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Ahad Kanak Prottay

murp250410@ku.ac.bd

Khulna University

Vargob Paul

Khulna University

Shazed Hossain Chamok

Khulna University

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Heat Risk Assessment at Union Level Using Multiplicative Hazard-Exposure-Vulnerability Framework Integrating Remote Sensing and Socio-Economic Data

Ahad Kanak Prottay^{1*}, Vargob Paul¹, Shazed Hossain Chamok¹

¹Urban & Rural Planning Discipline, Khulna University, Khulna, Bangladesh

*Corresponding author. E-mail: murp250410@ku.ac.bd

ORCID: 0009-0000-6265-5190

Abstract

Extreme heat risk is escalating across South Asian cities, yet spatially explicit assessments integrating thermal hazard, built environment exposure, and census-derived vulnerability at fine administrative scales remain scarce outside major metropolitan areas. This study presents the first union-level Heat Risk (HR) assessment for Rajshahi Division, Bangladesh, covering all 654 administrative unions across eight districts through a multiplicative Hazard-Exposure-Vulnerability (HEV) framework grounded in the IPCC AR5 risk conceptualization. Fifteen indicators from MODIS LST, Sentinel-2 imagery, OpenStreetMap, and BBS 2022 Census data were normalized division-wide and weighted through a conditional PCA strategy. The Urban Thermal Field Variance Index (UTFVI) served as the sole hazard indicator; Exposure was quantified through population density, building density, NDBI, MNDWI, and distance to health facilities; Vulnerability was decomposed into Sensitivity and Adaptive Capacity across nine indicators. The risk distribution was right-skewed: 45.1% of unions fell in the Very Low class and only 1.5% (10 unions within Rajshahi City Corporation) in the Very High class. Spatial autocorrelation confirmed strong positive clustering (Global Moran's $I = 0.813$, $Z = 36.89$, $p < 0.001$); LISA identified three High-High hotspot zones: the Rajshahi City core, the Pabna Sadar-Santhia corridor, and the Natore-Nawabganj cluster and a Low-Low coldspot belt across Bogura, Naogaon, and Sirajganj. Nawabganj District recorded the highest division-wide vulnerability despite ranking fourth in overall HR, underscoring the need for spatially differentiated adaptation addressing built environment cooling in high-hazard cores and social infrastructure investment in high-vulnerability peripheries. The pipeline is replicable across Bangladesh's divisions and transferable to comparable data-scarce contexts.

Keywords: heat risk; Rajshahi Division; UTFVI; hazard-exposure-vulnerability; spatial autocorrelation; LISA

1 Introduction

Extreme heat exposure in urban areas nearly doubled globally between the 1980s and 2010s, with the highest concentration in developing-country cities [1]. South Asian urban populations experience among the world's most intense thermal stress, with heat-related excess mortality documented across the region and projected to escalate sharply under future warming scenarios [2]. Rapid urbanization, impervious surface expansion, and vegetation loss are converging to amplify these pressures, creating escalating heat risk disparities across and within cities.

The increased land surface temperature (LST) and enhanced urban heat island (UHI) effects are the main factors caused by higher impervious surface and less vegetation cover [3]. In South Asian cities, NDVI is always negatively correlated with LST, whereas built-up indices are strongly positively correlated [4]. In Bangladesh, the surface UHI has been found to be more pronounced in the five major cities over the last 20 years, driven by urbanization and vegetation loss [4], while vegetation loss is the main driver of SUHI in rapidly growing peri-urban areas like Gazipur [5].

Rajshahi Division is the hottest administrative division of Bangladesh, with 369 heatwave days during 1980-2022 at a warming rate of $\sim 1^\circ\text{C}$ per decade. UHI intensity is concentrated in the central-northern core of Rajshahi City and is closely related to built-up expansion [6]. This pattern is similar to the UHI intensification found in major urban centres in Bangladesh [4, 7]). However, this thermal vulnerability has received comparatively little systematic heat risk attention in Rajshahi Division compared to Dhaka or Chattogram.

The IPCC AR5 Hazard-Exposure-Vulnerability (HEV) framework is increasingly being applied at fine administrative scales employing remote sensing hazard data and census-based vulnerability indicators [8]. Applications are currently in use in wards in Johannesburg [9], cities in the Philippines [10] and

districts in Meghalaya and Karnataka [11]. These studies have consistently noted that fine scale analyses reveal localized risk concentrations (and spatial mismatch between hazard and vulnerability) that are not captured by national analyses.

A key takeaway from this literature is that thermal hazard intensity and socioeconomic vulnerability are seldom co-located spatially. Low-income groups, slum dwellers and outdoor workers have limited adaptive capacity, which increases their effective risk even in areas of moderate thermal stress [12, 13]. Most of the heat risk studies have been conducted for Dhaka [12], Chattogram [15], and Gazipur [5] cities in Bangladesh. Although there are some studies on LST and green space analysis at Rajshahi city [14, 7], no systematic division-level vulnerability integration has been made. There is no spatially explicit heat risk assessment at union level in Rajshahi Division, a heterogeneous area of 18,174 square kilometers consisting of 654 administrative unions in eight districts.

This study is the first application of the Heat Risk (HR) assessment at the union level for Rajshahi Division, Bangladesh, using MODIS LST-derived UTFVI, Sentinel-2 spectral indices, OSM building footprints, and health facility data and socioeconomic indicators from the BBS 2022 population and housing census within a multiplicative Hazard-Exposure-Vulnerability framework. Three objectives are addressed: (i) estimation and spatial representation of hazard, exposure, sensitivity, adaptive capacity and vulnerability components over all 654 unions; (ii) assessment of a composite Heat Risk Index using a conditional PCA-based weighting approach (equal weights where PCA conditions are not fulfilled) within a multiplicative $\text{Risk} = H \times E \times V$ framework; and (iii) Global Moran's I and LISA analysis of the HR surface to identify statistically significant hotspot and coldspot clusters and assess inter-district heat risk disparities.

2 Methods

2.1 Study Area

Rajshahi Division is situated in northwestern Bangladesh ($24^{\circ}07' - 25^{\circ}12'N$, $88^{\circ}01' - 89^{\circ}22'E$), covering a total area of approximately 18,174 km² across eight districts: Bogura, Joypurhat, Naogaon, Natore, Nawabganj, Pabna, Rajshahi, and Sirajganj, comprising 69 upazilas and 654 unions [16]. The district supports a total population of approximately 20.35 million [16]. Geographically, it is located in the high interfluvial area of the Ganges-Brahmaputra floodplain, within the Barind Tract, a physiographic unit of Pleistocene terrace with high clay content, uneven topography and marked seasonal aridity [14, 17]. As the annual average temperature is greater than 26°C and the maximum temperature in the pre-monsoon season is always greater than 38°C, it is the hottest among the divisions of Bangladesh and therefore fit for the present study. The extent of the study area is presented in Fig. 1 [6].

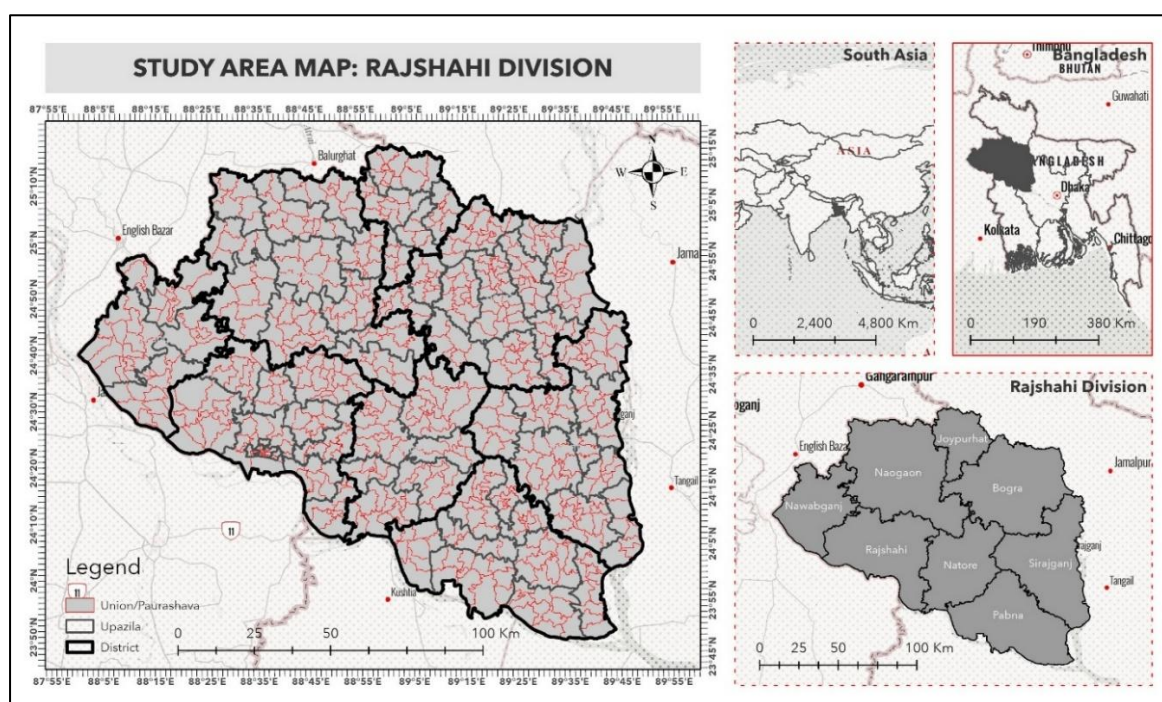


Fig. 1 Study area map: Rajshahi Division

2.2 Data Sources

Data were collected from three major sources, including satellite remote sensing platforms, accessed through Google Earth Engine (GEE), volunteered geographic information (OpenStreetMap, OSM) and socioeconomic data from the Bangladesh Bureau of Statistics (BBS) 2022 Population and Housing Census. Table 1 provides a summary of each dataset, including source, spatial resolution, and processing approach.

