassland Analysis The prior section shows that reduction in transaction costs improves both forest and agricultural cover. However, since land is finite, improvements in these two domains must come at the cost of reduction in some other land use types. We investigate the impact of digitization on other land use categories and find null effects on most other categories except for savannas and grasslands (Supp. Mat. Fig. A7, Tab. A10).

We find that share of savanna cover declines by 0.452 percentage points (SE = 0.085) or by about 5.1% and the share of grassland cover declines by 0.375 percentage points (SE = 0.071) or 6.4% (Supp. Mat. Fig. A8, Tab. A11). We disaggregate these measures by our high-low agricultural and forest cover subsamples. Savannas decline most sharply in low agricultural and high forest cover subdistricts: the same places where we see improved forest cover (Supp. Mat. Fig. A9, Tab. A12). Grasslands decline most in low agricultural and low forest cover subdistricts, where agricultural areas increase the most (Supp. Mat. Fig. A9, Tab. A12).²⁶ Decline in grasslands and savannas, but not in forests, is consistent with formal environmental protections shielding forest lands and leaving other areas exposed to land use change. Grasslands and savannas are often classified as "wastelands" by the Indian government, which indicates that the government sees these areas as having little environmental or economic value (40). This classification makes land use change

²⁵Author's interview with forest department official in Kochi, 2026.03.03., Ernakulam district.

²⁶We also see a decline in grasslands in low agricultural-high forest cover subdistricts, but the event study shows an existing downward trend prior to digitization. This means we cannot interpret this decline causally.

much easier, whether towards agricultural use or afforestation.

6 Discussion

We evaluate the world’s largest land-records digitization program and find that it produced simultaneous gains in agricultural cover and forest cover, with the two improvements arising in spatially distinct parts of the Indian landscape. Subdistricts with low pre-reform agriculture saw cultivation expand most, while heavily forested but lightly cultivated subdistricts were the most likely to see forest cover improve; in border areas where a frontier dynamic would be most visible, we detect no displacement of forests by agriculture. We find that the reform’s effectiveness operates through reduced transaction costs on both sides of the state-society relationship: ongoing land conflicts fall sharply, agricultural gains concentrate in under-banked subdistricts, and forest gains concentrate in legally protected areas.

These results sit in tension with the dominant trade-off finding in the rainforest-frontier literature. The theoretical case for a trade-off is laid out by Angelsen (2010)(94): stronger tenure raises the net present value of clearing forests, therefore, improvements in tenure can produce a “race to the frontier” in which landowners and squatters clear preventively to secure ownership. Empirical work has consistently confirmed this prediction in tropical rainforests (3, 4, 91–93).²⁷

Three features distinguish our setting and reform from this prior work. First, India’s tropical dry forests are spatially interspersed with cultivation rather than arrayed along an active frontier, so a property-rights shock that raises the value of farming need not bring agriculture and forest into spatial competition (64, 94). Second, India’s agriculture is dominated by smallholder, labor-intensive agriculture, whereas many rainforest settings are more suited to large, capital-intensive agriculture, especially at the forest frontier. Angelsen identifies labor-intensive smallholder agriculture as the context in which improved tenure security is most likely to create a double dividend for forest and agriculture: these spaces tend to produce greater intensification of agricultural production rather than deforestation (96). Lastly, DILRMP holds *de jure* rights fixed and changes the legibility of existing rights by digitizing textual records, computerizing maps, and integrating them into central platforms, rather than granting or formalizing claims. The systematic-review evidence is largely silent on this kind of administrative-capacity reform (38, 42), which means we know little about the consequences of capacity-building for the agriculture-forest cover trade-off.²⁸

Three caveats temper our conclusions. First, our outcomes are measured by satellite, so detected forest gains likely reflect a mix of stronger protection of existing canopy, regeneration on degraded plots, and reduced encroachment, but not the species composition or biodiversity quality of those gains. Second, our reduced-form estimates do not separate the relative contribution of dry-forest spatial structure, smallholder labor-intensive

²⁷The countervailing strand on collective and indigenous titling does find forest gains (34, 35, 95), but focuses specifically on forest conservation instead of its trade-off with agriculture.

²⁸Tseng et al. count only 7 of 117 causal land-tenure studies as capacity-building (38). Lawry et al. explicitly exclude justice, capacity-building, outreach, and inheritance reforms from their review (42).

agriculture, and the legal protection of forests; future work distinguishing these channels across settings would clarify the external scope of our findings.

Third, while we do not find evidence of a trade-off between agriculture and forests, we detect a reduction in grasslands and savannas exactly in the places where agriculture and forests improve. This makes the net impact of the reform more ambiguous. This is especially so in a developing country context where environmental and economic pressures are both acutely felt. To evaluate the net impact, we would have to account for the carbon stored in every type of land cover and tally the gains and losses from each type of land-use change into a single net figure. An economic accounting would also require us to value the agricultural output gained by increased cropland cover against the economic value of lost grassland and savannas. While we leave this accounting to future work, our results do suggest that stronger administrative capacity does not necessarily eliminate land-use trade-offs, but may shift pressure toward ecosystems receiving weaker legal and administrative recognition.

The broader implication is that administrative legibility, by itself, can be a high-leverage conservation and development instrument. In settings where agriculture and forest are spatially interspersed and where forests already enjoy legal protection, our work shows, capacity-building reforms of this kind appear to offer a rare double dividend that titling and formalization reforms have rarely delivered.

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SUPPLEMENTARY MATERIALS

A Treatment Data Construction

We collect information on the implementation of DILRMP from the program’s official website, which both reports each subdistrict’s status on the program’s four objectives: (1) digitization of land records, (2) distribution of software, (3) linkage with Aadhaar, and (4) digitization of land ownership changes, as well as the date of last update. Our analysis focuses on the first objective, the digitization of land records.

The website reports a single date on which the record was last updated rather than a separate completion date for each objective. A subdistrict that completed objective (1) in May 2014 but its final objective in September 2016 therefore appears with a recorded date of September 2016. To ensure that we recover the earliest date for each location, we scraped the website three times (in July 2020, August 2023, and May 2024). We have also tracked changes to the website prior to our first data scrape using the Internet Archive which suggests that our first data scrape captures the first set of data uploaded.

Three features of this procedure give us confidence in the resulting coding. First, because the website reports only the most recent update, our procedure can assign a subdistrict a treatment date later than the true date of digitization, but never earlier. Second, scraping the website at several points means that we can trace the completion of program objectives through several points in time. By assigning each subdistrict the earliest date recorded across our three scrapes, we recover digitization dates that a single scrape would miss. Third, we validate and confirm digitization dates with local land administration officials against local records during fieldwork in two states, Kerala and Tamil Nadu.

Any remaining measurement error makes our estimated treatment effects conservative. If a subdistrict is coded as digitized later than it actually was, periods in which it was in fact treated are assigned to the pre-treatment window, and some genuinely treated subdistricts enter the not-yet-treated comparison group. Both push estimated effects toward zero, so our estimates can be read as a lower bound on the effect of digitization.

A.1 Merging Names

We combine information from two village-level data sources: (i) village boundary shapefiles from the 2011 Census of India, which contain the official Census village codes, and (ii) DILRMP administrative data, which report the timing of land-record computerization and related reforms at the village level but do not include these Census codes. We treat the 2011 Census as the master dataset and the DILRMP data as the merging dataset. We merge them using state, district, subdistrict, and village names. A key challenge with this strategy is that village names are not unique at the village level in either source, so a purely name-based merge can yield multiple candidate matches. To resolve these exact-name duplicates, we exploit information on the number of households reported in both datasets. The government DILRMP dataset includes a variable, **Total RORs**, which we interpret as the number of Record-of-Rights entries and expect to be closely related to the number of

households. From the official Census 2011 repository we obtain the number of households at the village and town levels (97) ²⁹, and we first merge DILRMP and Census records on names and then refine this merge using the (ranked) household counts.

