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Assessing Urban Heat Stress and Thermal Vulnerability in Colombo Using Remote Sensing and Spatial Statistics for Sustainable Urban Planning

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Abstract

Urban heat stress is increasing worldwide with rapid urbanization and climate change, especially in tropical cities where built-up areas are expanding, blue-green infrastructure is declining, and anthropogenic heat emissions are rising. These changes intensify thermal discomfort and climate risk, affecting Sustainable Development Goals (SDG) 11 and 13. Colombo, Sri Lanka, has experienced rapid urban growth and increasing exposure to extreme heat, creating a need for spatially explicit heat vulnerability assessment. This study investigates urban heat stress, anthropogenic heat flux (QF), and urbanization in Colombo during the March 23-28, 2020 heatwave using remote sensing and spatial statistics. Land Surface Temperature (LST), Normalized Difference Built-up Index (NDBI), Normalized Difference Water Index (NDWI), Built-up Index (BUI), QF, Heat Index (HI), Humidex (HD), and Discomfort Index (DI) were integrated within a 500 m grid framework. Global Moran's I and bivariate Moran's I were used to assess spatial clustering and relationships among thermal, urbanization, and anthropogenic variables. A reanalysis-based consistency assessment compared Zenodo-derived heat stress indicators with independently derived ERA5-Land estimates using Root Mean Square Error (RMSE), Mean Absolute Error (MAE), Mean Bias Error (Bias), Pearson correlation coefficient (r), and coefficient of determination (R^2). Results showed significant clustering of QF, LST, and heat stress indicators in densely urbanized areas. HI ranged from 30.5°C to 31.8°C, while LST ranged from 27°C to 37°C, with the highest thermal intensities in commercial, industrial, and transport-intensive zones. Positive associations were observed between LST, built-up intensity, and QF, while NDWI showed a cooling influence.

Keywords: Anthropogenic Heat Flux, Land Surface Temperature, Remote Sensing, Spatial Autocorrelation, Sustainable Urban Planning, Urban Heat Stress

1 Introduction

Globally, rapid urbanization, climate change, and land-use transformation are intensifying urban heat stress, creating a growing sustainability challenge for cities worldwide. The surface energy balance is changed, heat storage is increased, evapotranspiration is decreased, and the effects of Urban Heat Islands (UHI) are intensified when vegetated and permeable surfaces are replaced with impervious built-up materials (Debbage & Shepherd, 2015; Taha, 1997; Voogt & Oke, 2003; Yang et al., 2016). Because higher urban temperatures increase thermal discomfort, cooling-energy demand, air-quality stress, and heat-related risks among exposed urban populations, these thermal changes are not only environmental concerns but also planning and public health issues (Mazumder et al., 2024; Moonen et al., 2012; Santamouris et al., 2001). High humidity in tropical cities contributes to the issue by decreasing human thermal comfort and raising the perceived severity of heat exposure. Thus, urban heat stress has a direct bearing on sustainable urban development, especially Sustainable Development Goal 13 on climate action and Sustainable Development Goal 11 on sustainable cities and communities. Urban heat must be viewed as a spatial planning challenge shaped by urban form, land-cover composition, blue-green infrastructure, local climate zones, and social exposure, according to recent studies (Li et al., 2022; Liu et al., 2024; Marando et al., 2022; Palanisamy et al., 2024; Sützl et al., 2024; Zhang et al., 2023). The cooling effectiveness of green and blue infrastructure, for instance, differs depending on the urban design, land-cover composition, and local climate-zone circumstances,

according to recent research (Liu et al., 2024; Marando et al., 2022). Similarly, it has been demonstrated that land-use change, built-up expansion, and neighborhood morphology affect land surface temperature and heat-prone urban zones, underscoring the significance of spatially targeted mitigation strategies as opposed to broad citywide responses (Thien et al., 2025). This requires spatially explicit data that can pinpoint the areas where heat stress is most prevalent, the urban characteristics that lead to thermal intensification, and the areas that should receive priority for mitigation measures like blue-green corridors, wetland protection, reflective surfaces, ventilation pathways, and heat-sensitive zoning.

An essential tropical metropolitan setting for analyzing these problems is Colombo, Sri Lanka. As the primary commercial, administrative, transportation, and economic hub of the nation, Colombo has seen tremendous urbanization, infrastructure development, an increase in traffic volume, and the gradual replacement of open spaces, vegetation, and wetlands with compact built-up areas. Commercial districts, industrial sectors, transportation corridors, residential zones, canals, marshes, coastal areas, and inland waterbodies are all mixed throughout the city. Urban thermal conditions vary greatly because of this geographical heterogeneity. Due to Colombo's humid tropical monsoon climate, heat stress is impacted by humidity, human perception of thermal discomfort, and land surface temperature. The heatwave that occurred from March 23 to 28, 2020, is a good time to evaluate the interactions between anthropogenic heat emissions, urbanization intensity, thermal stress, and blue-green infrastructure throughout the city. Despite the tremendous expansion of urban heat research, there are still several gaps in tropical South Asian cities. First, even though Land Surface Temperature (LST) does not accurately reflect human thermal discomfort in humid tropical circumstances, many research continue to use LST as the primary indication of metropolitan heat. Second, few studies have combined anthropogenic heat flux (QF), built-up intensity, waterbody distribution, and radar-derived structural indicators with human-centered heat-stress indicators as Heat Index (HI), Humidex (HD), and Discomfort Index (DI). Third, while planning-oriented heat vulnerability assessment, LCZ-based analysis, and blue-green infrastructure evaluation have been advanced in recent studies, fewer studies have applied such integrated approaches to humid tropical South Asian cities where heat stress is shaped by both high humidity and rapid urban transformation (Liu et al., 2024). Fourth, most studies on urban heat are descriptive in nature and do not adequately use spatial statistical methods to investigate the spatial correlation and clustering behavior between heat stress and urban factors. Lastly, there is no evidence from Sri Lankan cities that connects human thermal stress, anthropogenic heat emissions, multi-source remote sensing, and the implications of sustainable planning within a unified analytical framework.

This work utilizes multi-source remote sensing and spatial statistics to evaluate urban heat stress and thermal vulnerability in Colombo during the March 23–28, 2020 heatwave in order to close these gaps. Within a 500 m grid framework, the study incorporates MODIS-derived LST, Sentinel-2-derived Normalized Difference Built-up Index (NDBI) and Normalized Difference Water Index (NDWI), ALOS PALSAR-derived Built-up Index (BUI), anthropogenic heat flux (QF), and human-centered heat stress indicators such as HI, HD, and DI. The spatial clustering and correlations between thermal, urbanization, and anthropogenic variables are assessed using global Moran's I and bivariate Moran's I. Furthermore, the coherence between the heat stress indicators and independently produced estimates from the ERA5-Land climate reanalysis dataset is evaluated. This study is unique in that it evaluates urban thermal vulnerability in a humid tropical urban setting by integrating surface temperature, anthropogenic heat flux, human heat-stress indicators, optical and radar-based urbanization indicators, and spatial autocorrelation analysis. The framework enhances knowledge of the spatial causes of urban heat stress and offers planning-relevant evidence for heat mitigation, blue-green infrastructure

protection, and climate-resilient urban development in Colombo and similar tropical cities. This is a methodological and practical contribution.

