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A Multi-Scalar Correlation Analysis of Urban Heat Resilience in Indian Cities

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ABSTRACT

Urban heat resilience is frequently assessed using aggregated city-level indicators that obscure intra-urban inequalities and cross-dimensional misalignments. This study applies a multi-scalar Heat Resilience Framework (HRF) to examine relationships between macro-scale and ward-level resilience indicators across Mumbai, Thane, and Nagpur, India. The HRF integrates 125 indicators across five dimensions, physical, social, economic, institutional, and natural, to compute a ward-level Heat Resilience Index (HRI; scored 1–5, where higher scores indicate stronger resilience). Dimension weights were derived using the Analytic Hierarchy Process (AHP) from twelve domain experts. Spearman's rank correlation analysis is employed to identify cross-dimensional alignments and scale mismatches. The Physical dimension records the highest mean scores across all three cities. Strong Physical–Economic coupling is observed in Nagpur ($r = 0.70$) and moderate coupling in Mumbai ($r = 0.45$), suggesting an association between climatic exposure and livelihood sensitivity. Weak Physical–Institutional alignment in Thane ($r = -0.23$) indicates constrained governance mediation. Remote sensing analysis (MODIS LST; Landsat 8 NDVI/NDBI) provides spatial contextual consistency for ward-level findings. All results are interpreted as exploratory and diagnostic. The findings demonstrate that urban heat resilience is emergent rather than additive, shaped by cross-dimensional coherence and scale-sensitive governance. Institutional capacity functions as an enabling but non-sufficient condition, while ecological buffers provide conditional relief depending on spatial integration. By linking systemic resilience diagnostics with remote sensing contextualisation, this study advances sustainability-oriented urban adaptation planning in rapidly urbanising regions.

KEYWORDS: climate adaptation; heat resilience; hyperlocal risk assessment; multi-scalar governance; sustainable urbanization; urban heat risk

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ABBREVIATIONS

AI/ML, artificial intelligence/machine learning; CDRI, climate disaster resilience initiative; HRF, heat resilience framework; HRI, heat resilience index; LST, land surface temperature; NDBI, normalized difference built-up index; NDVI, normalized difference vegetation index; RCP, representative concentration pathway; SDG, sustainable development goal

INTRODUCTION

Urban heat has emerged as one of the most pervasive and inequitable climate risks confronting rapidly urbanizing regions, particularly in the Global South [1,2]. Unlike sudden-onset hazards, heatwaves function as slow-onset stressors that accumulate over time, amplifying health risks, productivity losses, food insecurity, and livelihood instability [3,4]. In India, recent assessments indicate an increasing frequency, duration, and spatial extent of extreme heat events [5–7]. Empirical evidence demonstrates that heat-related morbidity and mortality are spatially uneven and are mediated by urban form, occupational exposure, social vulnerability, and access to cooling infrastructure [2,8]. Consequently, resilience to urban heat cannot be understood as a uniform city-wide attribute but must be examined as a differentiated and scale-dependent phenomenon.

Urban resilience theory conceptualises cities as complex adaptive systems in which resilience emerges from interactions among physical infrastructure, socio-economic structures, governance systems, and ecological buffers [9–11]. Systems-based interpretations emphasise nonlinearity, feedback loops, and cross-scale dynamics rather than the additive accumulation of isolated capacities [12,13]. Within this framing, resilience at the macro scale does not automatically translate into protection at the neighbourhood or household scale. Much empirical work continues to operationalise resilience through aggregated city-level indices, thereby masking intra-urban heterogeneity and obscuring structural mismatches between exposure and adaptive capacity.

Parallel to resilience index development, advances in remote sensing and machine learning have enabled hyperlocal heat exposure detection through land surface temperature (LST), normalised difference vegetation index (NDVI), and normalised difference built-up index (NDBI) analyses [14,15]. Studies across South and East Asia highlight the role of atmospheric circulation variability and oceanic drivers in amplifying extreme heat patterns [16,17]. However, these micro-scale exposure analytics often remain detached from systemic resilience frameworks and governance evaluation. As a result, macro-scale resilience narratives and micro-scale exposure diagnostics frequently operate in isolation.

In the Indian context, heat action plans have been introduced in several cities, yet implementation and governance translation remain uneven [18–20]. Nature-based solutions and blue-green infrastructure are increasingly promoted as mitigation strategies [21,22], but empirical integration of ecological buffering with systemic resilience diagnostics remains limited.

At the intra-urban scale, recent work by Kacker et al. (2026) demonstrates the importance of ward-level heat stress differentiation in Delhi, confirming that aggregate city-level assessments systematically underestimate exposure heterogeneity in dense Indian cities, a methodological motivation directly reflected in the ward-level analytical approach adopted here [23]. Kumari and Kitchley (2024) further illustrate the utility of composite indicator-based vulnerability indices for heritage Indian cities, demonstrating that context-specific indicator selection and aggregation can yield actionable heat vulnerability profiles comparable to those produced by the HRF [24]. For the integration of multiple risk drivers within a resilience-oriented framework, Cantatore et al. (2023) provide a multi-vulnerability mapping precedent from the Apulian region, demonstrating how simultaneous treatment of slow- and rapid-onset hazards within a single analytical architecture strengthens the robustness of resilience diagnostics, an approach this study extends to the heat-specific urban Indian context [25].

Despite substantial advances in multi-dimensional resilience frameworks and hyperlocal heat analytics, few studies explicitly correlate macro-scale and ward-level resilience indicators across all five dimensions in rapidly urbanising Indian cities. Moreover, integrating systemic correlation diagnostics with spatially consistent remote sensing evidence remains underexplored in the context of South Asian urban heat.

Research Objective and Contribution

Despite substantial advances in multi-dimensional resilience frameworks and hyperlocal heat analytics, few studies explicitly correlate macro-scale and ward-level resilience indicators across dimensions in rapidly urbanising Indian cities. Integration of cross-dimensional resilience diagnostics with remote sensing contextual evidence represents a gap this study addresses. The findings contribute directly to sustainable urban development and climate adaptation agendas by informing scale-sensitive interventions aligned with Sustainable Development Goals 11 (Sustainable Cities and Communities) and 13 (Climate Action).

This study applies a multi-scalar Heat Resilience Framework (HRF) to examine whether city-level resilience conditions align with ward-level heat resilience indicators across Mumbai, Thane, and Nagpur [26]. By integrating cross-dimensional Spearman correlation analysis with contextual remote sensing evidence from MODIS LST and Landsat 8 NDVI/NDBI, the study makes three contributions. First, it empirically demonstrates how urban heat resilience emerges from cross-dimensional alignment rather than isolated strengths [11]. Second, it identifies scale mismatches between macro preparedness and micro resilience capacity, echoing [12]. Third, it advances a transparent, replicable methodology for ward-level resilience diagnostics aligned with evidence-based climate adaptation planning under SDGs 11 and 13.

The remainder of this paper is structured as follows. Section Materials and Methods describe the materials and methods, including study area selection, indicator construction, AHP weighting, normalization, statistical analysis, and remote sensing contextual analysis. Section Results and Discussion presents dimension-wise HRI patterns, inter-dimensional correlations, and spatial contextualisation. Section Conclusions concludes with key findings, limitations, and implications for sustainable urban heat adaptation.

