Earth, Water, Fire, Air: Causal Impacts of Water Preservation Acts of Indian States*

Ashraf, Hisham Ali †
Indian Institute of Technology Delhi

A. Banerji ‡
Indian Institute of Technology Delhi

Debnath, Sisir §
Indian Institute of Technology Delhi

September 21, 2024

Abstract

This paper investigates the intended and unintended consequences of the Preservation of Subsoil Water Acts, enacted in 2009 in the Indian states of Punjab and Haryana. The Acts aimed to preserve groundwater by delaying the sowing and transplanting of paddy until the arrival of monsoon, thereby reducing the reliance on irrigation. Employing difference-in-differences and triple difference strategies, this paper demonstrates that while the policy had a small effect on groundwater preservation, it also had unintended adverse effects on air quality. By shortening the time available between the rice harvest and the sowing of wheat, the Acts prompted farmers to increasingly resort to crop residue burning as a quick means of clearing fields. This practice, in turn, contributed to a rise in particulate matter in the atmosphere, with significant implications for air quality in the region. The findings highlight a trade-off for policy makers: gains in groundwater preservation may come at the cost of worsening air quality.

Keywords: Groundwater, Crop residue burning, Air quality
JEL Codes: Q10, Q18, Q25, Q53

---

*We would like to thank Alau Adnan, Debayan Mukherjee, and Anaviggha Pradhan for their excellent research assistance. Existing errors are all ours.

†huz228242@iitd.ac.in
‡a_banerji@hss.iitd.ac.in
§sisirdebnath@iitd.ac.in

1 Introduction

In 2009, the Preservation of Subsoil Water Acts (henceforth, the Water Acts) were introduced in the agricultural powerhouse states of Punjab and Haryana in India, as a bold response to an escalating environmental problem: the steady decline of the groundwater table. These states, once heralded as the cradle of India's Green Revolution, had become heavily dependent on groundwater for their agricultural output, particularly in the cultivation of water-intensive paddy (rice). Groundwater extraction had reached unsustainable levels, with more than 70% of irrigation water being sourced from rapidly depleting aquifers (Rodell *et al.*, 2009). To address this, the Water Acts aimed to shift the agricultural calendar, delaying paddy sowing to coincide with the monsoon and thereby reducing the need for early-season irrigation.

In recent years, an opinion has formed that the Water Acts may also have had significant, continuing, *unintended* consequences. By delaying the sowing of paddy, the policy inadvertently compressed the time available for harvesting and field preparation for the subsequent Rabi season crop (typically wheat) (McDonald *et al.*, 2019). This led to a surge in crop residue burning, a quick and inexpensive method of clearing fields. Crop residue burning, concentrated in the months of late October and November, compounded the region's pollution problems as it coincided with cooler weather and more stable atmospheric conditions. This worsened air quality, contributing to severe public health risks due to increased particulate matter in the atmosphere (Chakrabarti *et al.*, 2019).

In this paper, we attempt to provide a comprehensive, causal assessment of the unintended and intended impacts of the Water Acts: air pollution and groundwater conservation[1]. We employ difference-in-differences (DiD) and triple difference techniques, using Punjab and Haryana as treatment groups and other Indian states that grow one paddy crop a year as the control group.[2] We utilize comprehensive panel data from Punjab and Haryana to isolate the policy's effects by comparing pre- and post-policy periods across treatment and control districts.

Our research reveals that the Water Acts successfully delayed the sowing of paddy. Their effect on groundwater preservation was small, however (about slightly more than half a meter in water depth for Haryana, and insignificant for Punjab[3]), while its unintended consequences were fairly severe. The delayed sowing pushed the harvesting period into late October and November, a time when the air is cooler and more stable, conditions that are conducive to the accumulation of pollutants. This shift in the agricultural calendar has been linked to an increase in crop residue burning, as farmers faced a compressed window to clear their fields for the next crop. Using multiple data sources, we find that the Water Acts led to a substantial increase in crop residue burning, contributing to a significant increase in particulate matter in the atmosphere. This worsened air quality in Punjab and Haryana, and also spilled over to neighboring states. Furthermore, the effects on air pollution spiked in the month of November, coinciding with the delayed harvest of rice, highlighting the impact of the compressed agricultural calendar on environmental outcomes. The trade-off of a slight gain in groundwater conservation (in a causal, DiD sense) at the expense of significant health costs from added air pollution underscores the need for policymakers to consider the full range of potential consequences when implementing environmental policies, recognizing that gains in one area can come at the cost of losses in

[1]More broadly, crop residue burning has potentially serious consequences in terms of releasing carbon into the atmosphere. Our analysis focuses on the consequences on air quality and $PM_{2.5}$.

[2]Figure 1 plots these states.

[3]These preliminary results measure impact using observation well depths of the Central Groundwater Board (CGWB).

another.

Our estimates indicate that the implementation of the Water Acts led to an average increase of 8 units in thermal anomalies in the districts of Punjab and 6 units in those of Haryana. Compared to pre-legislation averages, this corresponds to increases of 11.78% in Punjab and 57.91% in Haryana. Similarly, the burned area expanded by 7.22 km^2 (22.96%) in Punjab and 3.92 km^2 (47.72%) in Haryana. In terms of $PM_{2.5}$ concentrations, the Water Acts were associated with increases of 4.51 μg/m^3 (7.89%) in Punjab, 8.59 μg/m^3 (12.82%) in Haryana, and 4.13 μg/m^3 (6.5%) in the neighboring states of Delhi, Uttar Pradesh, Rajasthan, and Himachal Pradesh. These effects were most pronounced in the month of November. Typically, a negative effect is observed in September and October, followed by a substantial positive effect in November. This pattern suggests an increase in the intensity of crop residue burning in Punjab and Haryana, with the peak shifting towards November, reflecting a delayed harvest. Importantly, in models that control for crop residue burning in Punjab, the estimated effect on $PM_{2.5}$ concentrations in the neighboring states diminishes or disappears entirely, but only for the month of November. This indicates that a portion of the increased pollution in these states during November can be attributed to burning in Punjab. These findings formally trace the increase in $PM_{2.5}$ levels to crop residue burning in Punjab.

There is a growing literature that attempts to separately measure the impacts of the Water Acts on conservation of groundwater and on air pollution. Tripathi *et al.* (2016) is an early paper that uses panel data on 12 districts of Punjab to measure a first difference impact of the Act on groundwater (pre- versus post-2009). While they find that the Punjab Act resulted in significant groundwater savings, the restriction to a small number of districts and to only a first difference also restricts the ability to address confounds. A more recent study (Kishore *et al.*) studies the impact of the Punjab Act on groundwater, using a synthetic control method: it finds the perverse impact of further groundwater depletion.

Agarwala *et al.* (2022) finds, using a DiD framework, that the Water Acts had a significant impact in delaying the paddy season and increasing crop residue burning. McDonald *et al.* (2019) is a short study of the impact of the Acts on pollution.

The present paper is related to all the above studies, but makes the following contributions. First, it studies both the intended effect on groundwater and the unintended effect on air pollution, using a common set of controls to the extent possible. The caveat here is that the spillover of air pollution to downstream states is dealt with by a suitable adjustment in this estimation strategy. Second, it uses multiple data sources for robustness. Thus, we use both data on market arrival of paddy as well as satellite data on vegetation to estimate the impact of the Water Acts on delayed sowing and harvesting; and we estimate groundwater impact using data both on observation wells, as well as satellite data that estimates groundwater volumes [4]. Third, for air pollution, we establish formally that the impact pathway is via increased crop residue burning. Fourth, we are able to quantify the magnitude of contributions from Punjab and from Haryana, in the matter of downstream air pollution; they are qualitatively different, with Punjab being a significantly larger contributor. Finally, in ongoing work, we are measuring the impact on the Water Acts on groundwater pumping by farmers, and whether this is a potential channel to explain the impact on groundwater.

The remainder of this paper is organized as follows. Section 2 provides a detailed background on the historical context of irrigation-intensive cultivation in Punjab and Haryana, the role of key government policies in promoting paddy cultivation, and the subsequent environmental

[4]This latter is preliminary and available with the authors on request

challenges. Section 3 and Section 4 describe the data sources and outlines the methodology used in this study, while Section 5 presents the empirical findings. We discuss the robustness of the results in Section 6. Finally, Section 7 discusses the broader implications of these findings for agricultural policy and environmental sustainability and concludes.

2 Background

The Green Revolution, which began in the mid-1960s, transformed Indian agriculture, and Punjab and Haryana were at its core. Alluvial soils, well-developed canal systems and other support infrastructure were key to subsequent agricultural growth (Swaminathan, 2006), even though the states had only moderate rainfall at best (400mm-700mm per year) (Hira and Khera, 2000). A package of Government-led initiatives, particularly the promotion of high-yield variety (HYV) seeds, fertilizers, and pesticides, coupled with support for irrigation infrastructure, and public procurement of grain at pre-announced Minimum Support Prices (MSP) allowed for the large-scale cultivation of crops such as wheat and even water-intensive paddy (Sidhu *et al.*, 2011).

By the 1980s, paddy had firmly established itself as the *Kharif* crop of choice in these states, and the paddy-wheat annual cycle had become the norm. Since paddy requires far more irrigation than rainfall could provide, there was an accompanying rise in the role of irrigation, and groundwater irrigation in particular, which became the backbone of this agricultural expansion.

Over the decades from 1970 to 2010, the area under rice cultivation increased, respectively for Punjab and Haryana, from 0.5 and 0.2 million hectares to 2.8 and 1.2 million hectares (Singh, 2009; Bhalla and Singh, 1997). The growth of tube wells ran in parallel; in Punjab alone, the number of tube wells increased from about 190,000 in 1970 to over 1.2 million by 2010 (Shah, 2007). This growth was mirrored in Haryana, where groundwater extraction also reached unsustainable levels. By the early 2000s, over 80% of the agricultural land in Punjab and Haryana was irrigated using groundwater (Gandhi and Bhamoriya, 2011).

Central to the rise of paddy cultivation was the Minimum Support Price (MSP) regime referred to earlier, introduced in the 1960s to ensure that farmers received a guaranteed price for their produce, particularly for staple crops like wheat and rice (Ganesh-Kumar *et al.*, 2007). The MSP made paddy an economically attractive option, leading to its widespread adoption in a region traditionally unsuited for such water-intensive crops.

In addition to the MSP, input subsidies played a crucial role. The government provided significant subsidies on fertilizers, seeds, and, notably, electricity. The latter was particularly impactful because electricity for agricultural use was either heavily subsidized or not metered at all, making the cost of running tube wells negligible for farmers. This policy encouraged the over-extraction of groundwater; farmers faced little to no marginal cost for irrigation, which tended to increase irrigation volumes from existing tubewells, as well as the incentive to bore additional wells (Gupta, 2023).

The combination of these factors created a system where the cultivation of paddy became highly profitable and relatively low-risk, driving its expansion across Punjab and Haryana despite the unsuitability of the region's water resources to sustain such practices. As a result, the water table in these states began to decline rapidly, leading to widespread concerns about the sustainability of groundwater resources.

The shift to groundwater-dependent paddy cultivation had severe environmental repercussions. Numerous academic studies have documented the adverse impacts of this shift. For instance, a study by Rodell *et al.* (2009) using satellite-based estimates highlighted that Punjab and Haryana were among the regions with the highest rates of groundwater depletion globally. The annual rate of groundwater decline in these states was estimated to be between 0.33 and 0.75 meters per year during the 2000s. Another study by Fishman *et al.* (2015) found that the continued cultivation of paddy at such an intensive scale was unsustainable and projected that the region could face a critical water shortage within the next few decades if current practices continued.

In response to the alarming rate of groundwater depletion, the Punjab government enacted the Preservation of Subsoil Water Act in 2009, with Haryana implementing a similar law shortly thereafter. The Act prohibited the sowing and transplanting of paddy before a specified date in June[5], aligning the paddy-growing season with the arrival of monsoon[6]. The objective was to reduce the reliance on groundwater for irrigation during the early stages of paddy cultivation by taking advantage of the natural rainfall provided by the monsoon (Kishore *et al.*). The Act was expected to arrest the falling water table by 30 cm and save electricity to the tune of 276 million kWh (Singh, 2009).

3 Data

We collate data from multiple sources to assess the impact of the Water Acts on crop residue burning, air pollution, and groundwater levels in Punjab and Haryana. Our analysis primarily uses aggregated monthly data at the district level. To ensure consistency across datasets, we aggregate them in accordance with the district boundaries defined in the Census of India, 2011. This approach allows us to merge information from multiple sources effectively, eliminating the distortions arising from the formation of new districts over time. Table 1 summarizes the main variables used in our analysis.

3.1 Crop Arrivals

The Ministry of Agriculture and Farmers Welfare in India has been gathering data on the daily arrivals of agricultural commodities and their prices across government-regulated agricultural markets, commonly referred to as "mandis", since 2001. These data consist of information on 344 agricultural commodities from approximately 4,000 *mandis* spanning 650 districts, and constitute one of the most comprehensive sources of wholesale price and quantity information in India.[7] We compile data on crop arrivals for Punjab, Haryana, and the control states, covering the period from 2000 to 2024. We use this information to assess whether the Water Acts were effectively implemented in Punjab and Haryana by analysing the change in the distribution of rice/paddy arrivals over the rice-harvesting season in these two states.

[5]Non-compliance with this regulation attracts a penalty of Rs. 10,000 per hectare of paddy-cropped area or disconnecting supply of electricity or destroying paddy nurseries at farmer's expense or all of these.

[6]Rice transplanted in early May requires a 5-inch irrigation at puddling, followed by about 3-inch irrigation after every three days up to 15 June. During this period, the relative humidity in North India is lowest, the wind speed is highest, and the temperature is maximum, due to which water evaporates very fast (Singh, 2009).

[7]The data is available at Agmarknet and, in a simpler format, at CEDA

3.2 Vegetation

The MOD13Q1 (Version 6.1) data, generated every 16 days at a 250 m spatial resolution, provides two MODIS-based indices of vegetation: the Normalized Difference Vegetation Index (NDVI) and the Enhanced Vegetation Index (EVI).[8] The NDVI serves as the continuity index to the existing NOAA-AVHRR-derived NDVI, while the EVI offers improved sensitivity over high biomass regions.[9] These indices are derived from daily, atmosphere-corrected, bidirectional surface reflectance in the red, near-infrared, and blue wavebands. For each index, the algorithm selects the best available pixel value from all acquisitions over the 16-day period, using criteria such as low cloud cover, low view angle, and the highest NDVI/EVI value. We download this data in .hdf format using the MODIS Python API and compute the monthly averages of NDVI and EVI values, expressed on a scale from -2000 to 10000, for each 2011 Census district. This procedure results in a panel of 641 districts, covering the period from 2000 to 2024. We use EVI values to estimate the delay, if any, in the commencement of paddy cultivation in Punjab and Haryana after the enactment of Water Acts. We further use yearly data on area under rice cultivation during *Kharif* season collected from the Directorate of Economics and Statistics, Ministry of Agriculture and Farmers Welfare (DESAGRI), to demonstrate that the Enhanced Vegetation Index is a reliable proxy for rice cultivation.[10]

3.3 Thermal Anomalies

We construct a district-level monthly panel measuring crop residue burning based on thermal anomalies identified by the Moderate Resolution Imaging Spectroradiometer (MODIS) sensors aboard the Terra and Aqua satellites operated by NASA.[11] Thermal anomalies indicate possible fire activity. The anomalies flagged by the MODIS Fire and Thermal Anomalies algorithm are geocoded to the centre of a 1 km pixel, meaning that the presence of one or more fires is suggested within that pixel. Detection of these anomalies involves several intermediate algorithms that mask out cloud and water cover, ensuring only land-based heat sources are analyzed. The algorithm distinguishes between various types of anomalies, including vegetation fires, active volcanoes, fires from static land, and offshore sources. Our analysis focuses specifically on vegetation fires. The data also provide confidence estimates for each pixel prediction, ranging from 0 to 100, which indicate the reliability of the detected anomaly. We compute the monthly count of detected thermal anomalies classified as vegetation fires, with varying confidence estimates, at the level of districts. For precision, we consider only the thermal anomalies detected in arable land, with a confidence indicator of at least 20. This process yields a balanced monthly panel for 641 districts over 23 years, from 2000 to 2022. Panel A of Figure 2 compares the extent of thermal anomalies before and after the enactment of the Water Acts.

