A Spatial Analysis of the Indian Farmers' Protests

Abstract

In 2020-2021, 250 million people protested three agricultural laws' that threatened to suppress Indian farmers' autonomy, leading to the world's largest protest to date. These three laws promote globalization of the agriculture sector and decrease reliance on the minimum support price offered by each state. Farmers, traders, and affiliated groups faced the absence of state protection against global corporations having free entry into the market and potential control of the produce supply. We conduct a spatial analysis of the farmers' protests from 2020 to 2021 in India, focusing on the types of actors that were involved in the protest to observe their spatial variability across the country. We connect socioeconomic features, using the PRIO-GRID dataset, to the spatial intensity of protests across India. Our study relates the spatial socioeconomic features to the intensity of protests across different types of actors (such as religious or political organizations and different types of unions). We use this modeling framework to begin to understand the ability and motivations behind people protesting across a socioeconomically diverse nation. These findings provide insight into the spatial range and patterns of different groups within the farmers' protests. This research is valuable to further understanding the people and groups involved in the Farmers' Protests and the complex nature of continuous agricultural advancement in India.

Keywords: farmers' protest, India, point process, spatial statistics

1 Introduction

Agriculture is central to India's economy and is the primary source of livelihood for over 55% of the population [1]. Any changes to the existing agricultural system would cause significant changes in the lives of 1.3 billion people. In June 2020, the central government of India proposed three temporary agricultural laws, which were later passed by both houses of the parliament, the Lok Sabha and the Rajya Sabha, by mid-September 2020 [2]. These three laws deregulated the existing system of government-run wholesale markets, allowing farmers to sell directly to food processors. The three laws proposed were:

- **The Promotion and Facilitation Act**: This act removes the state-level Agriculture Produce Market Committees (APMC), and the basal market price. It allows farmers to sell their produce outside of *mandis* (free market structure).

- **The Empowerment and Protection Act**: This act allows farmers to establish contracts with vendors and sponsors, enabling them to operate outside of the APMC security.
- **The Amendment of the Essential Commodities Act**: This act amended the previous restriction on private companies from hoarding and manipulating markets and stocks. Under "special circumstances" private large companies would now have the legal right to some of these practices [3].

While the government claimed the bills to be in the interest of farmers' welfare, farmers and trade unions argued that the government shifted the power of decision-making from independent farmers to private companies [4, 5] and left the farmers without the security of government-guaranteed minimum prices [6]. A guaranteed minimum price, also called "Minimum Support Price (MSP), acts as a price floor for selling crops and protects farmers from volatile prices. As opposed to global corporations, the majority of marginal farmers in India have limited access to markets and would be disproportionately disadvantaged by the deregulated market (proposed by the new laws) [7]. In fear and outrage of increased exposure to exploitation by corporations, these laws led to the largest protest in the world. Over 250 million people from all over the country traveled to the capital city, New Delhi, and other state centers to contest the alterations made to farming legislation, market structure, and privatization of food storage [8]. The Farmers' Protests also illustrated the changing dynamics of nationalism in India [9]. Different religious and political groups outside of the majority (Hindus, male-dominated political parties), such as Sikh farmers, female farmers, and *Khaps/khaaps* (caste/clan-based political leaders), were at the forefront of the movement [7, 9]. Existing literature on the farmers' protests reveals three broad themes: analysis of the nature of the protests (e.g. level of violence), the actors involved in the protests, and the portrayal of the protests in mainstream media. We will outline some of the major contributions to these areas in the following sections.

1.1 Nature of the Protest

Existing literature on the protests analyzes evidence presented by the media of the turbulent nature of the protests characterized by a massive, intimidating police presence enforcing laws that offer free trade while blocking the free movement of the protesters [6, 10]. For example, tear gas was used in the state of Haryana to prevent people from organizing [11]. Existing work has documented videotape and film evidence shared on social media of police violence in the city of Karnal when farmers blocked a highway [12, 13]. Representatives of the justice system of India submitted court files about the police using batons on protesters ("lathi charge") and injuring more than ten people [14]. There has been a recurring discussion about whether using water cannons, a military weapon operated by the police during the protests [11, 12], was justified in its efforts to stop protesters from reaching India's capital, New Delhi. Many media sources have also been shown to side with the government's narrative and many of the concerns of farmers were not highlighted by these media outlets [15]. An additional study analyzed the difference in government and elite-sponsored media portraying the farmers as violent as if they are the ones holding the weapons, whereas other media sources contrast that with images of armed police forces [13]. This research raises questions about the motives of different actors that may be causing turbulence.

