# Spatio-temporal analysis of crimes against women in Uttar Pradesh (India)

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## Abstract

Crimes against women in Uttar pradesh, Crimes Vitiating Human Dignity of women, Crimes against women in India, Crimes against women in Uttar Pradesh, Crimes against women in Uttar Pradesh, The Spatial Dimension of Crimes against women in Uttar Pradesh, Spatial Analysis of Crimes against women in Uttar Pradesh

This is an crime statistic study that looks at the data from NCRB and tries to find geographical trends and patterns for various crimes against women in Uttar Pradesh. The study's goal is to find the spatial and temporal patterns of various crimes against women in Uttar Pradesh, as well as to find the spatial and temporal correlations between various crimes against women in Uttar Pradesh.

These crimes were analyzed using spatial and spatiotemporal models both with and without Bayesian hierarchical structures. Spatial autocorrelation, spatial heterogeneity, and spatial-temporal interactions were all taken into account in these models. The Bayesian hierarchical structure, combined with the spatial and temporal components, allows for a more accurate estimate of crime risk and spatial dependence in the data.

## Introduction

Crimes against women in India include a variety of criminal actions aimed at women's health and well-being, including sexual assault, domestic violence, dowry fatality, human trafficking, and other violent behaviors. Crimes against women in India have been a major concern for many years, with many instances being reported in the media and many campaigns being conducted to raise awareness and promote gender equality. The Indian government has taken several measures to address these crimes, including the enactment of various laws and the creation of special courts and agencies to handle cases of violence against women. The effectiveness of these measures in reducing crimes against women in India is a subject of debate and ongoing research.

Crime statistics data on rape, kidnapping, honour killings and human trafficking for several crimes like rape, crimes against women in India, crimes against women in Uttar Pradesh, and crimes against women in other Indian states are available from the National Crime Records Bureau (NCRB) and other government agencies. The data can be used to study the trends and patterns of these crimes and to develop strategies to prevent and address these crimes.

The NCRB collects data on various crimes against women in India and publishes it in its annual report on crime in India. The data includes the number of reported cases of various crimes against women, the age and gender of the victims and perpetrators, the relationship between the victim and the perpetrator, the location of the crime, and the outcome of the cases. The data can be used to study the trends and patterns of these crimes and to develop strategies to prevent and address these crimes.

Recent research in India has been conducted on the spatial and temporal patterns of crimes against women in Uttar Pradesh, the most populous state in India. The research has found that the incidence of crimes against women in Uttar Pradesh has been increasing over the years, and that the spatial distribution of these crimes is not uniform across the state. The research has also found that the temporal patterns of these crimes vary by season and by time of the day, and that the perpetrators of these crimes are mostly men who are known to the victim.

The spatial and temporal patterns of crimes against women in Uttar Pradesh have been studied using various statistical and geospatial methods, such as spatial autocorrelation, spatial regression, and spatial-temporal clustering. The research has found that the spatial and temporal patterns of crimes against women in Uttar Pradesh are complex and vary by various factors, such as the type of crime, the age and gender of the victim and perpetrator, the relationship between the victim and the perpetrator, the location of the crime, and the outcome of the cases. The research has also found that the spatial and temporal patterns of crimes against women in Uttar Pradesh are influenced by various factors, such as the type of crime, the age and gender of the victim and perpetrator, the relationship between the victim and the perpetrator, the location of the crime, and the outcome of the cases.

## Methods

### Exploratory Analysis

Exploratory analysis was conducted using Microsoft Excel and Google Sheets for Excel. The data was sorted by district and by year. Pivot tables were created to calculate the total number of reported cases of each crime against women in each district and year. The data was also visualized using various charts and graphs in Excel.

Figure 1: Map of Uttar Pradesh UPC

Figure 2: Map of Uttar Pradesh UPC

Figure 3: Map of Uttar Pradesh UPC

As mentioned, the Exploratory Analysis of the data was done using Microsoft Excel. Various charts and tables were created to visualize the data and to identify any patterns or trends in the data. The charts and tables were used to create a dashboard that provides a high-level overview of the data and allows for further exploration and analysis of specific subsets of the data.