The Census 2011 town data present an additional complication: for some towns, the database reports two records for the same town identifier—one for the statutory Municipal Council alone and another for the combined Municipal Council and its Out Growth (which is part of the Census urban agglomeration but outside the statutory municipal boundary). To avoid double counting and ensure consistency with the DILRMP coverage, we retain, for each town identifier, the record with the larger number of households.

A second challenge is the creation of new districts over the 14-year period covered by the DILRMP data. We construct a state–district crosswalk that harmonizes district names between the 2011 Census and the DILRMP dataset. This crosswalk is generated manually using online documentation and official government sources, including the Local Government Directory (98). In almost all cases, a district in the government data maps to a single 2011 Census district. However, a small number of new districts (four in our data) are carved out of more than one 2011 district. For these districts, we use a 2022 district boundary shapefile to identify the set of 2011 villages that fall within the new district’s 2022 boundary and then merge the Census and DILRMP data for these villages using subdistrict and village names. Because there are only a few such cases, we inspect and finalize these matches manually. This procedure yields a district-level harmonization that is effectively exact. After these preliminary steps, we use the resulting harmonized structure to merge the 2024 India list of state, district, subdistrict, and village names with the 2011 Census master file. We follow the following procedure for the matching:

- We first clean all names by removing non-alphanumeric and other spurious characters from both ends of each string. We then perform an exact merge, using the number of households rank to break ties when necessary.
- For the remaining observations, we restrict to records with unique combinations of state, district, and village names and attempt a second exact merge using only these non-duplicate triplets.
- We then repeat this procedure for the remaining unmatched observations, now using unique combinations of state and village names.
- Finally, for all observations that are still unmatched, we implement a fuzzy matching step using the *LinkTransformer* deep learning model (99), based on subdistrict and village names only (since districts are already perfectly matched). We retain only links with a predicted accuracy of at least 90%, which is the threshold at which manual inspection indicates that most matches are correct.

B Measurement Error in Spatial Data

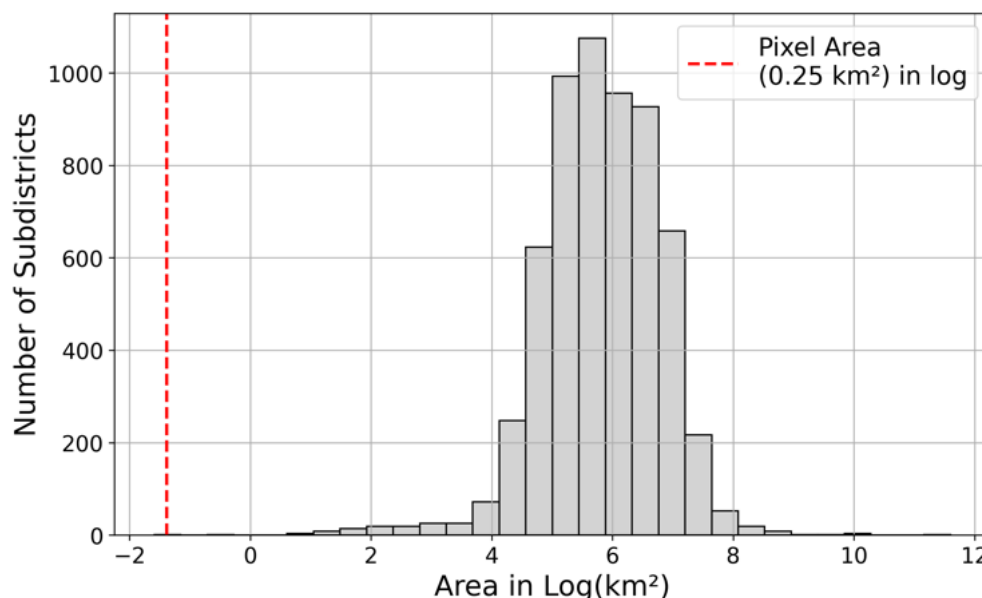
We use the Collection 6 MODIS Land Cover Type (C6 MLCT) product (100). This remote-sensing dataset is generated by a Random Forest classifier applied to MODIS Nadir

²⁹The original source is the Census of India Population Finder, available at this link.

BRDF-Adjusted Reflectance (NBAR), a 16-day composite that reduces view-angle effects and short-term atmospheric disturbances (e.g., clouds, haze, pollution). As with any classified satellite product, however, C6 MLCT may still exhibit systematic classification errors, where certain land-cover classes are consistently confused with others (101, 102). Our confidence in overcoming these issues relies both on the refinements embedded in the C6 processing chain and on aggregating data to a higher spatial level. The C6 MLCT algorithm reduces spurious land-use changes by combining prior information with Random Forest outputs and then applying a hidden Markov model. First, class-conditional probabilities from the Random Forest are updated using class- and location-specific priors via Bayes' rule, returning a refined and more credible posterior classification. Second, a hidden Markov model uses the full time series of these posteriors to smooth pixel-level classifications across years, strongly dampening isolated, noisy year-to-year label changes.

Although pixel-level classification changes may still be uncertain, our analysis is conducted at the Indian subdistrict level. Figure A1 shows the distribution of subdistrict areas (in logs) and highlights that the median subdistrict is much larger than a single pixel, at roughly 340 km^2 —about 1,360 MODIS pixels of 0.25 km^2 each. At this level of spatial aggregation, the C6 MLCT product reliably captures the large-scale land use changes we study (100). Moreover, any remaining systematic errors that are approximately constant within subdistricts or years are absorbed by unit and time fixed effects in our econometric specifications.

Figure A1: Subdistrict Area Distribution



Notes: This figure shows the distribution of the logarithm of subdistricts area (km^2). The red dashed line shows the pixel size of MODIS data.

Table A1: MODIS MCD12Q1 IGBP Land Cover Classification Legend

Land Cover Class	Description
Evergreen Needleleaf Forests	Dominated by evergreen conifer trees (canopy >2m). Tree cover >60%.
Evergreen Broadleaf Forests	Dominated by evergreen broadleaf and palmate trees (canopy >2m). Tree cover >60%.
Deciduous Needleleaf Forests	Dominated by deciduous needleleaf (larch) trees (canopy >2m). Tree cover >60%.
Deciduous Broadleaf Forests	Dominated by deciduous broadleaf trees (canopy >2m). Tree cover >60%.
Mixed Forests	Dominated by neither deciduous nor evergreen (40–60% of each) tree type (canopy >2m). Tree cover >60%.
Closed Shrublands	Dominated by woody perennials (1–2m height) >60% cover.
Open Shrublands	Dominated by woody perennials (1–2m height) 10–60% cover.
Woody Savannas	Tree cover 30–60% (canopy >2m).
Savannas	Tree cover 10–30% (canopy >2m).
Grasslands	Dominated by herbaceous annuals (<2m).
Permanent Wetlands	Permanently inundated lands with 30–60% water cover and >10% vegetated cover.
Croplands	At least 60% of area is cultivated cropland.
Urban and Built-up Lands	At least 30% impervious surface area including building materials, asphalt, and vehicles.
Cropland/Natural Vegetation Mosaics	Mosaics of small-scale cultivation 40–60% with natural tree, shrub, or herbaceous vegetation.
Permanent Snow and Ice	At least 60% of area is covered by snow and ice for at least 10 months of the year.
Barren	At least 60% of area is non-vegetated barren (sand, rock, soil) areas with less than 10% vegetation.
Water Bodies	At least 60% of area is covered by permanent water bodies.