Table 1 Data sources and processing summary

Indicator	Type	Source	Resolution	Processing
LST / UTFVI	Hazard	MODIS MOD11A2 (GEE)	1 km / 8-day	Median composite Jan-Jun 2026
NDBI, NDVI, MNDWI	Exposure / Adaptive Capacity	Sentinel-2 SR (GEE)	10 m	Median composite Jan-Jun 2026; cloud mask <5%
Building Density (BD)	Exposure	OSM via Overpass API	Vector	Polygon to centroid points; Kernel Density Estimation (ArcGIS Pro)
Population Density (PD)	Exposure	BBS Census 2022 + ArcGIS geometry	Union	Population ÷ Area (km ²)
Distance to Health Facilities (DistToHF)	Exposure	OSM HotOSM Health (GEE)	30 m	Cost-distance surface; zonal mean per union
HHS, HQ, DT, NWR, WU, EP	Sensitivity / Adaptive Capacity	BBS Census 2022	Union	Extracted from Tables HH-01, HH-06, HH-09, HH-11, P-02, P-08, P-12, P-16

MODIS MOD11A2 (Terra, 1 km, 8-day composite) was processed as a median composite for January-May 2026 to represent the peak pre-monsoon thermal conditions. The Urban Thermal Field Variance Index (UTFVI) was calculated following Chen et al. (2006) and has been widely used in South Asian urban heat studies [19, 15]:

$$UTFVI = \frac{T_s - T_m}{T_m}$$

The UTFVI was chosen as the only indicator of hazards for four reasons. Firstly, it adjusts each pixel's LST value based on its mean for the entire division as follows: $UTFVI = (T_s - T_m) / T_m$, where the change in absolute temperature is transformed into the relative thermal anomaly surface and becomes more comparable between heterogeneous land use types and easily aggregated at administrative units scale [20, 21]. Secondly, UTFVI consistently shows urbanization-induced thermal hazards in South Asian and African cities at ward, subdistrict, and district levels: the most degraded UTFVI class increased from 1.69% to 27.53% of the Chattogram city due to the increase in urban land [15]; in Dhaka, the stronger and strongest UTFVI classes made up to 72% of the city in 2030 due to urbanization [20]; and in Addis Ababa and Tianjin, the UTFVI deterioration correlated with the increase in the proportion of the impervious surface [62, 63]. This serves as further validation of UTFVI as a dependable proxy of thermal hazards associated with UHI. Thirdly, UTFVI has been incorporated into a hazard or environmental exposure variable in HEV composite models in Johannesburg [10] and Mekelle [54], thus showing its ability to be used as a hazard layer for administrative units in combination with socio-economic vulnerability indicators. Lastly, MODIS MOD11A2 data have been selected rather than Landsat-based LST, due to the latter's 16 days period in comparison with MOD11A2's 8 days one, enabling stable averaging for all 654 union administrative units at once [58]. Previous MODIS heat wave climatologies have already been incorporated into heat vulnerability models [59] and, in areas lacking meteorological station inputs, 8-day MODIS averages have proven to be superior compared to daily data [60]. The use of a spatial resolution of 1 km implies a clear support inconsistency between the MODIS data and smaller-scale layers for social and built environment, one pixel might contain several urban unions, which is somewhat overcome by zonal averaging. However, further studies must consider downscaling or fusion of LST data to maintain the consistency of spatial accuracy.

Although hazard composites of multiple indicators: air temperature from ERA5, WBGT, UTCI, or frequency of heatwaves, are being used increasingly in studies on heat risks in cities, lack of continuous meteorological records at the union level in Bangladesh makes it impossible to use this technique. The meteorological networks in Bangladesh are not dense enough to detect differences within unions, while

ERA5, for instance, is available only at 0.1° to 0.25° resolution, whereby one pixel covers several unions [66]. Only one satellite-based thermal layer has proven to be the pragmatic and rational component of hazard in HEV appraisals for developing countries precisely due to the fact that it provides spatially continuous and zonal mean-compliant coverage while finer meteorological layers cannot be aligned with the chosen target administrative units [65, 66]. Single indicator usage is recognized as a shortcoming of the study; usage of indicators related to heat wave frequency, duration, and night thermal conditions is an important task for the future. Six-class criteria for ecological quality are given in Table 3.

Three spectral indices were extracted from Sentinel-2 Surface Reflectance imagery, and used to characterize built-up intensity, vegetation cover and surface water content at 10 m resolution. The Normalized Difference Built-up Index (NDBI) separates the built-up surface from the non-built-up land based on the shortwave infrared and near-infrared reflectance [21]:

$$NDBI = \frac{SWIR - NIR}{SWIR + NIR}$$

where SWIR is Sentinel-2 Band 11 (1,610 nm) and NIR is Band 8 (842 nm). The Normalized Difference Vegetation Index (NDVI) is a measure of the density of surface vegetation from the difference in near-infrared and red reflectance [22]:

$$NDVI = \frac{NIR - Red}{NIR + Red}$$

where NIR is Band 8 (842 nm) and Red is Band 4 (665 nm). The Modified Normalized Difference Water Index (MNDWI) is based on green and shortwave infrared reflectance to detect open water and moisture surfaces [23]:

$$MNDWI = \frac{Green - SWIR}{Green + SWIR}$$

where Green is Sentinel-2 Band 3 (560 nm) and SWIR is Band 11 (1,610 nm). All three indices were calculated as median composites for January-June 2026 using Google Earth Engine with a cloud masking threshold of less than 5% per pixel, and zonal mean statistics were extracted per union polygon in ArcGIS Pro [4, 3].

Building footprint polygons were downloaded from OSM via the Overpass API, clipped to the division boundary, converted to centroid points, and subjected to Kernel Density Estimation (KDE) with a bandwidth determined by Silverman's rule of thumb [25, 24]:

$$h = 0.9 \times \min\left(\sigma, \frac{IQR}{1.34}\right) \times n^{-\frac{1}{5}}$$

where σ is the standard deviation, IQR is the interquartile range, and n is the number of input points. KDE was applied with a cell size of 30 m and a quartic kernel function in ArcGIS Pro, producing a continuous building density raster subsequently resampled to union-level zonal means. OSM building data have demonstrated sufficient completeness for urban morphology and climate risk applications [26, 27]. Distance to health facilities (DistToHF) was derived using cumulative cost-distance analysis on OSM HotOSM Health point features within GEE. Population density was computed as BBS 2022 census population divided by union area (km²) from the administrative shapefile geometry.

Socioeconomic indicators obtained from BBS 2022 district census reports at union level are: Average Household Size (HH-11), Percentage of Non-Permanent Floor (HH-01), Slums and Floating Population Percentage (P-02), Non-Working Rate (P-12), Percentage of Financially Excluded People (P-16), Unsafe Water Source (HH-06), Energy Poverty Percentage (HH-09), and Literacy Rate (P-08). Extraction was done using automated Python scripts, and name of union was verified manually through comparison with BBS administrative naming and the shapefile. The distribution of all 15 indicators is shown in Fig. 2.

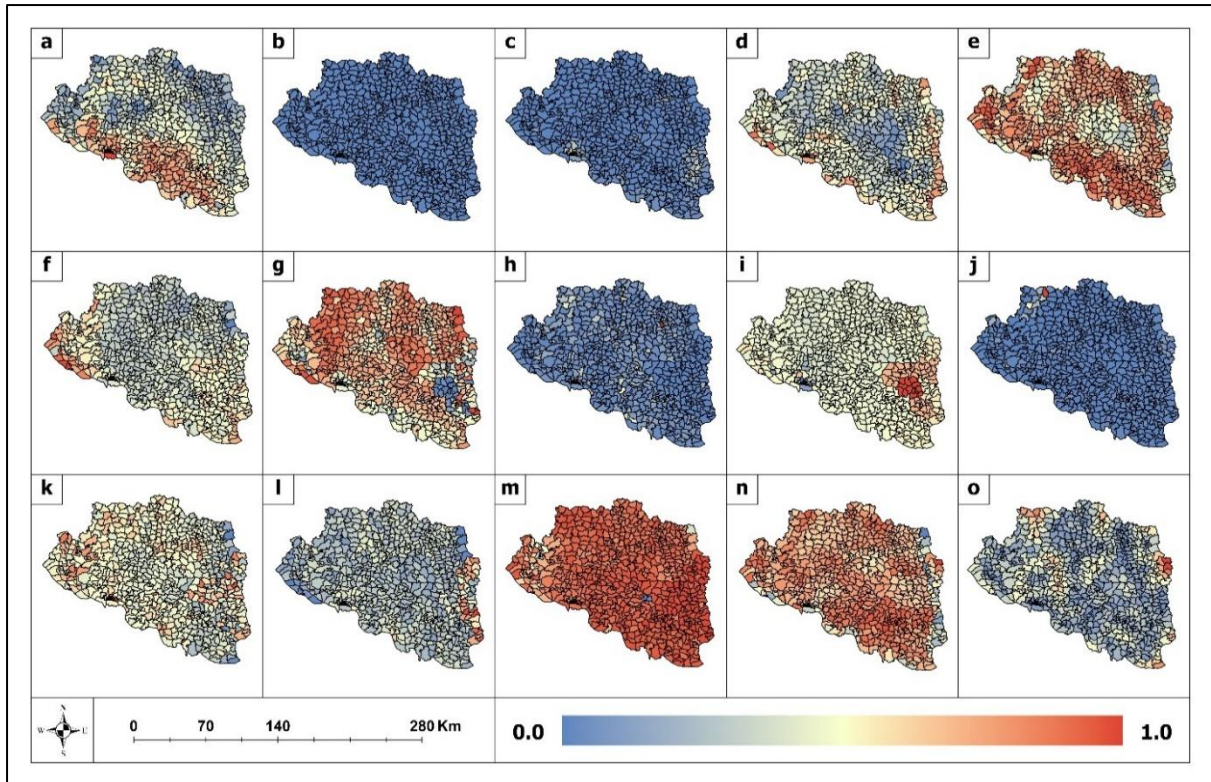


Fig. 2 Spatial distribution maps of all 15 indicators across 654 unions of Rajshahi Division: (a) UTFVI, (b) PD, (c) BD, (d) NDBI, (e) MNDWI, (f) DistToHF, (g) HHS, (h) HQ, (i) DT, (j) NWR, (k) WU, (l) LR, (m) FE, (n) EP, (o) NDVI

2.3 Analytical Framework

This study operationalizes the IPCC AR5 risk framework, which conceptualizes climate risk as the product of hazard, exposure, and vulnerability [8]. Heat Risk (HR) is computed as:

$$UHR = H \times E \times V$$

Hazard sub-index, Exposure sub-index, and Vulnerability sub-index. The multiplicative structure ensures that a union with negligible hazard or near zero exposure results in a near zero risk score, consistent with the physical logic of climate risk [38]. Vulnerability is broken down into Sensitivity (S) and Adaptive Capacity (AC) following the IPCC AR5 vulnerability framework [8], and consistent with its operationalization in fine-scale heat studies [39, 34].

$$V = \frac{S + (1 - AC)}{2}$$

Table 2 shows the entire set of indicators that includes the assignment to sub-index, the normalization direction and the weighting factors. Fifteen indicators include four sub-indices, namely, one hazard (UTFVI), five exposure (PD, BD, NDBI, MNDWI, DistToHF), five sensitivities (HHS, HQ, DT, NWR, WU) and four adaptive capacity (LR, FE, EP, NDVI) indicators. The classification thresholds of the ecological quality indicators UTFVI are listed in Table 3. The entire workflow of analysis is shown in Fig. 3.

Table 2 Indicator framework, normalization, and weights

Sub-index	Code	Indicator	Normalization	Weight	Method
Hazard (H)	UTFVI (a)	Urban Thermal Field Variance Index	Standard	100%	Single indicator
Exposure (E)	PD (b)	Population Density	Standard	25.21%	PCA (KMO=0.67)
	BD (c)	Building Density	Standard	27.42%	PCA (KMO=0.67)
	NDBI (d)	Normalized Difference Built-up Index	Standard	22.95%	PCA (KMO=0.67)
	MNDWI (e)	Modified Normalised Difference Water Index	Inverse	8.81%	PCA (KMO=0.67)
	DistToHF (f)	Distance to Healthcare Facilities	Standard	15.61%	PCA (KMO=0.67)
Sensitivity (S)	HHS (g)	Average Household Size	Standard	20.00%	Equal (KMO=0.39)
	HQ (h)	Non-Permanent Floor (%)	Standard	20.00%	Equal (KMO=0.39)
	DT (i)	Slum & Floating Population (%)	Standard	20.00%	Equal (KMO=0.39)
	NWR (j)	Non-Working Rate (%)	Standard	20.00%	Equal (KMO=0.39)
	WU (k)	Unsafe Water Access (%)	Standard	20.00%	Equal (KMO=0.39)
Adaptive Capacity (AC)	LR (l)	Literacy Rate 15+ (%)	Standard	30.40%	PCA (KMO=0.54)
	FE (m)	Financial Exclusion (%)	Inverse	33.44%	PCA (KMO=0.54)
	EP (n)	Energy Poverty (%)	Inverse	17.07%	PCA (KMO=0.54)
	NDVI (o)	Normalized Difference Vegetation Index	Standard	19.09%	PCA (KMO=0.54)

Table 3 UTFVI ecological quality classification. The complete analytical workflow is illustrated in Fig. 3.

