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RESEARCH ARTICLE

Electoral cycles in environmental outcomes in India

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Abstract

Environmental outcomes can be shaped by underlying politics. This study investigates whether pre-determined election timings affect these outcomes by combining electoral data with remote sensing data on crop burning, forest fires, slash-and-burn activity, and tree cover for 28 major states (covering approximately 3800 assembly constituencies) in India from 2008 to 2019. Analysing 71 elections during this period reveals evidence of the presence of electoral cycles in environmental outcomes, with non-election years experiencing higher levels of environmentally harmful activities compared to election years. These cycles are more pronounced when the incumbent's party wins without a supermajority in state elections. The study further shows that specific factors, such as high-yield crop varieties, poverty levels, and Scheduled Tribe population proportions, also shape these environmental outcomes across the electoral cycle.

Keywords: crop burning; electoral cycles; forests; India; wildfires

JEL classification: D72; O13; Q23; Q54

1. Introduction

A large segment of the Indian population relies heavily on natural resources for sustenance, leading to concerns over environmental degradation. Elected leaders play a crucial role in this context, as the success and on-ground implementation of environmental policies are largely influenced by their decisions, which are often guided by political incentives. These incentives, such as re-election prospects, are inherently tied to electoral cycles and have critical implications for environmental outcomes like forest fires and deforestation (Pailler, 2018, Balboni *et al.*, 2021, 2023, Cisneros *et al.*, 2021).

Electoral cycles in India have been empirically linked to various non-environmental outcomes, reflecting a pattern of political opportunism in the distribution of resources and policy manipulation. For instance, Fagernäs and Pelkonen (2020) document a significant increase in the hiring and transfer of teachers in the aftermath of state

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elections. This phenomenon is hypothesized to be driven by corrupt practices, such as the payment of bribes to political actors in exchange for favourable transfers, or by politicians strategically using these transfers to consolidate political support. The resulting disruptions in staffing are shown to negatively impact student learning outcomes. Similarly, Cole (2009) and Baskaran *et al.* (2015) identify electoral cycles manifesting as increased provision of agricultural credit and enhanced electricity services during election years, suggesting that incumbent politicians manipulate public goods distribution to maximize electoral returns.

In a related study, Sukhtankar (2012) provides evidence of political embezzlement in the agricultural sector, where politically controlled sugarcane mills suppress prices paid to farmers during election years to raise funds for campaign financing. This practice reduces farmer incomes, with compensation typically occurring after the politicians are elected. Furthermore, Dar *et al.* (2018) examine price manipulation of onions – a politically sensitive commodity in India – finding that onion prices are systematically reduced before elections to sway voter sentiment. Similarly, Basistha *et al.* (2024) show that incumbents strategically sanction new road construction projects just before elections to signal their competence, leveraging the visible aspects of road building.

This study expands the existing body of literature by examining the role of electoral cycles in influencing environmental outcomes in India. It specifically focuses on key environmental issues, including stubble burning, forest fires, slash-and-burn fires, and tree cover. These environmental outcomes warrant attention as they adversely impact air quality (Jain *et al.*, 2014) and public health (Rangel and Vogl, 2019, Tan-Soo and Pattanayak, 2019). Despite these public and private costs, farmers continue to burn stubble because it remains the cheapest and quickest method for clearing crop residue. Additionally, both natural factors (such as high temperatures and dry weather leading to wildfires) and human-induced activities (including the use of fire for clearing forests or deforestation to expand agricultural land) contribute to the degradation of forest land. Although many of these human activities are environmentally damaging and illegal, widespread violations of existing bans persist, undermining efforts to curb such practices.

Political incentives form the foundation of political budget cycles. Nordhaus (1975) established the theoretical framework for these cycles based on a few critical assumptions: voters are imperfectly informed and myopic, and political parties prioritize winning elections above all else. In this context, the likelihood of re-election increases when voters' utility improves ahead of elections. This boost in utility can be achieved through various measures targeting prospective voters. For instance, politicians may enhance the provision of tangible public goods such as roads (Basistha *et al.*, 2024), electricity (Baskaran *et al.*, 2015), or healthcare services to improve neonatal mortality (Bhattacharjee, 2022), thereby signaling their competence to the electorate. Similarly, Vadlamannati (2015) shows that states with strong governance, where corruption is either low or actively addressed, tend to experience a rise in registered corruption cases during election periods, as political leaders attempt to showcase their commitment to good governance. Furthermore, Chaudhuri *et al.* (2006) notes that the shadow economy – a proxy for illegal activities – contracts by 4 per cent during election years in India.

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Conversely, politicians may also face incentives to engage in corrupt practices (Sukhtankar, 2012), illicit activities like bribing officials for favourable transfers (Fagernäs and Pelkonen, 2020), or neglecting environmental governance (Klopp, 2012, Balboni *et al.*, 2021). Patronage politics plays a pivotal role in this context, benefiting special interest groups that can reward politicians with campaign contributions or active voter mobilization efforts (Khemani, 2004).

In the environmental domain, politicians aiming to retain power can either invest in protection measures, such as conserving forests and curbing biomass burning, or weaken enforcement efforts, allowing illegal activities like stubble burning, forest fires, or deforestation for resource extraction to continue. In navigating these choices, political parties in India often highlight legitimate public concerns – such as curbing air pollution,[1] preventing forest degradation, and addressing climate change – in their party manifestos.[2] However, despite these commitments, many states continue to experience widespread non-enforcement of legal bans aimed at curbing illegal activities like crop burning and deforestation.

The benefits of conserving forests or reducing fire events, such as improved air quality and health outcomes, have several distinct characteristics. First, these benefits are public rather than private, meaning they are broadly shared and non-targeted. In contrast, targeting benefits to special interest groups generates direct and attributable gains, which are more likely to translate into political support (Khemani, 2004, Drazen and Eslava, 2010). Second, improvements in forest health are realized only in the medium term, whereas the electoral advantages of allowing forest access for resource extraction are more immediate (Cisneros *et al.*, 2021, Sanford, 2021). Third, it is difficult to attribute improvements in air quality or forest cover to a particular politician, making it challenging for them to claim credit and signal their effectiveness. Consequently, politicians often adopt strategies that prioritize immediate electoral gains by permitting these illegal activities, thereby appeasing their agriculturally or forest-dependent constituents.

To examine the relationship between election timings and environmental outcomes, this study combines election data with remote sensing data on environmental indicators. India's state elections are held every five years in assembly constituencies (ACs),

[1]Studies from countries like China, Germany, the USA, and Vietnam show that environmental issues, such as air pollution, negatively affect public opinion and reduce support for the government (Gerber and Neeley, 2005, Alkon and Wang, 2018, Kim *et al.*, 2020, Bellani *et al.*, 2021).

[2]Deforestation and broader environmental issues have also been key election topics in several Indian states, particularly those with extensive forest cover and a high dependency on natural resources, such as Madhya Pradesh, Chhattisgarh, Jharkhand, Uttarakhand, and the Northeastern states. These items have appeared in party manifestos across various elections. For instance: (a) During the 2017 Punjab state elections, where stubble burning has led to the highest number of fire incidents, the Aam Aadmi Party proposed incentives for farmers to avoid crop burning (Aam Aadmi Party, 2017), (b) In Uttarakhand, where forest fires are a major issue, the Bhartiya Janata Party promised measures in their manifesto to combat fires through early detection systems and rapid response infrastructure (Bharatiya Janata Party, 2022), (c) The protection of forests has also been a central concern for many states, with multiple party manifestos emphasizing forest conservation, such as the Left Front's manifesto for West Bengal in 2021 (Communist Party of India, 2021), (d) Climate change is increasingly becoming a recognized election issue, reflecting a growing voter preference. This is evident in the Indian National Congress's 2018 manifesto for the state of Nagaland, which addressed climate change policies (Indian National Congress, 2018).