Notes: This table presents the International Geosphere-Biosphere Programme (IGBP) land cover classification scheme used in the MODIS MCD12Q1 product. Source: Friedl & Sulla-Menashe (103).

Table A2: IUCN Protected Area Categories from OpenStreetMap

Category	Description
Ia – Strict Nature Reserve	Strictly set aside to protect biodiversity and also possibly geological or geomorphological features, where human visitation, use, and impacts are strictly controlled and limited to ensure protection of conservation values.
Ib – Wilderness Area	Usually large unmodified or slightly modified areas, retaining their natural character and influence, without permanent or significant human habitation, protected and managed so as to preserve their natural condition.
II – National Park	Large natural or near-natural areas set aside to protect large-scale ecological processes, species, and ecosystems, which also provide a foundation for environmentally and culturally compatible spiritual, scientific, educational, recreational, and visitor opportunities.
III – Natural Monument or Feature	Areas set aside to protect a specific natural monument, which can be a landform, sea mount, submarine cavern, geological feature such as a cave, or even a living feature such as an ancient grove. Generally quite small and often with high visitor value.
IV – Habitat/Species Management Area	Areas that aim to protect particular species or habitats and where management reflects this priority. Many will need regular, active interventions to address the requirements of particular species or to maintain habitats.
V – Protected Landscape/Seascape	Areas where the interaction of people and nature over time has produced a distinct character with significant ecological, biological, cultural, and scenic value, and where safeguarding the integrity of this interaction is vital.
VI – Protected Area with Sustainable Use	Areas that conserve ecosystems and habitats together with associated cultural values and traditional natural resource management systems. Generally large, with most of the area in a natural condition and low-level non-industrial use of natural resources.

Notes: This table shows the IUCN classification information available from the OpenStreetMaps dataset. Source: (104).

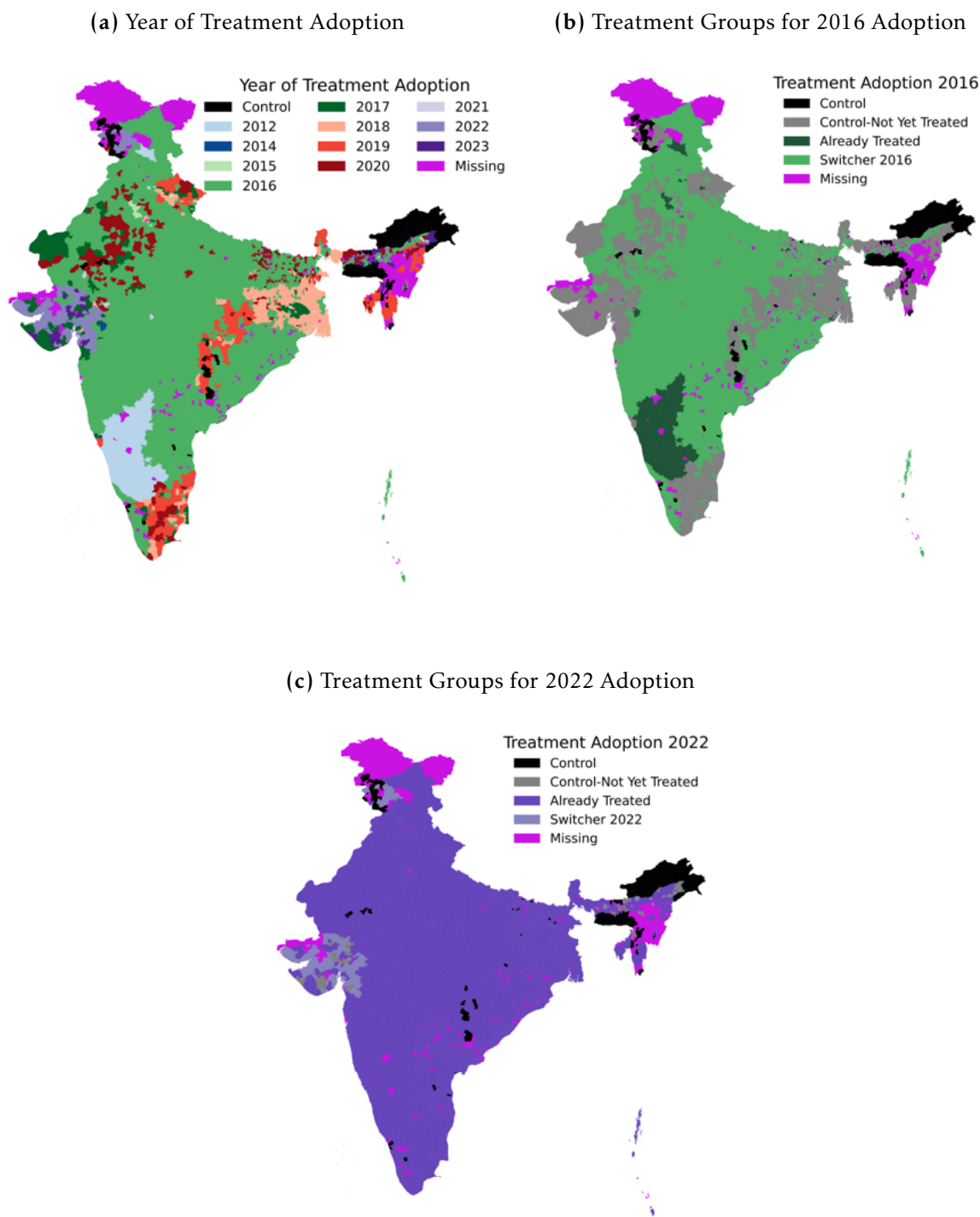
C Summary Statistics

Table A3: Summary Statistics

Variable	N	Mean	SD	Min	Max
Subdistrict ID	131208	2982.500	1721.665	1	5964
Year	131208	2011.500	6.344	2001	2022
First Year Program Adoption (Adopters Only)	116820	2016.816	1.897	2012	2023
Treatment	123552	0.266	0.442	0	1
Agriculture Cover	131186	66.876	36.299	0	100
Forest Cover	131186	9.315	21.575	0	100
Ongoing Conflicts (All Sectors)	131208	0.094	0.392	0	11
Protected Areas	131208	1.378	0.485	1	2
Above Median Agriculture Cover	131208	1.469	0.499	1	2
Above Median Forest Cover	131208	1.214	0.410	1	2
Above Median Banks Branches in 2011	131208	1.450	0.497	1	2
Ongoing Conservation and Forestry Conflicts	131208	0.010	0.110	0	4
Ongoing Industry Conflicts	131208	0.009	0.101	0	4
Ongoing Infrastructure Conflicts	131208	0.032	0.235	0	11
Ongoing Land Use Conflicts	131208	0.015	0.133	0	7
Ongoing Mining Conflicts	131208	0.010	0.106	0	3
Ongoing Power Conflicts	131208	0.018	0.137	0	4
Agriculture Cover in 2010	131186	67.983	36.221	0	100
Forest Cover in 2010	131186	9.649	21.998	0	100
Agriculture Cover in 2010 (quintiles)	131208	2.878	1.452	1	5
Forest Cover in 2010 (quintiles)	131208	1.854	1.354	1	5
Agriculture Cover in 2010 (deciles)	131208	5.225	2.984	1	10
Forest Cover in 2010 (deciles)	131208	2.923	2.912	1	10
Evergreen Needleleaf Forests	131186	0.628	3.485	0	47.251
Evergreen Broadleaf Forests	131186	4.475	16.052	0	100
Deciduous Needleleaf Forests	131186	0.000	0.002	0	0.344
Deciduous Broadleaf Forests	131186	2.215	6.651	0	85.866
Mixed Forests	131186	1.997	6.284	0	94.030
Open Shrublands	131186	0.657	5.851	0	99.974
Woody Savannas	131186	3.961	11.151	0	99.052
Savannas	131186	5.534	11.985	0	99.468
Grasslands	131186	6.134	12.194	0	98.351
Permanent Wetlands	131186	0.559	4.140	0	91.032
Urban and Built-up Lands	131186	2.507	10.219	0	100
Cropland/Natural Vegetation Mosaics	131186	2.955	9.385	0	100
Permanent Snow and Ice	131186	0.039	0.578	0	22.339
Barren	131186	0.652	4.698	0	95.684
Water Bodies	131186	0.807	3.703	0	75.342