UTFVI Range	Heat Hazard Intensity	Ecological Quality	Heat Risk Level
< 0	None	Excellent	Negligible
0 - 0.005	Weak	Good	Low
0.005 - 0.010	Middle	Normal	Moderate
0.010 - 0.015	Strong	Bad	High
0.015 - 0.020	Stronger	Worse	Very High
> 0.020	Strongest	Worst	Extreme

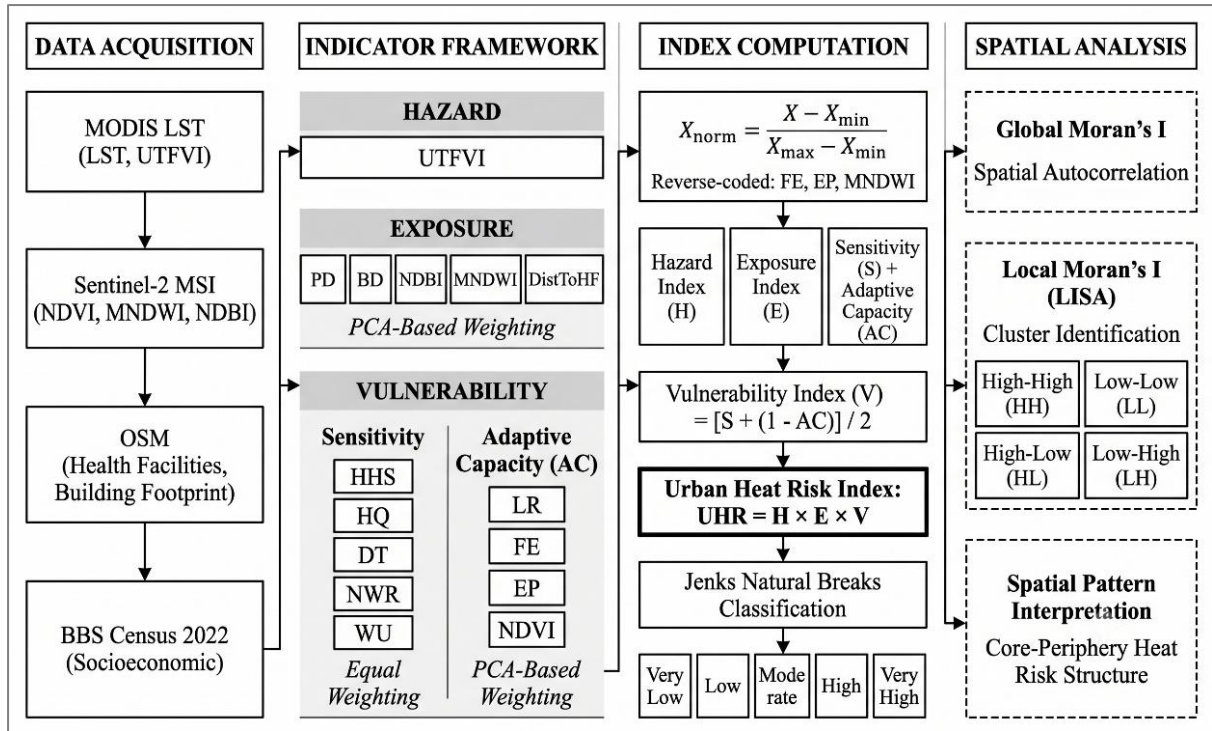


Fig. 3 Analytical framework flowchart

2.4 Indicator Normalization

All indicators were rescaled to a dimensionless 0-1 range using division-wide min-max normalization, the most widely adopted standardization method in composite climate and environmental vulnerability indices [28, 29]. For indicators where higher raw values signify greater hazard, exposure, or sensitivity, the standard formula was applied:

$$X_{norm} = \frac{X - X_{min}}{X_{max} - X_{min}}$$

For indicators where higher raw values indicate greater adaptive capacity (LR, NDVI) or lower exposure (MNDWI), and for indicators representing deficits in adaptive capacity (FE, EP), inverse normalization was applied:

$$X_{norm} = \frac{X_{max} - X}{X_{max} - X_{min}}$$

All bounds were set to the observed division-wide minimum and maximum of each indicator, retaining the full spatial variation across all 654 unions. The min-max bounds implicitly constitute a weighting decision; the choice of these thresholds influences the effective contribution of each indicator to the composite index [30].

2.5 Indicator Weighting

The weights of the indicators were determined using a conditional PCA-based approach that was based on two pre-conditions: the overall Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy was greater than 0.50 [31, 32]; and Bartlett's Test of Sphericity was significant at $p < 0.05$. If both conditions were satisfied, weights were calculated from the absolute PC1 component loadings rescaled to unity, meaning that indicators with higher loadings on the dominant latent dimension of each sub-index block were assigned higher weights [35, 33, 34]. If either condition did not apply, equal weights were given.

For the Exposure block (KMO = 0.67, Bartlett $p < 0.001$), PCA was applicable; PC1 explained 46.88% of variance, yielding weights of BD = 27.42%, PD = 25.21%, NDBI = 22.95%, DistToHF = 15.61%, and MNDWI = 8.81%. For the Adaptive Capacity block (KMO = 0.54, Bartlett $p < 0.001$), PC1 explained 38.12% of variance, yielding weights of FE = 33.44%, LR = 30.40%, NDVI = 19.09%, and EP = 17.07%. For the Sensitivity block, KMO = 0.39 fell below the 0.50 threshold; equal weights of 20.00% were

therefore assigned to all five indicators, reflecting the theoretical equivalence of the five deprivation dimensions [33].

2.6 Risk Classification

The HR scores were divided into five categories: Very Low, Low, Moderate, High, and Very High, following the Jenks Natural Breaks classification method that has been widely used in GIS-based studies to classify composite environmental vulnerability indices, which minimizes within-class variance and maximizes between-class variance [36, 37]. The classification was used throughout the division, in all 654 unions.

2.7 Spatial Autocorrelation Analysis

Global Moran's I and Local Indicators of Spatial Association (LISA) were computed to examine spatial clustering of HR. Global Moran's I quantify whether the HR distribution is clustered, dispersed, or random, with statistical significance assessed via 999 conditional permutations [37, 38]. LISA was computed using Local Moran's I to delineate statistically significant local cluster types at union level: High-High (HH) hotspots, Low-Low (LL) coldspots, and High-Low / Low-High (HL/LH) spatial outliers [12]. Both analyses used Queen contiguity spatial weights with row standardization, implemented in *libpysal/esda*. Significance was assessed at $p < 0.05$.

3 Results

3.1 Sub-index Distributions and Descriptive Statistics

Table 4 provides descriptive statistics for all sub-indices and the overall HR score for 654 unions. The spatial range of the Hazard sub-index (H) is the largest (0.000-1.000, mean = 0.414, SD = 0.197), and it is consistent with the urban-rural thermal gradient observed in administrative-unit-level studies in other parts of the world [41, 42], where the core urban areas are the hottest and the vegetated rural areas are the coolest. The Exposure sub-index E ranges from 0.040 to 0.930 (mean = 0.212, SD = 0.109), and the maximum is due to the extreme building and population density of the wards of Rajshahi City Corporation (RCC) [41, 43].

Table 4 Sub-index descriptive statistics

Sub-index	Formula / Method	Min	Max	Mean	SD
Hazard (H)	UTFVI	0.000	1.000	0.414	0.197
Exposure (E)	PCA weighted mean	0.040	0.930	0.212	0.109
Sensitivity (S)	Equal weighted mean	0.150	0.630	0.324	0.049
Adaptive Capacity (AC)	PCA weighted mean	0.120	0.820	0.557	0.079
Vulnerability (V)	$[S + (1 - AC)] / 2$	0.210	0.600	0.384	0.051
Heat Risk (HR)	$H \times E \times V$	0.000	0.220	0.035	0.029

The Sensitivity sub-index (S) shows a comparatively compressed range (0.150-0.630, mean = 0.324, SD = 0.049), indicating relatively homogeneous socioeconomic deprivation across the division without the sharp spatial contrast seen in hazard and exposure. The average Adaptive Capacity (0.557) is higher than that of Sensitivity, suggesting a more common level of moderate literacy and partial financial inclusion, though the spread (0.120-0.820) confirms there are significant spatial variations in coping resources. Vulnerability (V) varies between 0.210 and 0.600 (mean=0.384, SD=0.051) and it is vital to note that this spatial pattern of vulnerability does not coincide with hazard or exposure as in Santiago de Chile and Johannesburg where hotspots of vulnerability are located in suburban and peri-urban areas outside the thermal core [39, 9]. The final HR score ranges from 0.000 to 0.220 (mean = 0.035, SD = 0.029). The compressed range is due to the multiplicative model, which constrains scores that have any single sub-index close to zero [40].

3.2 Heat Risk Spatial Distribution and Risk Classification

HR distribution is heavily right-skewed, with most unions in the lower risk classes and only a few dense urban units at the high end of the distribution [41, 43]. In the Very Low class, there are 295 unions (45.1%). These unions have a population of approximately 8.49 million people (42.8% of the division

population). 199 unions (30.4%) are classified as Low risk (5.94 million residents, 29.9%), and 127 unions (19.4%) are classified as Moderate (4.39 million, 22.1%).

Table 5 HR risk category distribution

Risk Class	HR Range	No. Unions	% Unions	Population Exposed	% Population
Very Low	0.000 - 0.025	295	45.1%	8,491,526	42.8%
Low	0.025 - 0.046	199	30.4%	5,936,437	29.9%
Moderate	0.046 - 0.084	127	19.4%	4,390,875	22.1%
High	0.084 - 0.145	23	3.5%	746,127	3.8%
Very High	0.145 - 0.220	10	1.5%	276,230	1.4%
Total		654	100%	19,841,195 ^a	100%

^a Total population [19,841,195] reflects union-level BBS 2022 census sum. The division-level total of approximately 20.35 million cited in the text is from the BBS division-level summary; the ~0.5 million difference reflects rounding between union-level and division-level tabulations.