1.2 Actors and People Involved

There is a major focus in recent work on the Farmers' Protests of identifying the major actors/groups involved in the movement and their motivations. Bharatiya Kisan Union (BKU) is a major farmers' organization that played an important role in the protests through the historical and current mobilization of farmers [16]. BKU was one of the first farmers' unions to consist of a diverse socioeconomic and religious population [16]. Around 200 groups/unions were recognized as active participants in the farmers' protests [4]. These included independent trade unions, trade unions with political standing, farmer unions, indigenous farmers, and religious groups among others [17, 18]. The unions were protesting not only the three new agricultural laws, as listed earlier but also new labor codes introduced by the government in 2020 [4]. These labor codes were deemed anti-labor and company-favored as laborers/traders who were not immediately considered successful could be laid off and their contracts could be terminated [6, 19]. Therefore, demands of the farmers' movement also included abolishing the newly introduced labor codes, increase in *mandis* (free produce market structure) and public procurement of a greater range of crops, and the waiving of loans and interest payments on the loans because of severe crop failure [4, 6, 17, 18]. Due to these demands, media outlets labeled the unions as defenders of a fiscally and agro-ecologically harmful regime [10], and the movement as a defensive, regional mobilization rather than a progressive, national movement [10, 18]. The farmers were blamed for destructive ecological practices and farmer unions were at odds with the trade unions because *Arthias* (traders/middlemen) are creditors to the small farmers within the *mandis*[18]. Consequently, there was a pervasive debate about the comprising actors of the movement, their varying motivations, and the resulting implications.

1.3 Existing Literature on Statistical Analysis

Most existing statistical analyses on the farmers' protests, motivated by the presence of conflicting stories and narratives in mainstream media, use text analyses to identify influential actors and explore their sentiments about the protests. Analyses have shown how mainstream media, such as newspapers/news channels, used Twitter to share news about the protests [20]. These mainstream media sources are generally broadcast on a national scale. Titles of tweets that included government actors were found to have a higher proportion of opposing sentiments than other actor types [20]. The two news sources that tweeted the most, NDTV and Zee News (both TV news), were known for their specific narratives about the protests. Specifically, NDTV focused on farmer actions and opinions, whereas Zee News mainly tweeted government and celebrity opinions [20]. An additional study conducted hypothesis tests and created predictive models based on 17,000 tweets about the protests to understand their sentiments [21]. The study found that most published tweets had neutral sentiment, followed by positive sentiment. A limitation of this study is that it does not report the distribution of stances (for or against) regarding the farmers' protests [21]. Further research analyzes whether there was an association between the views stated in tweets and retweets published by celebrities, politicians, etc., and other subsequent engagements on Twitter [22]. Celebrities with more followers were less likely to engage with tweets supporting the farmers' protests. Results from multiple studies showed that irrespective of their stance on the Farmers' Protests, influencers who engaged in Twitter discourse saw a significant increase in their Twitter following or other forms of popularity [13, 22]. South Asian celebrities used social media such as Twitter to reach and mobilize the diaspora in other countries to share their sentiments [13, 23]. An additional study analyzed the rise of Punjabi and folk music during the protests, noticing that artists such as Sidhu Moosewala, Kanwar Grewal, Shree Brar, Rajvir Jawanda marched in support of the movement and used their platform to share the sentiments of despair, betrayal, and enthusiasm of the farmers [24]. Most of the existing research involving data and/or statistical methods has focused on text analysis of social media data. Instead, our analysis focuses on a spatial analysis of the protests.

1.4 Current Study

Within the current study, we seek to analyze the spatial distribution of the farmers' protests. We aim to understand how the farmers' protests are related to the socioeconomic and demographic characteristics of the surrounding area where the protest is taking place. We return to the analysis of actor types, where we use the actors involved in the protest to distinguish where protest events occurred. We compare across actor types how the frequency of protests may be related to socioeconomic characteristics. We draw on recent work analyzing actor involvement to bring out potentially relevant actor types, including trade/farmers' unions, regional/central organizations, police forces, and political groups. The goal of our analysis is to increase understanding of the spatial dynamics of the farmers' protests, direct attention to the spatial patterns of different groups involved in the farmers' movement, and encourage future policy work about the motivations and behaviors of these actors.

2 Data

The study uses farmer's protest event data ranging from 2020-2021 across India using the Armed Conflict Location & Event Data Project (ACLED) data extraction tool [25]. ACLED publishes data on the dates, associated individuals/actors, geo-coded locations at the sub-district level, and types of reported political violence and protests using different news sources and NGO databases (ACLED). The dataset was created using keywords such as "Farmer" and *Kisan* in the ACLED data export tool so that protests relating to other movements were not included. The dataset initially included event data for all protests ranging from 2018 - April 2021, and this was filtered to contain only events occurring between 2020 and 2021 to represent the current movement. After the initial subsetting, the dataset contains 5,508 protests.