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where the winners are elected as Members of the Legislative Assembly (MLAs).[3] The timing of these elections are asynchronous across states, and their timing is predetermined, independent of the socio-economic characteristics of individual ACs. The findings indicate that, for all environmental outcomes (except for slash-and-burn-the estimates) are notably stronger and larger in the pre-election years leading up to elections. This pattern aligns with Nordhaus's (1975) theory, which suggests that imperfectly informed voters are more likely to emphasize politicians' recent performance when making decisions, particularly in the years just before elections. This pattern is further influenced by factors like the strength of the incumbent party and the political alignment between ACs and the state government. Notably, electoral cycles are more pronounced when the incumbent's party wins without a supermajority. Additionally, stubble burning is significantly impacted by the political alignment between local leaders (elected MLAs at the AC level) and the state government. The analysis also suggests that other factors – such as high-yield crop varieties, poverty levels, and the proportion of the Scheduled Tribe population – play a critical role in shaping these environmental outcomes throughout the electoral cycle.

Our work contributes to the political economy literature on environmental degradation, positioned within the broader framework of factors influencing environmental outcomes. National conservation policies, such as the blacklisting of administrative units to curb deforestation in Brazil (Cisneros *et al.*, 2015, Assunção and Rocha, 2019), have proven effective (Wuepper *et al.*, 2024). However, other determinants also play a crucial role. For instance, decentralization through government fragmentation, exemplified by the creation of new administrative units, has been linked to both increased (Burgess *et al.*, 2012) and temporarily reduced deforestation (Cisneros *et al.*, 2023) in Indonesia. Additionally, public discourse whether driven by public attention (Araujo *et al.*, 2024) or government rhetoric (Magalhães de Oliveira *et al.*, 2023) has been identified as a significant factor shaping deforestation patterns.

Our study closely aligns with research investigating local election incentives and other embedded economic factors that influence environmental outcomes over electoral cycles (Pailler, 2018, Balboni *et al.*, 2021, Cisneros *et al.*, 2021).[4] However, this paper expands the scope of environmental outcomes traditionally examined in this literature (primarily deforestation) to include new, contextually significant issues for India, such as crop burning. This is one of the first studies on India to examine political cycles across multiple environmental outcomes including stubble burning, tree cover, slash-and-burn activities, and forest fires yielding consistent results across all these measures. Moreover, unlike prior studies (Baskaran *et al.*, 2015), this research focuses on a more recent period (2008–2019), following the delimitation exercise that finalized AC boundaries. It also analyses environmental outcomes at a more granular level, specifically the AC level, rather than the state level (Khemani, 2004) or district

[3] A state may conduct early elections if the ruling coalition loses its majority; however, no early elections were observed in the sample comprising 28 major states.

[4] Other relevant political economy studies in this domain explore the effects of specific characteristics of elected politicians, such as gender (Jagnani and Mahadevan, 2023), age (Dahis *et al.*, 2024), or sectoral connections (e.g., ties to agriculture in the case of Brazil (Bragança and Dahis, 2022)).

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level (Cole, 2009). Finally, this study underscores the role of political mechanisms, such as incumbent strength, in shaping the trajectory of environmental outcomes.

This study is organized into six sections. Section 2 outlines the institutional background, while section 3 details the datasets used in the analysis. Section 4 presents the empirical model. Section 5 discusses the main empirical results, explores possible mechanisms, examines heterogeneous effects, and includes several robustness checks. Finally, section 6 concludes the study.

2. Background

2.1. Institutional background

India's state-level governance is primarily structured around State Legislative Assemblies. These assemblies are composed of representatives, known as MLAs, who are elected through state elections from defined ACs to represent their respective electorates. Elections are held every five years using a first-past-the-post system. The party or coalition that secures a majority of seats in the assembly forms the state government. The size of each legislative assembly, i.e., the total number of ACs, varies across states based on factors such as population and geographical area.[5]

Assembly Constituencies play a vital role in shaping local politics, resource distribution, and policy implementation. Each AC is represented by a single MLA, who wields considerable influence over local governance, resource allocation, and constituency development. These elected representatives serve as crucial intermediaries between the local population and the state government, articulating their constituents' concerns within the legislative assembly. However, the role of MLAs extends beyond political representation; they are instrumental in directing state resources, executing state-level policies, and overseeing constituency-specific development initiatives. The MLAs do not possess independent legislative powers but are key players in determining how state policies are adapted and enforced at the local level.

In India, the division of responsibilities between the Center and the States is defined by the Constitution through three distinct lists: the Union List, the State List, and the Concurrent List. Subjects under the Union List fall exclusively under central jurisdiction, such as defense, foreign affairs, and atomic energy, while the State List covers areas such as police, public health, and local governance. The Concurrent List includes subjects like environment, education, marriage, and criminal law, where both the Center and States can legislate, but central laws take precedence in case of a conflict. Agriculture is predominantly a state subject, with states having the power to legislate on matters such as crop production, land use, and local agricultural practices. The environment, categorized under the Concurrent List, allows both Central and State governments to legislate on issues related to forests, wildlife, and environmental protection. While states manage local environmental issues and forest resources, the central government sets broader environmental policies, ensuring a unified framework for sustainable development.

[5]In the sample of 28 major Indian states used in this study, the number of assembly seats ranges from 32 in Sikkim to 403 in Uttar Pradesh. The Election Commission of India determines the boundaries of these constituencies through a process called delimitation, considering demographic and geographic factors.

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The role of MLAs in influencing agricultural activities and environmental outcomes is significant. MLAs, by virtue of their position, have substantial control over agricultural subsidies, crop insurance schemes, and the distribution of inputs like seeds and fertilizers. Additionally, MLAs can impact land-use decisions, forest management, and environmental policy enforcement, making them key players in shaping local agricultural and environmental landscapes.

Monitoring and enforcement at the AC level in India are carried out by a combination of local administrative officers, regulatory agencies, and law enforcement bodies. Key figures include District Collectors, Sub-Divisional Magistrates, and Block Development Officers, who are responsible for enforcing land-use, agricultural, and environmental policies. Forest and environmental officers, such as Divisional Forest Officers and State Pollution Control Board officers, oversee compliance in forested and ecologically sensitive areas, while local police assist in maintaining law and order. Panchayati Raj Institutions, comprising village, block, and district councils, also play an essential role in managing local resources and monitoring compliance, often serving as intermediaries between communities and state officials. MLAs are pivotal to this enforcement framework as they use their political authority to shape the implementation of policies and prioritize issues within their constituencies. Their involvement is crucial for determining resource allocation, influencing local administrative decisions, and ensuring the effective execution of state-level policies.

2.2. Timing of state elections

State elections in India are held every five years, with the first set of elections conducted in 1951 for all existing states at the time. The subsequent varying election timings and cycles across Indian states are largely due to factors that are external but partially influenced by historical and political developments. These factors include the timing of the first elections in newly formed or reorganized states, dissolution of state assemblies due to political crises (early elections also called midterm elections), imposition of President's Rule, and court rulings. For instance, the state of Chhattisgarh was carved out of Madhya Pradesh in 2000, held its first elections in 2003, and subsequently followed a consistent five-year cycle with elections in 2008, 2013, and 2018. Similarly, the state of Jharkhand was carved out of Bihar in 2000 and held its first state elections in 2005. However, due to political instability and the imposition of President's Rule, the subsequent elections were held early in 2009, creating a unique election cycle distinct from Bihar, which adheres to a different timeline.

Additionally, logistical considerations such as the availability of security forces and administrative readiness as determined by the Election Commission also contribute to staggered elections across states. While certain factors, like early dissolution of assemblies, are political, the overall timing is primarily shaped by constitutional mandates and external events beyond the control of any single political entity. During the study period (2008–2019), which began with the delimitation exercise that redefined AC boundaries, states entered the analysis sample as their first elections were held post-delimitation. Since the first elections (for each state) following the delimitation exercise, the period has been characterized by relative political stability (i.e., no midterm elections) across all 28 states in the sample (see table 1).

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Table 1. State election years

State name	Election years	State name	Election years
Chhattisgarh	2008, 2013, 2018	Andhra Pradesh	2009, 2014, 2019
Karnataka	2008, 2013, 2018	Arunachal Pradesh	2009, 2014, 2019
Madhya Pradesh	2008, 2013, 2018	Haryana	2009, 2014, 2019
Meghalaya	2008, 2013, 2018	Jharkhand	2009, 2014, 2019
Mizoram	2008, 2013, 2018	Maharashtra	2009, 2014, 2019
Nagaland	2008, 2013, 2018	Odisha	2009, 2014, 2019
Rajasthan	2008, 2013, 2018	Sikkim	2009, 2014, 2019
Tripura	2008, 2013, 2018	Uttar Pradesh	2012, 2017
Jammu & Kashmir	2008, 2014	Manipur	2012, 2017
Kerala	2011, 2016	Gujarat	2012, 2017
West Bengal	2011, 2016	Goa	2012, 2017
Tamil Nadu	2011, 2016	Himachal Pradesh	2012, 2017
Assam	2011, 2016	Punjab	2012, 2017
Bihar	2010, 2015	Uttarakhand	2012, 2017

Notes: A total of 71 elections took place between 2008 and 2019 in 28 major states, covering approximately 3800 ACs in India. The scheduled elections in Jammu and Kashmir that were supposed to be held in 2013 were delayed until 2014 due to factors like security concerns and administrative reasons.