2 Review of Literature

An essential foundation for comprehending thermal intensification in cities is provided by the UHI effect. UHI is a general term for the higher temperatures found in urban areas compared to their less urbanized surroundings. It is linked to anthropogenic heat release, land-cover transformation, decreased evapotranspiration, changed surface radiative properties, and urban geometry (Taha, 1997; Voogt & Oke, 2003). By increasing sensible heat storage and reducing evaporative cooling, replacing vegetated and moisture-retaining surfaces with asphalt, concrete, roofing materials, and other impermeable surfaces alters the urban energy balance. However, development configuration, urban fabric continuity, and background climate all affect the amount and spatial expression of urban heating, suggesting that UHI processes cannot be understood in isolation from local urban and climatic contexts (Debbage & Shepherd, 2015). Since high temperatures impact building energy demand, outdoor comfort, environmental quality, and climate resilience, urban heat has evolved from a largely climatological problem into a more comprehensive sustainability challenge (Moonen et al., 2012; Santamouris et al., 2001). In tropical and subtropical settings, where high atmospheric moisture can exacerbate perceived thermal discomfort even when temperature conditions are similar to those in drier regions, this issue is especially crucial (Balogun et al., 2010). Urban heat assessment is therefore increasingly linked to heat vulnerability, neighborhood morphology, climate-sensitive design, and geographical prioritization of mitigation measures, according to current research (Sützl et al., 2024; Zhang et al., 2023). This shift is crucial for quickly urbanizing cities, as heat exposure results from a combination of meteorological, morphological, infrastructure, and human factors rather than just surface temperature.

Urban form and land-cover composition have a significant impact on the spatial dispersion of urban heat. By altering heat storage, shading, radiative exchange, evapotranspiration, and airflow, compact development, large impervious surfaces, and contiguous urban form can increase thermal accumulation (Debbage & Shepherd, 2015; Yang et al., 2016). Land-cover composition and spatial pattern both affect LST, indicating that thermal conditions depend not only on the number of different land-cover classes but also on how they are arranged within the urban landscape (Estoque & Murayama, 2017). Studies conducted in Southeast Asian megacities have demonstrated this. On the other hand, through evapotranspiration, shade, moisture availability, and local energy-balance alteration, plant and water-associated landscapes can reduce metropolitan temperatures. For instance, although the amount of cooling varies geographically, river habitats can affect local urban thermal conditions (Moyer & Hawkins, 2017). Although green infrastructure has shown quantifiable promise for reducing heat at larger urban scales, its efficacy varies depending on climatic conditions and urban layouts (Yeboah et al., 2025). According to more recent data, blue-green infrastructure interacts with local climate zone characteristics and urban spatial dynamics, indicating that cooling advantages are dependent on surrounding morphology rather than just the presence of water or vegetation (Kumar et al., 2024). In Colombo, where wetlands, canals, inland water bodies, coastal influences, and highly populated areas coexist within a fast changing metropolitan landscape, this distinction is especially pertinent. Therefore, rather than evaluating each component separately, a meaningful assessment of thermal vulnerability must look at the spatial interaction between potentially cooling blue-green elements and heat-generating urban structures.

Because it allows for the spatially continuous and reproducible measurement of surface temperature and land-cover characteristics across diverse urban landscapes, remote sensing has

emerged as a key component of urban thermal research (Weng, 2009). Surface UHI patterns, thermal gradients, and intra-urban temperature disparities have long been identified using thermal infrared data (Voogt & Oke, 2003). Still, there is an ongoing spatial-temporal trade-off in sensor selection. While Landsat delivers finer geographical detail but lower temporal frequency, MODIS offers frequent observations appropriate for multi-day and event-oriented monitoring; surface emissivity assumptions and retrieval methods also have an impact on LST retrieval success (Sekertekin & Bonafoni, 2020). Combining LST with built-environment and land-cover indicators frequently improves urban thermal interpretation. While multi-sensor techniques can enhance the representation of varied urban landscapes, optical indices can describe built-up intensity, vegetation, wetness, and water-associated surfaces. While built-up indices derived from optical and SAR sensors have been developed for impervious-feature extraction (Sinha et al., 2020), prior research has shown the complementary value of optical and Synthetic Aperture Radar (SAR) observations for impervious-surface estimation. The structural features of dense constructed environments may not be sufficiently represented by optical observations alone, which makes these research especially pertinent.

While city-specific studies have shown that LST reacts strongly to land-use dynamics (Patel et al., 2024), recent multi-temporal analyses have further highlighted the close association between urban development, land-use transformation, and changing UHI patterns (Mazumder et al., 2024). Significant diurnal thermal fluctuation has also been found through analysis across land-cover types and Local Climate Zones, highlighting the significance of urban environment in interpreting remotely sensed temperature patterns (Kan et al., 2026). However, a restricted set of thermal and optical markers is still used in many urban heat studies (Sinha & Banerjee, 2025). This suggests scope for frameworks that combine thermal observations with optical and radar-derived measures of urbanization.

The inclination to treat LST as a direct reflection of human heat exposure is a major conceptual restriction in urban thermal research. Although it is not comparable to near-surface air temperature or human thermal perception, LST monitors the radiometric temperature of the land surface, making it extremely useful for describing surface energy processes and spatial thermal anomalies (Voogt & Oke, 2003). Air temperature, humidity, wind speed, radiation, exposure time, clothing, activity, and physiological traits all have an impact on human heat stress (Schinasi et al., 2018). In humid tropical climes, where limited evaporative cooling can exacerbate physiological and perceived heat strain, this distinction is particularly crucial (Ahmed, 2003). Therefore, surface-temperature mapping is complemented by composite heat-stress indicators. To describe perceived heat or thermal discomfort, climatic factors are combined in various ways by the HI, HD, and DI (Mistry, 2020). By combining these indications with LST, it is possible to differentiate between situations that are more directly associated with human perception of heat and surface thermal intensity. However, especially in humid tropical South Asian contexts, relatively few urban studies seem to combine several human-centered heat-stress indicators with remotely sensed surface temperature and urban-form factors at the same time (de Souza e Silva et al., 2022).

QF refers to heat released by human activities, including transportation, industrial processes, building energy use, commercial activity, and domestic energy consumption. It is a recognized component of the urban energy balance and contributor to urban climate modification (Taha, 1997). A potentially self-reinforcing relationship may occur because elevated urban temperatures increase cooling demand, while energy consumption and building waste heat add further heat to the urban environment (Santamouris et al., 2001). Anthropogenic heat also interacts with urban geometry and atmospheric processes. Thermal forcing can influence airflow and pollutant dispersion (Cui et al., 2016), while urban microclimate modelling highlights the importance of coupled thermal and aerodynamic processes (Toparlar et al., 2017). QF remains unevenly represented in spatial heat-

vulnerability assessments compared with commonly mapped land-cover variables such as vegetation, water, and imperviousness (Kwon et al., 2020). This limitation is important because dense commercial, industrial, transport, and residential zones may experience thermal intensification through both surface properties and concentrated energy release.

Urban thermal conditions are also spatially dependent because neighbouring locations frequently share similar land-cover, morphological, infrastructural, and climatic characteristics. Descriptive maps may reveal apparent hotspots but cannot establish statistically significant clustering. Spatial autocorrelation methods therefore distinguish structured spatial patterns from random variation. Global Moran's I assesses overall spatial autocorrelation, whereas local statistics identify concentrated clusters and spatial outliers. Bivariate spatial association further examines whether values of one variable are related to neighbouring values of another, making it relevant for assessing relationships between thermal conditions and built-up intensity, water distribution, or anthropogenic activity. Broader developments in spatial cluster detection have also been reported (Anselin & Li, 2019). Morphology-based clustering has identified heat-prone neighbourhoods, while heat-vulnerability perspectives have informed Local Climate Zone allocation. Research has advanced thermal remote sensing, urban morphology analysis, blue-green infrastructure assessment, and spatially targeted heat mitigation, yet important gaps remain. Human-centred heat stress is less frequently integrated with surface-temperature assessment; QF is inconsistently combined with remote sensing and heat-stress indicators; radar-derived structural information remains underused relative to optical and thermal observations; and spatial associations among thermal conditions and urban drivers are not always explicitly tested. These gaps are particularly relevant to humid tropical South Asian cities. Accordingly, this study integrates LST, NDBI, NDWI, BUI, QF, HI, HD, and DI within a 500 m framework and applies Global Moran's I and bivariate Moran's I to support climate-sensitive planning in Colombo.

