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Spatiotemporal impact of education and employment on crimes: a case study of West Bengal districts

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ABSTRACT: Does human capital formation forestall crimes over space and time? The aim of this study is to examine this question by analysing the spatial impact of education and employment on criminal offences across the districts of West Bengal. This study proposes a Crime Severity Index by incorporating both the legal seriousness and the frequency of occurrence of different crimes. The index provides a single composite measure that complements the usual crime rate indicator to better understand regional crime profiles. The severity of crime is measured by assigning weights based on the years of imprisonment and the likelihood that the respective crimes will occur. To identify the determinants of crime over space and time, this study employs a pseudo-panel structure comprising 19 cross-sections across 5 time points, spanning 2000 to 2020, applying spatial regression models. A high and positive Moran's I score suggests that crime rates and the crime severity are closely linked across different regions within the state. Further analysis of the regression results shows that factors such as higher education among women, stable employment opportunities, and the number of police stations have a substantial impact on forestalling regional crime and reducing its severity.

KEYWORDS: crime rate | Crime Severity Index | education | employment | Moran's I | Spatial Panel Autoregressive Model | Spatial Panel Error Model | West Bengal

1. INTRODUCTION

Negative economic externalities arise when an individual's action imposes cost on others who are not directly involved. Crime is a common example of such a negative externality. Understanding crime patterns is important to understanding crime rates in developing countries like India for several reasons. High crime rates can impede economic development and increase costs for the legal system, healthcare, and law enforcement. India's history of crime is complicated and shaped by cultural variety, socioeconomic disparities, and colonial domination (Levitt, 2017). After independence, India continues to address different crimes, enacting the Indian Penal Code in 1960 by implementing numerous laws and reforms to keep pace with societal shifts. Underprivileged populations are more likely to be affected by crimes and insecurity (Sharma & Sunder, 2025). Thus, understanding crime patterns and their relationship with social development is essential for policymakers to develop targeted interventions, improve public safety, and promote sustainable development.

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In this study, West Bengal has been selected because of its distinct and complex socio-economic, cultural, and geographical profile compared to other Indian states. The state combines a diverse landscape of urban and rural areas with sharp intra-state socioeconomic disparities. The high population density in some districts creates social pressures that may increase economic stress and crime rates, while its strategic border location with Bangladesh (the world's fifth-longest land border, stretching 2,217 km) introduces additional challenges, such as cross-border access and migration issues that may affect economic stability. Further, the state's longstanding labour movements, significant economic disparities, high unemployment rates in certain sectors, and cross-border illegal migration enable an in-depth investigation into the association between human capital and crime. However, West Bengal is no exception in reporting different types of crime. The overall crime rate per one lakh population in 2022 was 266.6 (the national average was 486.5). Crime against women is even higher (66.7 per one lakh women) in West Bengal compared to the national average (64.5 per one lakh women). Crimes against children and property-related iniquities have also shown an increasing trend in West Bengal. Alongside, the overall literacy rate in West Bengal was 77.08% (the national average is 77.7%) in 2022, including 82.6% among men and 71.1% among women. According to various annual Periodic Labour Force Survey reports and National Sample Survey Organisation (NSSO) findings, the unemployment rate in West Bengal ranged from approximately 6% to 10% from 2000 to 2020. Lack of education, high poverty and limited employment opportunities may increase the likelihood of criminal activities, making these important determinants of regional crime.

This study addresses the lack of research on the association between human capital and criminal activity across space and time. Crime incidence refers to the frequency of recorded criminal offences per one lakh population and is measured by the Crime Rate (CR). Crime rate answers the question "How much crime occurs?" irrespective of the seriousness of different offences. Crime severity, in contrast, refers to the seriousness of the overall crime composition after accounting for both the legal gravity of offences and their likelihood of occurrence. It therefore answers a different question: "How serious is the crime profile of an area?" Two regions may record similar crime rates but different crime severity if one experiences relatively more serious offences, such as murder or crimes against women, while the other is dominated by less severe offences, like theft or forgery. To address this, the study has proposed a Crime Severity Index (CSI), which is not an alternative measure of crime rate but a complementary measure that captures the qualitative seriousness of criminal activity.

2. REVIEW OF LITERATURE

Crime is a multidimensional socio-economic phenomenon influenced not only by individual characteristics but also by neighbourhood conditions, institutional capacity, and geographical interactions (Bennett, 1991). Modern criminological theories suggest that criminal behaviour emerges from the interaction of economic opportunities, social organisation, and spatial context rather than from any single determinant. Consequently, understanding regional crime requires an integrated framework combining socio-economic (Aboya et al., 2022) and spatial perspectives (Zhou et al., 2023). The very first country-level crime index, i.e., the Global Organized Crime Index, was developed by the Global Initiative Against Transnational Organized

Crime (GI-TOC) in 2019. GI-TOC is used to calculate the country-level criminality score by combining three dimensions: criminal markets, criminal actors, and resilience, which includes 193 nations. Several previous international studies have shown that education level is strongly associated with criminal activity. According to the studies by Ehrlich (1975), Selke (1980), Lochner (1999, 2020), Lochner & Moretti (2004), Groot and van den Brink (2010), Hjalmarsson and Lochner (2012), Fella and Gallipoli (2014), Jonck et al. (2015), Bell et al. (2022), Agüero and Bharadwaj (2022), Miller and Alves (2023), it is concluded that completing higher studies significantly reduces the crime rates. A positive correlation between the unemployment rate, income inequality, and criminal offences has been studied by several researchers, including Paternoster and Bushway (2001), Raphael and Winter-Ebmer (2001), Edmark (2005), Lin (2008), Andresen (2012), and Zungu and Mtshengu (2023). Many studies on the issue of reducing inequalities through educational attainment and increasing the labour force participation rate in India have been done in the recent past (Chaudhuri et al., 2015; Ansari et al., 2015; Sharma, 2015; Ohlan, 2020; Rakshit & Neog, 2020; Mishra et al., 2021; Nagasubramaniyan & Joseph, 2024; Sharma & Sunder, 2024). Increasing employment opportunities and higher educational attainment among the youth cohort across the districts of West Bengal significantly reduce crime incidents against women and children, as discussed in several studies, including Deb et al. (2005), Ghosh and Kar (2008), and Pandit and Halder (2023). In addition to education and income-generating factors, several socioeconomic explanatory variables significantly affect the crime rate in India (Steffensmeier et al., 2019). Studies such as Drèze and Khera (2000), Kumar (2004), Dutta & Husain (2009) and Hazra (2019) have investigated the positive correlation between the urbanisation rate and the percentage of the socially backward class in India's crime rate. However, only a few studies have explored crime in India using spatial economics. Studies, including Mazeika and Kumar (2017), Kabiraj (2022), and Mukherjee et al. (2024), have shown that certain socioeconomic parameters have a spatial effect on crime prevalence. Another study by Bhattacharyya et al. (2022) explored the spatial determinants of crimes against women in India, particularly focusing on dowry deaths, rape, molestation, and torture, using spatial panel data regression. The research found that certain crimes exhibit spatial dependency, influenced by neighbourhood effects, especially in dowry deaths. Key factors like female workforce participation and the presence of police stations reduce dowry deaths, indicating that improved economic empowerment and law enforcement are significant determinants. They added that micro-level spatiotemporal exploration of crime could lead to a more prominent understanding. The existing literature identifies education, employment, urbanisation, income, and policing as important determinants of crime. International studies mainly examine the socio-economic causes of crime or the spatial clustering of criminal activities, while Indian studies largely focus on specific crime categories such as crimes against women, homicide, or violent offences. Only a handful of studies combine spatial econometric methods with district-level crime analysis in India. The existing evidence, therefore, provides useful insights into the determinants of crime, but comparatively little attention has been paid to examining overall crime patterns and crime severity simultaneously within a spatial framework.