3. Data

This study uses data on pre-determined election timings from the Election Commission of India and supplemented it with data from Agarwal *et al.* (2021) on each AC's winning margins and party affiliation.[6] The boundaries of ACs are determined by the Indian Delimitation Commission based on census information.[7] The most recent delimitation exercise was completed in 2008; it finalized new AC boundaries.[8] Consequently, the analysis includes all 71 state elections held between 2008 and 2019 (pre-COVID-19). The new boundaries became effective from the first state assembly elections held after the delimitation orders were officially published. During the study period, elections were held in 29 states and 2 Union Territories (Delhi and Puducherry). The focus is on 28 major states, excluding Union Territories and the newly formed state of Telangana, which has had a shorter four-year election cycle since its inception in 2014. The sample comprises approximately 3800 ACs, which serve as the primary units of analysis.

[6]All elections for ACs within the same state are conducted simultaneously. State elections are often held in multiple phases. For example, in Uttar Pradesh – the largest state in India with a population of 200 million (2011 Census) – a single state election is conducted in seven phases over a four-week period.

[7]Source: http://projects.datameet.org/maps/assembly-constituencies/

[8]The 2008 delimitation is yet to be implemented in six states (Jammu and Kashmir, Jharkhand, Assam, Manipur, Nagaland, and Arunachal Pradesh). For these states, the old AC boundaries from previous elections were used. Excluding these states from the analysis does not alter the results; details are available upon request.

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Next, election information was combined with environmental outcomes' remote sensing data to create an AC-year level panel dataset, capturing environmental degradation through multiple outcomes. The first set of outcomes focused on biomass burning activities, including crop, forest, and slash and burn fires. The first outcome variable, crop fires, refers to intentional crop residue burning; these are the fire events that occur in croplands. Sixty percent of land in India is under agricultural production and over the past few decades Indian agriculture has been marked with expansion of irrigation facilities, adoption of high yield variety seeds, labour exits and increased mechanization (such as use of the combine harvester). A combination of these factors led to adoption of multi-cropping system by farmers which leaves little time in between the harvest of one crop and the sowing of another. In this scenario, crop residue burning thus emerged as the quickest and cheapest way to get the farm ready for the next crop. Although legal bans have been put in place to curb crop residue burning (Bhuvaneshwari *et al.*, 2019), on the ground they have little impact. Additionally, stubble burning is regularly highlighted as a cause for seasonal deterioration in air quality (Kaskaoutis *et al.*, 2014, Bikkina *et al.*, 2019, Sahu *et al.*, 2021).

Around a quarter of the total population (350–400 million people as of year 2009) living in India rely partly or fully on forests for their livelihoods (MoEF, 2009, Schmerbeck and Kraus, 2015). Greater reliance on forests puts forest property at risk due to potential resource over exploitation. Additionally, close to 41 per cent of forests in India are degraded which is a source of dry raw material for wildfires (MoEF, 2009, Srivastava and Garg, 2013). The Ministry of Environment, Forest and Climate Change is the central body responsible for making laws and formulating policies related to forests in India, however the state government is responsible for implementation of these laws and monitoring of various policies. The analysis focuses on forest fires, which can be either unintentional (spontaneous combustion of dry vegetation during peak summers) or intentional (burned to clear land for agricultural production), and refers to fire incidents in forestland. Finally, an outcome measuring slash-and-burn activities is also assessed (similar to the outcome variable considered in Balboni *et al.* (2021)). This aims to capture fire events occurring in previously deforested land that is burned consistently over two years. This activity is primarily concentrated in Northeastern Indian states. The data on various kinds of fire activities is obtained from NASA's Fire Information for Resource Management System (FIRMS), a geocoded dataset that captures real-time active fire locations (i.e., fire pixels) across the globe at 1km*1km resolution.[9] Fire pixels from the FIRMS dataset are projected onto India's land mask cover to identify the land type where these fire incidents occur and help us in classifying fires into crop or forest fire category. The fire pixel data are aggregated at the AC level for each year, which serves as the unit of analysis.

[9]Specifically, the FIRMS data used has been sourced from MODIS (shortform for MODerate Resolution Imaging Spectro radiometer). This dataset also provides a confidence variable ranging from value 0 to 100, depicting the observations' quality as captured by the satellite. This variable is used in the robustness check in section 5.4.

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Specifically, the number of fire pixels occurring within the boundaries of each AC is counted.

Beyond biomass burning measures, forest health is assessed using tree canopy cover statistics. As discussed by Asher *et al.* (2020), a binary measure of deforestation from the Global Forest Change (GFC) dataset is more appropriate for tracking forest health in countries like Brazil and Indonesia, where deforestation is often substantial. In contrast, India frequently experiences partial forest loss rather than the extensive loss required to be classified as deforested in the GFC dataset. Therefore, the Vegetation Continuous Fields data is utilized (with a 250m resolution), the same dataset recommended by Asher *et al.* (2020), to obtain a more accurate measurement of forest cover. Each pixel in this dataset provides information on the percentage of pixels which is covered by tree canopy. The tree cover is derived from a machine learning algorithm which classifies tree cover based on the amount of light reaching the ground, i.e., denser forest will have a lesser amount of light reaching the ground due to crown area of the trees and will get assigned a higher tree cover percentage.[10] For the analysis, all pixels (within an AC boundary) for which canopy cover is greater than 10 per cent are counted.[11] A change in tree cover can be induced by both deforestation or any other activity which reduces tree crown area (leaf area) like forest fires. Literature in this domain (Coop *et al.*, 2020) suggests that fires have a direct impact on forest dynamics, i.e., they change trees and other vegetation to shrubs.

To summarize, all outcome variables are constructed as total count of pixels lying inside the boundary of an AC for each year. Table 2 provides further details on all outcome and control variables used in the analysis.

4. Model specification

The empirical estimation relies on a Poisson model to analyze count variables. The following equation is estimated:

$$E[y_{it}] = \gamma_i exp\Big(\alpha_{-2}Election_{i,t-2} + \alpha_{-1}Election_{i,t-1} + \alpha_1 Election_{i,t+1} + \alpha_2 Election_{i,t+2} + \delta_t + \rho X_{it}\Big), \quad (1)$$

where y_{it} is the count of outcome variable (total number of pixels for crop fires, forest fires, slash and burn fires or tree cover) in AC i in year t. The concept of electoral cycle is introduced using a set of four dummy variables with the dummy for election year being used as the omitted category. Together, these dummy variables capture a complete five-year election period and represent the AC-year position in the electoral cycle. For example, if a state had elections in 2015, then the observation for an AC belonging to this state in 2014 will have the $Election_{t-1}$ dummy turned on while all other dummy variables will be turned off. Several studies have employed similar estimation

[10]For further details related to the algorithm used for determining tree/canopy cover, refer to: https://lpdaac.usgs.gov/documents/1322/MOD44B_User_Guide_V6.pdf.

[11]A higher threshold of 20 per cent is used in the robustness checks in section 5.4.