Each event in the protest dataset has multiple actors associated with it. To analyze the relationship between actors and comprehend the demographics of the Farmers' protests, associated actors for each event were coded into various categories. Coding was done using information from the Election Commission of India [26], organization websites, and social media pages. Actors were grouped based on their affiliations within central, police/security, regional, political, police, agricultural unions, or trade unions. The codebook we developed also includes whether an organization uniquely represents scheduled caste, tribes, women, youth, military, or other minority groups. For this analysis, we used broad categories to label each actor. For example, "BKU: Bharatiya Kisan Union" is classified as a farmers' union and a regional organization (one actor can fit into multiple categories). The actor "INC: Indian National Congress" is classified as a central organization and a political organization. Lastly, the actor "Hindu Group (India)" is classified as a religious group.

A subset of the protest data is shown below in Figure 1. From this figure, we visualize the spatial distribution of protests involving a few selected actors. "All India Kisan Sabha" (AIKS) is a central organization and a farmers' union whereas "Bharatiya Kisan Union" (BKU) is a regional organization and a farmers' union. "Centre of Indian Trade Unions" (CITU) is one of the most prominent trade unions in southern India and a central organization. Indian National Congress (INC) is one of the oldest political parties in India and a central organization. Lastly, "Telangana Rashtra Samithi" (TRS) is a regional organization and a South Indian political party. We see that the actor type plays a large role in determining the locations of events affiliated with that actor. For example, regional organizations such as TRS and BKU have limited spatial range, whereas central organizations such as INC and CITU have more national reach. We incorporate information about actors to differentiate our model for the spatial distribution by actor type.

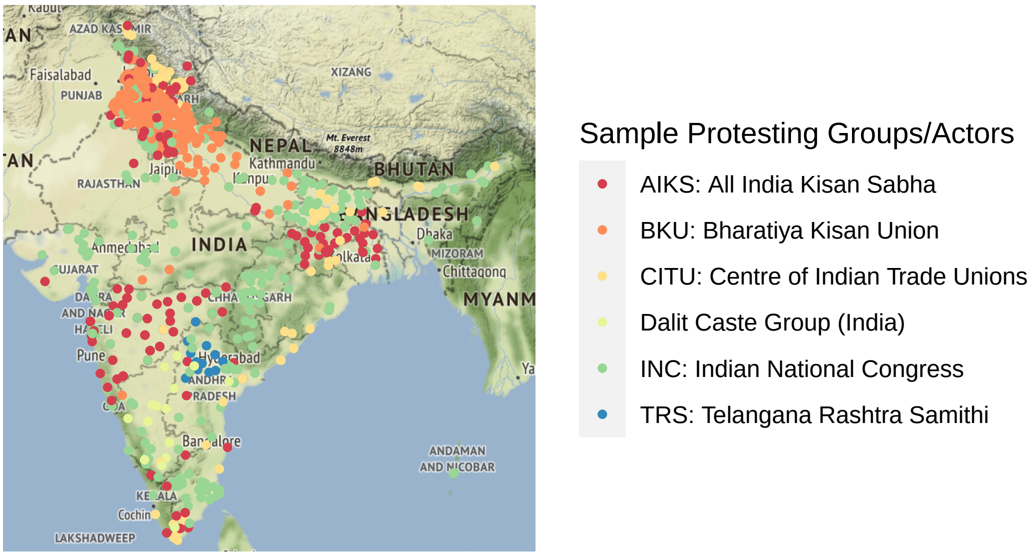

Fig. 1 ACLED Data

This study also uses the PRIO-GRID dataset, which is formed by a standardized spatial grid structure with global coverage [27]. The grid structure of PRIO-GRID allows for the compilation, management, and analysis of data within a time-consistent framework. We consider the PRIO-GRID cells that have a terrestrial cover of the Indian subcontinent. To access data for India, we subsetted the data using the Gleditsch and Ward identifier (GW) number for India, 750. The PRIO-GRID dataset also includes data on both static and time-varying variables where the grid has one realization total or one realization per calendar year respectively. This study uses the most updated version (v2) of the PRIO-GRID dataset. Understanding spatial patterns at the smallest possible scale is important to limit over-generalization. Data from the Indian census was not used for demographic and socioeconomic information largely for two reasons. First, we could not locate any open-source census datasets available at a finer granularity than the state level that could be aligned with a publicly available shapefile of the given areal units. District-level data that was located consisted of outdated population data. Second, India last conducted a census in 2011, and more up-to-date census information has not been made available at the time of this analysis.