D Treatment Rollout Statistics

Figure A2: Treatment Rollout



E Main Results

Table A4: Effect of Digitization on Land Cover

	Agriculture (1)	Forest (2)
Digitization	0.626*** (0.149)	0.135*** (0.044)
Observations	131,186	131,186
Clusters	5,963	5,963
Mean DV	67.983	9.649
Subdistrict FE	Y	Y
Year FE	Y	Y

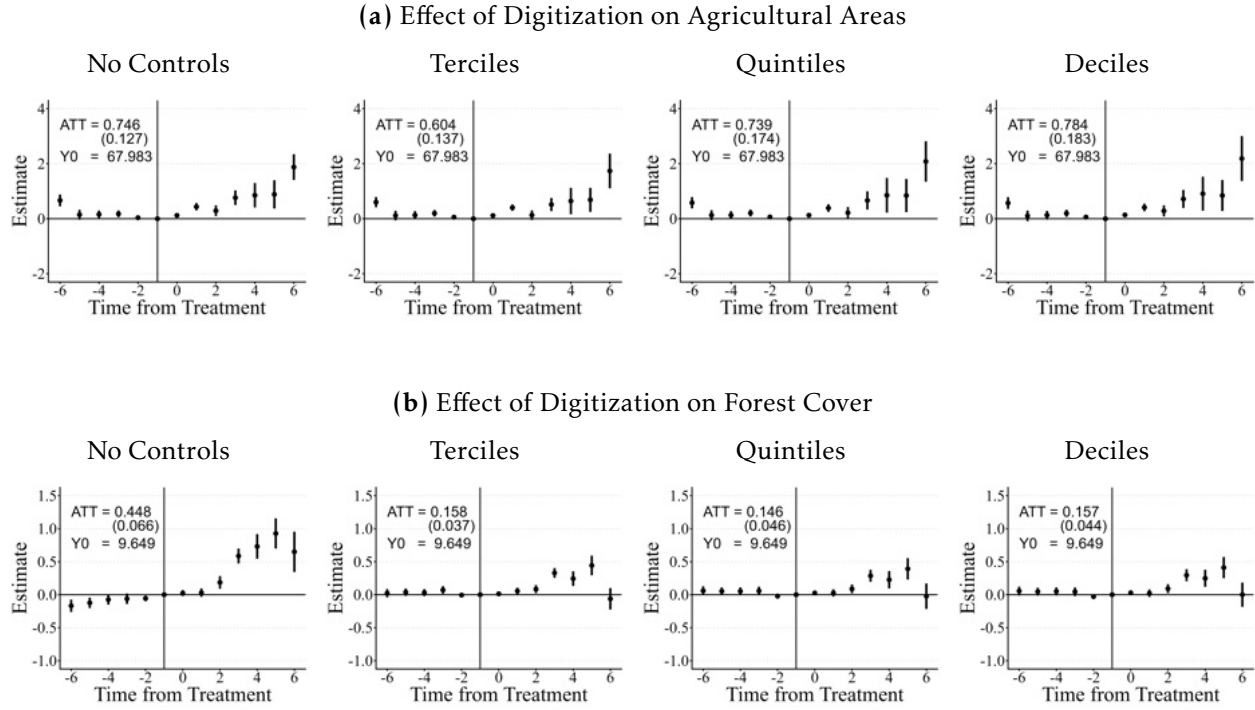
Notes: This table reports the overall ATT of digitization on agricultural and forest cover, each measured as the share of subdistrict area under that land use, from the doubly robust difference-in-differences estimator. Comparisons condition on above/below-median baseline cover in 2010, two years before the program started, with not-yet-treated and never-treated subdistricts as controls. Standard errors, clustered at the subdistrict level, are in parentheses. We also report the number of clusters (subdistricts) and the 2010 outcome mean. *** p-value < 0.01; ** p-value < 0.05; * p-value < 0.10.

Table A5: Effects of Digitization on Land Cover across different Specifications

	Agriculture Cover				Forest Cover			
	None (1)	Terciles (2)	Quintiles (3)	Deciles (4)	None (5)	Terciles (6)	Quintiles (7)	Deciles (8)
Digitization	0.746*** (0.133)	0.604*** (0.139)	0.739*** (0.175)	0.784*** (0.183)	0.448*** (0.069)	0.158*** (0.040)	0.146*** (0.049)	0.157*** (0.047)
Observations	131186	131186	131186	131186	131186	131186	131186	131186
Clusters	5963	5963	5963	5963	5963	5963	5963	5963
Mean DV	67.983	67.983	67.983	67.983	9.649	9.649	9.649	9.649
Subdistrict FE	Y	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y	Y

Notes: This table reports the overall ATT from the event studies in Figure A3, showing the effect of digitization on agriculture (columns 1–4) and forest cover (columns 5–8), each measured as the share of subdistrict area under that land use. Estimates come from the doubly robust difference-in-differences estimator across four specifications: no conditioning, and conditioning on terciles, quintiles, and deciles of the baseline outcome in 2010. Not-yet-treated and never-treated subdistricts serve as controls. Standard errors, clustered at the subdistrict level, are in parentheses. We also report the number of clusters (subdistricts) and the 2010 outcome mean. *** p-value < 0.01; ** p-value < 0.05; * p-value < 0.10.

Figure A3: Effect of Digitization on Land Use by Different Specifications

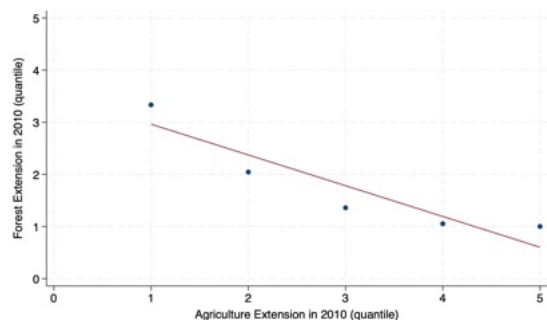


Notes: This figure shows the effect of digitization on agriculture (Panel (a)) and forest (Panel (b)) cover, each measured as the share of subdistrict area under that land use, across four specifications: no conditioning, and conditioning on terciles, quintiles, and deciles of the baseline outcome in 2010. Event time is measured in years before and after DILRMP adoption, with zero denoting the adoption year. Points are event-study aggregations of the cohort-period effects from the doubly robust difference-in-differences estimator, normalized to the year before adoption, with 95% confidence intervals, using not-yet-treated and never-treated subdistricts as controls. Each panel reports the overall ATT, its standard error in parentheses, and the 2010 outcome mean. Standard errors are clustered at the subdistrict level.