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Table 2. Variables description: assembly constituency-year level data compilation

Outcomes (Measured at AC-year Level)	**Definition**	**Source**	**Resolution**	**Unit of measurement**
Crop Fires	Count of fire pixels which occur in cropland	NASA FIRMS + NASA LP DAAC: MCD12Q1.006	1km	Count
Forest Fires	Count of fire pixels which occur in forestland	NASA FIRMS + NASA LP DAAC: MCD12Q1.006	1km	Count
Slash and Burn	Count of fire pixels in year t if deforestation occurred in 1km buffer area around the fire location in the previous year (*t-1*) and fire activity took place in the same 1km buffer area next year (*t+1*).	NASA FIRMS + Hansen Global Forest Change v1.8	1km	Count
Canopy Cover	Count of pixels for which canopy cover $>$ 10%	MOD44B.006 Terra Vegetation Continuous Fields Yearly Global 250m	250m	Count
Controls (Measured at AC-year Level)				
Precipitation	Annual average total rainfall	CHIRPS Pentad	5566m	mm/year
Net Primary Producitvity	Net primary productivity in cropland	NASA LP DAAC: MOD17A3HGF.006	500m	$kg * C/m^2$
Nightlight	Average radiance values	Li *et al.* (2020)	1km	Digital number values

specifications to assess electoral cycles in various domains, such as Cole (2009), Pailler (2018), Balboni *et al.* (2021), and Bhattacharjee (2022). Time-invariant factors, such as geography, are accounted for using AC-level fixed effects (γ_i)[12] and capture annual shocks common for all ACs by using year fixed effects (δ_t). Additional variables are also controlled for (X_{it}) which can potentially impact outcome variables. These include a proxy for development or income by using nightlights, an agricultural productivity

[12]State fixed effects are alternatively used to account for unobserved heterogeneity, such as unique time-invariant characteristics related to forest type, general political climate, etc., at the state level, and similar results are found. Results are available upon request.

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proxy (i.e., net primary productivity, see Zaveri *et al.* (2020) for reference), and precipitation. The coefficients of interest are α_{-2}, α_{-1}, α_1 and α_2, which represent the difference in the level of outcome variables in non-election years relative to the base category, i.e., election year.

5. Results

5.1. Main results

The results are presented graphically in figure 1, where estimates for α_{-2}, α_{-1}, α_1 and α_2 are plotted for each of the four environmental outcomes (coefficients are provided in table 5, columns (1)–(4) as well). For crop fires (figure 1, panel A), the coefficients for all non-election years are positive, signifying higher crop fire levels in non-election years relative to the election year. The crop burning level is dramatically higher by 14 per cent ($[e^{0.133} - 1] * 100$) just before the election year. The results for forest fires (in figure 1, panel B) are similar to crop fires, where non-election years observe higher forest fire activity levels (in the range of 9.6–18 per cent, except $t+1$ year). The effect sizes are relatively small compared to the Indonesian study (Balboni *et al.*, 2021), which found that forest fire ignitions rise by 57 per cent in the post-election year versus the election year. Slash and burn activity, which combines the concept of deforestation and forest fires and is mostly concentrated in northeastern Indian states (see figure 1 notes), witnesses a 9.2–15 per cent increase in levels during non-election years (except t-1 year) compared to an election year (figure 1, panel C). This pattern suggests that elected leaders allow more resource extraction in non-election years but possibly invest more in fire management and suppression strategies during elections. Next, the analysis focuses on forests by examining canopy cover (i.e., count of pixels in an AC with $>$ 10 per cent canopy cover). The results in figure 1, panel D reveal that canopy cover is lower during most non-election years by 2–9.3 per cent compared to election years.[13] Lastly, the results for the presence of any electoral cycle are reported by testing for the joint significance of all election dummies against the null hypothesis of no electoral cycle. For all outcomes, the null hypothesis of no electoral cycle is rejected (p-value < 0.01). Overall, it is observed that for all environmental outcomes (except slash-and-burn), the estimates are stronger and larger for pre-election years – those leading up to elections – supporting Nordhaus's (1975) theory that imperfectly informed voters tend to place greater weight on politicians' recent past performance when making decisions, particularly in the years immediately preceding elections.

5.2. Role of incumbent strength and political alignment

Elected members of parliament can influence the strictness of enforcement or advocate for relaxed regulations depending on local needs or political considerations. In this context, incumbents may behave differently depending on whether their party holds a

[13]The coefficient for the dummy for year $t + 1$ (the year post-elections) is positive and significant, probably due to canopy cover gains during election years, continuing into the next year.

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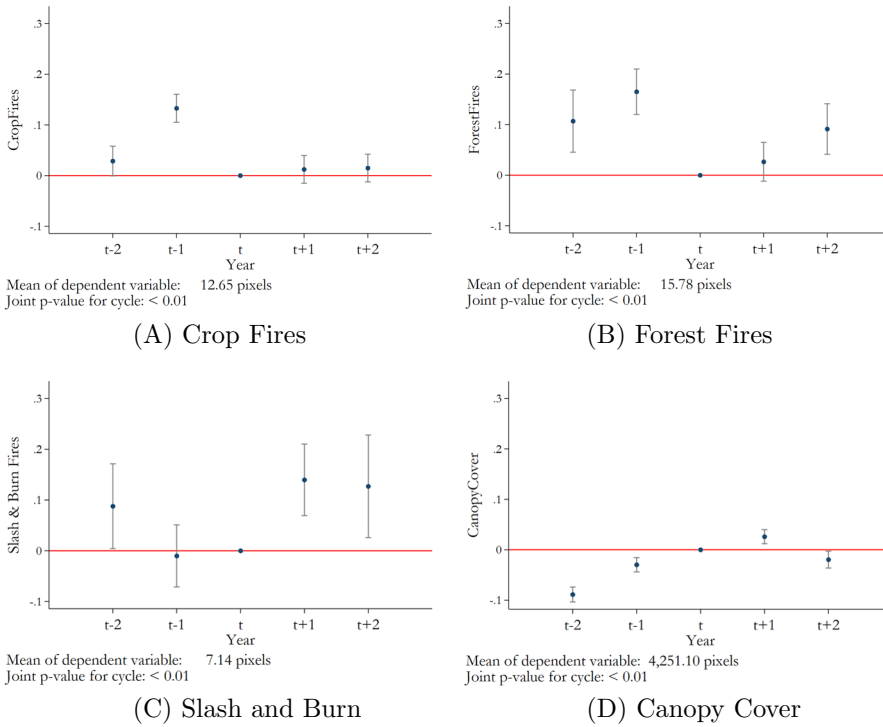


Figure 1. Electoral cycles and environmental outcomes.
Notes: Estimates from equation (1) for four environmental outcomes. Poisson model used with fixed effects for AC and year. Additional controls include nightlights, precipitation and net primary productivity. Standard errors clustered at AC level. *t* refers to dummy variable for election year (base category), *t-1* is the dummy for the year before the election year, *t-2* is the dummy the year 2 years before election year, and so on. Fixed effects Poisson regression drops those ACs from estimation for which the dependent variable takes value 0 for all years, i.e., no variation is observed in dependent variable in the analysis period. The number of ACs in the estimation sample is 3032 for crop fires, 2229 for forest fires, 948 for slash and burn fires and 3863 for canopy cover.

supermajority (more than two-thirds of the seats in the local state parliament) or not. The absence of a supermajority weakens the ruling party's political control, creating an incentive for elected politicians to tolerate more illegal activities as a strategy to secure political backing and consolidate their influence. Such activities often serve as "political currency" to maintain local support and prevent opposition leaders from gaining traction.

Numerous studies (Van der Ploeg, 2018, Balboni *et al.*, 2023) have emphasized that incumbents facing a significant threat of losing power tend to engage in extensive resource extraction. This concept has been further explored in political economy studies focusing on India (Baskaran *et al.*, 2015, Dar *et al.*, 2018). The present study builds on this framework by linking its findings to the role of incumbent strength in shaping environmental outcomes. Specifically, a variable called *Low Incumbent Strength* is defined, which takes the value of 1 when incumbents win without a supermajority

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(i.e., less than two-thirds of the seats at the state level)[14] and 0 otherwise. This variable is then interacted with electoral cycle dummies to explore how low-strength incumbents behave throughout the electoral cycle. For simplicity, pre-election dummies – $Election_{t-1}$ and $Election_{t-2}$ – are combined into a single variable labeled *PreElection* (similarly for post-election dummies).

Table 3 (panel A) presents these results. It is found that ACs with incumbents who won with low strength (i.e., without a supermajority) experience significantly higher levels of stubble burning, showing an additional increase of approximately 1 per cent[15] during the post-election period. Furthermore, these constituencies see an additional increase in forest fires by 2.5 per cent and a reduction in forest cover by 0.7 per cent.[16]

Next, the analysis tests whether the level of these environmentally harmful activities disproportionately changes in non-election years when an AC is politically aligned with the state government (same party rules an AC and the state government with potentially less chances of a crackdown due to aligned interests). No such effects are present for almost all outcome variables, except for crop fires (table 3, panel B). During pre-election years, ACs on average witness 5.86 per cent higher crop fire levels, which further increases to 9.01 per cent when ACs are aligned with the state government.