3.4 Burned Area

The MCD64A1 (Version 6.1) Burned Area data product provides monthly pixel-level information on global burned areas, with data recorded at 500 m grid cells using MODIS sensors aboard

[8] For data and documentation, see MODIS Vegetation Data

[9] NOAA-AVHRR stands for National Oceanic and Atmospheric Administration-Advanced Very High Resolution Radiometer.

[10] Data is available at DESAGRI

[11] The data is available at MODIS Thermal Anomalies

the Terra and Aqua satellites.[12] Burned areas are identified by an algorithm that analyzes daily surface reflectance dynamics, detecting rapid changes to approximate the date of burning. A GeoTIFF subset of this data corresponding to the region of South Asia is available from the University of Maryland server.[13] We download these files and compute the number of burned pixels, belonging to arable land, in each district for each month. To measure the total area burned in a district, we multiplying the proportion of burned pixels in that district by its total area. This process yields a monthly panel of 602 districts, spanning 2000–2022.[14] Panel B of Figure 2 compares the extent of burned area before and after the enactment of the Water Acts.

3.5 Air Pollution

We compile a satellite-derived estimate of monthly ground-level $PM_{2.5}$ provided by the Atmospheric Composition Analysis Group at Washington University in St. Louis (Van Donkelaar *et al.*, 2021).[15] These estimates are generated by combining Aerosol Optical Depth retrievals from various satellites (MODIS, MISR, SeaWiFS, and VIIRS) with the GEOS-Chem chemical transport model, calibrated to global ground-based observations using a Geographically Weighted Regression. We use the high-resolution ($0.01° \times 0.01°$) monthly average predicted $PM_{2.5}$ measures to compute district-level monthly averagess. This process resulted in a balanced monthly panel for 641 districts spanning 25 years, from 1998 to 2022. Figure 3 compares the satellite-derived measures of $PM_{2.5}$ before and after the enactment of the Water Acts.

To validate the satellite-derived measures of $PM_{2.5}$, we use ambient air quality data reported by 746 monitoring stations operated by the Central Pollution Control Board (CPCB) between 1987 and 2015.[16] This dataset encompasses measurements of several air pollutants, expressed as micrograms per cubic meter of air ($\mu g/m^3$). These pollutants include sulfur dioxide (SO_2), nitrogen dioxide (NO_2), respirable suspended particulate matter (RSPM), suspended particulate matter (SPM), and particulate matter ($PM_{2.5}$). It is important to note that not all stations consistently provided data throughout the entire period due to noncompliance with the National Ambient Monitoring Program (NAMP) guidelines. Some of the non-compliant stations were relocated or closed. Furthermore, from 2014 onwards, the collection of SPM data ceased and was replaced by $PM_{2.5}$ measurements. Consequently, $PM_{2.5}$ data are only available for the years 2014 and 2015.This data helps us to demonstrate the correlation between ambient $PM_{2.5}$ and satellite-derived $PM_{2.5}$ data.

To estimate the correlation between satellite-derived estimates of $PM_{2.5}$ and CPCB monitoring station data, we geocoded the location of monitoring stations using Google's Geocoding API and matched the resultant coordinates to corresponding pixels of satellite data. A geocoder matches a provided address to an address in their database and provides the corresponding latitude and longitude coordinates. The addresses of the monitoring stations available in CPCB data vary in completeness and accuracy, and the API provides coordinates of partial matches when it fails to obtain an exact match for a given address. We then constructed a combined dataset with CPCB and satellite-derived data for available measurements from CPCB. The correlation estimates are reported in Table A.1, with stronger correlations reported for exact address matches.

[12] For data and documentation, see MODIS Burned Area
[13] See the User Guide
[14] The GeoTIFF files do not cover 39 districts in Northeast India.
[15] The data is available at Satellite-Derived $PM_{2.5}$
[16] The data is available at CPCB

3.6 Groundwater

The Indian Central Ground Water Board (CGWB) monitors groundwater levels throughout the country four times yearly, in January, May, August, and November, through a network of dug wells and bore/tube wells, called piezometers, built specifically for water level monitoring.[17] The unit of measurement is meters below ground level (mbgl). Groundwater data from monitoring stations exhibit non-random missingness due to the presence of dry wells, which occur when the groundwater level falls below the monitoring well's maximum floor depth. Therefore, deleting missing values from the sample would lead to a biased estimate of the population mean of groundwater level over a spatial domain, such as a district (Ali and Arora, 2021). Despite recognizing this bias, we proceed with our estimates after deleting missing values for the time being, acknowledging the need for future methodological improvements.

The monitoring wells are distributed throughout the country and not concentrated in any specific area. Notably, wells have not been placed in regions experiencing the most severe groundwater depletion. This widespread distribution minimizes concerns about endogenous well placement affecting the analysis. Additionally, the dataset provides coordinates for each well, which we use to map each well to districts as defined in 2011, creating a district-level panel of monthly groundwater levels. These district-level groundwater depth measurements constitute a key outcome variable in this paper.

3.7 Cropland

To ensure that MODIS-detected thermal anomalies and burned area are reliable proxies of crop residue burning, we restrict out analysis to the thermal anomalies and burning incidents detected within arable area. Arable areas are identified using a unified cropland layer at 250 m resolution, with 2014 as the reference year, provided by Waldner *et al.* (2016).[18] Each pixel of this layer is assigned a value that ranges from 0 to 100, with higher values for relatively more arable areas. We consider areas with a value of at least five as arable, and construct our measures of thermal anomalies and burned area exclusively from this region. This procedure essentially excludes deserts, forests and urban spaces from the analysis of crop residue burning, improving precision.

3.8 Crop Area

The International Crop Research Institute for the Semi-Arid Tropics (ICRISAT) publishes a District Level Database (DLD) for 20 major states in India, covering a comprehensive set of variables in agriculture and allied sectors. These variables include crop area and production, irrigated area, operational holdings, population census data, and selected agroecological variables, all available annually. The data are collated from several government offices, including the Directorates of Agriculture and state Bureaus of Economics and Statistics.

The database comprises an apportioned dataset of 313 districts (consistent with the 1966 district boundaries) covering the period 1966 to 2016, and an unapportioned dataset (following the current district boundaries) spanning 1990 to 2016.[19] For our econometric specification, we use several variables from the ICRISAT unapportioned database, such as the area under

[17]Data is available at CGWB
[18]Available at Unified Cropland Layer
[19]The data are available at ICRISAT

different crops. The primary variables of interest include the net cropped area, the area under rice, and the area under wheat (measured in 1000 hectares). To ensure a consistent frame of analysis, we transform the data on these variables for the period between 2001 and 2022 into a panel of the 2011 Census districts. This is achieved by overlaying the bounding polygons of districts at three different points in time: 2001, 2011 and 2022.[20] Through this procedure, we are able to identify the districts formed in the interim, map them to their parent districts, and assign weights to the parent districts based on the proportion of their area that joined the new district. These weights, combined with hand-collected information on the dates of formation of the new districts, allow us to make necessary interpolations to the variable values so as to simulate a static configuration of districts with 2011 boundaries.

3.9 Climate Variables

To construct district-level estimates of climate variables, we use the open-source TerraClimate dataset[21], which offers climate data at a monthly temporal resolution and a spatial resolution of 1/24th degree (approximately 4 km) from 1958 to 2020. TerraClimate uses climatically aided interpolation, combining high-spatial-resolution climatological normals from WorldClim with time-varying data from the University of East Anglia's Climatic Research Unit Time series (CRU Ts4.0) and the Japanese 55-year Reanalysis (JRA55). The monthly dataset, which includes precipitation, maximum and minimum temperature, and wind speed among other variables, is produced by applying interpolated time-varying anomalies from CRU Ts4.0/JRA55 to the high-spatial-resolution climatology of WorldClim. We extract our variables of interest—maximum temperature, minimum temperature, precipitation accumulation, and wind speed—from the yearly NetCDF (Network Common Data Form) files and computed the monthly averages at the district level using the 2011 Census district boundaries. This process yields a monthly panel for each climate variable of interest for 641 districts spanning 23 years, from 2000 to 2022.

The International Crop Research Institute for the Semi-Arid Tropics (ICRISAT) also publishes a monthly district-level panel computed using data from TerraClimate, but with inconsistent district boundaries. Figure A.1 shows the comparison of our calculation of district-level aggregates for the climate variables of interest against those of ICRISAT, both using the TerraClimate dataset.

4 Estimation

As discussed earlier, our data is restricted to eight states that cultivate a single paddy crop annually during the *Kharif* season. The district-wise ratio of the area under paddy to the net-cropped area in these states is illustrated in Figure 1. The geographic contiguity of these states also ensures that their agroclimatic conditions are relatively homogeneous. Additionally, most of these states are grappling with the challenge of groundwater depletion. Among these eight states, Punjab and Haryana implemented the Water Acts in 2009. The primary objective of the legislation was to discourage the sowing of paddy before the onset of the Monsoon rains, reducing their dependency on groundwater irrigation. However, if the policy were enforced, it would reduce the gap between the harvesting of paddy and the sowing of the next crop. Consequently, farmers might adjust their agricultural practices to accommodate the shorter

[20] The required shapefiles were downloaded from Community Created Maps of India

[21] The data is available at TerraClimate

duration between crops. Many recent studies (Kant *et al.* (2022); McDonald *et al.* (2019); Agarwala *et al.* (2022)) have highlighted the increase in paddy residue burning by farmers in Punjab and Haryana as a means to quickly prepare their fields for the next crop. In this section, we outline the estimation strategy to explore the effects of the policy change on the delay in paddy harvesting, crop residue burning, air pollution, and groundwater levels.

Our main outcome variable of interest is crop residue burning, air pollution, and groundwater in response to the Water Acts. To this end, we estimate the following difference-in-difference specification:

$$y_{sdtm} = \beta_0 + \beta_{p\tau}\text{Punjab}_d \times \text{Post}_t + \beta_{h\tau}\text{Haryana}_d \times \text{Post}_t + \beta_{sd} + \beta_t + \beta_m + \beta_s t + \boldsymbol{\beta_X} \boldsymbol{X}'_{sdtm} + \epsilon_{sdtm} \quad (1)$$

where the indices s, d, t, and m represent state, district, year, and month, respectively. Punjab_d and Haryana_d are binary variables that take the value one if district d belongs to the states of Punjab and Haryana, respectively. Post_t is a binary indicator that takes the value one if year t is 2009, the year of implementation of the Water Acts, or later, and zero otherwise. Our main parameters of interest are the coefficients $\beta_{p\tau}$ and $\beta_{h\tau}$ measuring the average difference in the outcome variable y_{sdtm} for the treatment states of Punjab and Haryana before and after the implementation of the Water Acts in comparison to the same difference in the control states. District fixed effects (β_{sd}) control for time-invariant unobserved characteristics of districts that might have affected the implementation of the Water Acts and the outcome variables of interest simultaneously. The year fixed effects (β_t) control for events that might have affected the implementation of the Water Acts and the outcome variables simultaneously. As agricultural activities and environmental outcomes are weather-dependent and cyclical, we control for month-fixed effects (β_m) in all our specifications. State-specific linear time trends ($\beta_s t$) capture the trends in agricultural practices that affect the environment due to changes in input requirements or cropping patterns. The district and time-varying characteristics ($\boldsymbol{X}'_{sdt}$) include factors that could simultaneously influence agricultural practices and environmental outcomes, such as air pollution and groundwater levels. These factors include average monthly precipitation, minimum and maximum temperatures, and wind speed. The errors are clustered at the state level.

Given the seasonal variation in most of our outcome variables and agricultural activities, we also estimate the Act's effects by month in a triple-difference setup outlined below,

$$\begin{aligned} y_{sdtm} = \beta_0 &+ \sum_{m=1}^{12} \beta_{p\tau m}\text{Punjab}_d \times \text{Post}_t \times \text{Month}_m + \sum_{m=1}^{12} \beta_{h\tau m}\text{Haryana}_d \times \text{Post}_t \times \text{Month}_m + \\ &\sum_{m=1}^{12} \beta_{pm}\text{Punjab}_d \times \text{Month}_m + \sum_{m=1}^{12} \beta_{hm}\text{Haryana}_d \times \text{Month}_m + \sum_{m=1}^{12} \beta_{\tau m}\text{Post}_t \times \text{Month}_m + \\ &\beta_{p\tau}\text{Punjab}_d \times \text{Post}_t + \beta_{h\tau}\text{Haryana}_d \times \text{Post}_t + \beta_{sd} + \beta_t + \beta_m + \beta_s t + \boldsymbol{\beta_X} \boldsymbol{X}'_{sdtm} + \epsilon_{sdtm} \end{aligned} \quad (2)$$

where Month_m is an indicator variable that takes the value one for the m^{th} month of a year. The definition of the rest of the variables continues to be the same as in Equation (1). Our main parameters of interest are the coefficients $\beta_{p\tau m}$ and $\beta_{h\tau m}$ measuring the average difference in the outcome variable y_{sdtm} for the treatment states of Punjab and Haryana before and after the implementation of the Water Acts in comparison to the same difference in the control states for month m. We have excluded the interaction for the month of April.

We assess the assumption of parallel trends in the period 2003–2008 in the double interaction model, Equation (1), and reject the null of parallel trends for the outcomes of thermal anomalies and burned area (see Section 6). However, the null hypothesis of parallel trend is not rejected for $PM_{2.5}$ with the coefficient on the interaction being close to zero (Table 8). Considering the existing time trends in the outcome variables, we control for state-specific time trends in all our specifications. Additionally, we estimate a synthetic difference-in-differences approach to evaluate the policy, following the methodology outlined by Arkhangelsky *et al.* (2021). A detailed discussion of this approach is provided in Section 6.

In addition to examining changes in paddy cultivation patterns, we investigate the effects of the Water Acts on air pollution and groundwater depth. The errors associated with these outcomes may be correlated across contiguous districts. For instance, air pollution is likely influenced by wind speed and direction, while groundwater depth in districts that share the same aquifer is probably correlated. Making inferences from spatially dependent data may introduce bias in the estimated standard errors. Therefore, we report the results of our main regressions after correcting for spatial correlation in errors, as outlined by Colella *et al.* (2019), in Section 6.

5 Results

5.1 Delay in Puddling

The main objective of the Water Acts was to induce farmers to delay paddy transplantation and reduce their dependence on groundwater. To assess the effect of the policy on the delay in paddy transplantation, the ideal outcome variable would be the monthly area under paddy cultivation. Unfortunately, this specific data is unavailable. The area under crop data published by the Department of Agriculture only provides aggregated information for the entire *Kharif* season. Instead, we estimate the impact of the policy on the change in the distribution of the Enhanced Vegetation Index (EVI) over months and the arrival of paddy in the Agriculture Produce Marketing Committee *Mandis*.