Recent studies have also highlighted that crime patterns in international border regions (van Dijk et al., 2022) differ from those in interior regions because border areas experience continuous movement of people and goods, as well as informal economic activities. Earlier studies on the India–Bangladesh border show that everyday cross-border migrations remain common while informal trade, smuggling, and human trafficking continue to shape the local social and economic environment. Studies have also reported that illegal migration, trafficking, smuggling, and security concerns create additional challenges for border communities and influence local livelihoods. These cross-border criminal activities demonstrate that border districts operate under conditions distinct from those in inland regions (Subba, 2025). These studies suggest that socio-economic factors such as education and employment may influence crime differently in border districts than in interior districts because legitimate and illegitimate economic opportunities coexist in these regions. Since several districts of West Bengal share an international boundary with Bangladesh, incorporating the border context is important for understanding regional differences in crime incidence (Hassan & Bala, 2019) and crime severity. This perspective provides a useful background for interpreting the spatial patterns examined in the present study.

The conceptual framework of the study is grounded in the economic theory of crime, which suggests that criminal behaviour reflects both individual incentives and the surrounding socio-economic environment. The present study is conceptually informed by several complementary criminological and spatial theories. Routine Activity Theory (Cohen & Felson, 2010) suggests that criminal incidents arise when motivated offenders encounter suitable targets in the absence of effective guardianship. This perspective provides a theoretical basis for examining the role of urbanisation, police infrastructure, and population concentration in shaping regional crime patterns. Social Disorganization Theory (Shaw & McKay, 1942; Petee et al., 1994) further argues that communities characterised by weaker social institutions, lower educational attainment, and economic instability tend to experience higher levels of criminal activity because of reduced informal social control. In addition, Strain Theory (Merton, 1938) suggests that limited legitimate economic opportunities may encourage individuals to engage in criminal behaviour, thereby justifying the inclusion of employment and income-related variables in the empirical model. Existing criminology theories for measuring crime seriousness have generally followed two broad approaches. One approach evaluates crime by the legally prescribed sanctions, assuming that statutory punishments reflect society's collective judgment on the relative seriousness of different offences. An alternative approach emphasises the crime harm index, where offences are weighted according to victim harm, public impact, or sentencing outcomes (Sherman et al., 2016). The present study follows the first approach to define the weightage technique because legally prescribed imprisonment terms provide a transparent, objective, and consistently available basis for comparing offences across districts within a common legal framework. The spatial diffusion perspective recognises that crime is not geographically isolated but may spill over across neighbouring regions through socio-economic interactions, transportation networks, and population mobility. These theoretical perspectives provide the rationale for employing Moran's I, Local Indicators of Spatial Association (LISA) cluster analysis, and spatial panel regression models to explicitly account for spatial interdependence.

3. RESEARCH GAPS AND OBJECTIVES OF THE STUDY

A review of existing research reveals that only a few studies have examined micro-level crime patterns in India. Focusing on a specific criminal activity, such as Dowry death (Bhattacharyya et al., 2022), Human Assault (Abraham, 2012), or Crime against women (Lolayekar et al., 2022), creates gaps in understanding the complete crime scenario. Prior studies have mostly relied on the conventional crime rate (Chaudhuri et al., 2013), which measures only the frequency of recorded offences. Districts with similar crime rates may exhibit different crime profiles when accounting for crime severity. This study has attempted to address that limitation by proposing a CSI, which complements the crime rate. Further, this study has applied the spatial econometric models to explore the impact of educational improvement and employment generation on crime severity patterns over space and time. Moran's I statistics, LISA cluster maps, and spatial panel regression models are utilised to identify the determinants of both crime rate and crime severity.

The primary objective of this research is to investigate inter-district crime patterns within the state and explore socioeconomic determinants that could reduce the crimes. The objectives of this study are as follows:

(1) to develop a CSI for the districts of West Bengal over the period of five years.

(2) to examine the presence of spatial correlation in regional crimes across districts over time.

(3) to investigate the potential educational, employment, and regional determinants of crimes using spatial panel regression.

4. METHODOLOGY AND DATA SOURCES

In line with the primary objective of this study, the CSI is constructed using the National Crime Records Bureau's (NCRB) crime statistics for the West Bengal districts. This study incorporates seven broad categories of crimes reported by the NCRB. These categories include violent crimes, crimes against women, property offences, negligence-related offences, document-related offences, miscellaneous Indian Penal Code (IPC) offences, and hurt offences given in Tab. 1. Although these offences differ in their legal nature, victimisation patterns, reporting behaviour, institutional recording practices, and underlying socio-economic causes, they collectively reflect the overall crime profile of a region. The objective of the CSI is therefore not to explain the causes of individual crime types but to assess the aggregate seriousness of all legally recorded criminal activity within a geographical unit. Since public safety reflects the combined burden of diverse crimes, this composite index provides a broader measure of regional crime severity than analysing individual crimes separately.