3 Materials and Methods

3.1 Study Area

Colombo, Sri Lanka's economic and administrative center, was chosen as the study region because of its fast urban growth, high concentration of infrastructure, rising human activity, and increasing susceptibility to urban heat stress. Located between around 6.85°N and 6.98°N latitude and 79.80°E and 79.95°E longitude along Sri Lanka's western coastal plain, the city serves as the nation's main administrative, commercial, and economic hub. As a result of the increased urbanization, population concentration, infrastructure development, industrial growth, and the expansion of transportation networks, Colombo has seen significant land-use transformation in the past few decades. As a result of these urbanization processes, impermeable built-up surfaces have gradually replaced natural landscapes including wetlands, vegetation cover, and open spaces, exacerbating UHI impacts and uncomfortable thermal levels throughout the metropolitan area. Figure 1 shows Sri Lanka's monthly temperature and precipitation climatology, which clearly distinguishes a relatively drier December-April period from a wetter May-November monsoon-dominated period, providing the seasonal basis for the HOT and WET analytical framing applied to the Colombo metropolitan region.

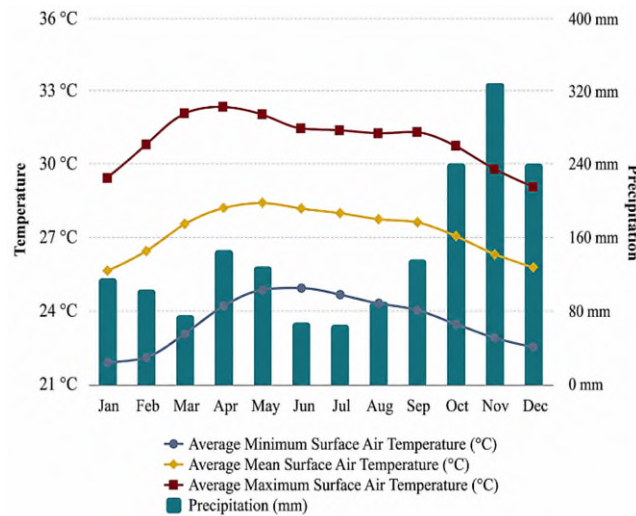


Fig. 1 Long-term monthly climate normals for Sri Lanka (1991–2020)(Sri Lanka - Climatology (CRU) | Climate Change Knowledge Portal, n.d.)

Colombo's tropical monsoon environment has a significant impact on the city's climate. While Colombo is located in the wet climate zone with significant rainfall linked to southwest and northeast monsoonal systems, Sri Lanka often has consistently high temperatures and humidity levels throughout the year. Average yearly temperatures often fall between 26°C and 32°C, and during periods of intense heat, high humidity exacerbates perceived thermal pain. Long-term climate normals show clear seasonal differences in temperature and precipitation patterns throughout the nation, with comparatively higher thermal intensities seen during drier months and increased rainfall during monsoonal times. In densely populated areas, where natural cooling processes are limited by decreased forest cover and rising anthropogenic heat outputs, these climatic features exacerbate urban heat stress.

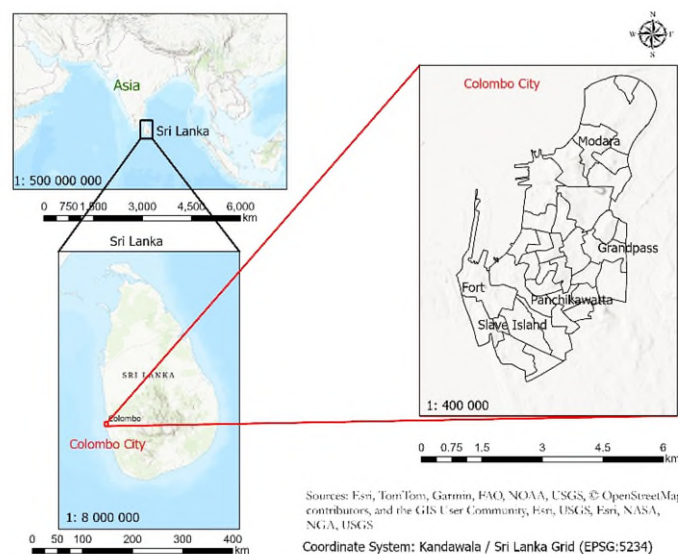


Fig. 2 Location and spatial extent of the Colombo study area

Strong regional variability in temperatures is caused by the dense industrial, commercial, transportation, residential, coastal, wetland, canal, and waterbody regions that make up Colombo's metropolitan landscape. The heatwave that occurred in March 2020 was chosen as it was an intense

thermal event that made comparable multi-source remote sensing research possible for evaluating urban heat stress and planning requirements.

3.2 Data Sources

MODIS are widely used in urban climate research because of their high temporal consistency, radiometric dependability, and capacity for large-scale thermal monitoring. They offer daily thermal observations at a spatial resolution of 1 km. Google Earth Engine was used to obtain daily daytime thermal images throughout the heatwave period of March 23–28, 2020. These images were then processed to produce mean temperatures throughout the study area. Standard scale factor correction techniques were used to convert thermal values from Kelvin to degrees Celsius, and quality verification layers included into the dataset were used to exclude abnormal thermal pixels and cloud-generated observations. By averaging daily observations throughout a chosen heatwave period, synthetic heat layers were created. Urbanization and water quality indicators, such as the NDBI and the NDWI, were derived using Sentinel-2 Level-2A multispectral images (Copernicus Data Space Ecosystem, n.d.). Sentinel-2 imagery provides high spatial resolution optical observations that are suitable for detailed urban land cover characterization and urban environmental analysis. Atmospherically corrected imagery corresponding to the study period was obtained from Google Earth Engine, and spectral bands, including Band 3 (Green), Band 8 (Near Infrared), and Band 11 (Shortwave Infrared), were utilized for index generation.

Table 1. Description of datasets used

Dataset	Provider	Spatial / temporal resolution	Variables used
LST	MODIS Terra MOD11A1 Version 6.1(Earth Science Data Systems, 2025)	1 km; daily	Daytime LST (°C); quality assurance (QA) layers
Built-up intensity and urbanization	Sentinel-2 Level-2A	10–20 m; multispectral imagery	NDBI; impervious urban surfaces
Waterbody and surface moisture distribution	Sentinel-2 Level-2A	10–20 m; multispectral imagery	NDWI; waterbody and moisture distribution
Built-up structural intensity	ALOS PALSAR	12.5 m; radar imagery	BUI; urban structural density
Heat stress indicators	Temporal and spatial heat exposure in Colombo - dataset	Daily; March 23–28, 2020	HI; HD; DI
QF	Zenodo Anthropogenic Heat Flux Dataset	500 m spatial framework	Anthropogenic heat emissions associated with transportation, industrial, and commercial activities
Study area boundary and urban spatial layers	OpenStreetMap (OSM)	Vector data	Roads; urban infrastructure; hydrography; administrative boundaries

Dataset	Provider	Spatial / temporal resolution	Variables used
Spatial analytical framework	Generated 500 m spatial grid	500 m	Integrated spatial analysis units for thermal and urbanization variables
ERA5-Land	ECMWF Copernicus Climate Data Store	~9 km; hourly	2 m air temperature; 2 m dew point temperature; derived RH, HI, HD, DI

The NDBI was calculated to identify impervious urban surfaces and built-up intensity using Eq.(1).

$$NDBI = SWIR - NIR / SWIR + NIR \quad \text{Eq(1)}$$

where NIR stands for near-infrared reflectance and SWIR for shortwave infrared reflectance. Increased densities of built-up structures and impermeable urban surfaces are indicated by higher NDBI values.