Table 6 Top five highest risk unions

Rank	District	Upazila	Union	H	E	V	HR	Class
1	Rajshahi	Rajpara	Ward No-03	0.760	0.670	0.440	0.220	Very High
2	Rajshahi	Boalia	Ward No-18 (part)	0.880	0.930	0.250	0.210	Very High
3	Rajshahi	Boalia	Ward No-15	0.760	0.690	0.350	0.190	Very High
4	Rajshahi	Rajpara	Ward No-06	0.710	0.680	0.390	0.190	Very High
5	Rajshahi	Boalia	Ward No-08	0.590	0.660	0.450	0.170	Very High

Table 7 Top five highest risk upazilas

Rank	District	Upazila	n	Mean H	Mean E	Mean V	Mean HR	Max HR
1	Rajshahi	Rajpara	6	0.688	0.613	0.390	0.163	0.220
2	Rajshahi	Boalia	19	0.682	0.668	0.290	0.131	0.210
3	Rajshahi	Shah Makhdum	2	0.880	0.505	0.265	0.120	0.140
4	Rajshahi	Matihar	3	0.490	0.460	0.317	0.070	0.080
5	Rajshahi	Paba	10	0.685	0.270	0.365	0.067	0.100

Geographically, the High and Very High classes are compact: 23 unions (3.5%) and 10 unions (1.5%) respectively, which put around 1.02 million (5.2% of total division population) people at higher heat risk. All 10 Very High risk unions are situated in the RCC in the Boalia and Rajpara thanas and have the maximum HR of 0.220 in Ward No-03 Rajpara (Table 6). The only non-RCC unit identified as the High risk is Pabna Municipality outside the RCC, showing increasing heat concentration in urban areas of the secondary cities on the Padma corridor. Table 7 shows the five upazilas with the highest risk. The complete spatial distribution of HR is illustrated in Fig. 4.

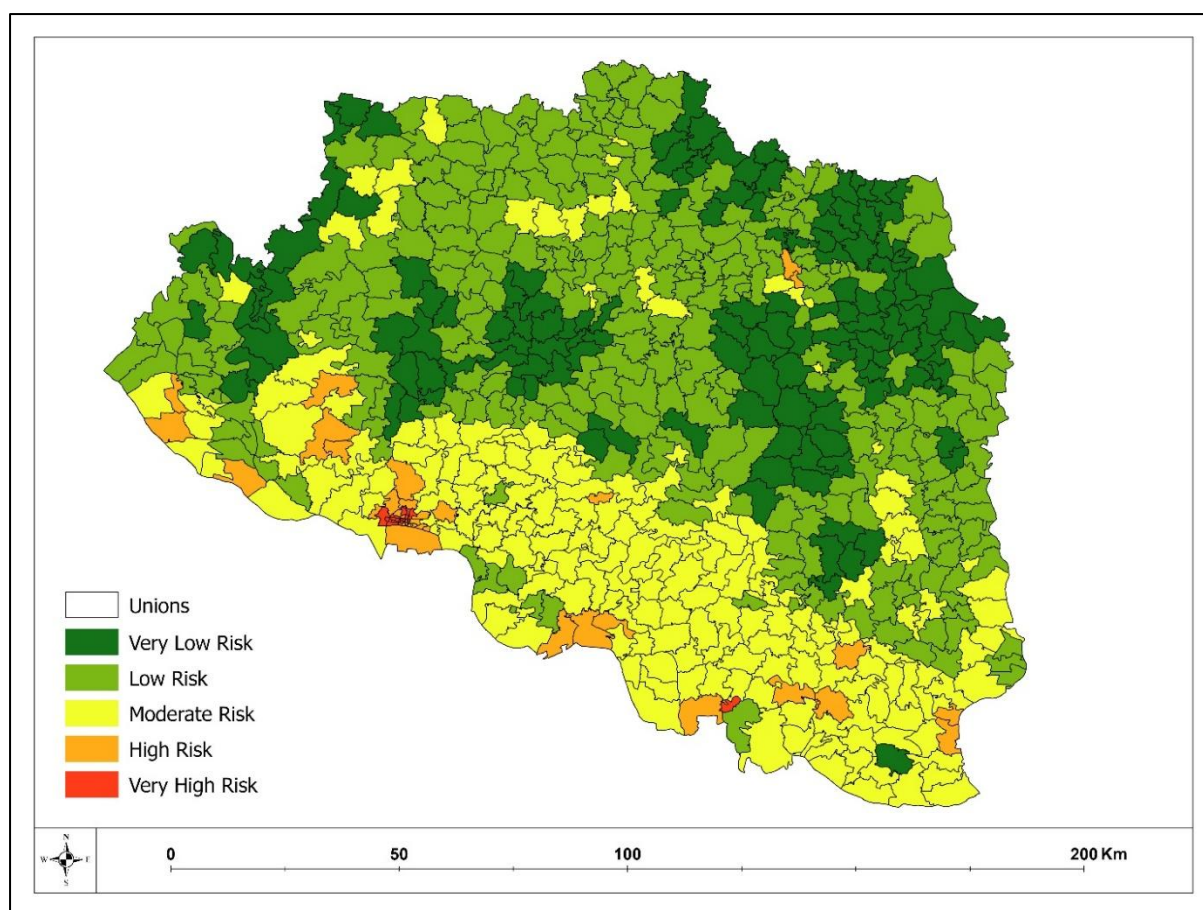


Fig. 4 HR choropleth map: five Jenks risk classes

3.3 Sub-index Spatial Patterns

Fig. 5 portrays the spatial distribution of each sub-index. The highest values ($H > 0.70$) are recorded in the Rajshahi City core, Pabna Sadar and Lalpur upazila in Natore, in line with the urban-rural UTFVI gradient, where the expansion of impervious surfaces leads to the highest thermal anomaly in the core of the city and district towns, and the lowest values are found in vegetated and riverine unions in Bogura and Sirajganj [41, 15]. The Exposure sub-index focuses on the extreme values of building density and population density, and the highest value ($E = 0.930$) is found in Ward No-18 Boalia, which is consistent with the findings of Hu et al. (2025) and Zou et al. (2024) that joint population and built-up intensity is what drives peak exposure in high-density urban cores (Table 6).

The Sensitivity sub-index elicits a more spatially uniform pattern relative to hazard and exposure, with moderately elevated values ($S > 0.40$) in rural unions of Nawabganj, Naogaon Sapahar, and Bogura Sariakandi, characterized by high proportions of non-permanent housing, large household sizes, and slum populations consistent with the spatial decoupling of sensitivity from hazard in low-income suburban districts [39]. The Adaptive Capacity sub-index is highest in Sirajganj and Joypurhat (mean $AC = 0.609$ and 0.577 respectively) and lowest in Bogura (mean $AC = 0.522$) (Table 8), driven by disparities in literacy rates and financial inclusion [9]. The Vulnerability sub-index demonstrates higher values in rural and peri-urban unions of Nawabganj, Bogura, and Naogaon rather than the high-hazard RCC core, a spatial mismatch between thermal stress and socioeconomic vulnerability consistent with composite HEV assessments elsewhere [39, 40].

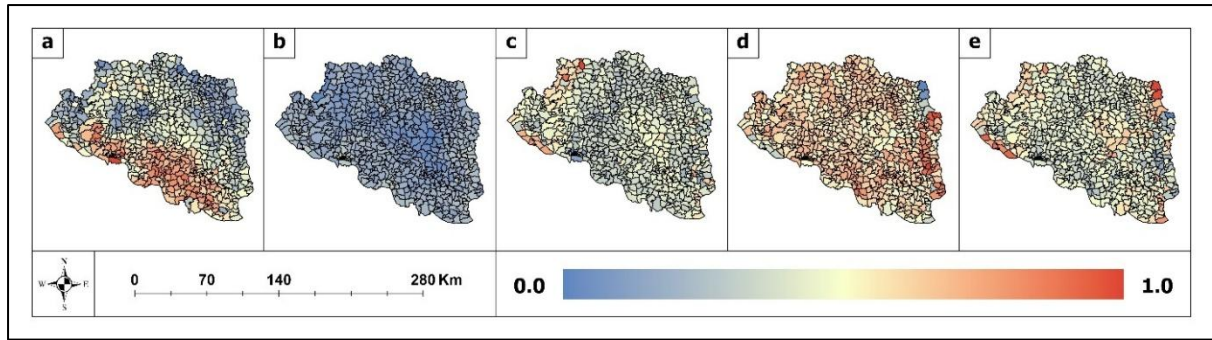


Fig. 5 Sub-index spatial distribution maps across 654 unions of Rajshahi Division: (a) Hazard, (b) Exposure, (c) Sensitivity, (d) Adaptive Capacity, (e) Vulnerability

3.4 District-level Comparison

Mean sub-index and HR scores aggregated by district are presented in Table 8.

Table 8 District-wise mean sub-index scores

District	n ^a	Mean H	Mean E	Mean S	Mean AC	Mean V	Mean HR	Rank
Rajshahi	115	0.550	0.314	0.296	0.572	0.363	0.064	1
Pabna	83	0.612	0.206	0.339	0.556	0.392	0.049	2
Natore	60	0.634	0.175	0.323	0.562	0.380	0.042	3
Nawabganj	49	0.316	0.214	0.364	0.530	0.417	0.030	4
Sirajganj	88	0.332	0.204	0.331	0.609	0.361	0.024	5
Naogaon	102	0.331	0.163	0.329	0.541	0.394	0.022	6
Joypurhat	36	0.306	0.186	0.304	0.577	0.364	0.021	7
Bogura	121	0.240	0.189	0.323	0.522	0.401	0.018	8

^a n = number of administrative unions per district.

The mean HR (0.064) is highest in the Rajshahi District, which is due to the highest mean exposure in the division (mean E = 0.314) and the highest hazard (mean H = 0.550) from the RCC metropolitan core. Pabna ranks second in mean HR (mean HR = 0.049) with the highest district mean hazard in the division (mean H = 0.612), indicating high pre-monsoon thermal stress in the unions adjacent to Padma in Pabna district. Although Natore has the highest district mean hazard across the division (mean H = 0.634), it has a relatively low mean exposure (mean E = 0.175) and ranks third (mean HR = 0.042), suggesting that high thermal intensity is not enough to create high composite risk without built environment exposure.

Nawabganj, Sirajganj, Naogaon and Joypurhat are in the middle ranks (4th-7th) with mean HR values in the range of 0.030-0.021. Nawabganj is particularly characterized by the highest mean vulnerability (mean V = 0.417) in the division, coupled with the highest mean sensitivity (mean S = 0.364) and lowest mean adaptive capacity (mean AC = 0.530), but its moderate hazard and exposure constrain the overall HR to 0.030. Bogura records the lowest mean HR (0.018) and the lowest mean hazard (mean H = 0.240), consistent with its northern floodplain position and high vegetation cover. This district-level decoupling of vulnerability from risk confirms the spatial heterogeneity of heat risk drivers across the division [11].

3.5 Spatial Autocorrelation Analysis

The Moran's I for the HR distribution was $I = 0.813$ ($Z = 36.89$, $p < 0.001$, 999 permutations), indicating highly significant positive spatial autocorrelation across the division. The observed I is much greater than the maximum simulated I under spatial randomness (0.40), suggesting that high-risk unions tend to cluster near other high-risk unions in a systematic way. This is significantly higher than the Global Moran's I of 0.42 found for the ward level heat vulnerability index (HVI) in Johannesburg [9] and is close to the extreme clustering of the LCZ-based assessment in Guangzhou ($I = 0.933$) [42]. The Moran scatterplot and the reference distribution of permutations are displayed in Fig. 6.