Enhanced Vegetation Index is a widely used remote sensing index to assess crop health and productivity, and land use. First, we establish the correlations between EVI and area under paddy cultivation. Table A.2 presents the regression results for rice-cropped area (in hectares) during the *Kharif* season against monthly EVI for districts where paddy is cultivated on more than 50% of the net cropped area. Columns (1)–(5) reports the estimated coefficients for the EVI index from May–September. The magnitude of these estimates increases, with May having the lowest value at 10.9 ($p < 0.01$) during the sowing period, and September the highest at 40.0 ($p < 0.01$) as the rice crop reaches maturity. The R^2 values of these regressions are also highest for September, indicating that EVI is highly positively correlated with the area under paddy cultivation and that this correlation strengthens as the crop matures.

We use the EVI as a proxy for the area under paddy and estimate the triple-interaction model outlined in Equation (2) for districts cultivating paddy on more than 50% of the net cropped area. This model evaluates the differential impact of the Water Acts in Punjab and Haryana on a monthly basis after 2009, compared to other *Kharif* rice-growing states. Figure 6 plots the estimated coefficients with their 95% confidence intervals. For Punjab (left-panel), the triple-interaction estimates for months January to May are statistically indistinguishable from zero. The estimates turn negative for the months of June and July, become positive for the months of August to October, and revert to negative for the months November and December. These estimates suggest that the vegetation index for predominantly rice-growing districts in Punjab declined in June and July, the period by which paddy transplantation is typically complete, compared to rice-growing districts in other states after 2009. Conversely, the index difference was positive for districts in Punjab in the later months, when the crop matures. We observe a similar but muted effect for the state of Haryana.[22]

The regression results on EVI suggest that the Water Acts delayed the sowing of rice in Punjab and, to a lesser extent, in Haryana. This delay in sowing would subsequently result in a delayed harvest. We then analyze the effects of the policy on the arrivals of rice compared to other major *Kharif* crops across government-regulated agricultural markets, commonly referred to as *mandis*, using the following triple interaction specification:

$$\begin{aligned}\text{Arrival Day}_{sdtnc} = \beta_0 &+ \beta_{p\tau p}\text{Punjab}_d \times \text{Post}_t \times \text{Paddy}_c + \beta_{h\tau p}\text{Haryana}_d \times \text{Post}_t \times \text{Paddy}_c + \\ &\beta_{p\tau}\text{Punjab}_d \times \text{Post}_t + \beta_{h\tau}\text{Haryana}_d \times \text{Post}_t + \beta_{\tau p}\text{Post}_t \times \text{Paddy}_c + \\ &\beta_{pp}\text{Punjab}_d \times \text{Paddy}_c + \beta_{hp}\text{Haryana}_d \times \text{Paddy}_c + \\ &\beta_{sd} + \beta_t + \beta_n + \beta_s t + \beta_q q_{sdtnc} + \epsilon_{sdtm}\end{aligned} \tag{3}$$

where the indices s, d, t, and n represent state, district, year, and *mandi*, respectively. Punjab_d, Haryana_d, and Post_t are binary indicators as defined earlier in Equation (1). Paddy_c is an indicator taking the value one for the arrivals of paddy and zeros otherwise.[23] Since arrival of crops depend on storage technology, crop cycles, etc., we continue to control for the fixed effects and trends defined earlier in Equation (1), with the exception of month fixed effects. In addition, we control for q_{sdtnc}, the quantity of crop sold for each arrivals, and include *mandi* fixed effects (β_n). The outcome variable $\text{Arrival Day}_{sdtnc}$ is defined as the day of the year for each arrival of crop c in *mandi* n in district d in state s in year t.[24]

The results from this regression are presented in Table 2. In Column (1), we report the estimated coefficients without any fixed effects and trends. The point estimates suggest that the arrival of rice in Punjab and Haryana *mandis* was delayed by 13.1 days ($p < 0.01$) and 22.7 days ($p < 0.01$), respectively, compared to other major *Kharif* crops and other single rice crop states following the enactment of the Water Acts. In the subsequent columns, we additionally control for district, year, and mandi fixed effects, as well as state-specific time trends; however, the point estimates on the triple interaction remain statistically significant. Our most preferred specification, in Column (4), indicates that the enactment of the Ware Acts led to an average delay of about two weeks in the arrival of harvested rice.

We observe similar patterns when we plot the distribution of arrivals of rice and cotton, one of the other most important *Kharif* crops in Figure 4. The figures in Panel A, plot the distribution of rice arrivals over the days of a year for the states of Punjab, Haryana, and all other single paddy crop states. The distribution of arrivals in the pre- and post-legislation periods are marked by dashed and solid lines, respectively. The distribution of rice arrivals

[22]Perhaps the difference in the area under paddy cultivation can explain the variation in the point estimates. According to the DESAGRI data described in Section 3, the area under paddy cultivation was 14,4525 and 57,450 hectares in Punjab and Haryana in 2009, respectively.

[23]Besides rice, other Kharif crops include maize, cotton, and soyabean.

[24]Since *Kharif* crops are typically harvested at the end of the year, their *mandi* arrivals can spill over to the following year. To accommodate this, we define the beginning of the year on the first of April and the end of the year on the 30th of April.

in Punjab and Haryana has clearly shifted to the right in the post-legislation period, while there is only a marginal change for the control states. In Panel B, we plot the distribution of cotton arrivals in the *mandis*. There are no discernible changes in the distributions before and after the policy change between the treatment and control states. The results from the earlier regressions and the observed shifts in the distribution of crop arrivals strongly suggest that the policy change substantially delayed the transplantation of paddy in the states of Punjab and Haryana.

5.2 Crop Residue Burning

The delay in paddy harvesting in Punjab and Haryana due to the policy change has compressed the time available to prepare the land for the winter or, *Rabi*, crop. The most prevalent *Rabi* crop in these two states is wheat, and delay in winter wheat sowing could reduce yield substantially. This situation has resulted in an increase in crop residue burning, a rapid and cost-effective method of clearing fields. Although crop residue burning is illegal and subject to penalties, it is not uncommon to observe extensive areas of burned crop residue following the rice harvest. In Panel A of Figure 5, we plot the geographic distribution of thermal anomalies for the month of November in the states that cultivate rice during the Kharif season, both before and after the policy change. The maps in the bottom panel illustrate the district-wise measure of burned area. The maps suggest that crop residue burning was practiced even before the implementation of the law; however, its intensity has increased substantially following the legislations. These changes are noticeably more pronounced in Punjab and Haryana compared to the control states.

We estimate the effects of the Punjab and Haryana sub-soil water preservation acts on thermal anomalies and satellite measured burned area using a difference-in-difference framework outlined in Equation (1) and report the results in Table 3 and Table 4, respectively.

Column (1) in Table 3 reports the estimates of the coefficients of $\beta_{p\tau}$ and $\beta_{h\tau}$ from Equation (1) without any additional fixed effects or other controls for the outcome of count of thermal anomalies in a district in a month. The point estimate for Punjab is 3.76 ($0.01 < p < 0.05$) suggesting an increase of 5.84% from the baseline average. The point estimate for Haryana is -0.89, but it is statistically indistinguishable from zero. In Column (2) we additionally control for state-specific time trends and district fixed effects. The points estimates for Punjab and Haryana increase to 7.05 and 5.18, both significant at one percent level. In Columns (3) and (4) we introduce year and month fixed and effects, and the point estimates marginally increase to 7.6 and 5.9 ($p < 0.01$), respectively. These results support the pattern we observed in Figure 5. To investigate whether the effects of the policy on thermal anomalies varied by the agriculture calendar, we estimate the triple difference specification in Equation (2) and plot the estimates of the coefficients $\beta_{p\tau m}$ and $\beta_{h\tau m}$, in Figure 7. Panel A plots the estimates for $\beta_{h\tau m}$ for all months.[25] Even though all the point estimates are statistically significantly different from zero, except for October and November, the point estimates are remarkably similar. For October the estimated coefficient plummets to -114.9 and ascends to 250.4 in the next month. Perhaps these results suggest that the practice of crop residue burning in October to prepare the field for winter wheat was prevalent in the Punjab before the acts was implemented. However, the delay in rice harvesting after 2009, shifted the process with increased intensity to the month of November. The estimates for Haryana, in Panel B, are much smaller in magnitude, but the point estimate for November is the largest among all months.

[25]The month of April is the baseline category.

Table 4 presents the estimates of $\beta_{p\tau}$ and $\beta_{h\tau}$ from Equation (1) for the outcome of burned area in a district in a month. Column (1) reports a specification without any additional fixed effects or other controls. The point estimate for Punjab is 4.04 ($p < 0.01$) suggesting an increase of 12.83 % from the baseline average. The point estimate for Haryana is -0.10, but statistically indistinguishable from zero. In Column (2) we additionally control for state-specific time trends and district fixed effects. The points estimates for Punjab and Haryana increase to 7.12 and 3.72, both significant at one percent level. In Columns (3) and (4) we introduce year and month fixed and effects, and the point estimates marginally increase to 7.22 for Punjab and 3.92 for Haryana, retaining statistical significance at one percent level. We then estimate Equation (2) and plot the estimates of the coefficients $\beta_{p\tau m}$ and $\beta_{h\tau m}$, in Figure 8. Panel A plots the estimates for $\beta_{h\tau m}$ for all months.[26] All the point estimates except for September, October and November are statistically indistinguishable from zero. For September and October, the estimated coefficient plummets to -38.4 and -34.7, respectively, and ascends to 186.0 in the next month. The estimates for Haryana in Panel B, although smaller in magnitude, shows that the effect in November is positive and the highest. Overall, the results from burned area mirror those from thermal anomalies.

5.3 Air Pollution ($PM_{2.5}$)

In Section 5.2, we demonstrate that the implementation of the Water Acts contributed to a rise in crop residue burning in Punjab and Haryana, with the peak shifting towards November. Stubble burning significantly increases the amount of particulate matter in the atmosphere, which, under suitable atmospheric conditions, can disperse into neighboring states. The worsening of air quality across North India during winter is frequently linked to crop residue burning in Punjab. This section presents our empirical findings that substantiate this hypothesis.

To estimate the effect of Water Acts on $PM_{2.5}$ in Punjab, Haryana and neighboring states[27], we modify Equation (1) as follows:

$$\begin{aligned} y_{sdtm} = \beta_0 + \beta_{p\tau}\text{Punjab}_d \times \text{Post}_t + \beta_{h\tau}\text{Haryana}_d \times \text{Post}_t + \beta_{n\tau}\text{Neighboring}_d \times \text{Post}_t + \\ \beta_{sd} + \beta_t + \beta_m + \beta_s t + \boldsymbol{\beta_X X'_{sdtm}} + \epsilon_{sdtm} \end{aligned} \tag{4}$$

Table 5 presents the estimates of $\beta_{p\tau}$, $\beta_{h\tau}$, and $\beta_{n\tau}$ from Equation (4), with $PM_{2.5}$ levels in a district-month as the outcome variable. Column (1) reports results without fixed effects or additional control variables. The point estimate for Punjab is 3.13, statistically significant at one percent level, indicating an increase of 5.48% from the baseline average. The estimate for Haryana is 4.40, also significant at the one percent level. The estimate for neighboring states is 1.96, but it is not statistically distinguishable from zero. In Column (2), the specification includes controls for state-specific time trends and district fixed effects. The point estimates for Punjab and Haryana rise to 4.66 and 8.9, respectively, both retaining statistical significance at one percent level. The estimate for neighboring states increases to 4.55 and attains statistical significance at five percent level. Columns (3) and (4) introduce year and month fixed effects. While the point estimates marginally decrease to 4.51 for Punjab, 8.59 for Haryana, and 4.13 for neighboring states, statistical significance remains robust across all estimates.

To estimate the differential impact for each month, we modify Equation (2) to include the neighboring states, taken together, as an additional treatment group. Figure 9 plots the esti-

[26]The month of April is the baseline category.

[27]Himachal Pradesh, Delhi, Rajasthan and Uttar Pradesh

mates of the month-specific effects.[28] The dashed lines join estimates from a specification that does not control for burned area, whereas the solid lines join estimates from a specification that controls for the average burned area in Punjab for the respective year-month. Two key patterns emerge. First, without controlling for average burned area in Punjab, the effect for November is positive across all states. For most states, except Himachal Pradesh and Rajasthan, this positive effect persists until March. The effect tends to be larger in December and January than in November, before declining in February and March, possibly indicating temporal autocorrelation. Notably, the magnitude of the effect in neighboring states, especially Delhi, is comparable to that in Punjab and Haryana, indicating strong spillover effects. Second, when controlling for the average burned area in Punjab, the differential effect for November diminishes in magnitude for other states and becomes statistically indistinguishable from zero for Himachal Pradesh and Rajasthan. This decline in magnitude is not observed in other months. This pattern implies that crop residue burning in Punjab likely explains the rise in $PM_{2.5}$ levels observed in neighboring states. In summary, the results indicate that the Water Acts led to increased $PM_{2.5}$ levels in Punjab, Haryana, and neighboring states due to heightened crop residue burning in Punjab, with effects persisting from November through March.

5.4 Groundwater

The primary objective of the Water Acts was to conserve groundwater resources by prohibiting the sowing and transplanting of paddy before the arrival of monsoon. The rationale behind this measure was that delaying paddy cultivation until monsoon would reduce the need for irrigation, thereby mitigating the pressure on groundwater resources. However, the intended outcome is not guaranteed, as various factors such as farmer adaptation and shifts in water usage patterns may influence groundwater levels in ways that the lawmakers did not anticipates. In this section, we present our empirical findings on the impact of Water Acts on groundwater levels in Punjab and Haryana.

Table 7 presents the estimates from Equation (1) with grundwater depth, measured in meters below ground level (mbgl), as the outcome variable. Column (1) corresponds to a specification without any fixed effects. The estimates suggest that the Water Acts deepened groundwater level in Punjab by 3.38 mbgl ($p < 0$). The effect on Haryana is positive, but statistically indistinguishable from zero ($0.05 < p < 0.1$). In the subsequent columns, we incrementally include district, year and month fixed effects, along with state-specific linear time trend, and the coefficients turn negative. The effect on groundwater in Punjab, however, is statistically insignificant. In Haryana, it is small (-0.63), and significant at five percent level. Notably, the magnitudes of both point estimates are negative, meaning a saving of water, though insignificant for Punjab.

6 Robustness

6.1 Synthetic Difference-in-Differences

The empirical strategy outlined in Section 4 relies on the standard assumption that the outcome variable for the treated and control units follows parallel trajectories during the pre-treatment

[28]The baseline category is April

period. We test this assumption by estimating the following specification:

$$y_{sdtm} = \beta_0 + \beta_{p\tau}\text{Punjab}_d \times t + \beta_{h\tau}\text{Haryana}_d \times t + \beta_{sd} + \beta_t + \beta_m + \boldsymbol{\beta_X X'_{sdtm}} + \epsilon_{sdtm}, \qquad (5)$$

where $t < 2009$. $\beta_{p\tau} \neq 0$ and $\beta_{h\tau} \neq 0$ suggest the presence of differential pretrends in Punjab and Haryana, respectively.

The coefficients from Equation (5) presented in Columns (1) and (2) of Table 8 suggest the presence of differential pre-trends in burned area and thermal anomalies. While no such pre-trends are observed for $PM_{2.5}$ (see Column (3)), our identifying assumptions may still be misplaced, as a specification like Equation (5) is insufficiently powered to reject the null of "no pre-trends" (Rambachan and Roth, 2023). Further, the month-specific estimates of differential pre-trends presented in Figure 11 do not support this assumption.