The NDWI was derived using Eq(2).

$$NDWI = Green - NIR / Green + NIR \quad \text{Eq(2)}$$

where NIR stands for near-infrared reflectance and green for green band reflectance. Greater surface moisture conditions and the presence of waterbodies are indicated by higher NDWI values. These indices were chosen because built-up density, waterbody distribution, and urban thermal variability have been shown to be strongly correlated in earlier urban thermal research (Estoque et al., 2017). Urban structure intensity throughout the study area was characterized and BUI information was obtained using Advanced Land Observing Satellite Phased Array L-band Synthetic Aperture Radar (ALOS PALSAR) datasets (Earth Science Data Systems, 2025). Because radar backscatter responses are extremely sensitive to impermeable urban buildings, building shape, and roughness of the surface, radar-based datasets are especially useful for urban study. To reduce geometric distortions and enhance spatial consistency, radiometric calibration and terrain correction techniques were used to preprocess ALOS PALSAR imagery. To identify heavily populated areas with higher radar backscatter signatures, built-up intensity layers were then created. Beyond what could be accomplished with optical datasets alone, the use of radar measurements allowed for better characterization of urban form (Sinha et al., 2020).

To assess the thermal distress conditions that urban populations faced during the chosen heatwave period, human-centered heat stress indicators such as the Heat Index (HI), Humidex (HD), and Discomfort Index (DI) were taken from the global heat stress dataset made available by Zenodo and integrated. Compared to land surface temperatures alone, these indicators provide a more complete picture of human thermal stress by including data on air humidity and temperature. These indicators provide a more complete picture of actual human thermal stress circumstances by considering air humidity and thermal perception features, in contrast to traditional surface temperature analysis. While the HD assesses thermal discomfort related to high humidity circumstances, the HI estimates apparent temperature experienced by people by combining air temperature and relative humidity. In a similar vein, the DI stands for the combined stress of wetness and heat in urban settings. A standardized

analytical approach was used to spatially integrate these metrics within a GIS environment. QF data were used to represent human-generated heat emissions related to transportation systems, industrial activities, commercial operations, dense infrastructure concentration, and urban energy consumption. These data were taken from the global anthropogenic heat emission dataset made available through Zenodo (Xie et al., 2023) densely populated areas, anthropogenic heat emissions are acknowledged as major causes of urban thermal buildup and UHI impacts (Taha, 1997). A thorough analysis of the spatial correlations between urban thermal sensitivity patterns and human activity was made possible by the integration of QF with thermal and urbanization data.

3.3 Data Preprocessing and Spatial Integration

To guarantee spatial consistency and precise geospatial analysis, all datasets were projected onto the World Geodetic System 1984 Universal Transverse Mercator Zone 44N coordinate system. Before integration, raster datasets with varying spatial resolutions were resampled and spatially aligned inside a shared analytical framework. Using algorithms built into Google Earth Engine, atmospheric correction and cloud masking techniques were applied to Sentinel-2 imagery to reduce atmospheric contamination and eliminate cloud-covered observations. Comparable to this, aberrant thermal observations and low-quality pixels were removed from MODIS thermal datasets by filtering them using quality assurance layers. In order to spatially integrate thermal, urbanization, anthropogenic heat, and heat stress datasets under a uniform analytical framework, a standardized 500 m spatial grid framework was created. The chosen spatial resolution minimized scale discrepancies between datasets obtained from sensors with different spatial resolutions while effectively balancing computational efficiency and spatial detail. Strong statistical comparisons between various variables within a single geographic framework were also made possible by the usage of a uniform spatial grid. Raster standardization, geographical resampling, zonal statistics extraction, attribute normalization, and geospatial database integration were all part of the spatial integration processes. To obtain mean values for the thermal and urbanization variables, zonal statistics were computed for every 500 m grid cell. The mean LST, mean HI, mean HD, mean DI, mean QF, mean NDBI, mean NDWI, and mean BUI values were then merged into each spatial unit. Comprehensive spatial comparison and statistical analysis of thermal and urbanization indicators throughout the metropolitan area were made easier by this integrated framework. To enhance comparability between variables with various numerical ranges and measurement units, spatial normalizing techniques were then carried out. The study area's anthropogenic heat variations, urbanization intensity, and thermal hotspot patterns could all be better understood thanks to standardized geographical layers. Effective display and overlay analysis between thematic data were also made possible by spatial integration inside a GIS framework.

3.4 Derivation of Urban Thermal and Urbanization Indicators

The remotely sensed datasets were used to create thermal and urbanization indicators, which were then incorporated into the analytical structure. To depict average thermal conditions throughout Colombo, mean composite LST layers were created using MODIS thermal readings throughout the heatwave period of March 23–28, 2020. During the chosen heatwave event, composite averaging techniques reduced temporal inconsistencies and made it possible to portray generic thermal patterns. Urban impervious surface distribution and built-up intensity were characterized using the NDBI obtained from Sentinel-2 imagery. Densely populated urban zones, such as commercial districts, industrial regions, and transportation corridors, were associated with higher NDBI values, whereas vegetated and water-dominated settings were associated with lower values. The distribution of waterbodies and the availability of moisture throughout the metropolitan area were also determined using NDWI. Wetlands, lakes, canals, rivers, and coastal waterbodies were typically found in areas

with high NDWI values. Urban structural density and built-up intensity were described using BUI layers created with ALOS PALSAR datasets. Enhanced detection of heavily urbanized areas with thick infrastructure and impermeable surfaces was made possible by radar backscatter responses. Thus, comparable information about built-up characteristics and urban morphology was obtained by the integration of optical and radar datasets. Human-centered urban heat stress patterns were assessed by integrating HI, HD, and DI layers that indicate thermal discomfort situations. These indicators offered more information about the thermal effects of high humidity and perceived temperature conditions in the tropical metropolitan setting of Colombo. Beyond traditional LST analysis alone, a more thorough evaluation of urban thermal vulnerability was made possible by the integration of several thermal indicators.

3.5 Spatial Statistical Analysis

Spatial autocorrelation analysis was employed to evaluate the clustering behavior and spatial dependencies among the thermal and urbanization variables within the study area. Moran's I and bivariate Moran's I statistics were calculated using GeoDa software to identify significant spatial clustering patterns and examine relationships among thermal stress indicators, urbanization intensity, and anthropogenic heat emissions. Global Moran's I was utilized to evaluate the overall spatial autocorrelation structure of thermal and urbanization variables across the Colombo metropolitan region. Positive Moran's I values indicate clustering of similar values, whereas negative values indicate spatial dispersion. Moran's I statistics were calculated using Eq(3).

$$I = \frac{n}{W} \frac{\sum_i \sum_j w_{ij} (x_i - \bar{x})(x_j - \bar{x})}{\sum_i (x_i - \bar{x})^2} \quad \text{Eq(3)}$$

where n represents the number of spatial units, w_{ij} represents the spatial weight matrix, x_i and x_j represent observed variable values, $\bar{x}$ represents the mean value, and W represents the total spatial weights. Bivariate Moran's I analysis was subsequently employed to evaluate the spatial relationships between the thermal and urbanization variables, including the LST-NDBI, LST-NDWI, LST-BUI, HI-QF, HD-QF, and DI-QF relationships. Bivariate Moran's I was calculated using Eq.(4).

$$I_{xy} = \frac{n}{W} \frac{\sum_i \sum_j w_{ij} (x_i - \bar{x})(y_j - \bar{y})}{\sum_i (x_i - \bar{x})^2} \quad \text{Eq(2)}$$

where x_i represents values of the first variable, y_j represents values of the second variable, and the remaining terms represent spatial weights and standardized spatial relationships.