MATERIALS AND METHODS

Study Area

This study examines three urban centres in Maharashtra, India: Mumbai, Thane, and Nagpur. These cities represent distinct climatic regimes, urban morphologies, and governance contexts, enabling comparative multi-scalar analysis (Figure 1).

Mumbai is a coastal megacity characterized by a tropical humid climate, extreme population density, vertical urban growth, and extensive informal settlements. Built density and limited ventilation create localized urban heat island amplification, making it a high-exposure coastal context. Thane, located adjacent to Mumbai, represents a rapidly expanding metropolitan transition zone with mixed land-use patterns, increasing residential high-rise development, and transport-oriented growth corridors. While influenced by coastal climatic conditions, Thane is exhibiting emerging urban characteristics in the interior. Nagpur, situated in central India, experiences a hot semi-arid climate with extreme summer temperatures often exceeding 45 °C. Unlike Mumbai and Thane, Nagpur's heat exposure is primarily climate-driven rather than density-driven, providing an inland comparative case.

The comparative selection enables examination of coastal–inland contrasts, megacity–secondary city dynamics, and varying degrees of institutional capacity and ecological buffering.

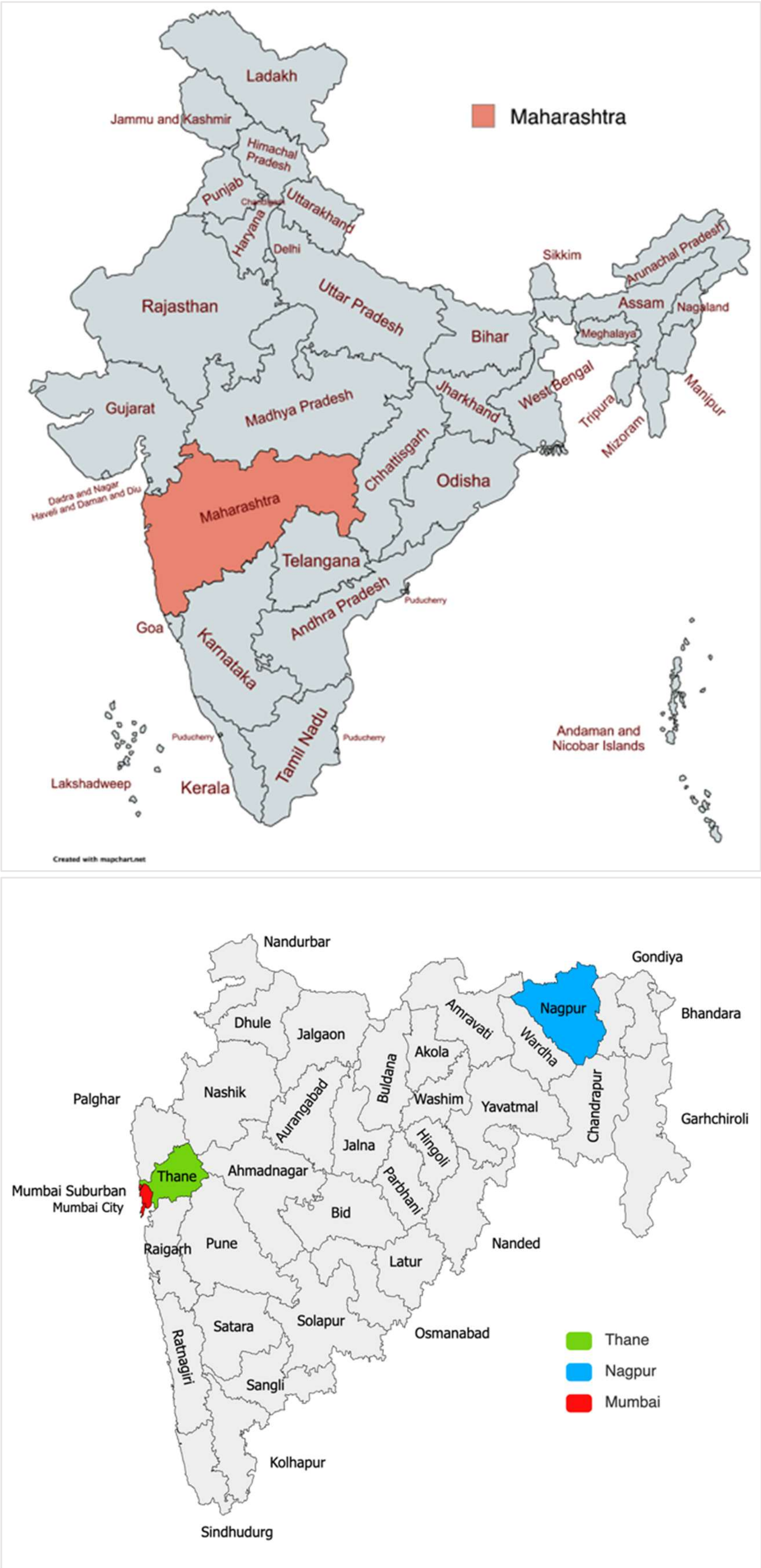

Figure 1. Study area location showing (**top**) India and Maharashtra state; (**bottom**) Maharashtra with selected cities of Mumbai (Red), Thane (Green), and Nagpur (Blue).

Heat Resilience Framework (HRF)

Urban heat resilience was assessed using the Heat Resilience Framework (HRF) developed and validated by Saunik and Shaw (2026) [26]. The HRF is a multidimensional assessment framework comprising five dimensions (Physical, Social, Economic, Institutional, and Natural), 25 parameters, and 125 indicators organised within the Climate Disaster Resilience Initiative (CDRI) structure. The conceptual development of the framework, indicator selection process, operational definitions, indicator scoring rubrics, data sources, and framework validation are described comprehensively in the companion methodology paper and are therefore not repeated here. In the present study, the published HRF was applied without modification to evaluate ward-level heat resilience across Mumbai, Thane, and Nagpur.

The complete list of 125 indicators, together with their operational definitions, scoring criteria, data sources, and indicator-level metadata, is available in Supplementary Material S1 of Saunik and Shaw (2026) [26].

Indicator Normalization and Heat Resilience Index (HRI) Construction

Indicator normalization and construction of the Heat Resilience Index (HRI) followed the procedures described by Saunik and Shaw (2026) [26]. Indicator values were normalised using min–max scaling, aggregated into parameter scores and dimension scores, and finally into a composite ward-level Heat Resilience Index.

Dimension weights were adopted directly from the validated HRF methodology. These weights were derived using the AHP based on pairwise comparisons conducted by twelve multidisciplinary experts. Details regarding expert selection, pairwise comparison matrices, eigenvalues, consistency indices, and consistency ratios are presented in the companion methodology paper (Supplementary Material S2) and are therefore not reproduced here [26].

