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Spatial heterogeneity in unintended pregnancy and its determinants in India

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Abstract

Background Understanding the geographic variation of unintended pregnancy is crucial for informing tailored policies and programs to improve maternal and child health outcomes. Although spatial analyses of unintended pregnancy have been conducted in several developing countries, such research is lacking in India. This study addresses this gap by investigating the geographic distribution and determinants of unintended pregnancy in India.

Methods We analysed data from the National Family Health Survey-5 encompassing 232,920 pregnancies occurring between 2014 and 2021 in India. We conducted a spatial analysis to investigate the distribution of unintended pregnancies at both state and district levels using choropleth maps. To assess spatial autocorrelation, Global Moran's I statistic was employed. Cluster and outlier analysis techniques were then utilized to identify significant clusters of unintended pregnancies across India. Furthermore, we employed Spatial Lag Model (SLM) and Spatial Error Model (SEM) to investigate the factors influencing the occurrence of unintended pregnancies within districts.

Results The national rate of unintended pregnancy in India is approximately 9.1%, but this rate varies significantly between different states and districts of India. The rate exceeded 10% in the states situated in the northern plain such as Haryana, Delhi, Uttar Pradesh, Bihar, and West Bengal, as well as in the Himalayan states of Himachal Pradesh, Uttarakhand, Sikkim, and Arunachal Pradesh. Moreover, within these states, numerous districts reported rates exceeding 15%. The results of Global Moran's I indicated a statistically significant geographical clustering of unintended pregnancy rates at the district level, with a coefficient of 0.47 ($p < 0.01$). Cluster and outlier analysis further identified three major high-high clusters, predominantly located in the districts of Arunachal Pradesh, northern West Bengal, Bihar, western Uttar Pradesh, Haryana, Delhi, alongside a few smaller clusters in Odisha, Madhya Pradesh, Uttarakhand, and Himachal Pradesh. This geographic clustering of unintended pregnancy may be attributed to factors such as unmet needs for family planning, preferences for smaller family sizes, or the desire for male children.

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Results from the SEM underscored that parity and use of modern contraceptive were statistically significant predictors of unintended pregnancy at the district level.

Conclusion Our analysis of comprehensive, nationally representative data from NFHS-5 in India reveals significant geographical disparities in unintended pregnancies, evident at both state and district levels. These findings underscore the critical importance of targeted policy interventions, particularly in geographical hotspots, to effectively reduce unintended pregnancy rates and can contribute significantly to improving reproductive health outcomes across the country.

Keywords Unintended pregnancy, Unplanned pregnancy, Unwanted pregnancy, Spatial analysis, Spatial autocorrelation, Spatial dependency, NFHS, Moran's I, Spatial clustering, India

Introduction

Unintended pregnancy is defined as either the mistimed (wanted later) pregnancy or the unwanted (no more desired) pregnancy [1]. A staggering 121 million unintended pregnancies occur worldwide annually [2]. Unintended pregnancies significantly impact women's health. Evidence suggests that such women often experience less weight gain, infrequent antenatal and delivery care, and higher prevalence of adverse health behaviours such as alcohol, drug use, and cigarette smoking. Six out of ten unintended pregnancies result in induced abortion, and limited access to safe abortion services leads many women to unsafe procedures, contributing to approximately 13% of all maternal deaths globally [3]. For foetuses and newborns, unintended pregnancies result in delayed prenatal care, which compromises foetal monitoring and complication detection. Maternal behaviours such as smoking or inadequate prenatal vitamin intake heighten risks of low birth weight, prematurity, and developmental issues. These pregnancies often lead to adverse birth outcomes like neonatal mortality and hinder postpartum care access, affecting breastfeeding initiation and maternal-infant bonding. Maternal stress from unintended pregnancies further impacts newborns, potentially leading to long-term health implications like neurodevelopmental challenges [3–6]. This intricate web of consequences transforms unintended pregnancies into a formidable global public health challenge, extending its repercussions from individual health to affecting broader societal and economic dimensions.

Governments and global organizations have recognized that all women, regardless of where they live, have the fundamental right to make informed decisions about having children and determining the timing of such decisions. To this end, efforts have been undertaken worldwide to decrease the occurrence of unintended pregnancies. As a result of these efforts, unintended pregnancy rates have shown a significant decline since 1990 [7]. The global rate has decreased from 79 to 64 per 1,000 women of reproductive age 15–49 years between 1990 and the present. Despite this progress, approximately half of all pregnancies globally are still unintended, revealing significant disparities in unintended pregnancy rates between regions and within countries. For instance, the unintended pregnancy rate per 1,000 women aged 15–49 is 34 in high-income countries, 66 in middle-income countries, and 93 in low-income countries. This disparity underscores the challenges faced by women in lower-income settings, where they are nearly three times as likely to experience unintended pregnancies as those in wealthier nations. In India, a lower-middle income country, the rate stood at 72 unintended pregnancies per 1,000 women aged 15–49 in 2019-21, equating to close to 50 million unintended pregnancies in absolute numbers [6, 8, 9].

While data on unintended pregnancy at the subnational scale remains limited in many developing nations, some researchers have made efforts to examine subnational spatial variation in unintended pregnancy. For example, Johnson et al. (2009) noted a higher incidence of unintended pregnancies in specific rural areas as compared to urban areas [10]. A different investigation conducted by Johnson et al. (2010) in Ghana analysing data from the 1998 and 2003 Ghana Demographic and Health Surveys found significant variations in unintended pregnancy rates both across and within ecological zones [11]. Kebede et al. (2021) studied geographical disparities in unintended pregnancy among young women aged 15–24 in Ethiopia and observed a significant clustering in unintended pregnancy. They identified 72 primary clusters in Ethiopia [12]. A different investigation in Ethiopia by Belay et al. (2022), utilizing data from the Ethiopia Demographic and Health Surveys spanning from 2000 to 2016, revealed a higher concentration of unintended pregnancies in the capital, Addis Ababa. Furthermore, these pregnancies were found to be disproportionately concentrated among socioeconomically disadvantaged groups [13]. Another study conducted by Zeru et al. (2023) to analyse the spatial distribution of unintended pregnancies in Ethiopia revealed variations both among regional and zonal states in the country [14]. In India, although there is an overall decline in unintended pregnancy rate, a national survey of six states conducted in 2015 showed that the unintended pregnancy rates varied considerably across the states [15]. This suggests that the national rate masks the subnational variation in the unintended pregnancy rate.

Several previous studies at various levels, including local, regional, national, and global, have explored the disparities in the rates of unintended pregnancy and the factors influencing it [5, 13, 16–21]. These studies have identified a number of sociodemographic, economic, cultural, and geographical variables linked to unintended pregnancy. Factors associated with unintended pregnancy include exposure to family planning information and services, the age of the couple, educational attainment, household wealth, religion, caste, women's autonomy, place of residence (urban or rural), birth interval, sex composition of previous children, ideal number of children, occupation, sex of the household head, and size of the household [5, 17, 19, 22–24].

Understanding geographical discrepancies and clusters of unintended pregnancies is vital for developing effective policies and programs. National and state-level data provide broad perspectives, but district-level data offer critical granularity for targeted interventions and efficient resource allocation. This approach helps policymakers identify vulnerable districts, optimize financial and logistical resources, and tailor interventions to local demographic and socioeconomic conditions. By using district-level data to inform policy formulation and implementation, governments can achieve more impactful and sustainable outcomes in addressing unintended pregnancies and improving health and socioeconomic indicators [11]. However, none of the previous studies in India has attempted to examine spatial distribution of unintended pregnancies at the subnational level, especially at the district level in India. The present study aims to identify the clustering of unintended pregnancy at the district level in India and investigate the associated factors shaping such a disparity at the district level.