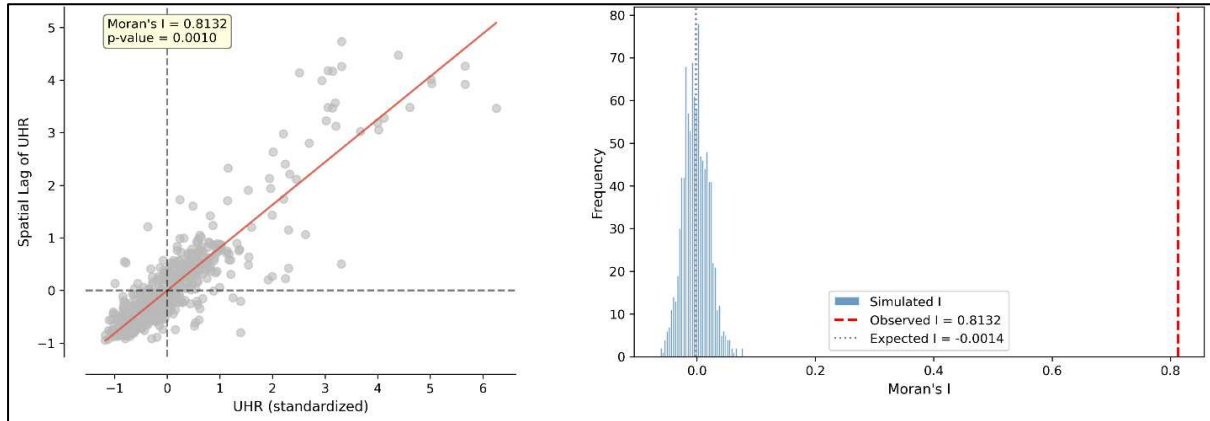


Fig. 6 Global Moran's I scatterplot (left) and permutation distribution (right)

LISA identified 255 statistically significant local clusters ($p < 0.05$) out of 654 unions, representing 39.0% of all unions (Table 9; Fig. 7). High-High (HH) hotspot clusters comprised 68 unions concentrated in three spatially distinct zones: the RCC metropolitan core (40 unions across Boalia, Rajpara, Shah Makhdum, Matihar, and Paba thanas), the Pabna Sadar-Santhia-Bera corridor (16 unions), and a Natore-Nawabganj cluster (12 unions). Low-Low (LL) coldspot clusters comprised 181 unions (27.7%), concentrated in Bogura (76 unions, 62.8% of the district), Naogaon (42 unions), and Sirajganj (25 unions), forming spatially coherent agricultural and floodplain belts consistent with LL clusters in vegetated low-urbanization zones identified elsewhere [37, 42]. Four High-Low (HL) spatial outliers are isolated urban nodes with high HR scores surrounded by low-risk rural areas, while one Low-High (LH) outlier in Joypurhat exemplifies localized vegetation buffering in a higher-risk neighborhood context (Table 9).

Table 9 LISA cluster classification by district

District	Total	HH	HL	LH	LL	Not Significant	% Significant
Rajshahi	115	40	1	0	4	70	39.1%
Pabna	83	16	1	0	1	65	21.7%
Natore	60	9	0	0	6	45	25.0%
Nawabganj	49	3	0	0	14	32	34.7%
Bogura	121	0	0	0	76	45	62.8%
Naogaon	102	0	2	0	43	57	44.1%
Sirajganj	88	0	0	0	25	63	28.4%
Joypurhat	36	0	0	1	12	23	36.1%
Total	654	68	5	1	181	399	39.0%

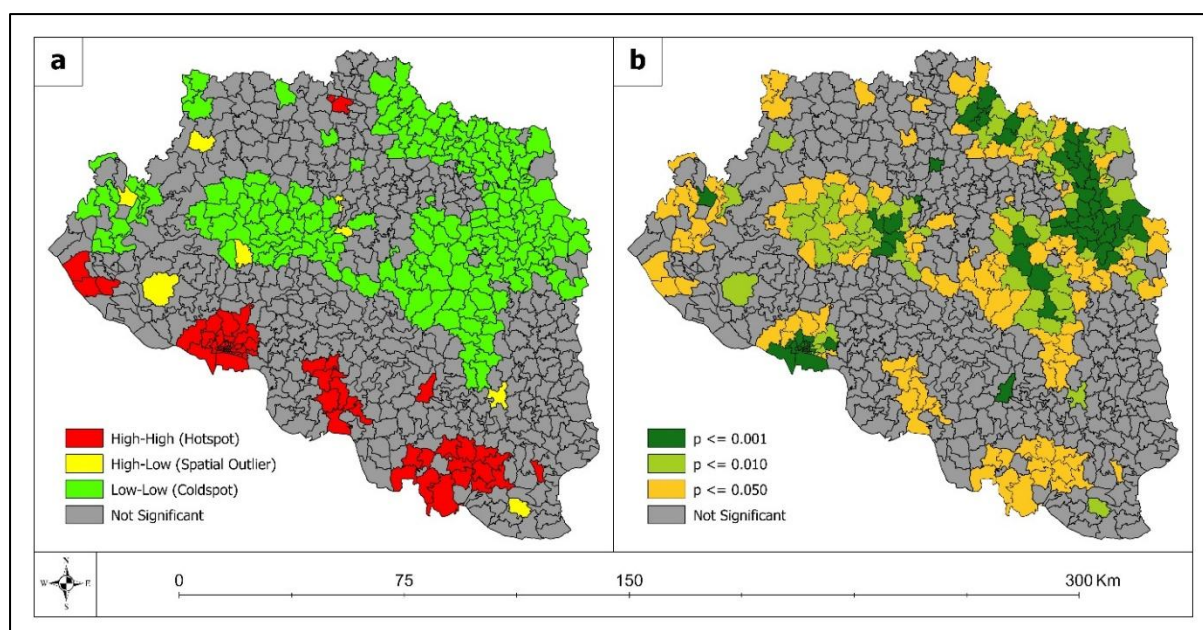


Fig. 7 LISA cluster distribution map (a) and significance map (b)

4 Discussion

The risk of urban heat has been increasingly recognized in South Asia; however, few studies have linked thermal hazard with built environment exposure and census-based vulnerability at fine administrative scales beyond major metropolitan areas. The study addresses this gap through the first union-level HR assessment for Rajshahi Division guided by three objectives: spatial mapping of the dimensions of the sub-indices, PCA-weighted construction of the composite index, and spatial autocorrelation analysis of the resultant risk surface. The findings of the three objectives are presented below, followed by contributions to methodology, limitations and policy implications.

4.1 Urban Core Dominance and the Core-Periphery Heat Risk Structure

The spatial distribution of HR scores exhibits a distinct core-periphery heat risk pattern across Rajshahi Division with Very High and High HR scores occurring only in the wards of Rajshahi City Corporation (RCC) and Pabna Municipality with the vast majority of rural and peri-urban unions being Very Low or Low risk. This pattern is similar to the high centre-low periphery risk gradient documented in Guangzhou, where old urban core districts demonstrated simultaneously high hazard, exposure and vulnerability, and cooling facility allocation was identified as the priority adaptive response [43]. High UTFVI, high building density and high population density in RCC's Boalia and Rajpara thanas converge to a pattern observed across the metropolitan areas of developing countries in a multi-country study that identified compact built-up landscapes as the primary contributor of heat health risk and urban green spaces as playing an effective but spatially differentiated mitigating role [44].

The only non-RCC unit identified as High risk is Pabna Municipality, which has the highest exposed population after Rajshahi. This highlights the need to extend heat risk assessment and action planning beyond the districtal capitals to the rapidly urbanizing district towns, which is a gap explicitly recognized for secondary cities in South Asia and the Global South [45, 7].

4.2 Hazard-Vulnerability Spatial Mismatch and Differentiated Adaptation

One of the important findings of this study is the spatial mismatch of thermal hazard and socioeconomic vulnerability in the Rajshahi Division. Although Nawabganj has the highest mean vulnerability (mean $V = 0.417$) in the division, the mean HR is moderate (mean $HR = 0.030$) and ranked fourth in the divisional hierarchy (Table 8) because of the highest mean sensitivity (mean $S = 0.364$) and the lowest mean adaptive capacity (mean $AC = 0.530$) in the division. However, the lowest mean sensitivity (mean $S = 0.296$) and adaptive capacity (mean $AC = 0.572$) is found in Rajshahi District where the main risk is not socioeconomic deprivation but the intensity of the built environment.

To concentrate heat adaptation resources only in high-HR urban cores may overlook the populations of Nawabganj, Naogaon Sadar and Manda upazilas, and Bogura Sariakandi where socioeconomic vulnerability is greatest. This spatial mismatch is consistent with findings from Johannesburg, where high vulnerability clusters aligned with historically disadvantaged townships that were spatially separated from the thermal core and where the authors argued that environmental greening alone would not be sufficient without parallel investment in healthcare and social infrastructure [9]. A study of the Durban metropolitan area similarly demonstrated that projected heat stress risk is primarily a function of social vulnerability and will be experienced across both rural and inner-city settings [46]. An Andalusian framework for heat hazard and climate shelter accessibility identified territorial inequalities in urban peripheries and disadvantaged neighborhoods as the priority intervention areas through explicit mapping of spatial mismatches between exposure and shelter access [47]. An ecosystem services study in Vitoria-Gasteiz found that cooling supply mismatches with heat vulnerability disproportionately affected socioeconomically disadvantaged groups [48]. Collectively, these studies argue that spatially differentiated adaptation targeting thermal mitigation in high-hazard cores and social infrastructure in high-vulnerability peripheries is more effective than thermally-focused approaches alone.

4.3 Multiplicative Framework: Strengths and Limitations

The multiplicative $HR = H \times E \times V$ formulation removes the compensability between sub-indices: a union with a low hazard or low exposure cannot have a high composite risk score, even if it has a high vulnerability profile, which is consistent with the physical logic of climate risk. Il Choi (2019) conducted a comparative analysis of aggregation frameworks for flood vulnerability, and concluded that a multiplicative utility function over hazard, exposure, and coping capacity yielded less volatile and more physically interpretable rankings than additive formulations.

However, the multiplicative model tends to compress scores for unions with moderate values across all three sub-indices, potentially underestimating the compound risk of peri-urban unions with moderate H, E, and V values whose HR scores are consequently compressed relative to their compound risk profile, a limitation addressable through sensitivity analysis across aggregation schemes. A critique of both additive and multiplicative aggregation in a Sydney heat stress vulnerability study proposed multi-criteria outranking as an alternative, arguing that both model types require strong assumptions about indicator independence that are rarely empirically justified [50]. The 127 unions classified as Moderate risk (19.4%, 4.39 million people; Table 5) may represent precisely this group.

4.4 Spatial Clustering and Core-Periphery Heat Risk Governance

The Global Moran's I of 0.813 ($Z = 36.89$, $p < 0.001$) is one of the highest spatial autocorrelation values for a composite heat risk index at administrative-unit scale, significantly higher than the $I = 0.42$ reported for Johannesburg [9] and close to the extreme clustering of Guangzhou's LCZ-based assessment ($I = 0.933$) [42]. This extreme clustering further validates the use of area-based intervention zoning at the upazila level as the heat risk is structurally organized in the form of spatially coherent hotspot and coldspot zones, which are aligned with the urbanization gradient of the division.

LISA identified three distinct HH cluster zones: the RCC metropolitan core, the Pabna Sadar-Santhia-Bera corridor, and the Natore-Nawabganj cluster; each representing a different stage of heat risk development with distinct governance implications (Table 9). The RCC core, with 40 HH unions, represents a mature, spatially consolidated heat risk zone. The Pabna corridor represents an emerging secondary city cluster with growing thermal and demographic exposure. The Natore-Nawabganj cluster represents a compound risk zone where high thermal hazard and high socioeconomic vulnerability co-occur: the most analytically complex configuration in the division [51].