The Heat Resilience Index (HRI) ranges from 1 (lowest resilience) to 5 (highest resilience), with higher values indicating greater resilience capacity. Interpretation of HRI values follows the definitions proposed by Saunik and Shaw (2026) [26]. The robustness of the weighting scheme has already been evaluated through sensitivity analyses reported in the companion methodology paper. The published analysis demonstrated that the overall ranking of Mumbai remained stable under alternative weighting assumptions, whereas the relative ranking of Thane and Nagpur varied modestly depending on the weighting scheme, confirming the transparency and robustness of the HRF methodology.

STATISTICAL ANALYSIS

Spearman's rank correlation coefficient was computed to examine inter-dimensional associations within each city. Spearman correlation was selected due to its suitability for non-parametric data and ordinal scaling of composite indices. Correlation strength was interpreted as strong ($|r| \geq 0.70$), moderate ($0.40 \leq |r| < 0.70$), and weak ($|r| < 0.40$). Statistical significance was evaluated at $p < 0.05$. Ward-level observations used in correlation analysis were N = 24 for Mumbai, N = 9 for Thane, and N = 10 for Nagpur, reflecting the administrative ward/zone structure of each city. Given the relatively small N in each city, correlation coefficients are interpreted with caution; results are reported as exploratory and diagnostic rather than inferential. All reported Spearman correlation coefficients reached statistical significance at $p < 0.05$. Given the number of pairwise comparisons across five dimensions per city (ten pairs per city, thirty total), a Bonferroni correction threshold of $p < 0.005$ was applied as a conservative check; coefficients meeting this threshold are noted in the results. Correlation matrices were generated separately for each city to avoid pooling across structurally distinct urban systems.

Correlation matrices were generated separately for Mumbai, Thane, and Nagpur to identify context-specific systemic alignments and mismatches. This correlation-based approach functions as a diagnostic tool rather than a causal model, enabling identification of reinforcing interactions and structural gaps within multi-dimensional resilience systems.

Remote Sensing Contextual Analysis of Heat Exposure Patterns

To provide spatial context for ward-level HRI findings, land surface temperature (LST), vegetation cover, and built-up intensity were mapped at the ward level using three openly available remote sensing datasets. MODIS MOD11A1 v6.1 daytime LST (March–June 2023, 1 km spatial resolution) was averaged at the ward level using administrative boundary polygons in QGIS 3.28. Landsat 8 OLI imagery (30 m resolution, cloud cover < 10%) from March–May 2023 was used to compute the Normalized Difference Vegetation Index (NDVI, Bands 4 and 5) and the Normalized Difference Built-Up Index (NDBI, Bands 5 and 6) at the ward level. MRSAC 2023 land-use classification (30 m) provided estimates of urban green space coverage and impervious surface area per ward. These spatial datasets serve as illustrative contextual evidence to examine whether ward-level HRI patterns are consistent with independently observed thermal and environmental conditions. This remote sensing analysis is descriptive and contextual; it does not constitute statistical validation of HRI scores, nor does it involve model-based prediction or proprietary classification.

Ward-level MODIS LST values ranged from 36 °C to 50 °C in Mumbai E Ward and from 37 °C to 47 °C in Dhantoli, Nagpur, during the March–June 2023 season. NDVI values ranged from 0 to 0.70 across study wards, with the lowest values in densely sealed central wards. NDBI values ranged from −0.46 to 0.35, indicating substantial variation in built-up intensity across and within cities. Ward-level LST, NDVI, and NDBI values were compared with ward-level HRI dimension scores to assess spatial consistency between remotely sensed thermal conditions and systemic resilience diagnostics. High-LST, low-NDVI wards were examined to determine whether they also exhibited lower HRI scores on the Natural and Physical dimensions, providing a descriptive cross-check of spatial coherence.

Methodological Replicability

The complete methodological documentation for the Heat Resilience Framework has been published separately Saunik and Shaw (2026) [26]. The companion publication provides the complete indicator framework, scoring rubrics, normalization procedure, AHP weighting process, sensitivity analyses, and ward-level HRI database. Accordingly, only methodological elements necessary for understanding the present application are summarized here, while readers are referred to the companion paper for full methodological details.

RESULTS AND DISCUSSION

Dimension-wise HRI Patterns

The ward-level HRI results reveal consistently higher scores on the physical dimension across all three cities, although the intensity and variability of exposure differ significantly by context. In Mumbai, physical scores exhibit pronounced intra-urban differentiation, with certain wards such as R Central and S registering values above 4.0, indicating extreme built density, constrained ventilation corridors, and high surface sealing. This spatial heterogeneity is consistent with literature on urban heat island effects associated with compact morphology and material composition [14,15]. The uneven distribution of exposure aligns with evidence that built density and impervious surfaces are associated with local heat accumulation in megacity environments.

Thane displays moderately high but relatively uniform physical scores, clustering around 3.7–3.8 across wards. Unlike Mumbai's sharp contrasts, Thane's exposure profile reflects systemic urban expansion characterized by transport-oriented growth and increasing vertical development. Similar transitional metropolitan configurations have been associated with rapid land-use change and insufficient integration of cooling infrastructure [22]. The relative homogeneity suggests that exposure operates as a city-wide baseline condition rather than sharply localized hotspots.

Nagpur exhibits moderate yet tightly clustered physical scores (approximately 3.1), indicating climate-driven uniform exposure rather than morphology-driven differentiation. Inland semi-arid cities experience extreme summer heat driven by large-scale atmospheric and oceanic variability [5,16]. Studies of Indian heatwave dynamics confirm that regional climatic intensity increasingly dominates local exposure patterns [6,7]. This explains the relatively consistent physical HRI values across wards in Nagpur, compared to the morphology-driven variability in Mumbai.

Across all cities, the economic dimension shows moderate variability, but its association with physical exposure varies by context. Institutional and natural dimensions consistently record lower scores relative to physical exposure, suggesting that governance and ecological buffers remain secondary or constrained components of resilience systems. This pattern is consistent with resilience theory indicating that physical exposure and socio-economic conditions interact in shaping vulnerability [9], though the direction and magnitude of these interactions cannot be established from correlational analysis alone.

These findings are consistent with Meerow et al. (2016), who argue that urban resilience is relational rather than additive [11]. Rather than isolated strengths in governance or ecology compensating for exposure, the system operates through cross-dimensional coupling. Similarly, Davoudi et al. (2012) emphasize cross-scalar misalignment in governance systems, which is reflected in the weak institutional buffering observed particularly in Thane [12].

Inter-Dimensional Correlation Analysis

The Spearman correlation matrices reveal structurally distinct resilience configurations across the three cities. In Mumbai, a moderate positive correlation between the physical and economic dimensions ($r = 0.45$) indicates that built-form exposure is associated with livelihood sensitivity. High-density wards with elevated surface temperatures also exhibit greater income precarity and occupational heat exposure, reinforcing vulnerability loops. This aligns with public health literature demonstrating that heat exposure disproportionately affects low-income populations and informal labour systems [2,3].

The correlation between physical and natural dimensions in Mumbai ($r = 0.64$) indicates a moderate association, yet ecological buffering remains spatially fragmented (Figure 2). While vegetation and coastal influences exist, their cooling effects are unevenly distributed and often disconnected from high-exposure residential clusters. Nature-based solutions literature emphasizes that green infrastructure must be spatially integrated to generate functional thermal mitigation [21,22]. The results suggest partial ecological buffering, lacking systemic integration.