The NCRB collects data on various crimes against women in India, including the number of reported cases of each crime, the age and gender of the victims and perpetrators, the relationship between the victim and the perpetrator, the location of the crime, and the outcome of the cases. The data can be used to study the trends and patterns of these crimes and to develop strategies to prevent and address these crimes.

Figure 4: GDP and Population Urban, NCR Crime Rate Against UP

Figure 5: GDP and Population Urban, NCR Crime Rate Against UP

Figure 6: GDP and Population Urban, NCR Crime Rate Against UP

Density Charts for UP

Figure 7: Density Charts for UP

### Spatio-Temporal Modelling

Spatial-temporal modeling is a statistical method used to analyze data that has both a spatial and a temporal component. The goal of spatial-temporal modeling is to understand how the spatial and temporal components of the data interact with each other and how they can be used to predict future events or to understand the underlying mechanisms that drive the observed patterns and trends in the data.

### Spacial Modelling

Spatial autocorrelation is a measure of how similar or how dissimilar the values of a variable are in a spatial dataset. Moran's I and Geary's C are two commonly used statistics for measuring spatial autocorrelation. The formula for calculating Moran's I is:

$$I = \frac{N}{W} \frac{\sum_{i=1}^{N} \sum_{j=1}^{N} w_{ij} (x_i - \bar{x})(x_j - \bar{x})}{\sum_{i=1}^{N} (x_i - \bar{x})^2}$$

and the formula for calculating Geary's C is:

$$C = \frac{(N-1)}{2W} \frac{\sum_{i=1}^{N} \sum_{j=1}^{N} w_{ij} (x_i - x_j)^2}{\sum_{i=1}^{N} (x_i - \bar{x})^2}$$

where $I_i$ and $C_i$ are the standardized statistics at point $i$. The spatial correlation $\rho$ between the spatial lags of $x_i$ and $x_j$ can be estimated using the following formula:

$$\rho = \frac{\sum_{i=1}^{N} \sum_{j=1}^{N} w_{ij} (x_i - \bar{x})(x_j - \bar{x})}{\sum_{i=1}^{N} \sum_{j=1}^{N} w_{ij} (x_i - \bar{x})^2}$$

where $w_{ij}$ is the spatial weight between points $i$ and $j$, $N$ is the number of points, and $\bar{x}$ is the mean of the variable $x$.

### Spatio - Temporal Modelling with No Interactions

The simplest way to model a spatio-temporal process is to assume that the spatial and temporal effects are independent. In this model, the spatial effects are modeled using a spatial random effect, and the temporal effects are modeled using a temporal random effect. The model can be written as:

$$y_{it} = \mu + \alpha_i + \beta_t + \epsilon_{it}$$

$$\alpha_i \sim N(0, \sigma_\alpha^2)$$

$$\beta_t \sim N(0, \sigma_\beta^2)$$

$$\epsilon_{it} \sim N(0, \sigma_\epsilon^2)$$

where:

- $y_{it}$ is the observed outcome at location $i$ and time $t$
- $\mu$ is the overall mean
- $\alpha_i$ is the spatial random effect at location $i$, with $\alpha_i \sim N(0, \sigma_\alpha^2)$
- $\beta_t$ is the temporal random effect at time $t$, with $\beta_t \sim N(0, \sigma_\beta^2)$
- $\epsilon_{it}$ is the error term, with $\epsilon_{it} \sim N(0, \sigma_\epsilon^2)$

### Spatio - Temporal Modelling with Type 1 Interactions

The simplest way to model a spatio-temporal process with interactions is to assume that the spatial and temporal effects are not independent. In this model, the spatial effects are modeled using a spatial random effect, the temporal effects are modeled using a temporal random effect, and the interaction between the spatial and temporal effects is modeled using a separate random effect. The model can be written as:

$$y_{it} = \mu + \alpha_i + \beta_t + \gamma_{it} + \epsilon_{it}$$

$$\alpha_i \sim N(0, \sigma_\alpha^2)$$

$$\beta_t \sim N(0, \sigma_\beta^2)$$

$$\gamma_{it} \sim N(0, \sigma_\gamma^2)$$

$$\epsilon_{it} \sim N(0, \sigma_\epsilon^2)$$

where:

