FORUM GEOGRAFI
ISSN: 0852-0682 | E-ISSN: 2460-3945

HTTPS://JOURNALS.UMS.AC.ID/INDEX.PHP/FG/

Research article

Assessing the Heat Vulnerability Index (HVI) in Klang Valley Using Principal Component Analysis (PCA) and an Equal-Weighted Approach

Normaisurah Samsuddin[1], Siti Aekbal Salleh[1,2*], Nafisah Khalid[1], Noraain Mohamed Saraf[1], Rostam Yaman[2], Lynlei Pintor[3], Girlie Rueda[3], Normalyana Samsuddin[4]

[1] Faculty of Built Environment, Universiti Teknologi MARA (UiTM), 40450 Shah Alam, Selangor, Malaysia; [2] Institute for Biodiversity and Sustainable Development (IBSD), Universiti Teknologi MARA, 40450, Shah Alam, Selangor, Malaysia; [3] Ecosystems Research and Development Bureau (ERDB), Department of Environment and Natural Resources, College, Laguna, Philippines; [4] Department of Quantity Surveying, College of Built Environment, Universiti Teknologi MARA (UiTM), 94300, Kota Samarahan, Sarawak, Malaysia.

*) Correspondence: aekbal@uitm.edu.my

Citation:
Samsuddin, N., Salleh, S. A., Khalid, N., Saraf, N. M., Yaman, R., Pintor, L., Rueda, G., & Samsuddin, N. (2025). Assessing the Heat Vulnerability Index (HVI) in Klang Valley Using Principal Component Analysis (PCA) and an Equal-Weighted Approach. Forum Geografi. 39(2), 188–208.

Article history:
Received: 14 February 2025
Revised: 16 May 2025
Accepted: 17 June 2025
Published: 29 July 2025

Abstract

Urbanization has led to more than 50% of the global population residing in urban areas, contributing to significant modifications in the urban climate that exacerbate the adverse effects of climate change, particularly on human health. This study aims to assess the Heat Vulnerability Index (HVI) in the Klang Valley, Malaysia, using Principal Component Analysis (PCA) and Equal-Weighted Index (EWI). It further compares both methods to determine which more effectively reflects the region's environmental and socio-economic context. Focusing on land surface temperature as an exposure, other sensitivity and adaptive variables were triangulated where the heat vulnerability index is developed. The findings show the Klang valley's regions are of varying degrees of vulnerability to heat stress, with the most affected cities being Kuala Lumpur and Petaling due to exposure-sensitivity and adaptive capacity factors. As can be seen, HVI-PCA covers 7.06% for Very Low, 12.87% for Low, 54.82% for Moderate, 14.99% for High, and 10.26% for Very High vulnerabilities, while HVI-EWI represents Very Low at 6.62%, Low at 51.29%, Moderate at 26.86%, High at 15.22% and Very High at 0.02%. These differences underscore the importance of methodological choice, where PCA supports empirical robustness based on data-driven methods. At the same time, EWI is suitable when expert consensus is lacking or when simplicity and broad stakeholder buy-in are needed. Recommendations include maximizing indicator representativeness for accurate assessments and resilient urban planning against heat-related stressors. The study could serve as a baseline HVI of the study area, enabling the development of pre-emptive techniques to mitigate extreme heat conditions.

Keywords: Heat Vulnerability Index (HVI); Principal Component Analysis (PCA); Equal-Weighted Index (EWI).

1. Introduction

Urbanization and climate change are closely intertwined in a complex relationship that affects both environmental and human systems. Urbanization, the increase in the proportion of people in a country living in urban areas, has significant impacts on climate change through increased energy use, gas emissions, and resource utilization. The result is environmentally destructive activities such as air pollution, water pollution, deforestation, and the destruction of habitats. Climate change, particularly global warming, can promote urbanization by increasing temperatures and exacerbating extreme weather events, such as heat waves and floods, which impact agricultural productivity and drive rural-to-urban migration (Helbling & Meierrieks, 2023; Salleh *et al.*, 2013). The ecological impacts of urbanization extend beyond city borders, including deforestation, habitat loss, and changes to freshwater ecosystems, which collectively contribute to disruptions in biodiversity and ecological balances (Piczak *et al.*, 2023).

The negative consequences of urbanization also extend to human health since the Urban Heat Island (UHI) phenomenon is a significant concern. Urbanization and climate change are intensifying the UHI effect, exacerbating the risks of heat-related morbidity and mortality in densely populated regions. The Klang Valley, as Malaysia's most urbanized region, is particularly susceptible to these impacts due to its rapid development, high population density, and environmental changes. The UHI phenomenon amplifies ambient temperatures, especially during heatwaves, posing significant health threats to vulnerable populations. UHI arises due to the concentration of built environments and human activities, leading to higher temperatures in urban regions when compared with adjacent rural zones (Isa *et al.*, 2017).

Urban areas are important zones of vulnerability to heat caused by climate change, which mainly affects vulnerable populations with economic and health inequalities. Heat vulnerability is determined by three interrelated components: exposure, sensitivity, and adaptive capacity. Exposure refers to the extent to which populations are subjected to extreme heat. Sensitivity encompasses the physiological and social characteristics that increase susceptibility, such as age, income, and pre-existing health conditions. Adaptive capacity denotes the ability of individuals and communities to cope with and recover from heat-related stress. The Heat Vulnerability Index (HVI) is one of the advanced methods used in the measurement of exposure characteristics to heat, for which the analysis takes into consideration several socio-economic, demographic, and infrastructural factors (U.S. Environmental Protection Agency (EPA) and Centers for Disease Control and Prevention (CDC), 2016). The wide application of HVI is attributable to its ability to gauge the risk of heat stress, detect people at different levels of risk, and provide information on adaptive capacity, which is key in resource allocation and developing intervention strategies aimed at reducing the respective vulnerabilities (Paterson & Godsmark, 2020; Cheng *et al.*, 2021).