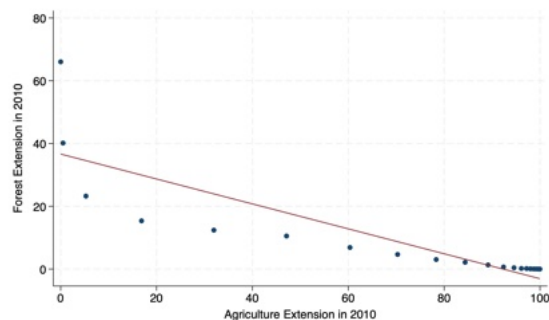
F Trade-off Analysis

Figure A4: Correlation between Agriculture and Forest Areas in India in 2010

(a) Forest vs agricultural area quantiles at sub-district level in 2010



(b) Forest vs agricultural area percentages at sub-district level in 2010



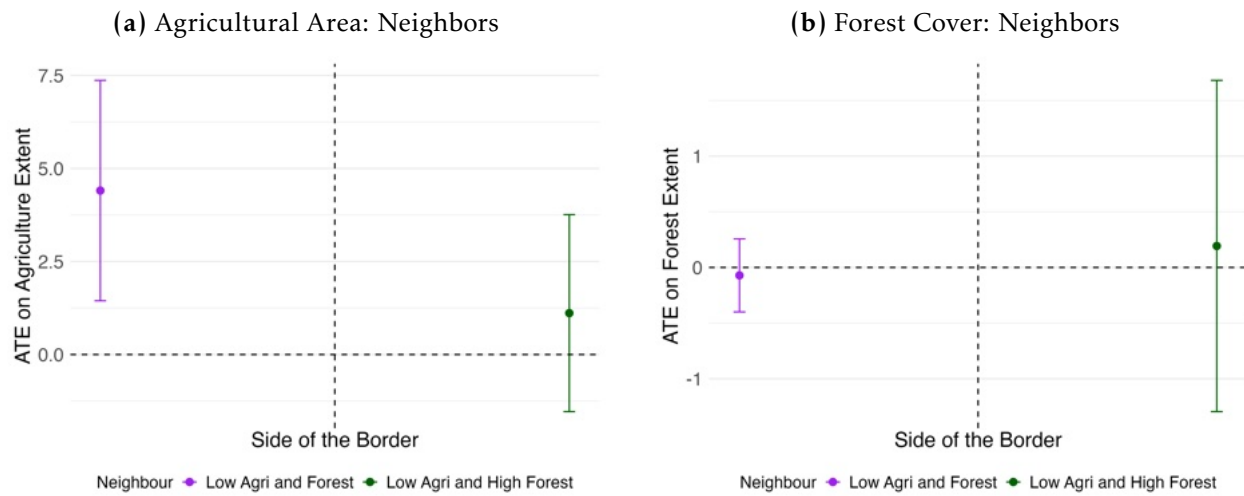
Notes: This figure shows the correlation between forest and agricultural cover in 2010 using quantile and continuous measures.

Table A6: Trade-offs Between the Effects of Digitization on Agricultural and Forest Cover

	Agriculture Cover (0-100%)			Forest Cover (0-100%)		
	Low Agri Low Forest (1)	High Agri Low Forest (2)	Low Agri High Forest (3)	Low Agri Low Forest (4)	High Agri Low Forest (5)	Low Agri High Forest (6)
Digitization	1.799*** (0.461)	0.162 (0.110)	-0.038 (0.277)	0.064 (0.057)	0.036*** (0.013)	0.448* (0.254)
Observations	41558	61600	28028	41558	61600	28028
Mean DV	55.886	97.006	22.132	1.593	0.224	42.309
Subdistrict FE	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y

Notes: This table reports the overall ATT of digitization on agricultural cover (columns 1–3) and forest cover (columns 4–6), each measured as the share of subdistrict area under that land use, from the doubly robust difference-in-differences estimator. Estimates are reported for three subgroups classified on 2010 values: low-agriculture, low-forest in columns (1) and (4); high-agriculture, low-forest in columns (2) and (5); and low-agriculture, high-forest in columns (3) and (6). Comparisons condition on above/below-median baseline cover in 2010, two years before the program started, with not-yet-treated and never-treated subdistricts as controls. Standard errors, clustered at the subdistrict level, are in parentheses. We also report the number of clusters (subdistricts) and the 2010 outcome mean. *** p-value < 0.01; ** p-value < 0.05; * p-value < 0.10.

Figure A5: Trade-off Results Neighbor Analysis



Notes: This figure shows ATT estimates by subgroup for the effect of digitization on agricultural (Panel A5a) and forest cover (Panel A5b), each measured as the share of subdistrict area under that land use. The sample is restricted to low-agriculture, low-forest subdistricts with at least one low-agriculture, high-forest neighbor, along with those low-agriculture, high-forest neighbors. Estimates come from the doubly robust difference-in-differences estimator, with comparisons conditioning on above/below-median baseline cover in 2010, two years before the program started, and not-yet-treated and never-treated subdistricts as controls. Standard errors are clustered at the subdistrict level; 95% confidence intervals are shown.

Table A7: Effects of Digitization on Land Cover in Neighboring Subdistricts

	Agriculture Cover		Forest Cover	
	Low-Low (1)	Low-High (2)	Low-Low (3)	Low-High (4)
Digitization	4.405*** (1.521)	1.113 (1.289)	-0.071 (0.165)	0.193 (0.706)
Observations	6886	7964	6886	7964
Clusters	313	362	313	362
Mean DV	54.938	21.422	2.236	39.987
Subdistrict FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y

Notes: This table reports the overall ATT of digitization on agriculture (columns 1-2) and forest cover (columns 3-4), each measured as the share of subdistrict area under that land use, from the doubly robust difference-in-differences estimator. Comparisons condition on above/below-median baseline cover in 2010, two years before the program started, with not-yet-treated and never-treated subdistricts as controls. Standard errors are clustered at the subdistrict level and reported in parentheses. The sample is restricted to low-agriculture, low-forest subdistricts with at least one low-agriculture, high-forest neighbor, along with those low-agriculture, high-forest neighbors. Sample in columns (1) and (3) comprises the low-agriculture, low-forest subdistricts; columns (2) and (4) their low-agriculture, high-forest neighbors. We also report the number of clusters (subdistricts) and the mean of the dependent variable in 2010. The control group sample consists of never-treated and not-yet-treated subdistricts. *** p-value < 0.01; ** p-value < 0.05; * p-value < 0.10.

G Mechanisms

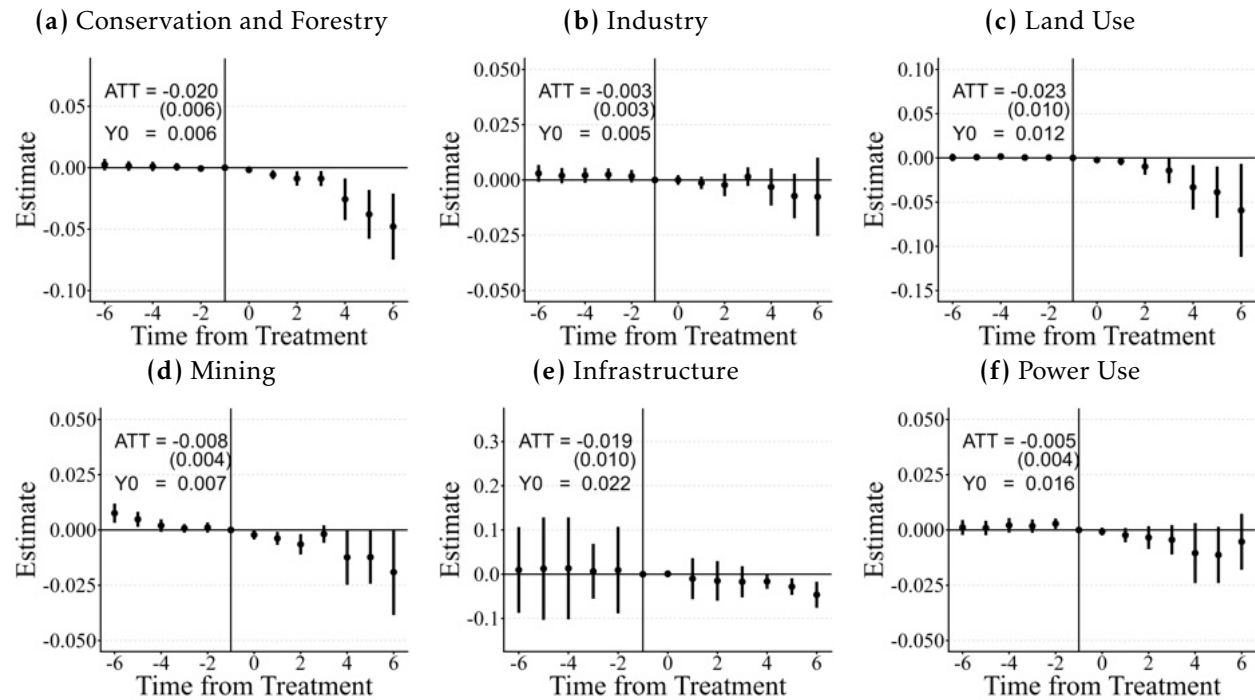
Table A8: Mechanism Tests for Digitization's Effect