5.3. Heterogeneity analysis

In this section, the heterogeneity of the results is explored by focusing on specific characteristics that influence the environmental outcomes of interest. For instance, the use of high-yield crop varieties in agriculture (as discussed in section 3) is associated with increased crop burning activity. This is due to the fact that high-yield varieties for rice produce a larger volume of crop residue (rice straw), which is frequently burned to expedite field preparation for the next planting cycle (Huang *et al.*, 2022). To conduct this analysis, district-level rice yield data from before the start of the analysis period (2007–08) is utilized, as reported by the Directorate of Economics and Statistics, Department of Agriculture and Cooperation, Ministry of Agriculture, Government of India.[17] Based on the distribution of rice yields at the district level, a variable (*HighRiceYield*) is constructed to identify districts in the top quintile of the yield distribution. This variable is then interacted with pre-election and post-election indicators to assess whether crop-burning activity varied between ACs in high- and low-yield districts across the electoral cycle. The findings (in table 4, column (1)) suggest that districts with high rice yields experience a higher incidence of crop burning

[14]A similar but more pronounced pattern is observed in the extreme scenario where the party wins less than one-third of the total seats. Detailed results are available upon request.

[15]Calculated as the increase in crop fires at the mean level of *LowIncumbentStrength* in the estimation sample, i.e., $1.03 = [e^{0.041*0.249} - 1] * 100$.

[16]The estimation equation compares low-strength incumbents with both non-incumbents and high-strength incumbents. Restricting the analysis to only incumbents (thus comparing high-strength versus low-strength incumbents) results in some estimates becoming even stronger. Detailed results are available upon request.

[17]Source: https://aps.dac.gov.in/

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Table 3. Role of incumbent strength and political alignment

	(1)	(2)	(3)	(4)
Panel A	CropFires	ForestFires	Slash and Burn	CanopyCover
Pre Election	0.079	0.110	0.048	-0.055
	(0.014)	(0.029)	(0.035)	(0.008)
Post Election	0.005	0.039	0.152	0.013
	(0.014)	(0.022)	(0.040)	(0.008)
Incumbent Low Strength (ILS)	-0.047	-0.020	0.141	-0.003
	(0.031)	(0.039)	(0.080)	(0.012)
Pre Election * ILS	0.030	0.093	-0.021	-0.017
	(0.030)	(0.047)	(0.067)	(0.015)
Post Election * ILS	0.041	0.071	-0.064	-0.027
	(0.024)	(0.049)	(0.069)	(0.013)
Mean ILS in Sample	0.249	0.261	0.255	0.259
Observations	30,413	22,935	9815	38,754
Number of ACs	3032	2229	948	3863
	(5)	(6)	(7)	(8)
Panel B	CropFires	ForestFires	Slash and Burn	CanopyCover
Pre Election	0.057	0.166	0.040	-0.057
	(0.021)	(0.036)	(0.059)	(0.011)
Post Election	0.019	0.085	0.149	0.010
	(0.017)	(0.034)	(0.058)	(0.010)
Aligned	0.019	0.028	-0.076	-0.000
	(0.027)	(0.036)	(0.061)	(0.010)
Pre Election * Aligned	0.050	-0.052	0.005	-0.004
	(0.026)	(0.041)	(0.068)	(0.013)
Post Election * Aligned	-0.006	-0.047	-0.022	-0.005
	(0.023)	(0.042)	(0.061)	(0.011)
Mean Aligned in Sample	0.62	0.61	0.62	0.63
Observations	30,413	22,935	9815	38,754
Number of ACs	3032	2229	948	3863
Assembly Constituency FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
Other Controls	✓	✓	✓	✓

Notes: Standard errors in parentheses are clustered by AC. Regression includes other controls for nightlights, total rainfall and net primary productivity. Fixed effects Poisson regression drops those ACs from estimation for which the dependent variable takes value 0 for all years, i.e., no variation is observed in the analysis period. The number of ACs in the estimation sample is 3032 for crop fires, 2229 for forest fires, 948 for slash and burn fires and 3863 for canopy cover.

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during non-election years, supporting the hypothesis that political actors may tolerate illegal activities, such as crop burning, outside election periods to maintain the satisfaction of their agriculturally reliant constituencies. This result is similar in spirit to the results in Cisneros and Kis-Katos (2024) who find that high dependency on farming interacts with embedded political incentives and leads to greater environmental degradation.

The next heterogeneity analysis examines fires occurring in forested areas. An in-depth report on the causes and patterns of forest fires in India (Dogra *et al.*, 2018), which draws on interviews with forest officers, found that over 75 per cent of forest fires within their jurisdiction are human-induced. Local communities utilize fire for various purposes, such as promoting the growth of new grass or tendu leaves, facilitating the collection of honey, sal seeds, mahua, and chiraunji, and preparing land for shifting cultivation. The report also highlighted a connection between poverty and the occurrence of forest fires.

To further explore this relationship, levels of development are examined using nightlight intensity as a proxy, which is inversely related to poverty (Chen, 2015). Specifically, the distribution of nightlights for ACs in 2008, the initial year of the study, is used to create a variable (*LowDevelopment*) that identifies constituencies in the bottom quintile of the distribution.[18] This variable is interacted with pre-election and post-election indicators, and the findings are presented in columns (2) and (3) of table 4. The hypothesis is that environmentally harmful activities are more prevalent in less developed areas (where people are more reliant on forest resources) during non-election years. The results confirm this expectation, showing that forest fires are 16 per cent higher in less developed areas during post-election years, while the coefficient for pre-election years is insignificant. Although the estimates for slash-and-burn activity are also positive, they are not statistically significant. This may be because slash-and-burn activity is primarily concentrated in the northeastern region of India, leading to insufficient data variation to fully capture the effect of low development.

Lastly, forest cover is examined in relation to the caste composition of the population, with a specific focus on Scheduled Tribes (STs).[19] STs hold a unique connection to forests and play a crucial role in their protection and conservation. As indigenous communities traditionally reliant on forests for their livelihoods, they possess deep-rooted ties to the natural environment. Their traditional knowledge and practices have contributed to the sustainable management of forest ecosystems for generations.[20]

[18]Similar results are obtained when using average nightlights over the entire analysis period, i.e., 2008 to 2019.

[19]There exists an overlap between ethnic and caste backgrounds in the case of STs in India, because STs are both an ethnic and socially categorized group. The ethnic identity of STs is intertwined with their caste-like status in the legal and social system. While their classification as STs comes from their ethnic distinctiveness, they are also treated as a socially disadvantaged group (like other caste groups) for the purposes of affirmative action.

[20]Further, the Forest Rights Act of 2006 formally recognizes the legal rights of STs in protecting and managing forests.

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Table 4. Heterogeneity analysis

	(1)	(2)	(3)	(4)
	CropFires	ForestFires	Slash and Burn	CanopyCover
Pre Election * High Rice Yield	0.100 (0.025)			
Post Election * High Rice Yield	0.126 (0.021)			
Pre Election * Low Development		-0.017 (0.041)	0.077 (0.069)	
Post Election * Low Development		0.148 (0.031)	0.010 (0.064)	
Pre Election * High ST Prop				0.123 (0.014)
Post Election * High ST Prop				0.085 (0.014)
Observations	30,413	22,935	9815	38,754
Number of ACs	3032	2229	948	3863
AC Fixed Effects	✓	✓	✓	✓
Year Fixed Effects	✓	✓	✓	✓
Other Controls	✓	✓	✓	✓

Notes: Standard errors in parentheses are clustered by AC. Additional controls include nightlights, precipitation and net primary productivity. Rice yield data has been sourced from Directorate of Economics and Statistics Department of Agriculture and Farmers Welfare for year 2007–08 (just before the start of the analysis period spanning 2008–2019). Caste background data, i.e., proportion of scheduled tribe population data, has been constructed at the district level using 2001 census of India (574 districts matched to the estimation analysis. Source of data: Socioeconomic High-resolution Rural-Urban Geographic Platform for India (SHRUG)). "High" refers to the top quintile in the distribution of rice yield or ST population proportion (at the district level). "Low Development" variable has been constructed using nightlights for the year 2008, the bottom-most quintile in the distribution of nightlights (at AC level) has been tagged as low development.