Data and methods

Source of data

Unintended pregnancy data in India is primarily sourced from national surveys such as the National Family Health Survey (NFHS), the India Human Development Survey (IHDS), and specialized studies like the Unintended Pregnancy and Abortion in India (UPAI). Among these, NFHS is uniquely designed to offer district-level estimates of unintended pregnancy. UPAI, on the other hand, was carried out in only six states, while IHDS, though conducted nationwide, lacks the design to provide district-level estimates. Thus, for this study, the data is derived from the latest round of the National Family Health Survey (NFHS-5) conducted between 2019 and 2021.

This large-scale survey provides a rich dataset with sufficient sample size at the district level. Moreover, NFHS-5 offers comprehensive information on a wide range of topics crucial to understanding reproductive health and related issues. These include reproduction, menstrual hygiene, family planning, maternal health, marriage and sexual activity, fertility preferences, women's empowerment, domestic violence, and various other health indicators [25]. It uses a two-stage stratified sampling to collect data. Further details about sampling techniques and procedures used by NFHS are specified elsewhere [1]. In this research, we utilized the births recode file of the NFHS-5. In this round of NFHS, 724,115 women aged 15–49 were interviewed. Among them, only 176,877 reported having given birth at least once in the five years prior to the survey, resulting in a total of 232,920 reported pregnancies. These pregnancies formed the basis of analysis for this paper. After removing inconsistent and missing observations, the final sample used in the study comprised 219,173 pregnancies.

Statistical analysis

First, we present the sample distribution of unintended pregnancies based on their biodemographic and socioeconomic background characteristics. Subsequently, we present the estimates of unintended pregnancy rate by selected maternal and household background characteristics. While the NFHS employs a robust multistage, stratified sampling design to ensure representativeness at both national and sub-national levels, it is imperative to acknowledge that variations in sample sizes across states and districts may influence the precision and reliability of our estimates, particularly in regions with smaller populations or higher heterogeneity. Therefore, we have provided detailed information on sample sizes for each district and incorporated confidence intervals for all district-level estimates of unintended pregnancy (see Appendix, Table A1).

In our study, we first visualized the geographical distribution of unintended pregnancy rates at state and district level through choropleth maps. Then, to explore spatial patterns at the district level, we calculated Global Moran's I to assess overall clustering. For a deeper analysis of localized clusters and outliers, we employed Anselin Local Moran's I. Finally, our investigation extended to regression modelling to uncover potential explanatory factors.

Global Moran's I serve as a prominent tool for evaluating spatial autocorrelation, examining the clustering of a phenomenon across geographical regions. Ranging from -1 to $+1$, Moran's I value depict spatial patterns, with 0 indicating randomness. Positive values signify clustering and spatial autocorrelation, while negative values suggest dispersion. Moran's I considers both feature locations and attribute values (of a single attribute) in its assessment, providing insights into the spatial distribution of the phenomenon [25]. The formula for computing Moran's I is as follows:

$$Global\ Moran's\ I = \frac{n}{\sum_i^n \sum_j^n W_{ij}} \frac{\sum_i^n \sum_j^n w_{ij}\left(x_i - \bar{x}\right)\left(x_j - \bar{x}\right)}{\sum_i^n \left(x_i - \bar{x}\right)^2}$$

Where, n is the number of the spatial features; x_i is the attribute value of feature i; x_j is the attribute value of feature j; $\bar{x}$ is the mean of this attribute; $W_{i,j}$ is the spatial weight between feature i and j, $\sum_i^n \sum_j^n w_{ij}$ is the aggregation of all spatial weights. The tool calculates the mean $\bar{x}$, deviation from mean ($x_i - \bar{x}$) and the data variance $\frac{\sum_{i=1}^n \left(x_i - \bar{x}\right)}{n}$. To construct cross-products, deviations from all neighbouring features are multiplied. The spatial weight is then multiplied by the covariance term. The index value is normalised using all other factors. For instance, normalisation for the number of adjacencies is achieved by aggregating the spatial weights. Using the same methods, the variance is employed to guarantee that a big variety in x values will not result in a huge value index [25].

Global Moran's I examine the existence of clustering but does not specify the exact location of the cluster. To identify the location of various types of clusters, we used Anselin Local Moran's I statistics [18], also known as Cluster and Outlier Analysis. For *n* spatial objects in a neighbourhood, the local Moran's I is calculated as [25]:

Local Moran's $I_i = \frac{x_i - \bar{X}}{m_2} \sum_j w_{ij}\left(x_j - \bar{X}\right)$

$$m_2 = \frac{\sum_i \left(x_j - \bar{X}\right)^2}{n}$$

In the equation given above, N represents the total number of observations or spatial objects. The attribute value of feature I is denoted by x_i, while x_j represents the attribute value of feature j. $\bar{X}$ denotes the mean of this attribute across all spatial objects. W_{ij} signifies the spatial weight between feature *i* and *j*, and m_2 is a constant for all locations. It is worth noting that m_2 is a consistent but not unbiased estimate of the variance. In preparing spatial weights, we utilized polygon contiguity edges and corners [25].

The Local Moran's I identify various types of clusters and outliers, which are as follows [25]:

1. High-High clusters: These are areas with high values surrounded by other areas with similarly high values, often referred to as hot spots.
2. Low-Low clusters: These are areas with low values surrounded by other areas with similarly low values, commonly known as cold spots.
3. High-Low outliers: These are areas with high values surrounded by neighbouring areas with low values.
4. Low-High outliers: These are areas with low values surrounded by neighbouring areas with high values.

To explain the variation in the unintended pregnancy rate at the district-level, we initially employed Ordinary Least Squares (OLS) regression. However, our data included spatial information, specifically the percentage of unintended pregnancies across different districts in India. Spatial data often shows spatial dependency, meaning that values in one location are influenced by neighbouring locations. This violates the assumption of independence among sample observations in OLS regression. Ignoring spatial dependency can lead to biased estimates and inaccurate results. So, we shifted to spatial regression models, which are designed to handle spatial data. These models consider spatial autocorrelation, capturing how observations in different locations are related to each other.

Specifically, we utilized spatial lag and spatial error models in our analysis. These models allow us to account for the influence of neighbouring observations on each other, thereby providing more accurate estimates of the relationships between variables. By employing spatial regression models, we aimed to ensure that our analysis accurately captured the spatial dynamics of unintended pregnancy and yielded robust findings that could inform policy and intervention strategies at the district level. While we shall not delve into the details of Spatial Lag Model (SLM) and Spatial Error Model (SEM) here due to space constraints, further information on these models can be found elsewhere [25]. To determine the most suitable model among the three, OLS, SLM, and SEM, we evaluated which model yielded the lowest Akaike Information Criterion (AIC) and Schwarz Criterion (SC) values, as well as the highest log-likelihood value [25].

As for the variable selection for regression model, we considered a number of variables representing district-level development and health-related indicators. Our choice of the independent or explanatory variables was theoretically informed and based on the previous literature available on unintended pregnancy. These variables are described under subheading 'Independent Variables' later in this section. Before including a variable, we ran an unadjusted regression to test one-to-one relationship between unintended pregnancy rate and the explanatory variable. We tested the statistical significance of each independent variable at a 5% significance level. Variables demonstrating statistical significance in these analyses were then considered for inclusion in the final multiple regression model.

In our analysis, we also conducted an assessment to determine if multicollinearity posed a problem using variance inflation factors (VIF). The mean VIF calculated was 1.19, significantly below the commonly accepted threshold of 4 [26]. Additionally, when examining the individual VIFs for each variable, none exceeded the limit of 2.4 [27, 28]. These results indicate that multicollinearity was not a significant issue in our model. In this study, we used GeoDa [29], Stata 16 [30] and ArcGIS 10.8 [31] were used to analyse the data.

Dependent variable

The dependent variable for this study is unintended pregnancy. Unintended pregnancy is defined as unwanted or mistimed pregnancy. The variable is based on the NFHS-5 question, "When you got pregnant with (NAME), did you want to get pregnant at that time?". The response options included (a) Yes and (b) No. Based on these responses, we created a binary outcome variable, intended and unintended pregnancy. If the respondent replied yes, then it was defined as intended pregnancy (coded as 0), and if no, then it was defined as unintended pregnancy (coded as 1) [25].