Sl. No.	Criminal Activity
1.	Murder *(Homicide/Attempted to Murder/Kidnapping and Abduction to Murder)*
2.	Crime against Women *(Rape/Attempted to Rape/Kidnapping/Assault/Outraging her Modesty)*
3.	Offense against Property *(Theft/Robbery/Burglary)*
4.	Causing Death by Negligence *(Hit & Run and Other Road Accidents)*
5.	Offense against Documents or Property Marks *(Breach of Trust/Forgery/Cheating/Fraud)*
6.	Miscellaneous Indian Penal Code Crimes *(Ransome/Arson/Dowry Death/Rash Driving, Cruelty by Husband or Relatives)*
7.	Simple Hurt or Grievous Hurt *(Use of Dangerous Weapons/Acid Attacks/ Endangering the Life or Safety of Others)*

Tab. 1. Selected Crime Variables to Develop the Crime Severity Index
Source: The author merged these different types of crime from the National Crime Records Bureau (NCRB)

These crime variables are provided as the unit values, i.e., the total number of specific crime incidents that have happened within a region. To make them comparable across districts, we converted them to the total number of incidents per 1 lakh population. These comparable values are then normalised by applying the UNDP Goalpost method, following equation (1),

$$\boldsymbol{C'_{ijt}} = \frac{(\boldsymbol{c_{ijt}} - \boldsymbol{Min}(\boldsymbol{c_{ij}}))}{(\boldsymbol{Max}(\boldsymbol{c_{ij}}) - \boldsymbol{Min}(\boldsymbol{c_{ij}}))} \quad \ldots\ldots (1)$$

C'_{ijt} represents the normalized score for the i^{th} crime indicator and j^{th} district in t^{th} year. c_{ijt} is the actual value of the i^{th} crime. *Max* and *Min* c_{ij} are the maximum and minimum values, respectively, considering all time points. By using this normalization procedure, each crime indicator is transformed into a zero-to-one range, where 1 denotes the highest crime rate, and 0 designates no crimes.

4.1. CONSTRUCTION OF CRIME SEVERITY INDEX

The conventional Crime Rate assigns equal importance to every recorded crime regardless of its seriousness. Two districts reporting identical crime rates may represent fundamentally different public safety situations if one district is dominated by relatively minor offences while the other experiences a larger proportion of serious crimes such as murder or crimes against women. Therefore, measuring only the crime rate is insufficient to understand a region's overall crime profile. To overcome this limitation, this study develops a CSI. By assigning appropriate weightages to individual crimes based on their severity and probability of occurrence, the index better reflects crime severity. The use of legally defined offence seriousness as a basis for weighting crime categories has precedent in criminological research. Similar approaches have frequently been adopted in research, including those of Wolfgang (1985), England (1966), and Statistics Canada (2009), in which legal penalties are used to classify or rank offences by severity when direct measures of social harm are unavailable. In this study, the statutory maximum term of imprisonment prescribed under the IPC is used as an operational proxy for the legally recognised seriousness of different crimes rather than as a direct measure of their intrinsic social harm. It should be noted that statutory punishment and the degree of social harm due to any offence are not identical. Certain crimes may receive comparatively severe statutory punishments because of constitutional values, public morality, historical developments, or legislative priorities rather than solely because they generate serious social harm. No single indicator can perfectly represent every dimension of crime severity. Legally prescribed punishment remains one of the most transparent, objective, and consistently available measures of the seriousness of an offence, making it widely used in official crime severity indices and comparative criminological research (Wolfgang, 1985; Statistics Canada, 2009). Accordingly, the present study operationalises severity as legally recognised seriousness rather than as a direct measure of social harm.

Although sentencing provisions are influenced by legal, historical, and policy considerations, they also represent the collective legislative assessment of the relative severity of offences within the criminal justice system. This serves only as an operational proxy for the seriousness of legally recognised crimes and is used exclusively for weighting purposes within the CSI. Since life imprisonment lacks a fixed numerical duration, an operational value is required for index construction. Rather than estimating the actual period served by offenders, the assigned value is intended solely to preserve the relative legal seriousness of such crimes within the weighting framework. This approach follows the principle of using standardised legal severity measures for quantitative crime indices and should not be interpreted as representing the actual duration of incarceration. According to the different IPC Acts, the maximum term of imprisonment is shown in Tab. 2.

Sl. No.	Type of Criminal Activity	Under Section (IPC Act.)	Years of Imprisonment		Maximum Custody (Years)
			Min	Max	
1.	Murder	302; 307; 354	2	Life Time	27*
2.	Crime against Women	376; 511	10		
3.	Offense against Property	379; 392; 393; 394; 397; 398; 380	3	14	14
4.	Causing Death by Negligence	304A; 304 Part II	2	10	10
5.	Offense against Documents	420; 465; 468-471	7	7	7
6.	Miscellaneous Indian Penal Code Crimes	279; 498A	0.5	3	3
7.	Simple Hurt or Grievous Hurt	337; 338	0.5	2	2
Total Possible Tenure of Custody (Years)					**63**

Tab. 2. Selected Crimes and their Respective Maximum Years of Imprisonment
Source: The Indian Penal Code, GoI (Click here for the List of Sections & IPC Acts.)
*Note: Under the Indian Penal Code, life imprisonment legally denotes imprisonment for the remainder of the convict's natural life unless modified through remission or executive clemency. There is no universally accepted unique numerical equivalent for empirical index construction; 27 years is assumed as the baseline operational value for index construction. The sensitivity of this operational assumption is subsequently evaluated through a robustness analysis reported in the Supplementary Materials.

The relative severity level of each crime is calculated using the formula,

$$SL_{c_i} = \frac{Years_{c_i}^{Max\ Custody}}{\sum_{i=1}^{7} Years_{c_i}^{Max\ Custody}} \quad \text{.......} (2)$$

Where, SLc_i = Severity level of the i^{th} crime, $Years^{Max\ Custody}$ denotes the maximum years of imprisonment for the i^{th} crime, which is an overall of 63 years. This will make the severity of crime relative across the selected crimes, where $\Sigma SLc_i = 1$. The relative severity and relative frequency of crimes happened are shown in Tab. 3.

Sl. No.	Type of Criminal Activity	Relative Severity Level (SL_{c_i})	Relative Frequency of Crime (%) (F_{c_i})
1.	Murder	0.429	10.13
2.	Crime against Women	0.429	1.40
3.	Offense against Property	0.222	6.98
4.	Causing Death by Negligence	0.159	3.50
5.	Offense against Documents	0.111	13.50
6.	Miscellaneous Indian Penal Code Crimes	0.048	47.21
7.	Hurt	0.032	17.27

Tab. 3. Relative severity level of crimes and their relative frequency of occurrence
Source: Author's calculation

The rest of the weight estimation technique is shown in Appendix A. The final distribution of standardised weights across the crimes is shown in Fig. 1.