Building up the HVI entails considerable review of area and population particularities, which are judged through socioeconomic status (SES), health status, and environment. Population metrics require age, poverty, education, housing, urban features, weather, and health care. These characteristics also form the so-called landscape of vulnerability, and they define how different populations cope and adapt to heat stress and its consequences (Soomar & Soomar, 2023; Cheng *et al.*, 2021).

Regarding heat impact vulnerability, trends occur around the built environment and cities and their geographical locations. For example, in urban situations, one important variable for assessment is Land Surface Temperature (LST), as it can help locate areas such as green space or housing conditions that are likely to be at risk (Zha *et al.*, 2024; Liu *et al.*, 2020). These criteria provide a broad understanding of heat vulnerability situations, which can help develop effective adaptation approaches. Managing HVI is of utmost importance, especially in fast-developing urban areas like Klang Valley, where there may be the risk of excessive heat, especially during hot periods. As cities grow and the effects of climate change persist, it is crucial to have an appropriate scoring system for heat vulnerability so that resilience strategies for low-income communities can be developed. In order to help in this function, HVI is used as a pointer to assist resource allocation efficiently and interventions targeted at exposed population subgroups by policymakers, city planners, and public health officials (Nayak *et al.*, 2018). HVI can therefore be used to identify areas most vulnerable to heat stress, thereby prioritizing areas for intervention to enhance resilience to heat stress and its related health impacts.

Ramli & Alias (2023) present a new method for evaluating vulnerability in several dimensions by combining Catastrophe Theory with Geographic Information Systems (GIS), and make a substantial contribution to the field of disaster risk management by offering an innovative methodology for assessing vulnerability. Advancements in geospatial technologies, such as remote sensing and GIS, have revolutionized the study of urban heat vulnerability. High-resolution satellite imagery, like that from Landsat and Sentinel, provides detailed information on land surface temperature, vegetation cover, and urban morphology (li *et al.*, 2024). This data, coupled with GIS tools, allows for the creation of detailed maps and spatial analysis of heat-related factors. Furthermore, advanced mesoscale meteorological models, such as the Weather Research and Forecasting model, enable researchers to simulate atmospheric conditions and predict the impact of heat waves on urban areas. These simulations can be combined with geospatial data to assess heat vulnerability at a fine scale and inform mitigation strategies (Salleh *et al.*, 2015; Salleh *et al.*, 2023). These technological advancements have significantly improved our ability to understand and address the complex challenges of urban heat.

Many studies of HVI have attempted to address the heat vulnerability factors in an integrated manner. Here, a range of approaches have been used: from Equal-Weights Index (EWI) to more advanced Principal Component Analysis (PCA) and many others (Tomlinson *et al.*, 2011; Cresswell, 2023). Usually, EWI is selected because of its simplicity, where all indicators are given equal weight. However, this method may overlook the importance of certain aspects in determining vulnerability, resulting in less detailed evaluations. Conversely, PCA is now a well-known approach capable of handling large datasets and also pinpointing major indicators by reducing dimensionality that contribute most to vulnerability (Cheng *et al.*, 2021). Moreover, local studies investigating heat vulnerability in built-up areas such as the Klang Valley have also explored various methods to improve HVI measurement accuracy. For example, specific weights are assigned to each indicator by PCA since it addresses broader aims of comprehensive assessments of vulnerability (Isa *et al.*, 2018; Latif *et al.*, 2023; Kayal & Chowdhury, 2025a; 2025b). In addition, the current research has used PCA for developing a more refined and context-based HVI for Klang Valley, which justifies its preference over simpler techniques such as EWI. Hence, this study aims to develop a heat vulnerability index for the Klang Valley using both Equal-Weighted Index (EWI) and Principal Component Analysis (PCA) methods, in order to spatially identify areas and populations most at risk from extreme heat events.

2. Research Methods

2.1. Study Area

Klang Valley, also known as Greater Kuala Lumpur, covers approximately 2,832 square kilometers, as shown in Figure 1. It is situated in the central part of West Coast Peninsular Malaysia and includes major areas like the Federal Territory of Kuala Lumpur, Putrajaya, Hulu Langat, Klang, and Petaling. The population of Klang Valley was estimated at 8.21 million in 2021. The population growth rate of the Klang Valley increased by approximately 2.4% from 2021 to 2023. Population density and growth are primarily concentrated within a 50 km radius of the city center, gradually extending outward into suburban regions, and the land surface temperatures have fluctuated between 22 and 32°C, with a mean annual temperature of 25.4°C. As one of the fastest urbanizing and economically developing regions in Southeast Asia, the Klang Valley serves as an ideal case study for this research, which focuses on the Heat Vulnerability Index (HVI). This city was chosen for the research because it has mixed urban morphology and urban environments. It is characterized by heterogeneous urban development, socio-economic diversity, and varying levels of infrastructure resilience. According to Lourdes *et al.* (2024), the landscape mosaic includes commercial, residential, and industrial areas, as well as green spaces such as agricultural zones, parks, forest reserves, and wetlands. The built-up area expanded from 20.58% in 2010 to 30.02% in 2020, driven by new building developments and influenced by infrastructure projects such as the Mass Rapid Transit (MRT) system (Man & Majid, 2024). The study by Wong *et al.* (2017) found that the working community in the city centre experienced the effects of UHI, including temperature rises, decreased water resources, and increased haze and air pollution.