The spatial covariates that we include from the PRIO-GRID dataset to explain the spatial distribution of the farmers' protests cover a wide array of socioeconomic and demographic characteristics. We utilize the percentage area of the cell covered by agricultural use (including both cultivated terrestrial areas and managed lands) [28]. Next, we include the average child malnutrition rate in each PRIO-GRID cell [29]. We include the population size with the Gridded Population of the World [30] and the gross cell product (GCP), measured in USD in 2011 [31]. These spatial variables are shown in Figure 2.

3 Methods

We utilize a log Gaussian Cox process (LGCP) to analyze the spatial distribution of the farmers' protests in India from 2020-2021. We define the spatial window (the country of India) as W and define the locations of n protest events as $s_1, ..., s_n$. We model the spatial intensity function, denoted $\lambda(s)$, as a function of a Gaussian process, denoted $\omega(s)$, and spatial covariates, denoted $z(s)$. The intensity function is defined in Equation 1. The spatial variables are sourced from PRIO-GRID, as mentioned in Section 2. The full set of spatial variables, $z(s)$, being considered for this study include information on agricultural use, population, as well as socioeconomic information on gross cell product and child malnutrition. We utilize a Bayesian Markov Chain Monte Carlo (MCMC) framework to estimate parameters associated with the spatial variables (β) as well as a parameter associated with the Gaussian Process (σ). We parameterize the Gaussian process as a multivariate normal distribution with mean 0 and an exponential covariance function, where $\Sigma_{ij} = cov(\omega(s_i), \omega(s_j)) = \sigma^2 exp\left(\frac{-|s_i - s_j|}{\phi}\right)$. Note that we fix the parameter ϕ due to computational difficulty in estimating both σ and ϕ. We fix ϕ as done in [32] such that the 95th percentile of distances has a correlation of 0.05 and the value of the 5th percentile of distances have a correlation of 0.95. We fix ϕ at the average of these two values.

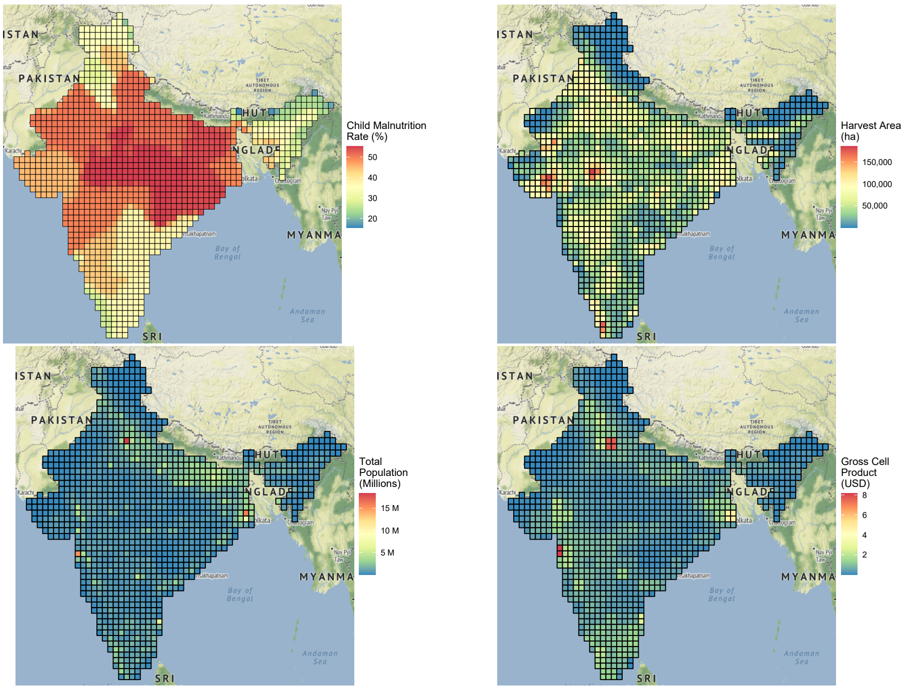

Fig. 2 Figures of spatial covariates from the PRIO-GRID Dataset

$$\lambda(s) = \exp\left(z(s)'\beta + \omega(s)\right) \tag{1}$$

The Markov Chain Monte Carlo approach for this study is implemented in an R package called NIMBLE [33]. We utilize Normal(0,100) priors for the regression coefficients (β) and an Inverse-Gamma(α=2, β=0.5) prior distribution for the σ parameter of the covariance function of the Gaussian process. These are typical, relatively uninformative priors, as used in previous work [32, 34]. We assess convergence using effective sample size and trace plots. In Section 6.3, we discuss other computational details of the log Gaussian Cox process modeling framework including the use of predictive processes to make this analysis computationally feasible, and methods for integrating the intensity function to calculate the likelihood function of this model.