Independent variables

The review of previous literature on unintended pregnancy suggests it is affected by a number of demographic, socio-economic, geographic and family planning variables (see Fig. 1) [3, 5, 11, 17].

For the regression analysis in this research work, we considered a number of variables representing district-level development and health-related indicators including percentage of SC/ST women in the district, percentage of Hindu women in the district, percentage of women not exposed to family planning messages through mass media in the district, percentage of women belonging to poor households in a district, percentage of women living in rural areas in a district, percentage of women not using any contraceptive or using a traditional contraceptive, percentage of young women (15–24 years) in a district, percentage of women with no schooling in a district, mean household size in a district, mean number of total children ever born to a woman in a district (parity), and mean age at first marriage in the district.

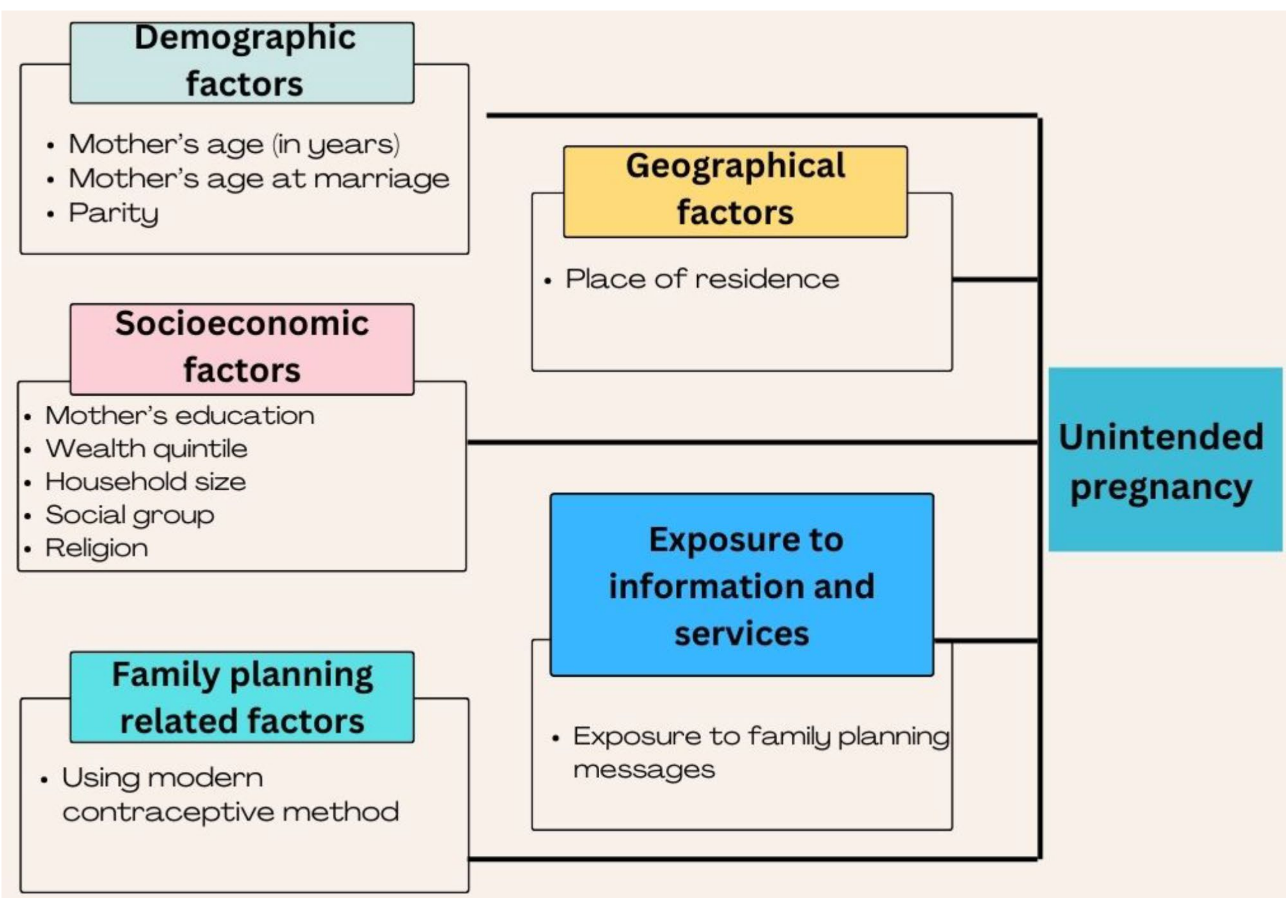

Fig. 1 Conceptual framework showing factors affecting unintended pregnancy

We also considered adding women's autonomy as a predictor variable, but we could not add it to the study due to its small number of observations. The predictor variables used in the study, their definition and categories are listed in Table 1.

Results

Sample characteristics

Table 2 presents an overview of the sample characteristics. Approximately 70% of the pregnancies were concentrated among women within the age bracket of 20–29 years. Around half of the pregnancies occurred among women with a secondary level of education, while just under a quarter were among those in the poorest wealth quintile. Approximately 46% and 25% of pregnancies were found among women belonging to the OBC and SC social groups, respectively. The majority, around 80%, of pregnancies were observed among Hindu women. Nearly three-quarters of pregnancies were among women residing in rural areas. More than half of the pregnancies happened among women who were not using any contraceptive method. Over 70% of pregnancies were among women exposed to family planning messages through mass media. 40% and 35% of pregnancies occurred among women with two and three or more children, respectively. Three-quarters of pregnancies were within households with 4 to 8 members.

Unintended pregnancy by background characteristics

In NFHS-5, among the total of 219,173 recorded pregnancies nationwide, approximately 9.1% were classified as "unintended". Table 3 presents the rate of unintended pregnancy by selected maternal and household background characteristics. The occurrence of unintended pregnancies rises with the mother's age, reaching a 15% rate for mothers aged above 40. Unintended pregnancies were more common among mothers who never attended school (11%), decreasing as the mother's education level rises. The proportion of unintended pregnancies was higher among the poorest households (11.1%) and lower among the wealthiest households (7%). The percentage of unintended pregnancies was higher among mothers from SC social groups (10%) and the Muslim religion (9.5%). Rates of unintended pregnancies were higher among mothers residing in rural areas (9.3%). Mothers using modern contraceptive methods had a higher rate of unintended pregnancies (9.4%). The prevalence of unintended pregnancies was higher among mothers not exposed to mass media family planning messages (10.5%) compared to those who were exposed (8.5%). Unintended pregnancies were more prevalent among mothers with three or more children (14%) compared to those with only one child (3.8%). The occurrence of unintended pregnancies was higher among households with more than eight members (10.4%).

Spatial pattern of unintended pregnancies across states and 707 districts of India

The map displayed in Fig. 2a illustrates the variation in unintended pregnancy rates across different states of India. States with higher rates (above 10%) include Bihar, Uttar Pradesh, Sikkim, Uttarakhand, Himachal Pradesh, Arunachal Pradesh, West Bengal, Haryana, and the union territory of Delhi. In contrast, states with lower rates (below 5%) include Nagaland, Mizoram, Gujarat, Jammu and Kashmir, Leh and Ladakh, Andhra Pradesh, Chhattisgarh, Tamil Nadu, and Karnataka. Although state-level analysis provides a general understanding of spatial distribution in unintended pregnancies, it obscures the nuances present at the district level. To capture the full extent of spatial heterogeneity, we mapped unintended pregnancies across India's districts (Fig. 2b). This approach enables a more detailed examination, uncovering localized patterns and disparities that might be missed in broader state-level analyses (See Appendix, Table A2).