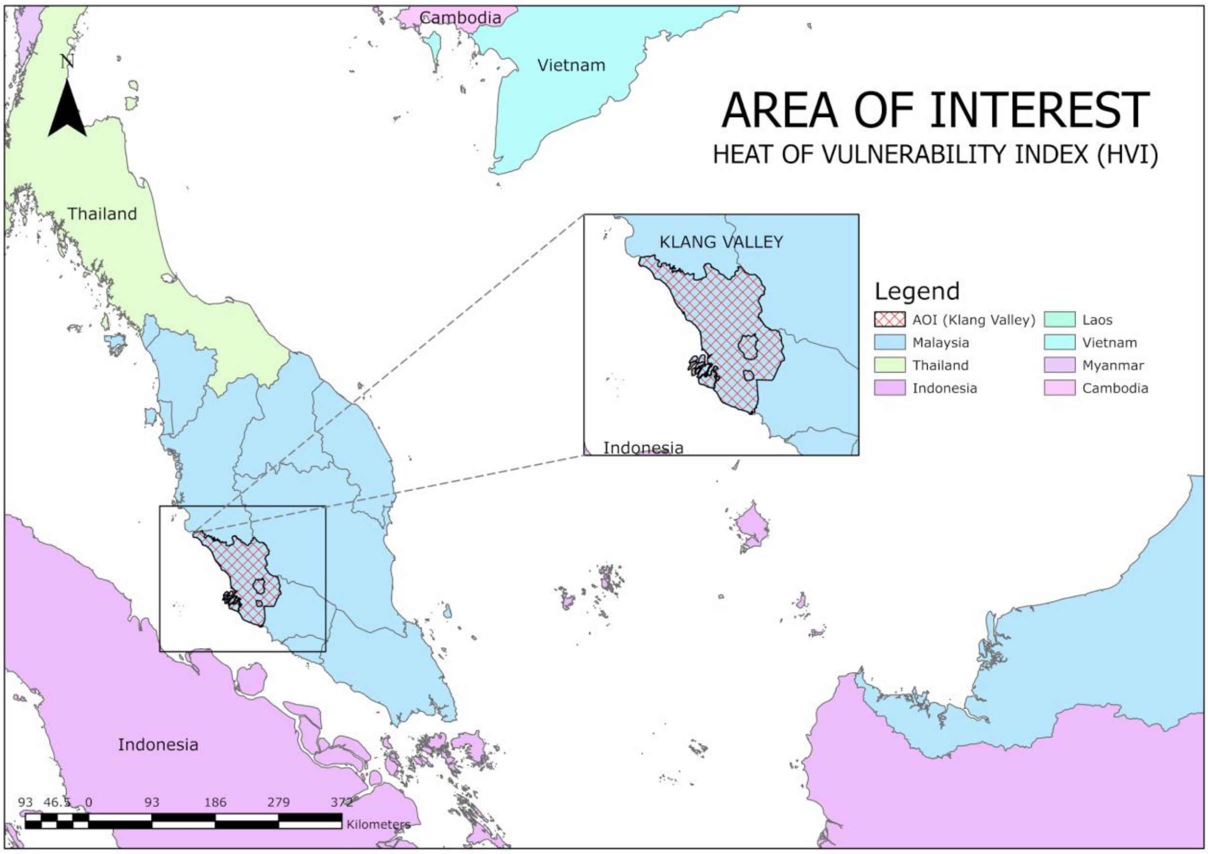

Figure 1. The Study Area.

2.2. Datasets

The study employed various datasets, which included Landsat-8 OLI/TIRS imagery, a Digital Elevation Model (DEM), statistical data, and vector data. We compiled data on demographic, socio-economic, and environmental indicators relevant to heat vulnerability. These included population density, age distribution, income levels, land surface temperature (LST), vegetation cover from the Normalized Difference Vegetation Index (NDVI), and access to healthcare facilities. From the United States Geological Survey (USGS), Landsat-8 OLI/TIRS data were obtained with important spectral bands for HVI analysis. It included bands of blue to long-wave thermal infrared, which contain information concerning land cover and land surface temperature or vegetation growth. With the assistance of the visualization software of the SNAP Desktop, a DEM of Klang Valley was also generated from Sentinel-2 images, which capture terrain elevation. The Department of Statistics Malaysia (DOSM) received extensive data on population age structure and citizenship, as these factors are necessary for estimating the HVI. Lastly, the Malaysian Public Works Department (JKR) supplied a vector map, from which the road data is extracted to indicate the road density used in Klang Valley (Table 1). The conceptual framework is structured around the triad of vulnerability components based on their relevance in the vulnerability literature (Qureshi & Rachid, 2022; Noori *et al.*, 2023; Tesfamariam *et al.*, 2024):

- Exposure: Land Surface Temperature (LST), urban land use.
- Sensitivity: Eight demographic indicators were included. These include population density, percentage of elderly population, percentage of very young population, median age, female population percentage, male population percentage, proportion of citizens, and proportion of non-citizens. These variables reflect susceptibility due to age-related health risks, social support networks, population structure, and potential barriers to accessing adaptive resources.
- Adaptive Capacity: Access to healthcare, education level, green space availability, normalized indices (e.g., Normalized Difference Vegetation Index (NDVI), Normalized Difference Water Index (NDWI), road density, slope, and land surface albedo.