To address this concern, we replicate our main results in a synthetic difference-in-differences (SDID) framework, developed in Arkhangelsky *et al.* (2021). This approach integrates the main elements of synthetic control and difference-in-differences methods. It assigns unit-specific weights to control units and time-specific weights to pre-treatment periods, thereby constructing a synthetic counterfactual that emphasizes comparability. The unit weights are optimized to ensure that the average outcome of treated units approximately parallels the weighted average of control units during the pre-treatment period. Likewise, the time-specific weights are optimized to maintain a constant difference between the average post-treatment outcome and the weighted average of pre-treatment outcomes for each of the control units. In contrast to the canonical model which applies equal weights to all units and time periods, the synthetic difference-in-differences model produces estimates of the average treatment effect with improved bias properties.

We employ the simplest form of the SDID framework which assumes a single adoption period for all treated units. Let W_{it} represent a binary variable equal to one if unit i is treated at time t. Our objective is to estimate the average causal effect of the treatment on the outcome variable Y_{it} by utilizing optimally selected unit and time weights. Formally, this entails estimating the following expression:

$$\left(\hat{\tau}^{sdid}, \hat{\mu}, \hat{\alpha}, \hat{\beta}\right) = \underset{\tau,\mu,\alpha,\beta}{\arg\min} \left\{ \sum_{i=1}^{N} \sum_{t=1}^{T} (Y_{it} - \mu - \alpha_i - \beta_t - X_{it}\gamma - W_{it}\tau)^2 \hat{\omega}_i^{sdid} \hat{\lambda}_t^{sdid} \right\}, \qquad (6)$$

where X_{it} represents a vector of covariates, and $\hat{\omega}_i^{sdid}$ and $\hat{\lambda}_t^{sdid}$ denote the weights assigned to unit i and time t, respectively. Note that the weights for control units sum to one, while the weights for treated units are set to $\frac{1}{N_{tr}}$, where N_{tr} represents the number of treated units. Similarly, the weights for pre-treatment periods sum to one, and the weights for post-treatment periods are set to $\frac{1}{T_{post}}$, where T_{post} is the number of post-treatment periods. $\hat{\tau}^{sdid}$ captures the average treatment effect.

The variance of $\hat{\tau}^{sdid}$ is estimated using the placebo-based inference procedure proposed in Arkhangelsky *et al.* (2021).[29] This method involves randomly selecting N_{tr} units from the N_{co} units without replacement, computing the placebo effect for this group, and repeating the process over B iterations.[30] In each iteration b, the placebo effect is denoted as $\hat{\tau}^b$. The

[29] We prefer the placebo method to alternative approaches, such as bootstrap and jackknife, to mitigate the limitations associated with the small number of treated units.

[30] We fix $B = 50$.

computed placebo-based variance of $\hat{\tau}^{sdid}$ is then calculated as:

$$\hat{V}_{\tau}^{placebo} = \frac{1}{B}\sum_{b=1}^{B}\left(\hat{\tau}^{b} - \frac{1}{B}\sum_{b=1}^{B}\hat{\tau}^{b}\right)^{2}. \tag{7}$$

We generate SDID estimates of the average effect of the Water Acts on thermal anomalies, burned area, and $PM_{2.5}$, separately for each of the twelve months. To isolate the effect on each treated state, we conduct the analysis using subsamples that exclude other treated states. For example, the subsample used to estimate the effect on thermal anomalies in Punjab during November includes all November observations from Punjab and the control states but excludes Haryana, the other treated state. Accordingly, for each outcome variable and each treated state, we estimate a series of twelve regressions.

The results of this estimation for thermal anomalies are presented in Figure 12. Panel A plots the effect on thermal anomalies in Punjab across months, while Panel B shows the corresponding estimates for Haryana. The findings closely align with the patterns observed in our baseline triple difference model. Specifically, in Punjab, the negative effect in October and a more pronounced positive effect in November remain evident. The estimates from Haryana are similar in direction but smaller in magnitude. The effects on burned area, shown in Figure 13, present a similar pattern. In Punjab, we observe a negative effect in September, its moderation in October, and a starker positive effect in November. In Haryana, both the magnitude and direction of the effects are largely unchanged. Taken together, the evidence from thermal anomalies and burned area supports our central claim regarding crop residue burning: the Water Acts led to increased burning in Punjab and Haryana, with the peak shifting towards November.

In Figure 14, we replicate the results for $PM_{2.5}$. Consistent with our baseline findings, we observe a positive effect in November that extends through December and into January for the treated states as well as their neighboring states. Among the neighbors, the magnitude of the effect is largest for Delhi and smallest for the hilly state of Himachal Pradesh. These results confirm our claim that the consequences of crop residue burning on air quality extend beyond the states where the burning occurs.

The results from the SDID procedure are qualitatively similar to those from the difference-in-differences models but are obtained under less restrictive assumptions. While the difference-in-differences method assumes that, on average, control units follow parallel trends with treated units, SDID only requires that some control units resemble the treated units during the pre-treatment period, and that their post-treatment periods are comparable to their pre-treatment periods. The SDID method assigns greater weights to such control units while estimating the average treatment effect on the treated. This approach enables a more flexible estimation procedure that accommodates potential violations of the parallel trends assumption.

6.2 Spatial Autocorrelation

The error terms associated with our outcome variables could be spatially correlated across neighboring districts. Particularly, air pollution might be affected by regional wind patterns, and groundwater levels could be correlated within the same aquifer system. Ignoring such spatial dependencies may lead to biased standard error estimates. To address this concern, we reproduce our results from Equation (1) with arbitrary clustering correction of standard errors proposed in Colella *et al.* (2019). This procedure allows any observation to be correlated with any other, where the strength of this correlation is a function of distance and time. It also assumed a distance cutoff beyond which the error terms are uncorrelated. We fix this cut off at 50 km. Table 9 reports the results from these estimations. Despite the change in standard errors, our main results remain robust to correction for spatial autocorrelation, retaining statistical significance.

7 Conclusions

This paper investigates the causal impacts of the Water Acts enacted by Punjab and Haryana in 2009, designed to mitigate groundwater depletion by regulating the sowing and transplanting timings of paddy crops. Employing difference-in-differences and triple difference techniques, we estimate the effect of Water Acts on various outcomes of interest, including groundwater levels, crop residue burning, and atmospheric $PM_{2.5}$ concentrations, and identify underlying causal mechanisms.

The Water Acts were introduced against the backdrop of growing concerns over the rapid depletion of groundwater resources, driven largely by the water-intensive cultivation of rice in these states. By delaying rice sowing and transplanting to the monsoon season, the policy sought to align the irrigation requirements of paddy cultivation with natural rainfall, thus reducing reliance on groundwater. Our findings suggest that the legislations achieved this objective to a minor extent, at least in Haryana.

However, an important unintended outcome of this policy was a reduction in the interval between rice harvesting and wheat planting, which left farmers with limited time to clear their fields for the subsequent wheat cycle. In response, farmers increasingly resorted to crop residue burning as a cost-effective method for clearing paddy residue. Satellite-derived data on thermal anomalies and burned area indicate a marked increase in the intensity of crop residue burning in the post-legislation period, particularly in Punjab. Our analysis further reveals a temporal shift in the peak of crop residue burning. Prior to the enactment of the Water Acts, burning peaked in October, coinciding with the rice harvest. Following the legislations, however, the peak shifted to November, reflecting the compression in agricultural calendar introduced by the delayed sowing of paddy. This shift has adverse consequences for air quality, as it coincides with a period characterized by atmospheric conditions that exacerbate the accumulation of particulate matter. Our results show a corresponding increase in $PM_{2.5}$ levels not only in Punjab and Haryana but also in neighboring states, highlighting the presence of spillover effects.

These findings point to a critical trade-off for policymakers. While the Water Acts addressed the need for groundwater preservation with partial success, they inadvertently exacerbated the problem of air pollution due to crop residue burning. This highlights the complex interdependencies that exist within agricultural systems, where interventions aimed at resolving one problem can lead to the emergence of fresh challenges.

References

Agarwala, M., Bhattacharjee, S. and Dasgupta, A. (2022). Unintended consequences of indian groundwater preservation law on crop residue burning. *Economics Letters*, **214**, 110446.

Ali, S. and Arora, G. (2021). Well-level Missingness Mechanisms in Administrative Groundwater Monitoring Data for Uttar Pradesh (UP), India, 2009-2018.

Arkhangelsky, D., Athey, S., Hirshberg, D. A., Imbens, G. W. and Wager, S. (2021). Synthetic difference-in-differences. *American Economic Review*, **111** (12), 4088–4118.

Bhalla, G. and Singh, G. (1997). Recent developments in indian agriculture: A state level analysis. *Economic and Political Weekly*, pp. A2–A18.

Chakrabarti, S., Khan, M. T., Kishore, A., Roy, D. and Scott, S. P. (2019). Risk of acute respiratory infection from crop burning in india: estimating disease burden and economic welfare from satellite and national health survey data for 250 000 persons. *International journal of epidemiology*, **48** (4), 1113–1124.

Colella, F., Lalive, R., Sakalli, S. O. and Thoenig, M. (2019). Inference with arbitrary clustering.

Fishman, R., Devineni, N. and Raman, S. (2015). Can improved agricultural water use efficiency save india's groundwater? *Environmental Research Letters*, **10** (8), 084022.

Gandhi, V. P. and Bhamoriya, V. (2011). Groundwater irrigation in india. *India infrastructure report*, p. 90.

Ganesh-Kumar, A., Gulati, A. and Cummings, J. R. (2007). Foodgrains policy and management in india.

Gupta, D. (2023). Free power, irrigation, and groundwater depletion: Impact of farm electricity policy of punjab, india. *Agricultural Economics*, **54** (4), 515–541.

Hira, G. and Khera, K. (2000). Water resource management in punjab under rice-wheat production system. *Research Bulletin*, **1**, 2000.

Kant, Y., Chauhan, P., Natwariya, A., Kannaujiya, S. and Mitra, D. (2022). Long term influence of groundwater preservation policy on stubble burning and air pollution over north-west india. *Scientific Reports*, **12** (1), 2090.

Kishore, P., Roy, D. and Birthal, P. S. (). Regulation and policy response to groundwater preservation in india.

McDonald, A. J., Srivastava, A. K. and Gerard, B. (2019). Tradeoffs between groundwater conservation and air pollution from agricultural fires in northwest india. *Nature Sustainability*, **2** (7), 580–583.

Rambachan, A. and Roth, J. (2023). A more credible approach to parallel trends. *Review of Economic Studies*, **90** (5), 2555–2591.

Rodell, M., Velicogna, I. and Famiglietti, J. S. (2009). Satellite-based estimates of groundwater depletion in india. *Nature*, **460** (7258), 999–1002.

Shah, T. (2007). The groundwater economy of south asia: an assessment of size, significance and socio-ecological impacts. *The agricultural groundwater revolution: Opportunities and threats to development*, pp. 7–36.

Sidhu, R., Vatta, K. and Lall, U. (2011). Climate change impact and management strategies for sustainable water-energy-agriculture outcomes in Punjab. *Indian Journal of Agricultural Economics*, **66** (3).

Singh, K. (2009). Act to save groundwater in punjab: Its impact on water table, electricity subsidy and environment. *Agricultural Economics Research Review*, **22**, 365–386.

Swaminathan, M. S. (2006). An evergreen revolution. *Crop Science*, **46** (5), 2293–2303.

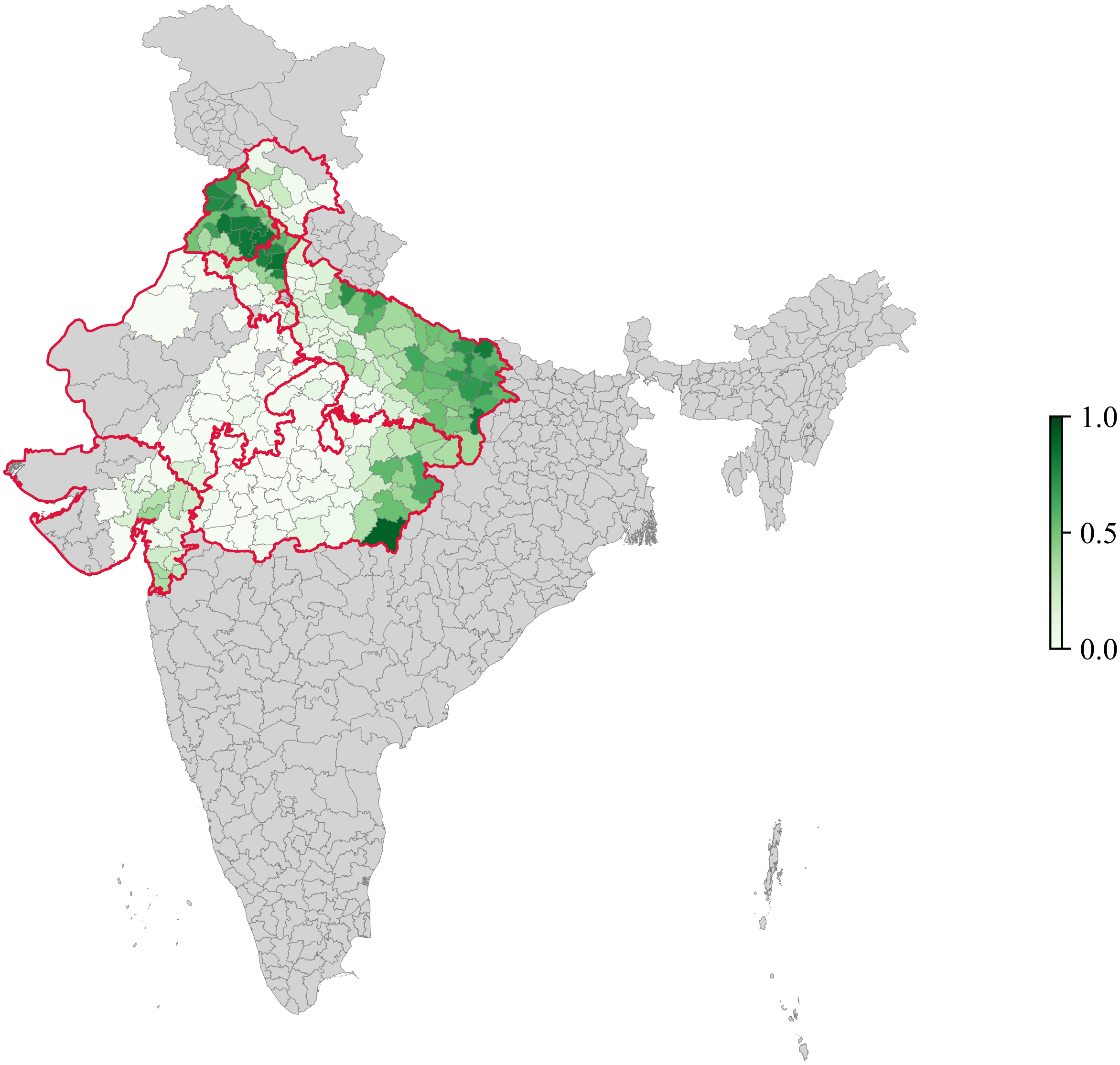
Tripathi, A., Mishra, A. K. and Verma, G. (2016). Impact of preservation of subsoil water act on groundwater depletion: the case of punjab, india. *Environmental management*, **58** (1), 48–59.

Van Donkelaar, A., Hammer, M. S., Bindle, L., Brauer, M., Brook, J. R., Garay, M. J., Hsu, N. C., Kalashnikova, O. V., Kahn, R. A., Lee, C. *et al.* (2021). Monthly global estimates of fine particulate matter and their uncertainty. *Environmental Science & Technology*, **55** (22), 15287–15300.

Waldner, F., Fritz, S., Di Gregorio, A., Plotnikov, D., Bartalev, S., Kussul, N., Gong, P., Thenkabail, P., Hazeu, G., Klein, I. *et al.* (2016). A unified cropland layer at 250 m for global agriculture monitoring. *Data*, **1** (1), 3.

