Is There a Tradeoff between Forest Expansion and Agriculture? Evidence from India

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Abstract

Expansion of forest area through afforestation and reforestation is a popular strategy to mitigate climate change. However, the vast land area required suggests a potentially large tradeoff between forest expansion and agriculture. From 2003-2010, one of the largest forest expansion programs in India was implemented in Rajasthan state. We estimate the effects of this program on the agricultural sector using two-way fixed effects and synthetic difference-in-differences approaches, finding the program had no impact on cultivated area in Rajasthan. Moreover, agricultural production and yield increased following the program's implementation. We discuss implications for afforestation and reforestation as climate mitigation strategies.

Keywords: afforestation, reforestation, agriculture, carbon sequestration, land use
JEL Codes: O13, Q15, Q23, Q56

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1 Introduction

Expansion of forest area through afforestation and reforestation has long been promoted as a climate change mitigation strategy due to forests' carbon sequestration properties (Nilsson and Schopfhauser, 1995; Sedjo and Sohngen, 2012). A recent report commissioned by the International Panel on Climate Change (IPCC) estimates the carbon removal potential of afforestation/reforestation to be between 0.5-10.1 gigatons of CO_2-equivalent per year (Shukla et al., 2019).[1]

Of key relevance to the net social benefit of carbon sequestration by forests is the apparent land-use tradeoff between forests and agriculture. It is a stylized fact that agriculture has been the largest driver of deforestation globally (Myers, 1994; Angelsen, 1999; Curtis et al., 2018); conventional wisdom is that expansion of agriculture necessarily leads to the destruction of forests, especially in rapidly developing economies. Recent research has shown that the impacts of agriculture on deforestation may be mitigated or exacerbated by a variety of institutional arrangements (e.g., land rights) and policy interventions affecting agricultural productivity (Robinson et al., 2014; Wehkamp et al., 2018; Abman and Carney, 2020a,b).

However, the converse hypothesis—that policies and other interventions designed to preserve, reclaim, or expand forest area come at an opportunity cost of forgone agricultural production—has, to our knowledge, not been studied in the literature. Forest expansion may not significantly displace agriculture if the land converted to forests is either (i) fallow or otherwise marginal agricultural land, or (ii) land that is unsuitable for agriculture but can support forests (e.g., steep hill- or mountainside terrain). When it comes to forest expansion projects as a climate mitigation strategy, therefore, the inverse relationship between forests and agriculture may not be as clear-cut as is generally believed.

Additionally, forests generate many social and environmental benefits beyond just carbon sequestration. For example, Plantinga and Wu (2003) find the conversion of agricultural land to forest results in reductions in several agricultural externalities—e.g., soil erosion and nitrogen run-off—suggesting these co-benefits "are an important factor for countries to consider in designing a portfolio of climate mitigation strategies." Similarly, the effect of forests on local rainfall levels represents a pathway through which forests may indirectly provide a crucial ecosystem service to the agricultural sector (Araujo, 2024; Grosset et al., 2024). Recent climate research finds that afforestation in semi-arid regions significantly increases moisture penetration and precipitation (Yosef et al., 2018). Dense forest cover intercepts rainfall by slowing down clouds (Brauman et al., 2010) and filters fog droplets causing fog precipitation (Prada et al., 2009). Forests also contribute to rainfall directly, as extra moisture on the surface of leaves evaporates. This process, known as *transpiration*, increases moisture levels in the surrounding air, which is then saturated faster, increasing rainfall (Staal et al., 2018).[2] Conversely, deforestation can disrupt the hydrological cycle due to the loss of transpiration-related rainfall, which can have detrimental effects on local agriculture (Leite-Filho et al., 2021; Paul et al., 2016; Lawrence and Vandecar, 2015). Forests also support biodiversity (Carnus et al., 2006), which may benefit agriculture through other ecosystem services (e.g., pollinators). These insights suggest potential co-benefits to the agricultural sector through increased rainfall and/or other ecosystem services that should also be accounted for when calculating the net social benefit of carbon sequestration through forest expansion initiatives.

This paper examines whether, and to what extent, a major forest expansion and recovery program in India (described below) had any effect on local agricultural activity. Given the complex relationships involved, the theoretical net impact of such a program on agriculture is ambiguous. On one hand, expanding forests may have displaced agriculture through land-use changes and diversion of labor and capital resources away from the agricultural sector. On the other hand, if greater forest area did not significantly displace agriculture and the resulting increase in forest cover led to an increase in rainfall or other ecosystem services, we might expect to observe net positive impacts on the local agricultural sector.

We study the Rajasthan Forest and Biodiversity Project (RFBP), launched in 2003 with financial assistance from the Japan International Cooperation Agency (JICA).[3] The explicit goal of the RFBP was to increase forest cover and preserve biodiversity in the rainfall catchment area (drainage basin) of Rajasthan's Aravali ranges. JICA extended a long-term loan of roughly 9000 million yen (USD 80 million) to the Rajasthan state government to facilitate the implementation of various initiatives to recover forest areas within these historically forested parts of the state. In contrast to a top-down approach, the RFBP followed a bottom-up approach that involved farmers and the local community, who were trained to plant and care for tree saplings on previously cultivated land, making them stakeholders with a direct interest in the project's success or failure.[4] As such, participating farmers likely had greater awareness both of the detailed costs and benefits of land-use tradeoffs and of changes in ecosystem services, responding accordingly in terms of their productive activities.

The RFBP provides a particularly rich context to study the effects of forest expansion on local agriculture in an important developing economy. Over the past half-century, the Indian sub-continent has experienced significant changes in its climate and weather patterns, which have strongly affected its agricultural sector. Especially concerning has been a consistent reduction in monsoon rains over time (Meher-Homji, 1980; Gupta et al., 2005; Kuttippurath et al., 2021). Historical analyses have found a trend of increasing drought frequency and severity across much of India over the course of the 20th Century (Sharma and Goyal, 2020; Mallya et al., 2016). Projections into the future indicate this trend will likely continue (Bisht et al., 2019). Emblematic of this adverse shift was the drought of 2002, considered by many to have been an exceptional natural disaster. Rainfall across India dropped 19 percent below normal levels. 29 percent of the geographic area of India suffered a 'moderate' or 'severe' drought. Some regions were impacted worse than others. In particular, districts in Rajasthan state received 64 percent less rain compared to historical averages.[5] Long-term analysis of rainfall in Rajasthan indicates a persistent decline in monsoon rains, increasing warm days, and increasing likelihood of drought in the region (Mundetia et al., 2015; Singh, 2016; Pingale et al., 2014).

Although this extreme change in Rajasthan's monsoon pattern can be attributed to several factors, one of the most important has been rapid deforestation over the past several decades (Kundu et al., 2017). The primary drivers include increased agricultural land use to feed a rapidly expanding population, urbanization, and industrialization (Sajjad and Iqbal, 2012; Basu and Nayak, 2011; Singh et al., 2017). As a key motivation for the RFBP, the government of Rajasthan recognized that this loss of forest and biodiversity had adversely impacted the state through reduced water resources, negative impacts on agriculture and economic livelihood, and increased pollution, among other factors.

Our study empirically estimates the local effects of the RFBP on three key agricultural indicators: cultivated area, total production, and yield per hectare.[6] As a first-order effect, converting scarce land and resources from agriculture to forests may have displaced agricultural activity in Rajasthan. However, we hypothesize that additional forest cover resulted in increased ecosystem services such as rainfall via the interception and transpiration mechanisms described previously, and that these ecosystem services may have had a countervailing, positive effect on local agriculture. Thus, our hypothesized net effect of the RFBP on agricultural outcomes is ambiguous. Finally, we expect any effects of the program to be delayed and increase over time as forest area increases and the planted trees grow. To test these hypotheses, we analyze data on cultivated area, total agricultural production, agricultural yield, and rainfall at the district level in India from 1991 to 2017, and condition on a variety of other factors including labor and capital inputs, subsidies, irrigation, and the availability of credit.

The isolated implementation of the RFBP creates a natural experiment that allows us to identify the effect of forest expansion on agricultural activity. Our empirical strategy compares outcomes in districts in Rajasthan before, during, and after the implementation of the program with districts outside of Rajasthan using a quasi-experimental design. We estimate average annual treatment effects of the program's phases using two-way fixed effects (TWFE) and synthetic difference-in-differences (SDID) approaches following

Arkhangelskyet al. (2021). Both estimation strategies produce similar results, but the SDID approach is generally superior at producing parallel pre-trends in the outcome variables between treatment and control units that our empirical strategy requires for an unbiased estimate of the treatment effect. Finally, we use an event-study specification to estimate the variation in the treatment effect over time.

Perhaps counterintuitively, we find that the agricultural sector in Rajasthan grew following the implementation of the RFBP. Estimates of the average treatment effects from our preferred specification suggest cultivated area was unaffected by the program, whereas agricultural yield increased by 27%, mainly due to a 24% increase in total production. Importantly, the event study specifications for production and yield suggest these increases were concentrated in what we refer to as the post-planting period, seven to fourteen years after the first trees were planted, which is consistent with our expectation that the effects of forest expansion would depend on the growth of the plantings and the resulting impacts on ecosystem services.