Through this analysis, we intend to explain the factors impacting the spatial distribution of protest events and differentiate these effects by the types of actors involved in those protest events. For example, we analyze the spatial intensity of protest events for protests that involved trade unions as well as protests that involved farmers' unions. We distinguish between regional, central, police, and political organizations involved in the protest events. We characterize, for all actor types, the spatial intensity of these protests and the distribution of the Gaussian process.

In total, we consider 6 models for the spatial intensities, one for each actor type. We show the number of protests for each actor type in Table 1. We note that between these different actor types, the number of protests in each category differs notably, and our results about actor types should be interpreted accordingly. Certain actor types, such as religious groups, represent a particularly small number of protests involving this actor type, and we, therefore, focus on actor types with more affiliated protest events.

Actor Type	Number of Events
Trade Unions	169
Farmers' Unions	2,740
Regional Org	2,006
Central Org	2,356
Political Org	1,162
Police Actors	436
Total events (all actor types)	5,494

Table 1 Number of Events by Actor Type

4 Results

We begin our analysis by describing the socioeconomic characteristics that have an impact on the spatial distribution of protest events, by actor type. First, we report the posterior means as well as 95% credible intervals for β parameters associated with the spatial PRIO-GRID variables in Table 2. We estimate models for events involving six categories of actors: trade unions, farmer unions, regionally located, centrally located, political organizations, and police/security. From Table 2, we see that the 95% credible intervals are consistent across actor types for the effect of the log of the total population on the spatial intensity of farmers' protest events in this time period. We see that where more people are living, there is a greater intensity of protest events. The effect of the childhood malnutrition rate on the intensity of protest events is consistently negative, with the effect being not statistically discernible (the credible overlaps with 0) for the events involving trade unions and political organizations. Aside from protests associated with trade unions and political groups, the overall intensity of the farmers' protests was higher where the child malnutrition rate was lower. Existing work analyzed the relationship between agricultural development and malnutrition [35]. Results from a correlation analysis and simple linear regression model showed that areas with high agricultural performance had lower rates of adult and child malnutrition. It is possible that more farmer unions were protesting with regional organizations close to their farmland.

We find that the harvest area variable is the differentiating factor in our covariate estimates. We note that for three of the actor types, the harvest area has a statistically discernible negative effect on the intensity of protest events (for the events involving trade unions, political organizations, and police actors). In contrast, it has a statistically discernible positive effect on the spatial intensity of events involving farmers' unions and regional organizations. Lastly, no statistically discernible effect of harvest area exists for the events involving centralized organizations. More farmers' unions were expected to protest in areas with more harvest area for the region's main crop. The positive effect of harvest area for regional organizations shows that protests in more agricultural areas, which tend to be more rural, are driven by regional unions such as *khaps/khaaps*(caste/clan-based political leaders), *Bharatiya Kisan* Unions, and regional political organizations. For the two types of organizations where a positive effect is indicated, we note that there is also a negative effect of the gross cell product (GCP, measured in USD); this effect is not statistically discernible for events involving other actor types. The negative effect of gross cell product indicates that areas with more protests with farmer unions and regional support (over central organizations' support) were associated with being more economically disadvantaged across the geographic area. This could potentially be true for two reasons. Firstly, farmers' unions and regional unions had a wider spread and larger presence across the country compared to other groups, giving them access to areas with low economic development. Secondly, villages and regions with lower gross cell product may have limited access to central resources and the ability to travel [7], and hence, rely on regional resources and community-based unions to protest and organize.

	β_0	β_1 (CMR Mean)	β_2 (Log Pop)
Trade Unions	-17.85 (-23.56, -13.25)	0.02 (-0.03, 0.07)	1.48 (1.2, 1.82)
Farm Unions	-13.04 (-16.2, -10.71)	-0.11 (-0.12, -0.09)	1.48 (1.36, 1.58)
Regional Org	-17.9 (-20.74, -14.68)	-0.11 (-0.13, -0.09)	1.68 (1.53, 1.83)
Central Org	-15.33 (-18.68, -11.53)	-0.05 (-0.07, -0.03)	1.51 (1.41, 1.61)
Political Org	-22.75 (-26.15, -19.93)	-0.02 (-0.04, 0.01)	1.79 (1.66, 1.97)
Police	-20.86 (-24.34, -17.25)	-0.06 (-0.1, -0.03)	1.78 (1.56, 2.02)
	β_3 (Harv Area)	β_4 (GCP Mer)	σ (GP Param)
Trade Unions	-1.3×10^{-5} (-2.2×10^{-5}, -5×10^{-6})	-0.1 (-0.42, 0.18)	3.24 (2.33, 4.44)
Farm Unions	1.1×10^{-5} (9×10^{-6}, 1.3×10^{-5})	-0.05 (-0.1, -0.01)	2.96 (2.46, 3.58)
Regional Org	1.4×10^{-5} (1.2×10^{-5}, 1.7×10^{-5})	-0.11 (-0.16, -0.05)	3.25 (2.58, 4.17)
Central Org	-2×10^{-6} (-4×10^{-6}, 1×10^{-6})	-0.01 (-0.06, 0.04)	3.11 (2.56, 3.80)
Political Org	-4×10^{-6} (-7×10^{-6}, -1×10^{-6})	-0.08 (-0.16, 0.01)	3.81 (3.00, 4.85)
Police	-5×10^{-6} (-1×10^{-5}, -1×10^{-6})	0.04 (-0.07, 0.15)	4.06 (3.16, 5.27)