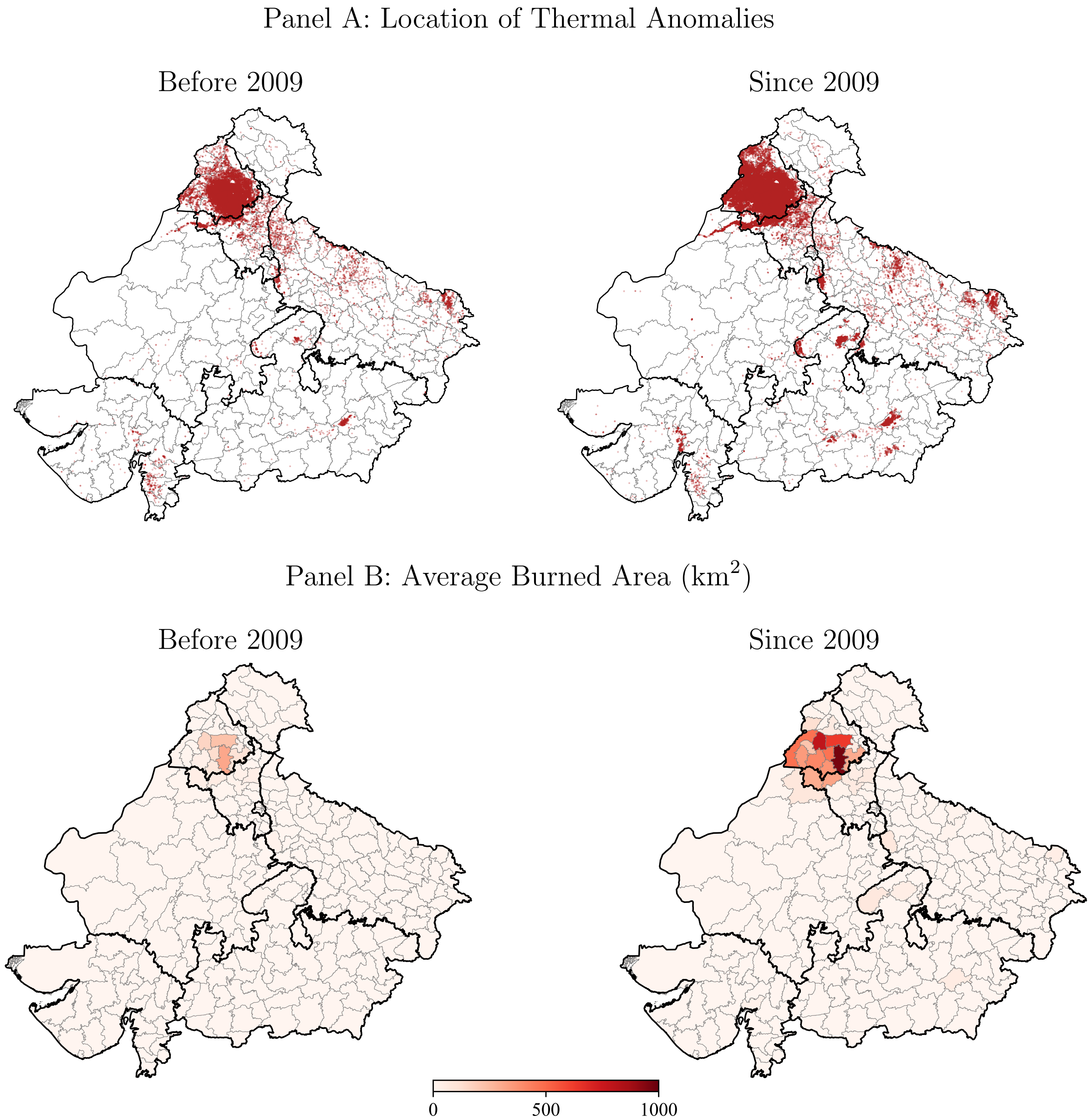
Figures

Figure 1: Area under Paddy Cultivation in India for Single Rice Crop (*Kharif*) States



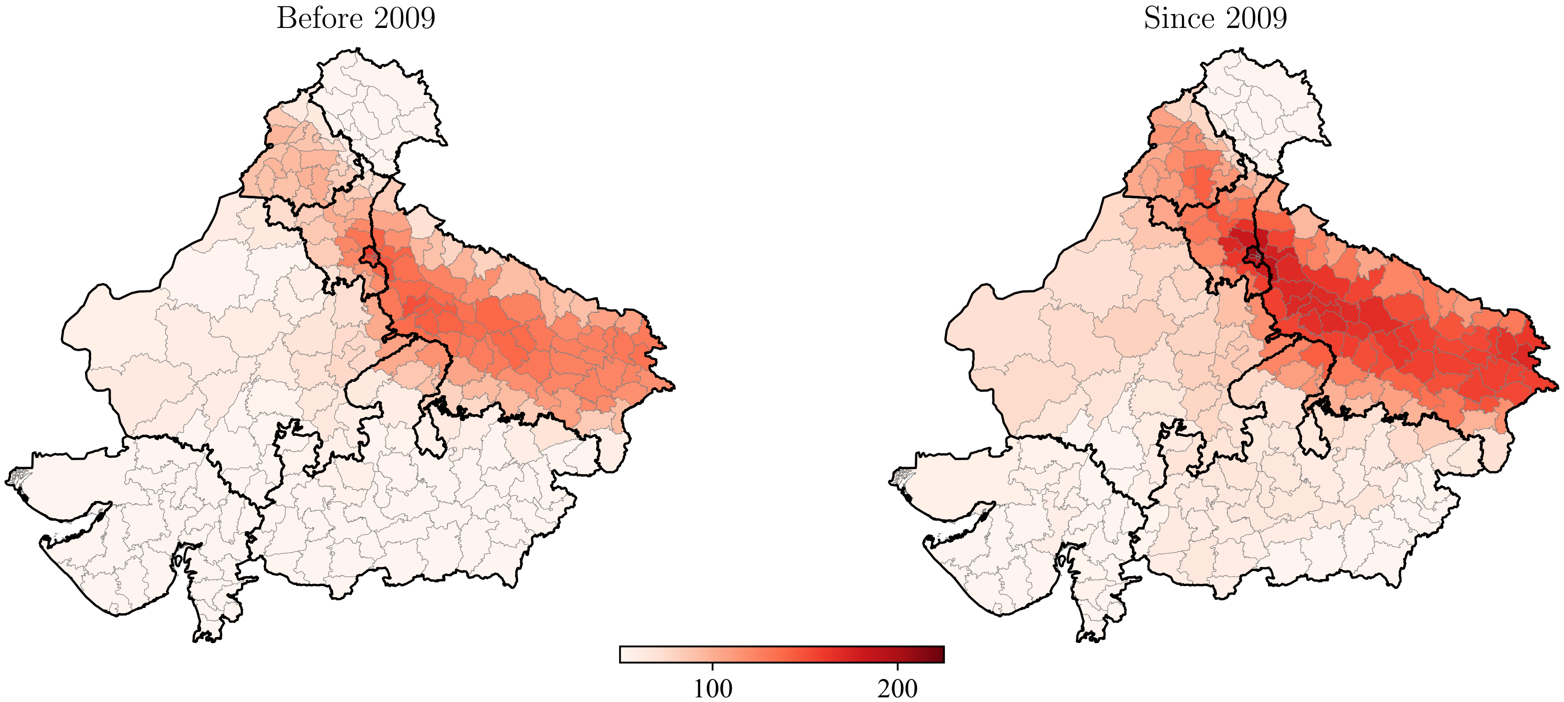
Notes: The figure illustrates the ratio of the area under rice cultivation to the net cropped area across districts in states where a single rice crop is cultivated (during the *Kharif* season). These states – Himachal Pradesh, Punjab, Haryana, Delhi, Uttar Pradesh, Rajasthan, Madhya Pradesh, and Gujarat – are highlighted with a thick red boundary. The remaining states and districts with unavailable data are shaded in grey.

Figure 2: Crop Residue Burning before and after the 2009 Sub-Soil Water Preservation Act in Punjab and Haryana.



Notes: The figure illustrates the change in crop residue burning in the month of November measured by thermal anomalies and burned area after 2009 across districts in states where a single rice crop is cultivated (during the *Kharif* season). These states – Himachal Pradesh, Punjab, Haryana, Delhi, Uttar Pradesh, Rajasthan, Madhya Pradesh, and Gujarat – are highlighted with a thick red boundary.

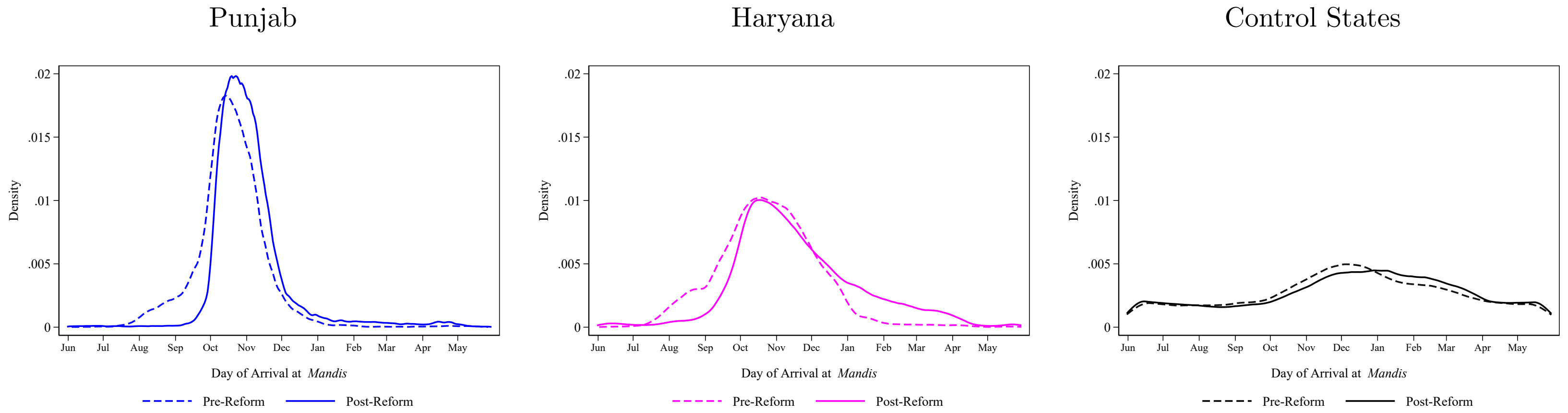
Figure 3: $PM_{2.5}$ before and after the 2009 Sub-Soil Water Preservation Act in Punjab and Haryana.



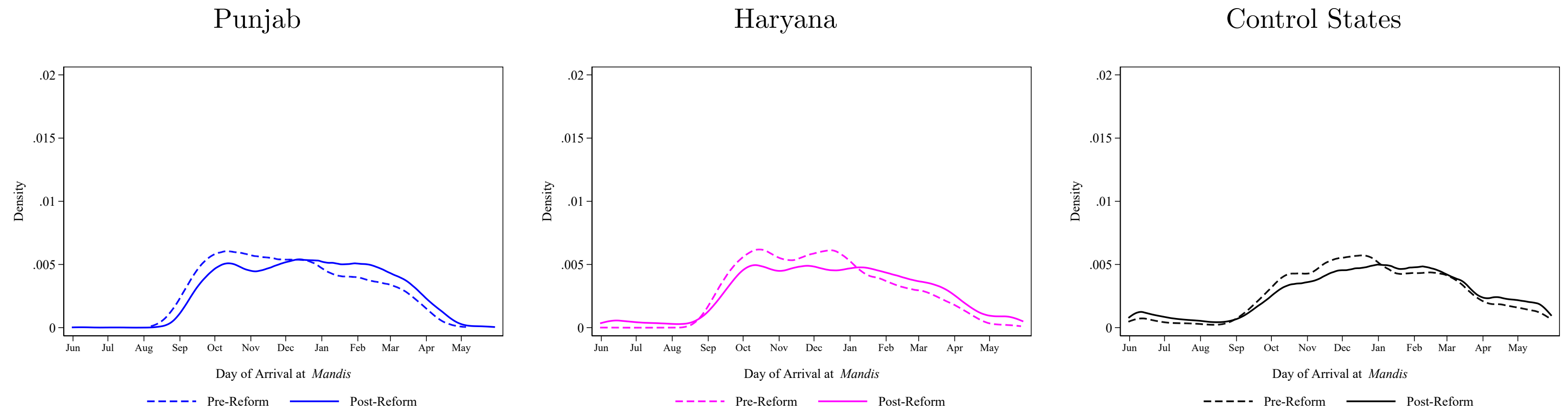
Notes: The figure illustrates the change in satellite-derived measures of $PM_{2.5}$ in the month of November after 2009 across districts in states where a single rice crop is cultivated (during the *Kharif* season). These states – Himachal Pradesh, Punjab, Haryana, Delhi, Uttar Pradesh, Rajasthan, Madhya Pradesh, and Gujarat – are highlighted with a thick red boundary.

Figure 4: Distribution of Arrival of Paddy and Cotton (major *Kharif* crops) by month before and after the 2009 Sub-Soil Water Preservation Act in Punjab and Haryana.

Panel A: Arrival of Paddy



Panel B: Arrival of Cotton

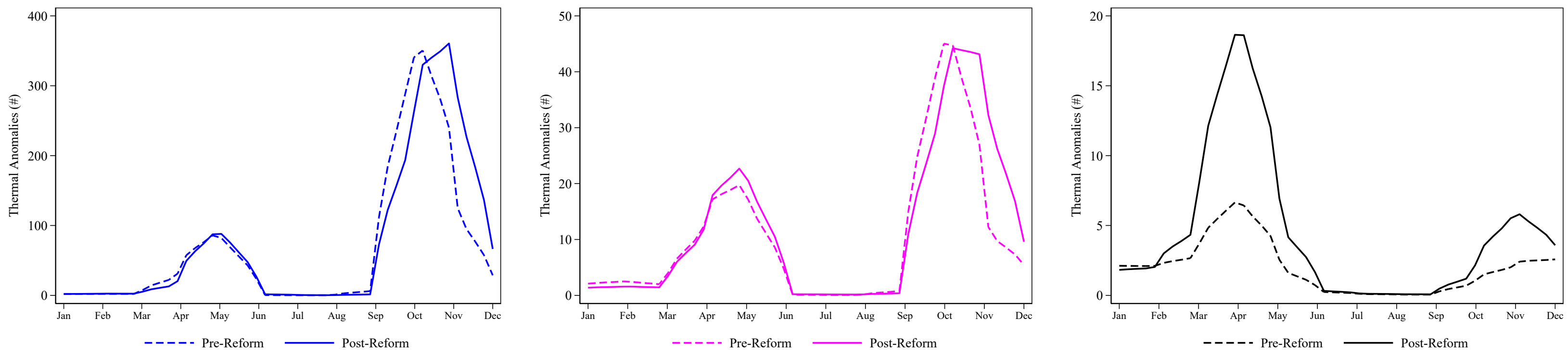


Notes: The figures plot the distribution of the day of arrival of paddy and cotton at *Mandis* before and after the legislations. Panel A and B correspond to paddy and cotton, respectively.

Figure 5: Crop Residue Burning (measured by thermal anomalies and burned area) in Punjab and Haryana, and the Control States, by month before and after the 2009 Sub-Soil Water Preservation Act in Punjab and Haryana.