To corroborate this interpretation, we also explore the impact of the RFBP on rainfall in Rajasthan. The average treatment effect estimated from our preferred specification indicates a 2% increase in rainfall in the post-planting period relative to our control group, although this effect is not statistically significant. Netting out the effect of rainfall on the agricultural variables shows that other ecosystem services (e.g., increased activity of pollinators driven by positive biodiversity effects) are likely to have been at work as well. However, we then show evidence that production and yields for individual non-water-intensive crops, which rely more on natural rainfall, generally increased in the period after the RFBP launched, whereas individual water-intensive crops, which rely more on irrigation, were unaffected. This provides additional, albeit circumstantial, evidence that increased rainfall is a plausible factor that explains the increase in agricultural productivity. This complements the findings of two other recent studies that report similar relationships between changes in forest cover, rainfall, and agriculture—one in the Brazilian Amazon region (Araujo, 2024) and the other in the midwestern United States in the early 20th Century (Grosset et al., 2024).[7]

More broadly, our results directly contradict the hypothesis, based on conventional wisdom, that an inherent tradeoff exists between forests and agriculture. We find the opposite result. Agricultural productivity in Rajasthan increased significantly following the implementation of the RFBP, and evidence suggests this increase may have been driven by improved ecosystem services provided by forests to the agricultural sector through increased rainfall and/or other channels. Taken together, these results imply that calculations of the net social benefit of afforestation/reforestation programs as a carbon sequestration approach to mitigate climate change should account for these effects. Otherwise, the net social benefit of such programs is likely to be significantly underestimated.

The rest of the paper is organized as follows. Section 2 discusses relevant literature to which our work contributes. Section 3 presents a background of forest conservation efforts in India and provides further details about the RFBP. Section 4 describes the data used to establish empirical evidence. In Section 5, we discuss our identification strategy, which includes exposition of the logic of the SDID approach. Section 6 discusses our results. Section 7 provides a brief discussion about the limitations of the study and the policy implications of our findings. An appendix contains supplemental analysis.

2 Review of Relevant Literature

This paper contributes primarily to research on the economic and environmental benefits of afforestation/reforestation programs. Second, it adds to the literature studying the effects of international assistance programs on agricultural practices in developing economies.

2.1 The Benefits (and Costs) of Forest Expansion

Analyses of afforestation/reforestation programs have largely focused on two broad categories of benefits: environmental benefits (carbon sequestration, mitigation of biodiversity loss) and economic development benefits (poverty reduction, provision of valuable ecosystem services) (Gregersen et al., 2011; Chazdon et al., 2017).

Forest cover has geophysical impacts including reducing ambient air and soil temperatures, retaining moisture and supporting microbial processes in soil, reducing erosion, and increasing precipitation (Farley et al., 2005; Savva et al., 2010; Betts, 2011; Jin and Wang, 2018). Deforestation is considered to be a primary driver of biodiversity loss (Barlow et al., 2016; Giam, 2017), and ecological research has further shown that this loss may be irreversible even after reforestation (Dupouey et al., 2002). The degree to which afforestation and reforestation support biodiversity gains is still a matter of scholarly debate (Brockerhoff et al., 2008; Gómez-González et al., 2020). Carbon sequestration via forests is a widely supported climate mitigation strategy (Sedjo and Sohngen, 2012; Gren and Aklilu, 2016), but local temperature benefits may be relatively small (Arora and Montenegro, 2011). Whether forest-based carbon sequestration is cost-effective depends on interactions between agricultural land markets, forest and timber product markets, and the carbon sequestration potential of geographically viable tree species (Richards and Stokes, 2004). Afforestation/reforestation programs targeted towards carbon sequestration may not have a permanent effect if areas shifted from agriculture to forests are allocated back to agriculture in response to increased opportunity costs (Alig et al., 1997).

Despite widespread support, afforestation/reforestation programs face numerous challenges and pitfalls (Le et al., 2012; Fleischman et al., 2020). The success or failure of large-scale forest projects has been linked to ecological factors that affect tree survival rates (Andivia et al., 2021). Tree-planting programs often target land that was previously covered with sparse vegetation or shrubland—-regions that can be ecologically sensitive and often inhabited by marginalized groups (Fleischman et al., 2022; Lahiri et al., 2023). Institutional factors such as the prevalence of political rent-seeking, the system of governance, and local rule-making also play a role, where democratic governance and political decentralization are generally seen as more conducive to long-term sustainability (Fleischman et al., 2014a,b). Moreover, forest expansion programs must carefully consider impacts on those living in areas identified for afforestation and reforestation; as argued by Fleischman et al. (2022), failure to "consider the existing land-use practices or legal rights of people" risks "undermining livelihoods and food security, displacing people from their lands, creating human-rights abuses, and compromising long-term conservation benefits." Several studies suggest that tree planting alone does not guarantee positive outcomes in terms of human development, poverty alleviation, and livelihoods (Hajjar et al., 2021; Jagger et al., 2022; Mensah et al., 2024). In a closely related study to our own, Coleman et al. (2021) found that a large-scale tree-planting program in the state of Himachal Pradesh in northern India did not, on average, increase forest canopy cover, but instead shifted forest composition away from more valued tree species, leading to little direct use by local populations or positive impact on livelihoods.

The relationship between forests and agriculture is complex and multi-faceted, and the economic benefits (and costs) of forest expansion programs are still being studied by economists and policy analysts (Dhubháin et al., 2009; Jones and McDermott, 2018; Li and Izlar, 2021). Forest expansion efforts may reduce total agricultural land area but increase agricultural intensity (Mather and Thomson, 1995). When weighing alternative land-use choices in the presence of forest expansion incentives, rural households' decisions to engage in forestry or agriculture depend on relative profitability and risk (Démurger and Yang, 2006). Some studies suggest greater forest area can positively impact household income (Moktan et al., 2016), while others have found no significant effect (Lu et al., 2020; Cuong et al., 2019; Bopp et al., 2020). Especially in an agrarian, developing economy like India, forest expansion programs must provide farmers with an alternative source of income or are otherwise unlikely to garner much response. Forests cannot alleviate rural poverty without income diversification and market accessibility (Wangdi and Tshering, 2006). Subsidies and financial support for upfront costs encourage participation (Bopp et al., 2020; Lu et al., 2020; Ruseva et al., 2015; Powlen and Jones, 2019), but other factors including education, annual income, tenure security/property rights, family size, and gender play a crucial role in program acceptance (Dolisca et al., 2006; Chang et al., 2021; Legesse et al., 2018).

Finally, while the studies of long-term effects of forests on rainfall and the agricultural sector in the United States (Grosset et al., 2024) and Brazil (Araujo, 2024) are closely related to our work here, these studies are unlikely to fully inform our understanding of the effects of the RFBP, given the significantly different ecological and institutional contexts. Rajasthan's climate is far more arid than both the Midwestern U.S. and the Brazilian Amazon, making it more suitable for different kinds of agricultural activities and implying that not all land in Rajasthan is ecologically suitable for afforestation. Parr et al. (2024) point out that there is even some confusion regarding accepted definitions of key terminology, leading to conflation of afforestation/reforestation with ecosystem restoration, which can threaten sensitive non-forest ecosystems similar to those found in Rajasthan. Relatedly, the Indian central government's *Wasteland Map of India*[8] has generated some controversy for its alleged misclassification of certain natural ecosystems (e.g., open grasslands) as "wastelands," which may unduly incentivize afforestation in areas that are ecologically sensitive or that support traditional livelihoods (Baka, 2013; Watve et al., 2021). For example, a recent article by *Mongabay*, an online magazine reporting on environment and conservation since 1999, points out that, "Nearly 70% of the areas which are open natural ecosystems overlap with those which the [Indian] government calls wastelands."[9] This problem is especially relevant in Rajasthan, where government programs like the RFBP may be misguided in converting natural grasslands—traditionally used for millet farming and cattle grazing—to plantation-style forests (Lahiri et al., 2023).

2.2 International Assistance and Agriculture

A complete discussion of the role of official development assistance in supporting agriculture is beyond the scope of this paper, and the RFBP is not an agricultural assistance program *per se*. Yet, our findings make an important novel contribution to this literature. Specifically, we show how a bilateral assistance program directed toward forest expansion and biodiversity may have yielded an economically significant co-benefit through enhancing ecosystem services beneficial to the agricultural sector. The key intuition is that official development assistance support for agriculture need not always be direct; indirect benefits to agriculture may be achieved through support for other, non-market environmental goods and services.

Agriculture is central to economic development, as it is typically the sector with the strongest comparative advantage in the early stages of development, is the dominant source of employment in the world's poorest regions, and is crucial for providing food security and adequate nutrition to vulnerable populations (Byerlee et al., 2009; Dethier and Effenberger, 2012; de Janvry and Sadoulet, 2020). Thus, agriculture has been a major focus of development assistance by organizations such as the Food and Agriculture Organization of the United Nations (FAO) and the International Fund for Agricultural Development (IFAD), among others (Hallam, 2011; Lowder et al., 2012; Lele et al., 2021). Climate and sustainability considerations have also become increasingly salient, marking another channel through which developing nations can benefit from international aid to agriculture (Kuyvenhoven, 2008; Pingali, 2010; Kotchen and Costello, 2018; Ssozi et al., 2019; Amadu et al., 2020).

As of 2017, India ranked second globally in total receipts of development aid to the Agriculture, Forestry, and Fishing sectors (Lele et al., 2021). Around two-thirds of India's population is dependent on agriculture and allied sectors for livelihood. There are many reasons to expect this flow of aid to continue for the foreseeable future. Sustainable agriculture will be crucial for India's continued development, not only to feed its growing population of more than 1.35 billion but also to reduce poverty. Climate change is adversely affecting India's agricultural sector through multiple pathways including increasing temperatures, more severe droughts, stronger storms, and sea level rise, with heterogeneous effects across regions (Senapati et al., 2013). Agriculture in developing countries is primarily dependent on rainfall due to the low intensity of irrigation, and a study in neighboring Nepal has shown that greater uncertainty over rainfall patterns discourages young workers from choosing agriculture as an occupation (Menon, 2009). Along with the higher quality inputs and infrastructure made affordable by agricultural assistance programs, increased availability of information and the opportunity to participate in cooperatives plays a major role in adopting sustainable agricultural practices (Caviglia and Kahn, 2001). Agricultural assistance promotes innovation and substitution toward less water-intensive crops (Singh et al., 2014; Zachariah et al., 2020).