The use of bivariate Moran's I made it possible to identify localized thermal hotspots and investigate the geographical relationships between anthropogenic heat outputs, urbanization severity, and thermal stress conditions. While Low-Low clusters represented cooler settings linked to waterbody concentration and vegetated landscapes, significant-High clusters represented areas where heightened thermal conditions spatially coincided with significant urbanization intensity or anthropogenic heat emissions. Spatial outliers with different thermal and urbanization characteristics from nearby spatial units were represented by High-Low and Low-High clusters. GeoDa's permutation techniques and false-significance tests were used to assess spatial importance. Moran scatterplots and cluster maps were then used to depict statistically significant clustering patterns in order to enhance the

understanding of urban exposure patterns and thermal hotspot structures. Spatial autocorrelation techniques were selected because conventional descriptive thermal mapping approaches often fail to capture localized clustering behavior and spatial thermal interactions within complex metropolitan environments.

3.6 GIS-Based Visualization and Hotspot Identification

ArcGIS Pro, ENVI, Google Earth Engine, and GeoDa were used for spatial processing, thematic mapping, and visualization. Composite maps were created by integrating heat stress indicators, anthropogenic heat flux, urbanization intensity, and spatial autocorrelation outputs. Cluster visualization and graduated symbology were used to identify thermal hotspot patterns and high-risk zones. Areas with consistent High–High clustering, elevated QF, dense built-up intensity, and high heat stress were interpreted as priority thermal vulnerability zones. Spatial visualization also highlighted the cooling influence of waterbodies and vegetation, while higher NDBI and BUI values confirmed the role of urban form in shaping Colombo’s heat patterns.

3.7 Methodological Framework

The Figure 3 shows the methodological framework employed in this study that is consisted of integrated stages including data acquisition, remote sensing preprocessing, thermal index generation, spatial integration, spatial statistical analysis, hotspot identification, and thermal vulnerability interpretation. Within a standardized 500 m spatial grid structure, thermal measurements from MODIS were combined with urbanization indicators produced from Sentinel-2 and ALOS PALSAR imagery. Urban thermal sensitivity conditions were then assessed by including anthropogenic heat flux measurements and heat stress markers. The thermal, urbanization, and anthropogenic heat variables were examined for spatial correlations and grouping behavior using spatial autocorrelation approaches such as Moran's I and bivariate Moran's I. The identification of localized thermal vulnerability zones with high levels of heat stress and intense urbanization was made possible by integrated hotspot analysis. Thus, a thorough analysis of urban thermal dynamics, anthropogenic heat exchanges, and urbanization-driven thermal intensification in Colombo was made possible by the analytical approach.

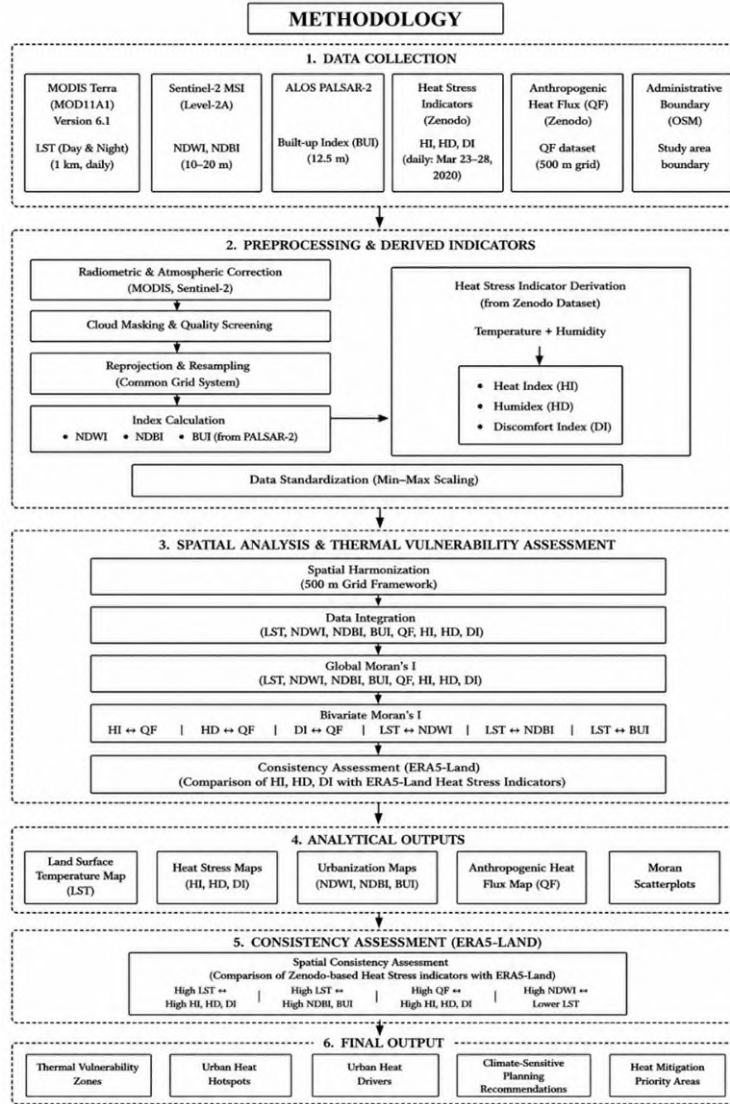


Fig. 3 Methodological framework for urban heat stress assessment using multi-source remote sensing and spatial statistical analysis

3.8 Consistency Assessment Using ERA5-Land Reanalysis Data

Independent heat stress indicators were calculated using hourly 2 m air temperature and 2 m dew point temperature data from the European Centre for Medium-Range Weather Forecasts (ECMWF) Reanalysis Version 5 Land (ERA5-Land) for March 23–28, 2020 (Copernicus Climate Change Service, 2019). Since ERA5-Land offers geographically and temporally continuous climate estimates at comparatively high spatial resolution and has been tested against unbiased in-situ and satellite-based standard datasets, it was chosen as an independent reanalysis-based reference (Muñoz-Sabater et al., 2021). The suitability of ERA5 and ERA5-Land temperature products for climate-related applications in data-scarce regions has also been demonstrated by prior studies that evaluated them against meteorological station observations using agreement statistics like Root Mean Square Error (RMSE), Pearson correlation coefficient, and bias (Dos Santos Ferreira et al., 2026; Yilmaz, 2023). Therefore, rather than being a direct observational verification source, ERA5-Land was utilized in this study for reanalysis-based consistency assessment. RMSE, Mean Absolute Error (MAE), Mean Bias Error (Bias), and Pearson correlation coefficient (r) were used to compare and contrast the generated HI, HD,

and DI layers with the relevant Zenodo-based indicators. The degree of agreement between the separately obtained ERA5-Land indicators and the Zenodo-based heat stress dataset was assessed using these statistical metrics.

4 Results

4.1 Spatial Distribution of Urban Heat Stress Indicators

During the heatwave period of March 23–28, 2020, there was a noticeable fluctuation in urban heat stress throughout Colombo, according to the spatial study. The findings show that heat stress was spatially concentrated in locations with high anthropogenic heat emissions, commercial land use, transportation activity, and dense built-up surfaces rather than being dispersed randomly throughout the city. Central and southern Colombo were consistently found to have higher levels of temperature discomfort by HI, HD, and DI. These regions correlate to densely populated residential and commercial sectors with few natural cooling surfaces and a predominance of impermeable surfaces. The average HI's geographical distribution throughout the study area is depicted in Figure 4. The greatest HI values were found in Colombo's heavily populated areas, and they ranged from 30.5°C to 31.8°C. Although the numerical range appears relatively narrow, its spatial distribution is important because even small changes in apparent temperature can increase thermal discomfort under tropical humidity conditions. The highest HI zones were mainly associated with compact urban areas, while relatively lower values appeared near water-associated and less densely built environments. This pattern suggests that urban morphology and surface cover strongly influence the spatial intensity of perceived heat stress.

