Excel International Journal of Technology, Engineering and Management
2026; Volume -13, Issue-2_Page_16-19

Excel International Journal of
Technology, Engineering & Management
Journal homepage: exceljournals.org.in
ISSN ONLINE: https://portal.issn.org/resource/ISSN/2349-8455
ISSN PRINT: https://portal.issn.org/resource/ISSN/2348-0378

A Technology-Driven Urban Heat Risk Assessment Framework for Sustainable Cities in India

Dr. R. Saradha,
Assistant Professor,
Department of Computer Science with Data Science
Saadhana G L[1], Divyadharshini J[2], Abirami V[3]
Shrimathi Devkunvar Nanalal Bhatt Vaishnav College for Women (Autonomous)
Chennai, Tamil Nadu, India
E-mail: drsaradhaganesh@gmail.com

Published online: April 2026
DOI Link: https://doi.org/10.64971/j.cph.eijtem.v13.i2.3.2026

Abstract
Indian cities are experiencing warmer conditions. Climate change and rapid urban expansion have made heat waves more common and perilous, threatening millions. We developed a new framework of urban heat risk for the selected big cities in India using weather, satellite land surface temperature (LST) and population. We obtained data from the India Meteorological Department (IMD), ERA5 reanalysis, and Meteostat. The data were cleaned and processed for analysis. Next, we constructed a Heat Risk Index and assigns certain relative weights to these factors (HRI) that takes into account air temperature, humidity, heat index, LST and number of people who are exposed. We categorized city areas to low, moderate and high risk zones using cut-off values. When we ran the model against historical heatwave data, it aligned nicely with known hotspots. The findings show wide disparities in heat risk among neighborhoods. This framework is not just for research, it can support real-time monitoring, early warnings and smarter city planning to help cities tackle rising heat.

Keywords: Urban heat, heat risk, land surface temperature, population exposure, heatwave monitoring, sustainable cities.

1.Introduction

The phenomena of rising temperatures in Indian urban areas has been increasingly observed and there's no mystery why. The relentless spread of cities, the degradation of green space and a changing climate are building one upon another to make heatwaves bigger, more frequent and able to push higher temperatures. The public health and economic damage is real. Yes, there are some Heat Action Plans for cities out there, but to be honest most do not have a good way of tracking real-time heat risk at the neighborhood level. And heat risk is not just about temperature — exposure and social vulnerability matter, too(Xu et al., 2025; Yao et al., 2024) yield the kinetics of dark matter co-spectrum transfer too. In this work, we introduce a new Urban Heat Risk Assessment Framework that combines together IMD weather data, ERA5 reanalysis, MODIS Land Surface Temperature and socio demographic statistics to provide a single combined weighted heat risk index. What distinguishes this approach is the careful integration of contributions of vulnerability and environmental factors. The result? Cities get heat mapped, neighborhood by neighborhood risk, making it easier to monitor hot spots and make smarter decisions.

2. Literature Review

2.1 Urban Heat Risk Modeling and Micro-Scale Assessment

Climate risk, under the IPCC's 2022 framework, derives from the interaction between hazard, exposure and vulnerability. In cities, heat risk is not only a function of the heat itself but also that of urban pattern, land cover and socio-economic variables. Historical research, in many cases using city-wide averages that blurred local differences, Repeatable microclimate and pedestrian model for use in charrette-style participatory decision-making in the early stripping operation equipment Zhang et al. (2024). Mirzaei said in 2015 that urban heat assessment is still a problem because of scale inconsistencies and fragmented datasets. This indicates that these discrepancies and scattered urban heat datasets are making it difficult for consumers to gain a picture of urban heat. The urban heat assessment is limited by these scale inconsistencies and fragmented datasets.

2.2 Heat Vulnerability and Socio-Environmental Integration

Hazard, exposure and vulnerability altogether constitute the risk. Wu et al. (2022) proposed a framework integrated in the modeling socioeconomic exposure, demographic sensitivity and adaptive capacity to predict inequality vulnerabilities. In India, Dasgupta et al. (2025) mentioned the governance gaps in the Heat Action Plans and Sharma and Kumar (2024) linked the increase exposure due to rapid urbanisation and reduced green cover.

2.3 Climate Reanalysis and Remote Sensing in Urban Heat Assessment

Urban heat is more and more readily monitored thanks to remote sensing and climate reanalysis. Weng (2004) improved DLSI calculation by using the land surface instead of air temperatures, and Peng et al. (2019) enhanced satellites for thermal mapping in hotspot detection.