3 RFBP Background

India's Forest Act, adopted in 1980, empowers both the state and central governments to manage forest resources. State forest departments (SFDs) act as agencies of the central government to prepare forest management plans within state boundaries and preserve public forest resources. The central government implemented additional policies in the National Forest Policy of 1988 (NFP), including a first-ever comprehensive policy on compensatory afforestation, restoration, and improvements in forest land.[10] Following the adoption of the NFP, India increased its forest cover from 9.7% of the total geographical area in 1988 to 23.4% by 2005. Over this period, forest cover in Rajasthan remained at around 9.5%.[11]

The RFBP was an ambitious initiative by the Rajasthan state government in cooperation with JICA, implemented under the NFP's framework. Figure 1 shows a rough timeline of the RFBP's phases, which we refer to as the *planning/outreach* phase and the *implementation* phase. Our empirical approach (described below) treats the planning/outreach and implementation phases as separate, sequential, multi-year treatments. Sample years prior to the start of the planning/outreach phase (1991-1996) are defined as our pre-treatment period, and sample years after the end of the implementation phase (2011-2017) are defined as the *post-planting* period.

[Figure 1 about here]

We define the planning/outreach phase as the period 1997-2002. It includes two feasibility studies that began in 1997 and 2001. The feasibility studies included baseline assessments of existing forest area and plantations; assessments of village-level activities in afforestation, reforestation, agro-forestry, and water conservation; preparation of a project budget and fund management plan; identification of project management teams at the village level; design of project monitoring and evaluation systems; economic cost-benefit analysis; environmental impact analysis; other recommendations. Thus, we hypothesize that the planning/outreach phase may have led to anticipatory effects in the agricultural sector if farmers expected the RFBP to be approved and ultimately implemented.

The implementation phase began in 2003, when JICA extended a loan of 9,054 million yen to the Rajasthan state government for the RFBP. Originally planned for 61 months from March 2003 to March 2008, the project overran by two years, ending in June 2010. A total of 10,058 million yen was ultimately disbursed. We therefore define the implementation phase as the period 2003-2010, during which the planting (and subsequent growth) of trees occurred, ending with the final disbursement of funds.

Rajasthan's SFD organized the RFBP around the operations and management of local projects, forming Village Forest Protection and Management Committees (VFPMCs) to assist officers and field functionaries. Over one thousand VFPMCs formed under the RFBP are responsible for the day-to-day operation and maintenance of projects in their area and for alerting forest officials about illegal grazing, encroachment, or tree felling. Each committee was given Rs. 100,000 to form a dedicated fund to support forest O&M activities. Local vigilance ensured the success of the RFBP by reducing incidences of illegal grazing and harvesting, and by increasing people's awareness and ownership of the project locally.

The RFBP's primary emphasis was on increasing forest cover in the rain catchment areas of Rajasthan's hilly districts. Figure A1 shows the 18 selected districts: 16 in the Aravalli Hills area, and two in the Indira Gandhi Nahar Project (IGNP) area. Districts were selected based on climate, geology, and vegetation, among other factors. In these regions, the primary livelihood of residents depends on forest resources. Deforestation and uncertain monsoons have threatened the sustainability of these populations' lifestyles.

Figure 2a details the cumulative progress of the RFBP in terms of trees planted. Planting began in 2004, covering 20,000 hectares and totaling just under 10 million trees. The bulk of planting occurred between 2005 and 2006. By 2007, a total of 50 million trees covering over 100,000 hectares had been planted. While data on the type of trees planted are not available, native trees in Rajasthan include teak, acacia, date palm, fig, Indian gooseberry, karira, khabar or toothbrush tree, khjri, and Banyan tree. Most of these species grow relatively rapidly—about 6-8 meters in 4-6 years—and the rate of transpiration varies by size and season. Similarly, we examine trends in satellite-measured forest cover using the fractional vegetation cover estimates for 1982-2016 from Song et al. (2018).[12] Figure 2b plots the demeaned log of fractional vegetation cover in Rajasthan versus the rest of India. These data document a decline in vegetation cover at the beginning of the planting period, followed by a rapid increase in vegetation cover at the end of the planting period and post-treatment period.[13] According to JICA's ex-post evaluation report of the RFBP, plant survival rates ranged from 80-88% in the Aravalli Hills region and from 80-91% in the INGP area.[14] These survival rates are consistent with the rates recently achieved in neighboring Pakistan as part of the much larger Billion Tree Afforestation Project (Ali et al., 2024).

[Figure 2 about here]

Table A1 presents a detailed project cost breakdown. Almost 56 percent of the cost was incurred for planting trees. This included reforestation of barren hills, rehabilitation of degraded forest, and fuelwood plantation in the Aravalli hill districts. In the more arid IGNP area, projects included canal-side plantation, dune stabilization, block plantation, and pasture development. The second major cost category, Joint Forest Management consolidation, included three types of cost: income-generation activities, the establishment of community funds, and small-scale infrastructure development. VFPMC members formed 'self-help' groups with seed money of Rs. 20,000 for income-generation activities to reduce the impact on livelihood due to displacement caused by the RFBP. By the RFBP's completion, over 1400 groups were engaged in income-generation activities from minor forest produce. To facilitate early adoption among villages, a small-scale infrastructure development plan funded the construction of community water tanks, reservoirs, community centers, bus stops, and the rehabilitation of public watersheds. The third largest cost category consisted of activities related to biodiversity conservation and moisture conservation. 1600 ha was set aside for natural rehabilitation, two sites were developed as biological parks, and several 400-ha areas were developed as eco-tourism sites. Nearly 2600 moisture conservation measures were undertaken, including building 'check dams' and 'anicuts' on rivers and waterways, which are obstructions built across water channels to control erosion and provide watering holes for animals. Both check dams and anicuts increase the moisture-retaining capacity of surrounding soil and are considered effective soil and moisture conservation measures. Community extension, comprising under 0.4% of the project budget, mainly involved the provision of 20 million seedlings, which were then sold to farmers between 2003-2010. Finally, to inculcate practical knowledge and skills on planting and tree-felling techniques, farmers, NGOs, VFPMC members, teachers, elected representatives of village councils, forest guards, and range officers were trained on best practices. All remaining funds were utilized on project overheads such as research, planning, monitoring, and administration expenses.[15]

To be clear, the overall economic and social impacts of the RFBP likely extended beyond the crops included in our analysis, and beyond the agricultural sector altogether. While a wider assessment of all local effects of the RFBP are beyond the scope of the current paper, some important issues not covered in our analysis are worth noting here and provide impetus for continuing research. For example, livestock is not included in our data, although livestock grazing is prominent in the treated Aravalli Hills region. Also, although we view the diversion of labor and capital resources away from the agricultural sector as a potential mechanism through which forest expansion might displace the agricultural sector, we do not explicitly analyze effects on labor, wages, capital investment, or other market outcomes in the current study. Similarly, we do not study potential cultural or socioeconomic impacts on the tribal communities who populate the treated districts, but recent studies emphasize the need to consider such effects of forest expansion (Pacheco and Meyer, 2022; Baragwanath et al., 2023; Govindarajulu et al., 2023). Continuing research should examine these dynamics carefully to ensure that the RFBP did not unintentionally harm traditional forest dwellers or displace livelihoods, as such effects would reduce the overall welfare impacts of the program. More generally, forest expansion projects—especially those in developing regions like Rajasthan—must respect tribal communities, who often have unique relationships with the land and distinct governance structures.

4 Data

To estimate the impact of the RFBP on agricultural outcomes in Rajasthan, we obtained district-level data on cultivated area (hectares), production (tons), and yield (kg/hectare), over the interval 1991-2017, from the International Crop Research Institute for the Semi-Arid Tropics (ICRISAT). Our sample includes more than 560 districts from 20 states in India.[16] These 20 states constitute 95 percent of India's population and 99 percent of agricultural production. We are interested in the effect of the RFBP on cultivated area to test for potential displacement effects of forests on agriculture, whereas production and yield allow us to test for effects on productivity from enhanced ecosystem services. The ICRISAT data include information on precipitation for 1991-2015, allowing us to test directly the hypothesis that the RFBP had an effect on local rainfall.

We supplement the agricultural data with district-level demographic data from the Socioeconomic High-resolution Rural-Urban Geographic Dataset on India (SHRUG), which includes variables such as population, the fraction of rural and urban population, literacy rate, and Scheduled Castes and Scheduled Tribes (SCST) population (Asher et al., 2019).[17] We also control for various sources of irrigation using district-level data from ICRISAT on irrigated farm area by source, including canals, tube wells, tanks, other wells, and other sources.

Agricultural credit is another important factor for the farming sector, as it facilitates the procurement of inputs and provides working capital for managing produce. This working capital is obtained from banks and other financial intermediaries by mortgaging assets (e.g., land). We control for access to agricultural credit using state-level data on the number of commercial banks and the number of rural bank branches. We also control for agricultural credit extended by banks, credit unions, and other institutions using outstanding debt at the end of each financial year. Data on banking facilities and agricultural credit were collected from the Reserve Bank of India's *Handbook of Statistics on Indian States* (2022).

To control for various subsidy programs that may have affected agricultural outcomes, we obtained data on state-level allocations of federal and state government agricultural subsidies through the Rashtriya Krishi Vikas Yojana (RKVY) program, which began in 2007. We also control for another important agricultural subsidy program called The Integrated Scheme of Oilseeds, Pulses, Oil Palm and Maize (ISOPOM) which was implemented from 2004-05 onwards across India. These subsidies are provided to farmers on the purchase of inputs such as seeds, fertilizers, pesticides, electricity, and machinery from a government-registered agricultural cooperative agency.[18] Statewise expenses on the ISOPOM scheme were acquired from the Department of Agriculture and Farmers Welfare. We also add controls for National Food Security Mission (NFSM) district-wise programs for wheat, rice, and cereals, which were launched in 2007.[19] Finally, we control for district-level implementation of the Mahatma Gandhi National Rural Employment Guarantee Act (MNREGA), which provided 100 days of guaranteed work to people in rural areas on government projects from 2006 onward.