Table 1. The Data Sources of the Research Study.

No	Dataset	Description
1	Landsat-8 OLI/TIRS	Remotely sensed data acquired from the Landsat satellite's Operational Land Imager (OLI) and Thermal Infrared Sensor (TIRS) Acquisition Date: August 13, 2022
2	Digital Elevation Model	Extracted from Sentinel images using the SNAP Desktop program Acquisition Date: October 29/2022
3	Statistical Data	Provided by the Department of Statistics Malaysia (DOSM) Parameters: Population Density, Population aged 65 years and over, Population aged 15 - 64 years, Population aged 0 - 14 years, Female Population, Male Population, Citizen Population, Non-Citizen Population
4	Vector Data	Road data obtained from the Malaysian Public Works Department (JKR)

3. Heat Vulnerability Index Construction

The methodology entails the use of a series of techniques that start from data processing and conclude with the determination of the Heat Vulnerability Index HVI using advanced spatial analysis and Geographic Information System GIS tools (Figure 2). This study applied two different approaches:

1. Equal-Weighted Index (EWI)

Each indicator was normalized and assigned an equal weight. This approach is simple, transparent, and commonly used when there is no clear rationale for assigning differential weights

2. Principal Component Analysis (PCA)

PCA was employed to reduce dimensionality and to identify the most significant contributors to heat vulnerability. This method is particularly useful in the Klang Valley context due to its ability to handle multicollinearity and to derive weights based on variance contribution empirically.

3. Natural Jenks Classification Techniques

The natural Jenks classification method was adopted. This technique is widely used in geospatial analyses due to its ability to minimize variance within classes and maximize variance between classes, making it ideal for highlighting natural groupings in heterogeneous datasets (Zhang *et al.*, 2022; Noori *et al.*, 2023). The Natural Jenks method is particularly appropriate for urban heat vulnerability analysis, where data distributions are often skewed or clustered.

4. Ordinal Spatial Scaling Measurement

The decision to use five ordinal categories, ranging from Very Low, Low, Moderate, High, and Very High, aligns with common practice in environmental risk assessments and facilitates comparability across different vulnerability indicators (Noori et al., 2023). This five-class provides sufficient scale to detect meaningful spatial differences while remaining intuitive for policymakers and planners. The combination of the Natural Jenks technique with a five-tier classification enables both statistical robustness and interpretability in mapping vulnerability patterns.

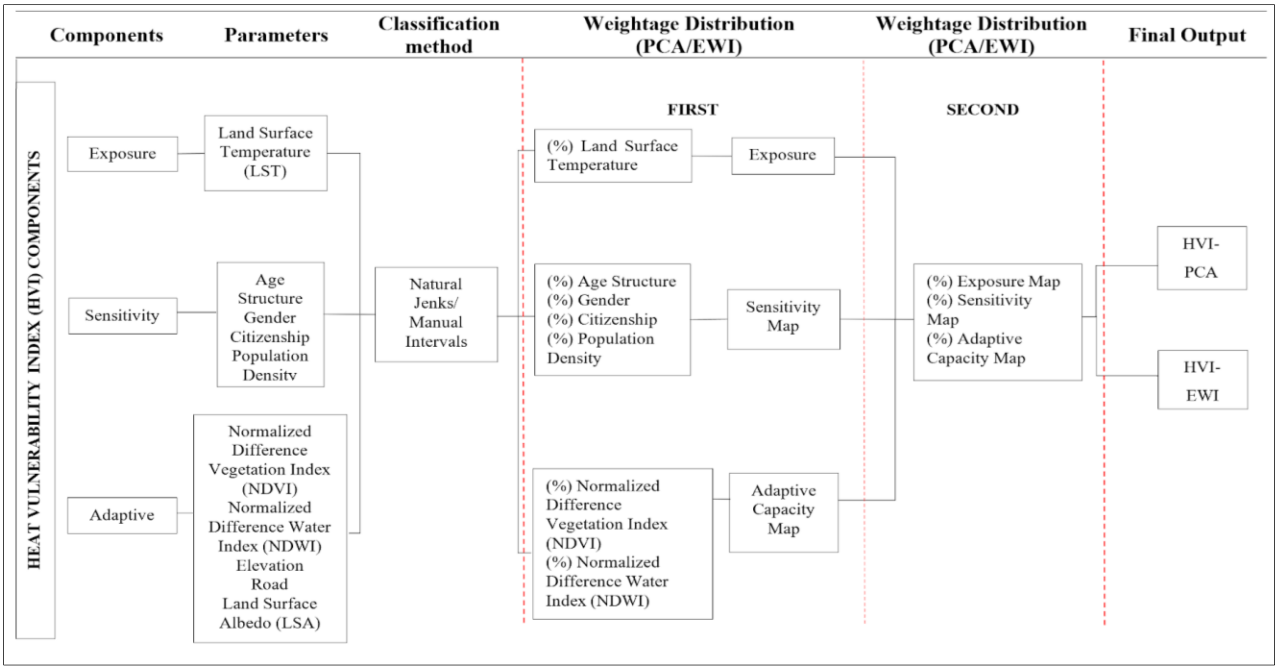

Figure 2. The Research Process of HVI.

3.1. Data Pre-processing

Prior to data processing, critical pre-processing steps were implemented to ensure that Landsat 8 OLI/TIRS and statistical data were of good quality for the research study's usage. For instance, images with less than 30% cloud cover were acquired. Then, cloud removal was performed on the Landsat data using the Sen2Cor Processor to remove atmospheric noise, enabling accurate analysis through high-quality results. On the other hand, these were submitted to a proper cleanup, thereby making them suitable for use with the ArcGIS Pro software. These steps were essential in ensuring maintenance of data quality and enhancing its utility, which made it possible to carry out meaningful analysis and interpretation of the data collected.