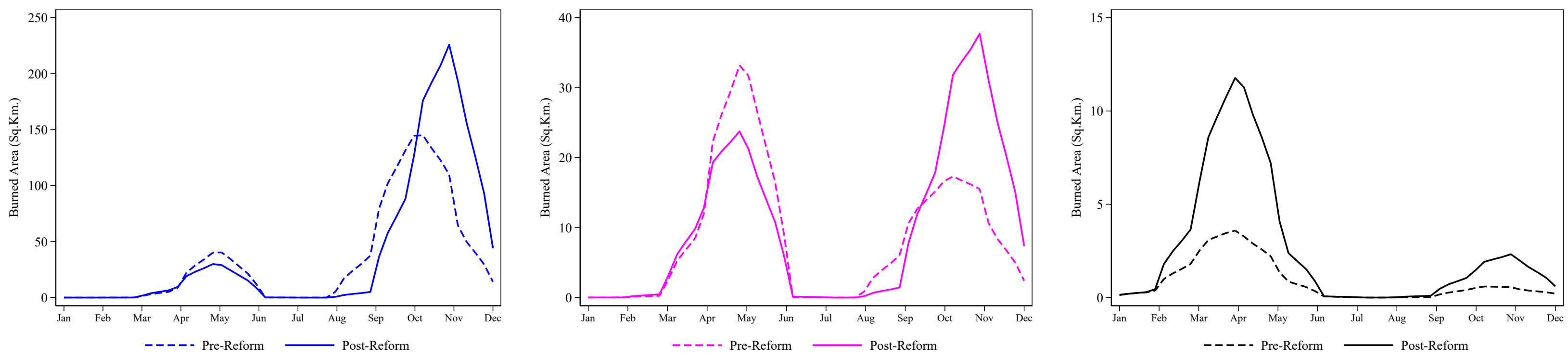
Panel A: Thermal Anomalies

Punjab | Haryana | Control States



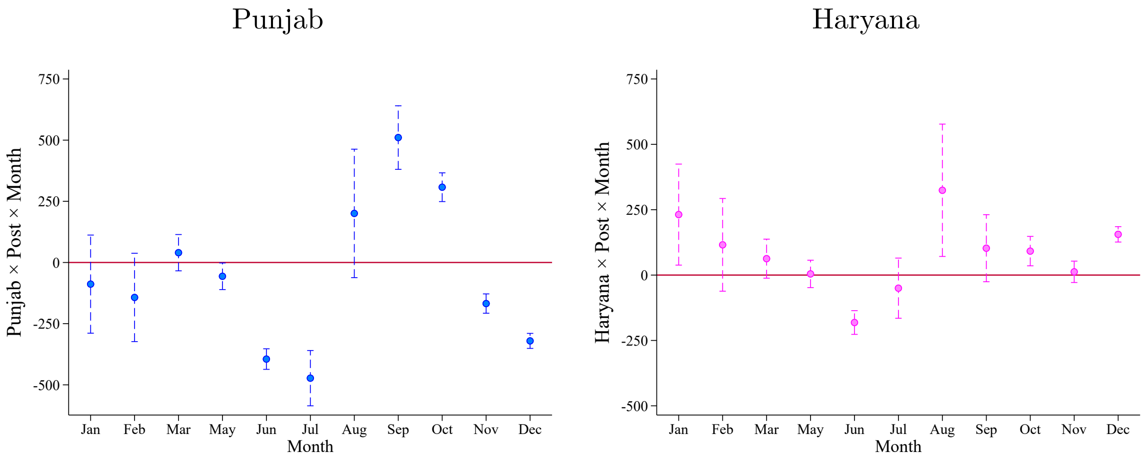
Panel B: Burned Area

Punjab | Haryana | Control States



Notes: The figures plot the distribution of crop residue burning by months before and after the legislations. Panel A and B correspond to thermal anomalies and burned area, respectively.

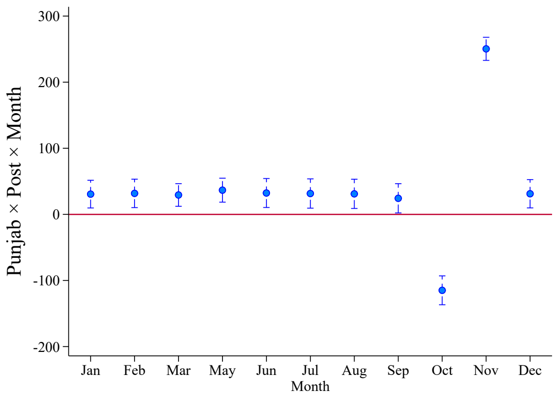
FIGURE 6: Effects of Sub-Soil Water Preservation Acts in Punjab and Haryana (2009) on Enhanced Vegetation Index



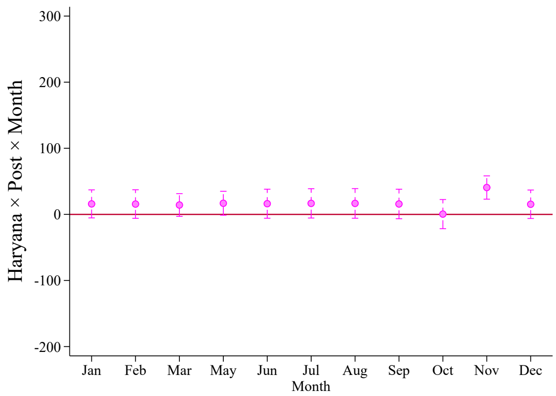
Notes: The figures plot coefficients from the triple interaction model described in Equation (2), on monthly district-level enhanced vegetation index measuring vegetation greenness of arable areas of a district. The specifications control for precipitation, temperature, state-specific linear time trends, and state, year and month fixed effects. The analysis is limited to one-paddy crop states and districts where more than 50% of the net cropped area is dedicated to rice paddy, and the period since 2003. April serves as the baseline month. Standard errors are clustered by state.

Figure 7: Effects of Sub-Soil Water Preservation Acts in Punjab and Haryana (2009) on Thermal Anomalies

Panel A: Punjab



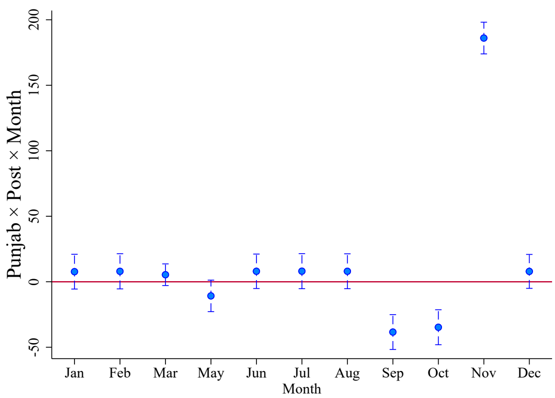
Panel B: Haryana



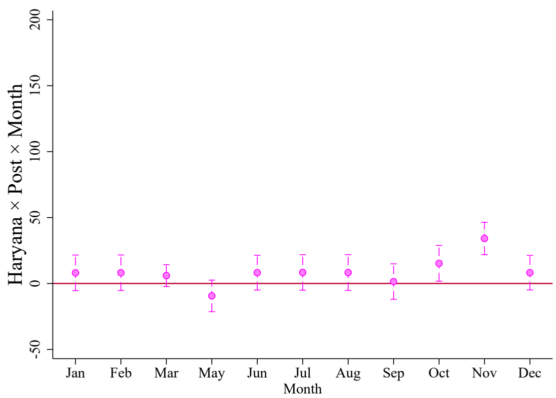
Notes: The figures plot coefficients from the triple interaction model described in Equation (2), on monthly district-level count of thermal anomalies with a confidence level of at least 20 in arable areas of a district. The specifications control for precipitation, temperature, state-specific linear time trends, and state, year and month fixed effects. The analysis is limited to one-paddy crop states, and the period since 2003. April serves as the baseline month. Standard errors are clustered by state.

Figure 8: Effects of Sub-Soil Water Preservation Acts in Punjab and Haryana (2009) on Burned Area

Panel A: Punjab



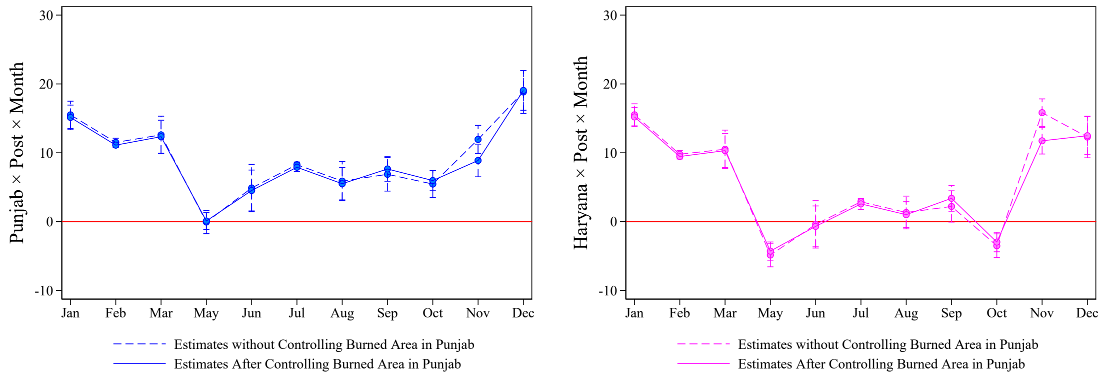
Panel B: Haryana



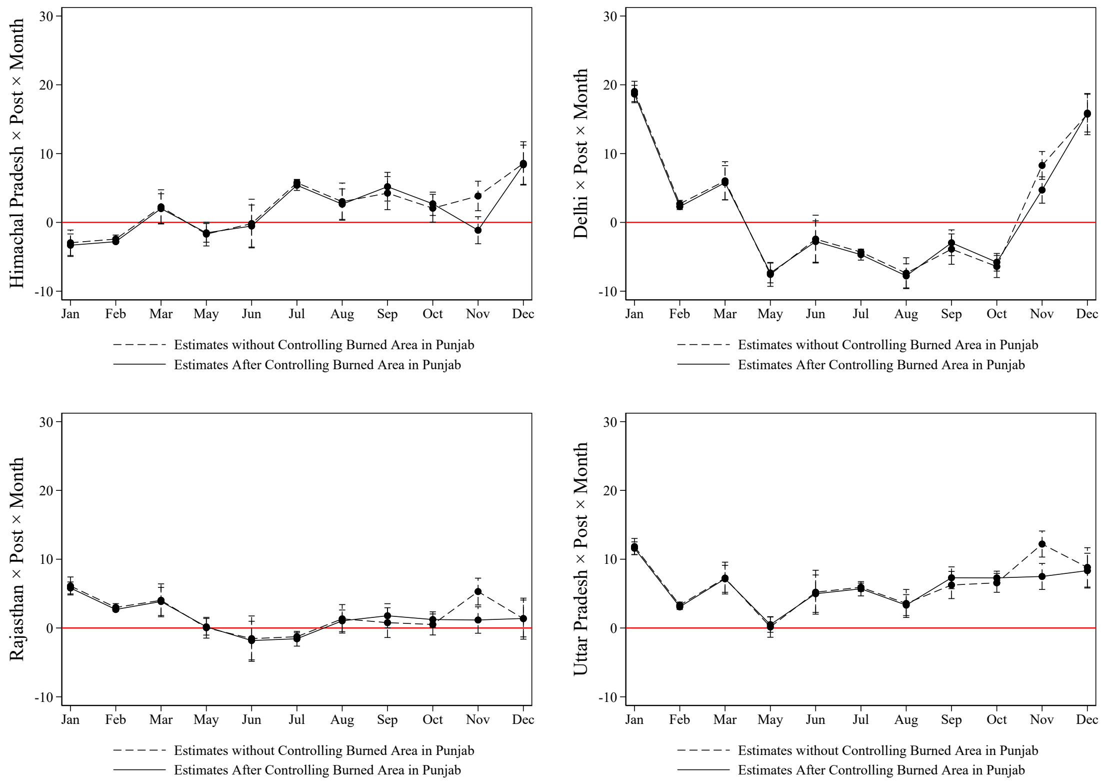
Notes: The figures plot coefficients from the triple interaction model described in Equation (2), on monthly district-level burned area (in square kilometers) in arable areas of a district. The specifications control for precipitation, temperature, state-specific linear time trends, and state, year and month fixed effects. The analysis is limited to one-paddy crop states, and the period since 2003. April serves as the baseline month. Standard errors are clustered by state.

Figure 9: Effects of Sub-Soil Water Preservation Acts in Punjab and Haryana (2009) on $PM_{2.5}$

Panel A: Punjab & Haryana

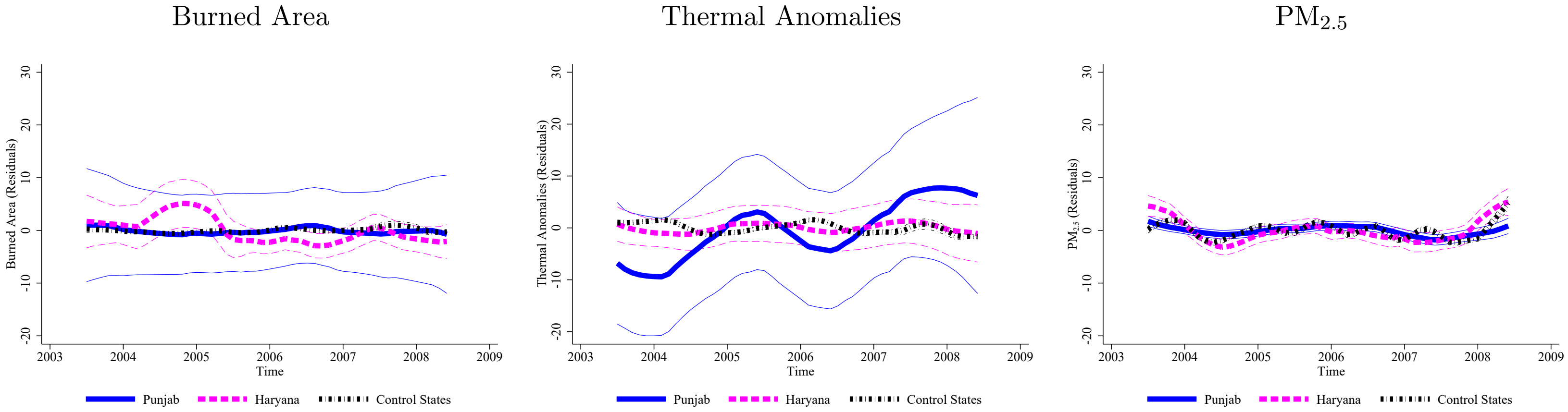


Panel B: Neighboring States



Notes: The figures plot coefficients from the triple interaction model described in Section 5.3, on monthly district-level measure of $PM_{2.5}$. The specifications control for precipitation, temperature, wind speed, state-specific linear time trends, and state, year and month fixed effects. The solid lines correspond to an alternative specification that controls for the average burned area in Punjab. The analysis is limited to one-paddy crop states, and the period since 2003. April serves as the baseline month. Standard errors are clustered by state.