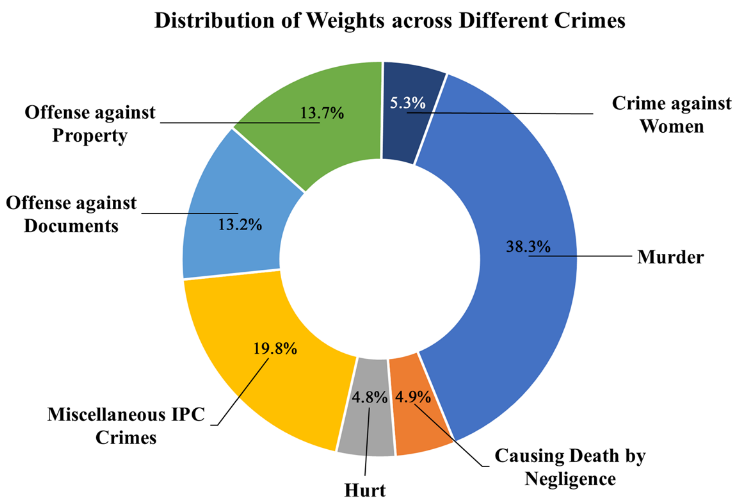

Fig. 1. Final Standardised Weights Distribution across Crimes
Source: Author's estimation based on the mentioned data sources

The construction of the final CSI follows the aggregation step. Taking the sum of normalised crime scores (equation 1) assigned with their respective weightage, i.e. $W'c_i$ (equation 7 in Appendix A), leads to the final district-level CSI scores. The aggregation process follows the equation (3),

$$\boldsymbol{CSI_{jt}} = \sum_{i=1}^{7}(\boldsymbol{C'_{ijt}} \times \boldsymbol{W'_{c_i}}) \qquad \ldots\ldots (3)$$

Where, C'_{ij} = Normalised score for the i^{th} crime indicator for j^{th} the district in t^{th} the year.

$W'c_i$ = Estimated weights for the i^{th} crime.

Composite indices used in public policy frequently aggregate heterogeneous indicators that represent complementary rather than interchangeable dimensions of a broader phenomenon. The Human Development Index, Multidimensional Poverty Index, and Environmental Performance Index, where conceptually different components are combined to summarise overall conditions rather than measuring a single latent behavioural criterion. Following these methods, the present study treats different categories of crime as complementary contributors to the overall severity of a district's crime profile, rather than assuming that all crimes originate from identical social processes or exhibit strong statistical interdependence. Different crimes, such as murder, property crime, negligence, fraud, and assault, are intentionally retained because each represents a different aspect of the legally recorded crime environment. The objective is to summarise the overall seriousness of district-level criminal activity rather than to identify a single homogeneous behavioural dimension. Therefore, conventional measures such as Cronbach's alpha (Cronbach, 1951) or factor analysis are not considered for the proposed CSI because they assume that indicators are interchangeable measures of the same latent construct, whereas the selected crime categories are complementary components of a multidimensional crime profile. A sensitivity of the CSI is evaluated through a robustness check of alternative life-imprisonment assumptions. The sensitivity analysis can be found in section D of the supplementary file.

In this study, we have examined the impact of several socioeconomic determinants, including the male labour force participation rate (MLFPR), urbanisation rate (URB), female education level (FGRAD), per capita gross district domestic product (PCGDDP), and the population-to-police-station ratio (PSPOP).

4.2. METHODOLOGY FOR SPATIAL ANALYSIS

To identify the existence of spatial interdependency in the dependent variable (Crime Rate and CSI), we use the Global Moran's I (GMI) statistics for the selected years. Following L. Anselin's (1988, 1995) methodology, the GMI coefficient can be calculated using equation (4),

$$\boldsymbol{I} = \frac{\boldsymbol{n}}{\boldsymbol{W}} \cdot \frac{\sum_{i=1}^{n}\sum_{j=1}^{n} \boldsymbol{w_{ij}}\,(\boldsymbol{x_i} - \bar{\boldsymbol{x}})(\boldsymbol{x_j} - \bar{\boldsymbol{x}})}{\sum_{i=1}^{n}(\boldsymbol{x_i} - \bar{\boldsymbol{x}})^2} \qquad \ldots\ldots (4)$$

Where n is the number of spatial units (districts), $W = \Sigma_i\Sigma_j w_{ij}$ is the sum of spatial weights, w_{ij} shows the matrix of row standardised spatial weights. x_i and x_j are the values of the variable for i^{th} and j^{th} region, respectively, $\bar{x}$ represent the mean of the variable. The value of Moran's I coefficient lies between (-1) and (+1), where 0 indicates no spatial interdependency, (-1) indicates perfect heterogeneity, and (+1) suggests a perfect spatial correlation. A first-order row-standardised Rook's contiguity method was used to construct the neighbourhood spatial weight matrix (Anselin, 1988; LeSage & Pace, 2009), in which two districts are considered neighbours only when they share a common administrative boundary. Rook contiguity was selected because district-level socio-economic interactions, policing administration, and routine movement of people commonly occur across directly adjoining districts (Kim & Jeong, 2026). Since the study examines administrative districts rather than small geographical units, restricting neighbourhood relationships to shared borders provides a simple and transparent representation of any spatial interaction. Queen's contiguity would also be used, but it includes districts connected at a single corner, which may overstate neighbourhood interaction in this administrative setup. Distance-based weights were not adopted because several districts differ considerably in geographical size and shape, making distance thresholds less comparable across the study area.

The *Z-score* of GMI indicates the degree of spatial correlation: a high positive *Z-score* represents a cluster of similar values, whereas a negative *Z-score* indicates spatial dissimilarities. A perfect zero score suggests no geographical autocorrelation is present. We performed two spatial panel regression models expressed in equations 5 and 6. The Spatial Panel Autoregressive Model (SPAM) estimates the impacts of crimes in neighbouring districts using a spatially lagged dependent variable, whereas the Spatial Panel Error Model (SPEM) captures spatial dependence arising from unobserved regional characteristics that are represented in the error term (Getis, 2010).