The prevalence of unintended pregnancies soared to over 15% in 82 districts across various states. Bihar reported the highest number with 30 such districts, including Katihar, Patna, Jamui, Buxar, Samastipur, Purba Champaran, Gaya, Arwal, Nawada, Muzaffarpur, Bhagalpur, Banka, Kishanganj, Purnia, Araria, Begusarai, Vaishali, Munger, Saran, and Lakhisarai. Uttar Pradesh followed with 14 districts, encompassing Gonda, Shahjahanpur, Allahabad, Barabanki, Bahraich, Mahamaya Nagar, Rampur, Unnao, Agra, Etah, Firozabad, Etawah, Mahoba, and Kansiram Nagar.

In Madhya Pradesh, eight districts, namely Bhind, Vidisha, Sehore, Hoshangabad, Raisen, Satna, Chhatarpur, and Sagar recorded unintended pregnancy rate of over 15%. Delhi and Arunachal Pradesh each had six such districts. In Delhi, they were South East, New Delhi, North West, Central, West, and North, while in Arunachal Pradesh, they included Upper Subansiri, Lower Subansiri, East Kameng, Upper Siang, West Kameng, and Papum Pare.

Additionally, numerous districts in various states recorded unintended pregnancy rates exceeding 15%. In Haryana, these districts included Panipat, Ambala, Palwal, and Jind. Himachal Pradesh witnessed such rates in Bilaspur, Hamirpur, and Kangra, while Uttarakhand's districts were Bageshwar, Garhwal, and Hardwar. Jharkhand had Dhanbad and Hazaribagh on the list, while Meghalaya reported Ribhoi and East Khasi Hills. West Bengal's districts with such high rates were Uttar Dinajpur, Maldah, and Birbhum, and Orissa reported Jagatsinghapur, Dhenkanal, and Jajpur. Chhattisgarh's district with over

Table 1 Operational definition of variables used in the study

Variables	Description
Social group	There are four official social groups, i.e., 'Scheduled Caste (SC)' (coded as 1), 'Scheduled Tribe (ST)' (coded as 2), 'Other Backward Classes (OBC)' (coded as 3) and 'Others' (coded as 0). These groups are recoded into binary categories: 'SC/ST' (1) and 'non-SC/ST' (0) (including OBC and others).
Religion	Religion has two categories- 'Hindu' (1) and 'non-Hindu (0)' (includes Muslim, Christian, Sikh, Buddhist/Neo-Buddhist, Jain, Jewish, Parsi/Zoroastrian, no religion, and others)
Exposure to family planning (FP) messages through mass media	Respondents were asked whether they had heard FP message on radio, seen anything about FP on the TV or read about FP in a newspaper or magazine. Based on their responses, we derived a dichotomous variable. Women were classified as having exposure to FP messages if they reported hearing, seeing, or reading about FP from any of these sources (coded as Yes (1)). Conversely, women were categorized as having no exposure to FP messages if they indicated no exposure across all three media platforms (coded as No (0)).
Wealth index	The wealth index is a composite measure of household amenities and assets, generated through principal component analysis. This index assigns scores to households based on the household amenities and assets they possess, thereby quantifying their relative wealth status. To create a national wealth index, household scores are attributed to each usual (de jure) household member. These scores are then used to rank individuals within the household population. Subsequently, the distribution of these scores is divided into five equal categories, each representing 20% of the population. These categories are commonly labelled as 'poorest', 'poorer', 'middle', 'richer', and 'richest', providing a systematic classification of individuals based on their relative wealth within the population. Further, we recoded these household wealth categories into two categories: poor (included poorest and poorer quintiles) (coded as 1) and non-poor (had middle, richer and richest quintiles) (coded as 0).
Place of residence	Whether the respondents live in a rural (coded 1) or an urban area (coded 0).
Using modern contraceptive method	Respondents were asked about their current contraceptive method. Based on responses, we have formed a dichotomous variable. Respondents were considered using 'no and traditional method' (1) if they were either using no method of contraception or a traditional method of contraception, and 'modern' (0) if they responded using the modern method of contraception. Traditional methods of contraception include periodic abstinence, withdrawal, and other traditional methods whereas the modern method include male and female sterilization, injectables, intrauterine devices (IUDs/ PPIUDs), contraceptive pills, implants, female and male condoms, diaphragm, foam/jelly, the standard days method, the lactational amenorrhoea method, and emergency contraception (25).
Mother's age	Respondents were asked about their current age. The age variable was recoded into a binary variable for the regression analysis. Those falling in age group '15–24' were coded 1 and those in '25–49' were coded as 0. For bivariate analysis, we have recoded the variables into 5-year age groups.
Mother's education level	The variable "education level" reflects the highest educational attainment of a respondent. It is categorized into two groups: "no education (1)" and "educated (0)." The category "educated" encompasses individuals who have attained education at the primary, secondary, or higher levels.
Household size	It is the total number of members residing in the household.
Parity	It is the total number of children ever born to a woman.
Mother's age at marriage	Respondents were asked about their age in years during their first marriage.

Table 2 Percentage distribution of pregnancies by selected background characteristics, NFHS-5 (2019–2021), India

Background characteristics	*n*	Weighted %
Mother's age (in years)		
15–19	4,852	2.5
20–24	62,636	30.2
25–29	87,613	40.5
30–34	42,864	18.6
35–39	16,321	6.5
40–44	3,834	1.4
45–49	1,053	0.3
Mother's education level		
No education	48,082	21.5
Primary	27,970	12.1
Secondary	1,12,472	50.4
Higher	30,649	16.0
Wealth quintile		
Poorest	58,795	24.1
Poorer	51,056	21.6
Middle	42,746	19.7
Richer	37,113	18.6
Richest	29,463	16.0
Social group		
Scheduled Caste	47,579	24.6
Schedule Tribe	46,408	10.5
Other Backward Classes	88,695	46.0
Others	36,491	18.9
Religion		
Hindu	1,65,993	81.8
Muslim	26,061	13.9
Others	27,119	4.4
Place of residence		
Urban	44,206	26.5
Rural	1,74,967	73.5
Using modern contraceptive method		
Yes	96,093	45.5
No	1,23,080	54.5
Exposure to FP messages		
Yes	1,55,539	71.8
No	63,634	28.2
Mother's age at marriage		
>=18 years	1,60,618	71.3
< 18 years	58,555	28.7
Parity		
One child	55,775	25.8
Two children	83,847	39.4
Three or more children	79,551	34.8
Household size		
1–3 members	17,707	7.9
4–8 members	1,66,387	75.2
More than 8 members	35,079	17.0
India	219,173	100

Note: n = Total number of observations; FP: Family Planning

15% unintended pregnancy rate was Bilaspur, Maharashtra's was Nashik, and Rajasthan's included Alwar and Bharatpur. Sikkim's East District was also among those having an unintended pregnancy rate of 15% or higher. Eight of the 14 districts of Kerala reported unintended pregnancy rates above 10%. The districts of Thrissur, Thiruvananthapuram, Kottayam, and Pathanamthitta reported a rate of greater than 15%.

Spatial autocorrelation in unintended pregnancy: results of Global Moran's I

A simple district-level choropleth map of unintended pregnancy rate does not reveal whether unintended pregnancies are clustered, dispersed or randomly distributed across the Indian districts. Therefore, we utilized Global Moran's I and assessed spatial autocorrelation in unintended pregnancy rate across the districts of India. The index yielded a value of 0.47, with a z-score of 20.06 and a p-value of <0.001 (Fig. 3), indicating the presence of statistically significant spatial autocorrelation in the data. Consequently, further investigation into spatial clustering of unintended pregnancies at the district level was warranted. To identify the specific locations of the clusters of high and low unintended pregnancy rate across Indian districts, we carried out a Cluster and Outlier Analysis.