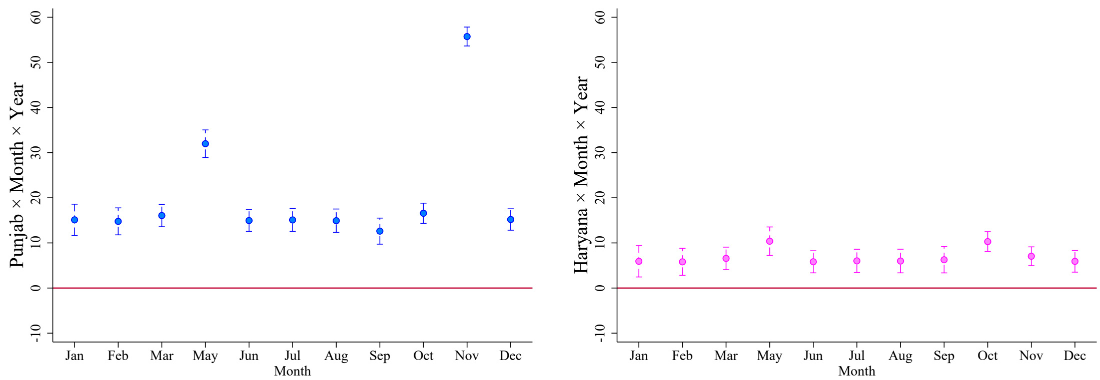
Figure 10: Pretrends in Thermal Anomalies, Burned Area and $PM_{2.5}$



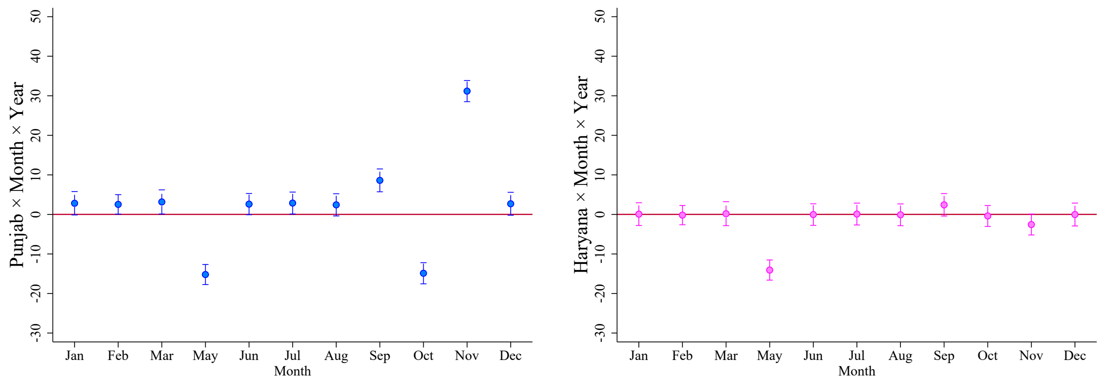
Notes: This figure plots the local polynomial smooths of thermal anomalies, burned area and $PM_{2.5}$ for the pre-treatment period (2003 – 2008), with 95% confidence intervals, after partialling out district, year and state-specific month fixed effects. The control states include Gujarat, Madhya Pradesh, Rajasthan, Uttar Pradesh, Delhi and Himachal Pradesh.

Figure 11: Pretrends in Thermal Anomalies, Burned Area and $PM_{2.5}$ by Month

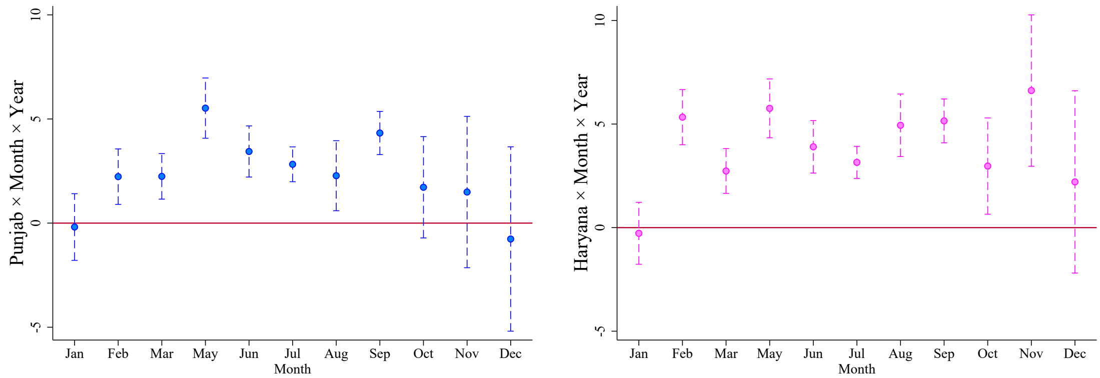
Panel A: Thermal Anomalies



Panel B: Burned Area

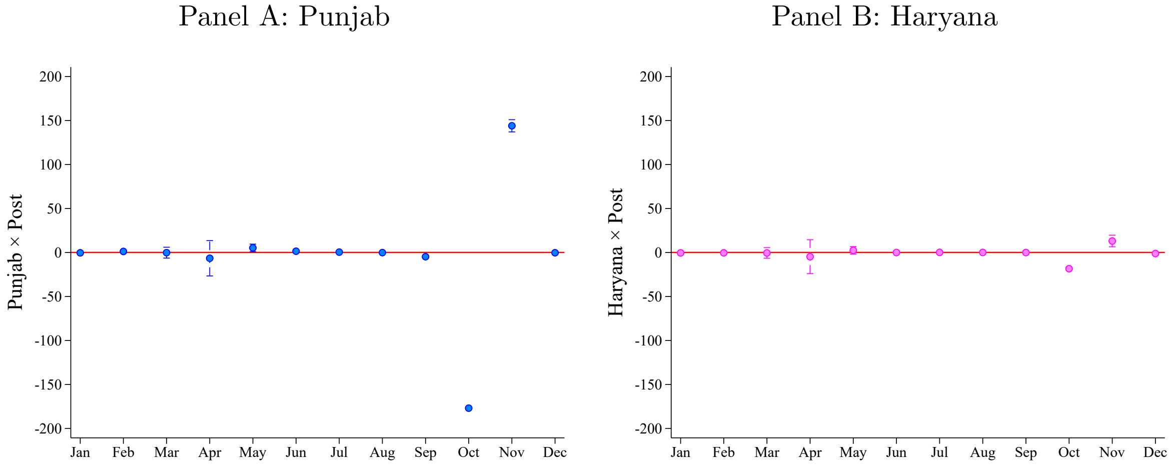


Panel C: $PM_{2.5}$



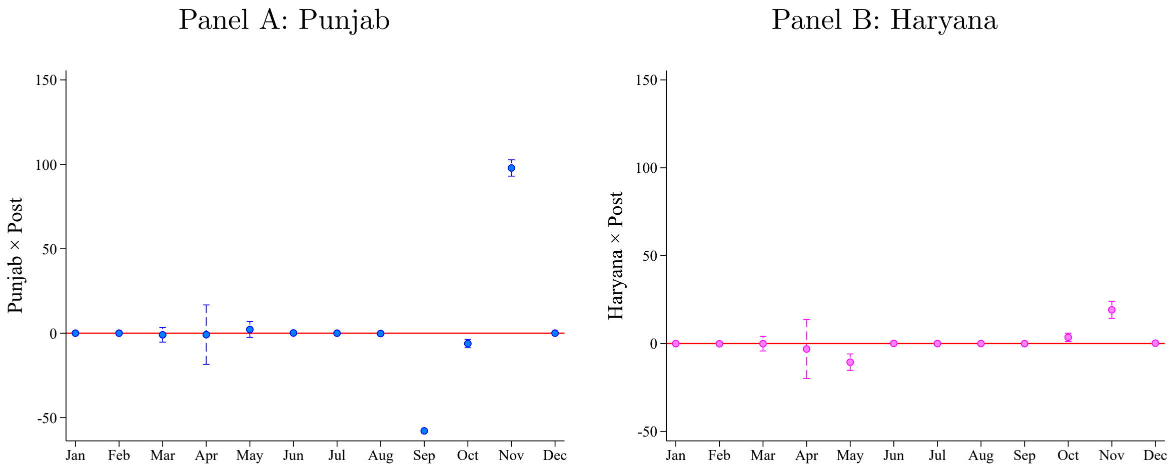
Notes: The figures plots the month-specific pretrends in thermal anomalies, burned area and $PM_{2.5}$. The specifications control for precipitation, temperature, and state, year and state-specific month fixed effects. Regressions of $PM_{2.5}$ include an additional control for wind speed. The analysis is limited to one-paddy crop states, and the period between 2003 and 2009. April serves as the baseline month.

Figure 12: Synthetic Difference-in-Differences: Thermal Anomalies



Notes: The figures plot coefficients from the synthetic difference-in-differences models described in Section 6, on monthly district-level count of thermal anomalies with a confidence level of at least 20 in arable areas of a district. The specifications control for precipitation, temperature, state-specific linear time trends, and state, year and month fixed effects. The analysis is limited to one-paddy crop states, and the period since 2003.

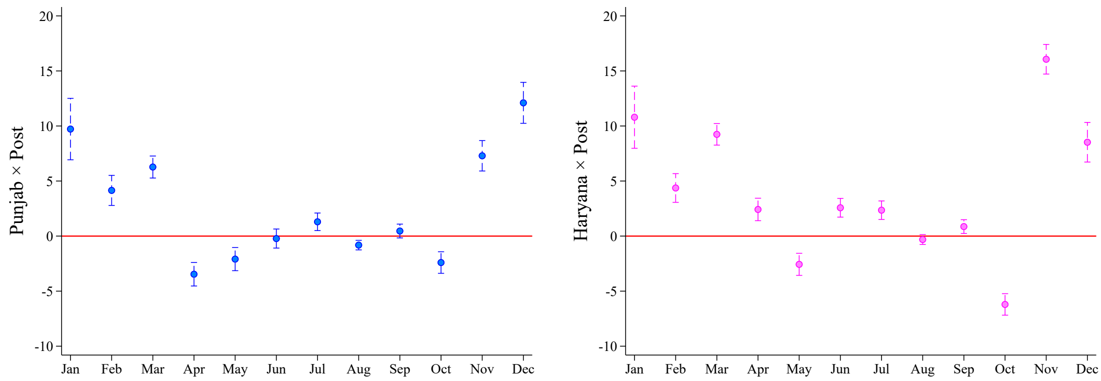
Figure 13: Synthetic Difference-in-Differences: Burned Area



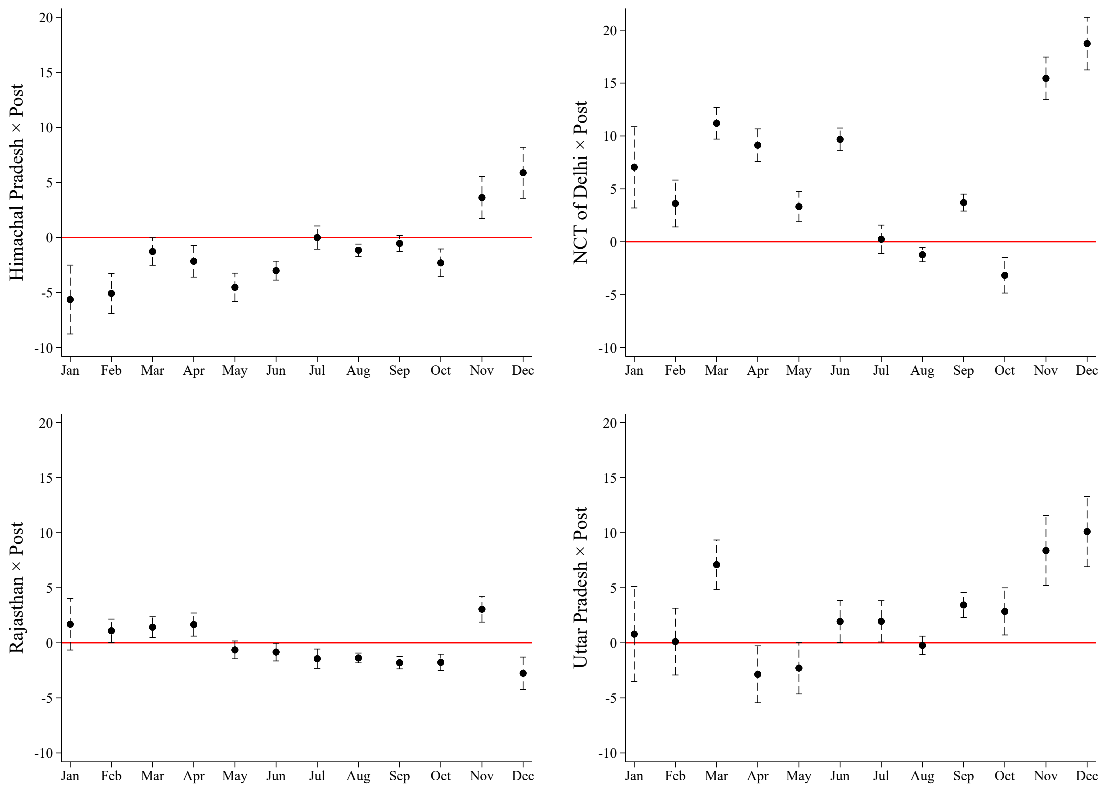
Notes: The figures plot coefficients from the synthetic difference-in-differences models described in Section 6, on monthly district-level burned area in arable areas of a district. The specifications control for precipitation, temperature, state-specific linear time trends, and state, year and month fixed effects. The analysis is limited to one-paddy crop states, and the period since 2003.

FIGURE 14: Synthetic Difference-in-Differences: $PM_{2.5}$

Panel A: Punjab & Haryana



Panel B: Neighboring States



Notes: The figures plot coefficients from the synthetic difference-in-differences models described in Section 6, on monthly district-level $pm_{2.5}$. The specifications control for precipitation, temperature, wind speed, state-specific linear time trends, and state, year and month fixed effects. The analysis is limited to one-paddy crop states, and the period since 2003.

Tables

Table 1: Descriptive Statistics

	Punjab & Haryana			Other States		
	Pre (1)	Post (2)	Diff (3)	Pre (4)	Post (5)	Diff (6)
EVI	2,856.64	3,133.44	276.80***	2,383.21	2,550.27	167.06***
	(1,276.14)	(1,427.77)	(26.75)	(1,071.62)	(1,150.96)	(5.72)
Burned Area	16.89	22.87	5.98***	0.87	2.07	1.20***
	(72.77)	(93.57)	(1.72)	(9.67)	(20.07)	(0.09)
Thermal Anomalies	28.83	40.00	11.17***	1.54	3.52	1.98***
	(116.90)	(134.66)	(2.47)	(7.90)	(17.62)	(0.07)
$PM_{2.5}$	56.81	69.40	12.59***	37.19	45.01	7.82***
	(26.98)	(33.71)	(0.56)	(26.14)	(31.11)	(0.14)
Groundwater	10.09	14.23	4.14***	7.01	7.67	0.66***
	(5.22)	(7.69)	(0.22)	(6.16)	(7.31)	(0.07)
Precipitation	49.71	55.49	5.78***	108.14	114.97	6.83***
	(74.99)	(81.49)	(1.52)	(163.46)	(172.93)	(0.85)
Minimum Temperature	17.89	18.10	0.22	18.90	18.99	0.09**
	(7.70)	(7.80)	(0.15)	(7.34)	(7.45)	(0.04)
Maximum Temperature	31.22	31.28	0.05	29.84	29.92	0.08**
	(6.27)	(6.37)	(0.12)	(6.94)	(7.01)	(0.04)
Windspeed	1.27	1.22	-0.05***	1.62	1.57	-0.05***
	(0.42)	(0.44)	(0.01)	(0.73)	(0.71)	(0.00)
Rice-Cropped Area	91.35	104.64	13.29***	83.59	83.75	0.16
	(72.98)	(75.61)	(1.65)	(95.06)	(94.22)	(0.62)
Wheat-Cropped Area	141.68	147.38	5.71***	51.03	59.59	8.56***
	(79.12)	(81.97)	(1.77)	(58.25)	(65.96)	(0.43)

Notes: ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 2: Estimates of Delay for Arrival for Paddy in *Mandis* after the 2009 Sub-Soil Water Preservation Act in Punjab and Haryana.

