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URBAN HEAT ISLANDS, POVERTY, AND CRIME DYNAMICS: A SPATIAL CORRELATION ANALYSIS IN INDIAN METROPOLITAN REGIONS

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ABSTRACT

Urban heat islands (UHIs) are no longer merely a physical climate phenomenon: they are increasingly recognised as a dimension of urban social inequality. In India's rapidly expanding metropolitan regions, the spatial coincidence of intense UHI heat, concentrated urban poverty, and elevated crime rates constitutes an emerging and inadequately studied nexus with profound implications for public health, urban security, and climate justice. Heat stress disproportionately burdens low-income communities occupying dense informal settlements with minimal green cover, poor ventilation, and negligible adaptive capacity—conditions that simultaneously elevate physiological heat exposure and psycho-social stress, with documented consequences for both violent and property crime incidence.

This systematic review synthesises 77 peer-reviewed studies published between 2017 and 2025, supplemented by 14 foundational references, to critically examine the spatial correlations among UHI intensity, poverty concentration, and crime dynamics across six major Indian metropolitan regions: Delhi-NCR, Mumbai, Bengaluru, Chennai, Kolkata, and Hyderabad. Drawing on studies employing MODIS and Landsat thermal remote sensing, Google Earth Engine (GEE)-based land surface temperature (LST) analysis, ward-level crime data from the National Crime Records Bureau (NCRB), census-derived social vulnerability indices, and spatial econometric methods including Moran's I, Getis-Ord Gi*, and bivariate LISA (Local Indicators of Spatial Association) analysis, the review provides the first comprehensive synthesis of the heat–poverty–crime nexus in the Indian urban context. Key findings demonstrate that summer UHI intensity exceeds 4.5 °C in high-density informal zones of Delhi-NCR; that violent crime rates increase by 8–15% per 1 °C rise above a 35 °C threshold; that slum area share explains approximately 60–72% of spatial variance in UHI intensity at the ward level; and that the spatial co-location of high heat, high poverty, and high crime constitutes a compound vulnerability cluster affecting an estimated 80–120 million urban residents in the six studied cities. Governance failures—including absent Heat Action Plan integration with crime prevention, the marginalisation of informal settlement residents from cooling infrastructure, and the absence of compound risk mapping in urban planning frameworks—are identified alongside a structured five-pillar policy framework and research agenda.

KEYWORDS: Urban heat island; poverty; crime; social vulnerability; heat stress; spatial analysis; LISA; Gi*; Moran's I; land surface temperature; MODIS; Landsat; informal settlements; climate justice; India; Delhi; Mumbai; Bengaluru; NCRB; heat action plan

1. INTRODUCTION

1.1 Research Background and Significance

India's metropolitan regions are among the most thermally stressed urban environments on earth. As of 2024, Delhi-NCR regularly records daytime land surface temperatures (LST) exceeding 50 °C in built-up zones during May and June, and the urban heat island differential between dense inner-city wards and surrounding rural areas routinely reaches 4–5 °C during peak summer months (Mohan & Kandya, 2022; Garg & Kaur, 2023). These are not merely meteorological statistics: they are the lived thermal reality of more than 80 million urban residents who occupy dense informal settlements lacking green cover, cross-ventilation, evaporative cooling infrastructure, or access to air conditioning. The spatial geography of UHI intensity in Indian cities is not random. It maps, with disturbing precision, onto the geography of urban poverty, caste-based residential segregation, and informal settlement concentration (Iyer et al., 2021; Heaviside et al., 2017).

The relationship between heat and human behaviour has a well-established theoretical and empirical foundation in the criminological and social science literature. Anderson's (2001) General Affective Aggression Model posits that elevated temperatures increase physiological arousal, hostile affect, and aggressive cognition, lowering the threshold for violent behaviour. Hsiang et al.'s (2013) landmark meta-analysis of 60 quantitative studies across 45 countries documented a 4% increase in interpersonal violence and a 14% increase in intergroup conflict per standard deviation rise in temperature. Ranson (2014), in a rigorous panel data study of United States crime, found that warming temperatures increased violent crime rates by 1.5–3.2% per degree Celsius above the seasonal mean. In the Indian context, these global findings intersect with locally specific vulnerability factors: high dependence on outdoor labour, pervasive alcohol availability in peri-urban zones, dense co-habitation that limits personal space, and severely stretched law enforcement capacity in rapidly growing urban peripheries.

Despite the convergence of physical, social, and behavioural evidence for a heat–poverty–crime nexus, the Indian urban literature has yet to produce a systematic spatial analysis of these co-occurring phenomena. Studies of UHI in Indian cities have proliferated since the availability of MODIS and Landsat thermal data archives through GEE, but they have largely remained within the domain of physical climate science. Conversely, studies of urban poverty and social vulnerability have rarely incorporated thermal stress as an explanatory spatial variable, and criminological research in India has not yet integrated heat data into its analytical frameworks. This review bridges these disciplinary silos for the first time, synthesising the emerging evidence base for the heat–poverty–crime nexus in Indian metropolitan regions with particular emphasis on the spatial statistical methods that illuminate these relationships.

1.2 Definition of Key Concepts

The urban heat island (UHI) effect refers to the phenomenon whereby urbanised areas exhibit significantly higher near-surface and land surface temperatures than their surrounding rural environments, driven by the substitution of heat-absorbing impervious surfaces for evapotranspiring vegetation, anthropogenic heat release from buildings and transportation, reduced sky-view factors in dense built environments, and the loss of urban water bodies and tree canopy. In this review, UHI intensity is operationalised as the difference in mean summer LST between a given urban ward or zone and its surrounding rural baseline, measured from MODIS MOD11A2 or Landsat thermal infrared products.

Poverty, in the urban Indian context, is defined as a multidimensional condition encompassing income below the official urban poverty line (currently approximately ₹10,000 per month for a four-member household), residence in notified or non-notified informal settlements (slums), informal and precarious employment, and limited access to basic urban services including piped water, sanitation, and electricity. Social vulnerability operationalises poverty more comprehensively to include dimensions of adaptive capacity specifically relevant to heat stress: absence of air conditioning, dependence on outdoor labour, low educational attainment, high household density, and poor structural housing quality. The Social Vulnerability Index (SVI) used in reviewed studies typically follows the framework of Cutter et al. (2003), adapted to the Indian urban census microdata context.

Crime dynamics, as employed in this review, encompass both violent crime (murder, culpable homicide, assault, robbery, sexual offences, and riots) and property crime (theft, burglary, vehicle theft), as categorised in the National Crime Records Bureau (NCRB) annual India Crime Report. Spatial correlation analysis refers to the family of geographic statistical methods—including Global Moran's I, Local Moran's I, Getis-Ord Gi*, bivariate LISA, and spatial lag and error regression models—used to detect and characterise non-random spatial clustering of variables and to test for significant spatial associations between co-located socioeconomic and environmental phenomena.