Identifying clusters of unintended pregnancy: results of cluster and outlier analysis (Local Moran's I)

Figure 4 displays a cluster and outlier map of unintended pregnancy, revealing three large and four small High-High clusters, or hot spots. The first major High-High cluster spans districts in Bihar, Sikkim, and northern West Bengal. This cluster included 29 districts of Bihar (Kishanganj, Purnia, Katihar, Araria, Bhagalpur, Banka, Jamui, Supaul, Khagaria, Sitamarhi, Bhojpur, Buxar, Rohtas, Patna, Arwal, Jehanabad, Aurangabad, Gaya, Nawada, Nalanda, Muzaffarpur, Vaishali, Darbhanga, Samastipur, Madhubani, Begusarai, Munger, Sheikpura, and Lakhisarai), 4 districts of northern West Bengal (Malda, Dakshin Dinajpur, Uttar Dinajpur, and Darjeeling), and 1 district of Jharkhand.

The second significant cluster is situated in Delhi, western Uttar Pradesh, northeastern Rajasthan, Haryana, and select southern districts of Punjab. It included 10 districts of Delhi (North, North West, Central, East, West, South, South East, South West, New Delhi, and Shahdara), 14 districts of western Uttar Pradesh (Bhaghpat, Mathura, Hathras, Aligarh, Agra, Firozabad, Mainpuri, Farrukhabad, Etah, Kasganj, Saharanpur, Ghaziabad, Gautam Buddha Nagar, and Badaun), 3 districts of northeastern Rajasthan (Bharatpur, Dholpur, and Dausa), 13 districts of Haryana (Panipat, Rewari, Rohtak, Sonipat, Karnal, Kaithal, Jind, Hisar, Rohtak, Jhajjar, Gurgaon,

Table 3 Unintended pregnancy rate (percent) by selected maternal and household background characteristics, NFHS-5 (2019-21), India

Background characteristics	Number of pregnancies	Unintended Pregnancy rate [95% CI]	Chi square statistic	*p*-value
Mother's age (in years)				
15–19	4,852	8.5 [07.3, 09.8]	321.13	< 0.001
20–24	62,636	8.9 [08.5, 09.4]		
25–29	87,613	8.5 [08.2, 08.9]		
30–34	42,864	9.1 [08.6, 09.6]		
35–39	16,321	11.6 [10.7, 12.5]		
40–44	3,834	15.2 [13.3, 17.3]		
45–49	1,053	15.4 [12.2, 19.3]		
Mother's education level				
No education	48,082	10.8 [10.3, 11.4]	388.77	< 0.001
Primary	27,970	9.9 [09.2, 10.6]		
Secondary	1,12,472	8.8 [08.5, 09.1]		
Higher	30,649	7.0 [06.5, 07.5]		
Wealth quintile				
Poorest	58,795	11.1 [10.6, 11.7]	601.92	< 0.001
Poorer	51,056	9.9 [09.4, 10.4]		
Middle	42,746	8.5 [08.0, 09.0]		
Richer	37,113	7.9 [07.4, 08.5]		
Richest	29,463	6.9 [06.4, 07.4]		
Social group				
Scheduled Caste	47,579	10.1 [09.6, 10.6]	207.60	< 0.001
Schedule Tribe	46,408	7.2 [06.6, 07.7]		
Other Backward Classes	88,695	8.7 [08.3, 09.1]		
Others	36,491	9.7 [09.2, 10.4]		
Religion				
Hindu	1,65,993	9.1 [08.8, 09.4]	35.50	0.010
Muslim	26,061	9.5 [08.8, 10.3]		
Others	27,119	7.5 [06.7, 08.4]		
Place of residence				
Urban	44,206	8.4 [07.8, 08.9]	47.82	0.003
Rural	1,74,967	9.3 [09.0, 09.6]		
Using modern contraceptive method				
Yes	96,093	9.4 [09.0, 09.8]	23.65	0.007
No	1,23,080	8.8 [08.5, 09.1]		
Exposure to FP messages				
Yes	1,55,539	8.5 [08.2, 08.8]	200.52	< 0.001
No	63,634	10.5 [10.0, 10.9]		
Mother's age at marriage			534.64	< 0.001
< 18 years	58,555	11.3 [10.8, 11.8]		
>=18 years	1,60,618	8.2 [07.9, 08.4]		
Parity			4169.28	< 0.001
One child	55,775	3.8 [03.6, 04.1]		
Two children	83,847	8.2 [07.8, 08.5]		
Three or more children	79,551	14.0 [13.5, 14.5]		
Household size			541.74	< 0.001
1–3 members	17,707	4.4 [03.9, 04.9]		
4–8 members	1,66,387	9.3 [09.0, 09.6]		
More than 8 members	35,079	10.4 [09.8, 11.0]		
India	219,173	9.1 [08.8, 09.3]		

Note: CI: Confidence interval, FP: Family planning,

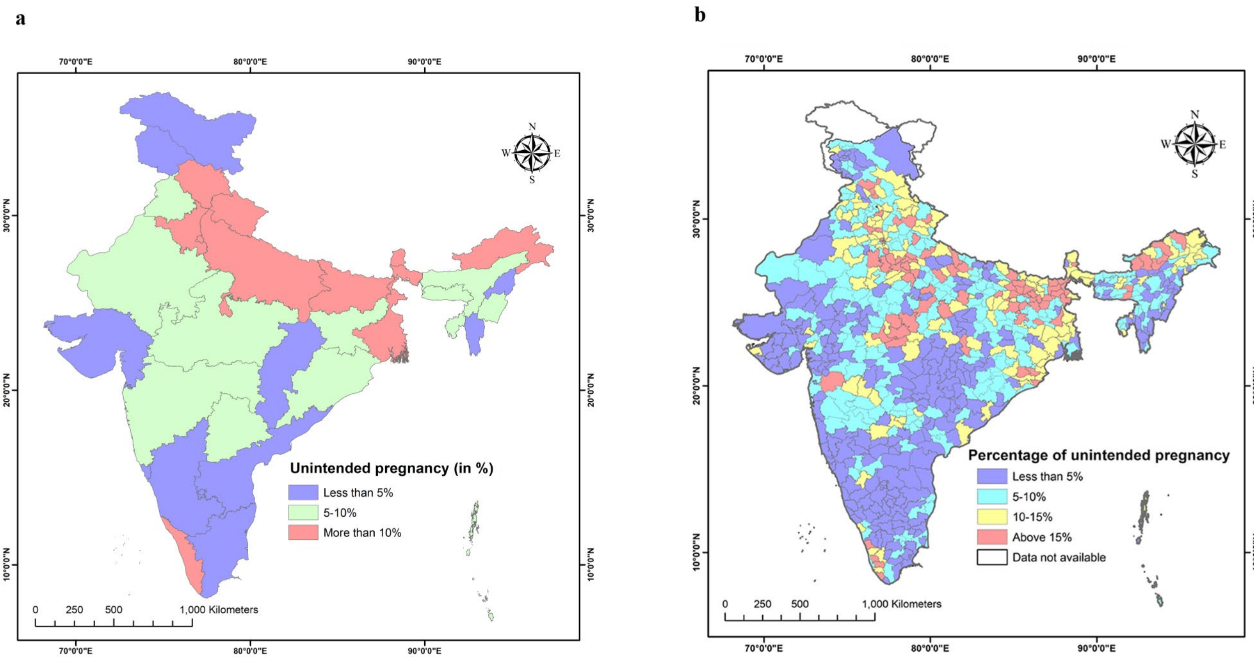

Fig. 2 Spatial variation in unintended pregnancy rate in India, NFHS-5 (2019-21). (**a**) State-level variation in unintended pregnancy (**b**) District-level variation in unintended pregnancy

Faridabad, and Palwal), and Patiala and Sangrur district of Punjab.

The third important High-High cluster was discerned in 9 districts of Arunachal Pradesh (Dibang Valley, Lower Dibang Valley, Upper Siang, West Siang, Siang, Upper Subansiri, Lower Subansiri, Kurung Kumey, and Papum Pare).