In this context, the hypothesis is that areas with a higher proportion of the ST population will experience less degradation and tree cover loss compared to areas with a lower proportion of the ST population. In table 4, column (4), this hypothesis is tested by interacting pre- and post-election dummies with an indicator for a high ST population proportion.[21] The findings support the hypothesis, showing that areas with a higher proportion of the ST population maintain greater tree cover in both pre- and post-election periods compared to areas with a low ST population proportion.

[21]District-level data on the ST population was sourced from the 2001 Census, which predates the study period. Data for 574 districts was used and mapped to the ACs included in the sample. Districts (and correspondingly ACs) falling within the highest quintile for ST population proportion were categorized as having a 'High ST Proportion'.

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5.4. Robustness checks

A series of tests were performed to assess the robustness of the results, described in greater detail below:

(1) First, existing pre-trends in the environmental outcomes studied can be a real concern, as they influence the evolution of these outcomes over time. To account for this, a subsequent analysis was performed that incorporated state-level trends, and the results remain unchanged (see online appendix, figure A1).
(2) Inverse hyperbolic sine transformation (Bellemare and Wichman, 2020) was also performed, which provides an alternative method for measuring the outcome variables used to model extreme values or zero values. The results were found to be robust to this transformation.[22]
(3) Spillover effects are a concern as fires can spread from one area to another, which might imply presence of spatially correlated errors. To address this concern, two additional analyses have been conducted:
    (a) Spatial correlation of errors is accounted for by employing Conley's standard errors. The results are presented in table 5. Columns (1)–(4) show the original results, while columns (5)–(8) display the results with spatially clustered errors. While some estimates lose statistical significance, many of the key estimates across the four outcome variables retain their significance. For instance, crop fires are more prevalent in the year preceding an election, and forest fires increase during pre-election periods. Slash-and-burn activity, concentrated largely in the northeastern states, tends to rise just after elections; however, due to the relatively smaller number of observations and spatial clustering, the estimates may contain more noise, rendering them insignificant. Finally, forest cover tends to decrease during pre-election years, with a slight but statistically insignificant increase observed in the post-election period. Overall, even with spatially clustered errors, the results convey a consistent narrative: environmental degradation tends to be greater during non-election years, particularly in the pre-election period, compared to election years.

        An alternative analysis is conducted in which standard errors are clustered at the state level instead of the AC level. This approach allows for correlation of errors over a larger geographic area (i.e., across ACs), while states are treated as being independent of one another in the error structure. The results of this analysis are presented in table 6. Clustering at the state level, however, poses challenges due to the small number of clusters (i.e., fewer than 30). In such cases, traditional cluster-robust standard errors may be unreliable, and Wild cluster bootstrapping provides a more accurate method for inference. Unfortunately, Wild cluster bootstrapping is not applicable for non-linear models, such as the Poisson models used in the

[22]Results not presented but available on request.

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Table 5. Spatial clustering

	Original				*Spatial clustering*			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	CropFires	ForestFires	Slash and Burn	CanopyCover	CropFires	ForestFires	Slash and Burn	CanopyCover
Election in 2 years (t-2)	0.029 (0.015)	0.107 (0.031)	0.088 (0.043)	-0.089 (0.008)	0.029 (0.039)	0.107 (0.056)	0.088 (0.043)	-0.089 (0.008)
Election next year (t-1)	0.133 (0.014)	0.165 (0.023)	-0.010 (0.031)	-0.030 (0.007)	0.133 (0.037)	0.165 (0.063)	-0.010 (0.031)	-0.030 (0.007)
Election this year (t=0)	Base category				Base category			
Election 1 year ago (t+1)	0.012 (0.014)	0.027 (0.020)	0.140 (0.036)	0.026 (0.007)	0.012 (0.032)	0.027 (0.031)	0.140 (0.036)	0.026 (0.007)
Election 2 years ago (t+2)	0.015 (0.014)	0.091 (0.025)	0.127 (0.052)	-0.020 (0.009)	0.015 (0.046)	0.091 (0.06)	0.127 (0.052)	-0.020 (0.009)
Observations	30,413	22,935	9815	38,754	30,413	22,935	9815	38,754
Number of ACs	3032	2229	948	3863	3032	2229	948	3863
Assembly Constituency (AC) FE	✓	✓	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓	✓	✓
Other Controls	✓	✓	✓	✓	✓	✓	✓	✓

Notes: In columns (1)–(4), standard errors in parentheses are clustered by AC. In columns (5)–(8), standard errors are spatially clustered. Regression includes other controls for nightlights, total rainfall and net primary productivity. Fixed effects Poisson regression drops those ACs from estimation for which the dependent variable takes value 0 for all years, i.e., no variation is observed in the analysis period.

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Table 6. Clustering at state level

	CropFires					ForestFires				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Poisson	OLS	WildCluster OLS	OLS: LogY	WildCluster OLS: LogY	Poisson	OLS	WildCluster OLS	OLS: LogY	WildCluster OLS: LogY
Election in 2 years (t-2)	0.029	-0.629	-0.629	0.008	0.008	0.107	1.876	1.876	0.071	0.071
	(0.015)	(0.172)	(0.640)	(0.010)	(0.030)	(0.031)	(0.448)	(0.852)	(0.013)	(0.041)
Election next year (t-1)	0.133	1.432	1.432	0.061	0.061	0.165	3.108	3.108	0.129	0.129
	(0.014)	(0.195)	(0.966)	(0.010)	(0.030)	(0.023)	(0.451)	(1.087)	(0.013)	(0.045)
Election this year (t=0)			*Base Category*					*Base Category*		
Election 1 year ago (t+1)	0.012	0.019	0.019	-0.005	-0.005	0.027	0.570	0.570	0.056	0.056
	(0.014)	(0.160)	(0.442)	(0.009)	(0.025)	(0.020)	(0.299)	(0.608)	(0.011)	(0.029)
Election 2 years ago (t+2)	0.015	-0.581	-0.581	-0.024	-0.024	0.091	1.496	1.496	0.030	0.030
	(0.014)	(0.175)	(0.520)	(0.010)	(0.028)	(0.025)	(0.354)	(1.266)	(0.013)	(0.040)
Observations	30,413	30,413	30,413	30,413	30,413	22,935	22,935	22,935	22,935	22,935
Number of ACs	3032	3032	3032	3032	3032	2229	2229	2229	2229	2229

(*Continued*)

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Table 6. (*Continued.*)

	Slash and Burn					Canopy Cover				
	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)
	Poisson	OLS	WildCluster OLS	OLS: LogY	WildCluster OLS: LogY	Poisson	OLS	WildCluster OLS	OLS: LogY	WildCluster OLS: LogY
Election in 2 years (t-2)	0.088	0.502	0.502	0.042	0.042	-0.089	-516.676	-516.676	-0.167	-0.167
	(0.043)	(0.292)	(0.542)	(0.017)	(0.024)	(0.008)	(29.996)	(162.527)	(0.011)	(0.067)
Election next year (t-1)	-0.010	0.026	0.026	0.006	0.006	-0.030	-216.215	-216.215	-0.009	-0.009
	(0.031)	(0.239)	(0.390)	(0.016)	(0.026)	(0.007)	(30.399)	(194.981)	(0.012)	(0.066)
Election this year (t=0)	*Base Category*					*Base Category*				
Election 1 year ago (t+1)	0.140	1.331	1.331	0.103	0.103	0.026	56.645	56.645	0.130	0.130
	(0.036)	(0.214)	(0.422)	(0.014)	(0.028)	(0.007)	(27.257)	(153.187)	(0.011)	(0.088)
Election 2 years ago (t+2)	0.127	1.237	1.237	0.062	0.062	-0.020	-246.622	-246.622	0.016	0.016
	(0.052)	(0.271)	(0.563)	(0.016)	(0.027)	(0.009)	(34.206)	(251.243)	(0.013)	(0.116)
Observations	9815	9815	9815	9815	9815	38,754	38,754	38,754	38,754	38,754
Number of ACs	948	948	948	948	948	3863	3863	3863	3863	3863
Assembly Constituency (AC) Fixed Effects	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Year Fixed Effects	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Clustering level	AC	AC	State	AC	State	AC	AC	State	AC	State