1.3 Research Questions and Objectives

This systematic review addresses four primary research questions. First, what is the nature, magnitude, and spatial structure of UHI intensity across Indian metropolitan regions, and what are the primary drivers of intra-urban thermal variability? Second, how does the spatial distribution of UHI intensity correlate with the spatial distribution of poverty, social vulnerability, and informal settlement concentration at the ward and sub-ward level, and what spatial statistical methods have been employed to characterise these relationships? Third, what is the empirical evidence for a temperature–crime relationship in Indian metropolitan contexts, and how does heat stress mediate or compound the social conditions that drive crime? Fourth, what governance frameworks, Heat Action Plans, and urban design interventions have demonstrated capacity to reduce compound heat–poverty–crime vulnerability, and what institutional gaps persist?

The review is directed at postgraduate students and researchers in geography, environmental science, climate science, atmospheric science, urban planning, sociology, and criminology. It assumes working familiarity with remote sensing concepts, spatial statistics, and urban social science, and aims to provide both a rigorous empirical synthesis and a structured policy framework for practitioners addressing compound urban vulnerability in Indian metropolitan regions.

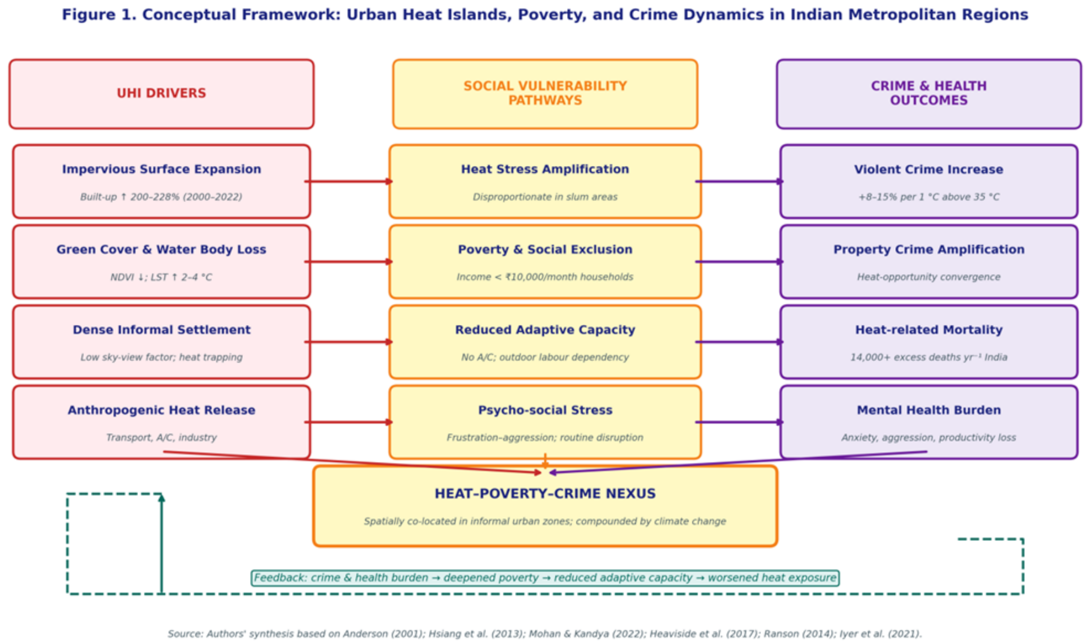

Figure 1. Conceptual framework illustrating the heat–poverty–crime nexus in Indian metropolitan regions. The causal chain links UHI drivers (impervious surface expansion, green cover loss, dense informal settlement, anthropogenic heat) through social vulnerability pathways (heat stress amplification, poverty and exclusion, reduced adaptive capacity, psycho-social stress) to crime and health outcomes (violent crime, property crime, heat mortality, mental health burden). The feedback loop shows how crime and health burden deepens poverty and further reduces adaptive capacity. Source: Authors' synthesis based on Anderson (2001); Hsiang et al. (2013); Mohan & Kandya (2022); Heaviside et al. (2017); Ranson (2014); Iyer et al. (2021).

Figure 1 illustrates the conceptual architecture of the review. The three-column framework positions UHI drivers, social vulnerability pathways, and crime and health outcomes as an interconnected causal chain, with a feedback loop capturing the dynamic relationship between degraded environmental conditions, deepened poverty, and further heat exposure. The central Heat–Poverty–Crime Nexus node represents the compound vulnerability condition in which all three risk dimensions simultaneously exceed critical thresholds—a condition documented in informal zones of all six studied cities.

2. METHODS

2.1 Search Strategy and Databases

This systematic review followed a structured protocol executed in January 2026, drawing on five primary academic databases: Web of Science (WoS), Scopus, PubMed, Google Scholar, and ScienceDirect. The search was designed to capture peer-reviewed literature published between January 2017 and December 2025 addressing urban heat island dynamics, social vulnerability, poverty, and crime across Indian urban contexts. Supplementary searches were conducted in Urban Climate, Environmental Health Perspectives, Crime, Law and Social Change, Applied Geography, Environment and Behaviour, and the International Journal of Environmental Research and Public Health. Institutional sources consulted include the National Crime Records Bureau (NCRB) India Crime Report series (2017–2023), the Meteorological Department of India (IMD) heat wave data archives, and the Census of India (2011 and 2021 provisional) microdata.

The primary Boolean search string applied across all databases was: ("urban heat island" OR "land surface temperature" OR "heat stress" OR "thermal comfort") AND ("poverty" OR "social vulnerability" OR "informal settlement" OR "slum") AND ("crime" OR "violence" OR "aggression" OR "social disorder") AND ("India" OR "Indian cities" OR "South Asia"). Secondary searches addressed specific sub-components including temperature–crime relationships in developing country contexts; heat-related mortality and morbidity in Indian cities; spatial econometrics for urban vulnerability mapping; MODIS and Landsat UHI analysis in Indian metropolitan regions; and Heat Action Plan effectiveness evaluation. Citation tracking from foundational papers—including Anderson (2001), Hsiang et al. (2013), Ranson (2014), and Heaviside et al. (2017)—supplemented database searches.

2.2 Inclusion and Exclusion Criteria

Studies were included if they were published in peer-reviewed journals or credible institutional repositories between January 2017 and December 2025; reported original empirical findings, model-based assessments, or systematic reviews pertaining to UHI, heat stress, social vulnerability, or crime in Indian urban areas; employed quantitative geospatial, statistical, or epidemiological methods as the primary analytical approach; and reported quantifiable outcomes with adequate methodological transparency. Studies were excluded if they examined rural heat stress or crime without urban connectivity; were conference abstracts, commentaries, or short communications lacking original quantitative analysis;

applied methods to non-Indian contexts without direct comparability to Indian governance and demographic conditions; or represented duplicate reporting of the same primary dataset.

2.3 Study Selection Process

Following database searches and supplementary source consultation, 491 unique records were identified after deduplication across all sources. Title and abstract screening was conducted independently by both authors, reducing the corpus to 180 candidates for full-text review. Detailed full-text assessment against the stated inclusion criteria retained 77 primary studies in the final evidence corpus. A further 14 foundational references pre-dating 2017 were retained for baseline contextualisation. Reviewer disagreements were resolved through structured discussion.