Additionally, four small High-High clusters are identified in Himachal Pradesh, northern Odisha, northern Uttarakhand, and central Madhya Pradesh. The one in the northern Odisha covered 5 districts, namely Jajpur, Cuttack, Kendrapara, Dhenkanal, and Bhadrak. The second minor High-High cluster comprised 4 districts of Himachal Pradesh, namely Mandi, Hamirpur, Una, and Sirmaur. An additional minor High-High cluster was located in 3 districts of Uttarakhand, namely Chamoli, Almora, and Pauri. The fourth minor High-High cluster covered 5 districts of Madhya Pradesh, namely Vidisha, Sagar, Damoh, Nasinghpur, Bhopal, and Raisen.

Furthermore, the analysis reveals the presence of three prominent large Low-Low clusters, alongside three smaller ones, indicative of cold spots. The primary large cluster encompasses districts in western Gujarat, western Madhya Pradesh, and southern Rajasthan, while the second significant cluster spans across northern Tamil Nadu, southern Andhra Pradesh, Karnataka, Kerala, Goa, Telangana and southwestern Maharashtra. The third major cluster is situated in districts of southern Chhattisgarh, eastern Maharashtra, southeastern Madhya Pradesh, and few districts of Odisha and Telangana. Additionally, smaller Low-Low clusters emerge in Jammu, eastern Nagaland, eastern Mizoram, and western Manipur.

Moreover, eleven districts scattered across Karnataka, Tamil Nadu, Andhra Pradesh, Maharashtra, Gujarat, Assam, Manipur, and Telangana demonstrate High-Low spatial outliers. In contrast, districts in Kerala, Haryana Madhya Pradesh, Odisha, Bihar, West Bengal, Jharkhand, Rajasthan, Arunachal Pradesh, Himanchal Pradesh, Punjab, Uttar Pradesh, Madhya Pradesh, Odisha, Jharkhand, Bihar, West Bengal, Arunachal Pradesh, Assam, and Uttarakhand exhibit 19 Low-High spatial outliers districts (see Appendix, Table A3).

Correlates of unintended pregnancy rate at the district level

To explain the district-level variation in unintended pregnancy rate, we employed Ordinary Least Squares (OLS), Spatial Lag Model (SLM), and Spatial Error Model (SEM). Table 4 presents the results of these models. Initially, we conducted a preliminary examination of the relationship between unintended pregnancy and its correlates using OLS estimation, without considering the spatial structure of the data. Subsequently, we observed that the values of AIC and Schwarz Criterion were lowest for SEM, prompting us to utilize SEM to investigate the spatial dependence of unintended pregnancies with its predictors. Notably, parity and the method used for contraception emerged as significant predictors of unintended pregnancy rate at the district level. Specifically,

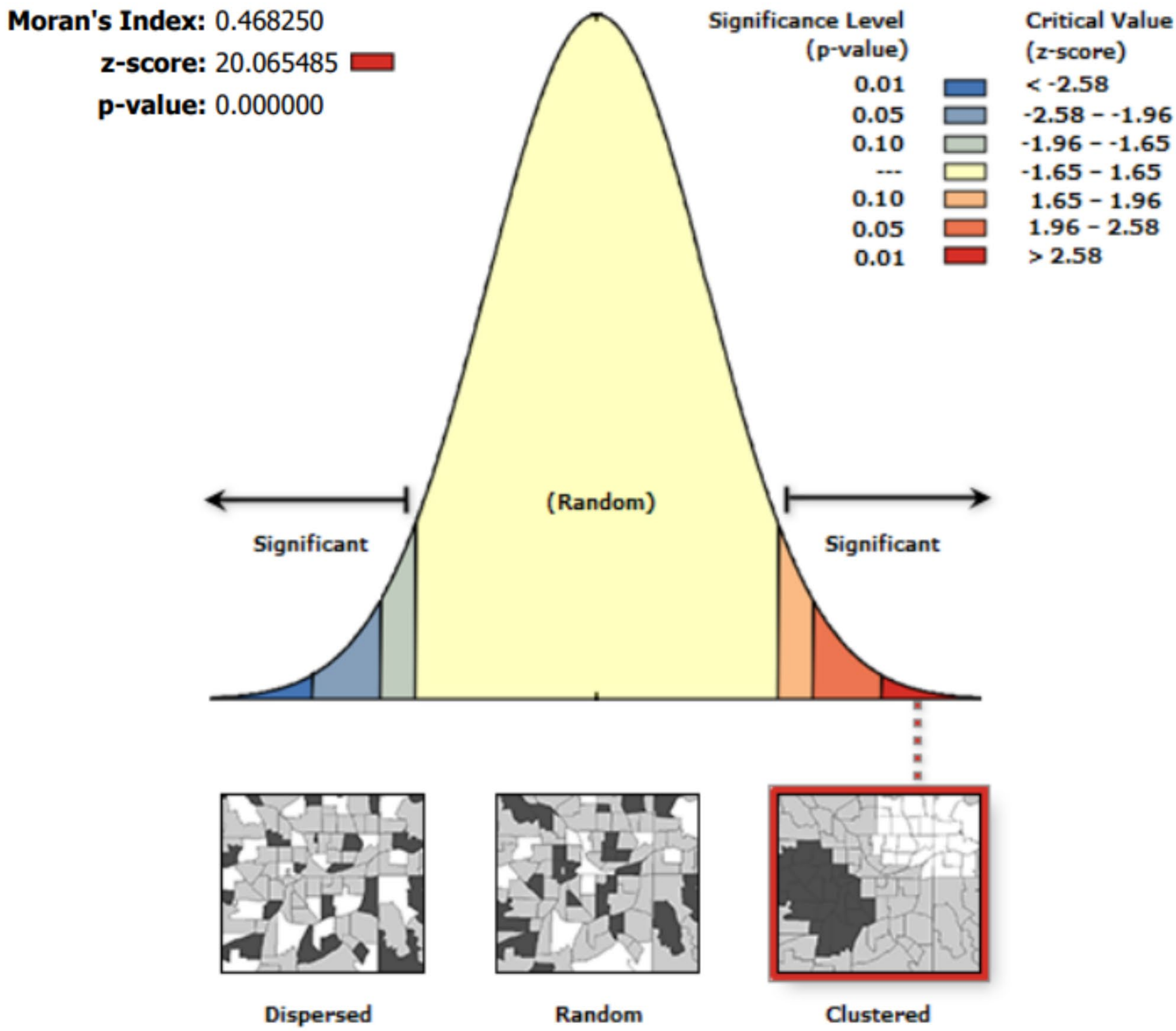

Fig. 3 Report of Global Moran's I

a 10% decrease in the proportion of women not using a modern contraceptive method was associated with a 0.57% point decrease in unintended pregnancy rate.

Discussion

This study sought to investigate spatial variation in unintended pregnancy rates across the states and districts of India. Approximately one out of ten pregnancies in India were unintended. A closer examination of state and district-level data uncovered notable disparities across regions and states. Particularly striking was the higher prevalence of unintended pregnancies in northern states, exceeding 10–15% in some areas. States such as Arunachal Pradesh, Himachal Pradesh, Sikkim, and Uttarakhand, nestled in the Himalayan region, along with the northern plain states of Delhi, Uttar Pradesh, and Bihar, and the southern state of Kerala also exhibited significantly elevated rates of unintended pregnancies. Furthermore, the analysis at the district level revealed even more nuanced variations within each state. The study noted three large clusters of high occurrences of unintended pregnancy. The first was located in Bihar, and northern West Bengal. In contrast, the second one was located in Delhi, western Uttar Pradesh, north-eastern Rajasthan, Haryana and few southern districts of Punjab. The third large High-High cluster was located in Arunachal Pradesh. A small High-High cluster was located in northern Odisha and central Madhya Pradesh.