The SDID approach requires a balanced panel, so we limit our sample to districts with non-missing observations for all variables over the entire sample period.[20] Table A2 displays summary statistics comparing Rajasthan to the rest of India during the pre-treatment period (1991-1996). Rajasthan is an agricultural desert state that experiences less rainfall relative to the rest of India. More land is devoted to agriculture in Rajasthan than in the rest of the country, but agricultural production and yields are comparatively low. The literacy rate is slightly below average, as is the fraction of paved roads (our proxy for income). Finally, the fraction of SCST and rural/urban populations are on par with the rest of India.

5 Empirical Strategy

Our empirical approach compares treated districts with untreated districts before, during, and after the implementation of the RFBP in both TWFE and SDID specifications. We denote $Y_{i,t}$ as the outcome of interest in district $i \in 1, \ldots, N\}$ in year $t \in \{1991, \ldots, 2017\}$. Let $j \in \{po, plant, post\}$ denote the planning/outreach, planting, and post-planting periods, respectively. We assume that each outcome evolves according to the following latent factor variable model:

$$Y_{i,t} = \alpha_i + \beta_t + \sum_{t=1997}^{2002} W_{i,t}^{po} \tau_t^{po} + \sum_{t=2003}^{2010} W_{i,t}^{plant} \tau_t^{plant} + \sum_{t=2011}^{2017} W_{i,t}^{post} \tau_t^{post} + \varepsilon_{i,t}, \tag{1}$$

where α_i are district-specific fixed effects, β_t are year-specific shocks affecting all districts, $W_{i,t}^{j}$ is a binary treatment variable for the RFBP project equal to one for treated districts during the years of treatment phase j (zero otherwise), and $\varepsilon_{i,t}$ is conditional-mean-zero heterogeneity. We expect the effect of the RFBP project to vary by year, first during the planning/outreach phase and then as planted trees grow; thus, $\tau = \tau_{1997}, \ldots, \tau_{2017}$ describe the dynamic treatment effects of the program on our outcome variables.

We seek to estimate the average treatment effects $\hat{\tau}^{ATE,j} = E\left(\tau_t^{j}\right)$and dynamic treatment effects, $\hat{\tau} = \hat{\tau}_{1997}, \ldots, \hat{\tau}_{2017}$, of the RFBP on cultivated area, agricultural production, yield, and rainfall. We hypothesize that the treatment effect will be positive for rainfall but may be either positive or negative for the agricultural outcomes depending on whether additional forested land complements or substitutes for each outcome. Furthermore, we expect the magnitude of the estimated effects to grow over time as more trees were planted and as the forests mature.

Our preferred approach compares outcomes in all districts in Rajasthan with untargeted districts outside of Rajasthan. During the planting phase (2003-2010), the RFBP planted trees in 18 of 32 districts in Rajasthan. This suggests several candidate treatment/control comparisons—for example, comparing targeted districts versus untargeted districts within Rajasthan, targeted districts in Rajasthan versus untargeted districts outside of Rajasthan, or all districts in Rajasthan to districts outside of Rajasthan.[21] We believe the local climate and agricultural effects of the program likely included spillover effects into the other districts in Rajasthan that were not targeted for afforestation, which would violate the stable unit treatment value assumptions (SUTVA) in a DID design comparing targeted and untargeted districts within Rajasthan. Furthermore, we believe the spillover effects to nearby districts should be included as a measurement of the treatment effect of forest expansion, so we favor the comparison of all Rajasthan districts to untargeted districts outside of Rajasthan.[22] Finally, if the spillover effects are smaller than the primary effects on targeted districts, our chosen comparison will yield conservative estimates of the treatment effect.

Importantly, we omit 2002 from the analysis. The 2002 Indian drought had strong effects on rainfall and agricultural outcomes across India, but particularly in Rajasthan. If we include the drought in the planning/outreach phase data, our estimates would mistakenly attribute the negative shock of the drought to the RFBP planning/outreach phase, affecting our estimates.

The standard approach to estimating the average treatment effects for each treatment phase j in the presence of control variables is a TWFE regression:

$$Y_{i,t} = \alpha_i + \beta_t + \sum_j W_{i,t}^{j} \tau^{ATE,j} + X_{i,t}\gamma + \varepsilon_{i,t},$$

(2)

where is a binary treatment variable equal to one for all Rajasthan districts in each treatment phase year, and $X_{i,t}$ is a vector of controls. As controls, we include total population, the fraction of rural population, literacy rate as a proxy for education levels, fraction of SCST population, fraction of paved roads as a proxy for income changes, state-level allocations of agricultural subsidies through the RKVY program, ISOPOM program, district-level coverage of NFSM scheme, MNREGA coverage, agricultural credit, banking facilities, and real GDP per capita. We can modify this equation to estimate the dynamic treatment effects in an event-study specification:

$$Y_{i,t} = \alpha_i + \beta_t + \sum_{\ell=1991}^{1995} W_i \cdot 1(t = \ell)\tau_\ell^{pte} + \sum_{\ell=1997}^{2001} W_{i,t}^{po}\tau_\ell^{plant} + \sum_{\ell=2003}^{2010} W_{i,t}^{po}\tau_\ell^{plant} + \sum_{\ell=2011}^{2017} W_{i,t}^{po}\tau_\ell^{plant} + X_{i,t}\gamma + \varepsilon_{i,t},$$

(3)

where W_i is a binary variable equal to one for all Rajasthan districts. This specification estimates pre-trends for the periods before the intervention and the dynamic treatment effects. Following convention, we omit the indicator for the final pre-treatment period (1996) as the base case. Estimating equations (2) and (3) via ordinary least squares yields unbiased estimates of the average treatment effects for each program phase and dynamic treatment effects under standard parallel trends, no spillovers, and strict exogeneity assumptions.

The parallel trends assumption requires that, in absence of the RFBP intervention, outcomes for treated and control groups would have evolved at the same rate. Yet for a variety of reasons, it is unlikely that the parallel trends assumption holds when comparing Rajasthan to all other districts in India. Thus, to overcome the problem of non-parallel trends in the pre-treatment data, we employ the SDID approach introduced by Arkhangelsky et al. (2021). The SDID approach estimates unit and time weights to create a synthetic control group that exhibits parallel trends compared to the treatment group in the pre-treatment period. To see this, in Figure A2, we plot averages of our outcome variables for the treatment group, evenly-weighted DID control group, and synthetic-DID-weighted control group. These plots show the improvement in parallel trends in the pre-treatment period achieved by the SDID weighting scheme. The plots also provide suggestive evidence of changes in all outcomes for Rajasthan after the RFBP began, relative to both control groups.

The SDID estimate of the average treatment effect for program phase j solves the following weighted least-squares problem:

$$\left(\hat{\tau}^{sdid,j}, \hat{\mu}, \hat{\alpha}, \hat{\beta}\right) = \underset{\tau,\mu,\alpha,\beta}{argmin}\left\{\sum_{i=1}^{N}\sum_{t=1991}^{2017}\left(\widetilde{Y}_{i,t} - \mu - \alpha_i - \beta_t - W_{i,t}^{j}\tau^{j}\right)^2 \widehat{\omega}_i^{sdid}\hat{\lambda}_t^{sdid}\right\}, \tag{4}$$

where $\widetilde{Y}_{i,t}$ are the residuals of outcome $Y_{i,t}$ after partialing out $X_{i,t}$ by applying the Frisch-Waugh-Lovell theorem on untreated districts (Kranz, 2022), and $\widehat{\omega}_i^{sdid}$and $\hat{\lambda}_t^{sdid}$ are the SDID weights for treatment phase period s from Arkhangelsky et al. (2021). Thus, in the first stage, we regress the agricultural outcomes $Y_{i,t}$ on controls $X_{i,t}$ in untreated units, obtaining OLS estimates $\hat{\beta}^{OLS}$. We then obtain the partialed-out agricultural outcomes and substitute these for the outcome variable in the SDID $\widetilde{Y}_{i,t} = Y_{i,t} - X_{i,t}\,\hat{\beta}^{OLS}$. The new agricultural outcome variables are now orthogonal to variation in the covariates, allowing us to estimate the direct effects of the RFBP, holding the covariates fixed. This partialing-out approach to including controls in the SDID is suggested in Arkhangelsky et al. (2021) and Kranz (2022). We do not control for additional covariates in the rainfall estimation as rainfall is not a function of demographic or economic factors.

To estimate the dynamic treatment effects, we modify the standard SDID approach to estimate a separate SDID for each post-treatment year, giving an estimate of the treatment effect for each year after the RFBP was implemented. Let $s \in \{1997, \ldots, 2017\}$ index post-treatment years, and let $\mathcal{T}_s = \{1991, \ldots, 1996, s\}$ be the set of pre-treatment years augmented with the treatment year s. We estimate the dynamic treatment effect τ_s^{sdid} for each treatment year s using the SDID-weighted regressions:

$$\left(\hat{\tau}_s^{\ sdid,j}, \hat{\mu}, \hat{\alpha}, \hat{\beta}\right) = \underset{\tau,\mu,\alpha,\beta}{argmin} \left\{ \sum_{i=1}^{N} \sum_{t \in \mathcal{T}_s} \left(\widetilde{Y}_{i,t} - \mu - \alpha_i - \beta_t - W_{i,t}^{j} \tau_s \right)^2 \widehat{\omega}_i^{sdid} \hat{\lambda}_t^{sdid,s} \right\}, \tag{5}$$

where $\widehat{\omega}_i$ and $\hat{\lambda}_t^{sdid,s}$ are the SDID weights for post-treatment period s. unit weights in equations 4 and 5 are the same while the time weights are different. This is because the SDID unit weights are estimated to ensure parallel pre-trends and are only based on the pre-treatment data, which is the same in each SDID. The SDID time weights are estimated to provide additional weight to pre-treatment periods with similar values to the post-period, which will be different for each post-period.[23]

Additionally, we hypothesize that districts in Rajasthan that were direct targets of forest expansion under RFBP may have been affected differently than nearby districts that potentially received environmental amenities without having to directly sacrifice land for forests. The direct effects of forest expansion may increase the scarcity of agricultural inputs, while nearby districts enjoy the spillovers of environmental amenities without having to sacrifice land for forests. To test the possibility of differences between direct and spillover effects, we estimate the effect of the RFBP separately for districts directly targeted and those (in Rajasthan) that were not targeted, using the SDID event-study approach (Eq. 5).