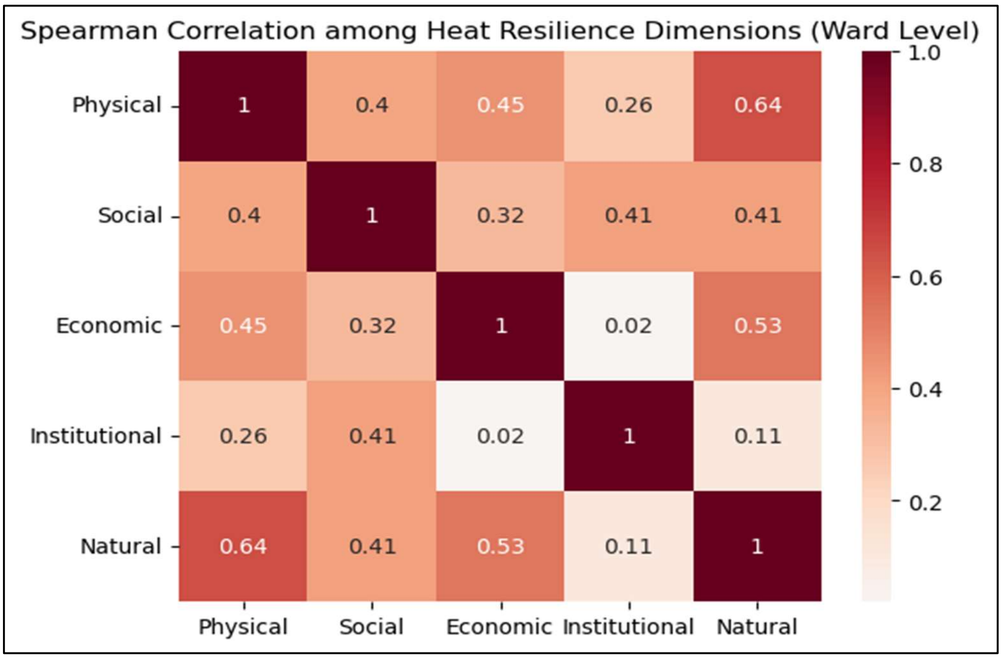

Figure 2. Interdimensional Correlation Matrix for Mumbai.

Institutional alignment in Mumbai remains comparatively weak (r = 0.26 between physical and institutional dimensions), indicating last-mile governance gaps. Although formal preparedness mechanisms exist, translation into ward-level resilience outcomes is inconsistent. Studies of Indian heat action plans highlight similar implementation asymmetries and uneven local penetration [18,19]. This supports the argument that macro preparedness does not automatically produce micro protection.

In Thane, the weak inverse relationship between physical and institutional dimensions (r = −0.23) suggests that institutional capacity does not scale proportionately with exposure intensity. This misalignment reflects governance thinness, often observed in rapidly expanding metropolitan regions (Figure 3). Gender-sensitive preparedness access challenges documented in Ahmedabad further demonstrate how institutional reach may not uniformly protect vulnerable groups [20].

Nagpur demonstrates the strongest physical–economic correlation (r = 0.70), suggesting an association between climatic exposure and livelihood sensitivity (Figure 4). Extreme ambient heat interacting with occupational exposure is consistent with the literature on the impacts of Indian heatwaves on mortality and productivity [4,8]. Climate projections further indicate potential intensification of such compound risks under warming scenarios [1,24]. Institutional coupling remains weak, and ecological buffering exhibits limited mitigation capacity under extreme inland conditions.

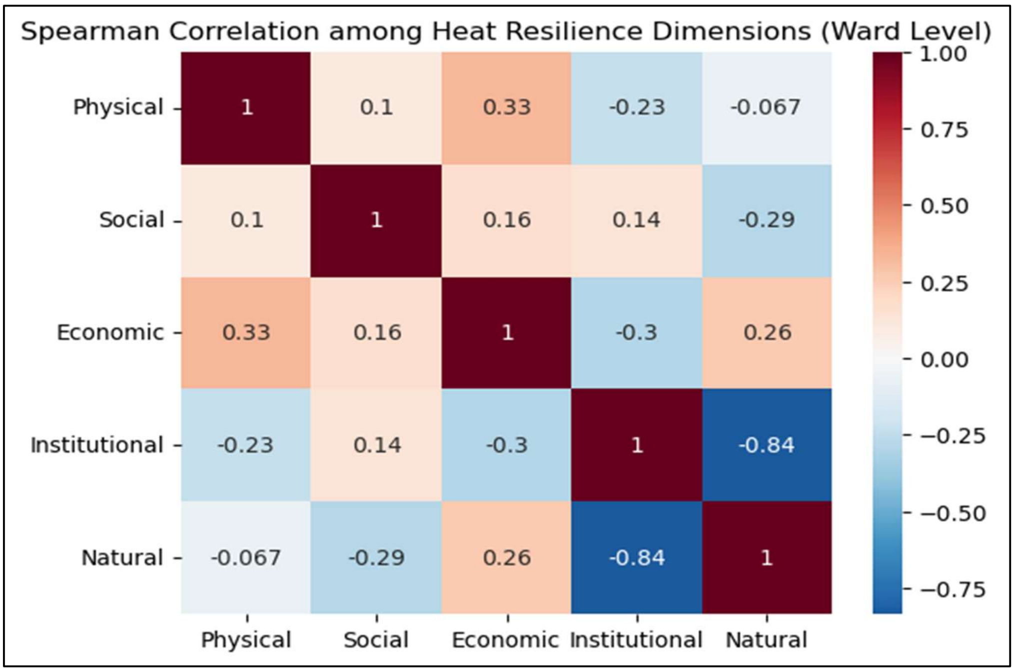

Figure 3. Interdimensional Correlation Matrix for Thane.