The spatial clustering of unintended pregnancies observed across different regions of India could have stemmed from a multitude of contributing factors. For instance, the first cluster of districts with high level of

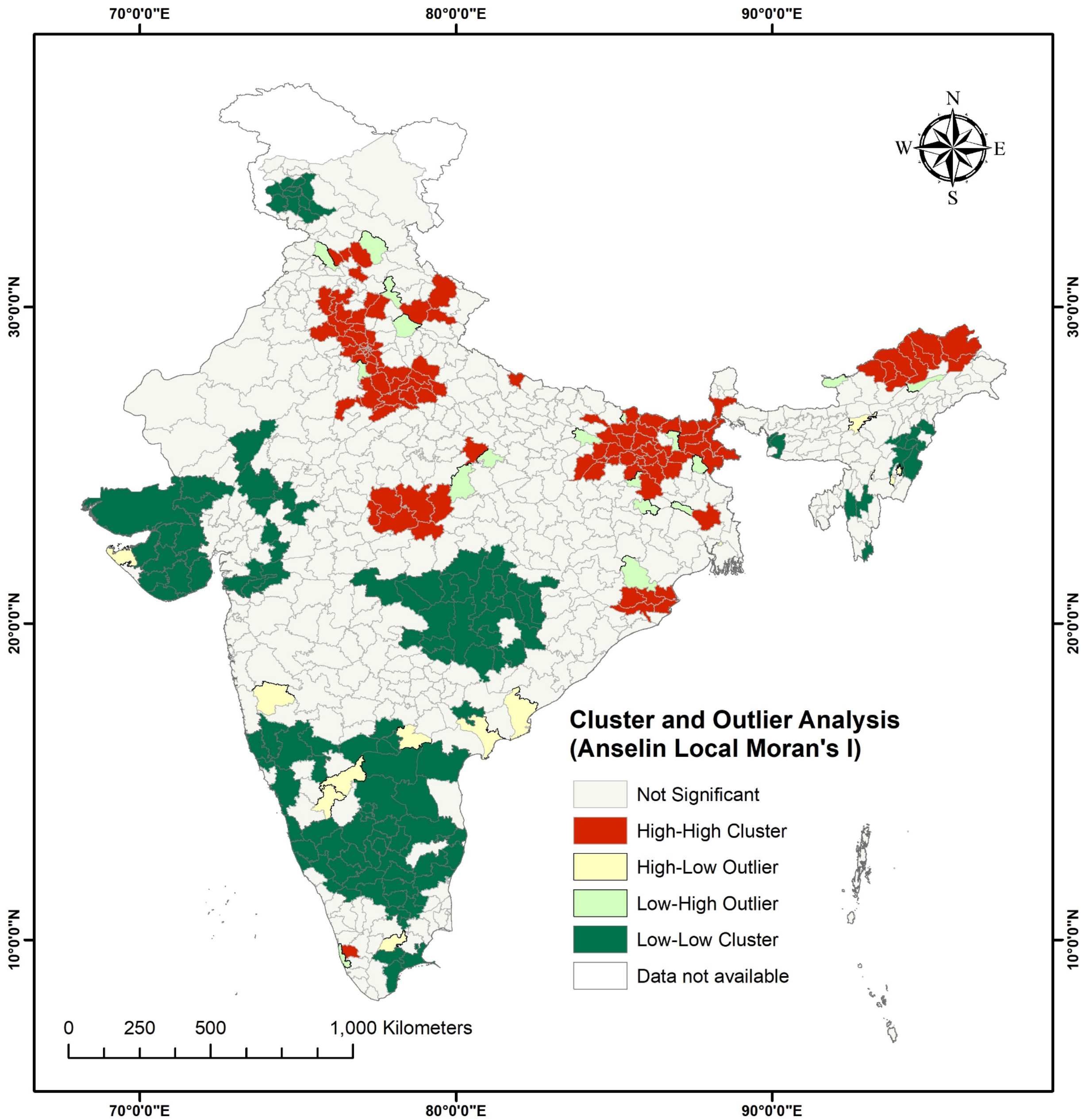

Fig. 4 Anselin Local Moran's I (Cluster and Outlier Analysis) map showing spatial clusters and outliers of unintended pregnancy across the district of India, NFHS-5 (2019-21)

unintended pregnancy was largely spread across Bihar, a state that stands out as one of India's most socioeconomically and demographically underdeveloped regions. Factors such as extreme poverty, low levels of education, early marriage among women, a predominantly rural population, limited awareness about contraceptive methods, and inadequate access to essential healthcare services are prevalent in this area [32, 33]. Together, these factors contribute to a significant unmet need for family planning, leading to a higher incidence of unintended pregnancies [15, 21]. The second cluster, spanning districts from Delhi, western Uttar Pradesh, northeastern Rajasthan, Haryana, and select southern districts of Punjab, starkly contrasts with the first cluster in its socio-economic and demographic makeup. This region is distinguished by its high per capita income, increased urbanization, elevated levels of educational attainment, enhanced access to healthcare, and relatively greater awareness regarding contraception [34, 35]. Despite these advantages, the notable concentration of unintended pregnancies in this area may stem from entrenched cultural norms of strong son-preference and societal

Table 4 Correlates of unintended pregnancy rate at the district level

Variables*	OLS		SLM		SEM	
	β	*p*-value	β	*p*-value	β	*p*-value
Proportion of SC/ST women	-0.014	0.118	-0.010	0.146	-0.010	0.286
Proportion of Hindu women	0.004	0.592	0.000	0.946	0.005	0.610
Proportion of women with no mass media exposure on family planning message	0.068	0.001	0.017	0.289	-0.002	0.914
Proportion of poor women	-0.031	0.016	-0.014	0.179	-0.023	0.120
Proportion of women residing in rural areas	-0.002	0.841	0.002	0.778	0.010	0.295
Proportion of women not using modern contraceptive	0.053	0.001	0.045	0.000	0.057	0.000
Proportion of women aged 15–24 years	0.030	0.159	0.022	0.185	0.032	0.156
Average age of women at marriage	-0.001	0.285	0.000	0.661	-0.001	0.356
Average parity	0.014	0.042	0.007	0.206	0.014	0.050
Average household size	-0.002	0.554	-0.001	0.733	-0.001	0.746
Proportion of women with no schooling	-0.048	0.012	-0.029	0.061	-0.039	0.066
Log-likelihood	1251.34		1365.120		1368.016	
AIC	-2478.68		-2704.240		-2712.03	
BIC/SC	-2423.9		-2644.900		-2657.25	
N	219,173		219,173		219,173	

Note: OLS: Ordinary Least Squares, SEM: Spatial Error Model, SLM: Spatial Lag Model, β: Regression Coefficient; AIC: Akaike Information Criterion, BIC: Bayesian Information Criterion, SW: Schwarz Criterion, SC/ST: Scheduled Caste/Scheduled Tribe, β: Regression Coefficient, N: Total number of observations included in the analysis, * For the definition of the variables used in this regression, please refer to Independent Variables section of this paper.

pressures that promote maintaining smaller family sizes [3]. The third cluster, situated in the northeastern Himalayan state of Arunachal Pradesh, primarily encompasses rugged hilly terrain with a sparse population, predominantly comprising diverse tribal communities [36]. This entire region is characterized by limited infrastructure development, including inadequate healthcare facilities and transportation and communication networks [37]. These deficiencies contribute to insufficient access to contraceptive methods and information, ultimately leading to a high incidence of unintended pregnancies [38]. More than half of the districts in the low-fertility southern state of Kerala reported high rates of unintended pregnancy. Despite Kerala's strong performance in maternal and child health indicators, this high prevalence may indicate a growing demand for accessible contraceptive options and increasing assertiveness among women in asserting their reproductive rights. Further in-depth studies are necessary to unravel the underlying factors contributing to this emerging trend.