	Cum. Ongoing Conflicts	Agriculture Cover		Forest Cover		
	(1)	Below Median Districts	Above Median Districts	Non Protected Areas	All Protected Areas	Selected Protected Areas
		(2)	(3)	(4)	(5)	(6)
Digitization	-0.073*** (0.015)	1.347*** (0.291)	0.255 (0.185)	0.048 (0.062)	0.313*** (0.062)	0.357** (0.148)
Observations	131208	54362	75724	81576	49610	10384
Subdistricts	5964	2471	3442	3708	2255	472
Mean of DV	0.069	78.960	60.944	7.018	13.976	20.404
Subdistrict FE	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y

Notes: This table reports the overall ATT of digitization on ongoing conflicts (column 1), agriculture cover (columns 2–3), and forest cover (columns 4–6), from the doubly robust difference-in-differences estimator. The protected area samples are defined as follows: non-protected areas, all protected areas, and selected protected areas (categories I, II, and III as classified by the International Union for Conservation of Nature), restricted to those established before 2012. Comparisons condition on above/below-median baseline values in 2010, two years before the program started, with not-yet-treated and never-treated subdistricts as controls. Standard errors, clustered at the subdistrict level, are in parentheses. We also report the number of observations, the number of unique subdistricts (clusters), and the 2010 outcome mean. *** p-value < 0.01; ** p-value < 0.05; * p-value < 0.10.

G.1 Conflict

Figure A6: Effect of Digitization on Conflicts by Type



Notes: The figure shows the dynamic effects of digitization on conflicts by type: conservation and forestry, industry, land use, mining, infrastructure, and power use. Event time is measured in years before and after DILRMP adoption, with zero denoting the adoption year. Points are event-study aggregations of the cohort-period effects from the doubly robust difference-in-differences estimator, normalized to the year before adoption, with 95% confidence intervals, using not-yet-treated and never-treated subdistricts as controls. Each panel reports the overall ATT, its standard error in parentheses, and the 2010 outcome mean. Standard errors are clustered at the subdistrict level.

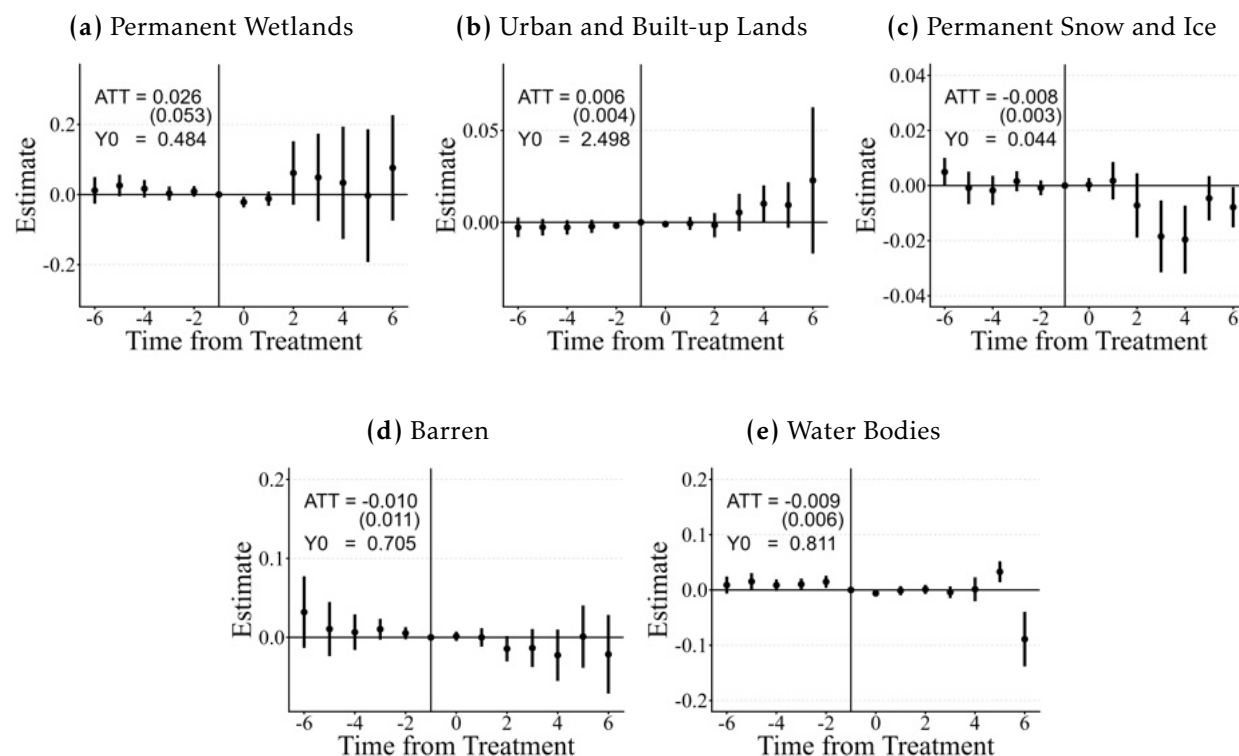
Table A9: Effects of Digitization on Ongoing Conflicts by Type

	(1) Conservation & Forestry	(2) Industry	(3) Land Use	(4) Mining	(5) Infrastruc- ture	(6) Power
Digitization	-0.020*** (0.005)	-0.003 (0.003)	-0.023** (0.010)	-0.008** (0.004)	-0.019** (0.009)	-0.005 (0.003)
Observations	131208	131208	131208	131208	131208	131208
Clusters	5964	5964	5964	5964	5964	5964
Mean DV	0.006	0.005	0.012	0.007	0.022	0.016
Subdistrict FE	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y

Notes: This table reports the overall ATT of digitization on ongoing conflicts by type: conservation and forestry (1), industry (2), land use (3), mining (4), infrastructure (5), and power (6), from the doubly robust difference-in-differences estimator. Comparisons condition on above/below-median baseline values in 2010, two years before the program started, with not-yet-treated and never-treated subdistricts as controls. Standard errors, clustered at the subdistrict level, are in parentheses. We also report the number of observations, the number of unique subdistricts (clusters), and the 2010 outcome mean. *** p-value < 0.01; ** p-value < 0.05; * p-value < 0.10.