4.5 Methodological Contributions, Limitations, and Future Directions

This study contributes to the heat risk literature in three methodological ways. First, it highlights that a division-wide assessment of the union level can be achieved using only publicly available data (MODIS, Sentinel-2, OSM, BBS 2022 census) without proprietary data or field surveys. The pipeline of processing with GEE and automated census extraction from district-level BBS reports using Python is directly replicable in other administrative divisions of Bangladesh. Second, the conditional PCA weighting strategy ($KMO > 0.50$ PCA, otherwise uniformly equal weights) yields more defensible sub-index weights than either the uniformly equal or the purely expert-assigned alternatives. Third, the combination of the Queen contiguity spatial autocorrelation and the HR surface change the index from

a ranking tool to a governance instrument, highlighting spatially coherent intervention zones instead of isolated administrative units.

Several limitations and sources of uncertainty warrant systematic acknowledgement. The HR index is subject to uncertainty propagating through four linked components: remote sensing, spatial aggregation, socioeconomic data, and model structure [71, 72].

Remote sensing uncertainty. Support mismatch occurs with the use of MODIS LST data at 1 km resolution due to the inclusion of both built up and vegetated land covers within a single pixel in small urban unions. This leads to the dilution of true thermal contrast and commonality of hazard scores in adjoining wards [58]. Cloud cover interference during the transition period of pre-monsoon season can be partly avoided through the median compositing approach for January to May period. The UTFVI model carries this LST uncertainty together with the implicit assumption that the divisional mean constitutes a stable reference surface, which holds true in multi-district area but underestimates thermal stress in secondary municipalities.

Spatial uncertainty. There are some difficulties associated with MAUP in the current study. This is because vulnerability indexes depend upon the union administration, and they would vary depending upon aggregation at upazilla and district levels [69]; large variations in size of unions from small urban to large rural unions of Rajshahi City Corporation and Bogura respectively; variation within union zones with regard to zonal means would also be high. There is a lot of literature available regarding scale effect on vulnerability indexes by principal component analysis; any change in spatial units results in inconsistent high vulnerability indexes [69]; in case of finer scale, the issue of weighting uncertainty is higher than transformation uncertainty [69].

Socioeconomic uncertainty. There is a temporal lag of four years between BBS 2022 census and remote sensing data from 2026. There will be a high likelihood of underestimation in terms of exposure due to quick increase in the extent of impervious surface and informal settlement in rapidly growing peri-urban fringes areas, especially around Rajshahi City, Pabna Sadar, and Lalpur upazila of Natore district. The other possible source of uncertainty in socioeconomic indicators is the error in slum population percentage and non-working rate reported in census due to self-reporting.

OSM uncertainty. The OSM buildings footprint completeness varies between urban and rural unions because of systematic underrepresentation of building information in rural and poorer areas according to completeness global analysis [27]; thus, building density can be overestimated in well-mapped urban core unions and underestimated in peripheral unions.

Statistical and model uncertainty. The weights obtained using the PCA technique depend upon the pattern of correlation between the indicators and the selected set of variables [72]; conditional technique which uses PCA attempts to solve the above issue by means of using equal weights when there is poor pattern of correlation. Min-max transformation is highly susceptible to outliers since the minima and maxima of exposure variables will be dictated by the values in RCC zones [34]. Jenks Natural Breaks Classification is a data driven process hence cannot be compared across different regions. Multiplicative nature of the aggregation technique sets upper and lower limits for the scores of those unions which have mid-range value in all three sub-indices [52, 53].

Nevertheless, there are specific features of the HR map surface which can be seen as rather stable despite the possible uncertainties. Extremely clustering of the distribution (Moran's $I = 0.813$) and great value of dissimilarity between RCC urban wards and rural agricultural unions cannot be attributed to any reasonable uncertainty range regarding the indicator values. The core-periphery pattern is additionally validated through the Rajshahi thermal analysis [7, 8], as well as through the gradient heat risk due to urbanization for similar cities [45, 47]. The primary relevance of the uncertainty effect is that of accurate rank-ordering within intermediate risk categories, for smaller secondary municipalities when MODIS data availability is low, as well as boundary unions whose categorization status may differ depending on the choice of normalization/classification alternatives. Uncertainty assessment approaches, including Monte Carlo PCA weight generation [70], bootstrap resampling of indicator combinations [71], as well as sensitivity analysis through additive and multiplicative aggregation, are still open questions. Globally available databases render the methodology transferable to other data-scarce administrative frameworks [45, 47].

Validation Strategy

Validation by comparison of composite indices to actual health outcomes data, such as hospitalizations, heat illness reports, or mortality figures, is the most rigorous method of validation, though such

information is not available for the region of Rajshahi Division. There is no spatially distributed database of heat-health information available at the union level in Bangladesh, which reflects the limitations in heat risk assessments performed in developing nations of South Asia and Sub-Saharan Africa [37, 67]. As per the results of a systematic review (PRISMA) analysis on heat vulnerability studies, it has been seen that only around one-fourth used validation procedures, and the main limitation in the majority of cases was the lack of fine resolution health data [67].

The plausibility and internal consistency of the HR surface model are collectively validated by five lines of indirect evidence. Firstly, the model is based on the risk conceptualisation by IPCC AR5 [9], an internationally established theoretical foundation, while past applications within the Philippines [65], Yangtze River Delta [18], and Johannesburg [10] offer relevant methodological precedent at similar scales of administration. Secondly, every single variable included has individually proven empirical basis: UTFVI has been consistently shown to reflect the thermal impact of urbanisation [15, 20, 21, 62]; NDBI and population density are known exposure factors influencing the occurrence of LST [3, 4]; NDVI has the effect of inhibiting the thermal anomaly [15]; and socio-economic indicators derived from census have proven valid as heat vulnerability measures in South Asia [13, 37]. Thirdly, the HR spatial pattern is corroborated by existing thermal studies in Rajshahi: RCC's Boalia and Rajpara thanas, as well as the Padma corridor, have previously been recognized as thermal hotspots [7, 8], which provides geographical corroboration for the same. Fourthly, the very significant Global Moran's I of 0.813 ($p < 0.001$) is proof that the HR map has non-random spatial structure; spatial clustering is an accepted form of indirect validation, having been used to verify spatial structure in both Johannesburg [10] and Lagos [68] in the absence of health data. Lastly, the high-high LISA hotspot zones coincide perfectly with the union divisions within the most densely populated area, whereas the low-low LISA coldspot regions coincide with the agricultural and floodplain zones, as seen in other studies [44, 68].

The validation methods described above cannot replace health outcome validation, yet they do support current best practices in HEV composite index development for data scarce regions [37, 67]. In future research, validation methods could include health facilities' utilization records, ambulance dispatch information, community level surveys of heat illness in high risk unions or data from wearable sensors, providing stronger evidence of causality between the HR surface and heat burden.

4.6 Planning and Policy Implications

The spatial distribution of heat risk revealed by this study suggests three intervention priorities for Rajshahi Division. Urban greening (street tree planting, rooftop vegetation and blue-green corridor development along the Padma riverfront) and albedo enhancement through cool surface programs are priority interventions in the high-hazard, high-exposure urban cores of Rajshahi City Corporation and Pabna Municipality [52]. Nature-based solutions are still largely limited to tree planting, and need to be scaled up to integrated blue-green infrastructure and heat-resilient building codes, while South Asian cities have started institutionalizing Heat Action Plans.

In the high-vulnerability but moderate-hazard districts of Nawabganj, Naogaon, and Bogura, adaptation investment should prioritise social infrastructure: healthcare accessibility, energy poverty reduction, financial inclusion, and housing quality improvement; rather than thermal mitigation alone [46, 9]. The four High-Low spatial outliers (Tentulia, Boalia-Naogaon, Raninagar, and Mohanpur); isolated emerging urban nodes where risk has detached from surrounding low-risk rural contexts: early monitoring and targeted infrastructure investment are warranted before risk escalates to levels observed in the RCC core [51]. Across all three intervention types, the LISA cluster results support a cluster-based approach that prioritizes spatially contiguous high-risk zones over isolated administrative units, enabling more efficient resource allocation and locally tailored adaptation measures [47].

5 Conclusion

This study, for the first time, assesses the Heat Risk (HR) at the union level for Rajshahi Division, Bangladesh, which includes all 654 administrative unions in eight districts, utilizing a multiplicative Hazard-Exposure-Vulnerability framework based on the IPCC AR5 risk conceptual framework. The study incorporates MODIS LST-derived UTFVI, Sentinel-2 spectral indices, OSM building footprints and health facility data and BBS 2022 census indicators to construct a spatially explicit composite risk index that is replicable from openly available data.

Three main findings stand out. Firstly, the heat risk is distinctly core-periphery in terms of spatial distribution, with 10 Very High-risk unions in the Rajshahi City Corporation and 23 High risk unions, of which the Pabna Municipality accounts for the highest HR among other areas outside RCC. The above

union zones only account for 5.2% of the district's population but require intervention most urgently due to their extremely high hazard-exposure combination. Secondly, there is clear evidence of the existence of spatial mismatch between thermal hazards and socio-economic vulnerability: Nawabganj District is the most vulnerable among all other divisions' districts although it has ranked fourth in the total HR index, suggesting that the structural deficiencies of heat risk policies exist in terms of ignoring socio-economic factors of adaptive capacity. Thirdly, the analysis of spatial autocorrelation shows that there is a strong positive clustering of HR (Global Moran's $I = 0.813$, $p < 0.001$) with three distinct LISA High-High hotspots and Low-Low cold spots in the spatial belt covering Bogura, Naogaon, and Sirajganj, offering an empirical basis for area-based heat risk governance. Together, these findings argue for a spatially differentiated adaptation strategy addressing both built environment cooling in high-hazard urban cores and social infrastructure deficits in high-vulnerability peripheral districts.

Methodologically, the conditional PCA weighting strategy produces more defensible and data-grounded sub-index weights than either uniform or expert-assigned alternatives. The GEE-and-Python-based analytical pipeline is directly replicable across Bangladesh's remaining administrative divisions. Its reliance on globally available remote sensing and census datasets renders it transferable to any administrative context where MODIS, Sentinel-2, OSM, and a national population census are available, conditions now met across most of South Asia, Southeast Asia, and sub-Saharan Africa.

Future research should address four priorities: incorporation of dynamic population exposure data and night-time light intensity to capture rapidly changing peri-urban conditions; sensitivity analysis across additive, multiplicative, and multi-criteria aggregation schemes to assess the robustness of divisional risk rankings; longitudinal HR tracking as the BBS 2031 census becomes available; and integration of community-level primary survey data in high-risk unions to validate census-derived vulnerability indicators. The outputs of this study: union-level risk surface, LISA cluster maps, and district-wise sub-index profiles; are directly actionable for Bangladesh's divisional and district heat action planning and provide a replicable template for spatial heat risk governance across the country's remaining administrative divisions.

Statements and Declarations

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Competing Interests

The authors have no relevant financial or non-financial interests to disclose.

Ethics Declaration

Ethics declaration: not applicable.

Author Contributions

Ahad Kanak Prottay conceptualized the study, developed the methodology, conducted data curation, software implementation, formal analysis, visualization, map and figure preparation, and wrote the initial draft of the manuscript. Shazed Hossain Chamok contributed to writing and drafting the Introduction and Methodology sections. Vargob Paul contributed to writing and drafting the Results and Discussion sections and played a key role in conceptualizing the interpretation and discussion of the findings. All authors reviewed and approved the final manuscript.