3.2. Exposure Variables: Land Surface Temperature (LST)

The thermal emissivity data of the remote sensing imageries is important while estimating land surface temperatures LST and assessing the regional heat environmental risks. Geographically, LST retrieval from Landsat 8 has been undertaken using a number of algorithms aimed at end users, which assist in some aspects of temperature distribution comprehension in the Klang Valley.

1. Top-of-Atmosphere (TOA)

To obtain LST, the TOA reflectance computation must be performed in particular. This procedure consists of the procedure of reflectance conversion from the raw digital numbers or radiance acquired through the space-borne sensors. This clean LST data will include algorithms that take into consideration rough estimation of spectral ratios of LST images, as well as measures of radiance for Landsat 8's band 10 (Equation 1).

$$TOA\,(L) = ML * QCAL + AL \tag{1}$$

Where TOA: Top of Atmosphere (TOA), ML: band-specific multiplicative rescaling factor from the metadata (RADIANCE_MULT_BAND_10), QCAL: thermal band (Band 10), AL: band-specific additive rescaling factor from the metadata (RADIANCE_ADD_BAND_10).

2. Normalized Difference Vegetation Index (NDVI)

The presence of vegetation can be assessed utilizing NDVI derived from the visible and near-infrared bands of Landsat, which is a significant determinant in ascertaining factors of vulnerability and sensitivity in the region (Equation 2).

$$NDVI = (NIR - RED)\,/\,(NIR + RED) \tag{2}$$

Where RED: DN values from the red band, NIR: DN values from the near-infrared band.

3. Proportion of Vegetation (PV)

The physical proportion of vegetation cover, represented as PV and valued in NDVI as previously discussed, plays a crucial role in assessing other aspects of vegetation cover in the study area (Equation 3).

$$Pv = Square\ ((NDVI - NDVIs) / (NDVIv - NDVIs)) \tag{3}$$

Where Pv: proportion of vegetation, NDVI: DN values from the NDVI image, NDVIs: minimum DN values from NDVI image, NDVIv: maximum DN values from NDVI image.

4. Land Surface Emissivity (LSE)

LSE is a proportionality factor used to scale blackbody radiance (Planck's law) to estimate the emitted radiance (Jimenez-Munoz *et al.*, 2009). LSE is the measured fraction of vegetation cover that contributes A parameter in thermal remote sensing where a value helps to form thermal attributes in Klang Valley (Equation 4).

$$\varepsilon = 0.004 * Pv + 0.986 \tag{4}$$

Where ε: LSE, Pv: proportion of vegetation.

5. Land Surface Temperature (LST)

LST may be predicted using parameters like Brightness Temperature, Emissivity, and other relevant data that yield information about the distribution of surface temperature over the Klang Valley region (Equation 5).

$$LST = (BT / 1) + W * (BT / 14380) * ln(\varepsilon) \tag{5}$$

Where LST: Land Surface Temperature, BT: top of atmosphere brightness temperature (C), W: wavelength of emitted radiance, ε: LSE.

6. Classification of the Parameter of Exposure Variables

Natural Jenks classification methods contain additional classification to classify Landsat data into LST, which allows for more information about temperature variations in the region. The classification uses the natural Jenks method, which results in five different categories, namely Very Low, Low, Moderate, High, and Very High.

3.3. Sensitivity Variable: Demographic Data

Eight parameters, which include demographic distributions and population density, are picked from census data to serve as sensitivity variables. These parameters estimate the exposure of populations to heat-related impacts. The next step in the analysis of these data, after determining sensitivity variable parameters, involves a series of steps. Eight parameters that were extracted are the population density, elderly population density, median age population density, very young population density, female population density, male population density, non-citizen population density, and citizen population density. The data are first extracted from the census database, and input as the spatial data attributes according to the districts. These data are then reclassed according to the natural jenks method. The same processes were repeated to all eight spatial layers where each representing each parameter.

3.4. Adaptive Capacity Variables: NDVI, NDWI, Road Density, Slope, and Land Surface Albedo

In the case of Klang Valley, certain parameters measuring the Adaptive Capacity of the HVI include NDVI, NDWI, Slope, Road Density, and Land Surface Albedo.

1. Normalized Difference Vegetation Index (NDVI)

NDVI is the parameter that determines the weightage of vegetation in the heat vulnerability index (HVI) based on assessing vegetative cover and its endurance against extreme temperatures. It indicates how effective the local vegetation stands and how it might provide green urban spaces that have a cooling effect. NDVI is given by Equation 2.

2. Normalized Difference Water Index (NDWI)

Heat vulnerability assessment involves using NDWI as an important parameter. It is derived from images captured by the Landsat-8 satellite to show areas at risk on the ground surface. This can be explained as high values refer to healthy water bodies and sufficient soil moisture, promoting regions' resilience against heat. At the same time, low readings may indicate areas prone to heat-induced water stress. Equation 6 then determines NDWI readings.

$$NDWI = \frac{(G - NIR)}{(G + NIR)} \tag{6}$$

Where G: DN values from the green band, NIR: DN values from the near-infrared band.