G.2 Effects on Alternative Land Use Types

Figure A7: Digitization's Effect on Other Land Use Categories



Notes: This figure shows the effect of digitization on five land cover categories: permanent wetlands (Panel a), urban and built-up lands (Panel b), permanent snow and ice (Panel c), barren areas (Panel d), and water bodies (Panel e), each measured as the share of subdistrict area under that land use. Event time is measured in years relative to DILRMP adoption, with zero denoting the adoption year and the prior year omitted as the reference period. Estimates are based on an event-study specification with subdistrict and year fixed effects, controls for baseline values, and standard errors clustered at the subdistrict level. The control group consists of never- and not-yet-treated subdistricts. Each panel reports the average post-treatment effect (ATE), its standard error (in parentheses), and the 2010 mean of the outcome.

Table A10: Digitization's Effect on Other Land Use Categories

	Permanent Wetlands (1)	Urban and Built-up Lands (2)	Permanent Snow and Ice (3)	Barren (4)	Water Bodies (5)
Digitization	0.026 (0.054)	0.006 (0.004)	-0.008** (0.004)	-0.010 (0.011)	-0.009 (0.006)
Observations	131186	131186	131186	131186	131186
Clusters	5963	5963	5963	5963	5963
Mean DV	0.484	2.498	0.044	0.705	0.811
Subdistrict FE	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y

Notes: This table reports the overall ATT of digitization on alternative land use categories: permanent wetlands (1), urban and built-up lands (2), permanent snow and ice (3), barren (4), and water bodies (5), each measured as the share of subdistrict area under that land use. Estimates aggregate the cohort-period effects from the doubly robust difference-in-differences estimator underlying the event studies in Figure A7, conditioning on above/below-median baseline cover in 2010, with not-yet-treated and never-treated subdistricts as controls. Standard errors, clustered at the subdistrict level, are in parentheses. We also report the number of observations, the number of unique subdistricts (clusters), and the 2010 outcome mean. *** p-value < 0.01; ** p-value < 0.05; * p-value < 0.10.

G.3 Savannas and Grasslands Analysis

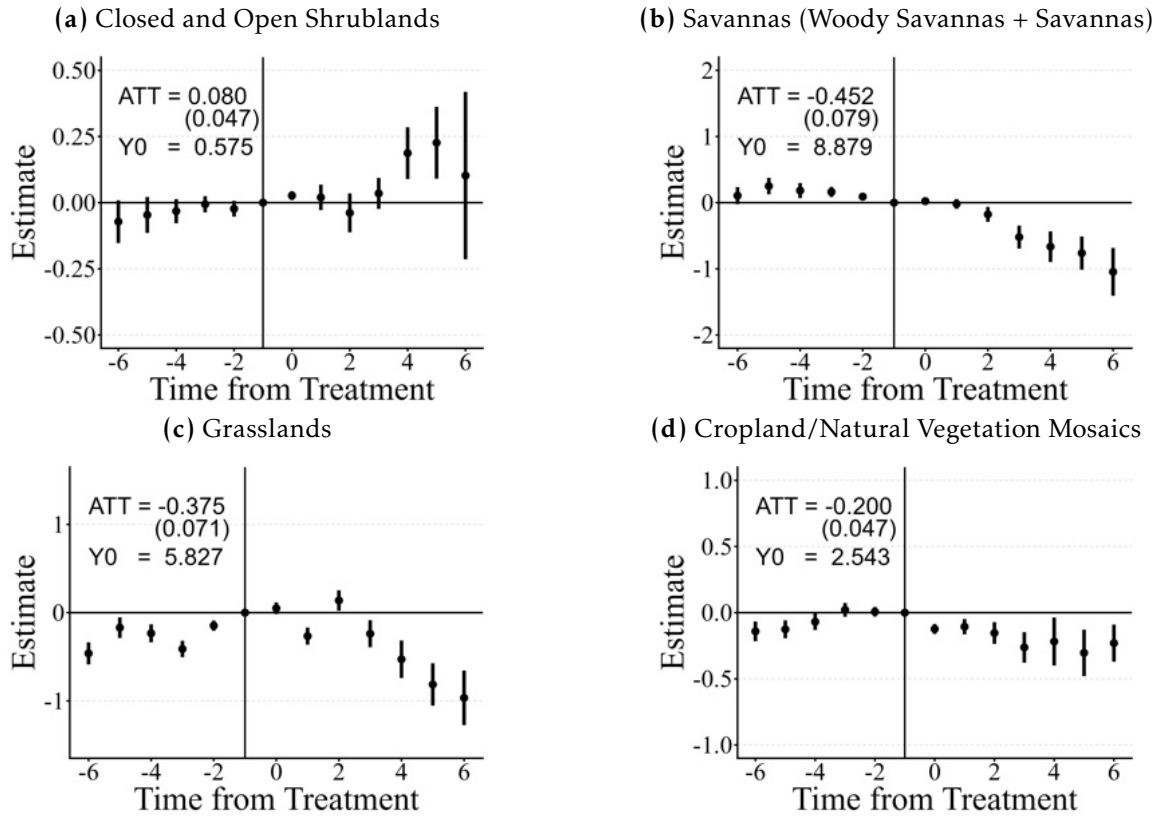
This section presents the analysis of digitization effects on savannas (woody savannas + savannas, MODIS layers 8 and 9) and grasslands (MODIS layer 10). These land cover types represent important categories that may be affected differently by property rights formalization.

Table A11: Effect of Digitization on Other Vegetation Covers

	Shrublands (1)	Savannas (2)	Grasslands (3)	Cropland/Natural Vegetation Mosaics (4)
Digitization	0.080* (0.043)	-0.452*** (0.085)	-0.375*** (0.071)	-0.200*** (0.052)
Observations	131,186	131,186	131,186	131,186
Clusters	5,963	5,963	5,963	5,963
Mean DV	0.575	8.879	5.827	2.543
Subdistrict FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y

Notes: This table reports the overall ATT of digitization on alternative land use categories: shrublands (1), savannas (2), grasslands (3), and cropland or natural vegetation mosaics (4) from the doubly robust difference-in-differences estimator. Comparisons condition on above/below-median baseline cover in 2010, two years before the program started, with not-yet-treated and never-treated subdistricts as controls. Standard errors, clustered at the subdistrict level, are in parentheses. We also report the number of observations, the number of unique subdistricts (clusters), and the 2010 outcome mean. *** p-value < 0.01; ** p-value < 0.05; * p-value < 0.10.

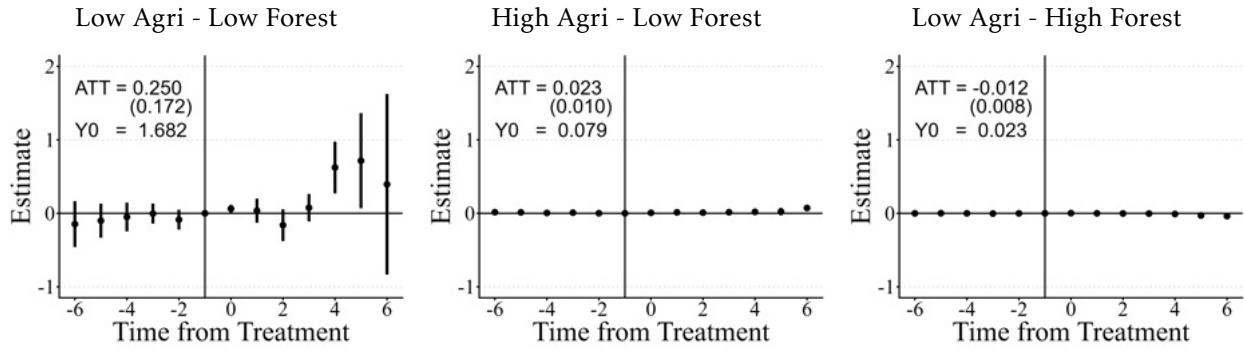
Figure A8: Effect of Digitization on Alternative Land Covers



Notes: This figure shows the dynamic effects of digitization on other vegetation covers: shrublands, savannas, grasslands, and cropland/natural vegetation mosaics. Event time is measured in years before and after DILRMP adoption, with zero denoting the adoption year. Points are event-study aggregations of the cohort-period effects from the doubly robust difference-in-differences estimator, normalized to the year before adoption, with 95% confidence intervals, using not-yet-treated and never-treated subdistricts as controls. Each figure reports the overall ATT, its standard error in parentheses, and the 2010 outcome mean. Standard errors are clustered at the subdistrict level.