SPAM:

$$\boldsymbol{y_{jt}} = \boldsymbol{\rho} \sum_{\boldsymbol{j=1}}^{\boldsymbol{N}} \boldsymbol{W_{ji} y_{jt}} + \boldsymbol{X_{jt} \beta} + \boldsymbol{\mu_j} + \boldsymbol{\varepsilon_{jt}}\ ;\ j = 1, 2, \dots, N;\ t = 1, 2, \dots, T \qquad \dots\dots (5)$$

and,

SPEM:

$$\boldsymbol{y_{jt}} = \boldsymbol{X_{jt} \beta} + \boldsymbol{\mu_j} + \boldsymbol{\varphi_{jt}},$$

$$\text{where, } \boldsymbol{\varphi_{jt}} = \boldsymbol{\lambda} \textstyle\sum_{\boldsymbol{j=1}}^{\boldsymbol{n}} \boldsymbol{W_{ji} \varphi_{it}} + \boldsymbol{\varepsilon_{jt}} \qquad \dots\dots (6)$$

Where in equation (5), $W_{ji}y_{jt}$ is the spatially lagged dependent variable vector for all units at time t; X_{jt} shows (1 x K) the matrix of independent variables at time t; β stands for (K x 1) parameters; μ_i is the individual region-specific effect, which is random in spatial models with zero mean and constant variance i.i.d$(0, \sigma^2)$; and, ε_{jt}; indicates the vector of idiosyncratic error terms at time t. And for equation (6), λ is the spatial error coefficient of the error term; φ_{jt} the spatially correlated error term at time t, which is not captured in the SPAM.

4.3. DATA SOURCES

This research is based on secondary data available in publicly accessible repositories. The district-level crime data are collected from the NCRB, Government of India. Explanatory variable data on education, employment, and police stations are estimated from several Primary Census Abstracts (2001 and 2011), District Reports, and various NSSO Survey Rounds (55th, 61st, 66th, 73rd & 78th Rounds). Our dataset comprises a pseudo-panel structure with five observation years (2000, 2005, 2010, 2015, and 2020). These years were selected because comparable socio-economic information is not consistently available.

During this selected period, the administrative structure of West Bengal underwent several reorganisations, with the number of districts increasing from 18 to 23 because of the creation of new districts through bifurcation. Since this study aims to examine the spatio-temporal dynamics of crime using balanced spatial panel models, a consistent geographical framework was maintained throughout the analysis. Newly created districts were therefore harmonised with their respective parent districts for all time periods to preserve a balanced panel structure and a constant spatial weights matrix. Specifically, Kalimpong was merged with Darjeeling; Jhargram with Paschim Medinipur; and Purba Bardhaman and Paschim Bardhaman with the undivided Bardhaman district, while Alipurduar was merged with Jalpaiguri for longitudinal analysis. Similarly, where crime statistics were reported separately for Police Commissionerates, Government Railway Police (GRP), Rural Police, or Police Districts, these administrative units were aggregated into their corresponding parent districts, following the prevailing administrative jurisdiction for each period. This harmonisation avoids an unbalanced spatial panel and ensures that spatial neighbourhood relationships remain comparable across all five time points. The geographical harmonisation strategy follows the standard principle of maintaining consistent spatial units in longitudinal regional analysis (Dey et al., 2024). This technique also reduces inconsistencies arising from administrative boundary changes during the study period. Since all observations are expressed using a common historical district framework, comparisons across time refer to identical spatial units. This approach cannot entirely eliminate the Modifiable Areal Unit Problem (MAUP), an inherent limitation of longitudinal regional studies that use administrative boundaries. The findings should therefore be interpreted within the harmonised district framework adopted in this study. Since Census information is available only at decennial intervals (2001 and 2011), the explanatory variables for 2005 were estimated using exponential interpolation.. Crime variables were obtained directly from the NCRB and were not interpolated.

5. RESULTS AND DISCUSSION

The summary statistics in Tab. 4 reveal a considerable variation in crimes and other socio-economic factors in West Bengal. The crime rate is widespread, indicating significant differences in crime levels across districts. The CSI also varies notably, with a minimum of 0.089 and a maximum of 5.482, reflecting the diversity in crime severity across districts.

Socio-economic variables exhibit substantial disparities as well. The maximum and minimum values of the URB suggest differing levels of urban development among districts. Similarly, the MLFPR and FGRAD also vary. Income levels, as measured by PCGDP, also exhibit wide variation, signalling inequality across districts. The police stations per 1 lakh population (PSPOP) indicate an uneven distribution of police infrastructure, which can affect law enforcement capacity. Our topic of interest is how these variations may impact criminal activities in West Bengal.

Variable (Notation)	Obs.	Mean	SD	Min	Max
Crime Rate (CR)	95	143.99	94.506	31.314	558.55
Crime Severity Index (CSI)	95	1.619	1.176	0.089	5.482
Urbanization Rate (URB)	95	36.126	27.068	7.322	100.00
Male Labour Force Participation Rate (MLFPR)	95	81.534	8.968	53.268	95.660
21+ Age Female Graduate (FGRAD)	95	11.494	7.390	0.580	36.306
Per Capita Gross District Domestic Product (PCGDDP)	95	49,479	36,118	7,774	1,80,026
Police Stations Per 1 Lakh Population (PSPOP)	95	0.623	0.358	0.281	1.979

Tab. 4. Descriptive Statistics of Crime and Selected Explanatory Variables
Source: Author's calculation

5.1. DISTRICT-WISE CRIME RATE AND SEVERITY INDEX SCORES

Tab. 5 shows substantial variation in both Crime Rate and CSI across districts.