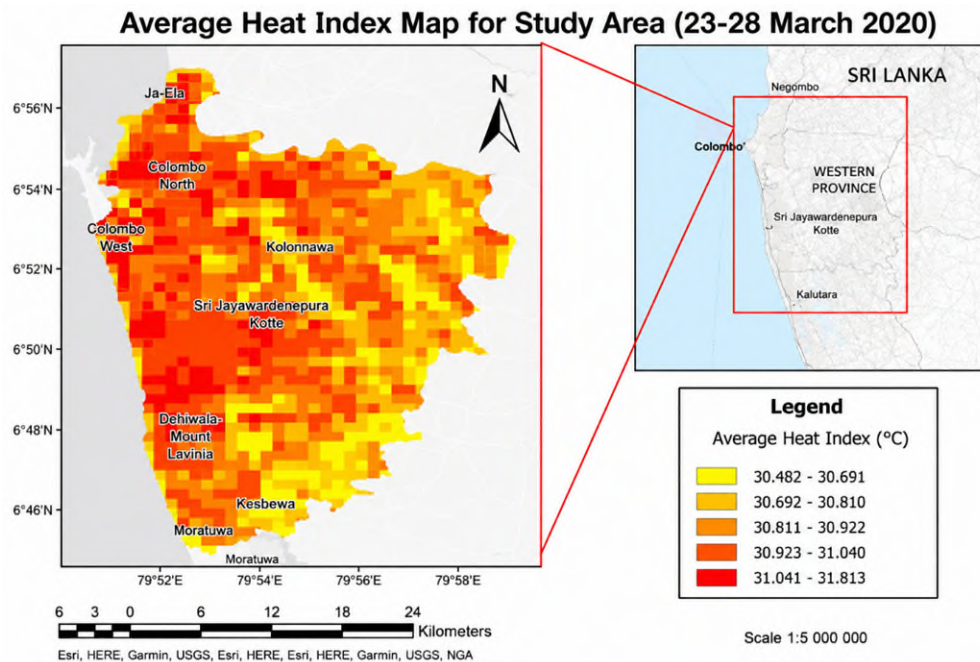


Fig. 4 Spatial distribution of average Heat Index (HI) in Colombo during the March 23–28, 2020 heatwave period

HD readings had a similar geographical tendency to HI and ranged from 36.9°C to 38.2°C. In populated locations, where high temperatures and humidity combine to create uncomfortable thermal conditions, elevated HD values were concentrated. The concentration of discomfort in central and

highly urbanized zones was further corroborated by DI values, which varied from 26.0°C to 26.7°C. The idea that heat stress in Colombo is not just a surface temperature problem but also a human thermal comfort issue influenced by humidity, apparent temperature, and urban land cover is strengthened by the consistency between HI, HD, and DI.

4.2 Land Surface Temperature and Urbanization Patterns

The research area's LST values varied from 27°C to 37°C. Dense commercial, industrial, and infrastructure-dominated zones had the highest LST values, whereas wetlands, waterbodies, and less compact urban regions had comparatively lower temperatures. This spatial difference demonstrates how surface properties have a significant impact on heat buildup. Higher surface temperatures occur during heatwaves because built-up surfaces are more effective at absorbing and retaining solar energy than vegetated or water-dominated surfaces. The link between urban surface characteristics and heat intensity is depicted in Figure 5. Higher impervious surface concentration and structure density were indicated by higher NDBI and BUI values, which were mostly found in commercial, industrial, and densely populated areas. These zones corresponded closely with elevated LST values. In contrast, higher NDWI values were associated with wetlands, canals, and waterbody areas, which generally showed lower thermal intensity. This confirms the cooling influence of blue infrastructure within the urban environment.

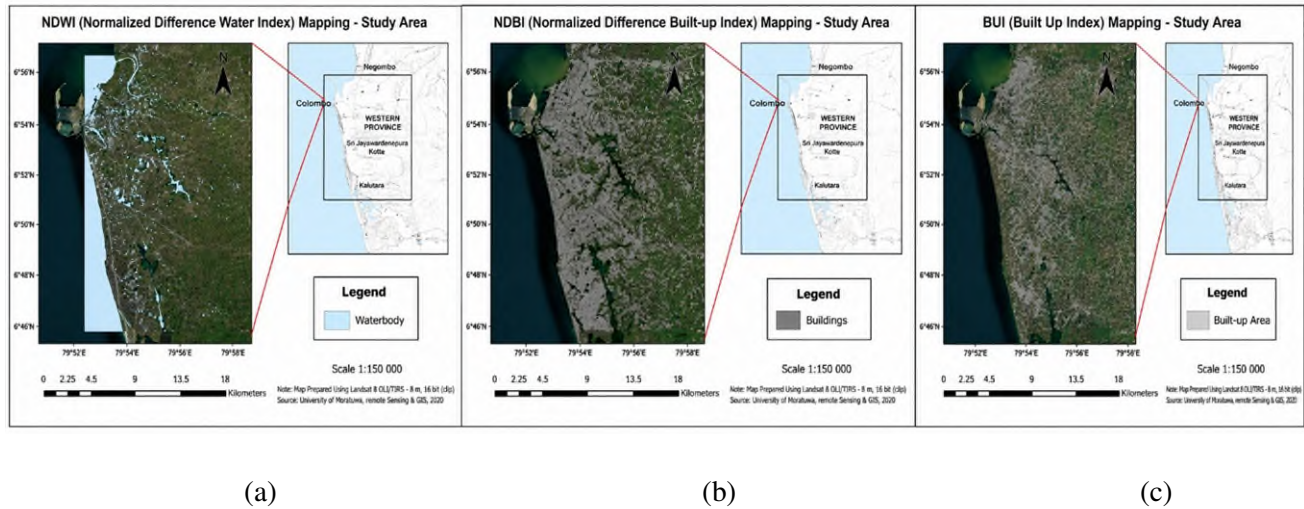


Fig. 5 Spatial distribution of (a)NDWI, (b)NDBI, and (c)BUI in Colombo

The BUI results offered more proof of the connection between urban thermal conditions and built-up structural intensity. Moderately built-up grids had BUI values between 1.5 and 1.7, and highly built-up grids had BUI values greater than 1.7. Particularly in Colombo's commercial, industrial, and infrastructure-dominated areas, areas with BUI values more than 1.7 were typically associated with thermally susceptible zones. This trend implies that while vegetation, wetlands, and other natural land-cover elements have a relative cooling effect, dense urban constructions and impermeable surfaces are linked to increased heat storage.

4.3 Spatial Autocorrelation of Heat Stress and Anthropogenic Heat Flux

Heat stress indicators and QF were spatially grouped rather than randomly distributed, according to the Global Moran's I findings. A positive spatial clustering pattern was indicated by HI's Moran's I

value of 0.511. With a Moran's I value of 0.778, HD had a stronger clustering pattern, indicating a significant degree of spatial concentration of adjusted for humidity heat stress. The non-random distribution of pain conditions was confirmed by DI's Moran's I value of 0.488. With a Moran's I value of 0.766, QF demonstrated high spatial clustering, suggesting that human-generated heat emissions were concentrated urban activity zones. High heat stress values typically occur close to other high values, generating High-High clusters, according to the positive Moran's I values. These clusters were primarily concentrated in dense urban zones, where commercial activity, traffic intensity, and built-up surfaces contribute to increased thermal stress. Low-Low clusters were more common in less urbanized or water-associated areas, suggesting relatively lower thermal stress and reduced anthropogenic heat influence.

4.4 Bivariate Spatial Relationships

Significant correlations between QF and heat stress measures were found by bivariate Moran's I analysis. A somewhat positive spatial correlation was shown by the bivariate Moran's I value of 0.489 for the HI-QF link. This indicates that regions with high HI values were frequently found close to regions with significant human heat emissions. A positive but lesser spatial relationship was revealed by the HD-QF relationship, which had a value of 0.309. Anthropogenic heat emissions were likewise spatially associated with discomfort conditions, according to the DI-QF connection, which had a value of 0.473. The regional correlations between QF and the three heat stress markers are displayed in Figure 6.