Data Availability

The remote sensing data used in this study are publicly available from Google Earth Engine: MODIS MOD11A2 Land Surface Temperature (LST) and Sentinel-2 Surface Reflectance (SR). Data on building footprints and health facilities were downloaded from OpenStreetMap using the Overpass API. The administrative boundary shapefiles are provided by Bangladesh Bureau of Statistics. The socioeconomic indicators were derived from the district level reports of Population and Housing Census 2022 conducted by the Bangladesh Bureau of Statistics. The normalised indicator dataset, composite HR scores and LISA cluster outputs produced in the course of this study are available from the corresponding author upon reasonable request.

References

- [1] Abdrabo, K. I., Kantoush, S. A., Esmail, A., Saber, M., Sumi, T., Almamari, M., Elboshy, B., & Ghoniem, S. (2023). An integrated indicator-based approach for constructing an urban flood vulnerability index as an urban decision-making tool using the PCA and AHP techniques: A case study of Alexandria, Egypt. *Urban Climate*, 48. <https://doi.org/10.1016/j.uclim.2023.101426>
- [2] Abrar, R., Sarkar, S. K., Nishtha, K. T., Talukdar, S., Shahfahad, Rahman, A., Islam, A. R. M. T., & Mosavi, A. (2022). Assessing the Spatial Mapping of Heat Vulnerability under Urban Heat Island (UHI) Effect in the Dhaka Metropolitan Area. *Sustainability (Switzerland)*, 14[9]. <https://doi.org/10.3390/su14094945>
- [3] Aznarez, C., Kumar, S., Marquez-Torres, A., Pascual, U., & Baró, F. (2024). Ecosystem service mismatches evidence inequalities in urban heat vulnerability. *Science of the Total Environment*, 922. <https://doi.org/10.1016/j.scitotenv.2024.171215>
- [4] Badaloni, C., De Sario, M., Caranci, N., de' Donato, F., Bolognani, A., Davoli, M., Leccese, L., Michelozzi, P., & Leone, M. (2023). A spatial indicator of environmental and climatic vulnerability in Rome. *Environment International*, 176. <https://doi.org/10.1016/j.envint.2023.107970>
- [5] Bangladesh Bureau of Statistics. (2022). Population and housing census 2022. Statistics and Informatics Division, Ministry of Planning, Government of Bangladesh. <https://bbs.gov.bd>
- [6] Chen, X. L., Zhao, H. M., Li, P. X., & Yin, Z. Y. (2006). Remote sensing image-based analysis of the relationship between urban heat island and land use/cover changes. *Remote Sensing of Environment*, 104[2], 133–146. <https://doi.org/10.1016/j.rse.2005.11.016>
- [7] Degirmenci, K., Desouza, K. C., Fieuw, W., Watson, R. T., & Yigitcanlar, T. (2021). Understanding policy and technology responses in mitigating urban heat islands: A literature review and directions for future research. In *Sustainable Cities and Society* (Vol. 70). Elsevier Ltd. <https://doi.org/10.1016/j.scs.2021.102873>
- [8] Dewan, A., Kiselev, G., Botje, D., Mahmud, G. I., Bhuian, M. H., & Hassan, Q. K. (2021). Surface urban heat island intensity in five major cities of Bangladesh: Patterns, drivers and trends. *Sustainable Cities and Society*, 71. <https://doi.org/10.1016/j.scs.2021.102926>
- [9] El-Zein, A., & Tonmoy, F. N. (2015). Assessment of vulnerability to climate change using a multi-criteria outranking approach with application to heat stress in Sydney. *Ecological Indicators*, 48, 207–217. <https://doi.org/10.1016/j.ecolind.2014.08.012>
- [10] Esha, E. J., & Rahman, M. T. U. (2021). Simulation of future land surface temperature under the scenario of climate change using remote sensing & GIS techniques of northwestern Rajshahi district, Bangladesh. *Environmental Challenges*, 5. <https://doi.org/10.1016/j.envc.2021.100365>
- [11] Estoque, R. C., Ooba, M., Avitabile, V., Hijikawa, Y., DasGupta, R., Togawa, T., & Murayama, Y. (2019). The future of Southeast Asia's forests. *Nature Communications*, 10[1]. <https://doi.org/10.1038/s41467-019-09646-4>
- [12] Eugenio Pappalardo, S., Zanetti, C., & Todeschi, V. (2023). Mapping urban heat islands and heat-related risk during heat waves from a climate justice perspective: A case study in the municipality of Padua (Italy) for inclusive adaptation policies. *Landscape and Urban Planning*, 238. <https://doi.org/10.1016/j.landurbplan.2023.104831>
- [13] Faisal, A. Al, Kafy, A. A., Al Rakib, A., Akter, K. S., Jahir, D. M. A., Sikdar, M. S., Ashrafi, T. J., Mallik, S., & Rahman, M. M. (2021). Assessing and predicting land use/land cover, land surface temperature and urban thermal field variance index using Landsat imagery for Dhaka Metropolitan area. *Environmental Challenges*, 4. <https://doi.org/10.1016/j.envc.2021.100192>
- [14] Gewers, F. L., Ferreira, G. R., De Arruda, H. F., Silva, F. N., Comin, C. H., Amancio, D. R., & Costa, L. D. F. (2022). Principal component analysis: A natural approach to data exploration. *ACM Computing Surveys*, 54[4]. <https://doi.org/10.1145/3447755>
- [15] Greco, S., Ishizaka, A., Tasiou, M., & Torrisi, G. (2019). On the Methodological Framework of Composite Indices: A Review of the Issues of Weighting, Aggregation, and Robustness. In *Social Indicators Research* (Vol. 141, Number 1, pp. 61–94). Springer Netherlands. <https://doi.org/10.1007/s11205-017-1832-9>
- [16] Herfort, B., Lautenbach, S., Porto de Albuquerque, J., Anderson, J., & Zipf, A. (2023). A spatio-temporal analysis investigating completeness and inequalities of global urban building data in OpenStreetMap. *Nature Communications*, 14[1]. <https://doi.org/10.1038/s41467-023-39698-6>
- [17] Hu, W., Guo, D., Wang, J., & Bao, S. (2025). A Decadal Assessment of the Coordinated Relationship Between Heat Risk and Cooling Resources in Guangzhou, China. *Sustainability (Switzerland)*, 17[17]. <https://doi.org/10.3390/su17177735>

- [18] Il Choi, H. (2019). Assessment of Aggregation Frameworks for Composite Indicators in Measuring Flood Vulnerability to Climate Change. *Scientific Reports*, 9[1]. <https://doi.org/10.1038/s41598-019-55994-y>
- [19] Inostroza, L., Palme, M., & De La Barrera, F. (2016). A heat vulnerability index: Spatial patterns of exposure, sensitivity and adaptive capacity for Santiago de Chile. *PLoS ONE*, 11[9]. <https://doi.org/10.1371/journal.pone.0162464>
- [20] Jacobs, C., Klok, L., Bruse, M., Cortesão, J., Lenzholzer, S., & Kluck, J. (2020). Are urban water bodies really cooling? *Urban Climate*, 32. <https://doi.org/10.1016/j.uclim.2020.100607>
- [21] Jagarnath, M., Thambiran, T., & Gebreslasie, M. (2020). Heat stress risk and vulnerability under climate change in Durban metropolitan, South Africa—identifying urban planning priorities for adaptation. *Climatic Change*, 163[2], 807–829. <https://doi.org/10.1007/s10584-020-02908-x>
- [22] Kacker, K., Utpal, A., Singh, S., Srivastava, P., Mukherjee, M., Subramanian, S. S., & Rakesh, R. (2026). A framework for impact based heat stress warning system for a coastal city in India. *Scientific Reports*, 16[1]. <https://doi.org/10.1038/s41598-026-38639-9>
- [23] Kelemen, A., Szabó, Z. K., Bozók, S., Szádóczi, Z., & Hartvig, Á. D. (2024). A sensitivity analysis of composite indicators: Min/max thresholds. *Environmental and Sustainability Indicators*, 23. <https://doi.org/10.1016/j.indic.2024.100453>
- [24] Khan, M., Qasim, M., Ahmad, A., Tahir, A. A., & Farooqi, A. (2024). Predicting land use dynamics, surface temperature and urban thermal field variance index in mild cold climate urban area of Pakistan. *Heliyon*, 10[19]. <https://doi.org/10.1016/j.heliyon.2024.e38787>
- [25] Li, F., Nan, T., Zhang, H., Luo, K., Xiang, K., & Peng, Y. (2025). Evaluating Ecological Vulnerability and Its Driving Mechanisms in the Dongting Lake Region from a Multi-Method Integrated Perspective: Based on Geodetector and Explainable Machine Learning. *Land*, 14[7]. <https://doi.org/10.3390/land14071435>
- [26] Masselot, P., Mistry, M., Vanoli, J., Schneider, R., lungman, T., Garcia-Leon, D., Ciscar, J. C., Feyen, L., Orru, H., Urban, A., Breitner, S., Huber, V., Schneider, A., Samoli, E., Stafoggia, M., de'Donato, F., Rao, S., Armstrong, B., Nieuwenhuijsen, M., ... Aunan, K. (2023). Excess mortality attributed to heat and cold: a health impact assessment study in 854 cities in Europe. *The Lancet Planetary Health*, 7[4], e271–e281. [https://doi.org/10.1016/S2542-5196\(23\)00023-2](https://doi.org/10.1016/S2542-5196(23)00023-2)
- [27] Moreira, L. L., De Brito, M. M., & Kobiyama, M. (2021). Review article: A systematic review and future prospects of flood vulnerability indices. In *Natural Hazards and Earth System Sciences* (Vol. 21, Number 5, pp. 1513–1530). Copernicus GmbH. <https://doi.org/10.5194/nhess-21-1513-2021>
- [28] Mühlhofer, E., Kropf, C. M., Riedel, L., Bresch, D. N., & Koks, E. E. (2024). OpenStreetMap for multi-faceted climate risk assessments. *Environmental Research Communications*, 6[1]. <https://doi.org/10.1088/2515-7620/ad15ab>
- [29] Naim, M. N. H., & Kafy, A. A. (2021). Assessment of urban thermal field variance index and defining the relationship between land cover and surface temperature in Chattogram city: A remote sensing and statistical approach. *Environmental Challenges*, 4. <https://doi.org/10.1016/j.envc.2021.100107>
- [30] Niu, Y., Li, Z., Gao, Y., Liu, X., Xu, L., Vardoulakis, S., Yue, Y., Wang, J., & Liu, Q. (2021). A Systematic Review of the Development and Validation of the Heat Vulnerability Index: Major Factors, Methods, and Spatial Units. <https://doi.org/10.1007/s40641-021-00173-3>
- [31] Parker, C., Mahlasi, C., Govindasamy, T., Radebe, L., Brink, N. B., Jack, C., Doumbia, M., Kouakou, E., Chersich, M., Cissé, G., Makhanya, S., Makanga, T., Luchters, S., Omar, S., Forget, R., Sibanda, R., Duffett, R., Satekge, R., Wolski, P., ... Bobola, A. (2025). Quantifying intra-urban socio-economic and environmental vulnerability to extreme heat events in Johannesburg, South Africa. *International Journal of Biometeorology*, 69[10], 2501–2517. <https://doi.org/10.1007/s00484-025-02971-y>
- [32] Patra, P. K., Behera, D., Chettry, V., Jena, K. M., Goswami, S., & Jothimani, M. (2025). Geospatial analysis of unplanned urbanization: impact on land surface temperature and habitat suitability in Cuttack, India. *Discover Sustainability*, 6[1]. <https://doi.org/10.1007/s43621-025-00920-8>
- [33] Präger, M., Kurz, C., Holle, R., Maier, W., & Laxy, M. (2023). A spatial obesity risk score for describing the obesogenic environment using kernel density estimation: development and parameter variation. *BMC Medical Research Methodology*, 23[1]. <https://doi.org/10.1186/s12874-023-01883-y>
- [34] Rahman, M. M., & Hasan, J. (2024). Evaluating the Impact of Green Spaces on Urban Heat Reduction in Rajshahi, Bangladesh Using the InVEST Model. *Land*, 13[8]. <https://doi.org/10.3390/land13081284>