Districts	Crime Rate	Rank	Crime Severity Index	Rank
Bankura	61.93	20	0.743	20
Bardhaman	115.57	14	1.120	16
Birbhum	82.45	18	1.348	13
Cooch Behar	117.62	12	1.478	12
Dakshin Dinajpur	115.68	13	1.667	10
Darjeeling	246.32	2	2.513	3
Hooghly	99.04	15	0.907	17
Howrah	188.80	3	1.716	9
Jalpaiguri	143.72	10	1.735	8
Kolkata	394.25	1	2.837	2
Maldah	124.40	11	2.222	4
Murshidabad	149.53	8	2.877	1
Nadia	153.68	7	1.764	7
North 24 Parganas	175.37	4	1.860	6
Paschim Medinipur	88.45	16	1.121	15
Purba Medinipur	87.53	17	0.848	18
Puruliya	68.65	19	0.769	19
South 24 Parganas	168.08	5	1.203	14
Uttar Dinajpur	154.91	6	2.038	5
Spearman's Rank Correlation Coefficient				**0.794**

Tab. 5. District-Specific Average Crime Rate and Crime Severity Index Score
Source: Author's calculation

Kolkata records the highest average crime rate, followed by Darjeeling and Howrah, whereas Murshidabad has the highest CSI despite not having the highest crime rate. Districts with similar crime rates may have substantially different CSI values if their crime profiles differ in composition. For example, districts like Howrah, North and South 24 Parganas have a high crime rate but a comparatively low severity level, while Murshidabad and Maldah districts have a low crime rate with a higher level of severe crimes. A basic panel regression model and a district-specific Least Squares Dummy Variable regression model are observed, available in the Supplementary Materials (sections A and B, respectively).

5.4. SPATIAL AUTOCORRELATION: GLOBAL MORAN'S I

Tab. 6 shows that both the crime rate and crime severity exhibit positive spatial correlation across time points, suggesting that crimes are correlated in space and time within the state.

Dep. Variable	Crime Rate			Crime Severity Index		
Year	GMI	*Z score*	*p-value*	GMI	*Z score*	*p-value*
2000	0.109***	1.764	0.078	0.070	1.124	0.261
2005	0.223*	2.363	0.018	0.266*	2.275	0.023
2010	0.310**	2.648	0.008	0.189***	1.441	0.076
2015	0.262*	2.346	0.019	0.072	0.891	0.373
2020	0.187***	1.764	0.078	0.420**	3.202	0.001

Tab. 6. Global Moran's I score of Crime Rate and Crime Severity Index
Source: Authors' estimation.
Significance parentheses: *p < 0.05; **p<0.01; ***p<0.10

To identify districts with high (low) crime, the LISA cluster maps are used, as shown in Fig. 2. LISA maps of the explanatory variables are shown in Fig. 3.

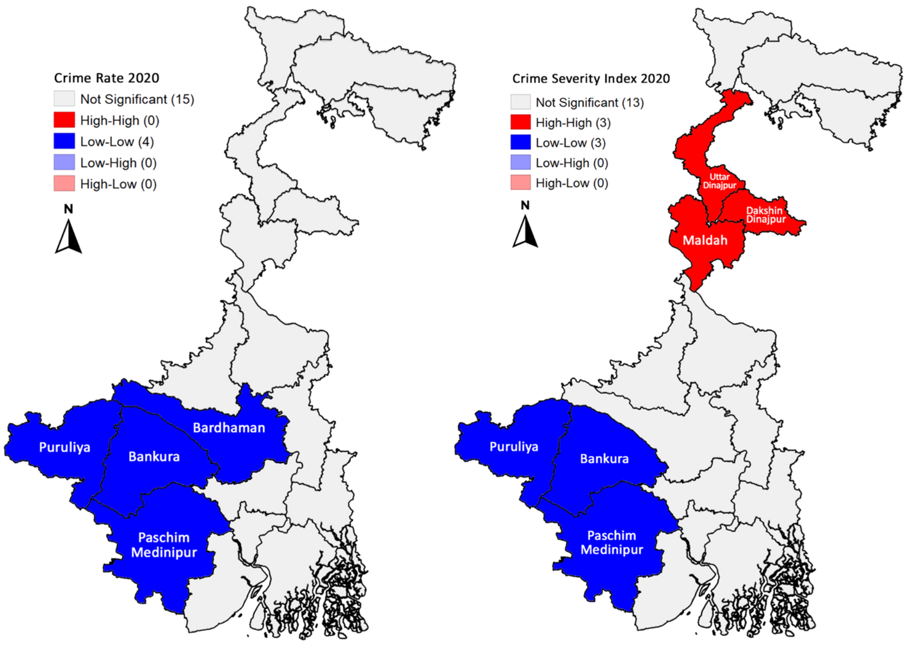

Fig. 2. LISA Cluster Map of Crime Rate and Severity Index 2020
Source: Author's creation using GeoDa
Note: District boundaries have been harmonised to maintain a consistent spatial framework over 2000–2020.

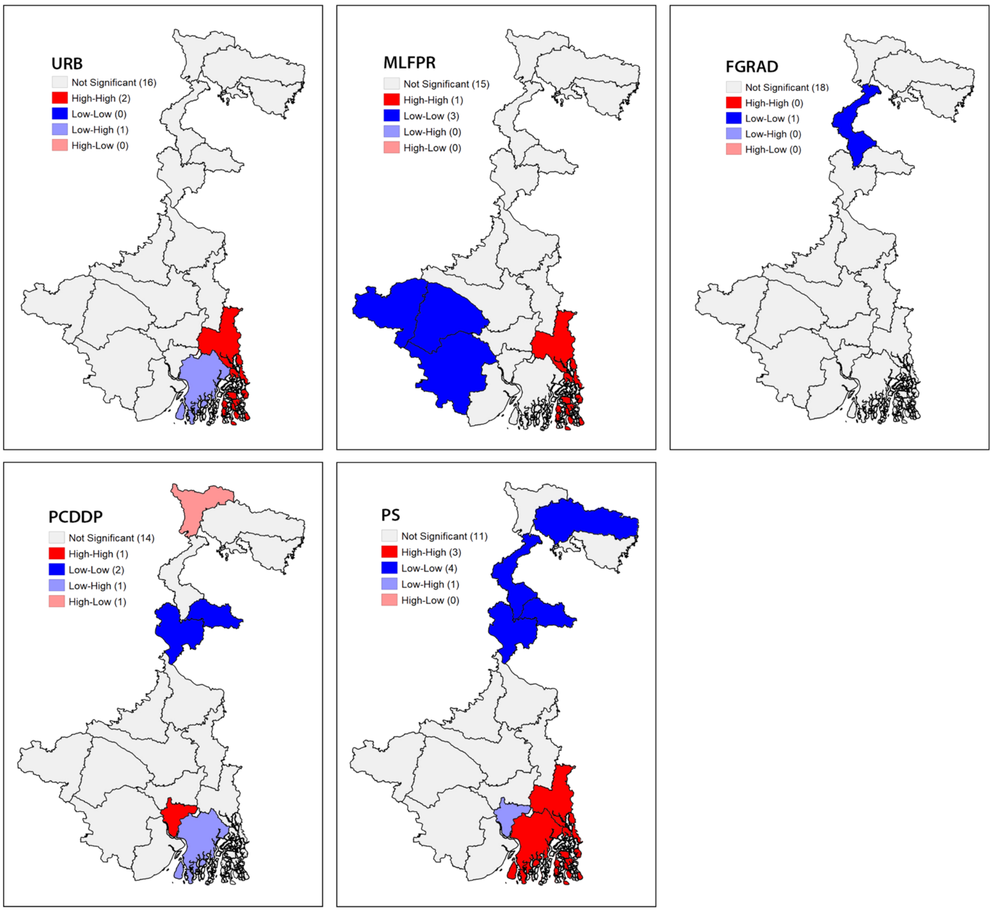

Fig. 3. LISA Cluster maps of Selected Explanatory Variables in 2020
Source: Author's creation using GeoDa
Note: District boundaries have been harmonised to maintain a consistent spatial framework over 2000–2020.