	Day of Arrival for Paddy			
	(1)	(2)	(3)	(4)
Punjab × Post × Paddy	13.1***	16.1***	13.1***	13.2***
	(3.02)	(3.73)	(2.41)	(1.69)
Haryana × Post × Paddy	22.7***	18.5***	14.9***	14.2***
	(3.02)	(3.73)	(2.06)	(1.34)
Observations	1716352	1716349	1716349	1716323
R-squared	0.013	0.034	0.043	0.056
District FE	No	Yes	Yes	Yes
Year FE	No	No	Yes	Yes
Mandi FE	No	No	No	Yes

Notes: This table reports the estimated delay in the arrival of paddy in *mandis*, relative to other major *Kharif* crops (maize, cotton, and soybean), due to the Punjab and Haryana Subsoil Water Preservation Acts. The interaction terms capture the differential impact of PSWA on the delay in the arrival of Paddy after the implementation of the Acts in Punjab and Haryana. The estimation sample is restricted to states that grow a single rice crop per year and covers the period after 2003. All specifications control for the quantity of crop arrivals. The specifications in columns 2, 3, and 4 additionally control for state-specific linear time trends. Standard errors are clustered at the state level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 3: Difference-in-Differences Estimates of the Effects of Sub-Soil Water Preservation Act in Punjab and Haryana (2009) on Thermal Anomalies.

	(1)	(2)	(3)	(4)
Punjab × Post	3.76**	7.05***	7.07***	7.57***
	(1.42)	(1.06)	(1.07)	(1.69)
Haryana × Post	-0.89	5.18***	5.20***	5.93**
	(1.42)	(0.95)	(0.96)	(1.74)
Observations	58080	58080	58080	58080
R-squared	0.10	0.16	0.16	0.20
District FE	No	Yes	Yes	Yes
Year FE	No	No	Yes	Yes
Month FE	No	No	No	Yes

Notes: This table reports the effect of Punjab and Haryana Subsoil Water Preservation Acts on crop residue burning measured by the number of thermal anomalies in arable land. Analysis is restricted to the period since 2003 and states that grow paddy once in a year. All specifications control for minimum temperature, maximum temperature and precipitation. Specifications in columns 2,3 and 4 control for state-specific linear time trends. The unit of analysis is district. Standard errors are clustered at the state level. ***, **, and * indicate statistical significance at the levels of 1, 5 and 10%, respectively.

Table 4: Difference-in-Differences Estimates of the Effects of Sub-Soil Water Preservation Act in Punjab and Haryana (2009) on Satellite-Measured Burned Area.

	(1)	(2)	(3)	(4)
Punjab × Post	4.04***	7.12***	7.13***	7.22***
	(0.77)	(0.72)	(0.73)	(0.90)
Haryana × Post	-0.10	3.72***	3.72***	3.92***
	(0.76)	(0.66)	(0.66)	(0.91)
Observations	57596	57596	57596	57596
R-squared	0.063	0.13	0.13	0.15
District FE	No	Yes	Yes	Yes
Year FE	No	No	Yes	Yes
Month FE	No	No	No	Yes

Notes: This table reports the effect of Punjab and Haryana Subsoil Water Preservation Acts on crop residue burning measured by burned area (in square kilometers) of arable land. Analysis is restricted to the period since 2003 and states that grow paddy once in a year. All specifications control for minimum temperature, maximum temperature and precipitation. Specifications in columns 2,3 and 4 control for state-specific linear time trends. The unit of analysis is district. Standard errors are clustered at the state level. ***, **, and * indicate statistical significance at the levels of 1, 5 and 10%, respectively.

Table 5: Difference-in-Differences Estimates of the Effects of Sub-Soil Water Preservation Act in Punjab and Haryana (2009) on Satellite-Measured $PM_{2.5}$.

	(1)	(2)	(3)	(4)
Punjab × Post	3.13***	4.66***	4.66***	4.51**
	(0.89)	(1.12)	(1.13)	(1.52)
Haryana × Post	4.40***	8.90***	8.90***	8.59***
	(0.82)	(1.12)	(1.12)	(1.58)
Neighboring States × Post	1.96	4.55**	4.52**	4.13**
	(1.54)	(1.52)	(1.52)	(1.52)
Observations	58080	58080	58080	58080
R-squared	0.44	0.66	0.67	0.74

Notes: This table reports the effect of Punjab and Haryana Subsoil Water Preservation Acts on satellite-derived measures of $PM_{2.5}$ expressed as micrograms per cubic meter of air ($\mu g/m^3$). The interaction terms capture the differential impact in Punjab, Haryana and their neighbouring states (Himachal Pradesh, Rajasthan, Uttar Pradesh and Delhi). Analysis is restricted to the period since 2003 and states that grow paddy once in a year. All specifications control for minimum temperature, maximum temperature, precipitation and wind speed. Specifications in columns 2,3 and 4 control for state-specific linear time trends. The unit of analysis is district. Standard errors are clustered at the state level. ***, **, and * indicate statistical significance at the levels of 1, 5 and 10%, respectively.

TABLE 6: Estimates of the Effects of Sub-Soil Water Preservation Act on $PM_{2.5}$.

	(1)	(2)	(3)
Punjab × Post × September	6.73***	7.47***	7.47***
	(1.04)	(0.77)	(0.77)
Punjab × Post × October	4.77***	5.40***	5.41***
	(0.71)	(0.49)	(0.49)
Punjab × Post × November	14.0***	10.2***	10.3***
	(1.11)	(1.47)	(1.48)
Punjab × Post × December	18.6***	18.8***	18.9***
	(1.24)	(1.12)	(1.12)
Punjab × Post × January	13.4***	13.0***	13.0***
	(1.41)	(1.35)	(1.35)
Haryana × Post × September	0.85	0.57	2.00*
	(1.04)	(0.80)	(0.87)
Haryana × Post × October	-4.14***	-4.79***	-3.48***
	(0.64)	(0.45)	(0.50)
Haryana × Post × November	18.3***	18.5***	13.3***
	(1.07)	(0.96)	(1.34)
Haryana × Post × December	11.2***	11.3***	11.4***
	(1.22)	(1.08)	(1.08)
Haryana × Post × January	13.5***	13.0***	13.1***
	(1.19)	(1.12)	(1.12)
Neighboring States × Post × September	3.16	2.77	4.20**
	(1.91)	(1.81)	(1.78)
Neighboring States × Post × October	3.32	2.92	4.22
	(2.35)	(2.30)	(2.27)
Neighboring States × Post × November	10.3***	10.3***	4.99*
	(2.39)	(2.15)	(2.19)
Neighboring States × Post × December	7.42**	7.09**	7.15**
	(2.77)	(2.56)	(2.57)
Neighboring States × Post × January	7.85***	7.46***	7.53***
	(1.81)	(1.77)	(1.77)
Burned Area (sq. km.)		0.026***	0.025***
		(0.00)	(0.00)
Average Burned Area in Punjab (sq. km.)			0.030***
			(0.00)
Observations	58080	57596	57596
R-squared	0.79	0.79	0.79

Notes: This table reports the effect of Punjab and Haryana Subsoil Water Preservation Acts on satellite-derived measures of $PM_{2.5}$ expressed as micrograms per cubic meter of air ($\mu g/m^3$). The interaction terms capture the differential impact in Punjab, Haryana and their neighbouring states (Himachal Pradesh, Rajasthan, Uttar Pradesh and Delhi) across *Kharif* months, relative to July. Analysis is restricted to the period since 2003, *Kharif* months (July to January), and states that grow paddy once in a year. All specifications control for minimum temperature, maximum temperature, precipitation, wind speed, state-specific linear time trends, and district, year and month fixed effects. The unit of analysis is district. Standard errors are clustered at the state level. ***, **, and * indicate statistical significance at the levels of 1, 5 and 10%, respectively.

Table 7: Estimates of the Effects of Sub-Soil Water Preservation Acts on Groundwater

	(1)	(2)	(3)	(4)
Punjab × Post	3.38***	-0.40	-0.39	-0.30
	(0.34)	(0.31)	(0.31)	(0.29)
Haryana × Post	1.18*	-0.63*	-0.64**	-0.63**
	(0.56)	(0.27)	(0.26)	(0.24)
Observations	11112	11112	11112	11112
R-squared	0.10	0.92	0.92	0.92
District FE	No	Yes	Yes	Yes
Year FE	No	No	Yes	Yes
Month FE	No	No	No	Yes

Notes: This table reports the effect of Punjab and Haryana Subsoil Water Preservation Acts on groundwater levels expressed as meters below ground level. The interaction terms capture the differential impact in Punjab and Haryana. Analysis is restricted to the period since 2003–2015 and states that grow paddy once in a year. All specifications control for temperature, precipitation, proportion of missing values and state-specific linear time trends. The unit of analysis is district. Standard errors are clustered at the state level. ***, **, and * indicate statistical significance at the levels of 1, 5 and 10%, respectively.

Table 8: Pretrends in Thermal Anomalies, Burned Area and PM2.5

	Thermal Anomalies	Burned Area	$PM_{2.5}$
Punjab × Year	3.67***	-0.22	0.013
	(0.12)	(0.13)	(0.37)
Haryana × Year	0.51***	-1.12***	0.36
	(0.15)	(0.14)	(0.35)
Observations	14520	14520	14520
R-squared	0.57	0.34	0.90

Notes: This table reports the pretrends in thermal anomalies, burned area and $PM_{2.5}$. Data is restricted to the period between 2003 and 2009. All specifications control for temperature, precipitation, and district, year and state-specific month fixed effects. ***, **, and * indicate statistical significance at the levels of 1, 5 and 10%, respectively.

Table 9: Estimates Adjusted for Spatial Autocorrelation

	Thermal Anomalies	Burned Area	$PM_{2.5}$
Punjab × Post	7.57**	7.22**	4.51***
	(3.68)	(3.55)	(1.06)
Haryana × Post	5.93***	3.92**	8.59***
	(2.00)	(1.58)	(1.22)
Neighboring × Post			4.12***
			(1.14)
Observations	58080	57596	58080
R-squared	0.00017	0.00026	0.0014

Notes: This table reports the effects of the Water Acts on thermal anomalies, burned area and $PM_{2.5}$ as estimated by Equation (1), corrected for spatial autocorrelation. ***, **, and * indicate statistical significance at the levels of 1, 5 and 10%, respectively.

A Appendix

TABLE A.1: Correlation between Satellite-Derived $PM_{2.5}$ and CPCB Monitoring Station Readings

	Satellite-Derived $PM_{2.5}$		
	Exact Matches	All Matches	All Matches
CPCB $PM_{2.5}$	0.79***	0.54***	
	(0.07)	(0.05)	
CPCB $PM_{2.5}$/SPM			0.11***
			(0.00)
Observations	445	1213	17722
R-squared	0.55	0.36	0.26

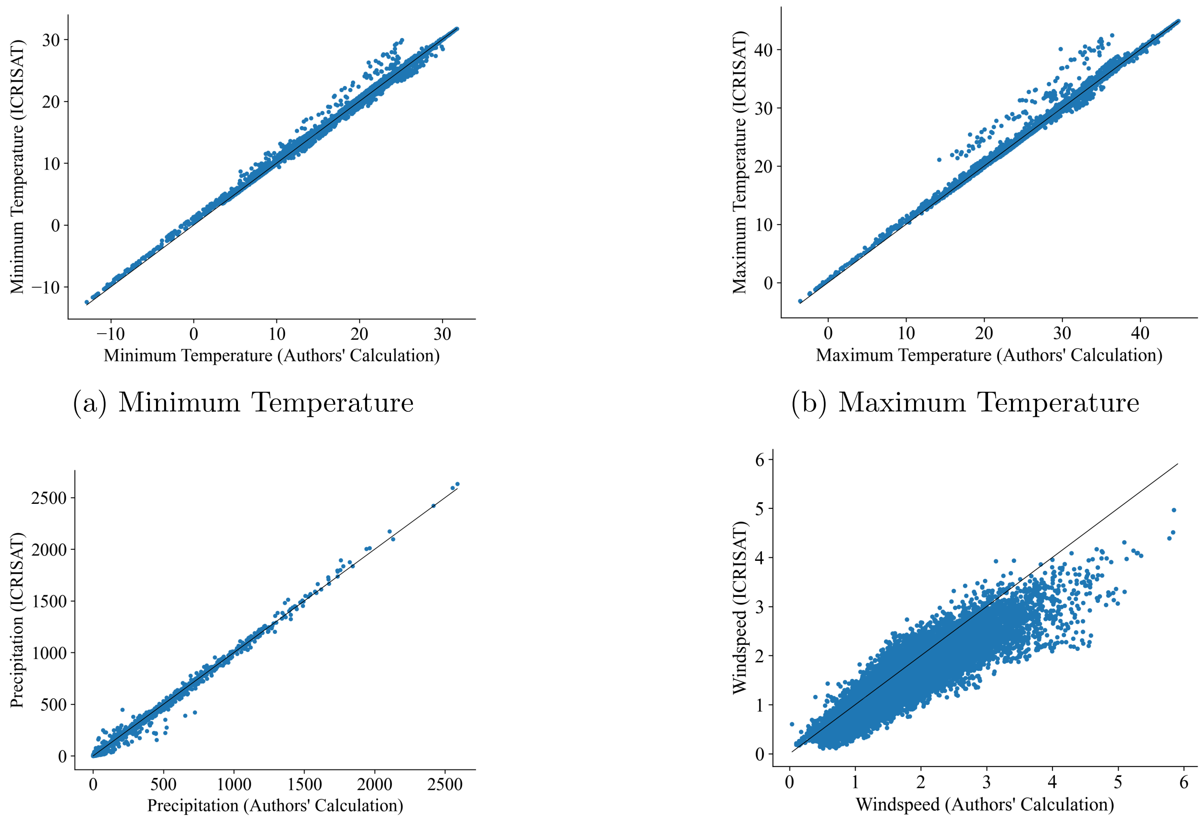
Notes: This table reports the slope coefficient from regressions of satellite-derived $PM_{2.5}$ on corresponding CPCB measures from monitoring stations. To match the satellite-derived measure with the readings from the monitoring stations we find the geocodes of the stations using their physical address and Google's Geocoding API. In Column 1 the estimation sample is restricted to the cases where monitoring stations could be geocoded to an exact address match, while columns 2 and 3 additionally include cases of partial matches. A partial match occurs when the geocoder fails to match the full address and is only able to match a part of the address, thus decreasing the accuracy. Column 3 replaces missing values of $PM_{2.5}$ in CPCB data with corresponding values of SPM. ***, **, and * indicate statistical significance at the levels of 1, 5 and 10%, respectively.

Table A.2: Correlation between EVI and Rice Production

	(1)	(2)	(3)	(4)	(5)
EVI (May)	10.9***				
	(3.84)				
EVI (Jun)		16.4***			
		(3.31)			
EVI (Jul)			32.1***		
			(2.41)		
EVI (Aug)				33.1***	
				(1.86)	
EVI (Sep)					40.0***
					(1.90)
Observations	942	942	942	942	942
R-squared	0.0085	0.025	0.16	0.25	0.32

Notes: This table reports the regression of rice-cropped area (in hectares) during Kharif season on the Enhanced Vegetation Index for different months. specifications are restricted to districts with greater than 50% of net cropped area under paddy cultivation, and the period 2003 – 2009. ***, **, and * indicate statistical significance at the levels of 1, 5 and 10%, respectively.

Figure A.1: Comparison of ICRISAT's Calculation against Author's Calculation of Climate Variables using Terra Climate Satellite Data



(a) Minimum Temperature

(b) Maximum Temperature

(c) Precipitation

(d) Windspeed

Notes: This figure compares the climate variables derived from Terra Climate satellite data to those from the ICRISAT data.