- [35] Rahman, M. R., & Mark, B. G. (2025). Geospatial Analysis of Urban Warming: A Remote Sensing and GIS-Based Investigation of Winter Land Surface Temperature and Biophysical Composition in Rajshahi City, Bangladesh. *Sustainability (Switzerland)*, 17[11]. <https://doi.org/10.3390/su17115107>
- [36] Rouse, J. W., Haas, R. H., Schell, J. A., Deering, D. W., & Harlan, J. C. (1974). *Monitoring vegetation systems in the Great Plains with ERTS. NASA Special Publication*, 351[1], 309–317..
- [37] Salam, M., Islam, M. K., Jahan, I., & Chowdhury, M. A. (2024). Assessing the impacts of vegetation loss and land surface temperature on Surface Urban Heat Island (SUHI) in Gazipur District, Bangladesh. *Computational Urban Science*, 4[1]. <https://doi.org/10.1007/s43762-024-00136-y>
- [38] Silverman, B. W. (1986). Density estimation for statistics and data analysis. Chapman and Hall. <https://doi.org/10.1007/978-1-4899-3324-9>
- [39] Simpson, N. P., Mach, K. J., Constable, A., Hess, J., Hogarth, R., Howden, M., Lawrence, J., Lempert, R. J., Muccione, V., Mackey, B., New, M. G., O'Neill, B., Otto, F., Pörtner, H. O., Reisinger, A., Roberts, D., Schmidt, D. N., Seneviratne, S., Strongin, S., ... Trisos, C. H. (2021). A framework for complex climate change risk assessment. In *One Earth* (Vol. 4, Number 4, pp. 489–501). Cell Press. <https://doi.org/10.1016/j.oneear.2021.03.005>
- [40] Tahasin, A., Haydar, M., Hossen, M. S., & Sadia, H. (2024). Drought vulnerability assessment and its impact on crop production and livelihood of people: An empirical analysis of Barind Tract. *Heliyon*, 10[20]. <https://doi.org/10.1016/j.heliyon.2024.e39067>
- [41] Tesfamariam, S., Govindu, V., & Uncha, A. (2024). Urban ecology in the context of urban heat island vulnerability potential zone mapping: the case of Mekelle city, Ethiopia. *Frontiers in Climate*, 6. <https://doi.org/10.3389/fclim.2024.1446048>
- [42] Thakkar, V., Srinivas, V., Marula Siddhappanavara, P., Madappa, T., Jeganathan, A., & Murthy, I. K. (2025). Heatwave health risk index for Karnataka, India. *Journal of Climate Change and Health*, 22. <https://doi.org/10.1016/j.joclim.2025.100428>
- [43] Tuholske, C., Caylor, K., Funk, C., Verdin, A., Sweeney, S., Grace, K., Peterson, P., & Evans, T. (2021). *Global urban population exposure to extreme heat*. Proceedings of the National Academy of Sciences, 118[41]. <https://doi.org/10.1073/pnas.2024792118>
- [44] Vargas Molina, J., Sortino Barrionuevo, J. F., & Castro Noblejas, H. (2026). An integrated assessment of heat hazard, vulnerability, and accessibility to climate shelter networks for identifying urban adaptation priority areas in Andalusia (Spain). *International Journal of Disaster Risk Reduction*, 136. <https://doi.org/10.1016/j.ijdrr.2026.106057>
- [45] Wu, C.-D., Shui, W., Huang, Z., Wang, C., Wu, Y., Wu, Y., Xue, C., Huang, Y., Zhang, Y., & Zheng, D. (2022). Urban heat vulnerability: A dynamic assessment using multi-source data in coastal metropolis of Southeast China. *Frontiers in Public Health*, 10. <https://doi.org/10.3389/fpubh.2022.989963>
- [46] Wu, T. (2021). Quantifying coastal flood vulnerability for climate adaptation policy using principal component analysis. *Ecological Indicators*, 129. <https://doi.org/10.1016/j.ecolind.2021.108006>
- [47] Xu, H. (2006). Modification of normalised difference water index (NDWI) to enhance open water features in remotely sensed imagery. *International Journal of Remote Sensing*, 27[14], 3025–3033. <https://doi.org/10.1080/01431160600589179>
- [48] Yu, J., Castellani, K., Forsysinski, K., Gustafson, P., Lu, J., Peterson, E., Tran, M., Yao, A., Zhao, J., & Brauer, M. (2021). Geospatial indicators of exposure, sensitivity, and adaptive capacity to assess neighbourhood variation in vulnerability to climate change-related health hazards. *Environmental Health: A Global Access Science Source*, 20[1]. <https://doi.org/10.1186/s12940-021-00708-z>
- [49] Yu, W., Yang, J., Sun, D., Xue, B., Sun, W., Ren, J., Yu, H., Xiao, X., Xia, J., & Li, X. (2024). Shared insights for heat health risk adaptation in metropolitan areas of developing countries. *IScience*, 27[5]. <https://doi.org/10.1016/j.isci.2024.109728>
- [50] Zha, Y., Gao, J., & Ni, S. (2003). Use of normalized difference built-up index in automatically mapping urban areas from TM imagery. *International Journal of Remote Sensing*, 24[3], 583–594. <https://doi.org/10.1080/01431160304987>
- [51] Zhou, D., Zhao, S., Liu, S., Zhang, L., & Zhu, C. (2014). Surface urban heat island in China's 32 major cities: Spatial patterns and drivers. *Remote Sensing of Environment*, 152, 51–61. <https://doi.org/10.1016/j.rse.2014.05.017>
- [52] Zou, B., Fan, C., & Li, J. (2024). Quantifying the Influence of Different Block Types on the Heat Risk in High-Density Cities. *Buildings*, 14[7]. <https://doi.org/10.3390/buildings14072131>

771 [58] Yao Y, Lu L, Guo J, Zhang S, Cheng J, Tariq A, Liang D, Hu Y, Li Q. Spatially explicit
772 assessments of heat-related health risks: A literature review. *Remote Sens.*
773 2024;16[23]:4500. <https://doi.org/10.3390/rs16234500>

774 [59] Hulley G, Shivers S, Wetherley EB, Cudd R. New ECOSTRESS and MODIS land surface
775 temperature data reveal fine-scale heat vulnerability in cities: A case study for Los Angeles
776 County, California. *Remote Sens.* 2019;11[18]:2136. <https://doi.org/10.3390/rs11182136>

777 [60] Kporha VK, Fox DM, Banitalebi M, Bouroubi Y, Fournier R. Comparing daily and 8-day MODIS
778 land surface temperature data for urban heat island assessment using random forest
779 modeling in data-limited regions. *Remote Sens Appl Soc Environ.* 2026.
780 <https://doi.org/10.1016/j.rsase.2026.101904>

781 [61] Waleed M, Sajjad M, Acheampong AO, Alam MT. Towards sustainable and livable cities:
782 Leveraging remote sensing, machine learning, and geo-information modelling to explore and
783 predict thermal field variance in response to urban growth. *Sustainability.* 2023;15[2]:1416.
784 <https://doi.org/10.3390/su15021416>

785 [62] Moisa MB, Gemedo DO. Assessment of urban thermal field variance index and thermal comfort
786 level of Addis Ababa metropolitan city, Ethiopia. *Heliyon.* 2022;8.
787 <https://doi.org/10.1016/j.heliyon.2022.e10185>

788 [63] Ullah N, Siddique MA, Ding M, Grigoryan S, Zhang T, Hu Y. Spatiotemporal impact of
789 urbanization on urban heat island and urban thermal field variance index of Tianjin City,
790 China. *Buildings.* 2022;12[4]:399. <https://doi.org/10.3390/buildings12040399>

791 [64] Zhang M, Tan S, Zhang C, Chen E. Machine learning in modelling the urban thermal field
792 variance index and assessing the impacts of urban land expansion on seasonal thermal
793 environment. *Sustain Cities Soc.* 2024. <https://doi.org/10.1016/j.scs.2024.105345>

794 [65] Estoque RC, Ooba M, Seposo X, Togawa T, Hijioka Y, Takahashi K, Nakamura S. Heat health
795 risk assessment in Philippine cities using remotely sensed data and social-ecological
796 indicators. *Nat Commun.* 2020;11. <https://doi.org/10.1038/s41467-020-15218-8>

797 [66] Sara K, Rajasekaran E. High spatiotemporal resolution land surface temperature reveals fine-
798 scale hotspots during heatwave events over India. *Environ Res Commun.* 2025;7.
799 <https://doi.org/10.1088/2515-7620/adc0f2>

800 [67] Li F, Yigitcanlar T, Nepal M, Thanh KN, Dur F. Understanding urban heat vulnerability
801 assessment methods: A PRISMA review. *Energies.* 2022;15[19]:6998.
802 <https://doi.org/10.3390/en15196998>

803 [68] Obe OB, Morakinyo TE, Mills G. Assessing heat risk in a sub-Saharan African humid city, Lagos,
804 Nigeria, using numerical modelling and open-source geospatial socio-demographic datasets.
805 *City Environ Interact.* 2023. <https://doi.org/10.1016/j.cacint.2023.100128>

806 [69] He B, Guan Q. Investigating the effects of spatial scales on social vulnerability index: A hybrid
807 uncertainty and sensitivity analysis approach combined with remote sensing land cover data.
808 *Risk Anal.* 2024;44:2723-2739. <https://doi.org/10.1111/risa.14342>

809 [70] Kropf CM, Ciullo A, Otth L, Meiler S, Rana A, Schmid E, McCaughey J, Bresch D. Uncertainty
810 and sensitivity analysis for probabilistic weather and climate-risk modelling: An
811 implementation in CLIMADA v.3.1.0. *Geosci Model Dev.* 2022. <https://doi.org/10.5194/gmd-15-7177-2022>

813 [71] Harrington L, Schleussner C, Otto F. Quantifying uncertainty in aggregated climate change risk
814 assessments. *Nat Commun.* 2021;12. <https://doi.org/10.1038/s41467-021-27491-2>

815 [72] Samsuddin N, Salleh SA, Khalid N, Saraf NM, Yaman R, Pintor LL, Rueda G, Samsuddin N.
816 Assessing the heat vulnerability index (HVI) in Klang Valley using principal component
817 analysis (PCA) and an equal-weighted approach. *Forum Geografi.* 2025.
818 <https://doi.org/10.23917/forgeo.v39i2.8633>