3. Road Density

Klang Valley's road density can be computed by employing the ArcGIS Pro Line Density Tool (with a search radius of 0.037 and an output cell size of 4.48). Using data sourced from Selangor Public Works Department (Jabatan Kerja Raya Selangor), these values are autogenerated based on the extent of the input features and cell size. This is often reasonable for exploratory analyses. Because Cell size (inherits from the environment settings or source layer), while Search radius (automatically calculated based on feature distribution and extent).

Such factors as accessibility and transport infrastructure in the Klang Valley will help to assess how well the region can resist or recover from long-lasting high temperatures. High Road density can facilitate quicker emergency responses and better access to cooling resources or healthcare during heat events, hence enhancing a community's capacity to adapt.

4. Slope

Evaluation of the Heat Vulnerability Index's adaptive capacity for Klang Valley makes it crucial that slope analysis is conducted over the Klang Valley region. The slope data were derived from the Shuttle Radar Topography Mission (SRTM) Digital Elevation Model (DEM) at a spatial resolution of 30 meters. To ensure consistency in vulnerability assessment, slope values were standardized and reclassified into five ordinal categories (Very Low to Very High) using the Natural Jenks classification method. To assess the capacity to withstand heat waves, it is important to know about the topography of a place.

5. Land Surface Albedo (LSA)

Albedo, which has been reported as an ignored factor in most studies on surface radiation and thermal properties, can be quantified through time-series analysis showing its periodicity or amplitude concerning land use and cover, thereby offering another perspective on climate modeling (Isa et al., 2013). Calculating surface albedo utilizes Landsat imagery converted to Top of Atmosphere (TOA) reflectance. The TOA is given by Equation 7.

$$P\lambda = Mp\,Qcal + Ap \tag{7}$$

Where Mp: Band-specific multiplicative rescaling factor from the metadata, Qcal: Quantized and calibrated standard product pixel values (DN), Ap: Band-specific additive rescaling factor from the metadata.Finally, from the computation of TOA reflectance by Smith (2010), shortwave albedo is computed using Landsat data (Equation 8).

$$Pshort = \frac{(0.356p1 + 0.130p3 + 0.373p4 + 0.085p5 + 0.072p7 - 0.0018)}{(0.356 + 0.130 + 0.373 + 0.085 + 0.072)} \tag{8}$$

Thus, Land Surface Albedo can be calculated using bands 1, 3, 4, and 7 for Landsat. It is important to include LSA because it represents the reflectivity of surfaces and directly influences the amount of solar energy absorbed by urban areas. Surfaces with higher albedo reflect more solar radiation and retain less heat, thus helping to moderate local temperatures.

6. Classification of the Parameters of the Adaptive Capacity Variables

After defining the parameters for adaptive capacity variables, these are classified according to the prevailing procedures used in previous research work. Each parameter is further divided into five classes: Very Low, Low, Moderate, High, and Very High. It is a systematic approach that assists in assessing the overall level of resilience against heat stress across a region. This systematic approach supports the evaluation of the extent of the capability of regions to withstand heat stress.

3.5. Heat Vulnerability Index (HVI): The Comparative Analysis

The material in this chapter encompasses the Heat Vulnerability Index (HVI) construction for Klang Valley in two ways, using the Principal Component Analysis (PCA) and the EqualWeighted Index (EWI).

1. Principal Component Analysis (PCA)

The first process of PCA is a two-tiered system using the "Principal Component" Tool in ArcGIS Pro to handle parameterization of each variable's parameters. It is the design of the index that makes it possible to define the importance (inter relevant) of the given criteria for solving the Heat Index. In this case, all three variables, sensitivity, exposure, and adaptive capacity, are analyzed in a sequential manner using principal component analysis. This combines all the above obtained weights into maps of exposure, sensitivity, and adaptive capacity through the 'Weighted Overlay Analysis' Tool. In the center of gravity, PCA is used in the second stage for the iterative modification of HVI, which then undergoes another stage of Weighted Overlay Analysis. This finally leads to the HVI.

2. Equal-Weighted Index (EWI)

In this method, weightage is distributed equally on all layers. This tool applies a similar percentage to each feature while operating the Weighted Overlay Analysis Tool at Tier 1, where EWI was perceived as well. From these maps, those depicting exposure, sensitivity, and adaptive capacity are generated. Though on tier 2, the weighted overlay analysis tool is again utilized to generate HVI, but this time around, weights are not distributed among the three variables in any manner.

3. Comparative Analysis

A detailed comparative analysis of both PCA and EWI has been conducted, considering various qualitative and quantitative parameters that influence the understanding of heat vulnerability about urban development of the population characteristics of Klang Valley, as well as the architectural design of the buildings in the region under study. The qualitative analysis combines the findings of the two approaches. In contrast, the quantitative analysis determines an increase in geographic spatial extent across varying degrees of vulnerability using GIS, as detailed procedures in investigating knowledge-based outcomes. The attributes, advantages, and disadvantages of all these methods were also investigated in order to find out the differences and similarities. However, quantitatively, she only compares and contrasts the numbers, and all the rest of the qualitative analysis deals with how the results are related to the information and circumstances surrounding the outcomes.

4. Results and Discussion

The PCA-derived HVI revealed distinct spatial patterns compared to the EWI-based index. PCA captured nuanced relationships among indicators and highlighted high-vulnerability zones not evident in the EWI map. The Klang Valley's urban core showed consistent high vulnerability, but PCA identified peripheral areas with latent risks due to socio-economic fragility.