Finally, we examine the extent to which increases in rainfall versus other direct or indirect effects of afforestation account for the observed differences in Rajasthan's agricultural output. The program may have had a direct effect on a district by diverting resources away from agriculture but an indirect effect via the mechanism of increased rainfall, while ecosystem services other than rainfall may have also benefited the agricultural sector. To distinguish these effects from the rainfall effect, we augment our control variables $X_{i,t}$ with the amount of rainfall in the district, which controls for variation in the cultivated area, production, and yield that depends on rainfall. We then apply the SDID event-study approach in Eq. 5. If these estimates differ from the mainline estimates, this is evidence that any effects of the RFBP are occurring through the rainfall channel.

6 Results

[Table 1 about here]

Table 1 displays our estimates of the RFBP's average treatment effect on cultivated area, production, and yield, as well as the effect on rainfall. All standard errors account for clustering at the district level, the level of treatment assignment in the program (Abadie et al., 2022). We display estimates from the TWFE specification from equation (2) and the SDID specification from equation (4). SDID is our preferred approach given the improvement in parallel pre-trends (Figure A2), but our results are roughly consistent across both specifications.

Relative to the SDID control group, our SDID estimates indicate that the RFBP had no statistically significant average treatment effects on cultivated area during either of the program's phases or afterward, in the post-planting period, contradicting the hypothesis that forest expansion displaces agriculture. We find no effects on any of the agricultural variables in the planning/outreach phase, suggesting local farmers did not alter their behavior in anticipation of the RFBP being implemented. The most striking results, however, are that agricultural production increased by 24%, and yield increased by 27% in the post-planting period. Consistent with our expectation, the statistically significant effects on production and yield did not emerge during the planting phase, as the trees would not yet have had sufficient time to grow. The large increases in productivity and yield in the post-planting period suggest positive co-benefits to the agricultural sector of the additional forest cover in Rajasthan, to which farmers responded. Finally, the estimates in columns 7 and 8 indicate rainfall may have increased. Our TWFE specification suggests rainfall increased by 8% in the post-planting period, although our SDID point estimate is a more modest 2% increase that is not statistically significant.

[Figure 3 about here.]

Figure 3 displays event-study estimates of the effect of the RFBP's phases. Here also, we prefer the SDID event-study to the TWFE specification, so our discussion below focuses on the SDID estimates. Each coefficient is interpreted as the approximate percentage change in the outcome for Rajasthan relative to the control group and relative to the pre-treatment period (1991-1997). For the three agricultural outcomes, the event study estimates largely corroborate the average treatment effects reported in Table 1, where TWFE and SDID estimates are roughly similar. Our dynamic treatment effect estimates in Figure 3a show that cultivated area in Rajasthan was largely unaffected by the RFBP, again suggesting no displacement of agriculture by forests. Figure 3b shows that production increased relative to the control group and pre-period in the first two years of the planting phase and in all but one year of the post-planting period. With the exception of 2013, agricultural production in Rajasthan during the post-planting period was between roughly 20-65 percent higher relative to the control group and pre-period. The dynamic treatment effects for yield tell a similar story. As production increased in the post-planting period while area remained roughly the same, it follows that yields increased significantly as well.

For rainfall (Figure 3d), despite the appearance of parallel trends produced by SDID in Figure A2, our event study estimates suggest large, statistically significant differences between Rajasthan and the controls in the pre-treatment period that could not be overcome by SDID, calling into question the average treatment effect estimates on rainfall in Table 1. Estimates across specifications also differ more for rainfall, likely due to a larger number of districts given zero weight by the SDID algorithm. Although we did not expect any early positive effects on rainfall until plantings had begun to grow and mature, statistically significant negative dynamic treatment effects in the planning/outreach and planting phases are difficult to explain. One possible explanation is that land first had to be cleared of other vegetation to make room for tree plantings, which may have negatively impacted rainfall in the early years of the program. Again, however, due to the apparent lack of parallel trends for rainfall in the pre-treatment period, we cannot draw any definitive conclusions. Thus, while we find evidence of a positive effect of the RFBP on production and yield that may be due to increased ecosystem services related to increased forest area, on balance we consider these results to be inconclusive as regards the rainfall channel specifically; future studies using a longer time horizon and/or better rainfall data may prove more fruitful.

6.1 Targeted district effects versus spillovers

Our main approach considers outcomes for all of Rajasthan—however, the RFBP only targeted roughly half of the districts in Rajasthan for forest expansion. We investigate the difference between direct effects versus spillover effects by analyzing the effect of the RFBP on our dependent variables separately for targeted and untargeted districts in Rajasthan across the program's phases. If the direct effects of the program had a net displacement effect on agricultural activities, we might expect a negative estimated effect on agriculture for targeted districts, but not for untargeted districts. Conversely, if the direct effects of the program had a beneficial effect on agricultural activities, we might expect a larger positive estimated effect on agriculture for targeted districts relative to untargeted districts. We do not expect to see differences in the effect on rainfall because we expect any local weather effects to have geographic spillovers. To test these hypotheses, we estimate two separate SDID event studies (Equation 5) for targeted and untargeted districts.

Figure 4 displays our differentiated SDID estimates of the target effects versus spillover effects of the RFBP. Across all outcomes, the estimates follow similar patterns for directly targeted versus spillover districts. However, because the set of SDID controls changes as a result of the narrower set of treated districts for each sub-sample, the dynamic treatment effect estimates change some relative to those displayed in Figure 3. Cultivated area (Figure 4a) in both targeted and spillover districts declined in the final two years of the planning/outreach phase, suggesting anticipatory effects, but then recovered in the first three years of the planting phase before declining again, suggesting displacement effects. In the post-planting phase, however, cultivated area generally increased for spillover districts but was largely unaffected for targeted districts. For agricultural production (Figure 4b), estimates for both targeted and spillover districts are mostly negative throughout the planning/outreach and planting phases, but then increase markedly in the post-planting period, with spillover districts seeing more consistent increases. Agricultural yields (Figure 4c) stayed mostly level throughout, with targeted districts experiencing relatively larger effects in the post-planting period. Rainfall effects (Figure 4d) are again mostly inconclusive. Overall, we conclude that the effects of the afforestation on agricultural outcomes accrued to the region broadly and were not concentrated in directly targeted districts.

[Figure 4 about here.]

6.2 Effect net of rainfall

The effect of the RFBP on agriculture may come through a direct impact (e.g., competition for land or labor resources) or via indirect impacts by increasing rainfall and other ecosystem services. We estimate the effects of the program that were unrelated to rainfall by partialing out the effect of rainfall on the agricultural variables. We then re-estimate the SDID on the residualized agricultural outcomes to estimate the effect of the program net of any rainfall effects. Because we only have district-level rainfall data through 2015, we can only estimate the effects net of rainfall through 2015.

We display our SDID estimates using the residualized agricultural outcomes in Figure 5, which we compare to our main estimates from Figure 3. For area, the largest difference is that we begin to see some statistically significant increases as early as the planting phase, followed by large increases in the post-planting phase (Figure 5a). For production and yield, we see large increases beginning in the planning/outreach phase, although these are less trustworthy due to the apparent lack of parallel trends in the pre-treatment period (Figures 5b and 5c, respectively). Overall, these results suggest that any effects of the RFBP through the rainfall channel were small and that net of rainfall, other direct and indirect effects of the program on agricultural outcomes were positive rather than negative.

[Figure 5 about here]

6.3 Crop-level Analysis

Next, we estimate the average treatment effects of the RFBP on area, production, and yield for specific crops using a TWFE specification to compare districts in Rajasthan with all other districts in India. Here, we adopt a simpler design, defining 2003, the start of the planting period, as the year of treatment.

Rajasthan's major crops are pearl millet (28% area in the pre-treatment period), oilseeds (22%), wheat (14%), minor pulses (12%), chickpeas (9%), corn (6%), sorghum (4%), and cotton (3%), along with small amounts of barley, soybeans, and rice. To gain insight into how farmers might have responded to changes in rainfall, we categorize each crop as either water-intensive or non-water-intensive based on definitions found in Sharma et al. (2018). Rajasthan is an arid state; consequently, Figure A3 shows that only around one-quarter of the total cultivated area in Rajasthan was devoted to water-intensive crops (rice, wheat, cotton, soybeans, corn) over our sample period, and roughly three-quarters to non-water-intensive crops (pearl millet, oilseeds, minor pulses, chickpeas, sorghum, and barley). This distribution across water-intensive and non-water-intensive crops appears to remain fairly stable over time—that is, Figure A3 does not suggest that Rajasthan farmers significantly altered their crop mix in the post-RFBP period.

However, Table 2 shows the average treatment effects for each crop, grouped into water-intensive crops and non-water-intensive crops, from which a clear pattern emerges. Specifically, we find little effect of the RFBP on water-intensive crops. The two exceptions are wheat, which increased in area, production, and yield in the post-treatment period, and corn, which *decreased* in area and production. Contrast this to the results for the six non-water-intensive crops; we find statistically significant increases in the area for four of six, increases in production for five of six, and most importantly, increases in yield for all six non-water-intensive crops.