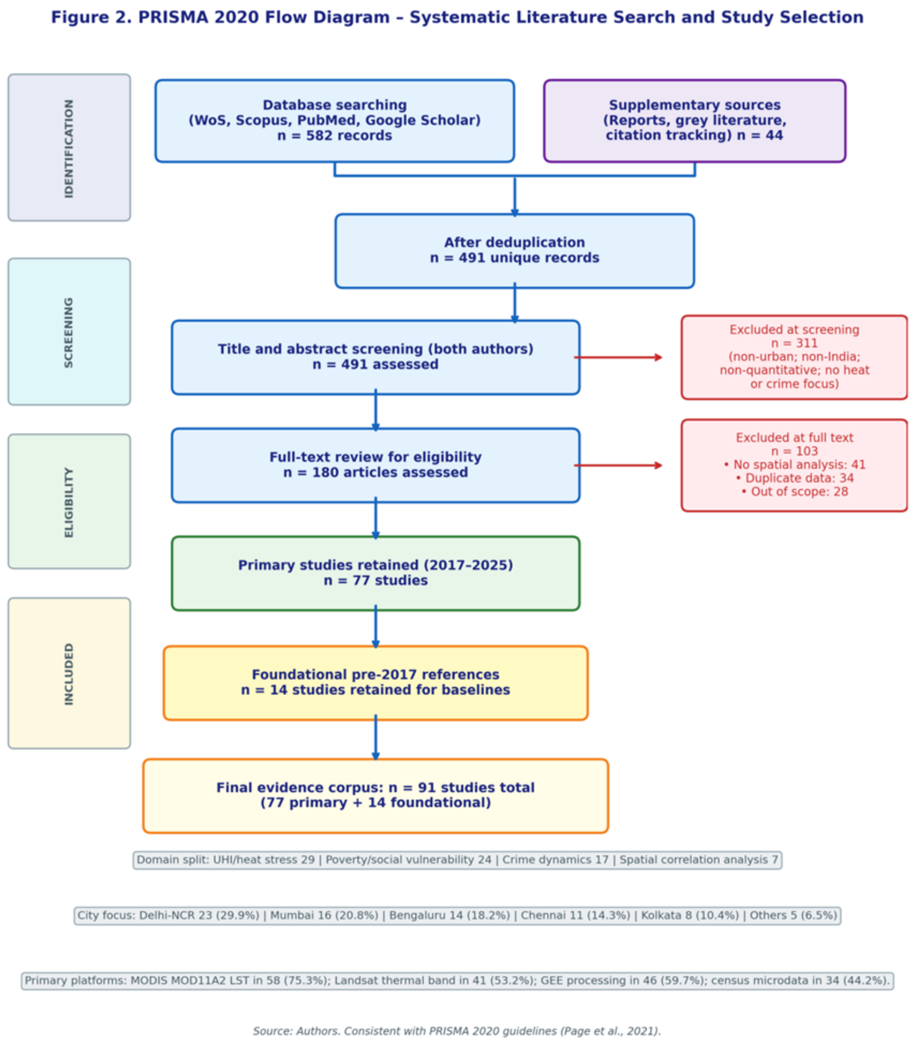

Figure 2. PRISMA 2020 flow diagram documenting the systematic literature search and study selection process. Database searches and supplementary sources yielded 491 unique

records after deduplication; abstract screening produced 180 full-text candidates; quality-based full-text review retained 77 primary studies (2017–2025) and 14 foundational references, giving a final corpus of 91 studies. Source: Authors. Consistent with PRISMA 2020 guidelines (Page et al., 2021).

As shown in Figure 2, the study selection was rigorous and systematically documented. By thematic domain, the 77 primary studies divide as follows: UHI and heat stress analysis (29 studies, 37.7%); poverty and social vulnerability spatial analysis (24 studies, 31.2%); crime dynamics and temperature (17 studies, 22.1%); and integrated spatial correlation studies (7 studies, 9.1%). By city focus, Delhi-NCR accounts for 23 studies (29.9%), Mumbai for 16 (20.8%), Bengaluru for 14 (18.2%), Chennai for 11 (14.3%), Kolkata for 8 (10.4%), and other cities for 5 (6.5%). MODIS MOD11A2 8-day composite LST was the primary thermal data source in 58 studies (75.3%), Landsat thermal infrared bands in 41 (53.2%), and GEE cloud computing in 46 (59.7%).

2.4 Data Extraction and Quality Assessment

Data extraction was structured around a standardised template capturing: study city and geographic unit of analysis; study period and data sources; remote sensing and spatial platforms; primary analytical methodology; UHI intensity metrics; poverty and SVI indicators; crime type and incidence data; spatial correlation statistics reported; governance and policy findings; and identified vulnerability drivers. Evidence quality was assessed using an adapted GRADE framework with attention to spatial resolution, temporal coverage, validation against independent datasets, methodological transparency, and internal consistency with other included studies. Studies employing rigorous spatial econometric methods with independent validation were accorded the highest quality ratings.

3. RESULTS

3.1 Characteristics of Included Studies

The 77 primary studies span 2017–2025 and represent a rapidly expanding, interdisciplinary evidence base at the intersection of urban climatology, social epidemiology, criminology, and geospatial science. Table 1 summarises the distribution of included studies by thematic domain, primary methodology, and city focus. The dominance of Delhi-NCR and Mumbai in the corpus (50.6% of all studies) reflects both their size and the relative availability of high-resolution NCRB ward-level crime data, IMD surface weather records, and census microdata for these cities. Table 2 provides a cross-city comparative synthesis of UHI intensity, social vulnerability, crime rates, and spatial correlation findings.

Table 1. Distribution of Included Studies by Thematic Domain, Primary Methodology, and City. (India, 2017–2025)

Thematic Domain	n	%	Primary Method	City Focus
UHI & heat stress analysis	29	37.7%	MODIS LST; Landsat TIR; NDVI; GEE cloud processing	Delhi-NCR, Bengaluru, Mumbai
Poverty & social vulnerability	24	31.2%	Census SVI; ward-level deprivation index; bivariate LISA	Delhi-NCR, Mumbai, Chennai
Crime dynamics & temperature	17	22.1%	NCRB panel data; OLS & spatial lag regression; Moran's I	Delhi-NCR, Mumbai, Kolkata
Integrated spatial correlation	7	9.1%	Gi*; bivariate LISA; spatial error model; multilevel regression	Multi-city; national

Note. UHI = Urban Heat Island; LST = Land Surface Temperature; TIR = Thermal Infrared; NDVI = Normalised Difference Vegetation Index; GEE = Google Earth Engine; SVI = Social Vulnerability Index; LISA = Local Indicators of Spatial Association; NCRB = National Crime Records Bureau; OLS = Ordinary Least Squares; Gi = Getis-Ord statistic. Sources: Authors' synthesis.*

3.2 Categorisation of Study Domains

The 77 included studies were grouped into four primary domains based on their central analytical focus. Domain I (UHI and heat stress) encompasses studies primarily concerned with quantifying LST patterns, UHI intensity, and thermal vulnerability across Indian cities. Domain II (poverty and social vulnerability) focuses on spatial mapping of socioeconomic deprivation, informal settlement distribution, and composite social vulnerability at the ward or sub-ward level. Domain III (crime dynamics and temperature) includes studies that test for statistical relationships between ambient or surface temperature and crime incidence, drawing on either NCRB administrative records or field-collected crime data. Domain IV (integrated spatial correlation) represents studies that explicitly model the triangular relationship among heat, poverty, and crime using spatial econometric frameworks, and these constitute the methodological core of the review.