4.1. Exposure Variable of the Heat Vulnerability Index of Klang Valley

In this section, the Exposure Variables of the Heat Vulnerability Index (HVI) Specific to Klang Valley are focused on. Land Surface Temperature (LST) is one of the most important exposure determinants, and its distribution over the valley is shown in Figure 3. Temperatures range from 15°C to 33.2°C, with the middle section experiencing the highest temperatures due to urbanization, while the northwest, with less urbanization, sees lower temperatures.

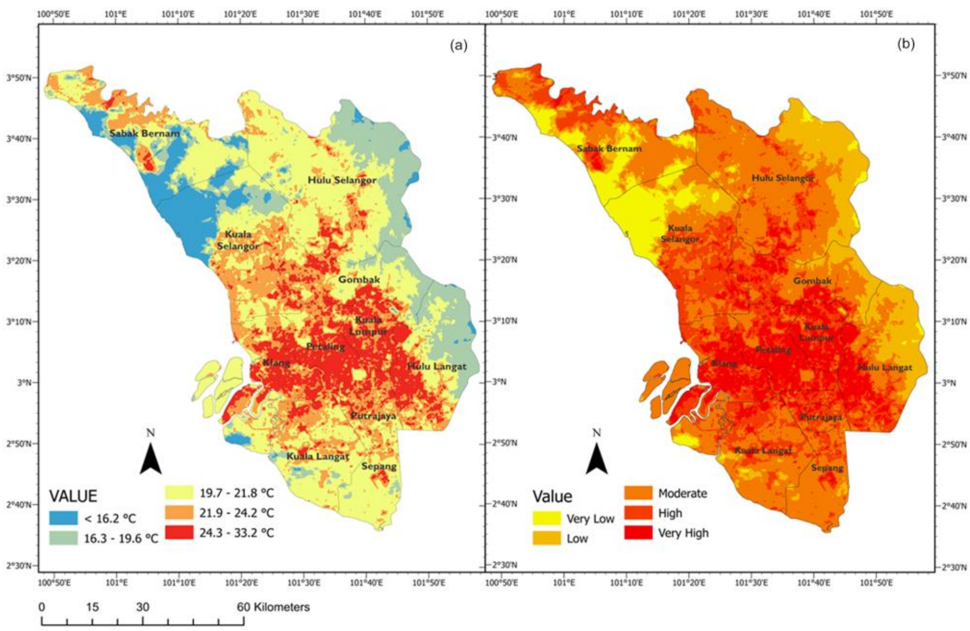

Figure 3. Exposure Variable. a) LST, b) The reclass of the LST.

Using the Natural Jenks classification technique, five groups are developed for parameters after LST calculation. It is designed to enhance both internal and external heterogeneity of data partitioning. These classes are Very Low, Low, Moderate, High, and Very High with specific temperature ranges as shown in Figure 4. This figure visualizes this classification, while Table 2 presents temperatures for each category in detail. This classification will be useful in creating an exposure map.

Table 2. The classification of the Land Surface Temperature.

No	Classification	Classification Method	Land Surface Temperature (LST)
1	Very Low		< 16.2 °C
2	Low		16.3 – 19.6 °C
3	Moderate	Natural Jenks	19.7 – 21.8 °C
4	High		21.9 – 24.2 °C
5	Very High		24.3– 33.2 °C

4.2. Sensitivity Variable of the Heat Vulnerability Index

The section begins by examining the variation in population density across various age groups, including the elderly, 15-64-year-olds, and 0-14-year-olds. Moreover, it discusses gendered population densities, revealing differences among districts. In particular, female population density mirrors overall population density patterns, whereby higher concentration rates appear in central areas. Male population density follows a similar pattern but with some variations, especially within the southern parts. Moreover, spatial distributions are explained by contrasting the densities of Malaysian citizens against those of non-citizens. For instance, non-citizen residents are mainly concentrated in central places, while Malaysian citizenry varies from one district to another. Figure 5 and Table 3 present categorization based on population density levels; thus, they are necessary for generating the Sensitivity Map of the Klang Valley, which provides an overview of demographic landscapes and socio-economic dynamics across various regions