Perhaps counterintuitively, this contrast in treatment effects across water-intensive and non-water-intensive crops is consistent with the hypothesis that the agricultural sector in Rajasthan responded to, and benefited from, an increase in local rainfall in the post-RFBP period. Although not universally true, in general, water-intensive crops are relatively more reliant on irrigation than rainfall, because rainfall is, by nature, more variable and therefore less reliable than irrigation. Thus, we should not expect an increase in rainfall in the post-RFBP period to have had much impact on the cultivation of heavily irrigated water-intensive crops. Conversely, non-water-intensive crops are typically relatively less reliant on irrigation and can survive more readily on natural rainfall levels. Thus, that we find statistically significant increases in yield for all six non-water-intensive crops in the post-RFBP period is consistent with, and provides additional evidence in support of, the hypothesis that the RFBP led to beneficial increases in local rainfall levels.

[Table 2 about here]

7 Discussion and Conclusion

This paper explores the impact of a major forest expansion program, the Rajasthan Forest and Biodiversity Project (RFBP), on the local agricultural sector in Rajasthan, India. Generally, we find evidence that the agricultural sector was not displaced by forest expansion and, in fact, may have benefited from the increased forest area. Our results have important implications for afforestation/reforestation programs in developing agricultural regions. First, our empirical estimates suggest that the cultivated area in Rajasthan was largely unaffected by the RFBP. Moreover, we found large and statistically significant increases in production and yield after the trees had been planted and had time to mature. We conclude that the increased forest area led to improved ecosystem services beneficial to the agricultural sector resulting from the RFBP. This interpretation is further supported by the lack of difference in estimates for districts directly targeted by the RFBP versus those nearby. Although we do not find consistent evidence of a statistically significant effect on rainfall, we showed other evidence that rainfall may have been a factor. We conclude that any increase in rainfall was, at best, only partly responsible for the observed agricultural increases. Although other ecosystem services might explain the large increases in agricultural productivity, we do not test for them and leave such effects to future research. Nevertheless, these findings are important evidence against the hypothesis of displacement of agriculture; forest expansion does not appear to be an impediment to agricultural development.

This non-displacement of the agricultural sector may have been influenced by three factors: the size of the forest expansion project, the land targeted for forest expansion, and stakeholder engagement. Just over 100,000 hectares were targeted for forest expansion under the program. While this is a large effort, it pales in comparison to some of the most ambitious forest expansion projects, which can cover millions of hectares.[24] To put the forest expansion effort into perspective, each district in Rajasthan had over 100,000 hectares of agricultural land in 2017. Larger forest expansion efforts may result in a displacement effect. Furthermore, in the case of the RFBP, most of the land targeted for forest expansion was located in hilly regions, which are less likely to be used for agricultural purposes. Finally, stakeholder engagement was a major focus of the RFBP effort. Recent studies have emphasized the importance of community involvement for the sustainability of these projects (Baragwanath et al., 2023). Farmers in tribal areas were involved in forest management and operations while incentivizing them to use forest produce to generate livelihood. This engagement may have also played a role in ensuring that land valuable for agriculture (or other uses) was not targeted for forest expansion (Hristov et al., 2020).

Our approach has limitations, which suggest promising avenues for ongoing research. For example, we do not observe what species of trees were planted, nor do we have information on whether they provided other locally useful forest products that may have augmented local residents' livelihoods. Determining impacts beyond the agricultural sector would further enhance our understanding of the potential co-benefits of forest expansion in addition to carbon sequestration. Second, we do not analyze impacts on livestock grazing, despite its prominence as a major agricultural activity in the region. Clearing forestland to make way for pasture has been a major driver of deforestation globally,[25] implying a complementary study on the potential interactions between the RFBP and livestock grazing activity would be useful in gaining a clearer picture of the program's overall impact on the agricultural sector in Rajasthan. Third, given the granularity of our data, our analysis is restricted to district-level effects. Yet the average geographic area of a district in India is still large enough that our analysis likely masks highly localized impacts, particularly with respect to intra-district variation in (potentially sensitive) ecosystems and micro-climates. Picking up this level of variation would require the use of spatially detailed satellite data that, while beyond the scope of the current study, would provide a more focused lens through which to view more localized effects than a district-level analysis can achieve.

While our results are, in many ways, context-specific to the RFBP, there are broader lessons to be learned. There are many developing regions that, like Rajasthan, are arid or semi-arid and yet highly agricultural. These include much of the Middle East and coastal north Africa, as well as parts of southern Africa, Mexico, and the Pacific coast of South America. Although parts of these regions may not be suitable for forest expansion projects like the RFBP, there may be opportunities in certain cases for forest expansion to play a role in both carbon sequestration and support of local agriculture. Our results suggest, at a minimum, that these are not necessarily conflicting goals.

Although more research is needed to better assess the extent to which forest expansion supports an increase in local rainfall or other ecosystem services, such effects would increase the value of carbon-sink-induced forest expansion, particularly in arid regions and regions where rainfall is an important input to agriculture. Our findings suggest that targeting forest expansion projects in arid regions may have substantial local co-benefits in addition to the global benefits of sequestered carbon. Not included in our analysis were potential cost savings to the agricultural sector from the reduced need for irrigation. Similarly, a reduction in severe drought risk may further increase the size of potential co-benefits from forest expansion projects. Further research is needed to quantify these and other possible co-benefits of forest expansion and to re-optimize climate mitigation strategies to account for these potentially significant indirect impacts on the agricultural sector.

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Tables

Table 1: Average treatment effects.

	ln(Area)		ln(Production)		ln(Yield)		ln(Rainfall)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	TWFE	SDID	TWFE	SDID	TWFE	SDID	TWFE	SDID
Planning/Outreach	-0.03	0.00	-0.04	0.05	-0.01	0.06	-0.08***	-0.01
	(0.04)	(0.03)	(0.06)	(0.06)	(0.04)	(0.04)	(0.01)	(0.01)
Planting	0.11*	0.07	0.19**	0.04	0.08	0.01	0.03	-0.06**
	(0.05)	(0.05)	(0.07)	(0.07)	(0.04)	(0.05)	(0.02)	(0.02)
Post-planting	0.03	0.02	0.20	0.24*	0.17*	0.27***	0.08***	0.02
	(0.09)	(0.08)	(0.11)	(0.10)	(0.07)	(0.06)	(0.01)	(0.01)
N	9516	9516	9516	9516	9516	9516	8784	8784
Unit FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Covariates	Yes	Yes	Yes	Yes	Yes	Yes		

Notes: TWFE results estimated from Eq. 2. SDID results estimated from Eq. 4. Standard errors clustered at the district level. SDID standard errors derived from cluster-bootstrap with 500 replications. Dependent variables are log agricultural area (hectares), log agricultural production (tons), log yield (kg/hectare), and log rainfall (mm) in the treated group and specified control districts, 1991-2017. All regressions include district and year fixed effects. Controls include NFSM dummy, MGNREGA dummy, ISOPOM expenditure, RKVY expenditure, agricultural credits, rural bank branches, total population, rural population, literacy rate, SC-ST population, fraction of villages with paved roads. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 2: Crop-level average treatment effects.

Water Intensive Crops

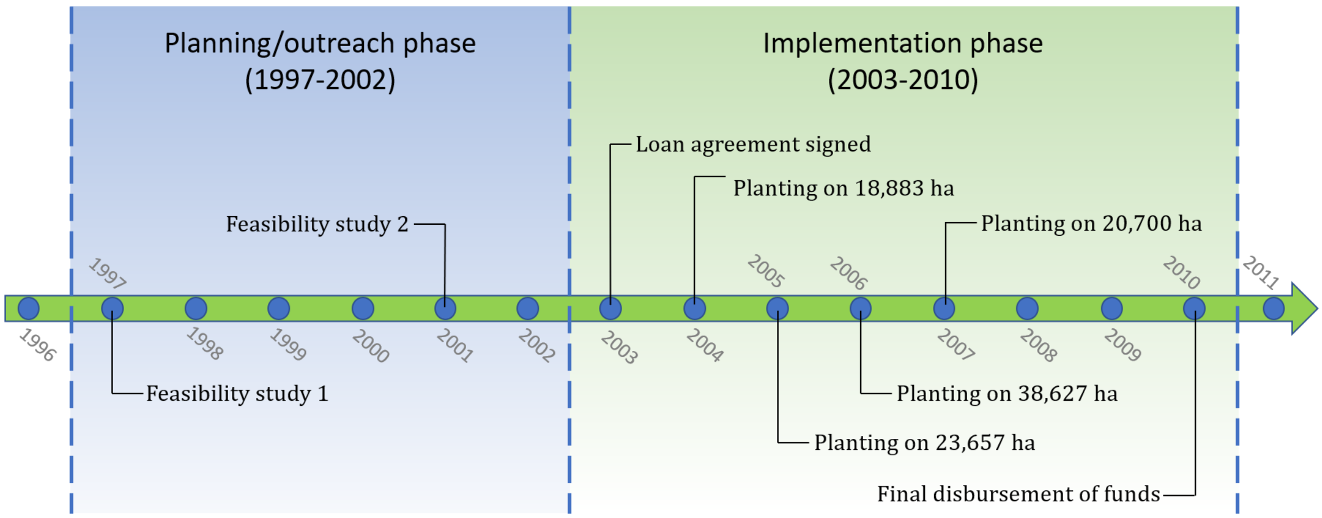
Dep. Var.	Wheat	Corn	Cotton	Rice	Soybeans
Area	0.11*	-0.23***	0.05	0.04	-0.06
	(0.06)	(0.06)	(0.09)	(0.06)	(0.06)
Production	0.20**	-0.31***	-0.07	0.13	-0.08
	(0.07)	(0.09)	(0.07)	(0.08)	(0.06)
Yield	0.09*	-0.08	-0.13**	0.09	-0.01
	(0.04)	(0.04)	(0.04)	(0.05)	(0.02)
N	8655	8797	7726	8822	7337