5.5. SPATIAL PANEL REGRESSION ANALYSIS: SPAM AND SPEM

The Moran's I statistics and LISA maps indicate the presence of spatial interdependence in crime; however, to identify the determinants of crime and its severity across space, this study has used two spatial panel regression models – SPAM and SPEM. The Rho (ρ) and Lambda (λ) coefficients of SPAM and SPEM, respectively, indicate the degree of spatial interdependency. From the results in Tab. 7, we found that the Rho coefficients (0.191) and (0.155) are statistically significant. The significant rho coefficient indicates that changes in the dependent variable in one area spill over to its neighbourhoods. According to the results, an increase in URB in one district influences crime incidents not only in that region but also in neighbouring districts, possibly because high population density creates opportunities for more severe criminal activity. The inverted-U-shaped relationship between the MLFPR and crime rate suggests that more stable working opportunities for males can reduce the crime rate within the state.

Dep. Var	Crime Rate		Crime Severity Index	
Exp. Var	SPAM	SPEM	SPAM	SPEM
lnURB	0.119	**0.118*** **	**0.214*** **	**0.224*** **
	(1.58)	(1.68)	(1.87)	(1.87)
lnMLFPR	**62.273** **	**72.827** **	47.559	52.872
	(4.62)	(4.62)	(1.55)	(1.60)
$(\text{lnMLFPR})^2$	**-7.516** **	**-8.824** **	-5.792	**-6.469*** **
	(-4.68)	(-4.69)	(-1.60)	(-1.66)
lnFGRAD	-0.531	**0.053*** **	**0.133* **	**0.140* **
	(1.45)	(1.78)	(2.39)	(2.38)
lnPCGDDP	1.534	**2.037*** **	-0.557	-0.558
	(1.54)	(1.81)	(-0.51)	(-0.55)
$(\text{lnPCGDDP})^2$	-0.068	**-0.090*** **	0.042	0.046
	(-1.44)	(-1.69)	(0.81)	(0.97)
lnPSPOP	**-0.613* **	-0.474	**-1.436** **	**-1.335** **
	(-2.05)	(-1.56)	(-3.73)	(-3.18)
Rho (ρ)	**0.191* **	-	**0.155*** **	-
	(2.26)		(1.80)	
Sigma (σ)	**0.038** **	**0.039** **	**0.076** **	**0.078** **
	(6.36)	(6.38)	(5.11)	(5.24)
Lambda (λ)	-	0.001	-	-0.031
		(0.01)		(-0.24)
AIC	*-23.056*	*-20.303*	*43.186*	*44.882*
BIC	*-0.0719*	*2.681*	*66.171*	*67.866*
Log-likelihood	*20.528*	*19.151*	*-12.593*	*-13.441*
N	*95*	*95*	*95*	*95*

Tab. 7. Spatial Regression Result of Crime Rate and Crime Severity Index
Source: Authors' estimation.
Significance parentheses: *p < 0.05; **p<0.01; ***p<0.10
Note: The SPAM specification reports lower AIC and BIC values with higher log-likelihood values than the corresponding SPEM specification, indicating a comparatively better model fit.

A positive association is observed between FGRAD and recorded crimes and their severity across districts, which again suggests that improvements in female education strengthen awareness of legal rights to report cases and increase access to the criminal justice system. An increasing number of police stations can significantly reduce crime in severely affected districts like the Maldah and Dinajpur regions. Hotspots of violence, crime-severe zones, and the explanatory variables in the latest year (2020) are shown in Fig. 4.