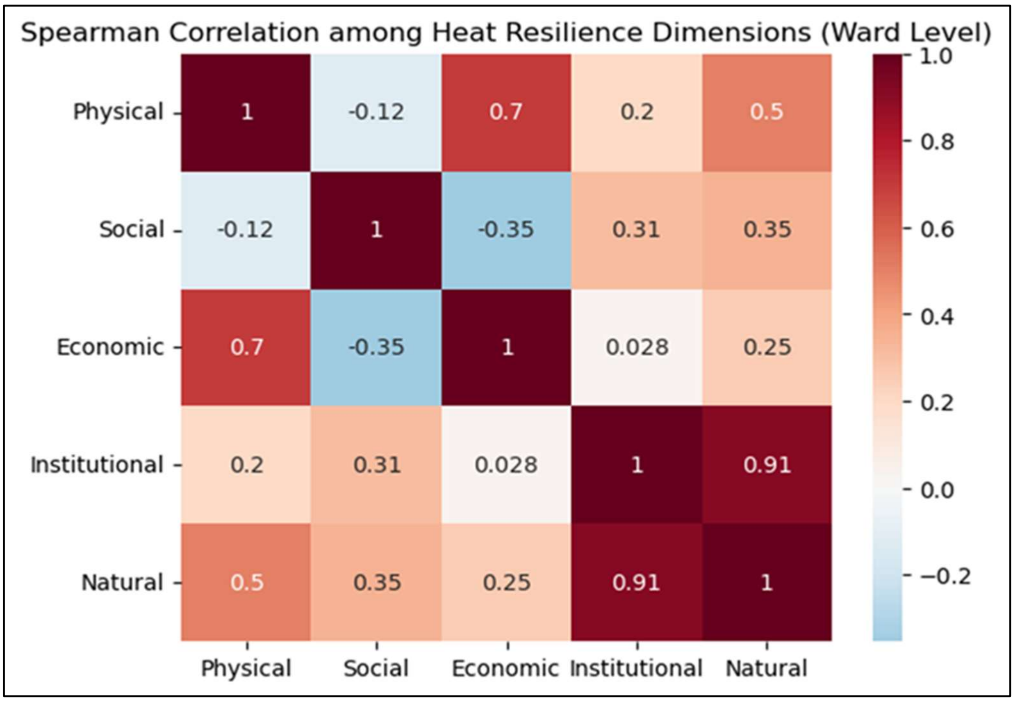

Figure 4. Interdimensional Correlation Matrix for Nagpur.

Collectively, these inter-dimensional patterns reinforce systems-based resilience theory emphasizing cross-dimensional feedback rather than additive accumulation [10,13]. Resilience emerges where alignment exists among exposure, livelihood security, governance reach, and ecological buffering; conversely, misalignment produces reinforcing vulnerability loops.

Illustrative Spatial Heat Exposure Patterns from Remote Sensing

Remote sensing analysis provides spatial context for ward-level HRI findings. In Mumbai E Ward, a low-resilience ward (Institutional dimension score: 1.77; Natural dimension score: 2.33), MODIS daytime LST ranged from 36 °C to 50 °C during the study period, among the highest values recorded across Mumbai's 24 wards. NDVI values in E Ward were consistently low (near 0), consistent with dense sealing and minimal urban vegetation, while NDBI values were elevated, confirming high built-up intensity. This spatial pattern is consistent with the ward's low Natural and Physical HRI scores, suggesting that thermal exposure and green infrastructure deficits co-occur with systemic resilience gaps (Figure 5).

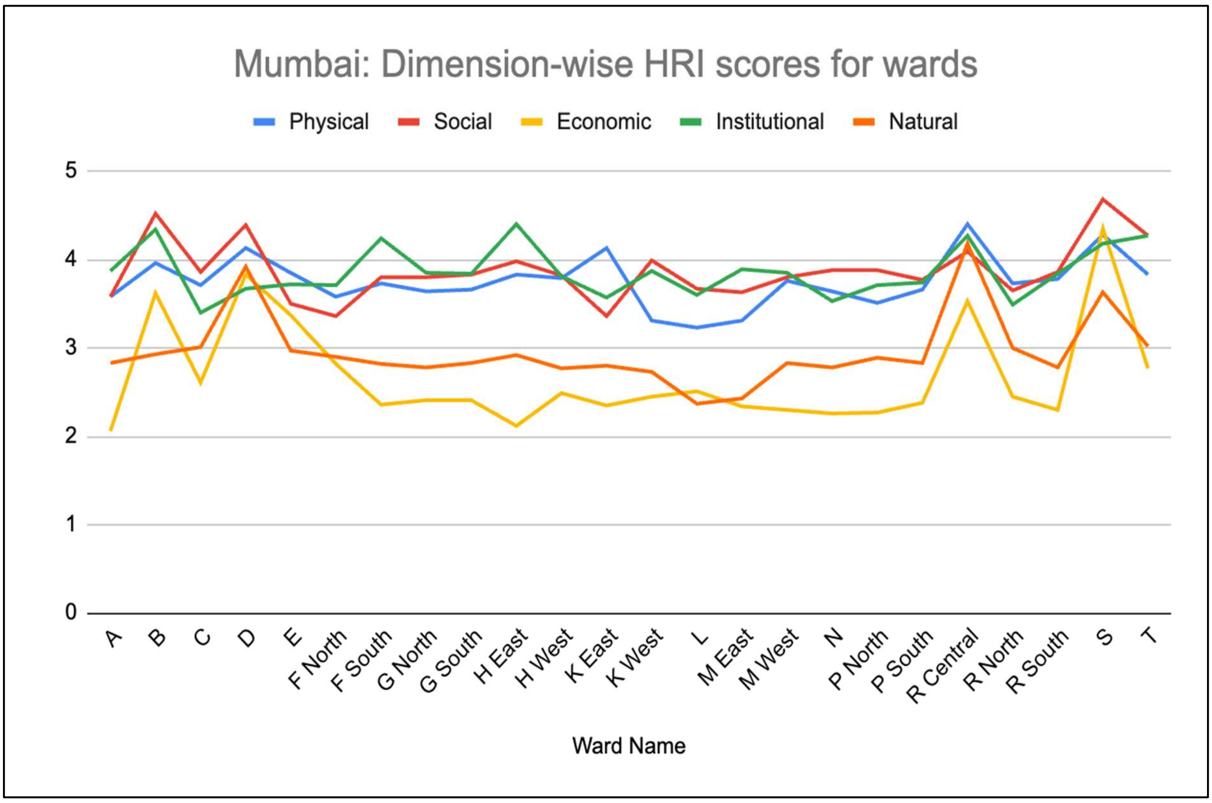

Figure 5. Dimension-wise HRI scores for all 24 administrative wards of Mumbai (N = 24).

In Thane, the ward of Thane West exhibits elevated MODIS LST values and low NDVI, spatially consistent with its comparatively lower Natural dimension HRI score among the nine Thane wards. Despite Thane's moderately high Physical dimension scores (averaging 3.75 across wards), the low Institutional dimension (city average: 2.24) is reflected in the absence of integrated heat governance infrastructure at the ward level. This mismatch between physical infrastructure capacity and institutional preparedness is the defining characteristic of Thane's resilience configuration and is consistent with the weak Physical–Institutional correlation (r = −0.23) identified in the Spearman analysis (Figure 6).

In Nagpur, Dhantoli zone exhibits MODIS daytime LST of 37 °C–47 °C during March–June 2023, among the highest in the study. NDBI values are elevated, consistent with high built-up intensity, while NDVI values are low. Nagpur's central zones generally show the greatest thermal stress, spatially co-occurring with lower Institutional dimension scores. The strongest Physical–Economic correlation identified in Nagpur ($r = 0.70$) is consistent with LST patterns that intensify in economically active, densely developed zones, suggesting co-exposure of climatic and livelihood vulnerability (Figure 7).

The spatial correspondence between ward-level HRI patterns and independently observed remote sensing indicators (LST, NDVI, NDBI) provides contextual consistency for the systemic resilience diagnostics. Wards with lower HRI scores on the Natural and Physical dimensions tend to coincide with elevated LST and reduced vegetation cover in the MODIS and Landsat 8 datasets. This cross-source coherence supports the descriptive validity of the multi-scalar framework as a planning diagnostic tool, while noting that the remote sensing comparison is illustrative and contextual, not a formal statistical validation.