Notes: Standard errors in parentheses are clustered by AC or State level. Additional controls include state level trends, nightlights, precipitation and net primary productivity.

analysis for modeling the dependent variable, which is a count variable. As a result, linear models are used.[23]

Table 6 presents the results for various outcome variables. For each outcome, the first column replicates the original results from the Poisson model, while the second column provides results using an OLS model with the original clustering at the AC level. The third column presents OLS results with Wild-cluster bootstrapping, accounting for the small number of clusters at the state level in the sample. The fourth column shows results from an alternative OLS model where the dependent variable is the logarithm of Y, with clustering at the AC level. Finally, the fifth column displays results for the logarithm of Y with Wild-cluster bootstrapping at the state level. The results obtained with Wild-cluster bootstrapping (3rd and 5th column for each outcome variable) show patterns similar to those found with spatial clustering. Specifically, crop fires are more prevalent in the year preceding an election, and forest fires increase during pre-election periods. Slash-and-burn activity, concentrated primarily in the northeastern states, tends to rise just after elections. Additionally, forest cover decreases during pre-election years, with a slight but statistically insignificant increase in the post-election period.

Overall, even when clustering is performed at a broader level (i.e., state), the results support a consistent narrative: environmental degradation is more pronounced during non-election years, particularly in the pre-election period, compared to election years.

(4) The sensitivity of the results to different choices of base category in the analysis was also evaluated. In online appendix table A1, we present an alternative specification that focuses on election years, with non-election years serving as the base (i.e., omitted category). The results indicate that election years are associated with lower levels of environmental degradation, or conversely, that non-election years exhibit higher levels of environmental degradation. This analysis reinforces our original findings by demonstrating that the results are not driven by the choice of a specific base category. It also underscores the main takeaway: non-election years are marked by higher levels of resource extraction and environmental degradation.[24]

(5) Alternative measures (or definitions) for capturing the outcome variables were also employed to test the robustness of the results against these different way of measurements. In table 7, columns (1)–(3), a stricter definition for fire events was employed; only high-quality fire events with confidence values (a measure of the quality of observation taken by a satellite) are considered, i.e., those fires with greater than 70 per cent confidence level were counted. The results largely remained unchanged. For canopy cover, a stricter definition was applied by

[23]Using ordinary least squares (OLS) regression with count-dependent variables is troublesome, as predicted values can be negative on account of inappropriate model fit (Cameron and Trivedi, 2013).

[24]The results in table A1 for forest fires and slash-and-burn activities remain robust when clustered at the state level (using a linear model). For crop fires and canopy cover, the estimates retain the same sign but are not statistically significant.

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Table 7. Robustness checks

	(1)	(2)	(3)	(4)
	Confidence level > 70%			
	Cropfires	Forestfires	Slash and Burn	CanopyCover (> 20%)
Election in 2 years (t-2)	0.052 (0.022)	0.105 (0.036)	0.101 (0.053)	-0.032 (0.013)
Election next year (t-1)	0.194 (0.020)	0.142 (0.027)	-0.013 (0.039)	-0.012 (0.010)
Election year (t)	Base Category	Base Category	Base Category	Base Category
Election last year (t+1)	0.040 (0.020)	0.022 (0.024)	0.146 (0.038)	0.041 (0.008)
Election 2 years ago (t+2)	0.061 (0.020)	0.092 (0.028)	0.104 (0.058)	-0.013 (0.013)
Mean Dep Var	5.42	8.91	4.95	1821.00
Observations	25,896	17,387	7403	37,466
Number of ACs	2565	1671	705	3741
Assembly Constituency FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
Other Controls	✓	✓	✓	✓

Notes: Standard errors in parentheses are clustered by AC. Fixed effects Poisson regression drops those ACs from estimation for which the dependent variable takes value 0 for all years, i.e., no variation is observed in dependent variable in the analysis period.

selecting a higher threshold (more than 20 per cent of the pixel must be under canopy cover) for counting tree cover pixels. Although the estimates reduced in magnitude due to a lower number of pixels satisfying this criterion, overall they reflected a similar pattern to the original results.

Additional analysis was also conducted using the proportion of an AC covered by forest as the dependent variable instead of counting pixels (with canopy cover exceeding 10 per cent) to capture the extent of tree cover within an AC. The results are presented in online appendix table A2. Columns (1) and (3) reproduce the original results under different model specifications: column (1) represents the 5-year electoral cycle with four yearly dummy variables, while column (3) combines pre- and post-election dummy variables into single dummy variables. In these columns, the dependent variable is the count of forest pixels within an AC (with canopy cover exceeding 10 per cent). Columns (2) and (4) present results for similar specifications, but the dependent variable is the proportion of an AC covered by forest. Both sets of results – those using the original dependent variable and those using the proportion – exhibit a similar pattern: pre-election years overall show a decline in forest cover (column (4)), while post-election years demonstrate a small but positive increase in forest cover.

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6. Conclusion

This study highlights how electoral cycles influence environmental outcomes in India, showing that harmful practices such as crop fires, forest fires, slash-and-burn agriculture, and reduced tree cover are more prevalent in non-election years (especially pre-election years which lead up to an election). The findings indicate that political incentives can prompt leaders to permit environmentally damaging activities to secure the support of resource-dependent communities, especially in areas where the incumbent's political party's strength is weak. Additionally, stubble burning appears to be shaped by the political alignment between local leaders and the state government, highlighting how local and state-level political dynamics affect environmental policy enforcement. Socio-economic factors, including high-yield crop adoption, poverty levels, and the proportion of ST populations, also play a crucial role in moderating these outcomes. This study underscores the importance of considering local political contexts when formulating environmental policies, as electoral strategies can often overshadow long-term sustainability goals.

Supplementary material. The supplementary material for this article can be found at https://doi.org/10.1017/S1355770X25000221.

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References

Aam Aadmi Party (2017) AAP Punjab manifesto. Available at https://www.babushahi.com/upload/pdf/Punjab.

Agarwal A, Agrawal N, Bhogale S, Hangal S, Jensenius FR, Kumar M, Narayan C, Nissa BU, Trivedi P and Verniers G (2021) *TCPD Indian Elections Data v2.0.*, Trivedi Centre for Political Data, Ashoka University.

Alkon M and Wang EH (2018) Pollution lowers support for china's regime: Quasi-Experimental evidence from Beijing. *The Journal of Politics* **80**, 327–331.

Araujo R, Costa F and Garg T (2024) Going viral: Public attention and environmental action in the amazon. *Journal of the Association of Environmental and Resource Economists* **11**, 1605–1627.

Asher S, Garg T and Novosad P (2020) The ecological impact of transportation infrastructure. *The Economic Journal* **130**, 1173–1199.

Assunção J and Rocha R (2019) Getting greener by going black: The effect of blacklisting municipalities on amazon deforestation. *Environment and Development Economics* **24**, 115–137.

Balboni C, Berman A, Burgess R and Olken BA (2023) The economics of tropical deforestation. *Annual Review of Economics* **15**, 723–754.

Balboni C, Burgess R, Heil A, Old J and Olken BA (2021) Cycles of fire? Politics and forest burning in indonesia. *AEA Papers and Proceedings* **111**, 415–419.

Basistha A, Dhillon A and Chaudhuri AR (2024) Elections and rural road construction: Evidence from india. Available at https://papers.ssrn.com/sol3/papers.cfm?abstract_id=4773192.

Baskaran T, Min B and Uppal Y (2015) Election cycles and electricity provision: Evidence from a quasi-experiment with Indian special elections. *Journal of Public Economics* **126**, 64–73.

Bellani L, Ceolotto S, Elsner B and Pestel N (2021) Air pollution affects decision-making: Evidence from the ballot box. *IZA Discussion Paper No. 14718*.

Bellemare MF and Wichman CJ (2020) Elasticities and the inverse hyperbolic sine transformation. *Oxford Bulletin of Economics and Statistics* **82**, 50–61.

https://doi.org/10.1017/S1355770X25000221 Published online by Cambridge University Press

Bharatiya Janata Party (2022) BJP election manifesto 2022. Available at https://www.bjp.org/files/election-manifesto-documents/Manifesto.