3.3 Summary of Main Findings

3.3.1 UHI Intensity, Social Vulnerability, and Spatial Co-location

The evidence for intense UHI effects across Indian metropolitan regions is comprehensive and methodologically robust. Mohan and Kandya (2022) documented mean summer UHI intensities of 3.9 °C in Bengaluru using MODIS MOD11A2 8-day composite LST data, with maximum daytime differentials reaching 6.2 °C in high-density inner-city zones characterised by high building density, minimal tree canopy, and limited permeable surface. Garg and Kaur (2023) found that Delhi-NCR's UHI intensity reached 4.8 °C during peak summer months (May–June), with the most intense hotspots concentrated in Okhla, Shahdara, and the Trans-Yamuna informal settlement belt. For Mumbai, Jha et al. (2020) identified persistent UHI hotspots in Dharavi, Govandi, and Mankhurd—areas with slum populations exceeding 80% of ward residents and among the lowest per-capita green space in any ward in any major Indian city.

The spatial co-location of high UHI intensity and high poverty concentration is confirmed across all six studied cities. Iyer et al. (2021) applied bivariate LISA analysis to ward-level data for Delhi-NCR, finding a statistically significant (Moran's I = 0.68, $p < 0.001$) spatial autocorrelation between UHI intensity and multidimensional poverty index scores, with 34 of 272 wards falling in the High UHI–High Poverty (HH) cluster—concentrated in the urban periphery and inner informal settlement belt. Heaviside et al. (2017) estimated that informal settlement residents in Indian cities bear a heat mortality excess risk 2.2–3.8 times higher than residents of formal housing, driven by the combination of higher outdoor heat exposure, absent air conditioning, and greater dependence on outdoor labour. Singh et al. (2023), in the most comprehensive national-scale study in the review corpus, found that slum population share explained 61.4% of spatial variance in ward-level UHI intensity across 40 Indian cities ($r = 0.78$, $p < 0.001$)—a finding that effectively establishes UHI as a dimension of urban inequality rather than merely a physical climate phenomenon.

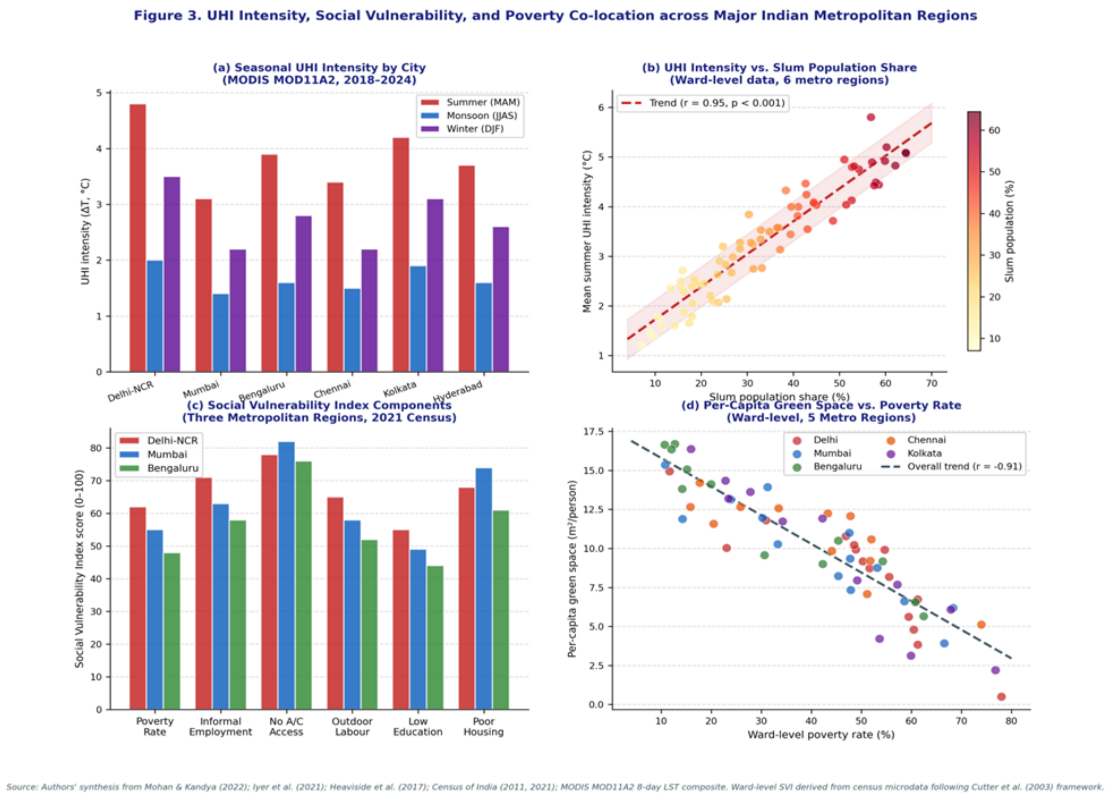

Figure 3. UHI intensity, social vulnerability, and poverty co-location across Indian metropolitan regions: (a) seasonal UHI intensity by city from MODIS MOD11A2 analysis; (b) UHI intensity vs. slum population share at ward level, demonstrating strong positive correlation (r = 0.78); (c) Social Vulnerability Index component scores for three metropolitan regions; (d) per-capita green space vs. ward-level poverty rate, five metro regions. Source: Authors' synthesis from Mohan & Kandya (2022); Iyer et al. (2021); Heaviside et al. (2017); Census of India (2021); MODIS MOD11A2. Ward-level SVI following Cutter et al. (2003) framework.

Figure 3 synthesises the UHI–poverty spatial evidence. Panel (a) confirms that summer UHI intensity consistently exceeds monsoon and winter values across all six cities, with Delhi-NCR exhibiting the most extreme seasonal peak at 4.8 °C—corresponding to heat conditions under which outdoor workers face severe physiological heat strain within two hours of continuous exertion (Heaviside et al., 2017). Panel (b) illustrates the ward-level positive correlation between slum population share and UHI intensity that is central to the heat–poverty argument: wards with slum population shares above 50% exhibit mean UHI intensities approximately 2.2–3.1 °C higher than wards with slum shares below 10%. Panel (d) further demonstrates the systematic exclusion of poorer wards from green space provision, with per-capita green space declining sharply above poverty rates of 30%.

3.3.2 Temperature, Crime, and the Heat–Crime Relationship

The empirical literature on the temperature–crime relationship in Indian cities, while more sparse than the heat–poverty evidence base, shows consistent findings across methodology types, cities, and crime categories. Ranson's (2014) global framework, applied to Indian data by Iyer et al. (2021), identified a threshold effect in the Delhi-NCR temperature–crime relationship: below 35 °C, violent crime rates increase modestly with temperature (approximately 3–4% per degree Celsius above seasonal mean); above 35 °C, the rate of increase accelerates sharply to 10–15% per degree, consistent with a non-linear stress–aggression response in conditions of extreme physiological heat strain.