Non Water Intensive Crops

Dep. Var.	Pearl Millet	Oil seeds	Minor Pulses	Chickpea	Sorghum	Barley
Area	0.26***	0.25***	0.24*	-0.19	0.17	0.13*
	(0.05)	(0.05)	(0.11)	(0.12)	(0.09)	(0.06)
Production	0.64***	0.35***	0.47***	-0.11	0.44***	0.30***
	(0.08)	(0.06)	(0.13)	(0.12)	(0.12)	(0.08)
Yield	0.37***	0.12***	0.22***	0.09**	0.27***	0.18***
	(0.06)	(0.04)	(0.06)	(0.03)	(0.08)	(0.03)
N	8034	7011	8302	8688	8135	8082

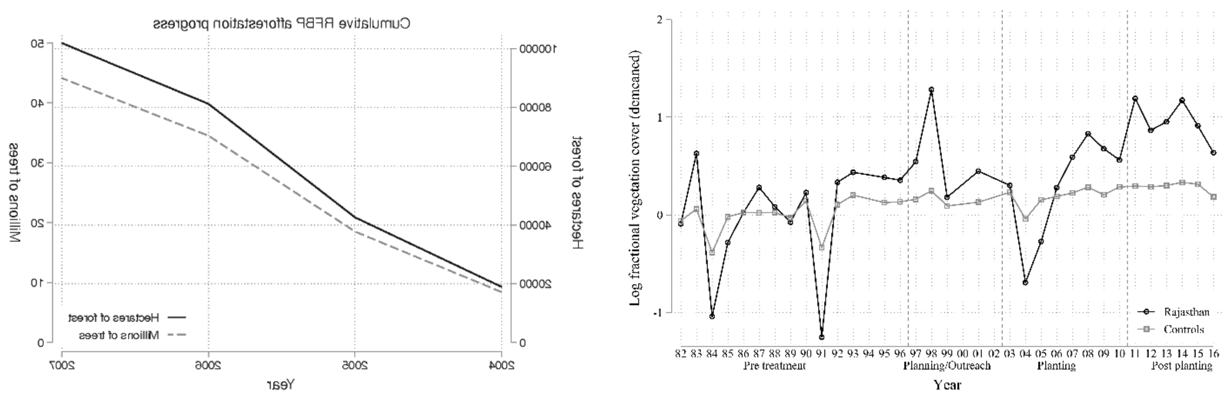
TWFE estimates using Eq. 2. Standard errors clustered at the district level. All regressions include district and year fixed effects. Dependent variables are log agricultural area (hectares), log agricultural production (tons), and log yield (kg/hectare) in the treated group and specified control districts, 1991-2017. Controls include NFSM dummy, MGNREGA dummy, ISOPOM expenditure, RKVY expenditure, agricultural credits, rural bank branches, total population, rural population, literacy rate, SC-ST population, fraction of villages with paved roads. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Figures



Source: JICA's Project Appraisal Document, Project Completion Report dated March 2022

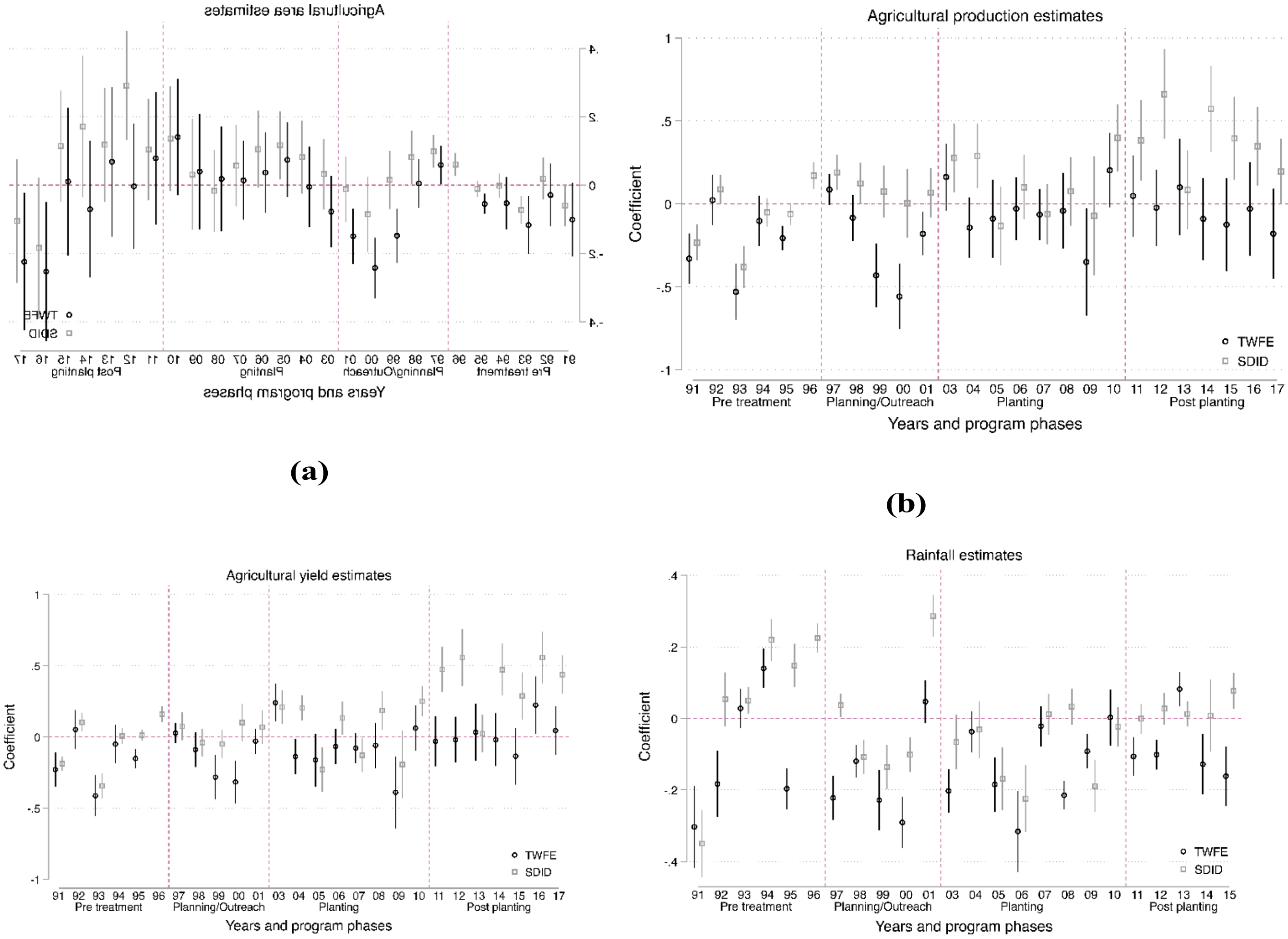
Figure 1: RFBP project Timeline



(a) **(b)**

Data: Figure 2a is generated using data from JICA's Project Appraisal Document, Project Completion Report dated March 2022. Fig. 2b is generated using satellite-measured fractional vegetation cover for both Rajasthan and the unweighted controls (Song et al., 2018).

Figure 2: Left: Cumulative forest expansion progress in treated districts. Right: Demeaned log of forest area, Rajasthan versus controls.

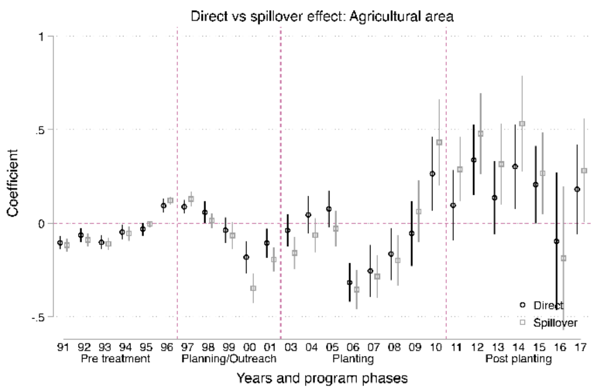


(a) **(b)**

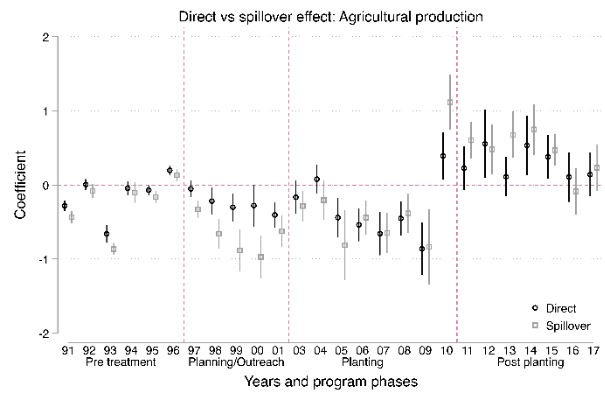
(c) **(d)**

Notes: TWFE results estimated from Eq. 3. SDID results estimated from Eq. 5. Standard errors clustered at the district level. SDID standard errors derived from cluster-bootstrap with 500 replications. Dependent variables are log agricultural area (hectares), log agricultural production (tons), log yield (kg/hectare), and log rainfall (mm) in the treated group and specified control districts, 1991-2017. All regressions include district and year fixed effects. Controls include NFSM dummy, MGNREGA dummy, ISOPOM expenditure, RKVY expenditure, agricultural credits, rural bank branches, total population, rural population, literacy rate, SC-ST population, fraction of villages with paved roads.