Figure A9: Land-Cover Effects by Agriculture-Forest Subgroups (continued on next page)

(a) Shrublands



(b) Savannas

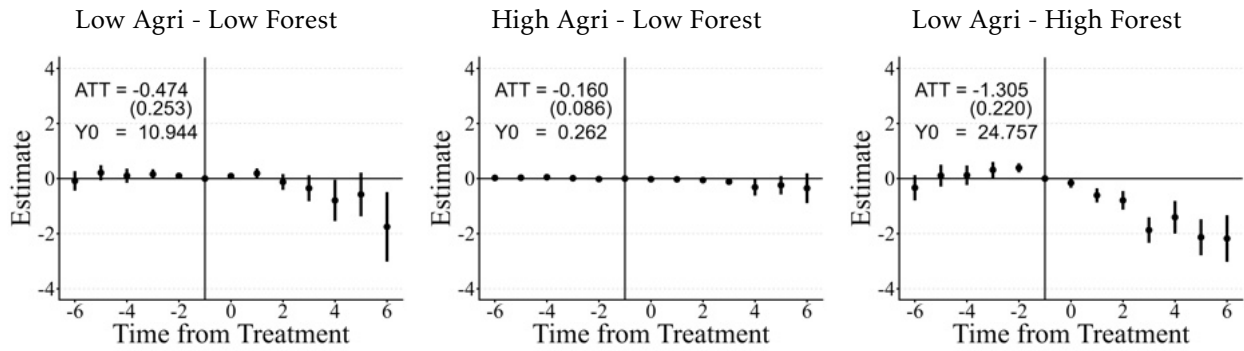
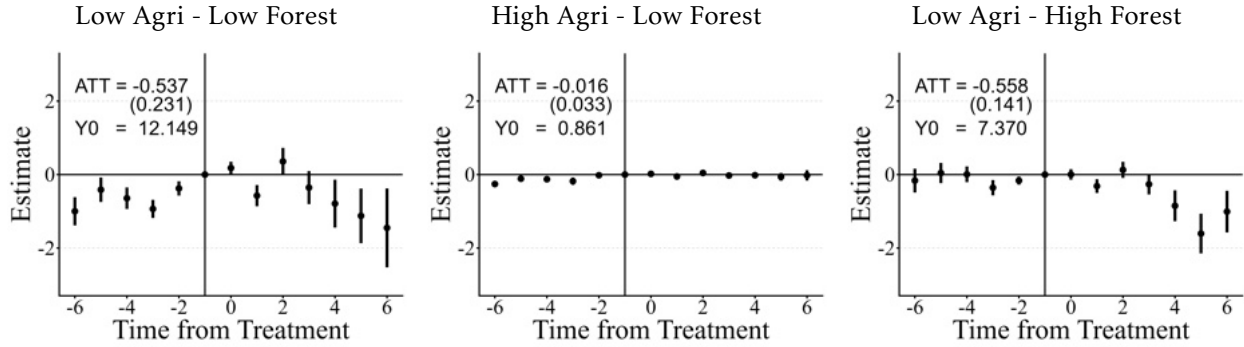
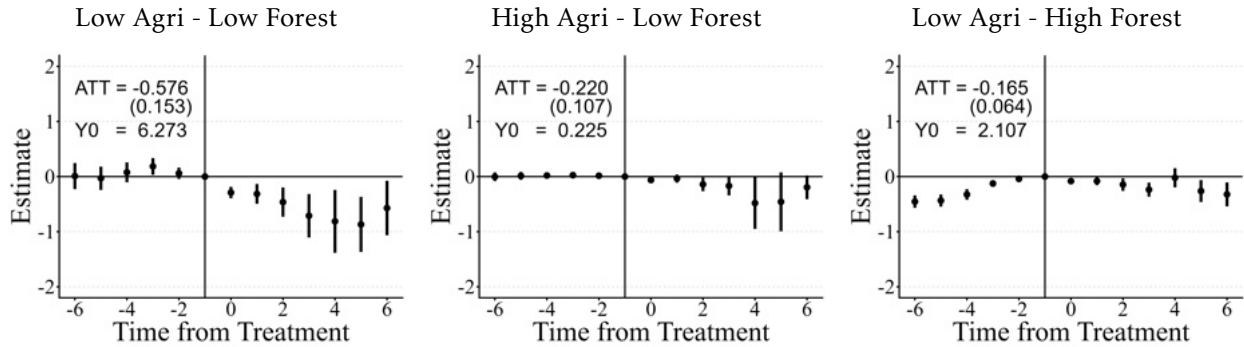


Figure A9: (continued)

(c) Grasslands



(d) Cropland/Natural Vegetation Mosaics



Notes: The figure shows the dynamic effects of digitization on alternative land covers: shrublands (Panel a), savannas (Panel b), grasslands (Panel c), and cropland/natural vegetation mosaics (Panel d). Event time is measured in years relative to DILRMP adoption, with zero denoting the adoption year. Points are event-study aggregations of the cohort-period effects from the doubly robust difference-in-differences estimator, normalized to the year before adoption, with 95% confidence intervals. Comparisons condition on above/below-median baseline cover in 2010, with not-yet-treated and never-treated subdistricts as controls. Each panel reports the overall ATT, its standard error in parentheses, and the 2010 outcome mean. Standard errors are clustered at the subdistrict level.

Table A12: Trade-off of Digitization on Alternative Land Covers

	Shrublands			Savannas			Grasslands			Cropland/Natural Vegetation Mosaics		
	Low Agri Low Forest (1)	High Agri Low Forest (2)	Low Agri High Forest (3)	Low Agri Low Forest (4)	High Agri Low Forest (5)	Low Agri High Forest (6)	Low Agri Low Forest (7)	High Agri Low Forest (8)	Low Agri High Forest (9)	Low Agri Low Forest (10)	High Agri Low Forest (11)	Low Agri High Forest (12)
Digitization	0.250* (0.150)	0.023** (0.010)	-0.012 (0.008)	-0.474* (0.265)	-0.160* (0.083)	-1.305*** (0.198)	-0.537** (0.217)	-0.016 (0.029)	-0.558*** (0.134)	-0.576*** (0.154)	-0.220** (0.108)	-0.165*** (0.063)
Observations	41,558	61,600	28,028	41,558	61,600	28,028	41,558	61,600	28,028	41,558	61,600	28,028
Mean DV	1.682	0.079	0.023	10.944	0.262	24.757	12.149	0.861	7.370	6.273	0.225	2.107
Subdistrict FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y

Notes: This table reports the overall ATT of digitization on shrublands (columns 1-3), savannas (columns 4-6), grasslands (columns 7-9), and cropland or natural vegetation mosaics (columns 10-12) from the doubly robust difference-in-differences estimator. Comparisons condition on above/below-median baseline cover in 2010, two years before the program started, with not-yet-treated and never-treated subdistricts as controls. Standard errors, clustered at the subdistrict level, are in parentheses. We also report the number of observations, the number of unique subdistricts (clusters), and the 2010 outcome mean. *** p-value < 0.01; ** p-value < 0.05; * p-value < 0.10.