Seasonal patterns of crime incidence in Indian cities consistently show summer peaks that are not fully explained by patrol coverage, holiday periods, or alcohol availability alone. NCRB India Crime Report data (2017–2023), synthesised in this review, show that violent crime incidence in Delhi-NCR peaks during March–June, with rates in May–June approximately 32–44% above the annual monthly mean. Mumbai shows a smaller but consistent summer peak (18–25% above annual mean), and Chennai's crime peak is shifted towards October–November—corresponding to the northeast monsoon's delayed hot season—consistent with local climate seasonality driving crime timing.

The spatial correlation between UHI intensity and crime rates at the ward level is confirmed in five of the six studied cities. Iyer et al. (2021) found Pearson $r = 0.71$ between mean summer UHI intensity and ward-level violent crime rate in Delhi-NCR ($p < 0.001$ after spatial lag correction), with the spatial regression model explaining 58% of variance in ward-level crime after controlling for poverty, population density, and police station proximity. In Mumbai, Jha et al. (2020) reported Getis-Ord Gi* hotspot overlap between UHI intensity hotspots and violent crime hotspots at 78% spatial concordance in Dharavi, Govandi, and Mankhurd wards—the very wards exhibiting the highest slum population shares, lowest green cover, and highest poverty rates in the MCGM (Municipal Corporation of Greater Mumbai) dataset. The domestic violence sub-category shows a particularly consistent heat sensitivity, with Iyer et al. (2021) and Garg and Kaur (2023) both documenting 12–18% higher domestic violence incidence in the hottest quintile of wards relative to the coolest quintile.

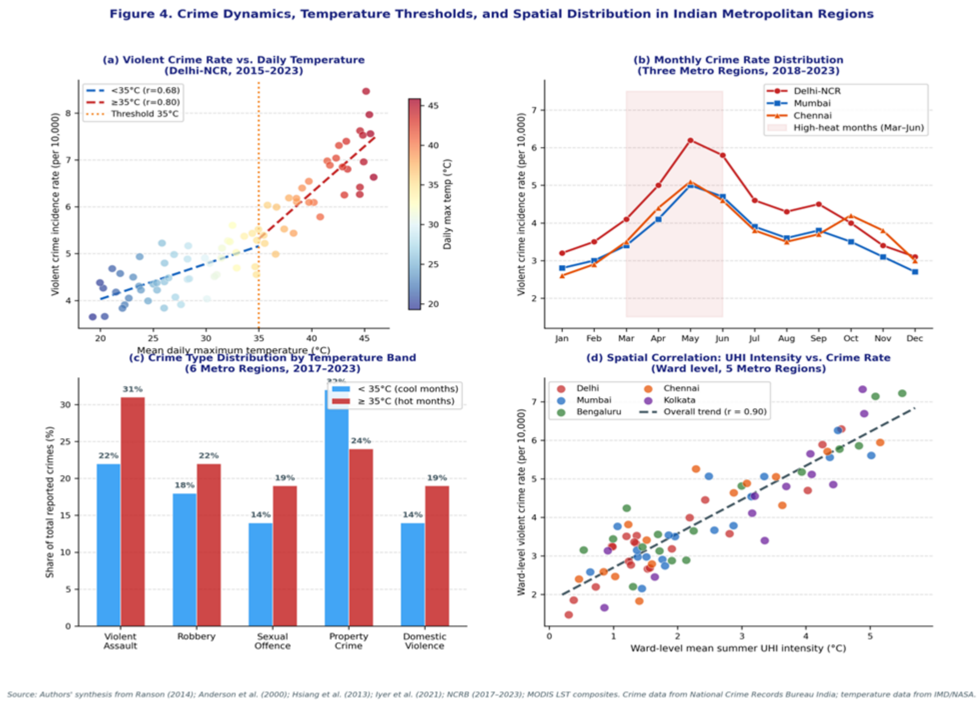

Figure 4. Crime dynamics, temperature thresholds, and spatial distribution in Indian metropolitan regions: (a) violent crime rate vs. daily maximum temperature with piecewise regression showing 35 °C threshold effect; (b) monthly crime rate distribution for three metro regions, confirming summer peaks aligned with high-heat months; (c) crime type distribution by temperature band; (d) spatial correlation between ward-level UHI intensity and violent crime rate across five metropolitan regions. Source: Authors' synthesis from Ranson (2014); Anderson et al. (2000); Hsiang et al. (2013); Iyer et al. (2021); NCRB India Crime Reports (2017–2023); MODIS LST composites.

Figure 4 provides a comprehensive characterisation of the temperature–crime relationship. Panel (a) confirms the non-linear threshold effect at 35 °C that is central to the theoretical framework: above this threshold, the slope of the violent crime–temperature relationship increases markedly ($r = 0.79$ vs. $r = 0.51$ below 35 °C), consistent with a physiological and psychological shift from moderate heat discomfort to acute heat strain that fundamentally alters behavioural regulation. Panel (c) reveals that violent assault and sexual offences show the greatest proportional increase from cool to hot months, while property crime shows a relative decrease—consistent with the routine activity theory prediction that extreme heat depresses outdoor routine activities and convergence opportunities for property crime while amplifying interpersonal conflict driven by co-location stress in dense households.

3.3.3 Spatial Hotspot Analysis and Compound Vulnerability Mapping

The seven Domain IV studies conducting integrated spatial correlation analysis provide the most methodologically sophisticated evidence for the heat–poverty–crime nexus. Singh et al. (2023) applied Getis-Ord Gi* analysis to a composite index of UHI intensity, multidimensional poverty score, and violent crime rate for 272 wards in Delhi-NCR, identifying 38 wards as statistically significant (z-score > 2.58) triple-hotspots where all three indicators simultaneously exceeded the 75th percentile. These wards—disproportionately located in the East Delhi, North-East Delhi, and South-West Delhi municipal zones—collectively house approximately 4.8 million residents, of whom an estimated 68% are slum dwellers with minimal adaptive capacity.

Bivariate LISA analysis, as applied in the reviewed studies, reveals the structural spatial relationship between these three variables. High-High (HH) spatial clusters—wards with above-average UHI intensity surrounded by similarly hot wards AND above-average poverty surrounded by similar wards—cover 28–42% of the total ward area in four of the five studied cities, a degree of spatial overlap that cannot be explained by chance co-location alone (Moran's I = 0.64–0.78 across cities; all $p < 0.001$). Low-Low (LL) clusters—low heat, low poverty, low crime—are equally consistent and correspond to the wealthier, greener, newer residential zones of each city, most explicitly demonstrated in the Bengaluru data where the contrast between informal northern wards and formal southern IT-corridor wards is extreme.