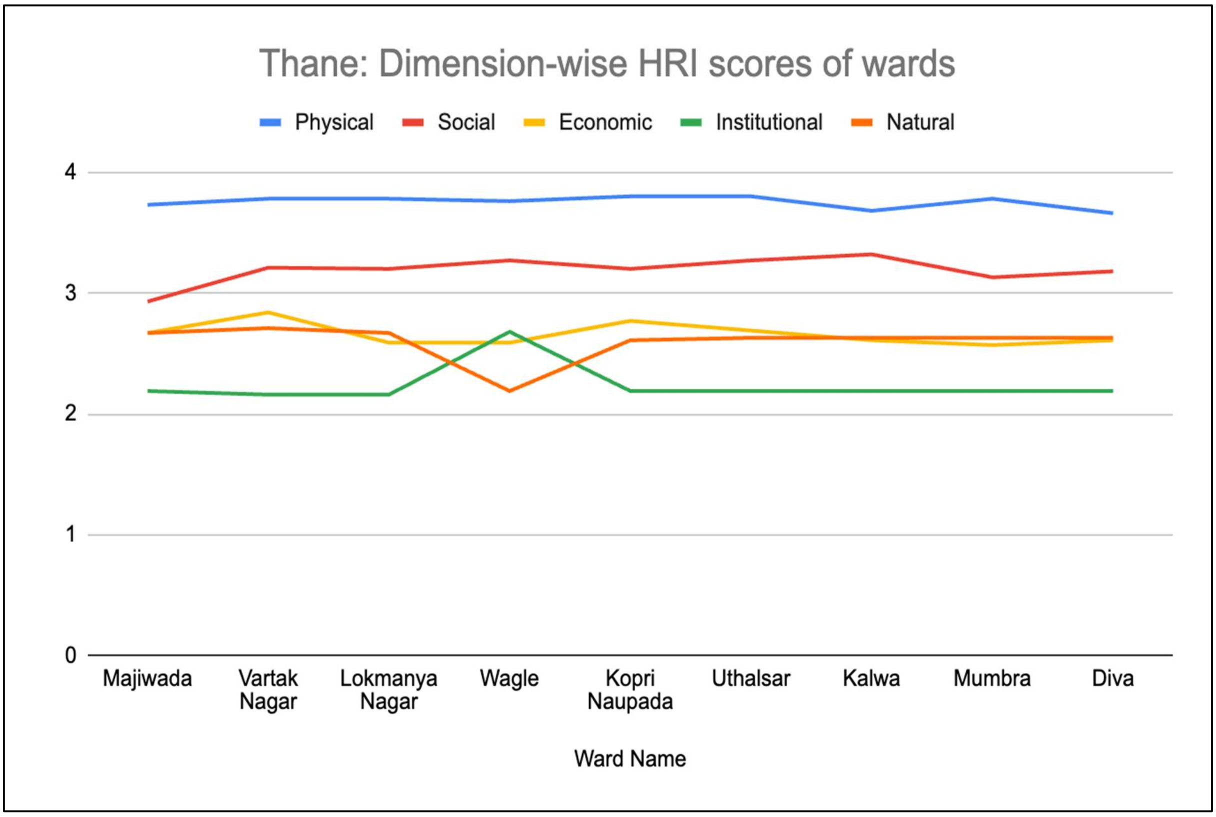

Figure 6. Dimension-wise HRI scores for all 9 administrative wards of Thane (N = 9).

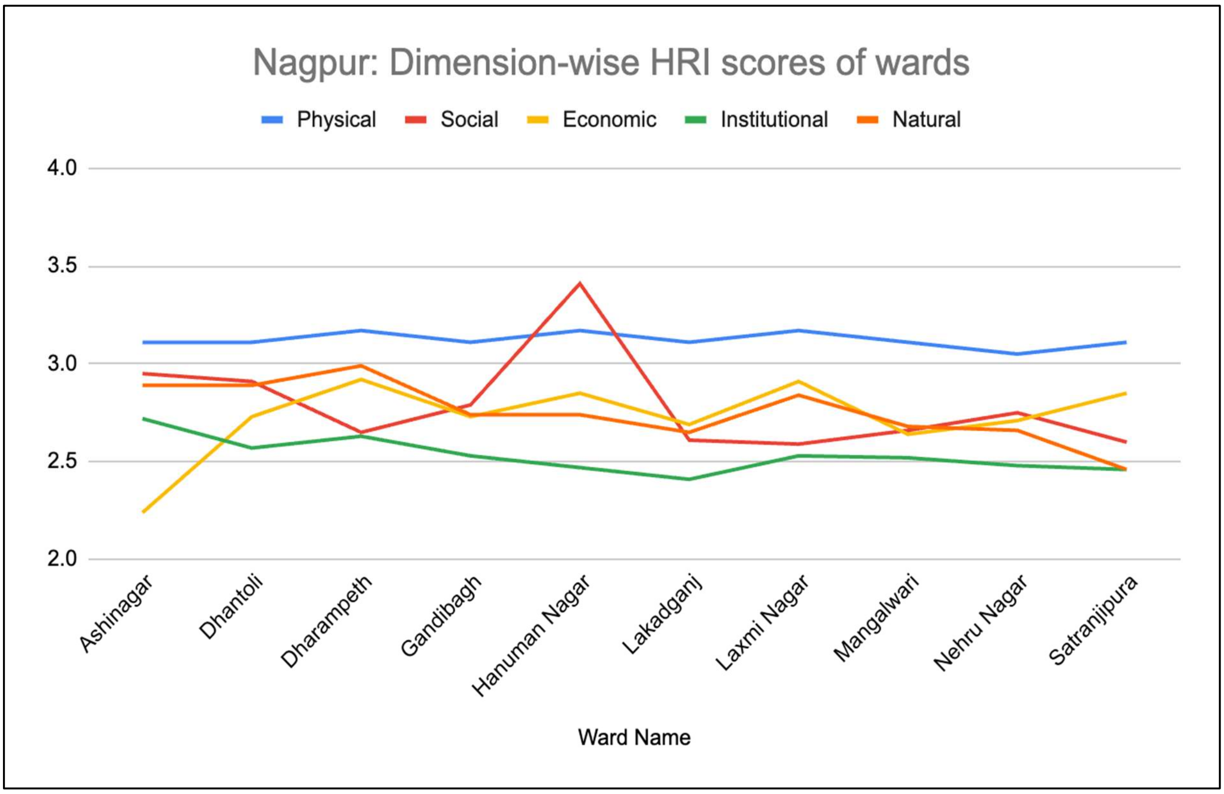

Figure 7. Dimension-wise HRI scores for all 10 administrative zones of Nagpur (N = 10).

Urban Heat Resilience as a Systemic Phenomenon

The comparative analysis reveals that urban heat resilience is emergent and system-dependent, varying substantially across cities and across wards within cities. Mumbai demonstrates the strongest composite resilience (city-level HRI: 3.42 under equal-dim weights; 3.67 under AHP weights), driven by high Institutional (3.85) and Physical (3.75) dimension scores, reflecting its established governance infrastructure and physical service provision. However, Mumbai's intra-urban variation is pronounced: low-resilience wards such as E Ward, characterized by extreme density, high LST, and weak ecological buffers, represent concentrated vulnerability pockets that composite city-level scores obscure (Figure 8).