Table 2 Posterior Estimates and 95% Credible Intervals (red/green indicates statistically discernible negative/positive effect, respectively)

Next, we visualize the intensity estimates across these actor types. In Figure 3, we see that the spatial intensity of protest events varies across the country by actor type. For example, the intensity of events involving trade unions tended to be distributed closer to the coast and rather isolated geographically. While a lot of farmers' unions did not mobilize in East India, our results support existing literature that the state of Assam in East India attracted several trade unions to join a two-day strike with the farmers' protests [36]. Historically, traders and farmers in the north and west had been exposed to risks of contract farming and poor contract enforcement [3]. Even though the newly proposed laws could increase exposure to similar contract farming risks, we do not observe trade unions organizing in the general west or central India, barring some regions in Gujarat. The lack of protests seen in that region suggests a potential area for future research. Protests affiliated with farmer unions, centralized organizations, and political organizations tended to be geographically similar. The difference between the spatial distribution of trade unions and farming unions emphasizes the discussion in the existing literature that both groups were protesting for different needs and outcomes. A lot of trade unions protested locally, while farming unions were joined by various regional and central, political, and religious groups (opposing and supporting them). The concentrated police intensity near New Delhi provides insight into the discussion of police presence during the "Delhi Challo" march organized by farmers, unions, and other groups [18]. Lastly, from the spatial intensities, we see that protest events affiliated with regional organizations and police tend to have relatively similar geographic distributions. High intensity of events involving police also seem to have overlapped with regions that have more political organization presence in protests. This analysis of spatial intensities indicates a largely national presence despite geographic clustering across all actor types, which conflicts with the argument that the farmers' protest was a regionally motivated movement [10].

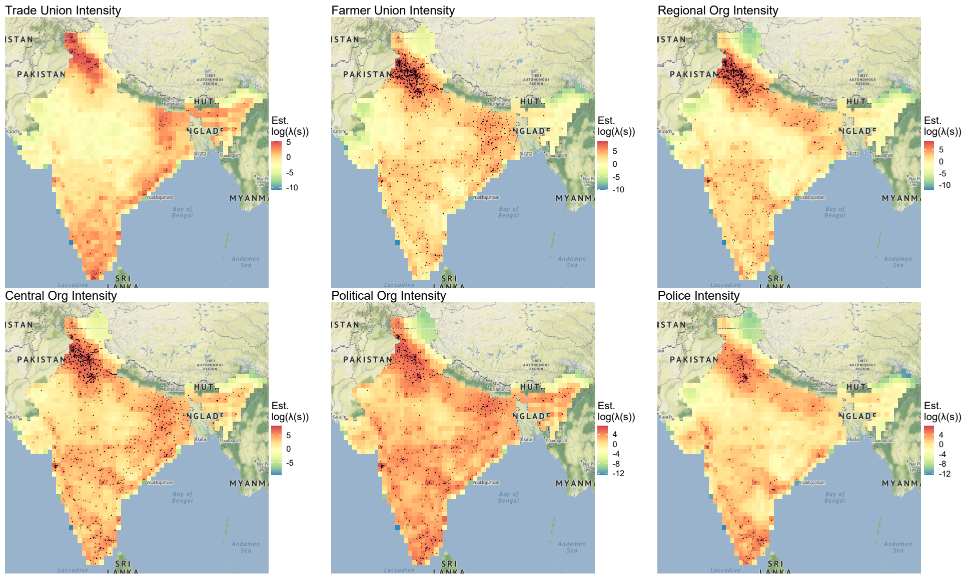

Fig. 3 Intensity Estimates for six actor types

Lastly, in Figure 4 we show the posterior estimates of the Gaussian Process for all six actor types. The plot shows the importance of using a model, such as the LGCP, that includes a spatially varying error term in addition to the spatial variables included in the model. There is considerable variation in the protest events beyond what we can capture using the spatial variables that we have chosen. This implies that there were additional socioeconomic/demographic features and/or spatially constrained drivers of the protests. Although the LGCP is considerably more computationally complex than other spatial models such as the non-homogeneous Poisson process, it helps to capture this variation in factors unexplained thus far.