2.4 Urban Heat Resilience and Transformative Paradigms

Resilience building will require the integration of vulnerability assessment into planning and policy (Chen et al., 2025).

2.5 Synthesis and Research Gap:

While advances have been made in urban heat modeling, vulnerability mapping and monitoring from satellites, they tend to work independently. A majority of Indian cities are yet to move from hand-waving heat advisories to a neighborhood level data driven assessment. This integrated use of meteorological, remote sensing and socio-demographic data in a common hazard-exposure-vulnerability framework is scarce. Furthermore, such research is hardly ever translated into easily applicable decision support tools for those planning for the future. This is the gap that calls for a scalable, composite heat risk model backed by an interactive dashboard for localized monitoring and policy action.

3. Methodology

This study employs a practical, quantitative methodology to analyzing urban heat risk. Basically, we pulled together meteorological data, satellite imagery, and socio-demographic numbers to construct a unified, integrated Urban Heat Risk Index. The process is conducted in four primary stages: gathering data, cleaning it up and building out features, creating the composite heat risk model, and then assessing its efficiency. We created this technique so that anyone in any Indian city may apply it. Figure 1 depicts the entire methodological workflow.

3.1 Data Acquisition:

3.1.1 Meteorological Data: We begin with daily weather data from the Indian Meteorological Department (IMD), such as the highest temperature, humidity, and rainfall. To fill in the gaps and maintain things consistent over time, we also used ERA5 global reanalysis data, which provides hourly weather data that lines up across the map.

3.1.2 Satellite Data: For land surface temperature (LST), we got data from both MODIS and Sentinel satellites. NDVI (which tells about how green an area is) comes from standard satellite band calculations. To determine the Urban Heat Island (UHI) effect, we simply subtracted air temperature from LST:

$$\mathbf{UHI = LST - Air\ Temperature}$$

All the satellite data was collected right to the city boundaries to maintain alignment.

3.1.3 Socio-Demographic and Land Use Data: Census of India and OpenStreetMap provides the land use data, population density and percentage of people living in slums. We made sure these figures matched the same city limits and time periods as the environmental data.

3.2 Data Preprocessing and Feature Engineering: Aligning Everything: Using city boundary shapefiles and GIS (GeoPandas), we joined all the data spatially. For time, we matched everything up day by day with pandas, so each dataset lined up perfectly.

3.3 Cleaning and Quality Control: We employed the modified Z-Score to detect outliers. We threw them out if they appeared wacky or very far outside normal ranges. For these small gaps (amounting to less than 5% missing data) we used linear interpolation. If more than was missing, we excluded the dataset to ensure integrity of the analysis.

3.3.1 Normalization: We normalized all continuous variables(min-max normalization) in the range of 0 to 1 so that it makes things comparable:

$$\mathbf{X\_norm = (X - X\_min) / (X\_max - X\_min)}$$

We normalized the following primary variables:
- Air temperature
- Relative humidity

- Land surface temperature
- NDVI
- Population density
- UHI intensity

3.4 Computing Heat Index: To calculate how hot it really feels, we used the NOAA Heat Index formula, which combines air temperature and humidity to estimate human thermal stress.

3.4.1 Constructing the Composite HRI: We integrated several factors (physical and social impediments) into a single HRI. We weighted them by:

-Heat Index: 30%
-Land Surface Temperature: 25%
-Population Density: 20%
-Slum Percentage: 10%
-Vegetation Lack (1 – NDVI): 10 %
-UHI Intensity: 5%

The formula looks like this

$$HRI = 0.30(HI) + 0.25(LST) + 0.20(PD) + 0.10(SP) + 0.10(1 - NDVI) + 0.05(UHI)$$

Where HI = Heat Index, PD = Population Density, and SP = Slum Percentage.

3.4.2 Risk Classification: We split the HRI scores into three risk levels—low, medium, and high. The cutoffs came from quantile-based binning, which basically means each group covers about a third of the city, making it easier to visualize and plan.

3.5 Validation Protocol

3.5.1 Temporal Validation: To find a strong connection between high-risk areas and actual impacts, we compared the HRI with historical heatwave deaths and official heatwave data.