The study identified a positive association between parity and unintended pregnancy, consistent with findings from numerous previous studies conducted in developing countries, including India [39–41]. As individuals reach their desired number of children, they may become less motivated to have additional births, inadvertently increasing the likelihood of unintended pregnancies. This underscores the importance of family planning interventions in addressing unintended pregnancies, particularly in regions with relatively high average parity [19]. The current use of modern contraceptive emerged as a significant correlate of unintended pregnancy in the regression analysis. This finding aligns with previous research indicating that the lack of contraceptive use or reliance on less effective traditional methods significantly contributes to unintended pregnancies [15, 24, 42–44]. Indeed, many unintended pregnancies occur precisely because effective contraception is not utilized. This underscores the importance of promoting the uptake of modern contraceptive methods, which are more reliable in preventing unintended pregnancies. Encouraging the adoption of modern contraceptives can help individuals move away from less effective traditional methods, thereby reducing the risk of unintended pregnancy or unplanned childbearing. Furthermore, addressing barriers to contraceptive access and information is crucial for empowering women to make informed decisions about their reproductive health and avoid unintended pregnancies [24, 44].

As majority of the states in the country have reached the replacement level fertility [45], there is a growing need for effective family planning measures, especially aimed at spacing childbirths and reducing unintended pregnancies. Recognizing this imperative, the Government of India, along with state governments, has been actively engaged in initiatives to enhance access to contraceptives and raise awareness about the conceptive use and the range of contraceptive options available for use. In line with an integrated Reproductive, Maternal, Newborn, Child, and Adolescent Health (RMNCH+A) approach, family planning services are currently being extended to all beneficiaries under the National Health Mission [46]. In 2016, the Mission Parivar Vikas (MPV) was launched in several states, including Uttar Pradesh, Bihar, Madhya Pradesh, Rajasthan, Chhattisgarh, Assam, and Jharkhand [47, 48]. Additionally, the implementation of the Family Planning Logistic Information System (FP-LMIS) and the Clinical Outreach Team (COT) scheme in 146 MPV districts aims to streamline the distribution of contraceptives and improve service delivery. Through innovative approaches like the *Nayi Pehel* (New Initiative) kits, *Saas-Bahu Sammelan* (mother-in-law and daughter-in-law gatherings), and *Saarthi* vans, the MPV scheme is also actively engaging communities in discussions about family planning, healthy birth spacing, and the benefits of smaller families. There is a focus on spacing methods, with the introduction of Injectable Contraceptive (*Antara*), Progestin Only Pills, and Centchroman (a nonsteroidal oral contraceptive) in the public sector. These additions represent a significant shift in the government's approach towards aligning its family planning program with the FP 2030 goals [48, 49]. Awareness campaigns using various media platforms, including television, radio, posters, and hoardings, are being employed to promote family planning and encourage the involvement of men and families in decision-making processes [47]. Furthermore, toll-free helplines have been established to provide information and address queries related to family planning, particularly targeting young and married couples [47, 49].

However, despite these commendable efforts, modern contraceptive use is still low in many northern and northeastern states leading to high incidence of unintended pregnancies. It is suggested to strengthening existing programs while introducing new ones to address barriers in accessing contraceptives, enhance knowledge about different contraceptive methods and their correct usage, dispel misconceptions, and tackle discontinuation of contraceptive use. Future efforts should prioritize enhancing the accessibility of contraceptives by fortifying distribution channels, particularly in remote districts with limited connectivity, such as those in Arunachal Pradesh, Sikkim, Uttarakhand and Himachal Pradesh [50]. Concurrently, addressing financial barriers for women from economically disadvantaged backgrounds is essential. Furthermore, concerns persist regarding the suboptimal utilization of funds allocated for family planning in several states, notably Uttar Pradesh and Bihar, which experience high rates of unintended pregnancies [51]. The high incidence of unintended pregnancies in the western Uttar Pradesh-Delhi-Haryana cluster is often attributed to societal pressures stemming from son preference [52]. This cultural preference can dissuade women from seeking contraception, heightening their risk of unwanted or closely spaced pregnancies. Hence, it is imperative to strengthen and effectively implement existing government programs promoting gender equality, such as *Beti Bachao*, *Beti Padhao* (English Translation: Save the Girl Child, Educate the Girl Child). Addressing these challenges will require sustained commitment and collaborative efforts to ensure effective implementation of family planning initiatives and achieve desired outcomes.

The study has several limitations which should be acknowledged. Since the data were compiled through self-reported interviews, it would be vulnerable to social-desirability bias. Using a case definition reliant on women's self-reporting of pregnancy intention may introduce some level of misclassification bias, particularly in retrospective surveys like the one utilized in our study, which collected data for the past five years. Furthermore, certain variables such as ideal family size, women's autonomy, and working status were not included in our analysis, which could have provided valuable insights. Future research could delve into these influencing factors to better understand the formation of cold and hot spots identified in our study. The classification of a pregnancy into unintended and intended may heavily depend on the opinions of spouses or other family members. Unfortunately, due to insufficient data, we were unable to include this variable in our study. Another limitation of this study is that Global Moran's I and Anselin Local Moran's I analysis will not work for small data set that is adequate number of observations should be present in each spatial unit and Global and Local Moran's I are sensitive to the choice of spatial weights matrices. Different weight structures can lead to different results, and the interpretation of spatial patterns may vary accordingly. Additionally, Global Moran's *I* assume that the variable being analysed follows a normal distribution. Violation of this assumption may impact the reliability of the results. Furthermore, the exclusion of approximately 6% of observations due to missing data in various variables used in the analysis is another limitation of our study. While necessary to maintain the integrity of the analysis, this exclusion could potentially introduce bias into the results. Consequently, caution is warranted when interpreting the findings, taking into account the potential impact of missing observations on the overall conclusions of the study. Lastly, the utilization of spatial regression models introduces additional limitations. While assuming nearby observations share greater similarity, these models may falter when spatial autocorrelation is weak or absent. Boundary effects pose challenges, particularly at the periphery of the study area, where neighbouring regions' influence may be inadequately captured. Moreover, the choice between contiguity-based or distance-based spatial weighting schemes significantly affects model outcomes. Data quality issues such as measurement error, missing data, and outliers also pose challenges, emphasizing the need for meticulous data preprocessing before model fitting.

Conclusion

The findings indicate significant regional variations in unintended pregnancy rates across India's districts. Areas with higher rates, particularly in the northern and Empowered Action Group (EAG) states, contrast with lower rates observed in southern regions. These variations emphasize the need for tailored interventions addressing the underlying causes of unintended pregnancies in specific geographic areas. Policymakers should prioritize regions with elevated rates, particularly those where modern contraceptive use is low, by bolstering initiatives like Mission Parivar Vikas. Moreover, policy design should account for existing spatial disparities to effectively address unintended pregnancies. Addressing these disparities and implementing targeted interventions can advance efforts towards ensuring equitable access to reproductive healthcare and empowering women across the nation to make informed decisions regarding their reproductive choices.

Supplementary Information

The online version contains supplementary material available at https://doi.org/10.1186/s12884-024-06850-z.

Supplementary Material 1

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Author contributions

ADS: conceptualisation, design, data analysis, interpretation of data, visualisation, supervision, writing – review and editing. ANS: data curation, data analysis, visualisation, interpretation of data, writing – original draft, writing – review and editing. MC: data analysis, visualisation, interpretation of data, supervision, writing – review and editing. SS: interpretation of data, supervision, writing – review and editing. RC: supervision, writing – review and editing. PT: writing – review and editing.

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Data availability

The dataset analysed during the current study is available in the Demographic and Health Surveys (DHS) repository, https://dhsprogram.com/data/available-datasets.cfm, and can be obtained for free by sending an online request. Codes used in the analysis can be made available by the corresponding author upon request.

Declarations

Ethics approval and consent to participate

The present study utilized secondary data sourced from the public domain, containing no identifiable information about survey participants. Therefore, ethical approval was not needed for this study.

Consent for publication

Not applicable.

Competing interests

The authors declare no competing interests.

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