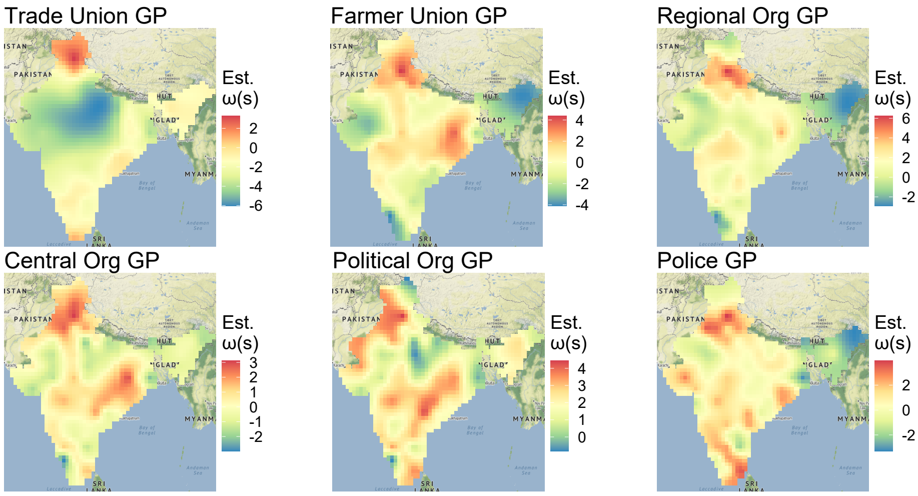

Fig. 4 Gaussian Process Estimates for six actor types

5 Discussion

This spatial analysis of the farmers' protests begins to shed light on the spatial variability of protests and how different actors have been involved in this movement. We see similarities and differences in the role of socioeconomic characteristics over space across different actor types. The distribution of political organizations' involvement was spread across the country, which indicates that throughout the movement, the political presence was not clustered in any one region. Similar conclusions can be made for the organizations that operate nationally. While there was a presence of farmers' unions across the nation, there was a higher intensity of their engagement around Delhi [18]. Regional organizations and trade unions were seemingly sparse in the western and central parts of the country, making them also a lot more concentrated around the parliament. Existing literature comments on the collective movement of protesters towards the parliament, which is in Delhi, and the high intensity of unions there illustrates the coalition of all the farming unions and other actors [11, 37].

Future research should consider the intersectional presence of the different actors across the country over time. Farmers across India have received a lot more support from state governments [3], indicating that in our data, we may see a higher intensity of protests with farmer unions and regional-political organizations over central-political organizations.

In future statistical work, we plan to incorporate bounded actors into the model for spatial intensity. For example, across all actor types, we hope to learn about the spatial factors that may be impacting the intensity of protests, while adjusting for the spatial range differing by actor, or more broadly actor type. This could introduce computational challenges but would allow for an increased understanding of the spatial range of potentially influential actors in protest events. Bounded actors would also be relevant to other areas of research, such as policing data, where actors are typically

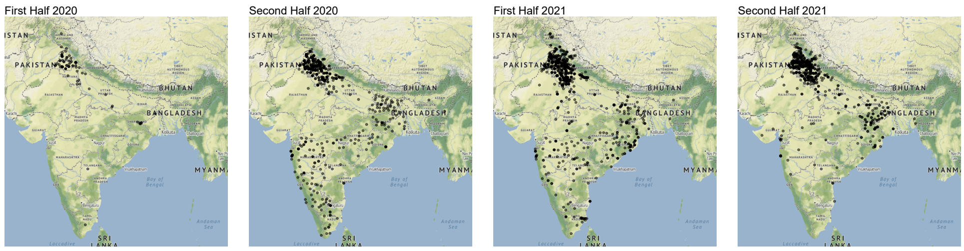

Fig. 5 Temporal variation in protests involving farmers' unions.

constrained to a specific geographic area. As an additional methodological concern, the ACLED dataset also includes some imprecision in the exact location of protest events, as indicated by a published variable on geographic precision [25]. This should also be investigated in future work, as an important caveat of our analysis is that the locations of protest events are treated as exact. In this analysis, we also assume that ACLED has representative data collection for the locations and descriptions of the protests- potential incompleteness of this data may be a concern.