Thane presents a constrained resilience configuration (HRI: 2.89/2.68) where moderate Physical capacity is undermined by the lowest Institutional dimension score across all three cities (2.24), creating a structural gap in governance reach (Figure 9). Nagpur, with a climate-dominated profile (HRI: 2.79/2.71), exhibits greater uniformity across zones but faces persistent livelihood–exposure co-vulnerability as reflected in the strong Physical–Economic correlation (r = 0.70) (Figure 10).

Figure 8. Mumbai E Ward—illustrative spatial heat exposure mapping. (**Left**) Study area with structures classified by heat-exposure risk. (**Right**) Spatial distribution of structures by heat-exposure risk.

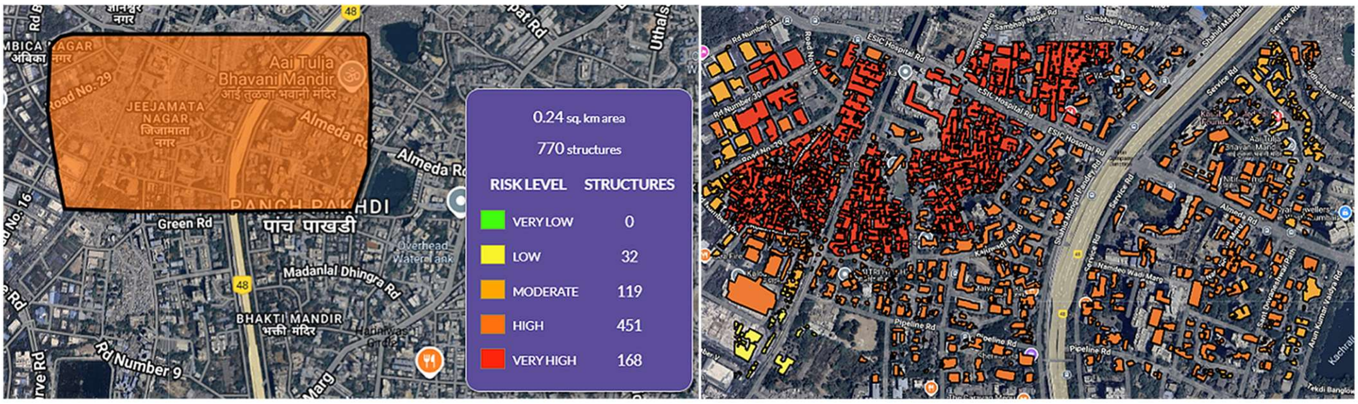

Figure 9. Thane West—illustrative spatial heat exposure mapping. (**Left**) Study area with structures classified by heat-exposure risk. (**Right**) Spatial distribution of structures by heat-exposure risk.

Figure 10. Nagpur (Dhantoli zone)—illustrative spatial heat exposure mapping. (**Left**) Study area with structures classified by heat-exposure risk. (**Right**) Spatial distribution of structures by heat-exposure risk.

Across all cities, the Institutional dimension emerges as the most consequential differentiator of composite resilience, consistent with its AHP weight of 0.551. Mumbai's high Institutional score (3.85) anchors its composite resilience leadership; Thane's low Institutional score (2.24) is the primary constraint on its composite standing despite competitive Physical scores; Nagpur's intermediate Institutional score (2.54) partially explains why it ranks above Thane under AHP weighting despite lower equal-weighted scores. Ecological buffers (Natural dimension) provide conditional mitigation but remain constrained by spatial fragmentation and limited integration into high-exposure residential environments across all three cities.

By empirically demonstrating that alignment across dimensions and scales, rather than isolated strength in any single domain, determines composite heat resilience, this study advances the evidence base for scale-sensitive climate adaptation policy. The ward-level HRI approach enables planners to identify which dimensions are constraining resilience in specific localities, supporting prioritized interventions rather than uniform city-wide programmes.

CONCLUSIONS

This study demonstrates that urban heat resilience is not an additive outcome of isolated physical, social, economic, institutional, or ecological strengths, but an emergent property shaped by cross-dimensional alignment and scale-sensitive governance. Across Mumbai, Thane, and Nagpur, the Physical dimension consistently records the highest mean HRI scores, while the Institutional dimension is the strongest predictor of composite resilience under AHP weighting (weight = 0.551). Spearman correlations reveal context-specific structural alignments that cannot be recovered from city-level aggregates alone. These associations are interpreted as exploratory and diagnostic; causal inference is not claimed. Mumbai's composite HRI of 3.42 (equal-dim)/3.67 (AHP) reflects the highest resilience across the three cities, anchored by strong Institutional and Physical capacity, though intra-urban inequality remains pronounced. Thane and Nagpur face distinct governance gaps that limit their composite resilience despite adequate physical infrastructure in some wards.

The comparative analysis reveals distinct resilience configurations. Mumbai's composite resilience is the strongest of the three cities, sustained by high Institutional and Physical scores; however, the pronounced intra-urban spread across its 24 wards-particularly the low-resilience cluster of wards with high thermal exposure and limited ecological buffers-underscores that city-level averages mask concentrated pockets of systemic vulnerability.

Thane represents a constrained resilience configuration characterised by moderate physical and social capacity but the lowest Institutional dimension score across the three cities (2.24), limiting cross-dimensional coherence and governance reach.

Nagpur reflects a climate-dominated resilience profile where adaptive capacity depends disproportionately on livelihood stability and social cohesion; its intermediate Institutional dimension score (2.54) is the primary reason it ranks above Thane under AHP weighting, despite lower equal-weighted scores.

These findings confirm that resilience pathways are context-specific and system-dependent, reinforcing the need for differentiated, scale-sensitive climate adaptation strategies. Composite HRI scores alone are insufficient; planners require dimension-level diagnostics to identify binding constraints and cross-dimensional mismatches that impede heat resilience in rapidly urbanizing Indian cities.

From a sustainability perspective, integrating multidimensional HRI diagnostics with spatial remote-sensing contextualisation provides a robust and transparent planning framework for aligning macro-level governance with micro-scale intervention priorities. By linking ward-level HRI patterns to independently observable thermal and built-environment indicators, this study advances evidence-based climate adaptation aligned with Sustainable Development Goals 11 and 13. The results underscore the importance of coordinated interventions that simultaneously address urban morphology, income security, governance reach, and ecological integration to achieve durable heat resilience in rapidly urbanising regions.

This study is subject to several limitations. AHP-derived dimension weights are based on expert judgement and may differ from weights derived through alternative elicitation methods; the sensitivity analysis confirms that Mumbai's first-place ranking is stable, while the Thane–Nagpur ordering is sensitive to the weight assigned to the Institutional dimension. Ward-level HRI scores reflect data provided by municipal officials at a single point in time; cross-sectional data may not capture temporal variability in heat exposure or adaptive behaviour. The remote sensing analysis is descriptive and ward-level; it does not provide building-scale resolution or enable causal inference. Future research should incorporate longitudinal heatwave event data, real-time sensor validation, and causal modelling approaches to examine dynamic resilience feedback loops. Expanding the framework to additional inland and coastal cities would strengthen generalisability and refine scale-sensitive resilience diagnostics.