- $y_{it}$ is the observed outcome at location $i$ and time $t$
- $\mu$ is the overall mean
- $\alpha_i$ is the spatial random effect at location $i$, with $\alpha_i \sim N(0, \sigma_\alpha^2)$
- $\beta_t$ is the temporal random effect at time $t$, with $\beta_t \sim N(0, \sigma_\beta^2)$
- $\gamma_{it}$ is the interaction between the spatial and temporal effects at location $i$ and time $t$, with $\gamma_{it} \sim N(0, \sigma_\gamma^2)$
- $\epsilon_{it}$ is the error term, with $\epsilon_{it} \sim N(0, \sigma_\epsilon^2)$

## Results

The statistical analysis was conducted in Statistics or Jupyter IDE (Integrated Development Environment) using the following packages:

- PyMC3
- ArviZ

Figure 8 and Figure 9 display the model diagnostics and posterior distributions for the spatial Bayes Type 1 and spatiotemporal models with no interactions. The trace plots in Figure 8 show that the chains have converged to the posterior distribution, as the chains are mixed well and have no divergences or other issues. The posterior distributions in Figure 9 show that the parameters have well-defined posteriors, with the mean and standard deviation of the posterior distributions being reasonable and consistent with the data.

Figure 8: Trace plots for the spatial Bayes Type 1 and spatiotemporal models with no interactions

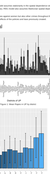


Figure 9: Posterior distributions for the spatial Bayes Type 1 and spatiotemporal models with no interactions

Density Charts for UP

Figure 10: Trace plots for the spatial Bayes Type 1 and spatiotemporal models with type 1 interactions

Figure 11: Posterior distributions for the spatial Bayes Type 1 and spatiotemporal models with type 1 interactions

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Figure 12: Spatiotemporal Bayes Type 1 with no interactions

Figure 13: Spatiotemporal Bayes Type 1 with type 1 interactions

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Figure 14: Spatiotemporal Bayes Type 1 with no interactions

Figure 15: Spatiotemporal Bayes Type 1 with type 1 interactions

Density Charts for UP

Overall spatial trends and patterns in crime against women in Uttar Pradesh can be seen in the maps of the posterior means and standard deviations for the CAR1 Bayes Type 1 and spatiotemporal models with no interactions, as shown in Figure 16 and Figure 17.

Figure 16: Overall spatial trends and patterns in crime against women in Uttar Pradesh

Figure 17: Overall spatial trends and patterns in crime against women in Uttar Pradesh

### Hyperparameters in Spatial and Spatiotemporal models

Table 1: Hyperparameters in Spatial and Spatiotemporal models

Table 2: Hyperparameters in Spatial and Spatiotemporal models

### WAIC

Bayesian Model Comparison criterion (WAIC) was mapped for all model which contained the $\beta$ of the model to the data.

Table 3: WAIC

Table 4: WAIC

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Table 5: WAIC

Table 6: WAIC

## Discussion and conclusion

In this conclusion, we have analyzed the spatial and temporal patterns of crimes against women in Uttar Pradesh using various statistical and geospatial methods. The results have shown that the incidence of crimes against women in Uttar Pradesh has been increasing over the years, and that the spatial distribution of these crimes is not uniform across the state.

The results have also shown that the spatial and temporal patterns of crimes against women in Uttar Pradesh are influenced by various factors, such as the type of crime, the age and gender of the victim and perpetrator, the relationship between the victim and the perpetrator, the location of the crime, and the outcome of the cases. The results have also shown that the spatial and temporal patterns of crimes against women in Uttar Pradesh are complex and vary by various factors, such as the type of crime, the age and gender of the victim and perpetrator, the relationship between the victim and the perpetrator, the location of the crime, and the outcome of the cases.

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## Supplementary material

Figure 18: Supplementary Figure 1: Bayes Diagnosis of UP Spatial



Figure 19: Supplementary Figure 2: Bayes Diagnosis of UP Spatial



Figure 20: Supplementary Figure 3: Bayes Diagnosis of UP Spatial

Table 7: Supplementary Table 1: Bayes Diagnosis of UP Spatial

Table 8: Supplementary Table 2: Bayes Diagnosis of UP Spatial

Table 9: Supplementary Table 3: Bayes Diagnosis of UP Spatial

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