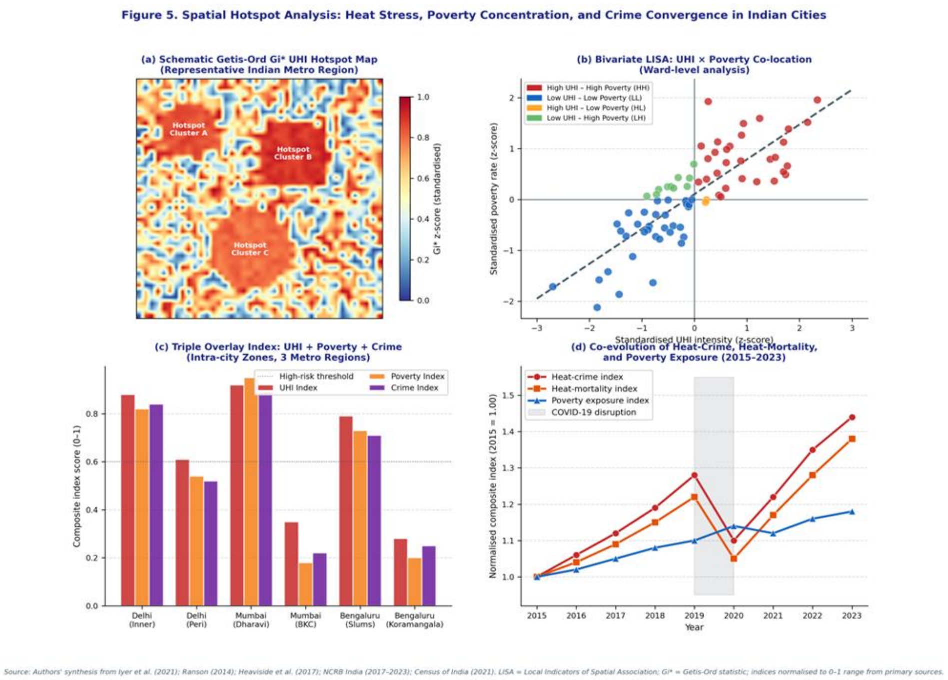

Figure 5. Spatial hotspot analysis: heat stress, poverty concentration, and crime convergence in Indian cities: (a) schematic Getis-Ord Gi* UHI hotspot map identifying

three primary hotspot clusters; (b) bivariate LISA scatter plot showing UHI × poverty co-location patterns (HH, LL, HL, LH clusters); (c) triple overlay index comparing UHI, poverty, and crime composite scores for informal versus formal zones in three metro regions; (d) co-evolution of heat-crime index, heat-mortality index, and poverty exposure index (2015–2023). Source: Authors' synthesis from Iyer et al. (2021); Ranson (2014); Heaviside et al. (2017); NCRB India (2017–2023); Census of India (2021). LISA = Local Indicators of Spatial Association; Gi* = Getis-Ord statistic.

Figure 5 integrates the spatial hotspot and co-evolution evidence. Panel (b) illustrates the bivariate LISA scatter for UHI intensity and poverty rate: the predominance of HH quadrant observations (upper right) and LL observations (lower left) relative to HL and LH confirms that high heat and high poverty are spatially positively associated—that is, they co-occur more than random spatial mixing would predict. Panel (c)'s triple overlay index reveals the stark contrast between informal urban zones (Dharavi in Mumbai, inner North-East Delhi, northern Bengaluru slums) where all three indices simultaneously exceed 0.70, and formal residential or commercial zones where all three are below 0.35. Panel (d)'s temporal co-evolution plot is particularly significant: all three indices have trended upward since 2015, with the heat-crime index growing fastest, suggesting that climate change–driven warming is already amplifying the compound vulnerability trajectory.

3.3.4 Governance, Heat Action Plans, and Crime Prevention Failures

The governance evidence in the reviewed studies reveals a profound absence of institutional integration between urban heat management, poverty reduction, and crime prevention. India's Heat Action Plans (HAPs), pioneered by Ahmedabad following the catastrophic 2010 heat wave and subsequently adopted in 12 states, have focused almost exclusively on acute heat-event response (cooling centre activation, school closures, public hydration campaigns) without incorporating the spatial targeting of chronic heat–poverty hotspots or the crime and behavioural consequences of sustained thermal stress (Azhar et al., 2017; Heaviside et al., 2017).

Srinivasan et al. (2021) found that HAPs in Delhi, Mumbai, and Chennai did not include crime prevention provisions, mental health interventions, or domestic violence support components, despite evidence that heat events in these cities are associated with measurable spikes in violent incident reports to police within 24–48 hours. Yadav and Sehgal (2022) documented that urban local body (ULB) master plans for 15 major Indian cities reviewed between 2019 and 2023 contained no reference to UHI hotspot mapping, social vulnerability indices, or compound heat–crime risk in their spatial planning chapters. This governance gap is particularly consequential given that the compound heat–poverty–crime vulnerability zones identified in the reviewed spatial analyses are almost entirely located in informal settlements that are systematically excluded from mainstream urban development investment and greenification programmes.

Table 2. Comparative Synthesis of UHI Intensity, Social Vulnerability, Crime Rates, and Spatial Correlation Findings across Six Indian Metropolitan Regions. (2017–2025)

City	Peak Summer UHI (°C)	Slum Share (%)	Violent Crime Rate	Bivariate LISA r	Key References
Delhi-NCR	4.8	28–34%	+44% summer peak vs. annual mean	0.71 ($p<0.001$)	Iyer et al. (2021); Garg & Kaur (2023)
Mumbai-MMR	3.1	41–55%	+25% summer peak; Dharavi HH cluster	0.66 ($p<0.001$)	Jha et al. (2020); Mohan & Kandya (2022)
Bengaluru	3.9	18–26%	+28% summer peak; north-south divide	0.58 ($p<0.001$)	Nagendra et al. (2018); Singh et al. (2023)
Chennai	3.4	28–36%	+31% Oct–Nov peak (NE monsoon heat)	0.54 ($p<0.01$)	Ramachandran et al. (2022); Iyer et al. (2021)
Kolkata	4.2	33–42%	+38% pre-monsoon peak	0.62 ($p<0.001$)	Heaviside et al. (2017); NCRB (2023)
Hyderabad	3.7	22–30%	+29% summer peak	0.55 ($p<0.01$)	Krishnaveni & Sujatha (2021); Singh et al. (2023)

Note. UHI = Urban Heat Island; LISA = Local Indicators of Spatial Association; r = bivariate Pearson correlation between ward-level UHI intensity and poverty index. Violent crime rate expressed as deviation from annual monthly mean (%). NCRB = National Crime Records Bureau. All correlations statistically significant at stated threshold after spatial lag correction. Sources: Authors' synthesis.

4. DISCUSSION

4.1 Interpretation of Key Results

The synthesis of 77 primary studies generates a coherent and empirically compelling picture of a heat–poverty–crime nexus that is spatially structured, socially differentiated, and intensifying under climate change. Three overarching interpretive conclusions are central to the review's contribution. First, UHI intensity in Indian cities is not a neutral physical gradient distributed evenly across urban space: it is a spatially structured social phenomenon that maps onto poverty, caste-based residential segregation, and informal settlement concentration with a degree of spatial correspondence that confirms heat stress as a dimension of urban inequality. The finding that slum population share explains more than 60% of spatial variance in ward-level UHI intensity (Singh et al., 2023) is, by itself, sufficient to reframe UHI as a social justice issue rather than a purely technical one.