DATA AVAILABILITY

The methodological framework together with the complete indicator definitions, AHP weighting procedure, sensitivity analyses, and ward-level Heat Resilience Index database are publicly available in the companion methodology paper Saunik and Shaw (2026) [26] and its supplementary materials. The present study additionally uses publicly available MODIS, Landsat 8, and MRSAC datasets as described in the Methods section. Questionnaire responses contain potentially identifiable information from municipal officials and are therefore available from the corresponding author subject to institutional ethical requirements.

AUTHOR CONTRIBUTIONS

Concept, methodology, supervision, writing review and editing, RS; Analysis, investigation, resources, validation, writing original, SS. All authors have read and agreed to the published version of the manuscript.

CONFLICT OF INTEREST

The authors declare that they have no conflicts of interest.

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REFERENCES

1. CLIMATE CHANGE 2023 synthesis report. 2023. Available from: https://cgspace.cgiar.org/items/7e70f98b-3a47-4881-8d8a-0e988c594ef4. Accessed on 2026 Mar 19.
2. Ebi KL, Capon A, Berry P, Broderick C, de Dear R, Havenith G, et al. Hot weather and heat extremes: health risks. Lancet. 2021;398(10301):698-708. doi: 10.1016/S0140-6736(21)01208-3
3. Kroeger C, Reeves A. Extreme heat leads to short- and long-term food insecurity with serious consequences for health. Eur J Public Health. 2022;32(4):521. doi: 10.1093/eurpub/ckac080
4. Sharma A, Andhikaputra G, Wang YC. Heatwaves in South Asia: characterization, consequences on human health, and adaptation strategies. Atmosphere. 2022;13(5):734. doi: 10.3390/atmos13050734
5. Dubey AK, Kumar P, Saharwardi MS, Javed A. Understanding the hot season dynamics and variability across India. Weather Clim Extremes. 2021;32:100317. doi: 10.1016/j.wace.2021.100317
6. Srivastava A, Mohapatra M, Kumar N. Hot weather hazard analysis over India. Sci Rep. 2022;12(1):19768. doi: 10.1038/s41598-022-24065-0
7. Rao KK, Jyoteeshkumar Reddy P, Chowdary JS. Indian heatwaves in a future climate with varying hazard thresholds. Environ Res: Climate. 2023;2(1):015002. doi: 10.1088/2752-5295/acb077
8. Malik P, Bhardwaj P, Singh O. Heat wave fatalities over India: 1978–2014. Curr Sci. 2021;120(10):1593-9. doi: 10.18520/cs/v120/i10/1593-1599
9. Adger WN. Vulnerability. Glob Environ Change. 2006;16(3):268-81. doi: 10.1016/j.gloenvcha.2006.02.006
10. Folke C, Carpenter S, Walker B, Scheffer M, Chapin T, Rockström J. Resilience thinking: integrating resilience, adaptability and transformability. Ecol Soc. 2010;15(4):20. doi: 10.5751/ES-03610-150420

11. Meerow S, Newell JP, Stults M. Defining urban resilience: a review. Landsc Urban Plan. 2016;147:38-49. doi: 10.1016/j.landurbplan.2015.11.011
12. Davoudi S, Shaw K, Haider LJ, Quinlan AE, Peterson GD, Wilkinson C, et al. Resilience: a bridging concept or a dead end? Planning Theory Pract. 2012;13(2):299-333. doi: 10.1080/14649357.2012.677124
13. Pelling M. Adaptation to climate change: from resilience to transformation. London (UK): Routledge; 2010. p. 224. doi: 10.4324/9780203889046
14. Pritipadmaja, Garg RD, Sharma AK. Assessing the cooling effect of blue-green spaces: implications for urban heat island mitigation. Water. 2023;15(16):2983. doi: 10.3390/w15162983
15. Tian F, Klingaman NP, Dong B. The driving processes of concurrent hot and dry extreme events in China. 2021. Available from: https://journals.ametsoc.org/view/journals/clim/34/5/JCLI-D-19-0760.1.xml. Accessed on 2026 Mar 19.
16. Hari V, Ghosh S, Zhang W, Kumar R. Strong influence of North Pacific Ocean variability on Indian summer heatwaves. Nat Commun. 2022;13(1):5349. doi: 10.1038/s41467-022-32942-5
17. Ha KJ, Seo YW, Yeo JH, Timmermann A, Chung ES, Franzke CLE, et al. Dynamics and characteristics of dry and moist heatwaves over East Asia. npj Clim Atmos Sci. 2022;5(1):49. doi: 10.1038/s41612-022-00272-4
18. Nastar M. Message sent, now what? A critical analysis of the heat action plan in Ahmedabad, India. Urban Sci. 2020;4(4):53. doi: 10.3390/urbansci4040053
19. Pillai AV, Dalal T. How is India adapting to heatwaves? An assessment of heat action plans with insights for transformative climate action. Available from: https://cprindia.org/briefsreports/how-is-india-adapting-to-heatwaves-an-assessment-of-heat-action-plans-with-insights-for-transformative-climate-action/. Accessed on 2026 Mar 19
20. Trahan A, Walshe R, Mehta V. Extreme heat, gender, and access to preparedness measures: an analysis of the heatwave early warning system in Ahmedabad, India. Int J Disaster Risk Reduct. 2023;99:104080. doi: 10.1016/j.ijdrr.2023.104080
21. Kabisch N, Korn H, Stadler J, Bonn A, editors. Nature-based solutions to climate change adaptation in urban areas: linkages between science, policy and practice. Available from: http://link.springer.com/10.1007/978-3-319-56091-5_1. Accessed on 2026 Mar 20.
22. Menon JS, Sharma R. Nature-based solutions for co-mitigation of air pollution and urban heat in Indian cities. Front Sustain Cities. 2021;3:705185. doi: 10.3389/frsc.2021.705185
23. Kacker K, Utpal A, Singh S, Srivastava P, Mukherjee M, Subramanian SS, et al. A framework for impact based heat stress warning system for a coastal city in India. Sci Rep. 2026;16(1):12254. doi: 10.1038/s41598-026-38639-9
24. Kumari RM, Kitchley JL. A framework to assess the contextual composite heat vulnerability index for a heritage city in India: a case study of Madurai. Sustain Cities Soc. 2024;101:105119. doi: 10.1016/j.scs.2023.105119

25. Cantatore E, Esposito D, Sonnessa A. Mapping the multi-vulnerabilities of outdoor places to enhance the resilience of historic urban districts: the case of the Apulian region exposed to slow and rapid-onset disasters. Sustainability. 2023;15(19):14248. doi: 10.3390/su151914248
26. Saunik S, Shaw R. Heat resilience framework: a methodological approach to assessing a city's preparedness for heatwaves. Climate. 2026;14(7):149. doi: 10.3390/cli14070149

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