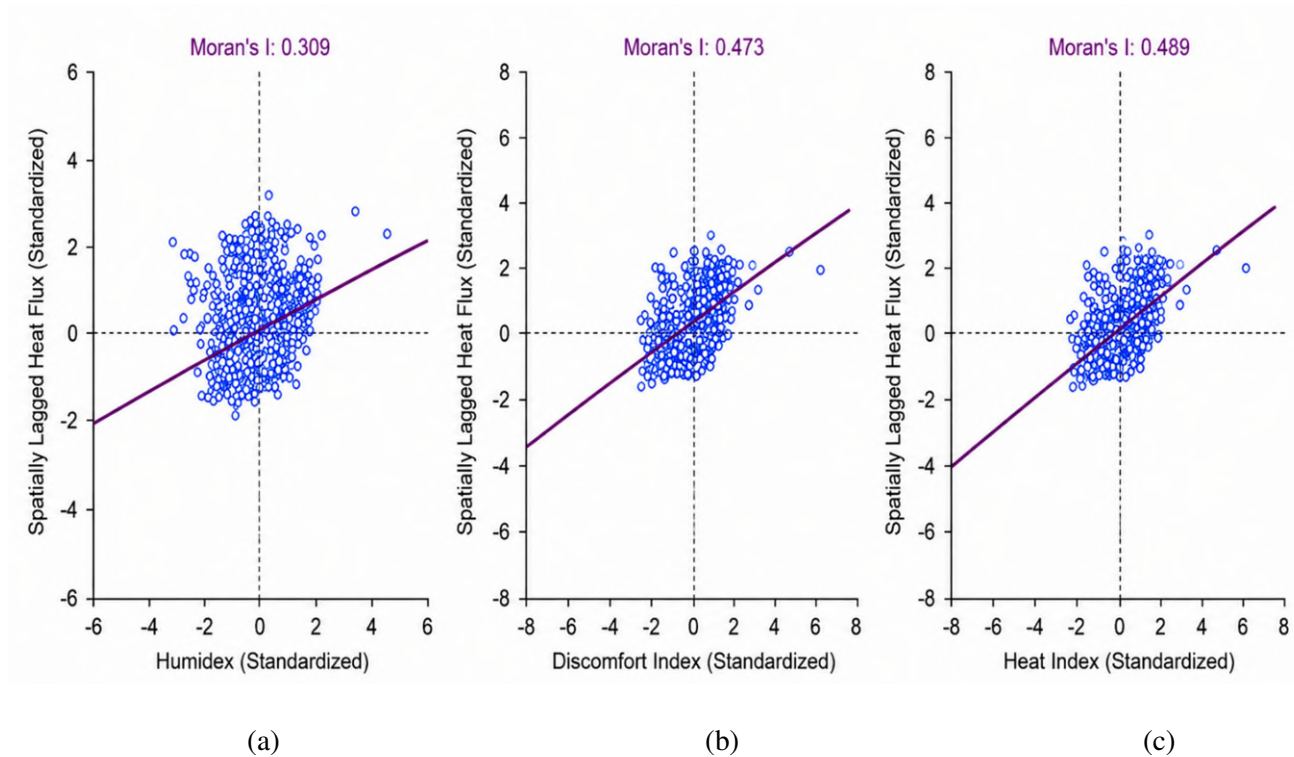


Fig. 6 Bivariate Moran's I scatterplots showing spatial relationships between (a)HD, (b)DI, (c)HI and anthropogenic heat flux (QF)

High-High clusters identified areas where elevated heat discomfort coincided with high QF, indicating localized intensification associated with human activities. Low-Low clusters represented

areas with comparatively low heat stress and QF, while spatial outliers suggested additional influences from built-up intensity, surface properties, and ventilation. The LST–NDWI association was negative (-0.153), indicating lower thermal intensity in areas with greater surface moisture and waterbody presence. Conditional maps further showed lower heat stress near blue-green infrastructure, whereas higher NDBI and BUI values were associated with elevated LST, particularly in dense commercial and industrial zones, emphasizing the influence of urban form.

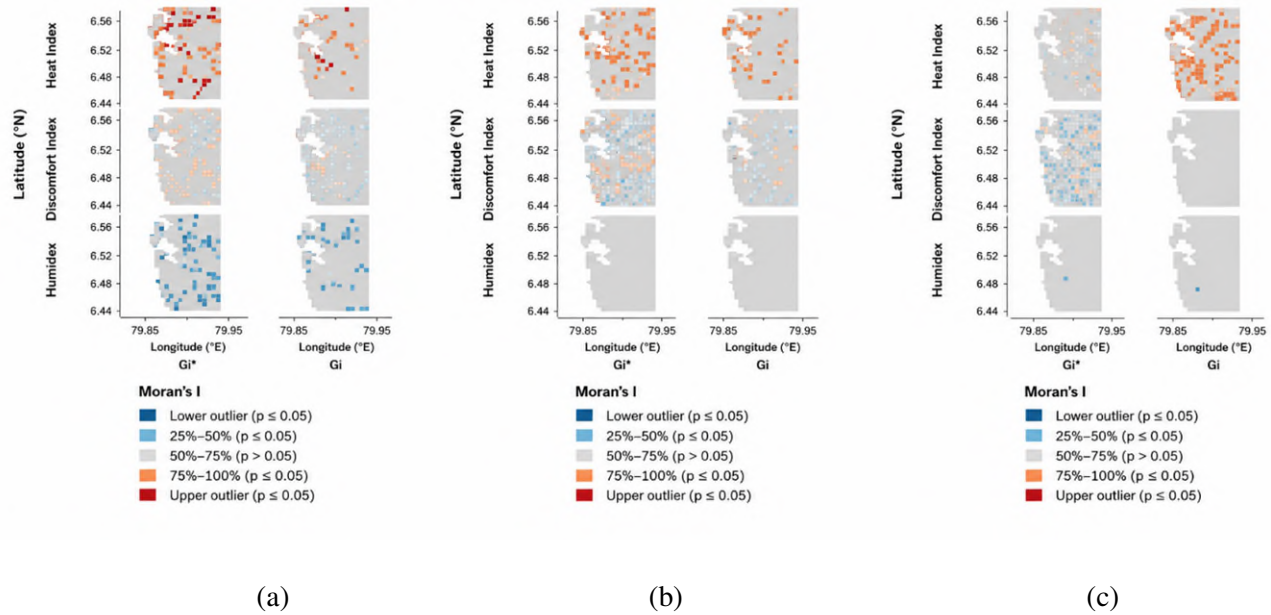


Fig. 7 Conditional spatial relationships between LST and urbanization indicators: (a) LST vs. NDWI, (b) LST vs. NDBI, and (c) LST vs. BUI

4.5 Summary of Key Results

Table 2 shows the main thermal, urbanization, and spatial autocorrelation results. The results collectively indicate that Colombo’s urban heat stress pattern is shaped by the interaction of built-up intensity, anthropogenic heat emissions, and the distribution of cooling surfaces such as waterbodies and wetlands.

Table 2. summary of the results

Indicator	Results	Spatial interpretation
HI	30.5–31.8 °C	Higher values concentrated within densely urbanized commercial and residential zones, indicating elevated apparent thermal stress.
HD	36.9–38.2 °C	High humidity-adjusted thermal discomfort was observed in compact urban areas with limited cooling influence.
DI	26.0–26.7 °C	Elevated discomfort values were spatially aligned with central and southern built-up zones.