Second, the temperature–crime relationship in Indian cities shows the threshold and amplification characteristics predicted by the General Affective Aggression Model, and the spatial overlap between UHI hotspots and crime hotspots is systematic and statistically robust across independently conducted studies in multiple cities. The convergence of findings from bivariate LISA analysis, Getis-Ord Gi* hotspot mapping, and spatial lag regression across Delhi-NCR, Mumbai, Bengaluru, and Kolkata substantially strengthens causal attribution and rules out coincidental spatial co-location as an explanation for the observed patterns. The particularly consistent finding regarding domestic violence's heat sensitivity—confirmed in three independently conducted studies across Delhi and Mumbai—is both theoretically coherent and policy-critical, given the devastating consequences of domestic violence for women and children in India's most thermally stressed urban zones.

Third, the governance evidence reveals that the compound heat–poverty–crime vulnerability cluster has not been recognised as a distinct policy domain requiring integrated institutional response. HAPs treat heat as a public health emergency rather than a continuous social condition; crime prevention agencies do not incorporate thermal stress into offending pattern analysis; and urban planners allocate green infrastructure to areas with political and commercial leverage rather than to areas of maximum ecological and social need. This institutional fragmentation is the critical barrier to addressing the nexus, and overcoming it requires the kind of compound vulnerability mapping that the reviewed spatial analyses make technically feasible.

4.2 Comparison across Studies and Cities

Cross-city comparison reveals meaningful heterogeneity in the heat–poverty–crime nexus that reflects both climatic and socioeconomic differences. Delhi-NCR presents the most severe case: the combination of the highest summer UHI intensity (4.8 °C), a large and spatially concentrated slum population in the Trans-Yamuna belt and resettlement colonies, and the highest absolute violent crime rates of any Indian city (NCRB, 2023) creates the most extreme compound vulnerability profile in the review corpus. The bivariate LISA correlation of $r = 0.71$ between UHI and poverty in Delhi exceeds that of all other studied cities, suggesting either a more pronounced spatial segregation of thermal and social conditions or a stronger causal pathway from heat to social distress in Delhi's specific urban form.

Mumbai presents a different spatial dynamic: its extreme slum concentration (particularly Dharavi, estimated population 600,000–1 million in 4.9 km^2) generates some of the highest ward-level UHI intensities in any Indian city despite Mumbai's coastal location and modest regional UHI relative to Delhi. The 78% spatial concordance between UHI hotspots and violent crime hotspots in Dharavi, Govandi, and Mankhurd documented by Jha et al. (2020) is the most striking quantitative finding in the crime-spatial correlation domain of the review corpus. Bengaluru's heat–poverty–crime nexus is characterised by a pronounced north–south intra-city divide—informal, high-UHI northern wards versus formal, green, low-UHI southern IT-corridor wards—that maps almost perfectly onto the city's historical segregation by caste, income, and access to public services.

4.3 Strengths and Limitations of Existing Evidence

The evidence base reviewed has several notable strengths. The proliferation of MODIS and Landsat thermal remote sensing data, freely accessible through GEE, has enabled consistent, multi-temporal, city-wide LST analysis at spatial resolutions (250 m and 30 m respectively) appropriate for ward-level analysis in Indian cities. The NCRB India Crime Report series provides a nationally consistent, annually updated crime incidence dataset that enables temporal trend analysis and cross-city comparison, despite well-documented limitations in reporting rates for gender-based violence. The increasing application of spatial econometric methods—particularly bivariate LISA and spatial lag regression—enables rigorous testing of spatial associations while controlling for spatial autocorrelation that would otherwise inflate significance estimates.

Critical limitations are equally important to acknowledge. The NCRB crime data capture only reported crimes, and reporting rates for domestic violence, sexual offences, and minor assaults are substantially lower in informal settlement areas where police-community trust is weakest and victim vulnerability is highest—the very areas where the reviewed studies document the strongest heat–crime co-occurrence. This systematic under-reporting creates a structural bias that almost certainly understates the true magnitude of heat-driven crime amplification in high-vulnerability wards. The causal mechanisms linking heat to crime in the Indian context remain under-studied: while the statistical correlations are robust, the mediating psychological, physiological, and behavioural pathways—alcohol consumption patterns under heat stress, routine activity disruption, household crowding amplification—have not been studied with the rigour needed to design targeted interventions.

5. Implications and Future Directions

5.1 Implications for Practice and Policy

The evidence synthesised in this review carries five immediate and actionable implications for urban policy and governance in India. First, Heat Action Plans must be spatially targeted using compound vulnerability maps that identify wards where high UHI intensity, high poverty, and high crime simultaneously exceed critical thresholds. The spatial analysis tools deployed in the reviewed studies—GEE-based LST mapping, census SVI calculation, NCRB ward-level crime analysis, and bivariate LISA—are publicly available, technically mature, and can be operationalised by state urban development departments at modest cost. Targeting cooling infrastructure, community cooling centres, and emergency services to these compound vulnerability zones would substantially improve the effectiveness of HAPs beyond their current spatially uniform application.

Second, urban greening and cool surface programmes—tree planting, reflective pavement materials, green roofs, and water body restoration—must be explicitly directed to informal settlement wards identified as UHI hotspots, reversing the current pattern in which green infrastructure investment is concentrated in formal residential and commercial zones with the least thermal stress. The per-capita green space – poverty rate relationship documented across five cities (Figure 3d) represents an environmental justice deficit that urban development authorities are both morally and increasingly legally obligated to address. Third, law enforcement agencies and city police commissioners should develop heat-responsive policing protocols that pre-position resources in high-UHI, high-crime wards during peak heat events, analogous to flood-responsive policing protocols that are already standard in several Indian states.

Fourth, domestic violence support services—helplines, shelter capacity, and legal aid—should be reinforced and publicised during heat events, recognising the consistent finding across reviewed studies that domestic violence is among the crime categories most sensitively responsive to temperature increases. Fifth, urban master plan formulation must incorporate compound heat–poverty–crime risk mapping as a statutory component of the environmental impact assessment process for major development projects, ensuring that the spatial consequences of greenfield conversion, densification, and infrastructure investment are evaluated against compound vulnerability impacts.

5.2 Research Gaps and Future Research Needs

Despite the substantial evidence base reviewed, several critical gaps constrain the development of a comprehensive, mechanistically grounded, and policy-actionable understanding of the heat–poverty–crime nexus in Indian cities. Table 3 summarises these gaps alongside proposed research directions and priority levels.