The laws introduced by the Indian government, arguably, affected every region across the country differently. Before these laws were introduced, agricultural trade was governed by the state and protected through the minimal support price (MSP) [6]. Farmers in Maharashtra protested the laws because it became evident in 2020, that private traders held power in regulating *mandis* (although they often buy crops below MSP) [10]. Inviting more prominent corporate buyers than existing private traders would leave the farmers increasingly exposed instead of protecting them. In 2014 (and again in 2020), Madhya Pradesh traders and farmers opposed the amendment allowing Indian Tobacco Company (ITC; a conglomerate company) to set up single license hubs outside regulated market yards [10]. Despite advocating for their local concerns, regional organizations crossed their state boundaries and created a movement with protesters from Uttar Pradesh, Haryana, and Punjab, together moving towards Delhi (the parliament center). Over 12 months, organizations from Kerala, Odisha, Assam, and Telangana either moved towards the state center or implemented complete state shutdowns [17, 24]. It is important to study the composition of organizations traveling across the country to protest and local organizations resisting from within their states. This spatial movement of the protests over time motivates the use of space-time models, beyond the purely spatial models considered in this paper.

In Figure 5, we visualize the spatial and temporal trends of the farmers' unions across the country. The unions began protesting in the second half of 2020 across the country and collectively clustered around Delhi beginning in 2021. The trend continued in 2021, and unions moved from central and southern India to the clusters in the northern half of the country. This temporal variation has direct implications in terms of the statistical methodology required to analyze the full complexity of this data. For example, space-time models could be used to more fully understand how the spatial variation in the protests changed throughout this time. This could include methods such as space-time clustering methods or spatial models of intensity that fluctuate over time. In the future, we hope to extend this modeling framework to capture the changing relationship between actors, the socioeconomic characteristics of neighborhoods, and the protests over time.

6 Appendix

6.1 Data Availability

The data for this study is publicly available through the ACLED (https://acleddata.com/data-export-tool/) and PRIO-GRID (https://grid.prio.org/) websites. The code and subsetted data for this analysis are posted in a Github repository: url placed after double-blind peer review.

6.2 Actor Classification

In our analysis of the farmers' protests, actors were categorized by the authors as types based on information about their backgrounds and activities. Full information on the coding of these actors can be found in supplementary information in our actor codebook. This codebook is posted online here: url placed after double-blind peer review, included as supporting document. The coding of actor types is subjective to the authors' research of the individual actors, we encourage further review of these classifications in future research in this area.

6.3 LGCP Computational Details

The work detailed in this paper involves a number of computational tools to make the use of a point process model computationally feasible. The likelihood function for a log Gaussian Cox process model (LGCP) is included below in Equation 2, where the intensity function $\lambda(s)$ is defined as $\lambda(s) = \exp\left(z(s)'\beta + \omega(s)\right)$. The Gaussian process becomes computationally intensive when estimating it over the original scale of the data (thousands of events). Therefore, we employ the predictive process approach [38] where the Gaussian process is estimated over a smaller dimension, as shown in Equation 3. Specifically, we estimate the Gaussian process over "knots" placed over the region ($\omega^*(s)$) and use a predictive process transformation to calculate the estimate of the Gaussian process at the data points ($\tilde{\omega}(s)$). In order to estimate the integral, $\int_W \lambda(s)ds$, we spread "integration points" across the country of India. Given that our integral involves a function with PRIO-GRID spatial variables (defined over a grid) and a Gaussian process initially estimated over knots, these integration points are spread out evenly across the country. The choice of both integration points and knots are shown in Figure 6.

$$\mathcal{L}(\boldsymbol{\theta}; \{s_{1:n}\}, s_i \in W) \propto \exp\left(-\int_W \lambda(s)ds\right) \times \prod_{i=1}^{n} \lambda(s_i) \tag{2}$$

. We also use predictive processes. [38]

$$\tilde{\omega}(s) = \text{cov}(\omega(s), \omega^*(s))\text{var}^{-1}\left(\omega^*(s)\right)\omega^*(s) \tag{3}$$

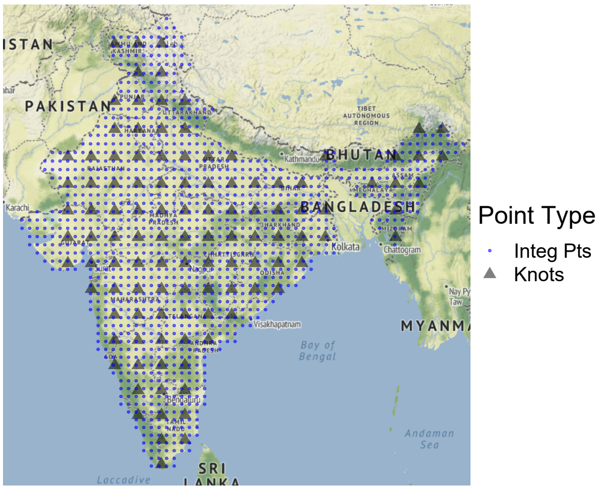

Fig. 6 Integration points and predictive process knots

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