LST	27–37 °C	Highest LST values were concentrated in dense commercial, industrial and infrastructure-dominated areas.
NDBI	Higher values observed in dense built-up zones	NDBI represented impervious surface concentration and was used as a continuous built-up intensity indicator.
NDWI	Higher values around wetlands, canals and waterbody zones	Water-associated areas corresponded with lower thermal intensity, indicating a cooling effect.
BUI	Moderate: 1.5–1.7; High: >1.7	Radar-derived built-up structural intensity showed higher values in compact commercial, industrial, and infrastructure-dominated areas.
Moran's I: HI	0.511	Positive spatial autocorrelation confirmed clustering of HI values.
Moran's I: HD	0.778	Strong clustering indicated spatial concentration of humidity-adjusted heat stress.
Moran's I: DI	0.488	Positive clustering showed non-random distribution of discomfort conditions.
Moran's I: QF	0.766	Anthropogenic heat flux showed strong spatial clustering in urban activity zones.
Bivariate Moran's I: HI–QF	0.489	Moderate positive spatial association indicated that QF contributes to apparent heat stress.
Bivariate Moran's I: HD–QF	0.309	Positive but weaker association suggested partial influence of QF on humidity-related discomfort.
Bivariate Moran's I: DI–QF	0.473	Moderate positive association showed co-location of anthropogenic heat and discomfort.
Bivariate Moran's I: LST–BUI	0.058	Weak positive relationship suggested localized influence of structural built-up intensity on LST.
Bivariate Moran's I: LST–NDWI	-0.153	Negative relationship indicated the cooling influence of waterbody and moisture-rich areas.

According to the summary findings, dense urban development was spatially correlated with HI, HD, DI, LST, and QF. Humidity-adjusted heat discomfort and human-generated heat emissions are concentrated in the urban core of Colombo, as evidenced by the strongest clustering seen for HD and QF. The significance of preserving and improving water-associated landscapes as part of urban heat mitigation techniques is shown by the negative LST-NDWI association. .

4.6 Consistency Assessment of Heat Stress Indicators

The comparison of heat stress indicators produced from Zenodo and ERA5-Land is shown in Table 3. HD had relatively poorer agreement ($r = 0.890$), whereas DI had the strongest correspondence ($r = 0.963$), followed by HI ($r = 0.950$). Overall, the findings show that the heat stress indicators' spatial

patterns are generally compatible with estimates from the independently obtained ERA5-Land reanalysis. .

Table 3. Agreement statistics between ERA5-Land-derived and Zenodo-derived heat stress indicators

Indicator	RMSE (°C)	MAE (°C)	Bias (°C)	r
HI	1.389	1.139		0.950
HD	1.495	1.234	-1.234	0.890
DI	0.783	0.624	-0.179	0.963

5. Discussion

The Zenodo-derived heat stress indicators demonstrated moderate to strong correlation with independently produced ERA5-Land values, according to the consistency assessment. While HD exhibited relatively little correspondence, HI and DI showed especially significant agreement. The spatial distribution of thermal discomfort and the observed hotspots of thermal sensitivity across Colombo are further supported by these findings. The findings also show that the distribution of blue infrastructure, anthropogenic heat emissions, and the degree of urbanization all have a significant impact on urban heat stress in Colombo. The concentration of elevated HI, HD, DI, and Land Surface Temperature (LST) values in commercial, industrial, and transportation-intensive districts suggests that human activity, infrastructure concentration, urban morphology, and climatic conditions all influence thermal vulnerability. The positive spatial correlations between QF and HI, HD, and DI, as well as the notable clustering of anthropogenic heat flux (QF) and thermal discomfort indicators, demonstrate how transportation, industrial activity, and energy consumption contribute to urban thermal intensification. The impact of urban structure on heat accumulation is further supported by the correlations between urbanization indicators and thermal conditions. Elevated LST was correlated with higher Normalized Difference Built-up Index (NDBI) and Built-up Index (BUI) values, whereas the cooling effect of wetlands, canals, rivers, and other water-associated landscapes was shown by the negative correlation between LST and Normalized Difference Water Index (NDWI). These results highlight how crucial it is to protect Colombo's blue infrastructure and incorporate blue-green networks into upcoming urban development plans. Planning-wise, the identified thermal hotspots are priority intervention zones where improving blue-green infrastructure, protecting wetlands, expanding urban trees, preserving ventilation corridors, reducing impervious surfaces, and using climate-responsive building materials can all help to improve urban thermal comfort by lowering localized heat accumulation. A workable and transferable strategy for assisting climate-sensitive urban planning and climate resilience initiatives in quickly urbanizing tropical cities is demonstrated by the integration of MODIS, Sentinel-2, ALOS PALSAR, anthropogenic heat flux, and heat stress indicators within a single spatial framework.

5.1 Limitations and Future Research

This study uses an integrated framework that integrates thermal, urbanization, anthropogenic heat, and heat stress indices to produce a regional assessment of urban heat stress during the March 2020 heatwave. With a focus on a particular heatwave event, the study was carried out at a 500 m spatial resolution, offering insights into the spatial features of thermal susceptibility under extreme circumstances. In order to better understand urban heat dynamics, future research could expand this paradigm by adding multi-season observations, higher-resolution thermal datasets, field-based microclimate measurements, and socioeconomic sensitivity indicators. The assessment of focused heat

mitigation techniques and climate-resilient urban development initiatives will benefit from further integration of human activity data and scenario-based planning methodologies.

6. Conclusion

In tropical cities where anthropogenic heat emissions, impermeable surface development, and compact urban growth exacerbate thermal discomfort, urban heat stress in Colombo constitutes a growing climate resilience problem. By combining MODIS LST, Sentinel-2-derived NDBI and NDWI, ALOS PALSAR-derived BUI, QF, and heat stress indices, such as HI, HD, and DI, within a 500 m grid framework, this study evaluated urban heat stress during the March 23–28, 2020 heatwave. The results show that urban heat stress in Colombo is spatially uneven, with commercial, industrial, transportation-intensive, and compact built-up regions having the largest thermal load. While HI, HD, and DI consistently identified central and southern Colombo as hotspots for thermal discomfort, LST ranged from 27°C to 37°C. These findings imply that localized thermal intensification is influenced by heat emissions produced by humans. On the other hand, the negative correlation between LST and NDWI validates the cooling function of water-associated landscapes, wetlands, and canals. In order to identify urban thermal susceptibility zones, the study shows the significance of combining multi-source remote sensing, anthropogenic heat flux, heat stress indicators, and spatial autocorrelation approaches. From a planning standpoint, the findings show that in thermally vulnerable neighborhoods, wetland preservation, blue-green corridors, urban tree growth, reflective materials, ventilation channels, and heat-sensitive zoning should be given top priority. The framework offers a transferable method for assisting climate-sensitive urban design and heat mitigation in quickly urbanizing tropical cities, despite the study's limitations because of its single-event emphasis, coarse thermal resolution, modeled QF data, and scant field-based validation.

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Statements and Declarations

Consent to Participate: Not applicable.

Ethics Declaration: Not applicable. This study did not involve human participants, animals, or protected biological materials and therefore did not require ethical approval.

Author Contribution declaration: H.S.R. Hettikankanama was responsible for the conceptualization, methodology development, investigation, formal analysis, data curation, software implementation, validation, visualization, and writing of the original draft. S.M. Dassanayake contributed to the conceptualization, methodology development, formal analysis, supervision, project administration, funding acquisition, validation, resources, and review and editing of the manuscript. I. Mahakalanda contributed to the conceptualization, methodology development, investigation, supervision, resources, and review and editing of the manuscript. T.S. De Silva contributed to the conceptualization, methodology development, supervision, and review and editing of the manuscript.

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Data Availability Statement: The datasets used in this study are publicly available from MODIS, Sentinel-2, ALOS PALSAR, OpenStreetMap, the Zenodo Heat Stress and Anthropogenic Heat Flux datasets, and the Copernicus Climate Data Store (ERA5-Land). The processed datasets and derived outputs supporting the findings of this study are available from the corresponding author upon reasonable request.

Competing Interests: The authors declare that they have no known competing financial or non-financial interests that could have appeared to influence the work reported in this paper.