Bhattacharjee S (2022) The timing of elections and neonatal mortality: Evidence from india. *The World Bank Economic Review* **36**, 972–998.

Bhuvaneshwari S, Hettiarachchi H and Meegoda JN (2019) Crop residue burning in India: Policy challenges and potential solutions. *International Journal of Environmental Research and Public Health* **16**, 832.

Bikkina S, Andersson A, Kirillova EN, Holmstrand H, Tiwari S, Srivastava A, Bisht D and Gustafsson O (2019) Air quality in megacity Delhi affected by countryside biomass burning. *Nature Sustainability* **2**, 200–205.

Bragança A and Dahis R (2022) Cutting special interests by the roots: Evidence from the Brazilian amazon. *Journal of Public Economics* **215**, 104753.

Burgess R, Hansen M, Olken BA, Potapov P and Sieber S (2012) The political economy of deforestation in the tropics. *The Quarterly Journal of Economics* **127**, 1707–1754.

Cameron AC and Trivedi PK (2013) *Regression Analysis of Count Data.*, Cambridge, UK: Cambridge University Press.

Chaudhuri K, Schneider F and Chattopadhyay S (2006) The size and development of the shadow economy: An empirical investigation from states of India. *Journal of Development Economics* **80**, 428–443.

Chen X (2015) Explaining subnational infant mortality and poverty rates: What can we learn from nighttime lights?. *Spatial Demography* **3**, 27–53.

Cisneros E and Kis-Katos K (2024) Unintended environmental consequences of anticorruption strategies. *Journal of Environmental Economics and Management* **128**, 103073.

Cisneros E, Kis-Katos K and Nuryartono N (2021) Palm oil and the politics of deforestation in indonesia. *Journal of Environmental Economics and Management* **108**, 102453.

Cisneros E, Kis-Katos K and Reiners L (2023) Losing territory: the effect of administrative splits on land use in the tropics. *ADB Economics Working Paper Series No. 708*.

Cisneros E, Zhou SL and Börner J (2015) Naming and shaming for conservation: Evidence from the brazilian amazon. *PLoS ONE* **10**, e0136402.

Cole S (2009) Fixing market failures or fixing elections? agricultural credit in india. *American Economic Journal: Applied Economics* **1**, 219–250.

Communist Party of India (2021) Left front election manifesto 2021. Available at https://cpimwb.org.in/wp-content/uploads/2021/03/Left-Front-Manifesto-2021.pdf.

Dahis R, de las Heras I, Saavedra S (2024) Young politicians and long-term policy. Available at https://ssrn.com/abstract=4265051.

Dar A, Gupta P and Verma R (2018). "Electoral Cycles in Food Prices: Evidence from India." Unpublished manuscript. Available at https://www.isid.ac.in/epu/acegd2019/papers/AadityaDar.pdf.

Dogra P, Mitchell AM, Narain U, Sall C, Smith R and Suresh S (2018) *Strengthening Forest Fire Management in India.*, Washington, DC: World Bank.

Drazen A and Eslava M (2010) Electoral manipulation via voter-friendly spending: Theory and evidence. *Journal of Development Economics* **92**, 39–52.

Fagernäs S and Pelkonen P (2020) Teachers, electoral cycles, and learning in India. *Journal of Human Resources* **55**, 699–732.

Gerber BJ and Neeley GW (2005) Perceived risk and citizen preferences for governmental management of routine hazards. *Policy Studies Journal* **33**, 395–418.

Huang T, Ma J, Song S, Ling Z, Macdonald RW, Gao H, Tao S, Shen H, Zhao Y, Liu X, Tian C, Li Y, Jia H, Lian L and Mao X (2022) Health and environmental consequences of crop residue burning correlated with increasing crop yields midst india's green revolution. *Npj Climate and Atmospheric Science* **5**, 81.

Indian National Congress (2018) Nagaland election manifesto 2018. Available at https://www.iocongress.org/uploads/manifesto/1550174267_Nagaland_Manifesto.pdf.

Jagnani M and Mahadevan M (2023) Women leaders improve environmental outcomes: Evidence from crop fires in India. *Technical Report* Working Paper.

Jain N, Bhatia A and Pathak H (2014) Emission of air pollutants from crop residue burning in India. *Aerosol and Air Quality Research* **14**, 422–430.

https://doi.org/10.1017/S1355770X25000221 Published online by Cambridge University Press

Kaskaoutis D, Kumar S, Sharma D, Singh RP, Kharol S, Sharma M, Singh A, Singh S, Singh A and Singh D (2014) Effects of crop residue burning on aerosol properties, plume characteristics, and long-range transport over northern India. *Journal of Geophysical Research: Atmospheres* **119**, 5424–5444.

Khemani S (2004) Political cycles in a developing economy: Effect of elections in the indian states. *Journal of Development Economics* **73**, 125–154.

Kim SE, Harish S, Kennedy R, Jin X and Urpelainen J (2020) Environmental degradation and public opinion: The case of air pollution in vietnam. *The Journal of Environment & Development* **29**, 196–222.

Klopp JM (2012) Deforestation and democratization: Patronage, politics and forests in Kenya. *Journal of Eastern African Studies* **6**, 351–370.

Li X, Zhou Y, Zhao M and Zhao X (2020) A harmonized global nighttime light dataset 1992–2018. *Scientific Data* **7**, 168.

Magalhães de Oliveira G, Sellare J, Cisneros E and Börner J (2023) Mind your language: Political discourse affects deforestation in the Brazilian amazon. Available at https://ssrn.com/abstract=4380343.

MoEF (2009) Asia pacific forestry sector outlook study II. Technical report, Ministry of Environment and Forests, Government of India.

Nordhaus WD (1975) The political business cycle. *The Review of Economic Studies* **42**, 169–190.

Pailler S (2018) Re-election incentives and deforestation cycles in the Brazilian amazon. *Journal of Environmental Economics and Management* **88**, 345–365.

Parks SA, Stevens-Rumann CS, Crausbay SD, Higuera PE, Hurteau MD, Tepley A, Whitman E, Assal T, Collins BM, Davis KT, Dobrowski S, Falk DA, Fornwalt PJ, Fulé PZ, Harvey BJ, Kane VR, Littlefield CE, Margolis EQ, North M, Parisien M-A, Prichard S and Rodman KC (2020) Wildfire-driven forest conversion in Western North American landscapes. *BioScience* **70**, 659–673.

Rangel MA and Vogl TS (2019) Agricultural fires and health at birth. *Review of Economics and Statistics* **101**, 616–630.

Sahu SK, Mangaraj P, Beig G, Samal A, Pradhan C, Dash S and Tyagi B (2021) Quantifying the high resolution seasonal emission of air pollutants from crop residue burning in india. *Environmental Pollution* **286**, 117165.

Sanford L (2021) Democratization, elections, and public goods: The evidence from deforestation. *American Journal of Political Science* **67**, 748–763.

Schmerbeck J and Kraus D (2015) Wildfires in India: Tools and Hazards. In Shroder JF and Paton D (eds). *Wildfire Hazards, Risks and Disasters*, Elsevier, pp.167–186.

Srivastava P and Garg A (2013) Forest fires in india: Regional and temporal analyses. *Journal of Tropical Forest Science* **25**, 228–239.

Sukhtankar S (2012) Sweetening the deal? Political connections and sugar mills in india. *American Economic Journal: Applied Economics* **4**, 43–63.

Tan-Soo J-S and Pattanayak SK (2019) Seeking natural capital projects: Forest fires, haze, and early-life exposure in indonesia. *Proceedings of the National Academy of Sciences* **116**, 5239–5245.

Vadlamannati KC (2015) Fighting corruption or elections? The politics of anti-corruption policies in India: A subnational study. *Journal of Comparative Economics* **43**, 1035–1052.

Van der Ploeg F (2018) Political economy of dynamic resource wars. *Journal of Environmental Economics and Management* **92**, 765–782.

Wuepper D, Crowther T, Lauber T, Routh D, Clec'h SL, Garrett RD and Börner J (2024) Public policies and global forest conservation: Empirical evidence from national borders. *Global Environmental Change* **84**, 102770.

Zaveri E, Russ J and Damania R (2020) Rainfall anomalies are a significant driver of cropland expansion. *Proceedings of the National Academy of Sciences* **117**, 10225–10233.

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