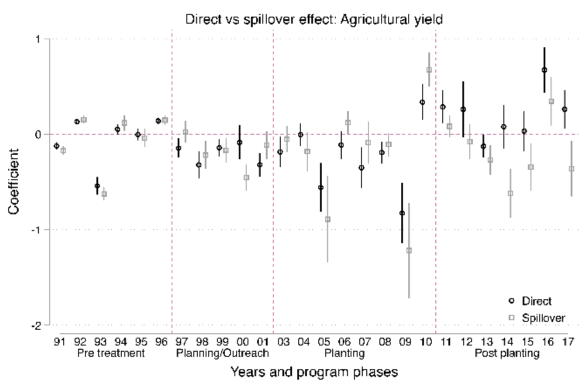
Figure 3: TWFE and SDID event-study estimates.



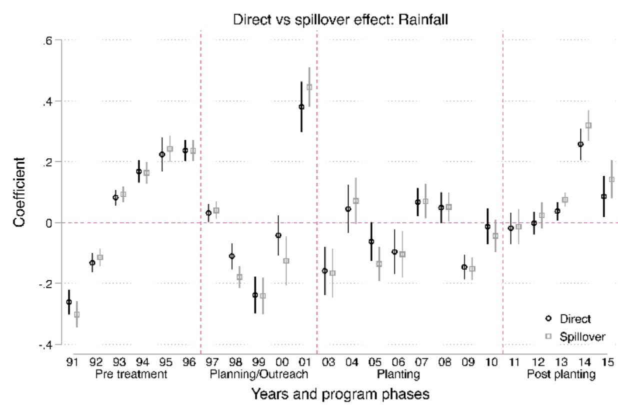
(a)



(b)



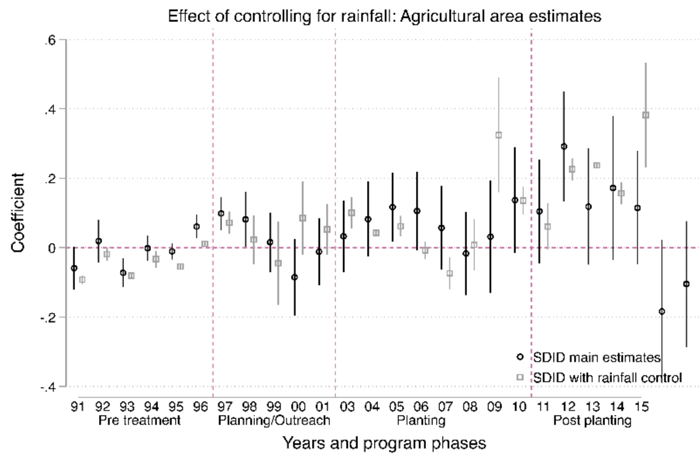
(c)



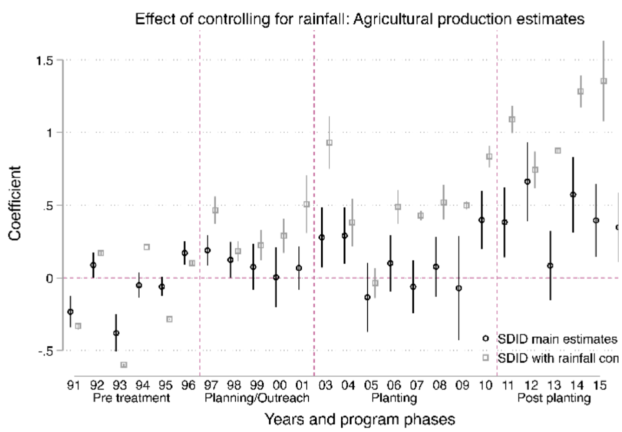
(d)

Notes: Results estimated using Eq. 5 in separate regressions for districts targeted and not targeted by the RFBP. Standard errors derived from cluster-bootstrap with 500 replications. Dependent variables are log agricultural area (hectares), log agricultural production (tons), log yield (kg/hectare), and log rainfall (mm) in the treated and specified control districts, 1991-2017. All regressions include district and year fixed effects. Controls include NFSM dummy, MGNREGA dummy, ISOPOM expenditure, RKVY expenditure, agricultural credits, rural bank branches, total population, rural population, literacy rate, SC-ST population, fraction of villages with paved roads.

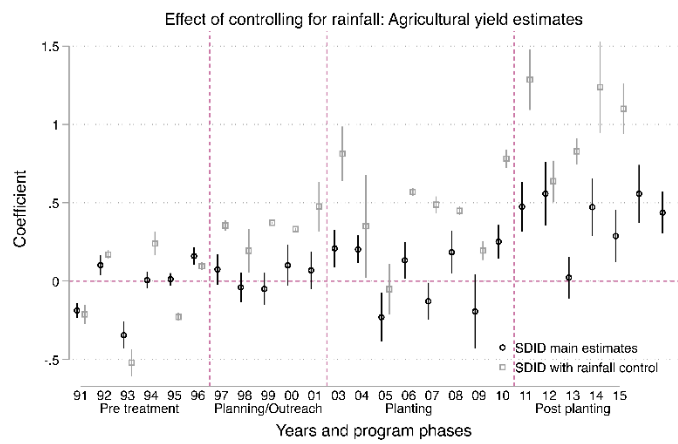
Figure 4: SDID event-study estimates comparing districts in Rajasthan targeted by the RFBP and districts that were not directly targeted.



(a)



(b)



(c)

Notes: Results estimated using Eq. 5 in separate regressions controlling and not controlling for rainfall. Standard errors derived from cluster-bootstrap with 500 replications. Dependent variables are log agricultural area (hectares), log agricultural production (tons), and log yield (kg/hectare) in the treated and specified control districts, 1991-2017. All regressions include district and year fixed effects. Controls include NFSM dummy, MGNREGA dummy, ISOPOM expenditure, RKVY expenditure, agricultural credits, rural bank branches, total population, rural population, literacy rate, SC-ST population, fraction of villages with paved roads.

Figure 5: Comparison of main event-study estimates with estimates net of rainfall

Notes

[1] As a semantic distinction, 'afforestation' generally refers to planting trees on land that had not previously been forested, whereas 'reforestation' refers to planting trees on land that had recently been forested but was converted to other uses (like agriculture). For our purposes, this distinction is inconsequential. For brevity, we use the term 'forest expansion' throughout.

2 Transpiration in plants depends on several factors, including leaf area, stem diameter, soil temperature, sapwood area, age of the plant, tree height, and canopy cover (Vertessy et al., 1995; Kostner et al., 2002; Wang et al., 2011).

3https://www.jica.go.jp/india/english/office/others/c8h0vm00004cesxi-att/brochure_03.pdf

4 Many forest expansion and/or recovery programs follow a top-down approach in which local communities are not involved in project operations and maintenance. Officials charged with oversight of such top-down programs may not be aware of, or pay attention to, important project co-benefits such as ecosystem service effects. A detailed description of the RFBP is provided below.

5 https://reliefweb.int/report/india/india-southwest-monsoon-2002-end-season-report

6 We exclude livestock grazing from our analysis, focusing only on cultivated crops.

7 While the findings of Araujo (2024) and Grosset et al. (2024) draw similar conclusions as to the effects of forests on rainfall, our study differs significantly from each in terms of the geographical and institutional settings, data, and empirical methodologies used. We view the three studies as jointly complementary to the emerging literature on such effects.

8 https://india.restorationatlas.org/atlas

9https://india.mongabay.com/2022/12/explainer-wastelands-or-grasslands-indias-history-with-defining-open-ecosystems/

10 https://pib.gov.in/newsite/erelcontent.aspx?relid=57051

11 Authors' calculations. See: https://forest.rajasthan.gov.in/content/raj/forest/en/resources/forest-statistics/area---land1/total-forest-area-by-legal-status-of-rajasthan.html

12 Fractional vegetation cover is often used as a measure for forest cover. Data are missing from 1994 and 2000 due to incomplete coverage. We omit 2002 due to the extreme drought that year.

13 In Appendix B, we provide a formal DID analysis of changes in forest cover that provides estimates consistent with the trends in Figure 2b.

14 https://www2.jica.go.jp/en/evaluation/pdf/2012_ID-P148_4_f.pdf

15 https://www2.jica.go.jp/en/evaluation/pdf/2012_ID-P148_4_f.pdf

16 Not all districts are included in our final sample due to missing data for one or more control variables over some part of the sample period.

17 The SHRUG data are collected at the village level from population census in 1991, 2001, 2011, and 2021. We aggregate the data to the district level and interpolate the data for years between censuses, following the interpolation approach taken by Greenstone and Hanna (2014).

18 These agencies sell the inputs to farmers at subsidized prices, then receive the difference in subsidized price and actual price in the form of subsidy from the government.

19 NFSM was launched in 2007-08 to boost the production of rice, wheat, and pulses in India. This scheme aims to ensure food security for the growing population of India. It was launched in 482 districts of 19 states.

20 20 percent of districts were missing data in at least one time period and were thus eliminated from our final sample. We find no substantial differences in the event study or TWFE regression results when we use the full versus the balanced panel.

21 In Appendix C, we also provide TWFE estimates for a sample with controls restricted to districts in the same agroecological zones as Rajasthan. Our findings are robust to this alternative approach.

22 Ultimately, either comparison yields similar treatment effect estimates, which we explore in Section 6.1.

23 Brewer and Cameron (2023) compare re-estimating the SDID for each time period in an event-study framework relative to using the same time weights estimated for the average value of post-period outcomes.

24 For instance, the world's largest forest expansion project is the African Green Great Wall, which has a goal of over 100 million hectares of forest restoration: https://www.greatgreenwall.org/2030ambition.

25 Cattle grazing also has other potentially detrimental ecological effects, including exacerbating the spread of invasive plant species if native grasses are over-grazed, disrupting ecosystems in complex ways (Finnoff et al., 2008; Strong and Oliver, 2014).