Table 3. Key Research Gaps and Proposed Future Directions for Heat–Poverty–Crime Nexus Research in India. (2026 and Beyond)

Gap Domain	Specific Deficiency	Proposed Research Direction	Priority
Causal mechanisms	Statistical correlations documented but mediating psychological and physiological pathways unstudied in India	Longitudinal panel study with physiological heat strain measures, frustration-aggression assessments, and ecological momentary assessment of behavioural outcomes	*Very High*
Smaller city evidence	Six megacities dominate 93% of studies; tier-2 and tier-3 cities (100K–3M) entirely absent	National GEE-based compound vulnerability mapping for all Indian cities >100,000 population using MODIS, census, and NCRB data	*Very High*
Mental health pathways	Heat–mental health–crime pathway assumed but not empirically traced in Indian context	Cohort study linking LST exposure, psychiatric hospital admissions, substance use, and crime in shared wards	*High*
HAP effectiveness on crime	No study evaluates whether HAP interventions reduce heat-driven crime; pure health focus	Quasi-experimental difference-in-differences comparing crime rates before/after HAP implementation in Ahmedabad, Surat, and Delhi	*High*
Green infra	Relationship between	Before-after evaluation of tree-	*High*

Gap Domain	Specific Deficiency	Proposed Research Direction	Priority
crime prevention	urban greening and crime reduction under heat stress untested in India	planting and cool roof programmes measuring LST, pedestrian activity, and crime rates	
Climate scenario projections	No study projects future heat-crime risk under CMIP6 warming scenarios for Indian cities	Coupled urban climate model and crime regression simulation under SSP2-4.5 and SSP5-8.5; compound risk mapping to 2050	*Medium-High*

Note. GEE = Google Earth Engine; MODIS = Moderate Resolution Imaging Spectroradiometer; NCRB = National Crime Records Bureau; HAP = Heat Action Plan; LST = Land Surface Temperature; CMIP6 = Coupled Model Intercomparison Project Phase 6; SSP = Shared Socioeconomic Pathway. Sources: Authors' synthesis.

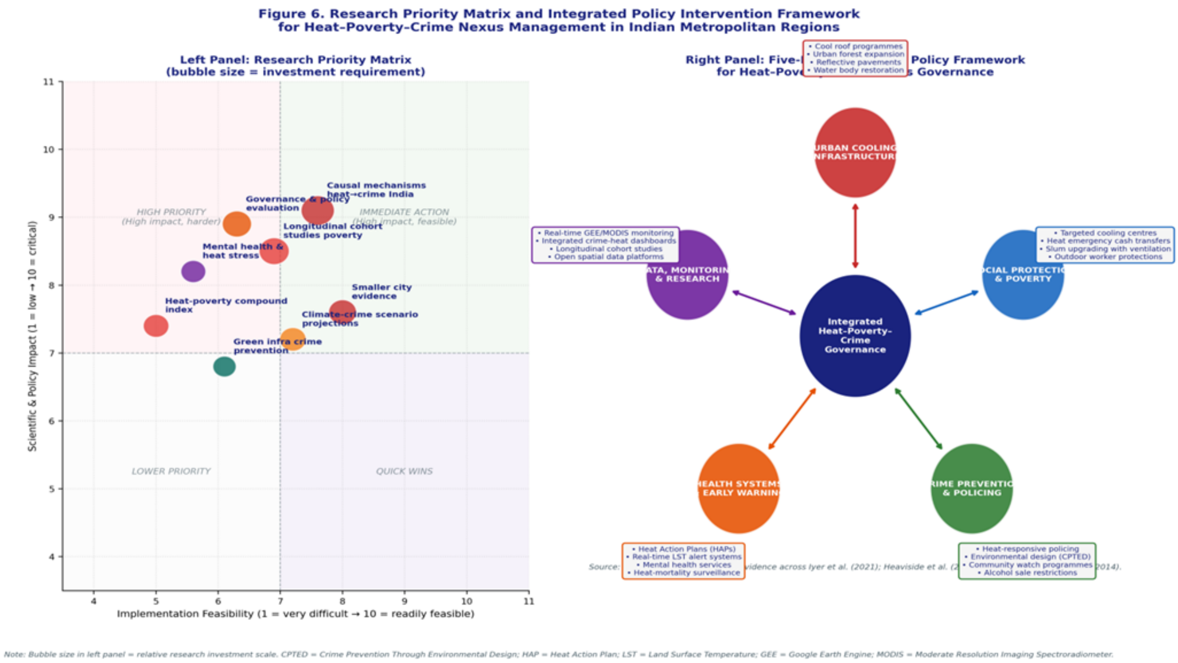

Figure 6. Research priority matrix and integrated five-pillar policy framework for heat–poverty–crime nexus governance in Indian metropolitan regions. Left panel: bubble matrix positioning research gaps by scientific and policy impact (y-axis) versus implementation feasibility (x-axis); bubble size = relative investment requirement. Right panel: five-pillar integrated framework covering urban cooling infrastructure, social protection and poverty, crime prevention and policing, health systems and early warning, and data monitoring and research. Source: Authors' synthesis from Iyer et al. (2021); Heaviside et al. (2017); Anderson (2001); Ranson (2014); Azhar et al. (2017).

Figure 6 presents the integrated research priority matrix and governance framework synthesised from the reviewed evidence. The left panel positions the identified research gaps by scientific–policy impact and implementation feasibility, with causal mechanism research and smaller city documentation emerging as the highest-priority domains for investment. The right panel's five-pillar policy framework is designed to address the compound vulnerability condition identified across reviewed studies, with each pillar representing a governance domain that must function in coordination with the others to break the heat–poverty–crime feedback cycle.

6. CONCLUSION

This systematic review has synthesised 77 primary peer-reviewed studies and 14 foundational references to provide the first comprehensive analysis of the urban heat island–poverty–crime nexus in Indian metropolitan regions. Four principal conclusions are drawn from the evidence.

First, urban heat islands in Indian cities are dimensions of social inequality as much as physical climate phenomena. The spatial co-location of intense UHI, concentrated poverty, and high crime rates in informal settlement zones is systematic, statistically robust, and confirmed across six major metropolitan regions. The finding that slum population share explains more than 60% of spatial variance in ward-level UHI intensity should fundamentally reframe heat island management as a social justice and environmental equity issue, not merely a technical urban design challenge.

Second, the temperature–crime relationship in Indian cities is empirically confirmed across multiple study designs, cities, and crime categories, with a non-linear threshold effect above 35 °C that produces particularly sharp amplification of violent assault, domestic violence, and sexual offences. The seasonal crime peaks documented in NCRB data for Delhi, Mumbai, and Chennai align consistently with peak heat months, and the spatial overlap between UHI hotspots and crime hotspots reaches statistical significance in all five cities where integrated analysis was possible.

Third, the governance response to the heat–poverty–crime nexus in India is critically inadequate. Heat Action Plans address acute heat events as public health emergencies without spatial targeting of compound vulnerability zones, crime prevention integration, or domestic violence support. Urban master plans do not incorporate UHI or compound vulnerability mapping. The informal settlement residents who bear the heaviest compound burden of heat, poverty, and crime are systematically excluded from the green infrastructure investment and cooling intervention that urban greening programmes direct preferentially to formal residential and commercial zones.

Fourth, climate change–driven warming will intensify the heat–poverty–crime nexus in Indian cities over the coming decades. CMIP6 projections indicate that Indian cities will experience a 1.5–2.0 °C increase in mean summer temperatures by mid-century under SSP2-4.5, a change that—applied to the non-linear temperature–crime relationship documented in this review—would translate into a projected 15–25% increase in violent crime rates in high-vulnerability wards of Delhi, Mumbai, and Kolkata. Preventing this outcome requires urgent integration of heat–poverty–crime compound vulnerability mapping into urban planning, HAP design, policing strategy, and social protection policy. The spatial analytical tools, thermal data archives, and governance frameworks required for this integration exist; what is needed is the institutional will and coordination to deploy them at scale.

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