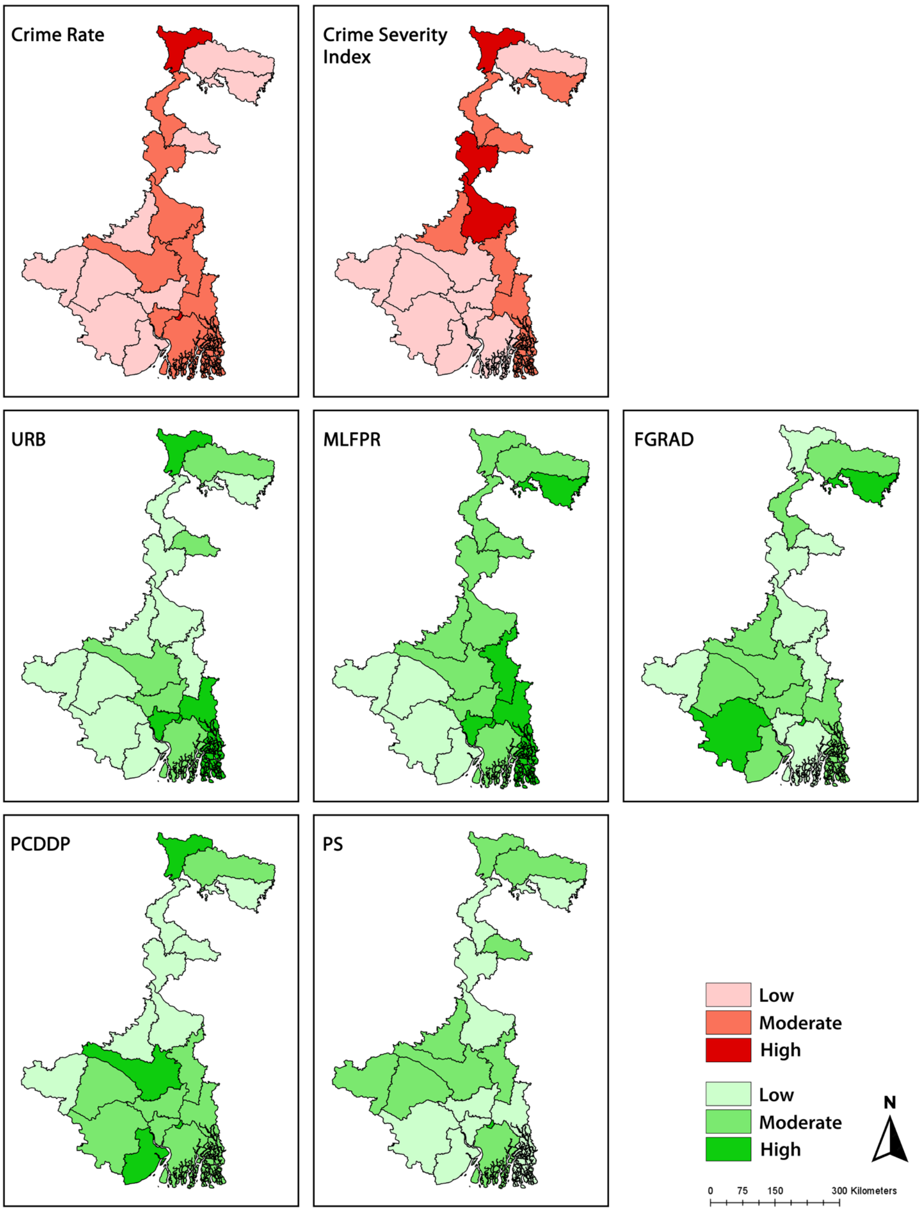

Fig. 4. Hotspots of Crimes, Severity, and Explanatory Variables in West Bengal, 2020
Source: All the maps are drawn by the author.
Note: District boundaries have been harmonised to maintain a consistent spatial framework over 2000–2020.

6. CONCLUSIONS

The crime rate in West Bengal has increased over the years, but the pattern of crimes has shifted drastically towards more severe crimes like murder, rape, and assault on women. It has been observed that the crime pattern in the state is shaped by its economic structure, cultural diversity, and geographic position. The spatial analysis suggests that determinants such as urbanisation, male labour force participation, and female educational attainment have noticeable spillover effects on nearby districts. An increasing urban population is associated with higher concentrations of serious crime, while unobserved factors also contribute to this spatial association (Gupta, 2020). Regional disparities in employment opportunities lead to more illegal activity and greater severity. The findings suggest that districts with high male employment rates may initially experience higher crime levels due to increased economic activity, but as labour markets stabilise with greater workforce participation, crime rate and its severity may fall. Female education level, which serves as a proxy for awareness and women's empowerment, shows a positive correlation with reported crime rates, suggesting that higher female educational attainment may be associated with higher rates of crime reported within the state (Biswas et al., 2022; Roy & Chowdhury, 2023; Pandit & Halder, 2023). The number of police stations is also negatively associated with crime severity, especially in border districts such as Maldah and Uttar Dinajpur.

However, the localised impact of human capital improvements on crime rates indicates a complex, interconnected crime landscape shaped by regional socioeconomic structures. Notably, the developed CSI should not be interpreted as a substitute for the Crime Rate. Rather, the two measures provide complementary information. While the Crime Rate quantifies the frequency of recorded crimes per 1 lakh population, the CSI measures the seriousness of the overall regional crime profile.

7. POLICY IMPLICATIONS

The Government of India has taken several initiatives in the past decade to prevent criminal offences in the country. The Criminal Law (Amendment) Acts of 2013 and 2018 modified the punishments for sexual offences and expedited the investigation process. Major cities, including Kolkata in West Bengal, have launched Safe City Projects to enhance urban safety by increasing police presence, improving street lighting, and enhancing monitoring. The West Bengal government has increased police recruitment and improved police infrastructure in the last few years to address local safety challenges. Acknowledging the initiatives undertaken by the central and state governments to prevent crimes, we propose a few policies supported by our findings:

1. Strengthening border security: Districts with high crime severity, particularly Murshidabad, Maldah, and Uttar Dinajpur, require stronger border surveillance.

2. Targeted police resources by crime severity: Police infrastructure and protection should be prioritised in high-severity districts. Lower-crime districts can focus on policing and community engagement.

3. Adopt urban-specific crime prevention: Highly urbanised districts such as Kolkata and Howrah may benefit from stronger urban policing, surveillance systems, and social awareness programs.

4. Promoting education and employment: Expanding female education and stable employment opportunities, particularly in high-crime districts, may help in reducing criminal activities.

8. LIMITATIONS OF THE STUDY

This study has a few limitations that should be considered while interpreting the findings. First, the analysis is based on officially recorded crimes reported by the NCRB. These data may not fully capture unreported crimes or differences in reporting behaviour across districts. Second, the CSI measures the legally recognised seriousness of offences using statutory punishment as an operational weighting technique. This approach provides an objective and transparent basis for comparison, but it does not capture every dimension of social harm, victim suffering, or public perception of crime. Third, the analysis is based on harmonising district boundaries to maintain a balanced spatial panel over time. The study focuses on district-level socio-economic determinants of crime and does not explicitly account for border-specific criminal activities or other institutional factors due to the unavailability of district-level data. Future research using more detailed spatial and administrative data may provide different interpretations for these aspects of regional crime dynamics in West Bengal.

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APPENDIX A

Estimation technique of the weights:

The relative frequency of each crime is calculated using the following equation,

$$\boldsymbol{F_{c_i}} = \frac{\boldsymbol{c_i}}{\sum_{i=1}^{7} \boldsymbol{c_i}} \qquad \ldots\ldots (7)$$

$\boldsymbol{F_{c_i}}$= Relative frequency of $\boldsymbol{i^{th}}$ crime

The final weights are measured by multiplying equation (2) in the main body by the above equation (7), i.e.,

$$\boldsymbol{W_{c_i}} = \left(\boldsymbol{SL_{c_i}} * \boldsymbol{F_{c_i}}\right) \qquad \ldots\ldots (8)$$

The final weights *($\boldsymbol{W'_{c_i}}$)* are normalised to range between 0 to 10 levels of severity, using the following formula,

$$\boldsymbol{W'_{c_i}} = \left[\left(\frac{\boldsymbol{W_{c_i}}}{\sum_{i=1}^{7} \boldsymbol{W_{c_i}}}\right) \times \mathbf{10}\right] \qquad \ldots\ldots (9)$$