3.5.2 Spatial Validation: We compared the modeled UHI and high-risk zones with real temperature readings from the ground. We used Spearman's rank correlation to see how well my model picked out actual heat hotspots.

3.5.3 Sensitivity Analysis: To make sure the model's reliable, we ran a Monte Carlo simulation, tweaking the weights by ±10%. If the risk classifications stayed the same at least 80% of the time and matched up well with historical heatwave events, I considered the model robust and ready to Use.

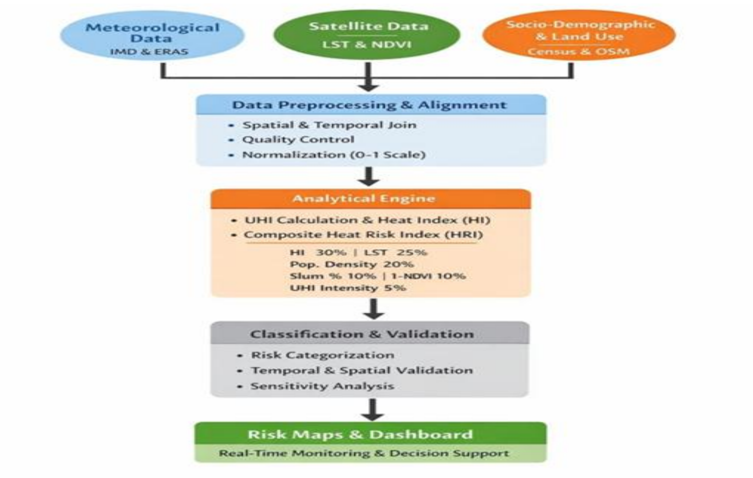

Figure 1: The HeatRisk methodology workflow is a vertical pipeline from multi-source data acquisition to interactive risk visualization outputs.

4. Results and Discussion

The Heat Risk Index really highlighted how heat risk can differ throughout a city. High-risk areas presented themselves primarily in densely populated and not-so-green neighborhoods, where the ground (typically asphalt) heats up quickly. Heat index values exceeded what's safe for people during the hottest part of summer, so they were dealing with hot air and just-as-sizzling surfaces. The data bear this out: Heat Index and land surface temperature co-varied ($\rho = 0.74$, $p < .01$), showing that the weather and the surfaces in the city both throw the risk upwards. Social factors made things worse. Neighborhoods with more people and higher slum populations bore even greater risks, while those with more plants (as measured by the health of vegetation in reflecting sunlight, or NDVI) stayed cooler. And that relationship between NDVI and temperature was a strong negative one (r = -0.68), which simply underscores how much plants do for us. When compared to real deaths from heatwaves, the model did fairly well. So, aggregating hazards and vulnerabilities really does help sharpen the picture- and gives city planners a better shot at targeting climate-resilient solutions.

5. Conclusion and Implications

This research offers a method that can be pocketed, relaunched and reapplied, presenting how exactly you might measure heat risk, mixing weather data with satellite information and social statistics into one index. The heat doesn't get distributed evenly; the densest, least green areas are hit hardest. By combining physical hazards like high heat and hot ground with social ones like crowdedness and lack of vegetation, the index presents a much more holistic view than looking at just one thing for the strong model fit achieved by this method emphasizes particular responses (more trees, cool roofs, shade structures and upgrades for slums) and lends itself to early warning and planning—it simply tells which areas need to be focused on first—i.e., it converts tons of environmental and social information into maps and intelligence that cities can use directly. It will eventually get better with real-time monitoring of the weather and more smart data on how to set weights, which means it should become even more accurate, but in my tests it worked just fine for now.

6. Limitations

Heat risk is not just about temperature but where people live, whether they are vulnerable to high temperatures and how exposed they tend to be in heatwaves (Xu et al., 2025; Yao et al., 2024). Though research papers call for alternative ways of measuring heat vulnerability, few have integrated weather, satellite and population data for Indian cities. This gap is filled in the present work by developing an Urban Heat Risk Assessment Framework and a web based dashboard to have insights of heat risk associated with all major cities of India.

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Dr. R. Saradha et.al, A Technology-Driven Urban Heat Risk Assessment Framework for Sustainable Cities in India, Excel International Journal of Technology, Engineering and Management, 2026; Volume -13, Issue-2_Page_16-19. DOI Link: https://doi.org/10.64971/j.cph.eijtem.v13.i2.3.2026