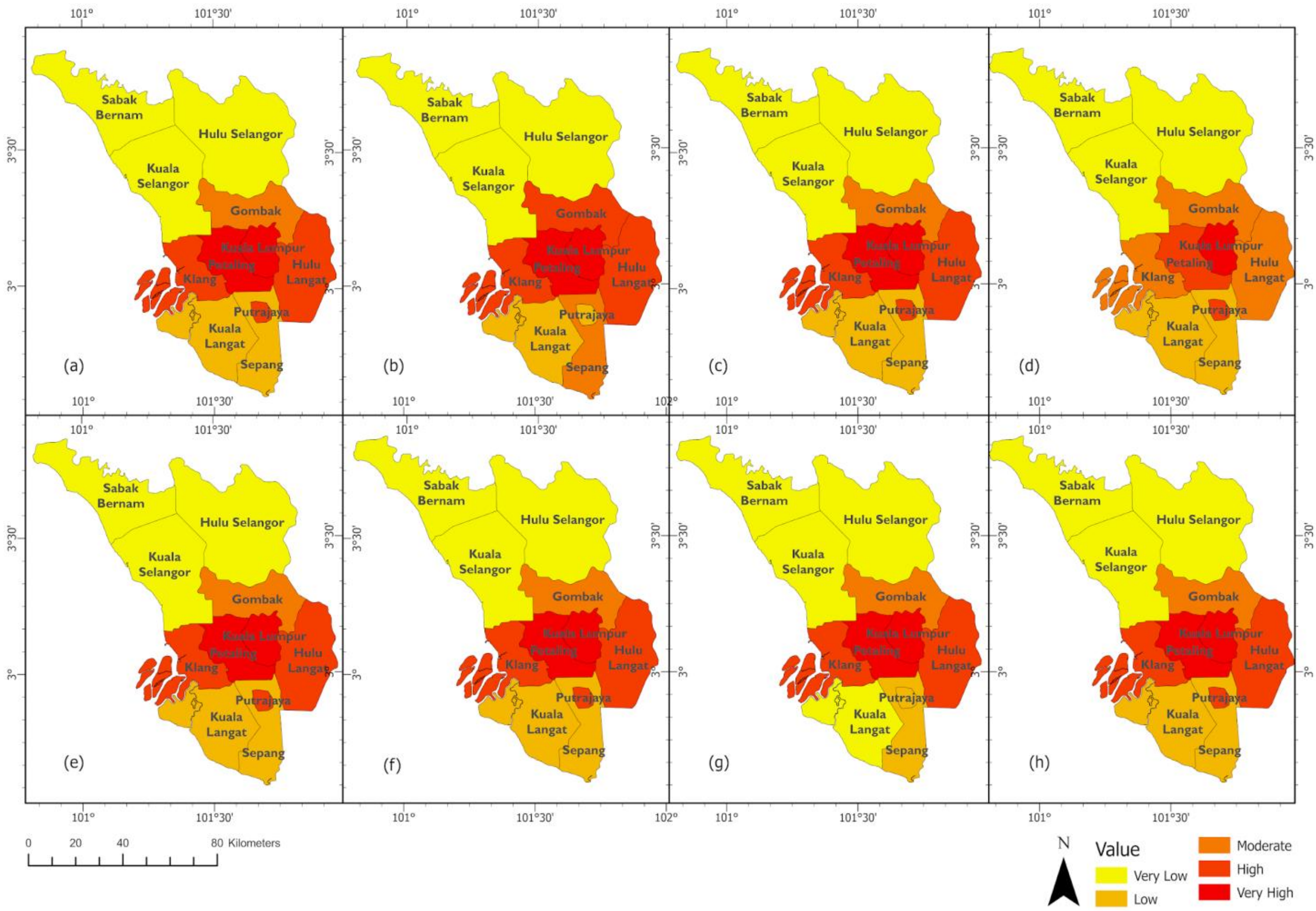

Figure 4. The Sensitivity Variables criterion maps. a) population density, b) elderly population density, c) median age population density, d) very young population density, e) female population density, f) male population density, g) non-citizen population density, and h) citizen population density.

Table 3. The Classification of the Parameters of the Sensitivity Variable.

Parameters	Classification	Classification Method	Ranges
Population Density	1 - Very Low		109 – 245
	2 - Low		246 – 600
	3 - Moderate	Natural Jenks	601 – 1448
	4 - High		1449 – 2418
	5 - Very High		2419 - 8045
Elderly Population Density	1 - Very Low		8 - 16
	2 - Low		17 - 31
	3 - Moderate	Natural Jenks	32 - 41
	4 - High		42 – 135
	5 - Very High		136 - 486
Median Age Population Density	1 - Very Low		77 - 171
	2 - Low		172 - 435
	3 - Moderate	Natural Jenks	436 - 1058
	4 - High		1059 - 1269
	5 - Very High		1270 - 5306
Very Young Population Density	1 - Very Low		28 - 58
	2 – Low		59 – 139
	3 – Moderate	Natural Jenks	140 - 363
	4 – High		364 - 1013
	5 - Very High		1014 - 1359
Female Population Density	1 - Very Low		54 - 120
	2 - Low		121 - 287
	3 - Moderate	Natural Jenks	288 - 719
	4 - High		720 - 985
	5 - Very High		986 - 3361
Male Population Density	1 - Very Low		58 - 126
	2 - Low		127 - 327
	3 - Moderate	Natural Jenks	328 - 777
	4 - High		778 - 957
	5 - Very High		958 - 3791
Citizen Population Density	1 - Very Low		107 - 234
	2 - Low		235 - 562
	3 - Moderate	Natural Jenks	563 - 1407
	4 - High		1408 - 1882
	5 - Very High		1883 - 6501
Non-Citizen Population Density	1 - Very Low		5 - 20
	2 - Low		21 - 58
	3 - Moderate	Natural Jenks	59 - 89
	4 - High		90 - 147
	5 - Very High		148 - 651

4.3. Adaptive Capacity Variable of the Heat Vulnerability Index

Slope analysis reveals differences in topography, with steeper elevations and slope angles in the northeastern part compared to other sections. It is important to understand these differences and their impact on topological factors and associated vulnerabilities. Also, local road density distribution and types of prevalence show other characteristics of the development network, highlighting greater densities within the dominant areas than in the border regions.

This is also important in the event of very high temperatures when movement and accessibility are a concern. Finally, Land Surface Albedo shows some important features of the surface that affect its ability to absorb heat. In this case, the central region has different ranges of albedo, which signifies different materials with different thermal properties, which will also alter the heat vulnerability in this region (Figure 6).

The parameters employ The Natural Jenks method over NDVI, Slope, and Road Density. Classification errors will be reduced owing to the strong classification within the example. As for NDWI and Land Surface Albedo, class intervals are applied that are constructed by the known literature how to increase their precision and relevance.

Thereby, a variety of classifications is created (Table 4), which will classify the Adaptive Capacity of Klang Valley as Very Low to Very High. Discussion of each parameter supported with visual aids promotes understanding of the region's overall adaptivity by classifying the outcomes of each parameter at a finer level, facilitating overall analysis (see Figure 6).

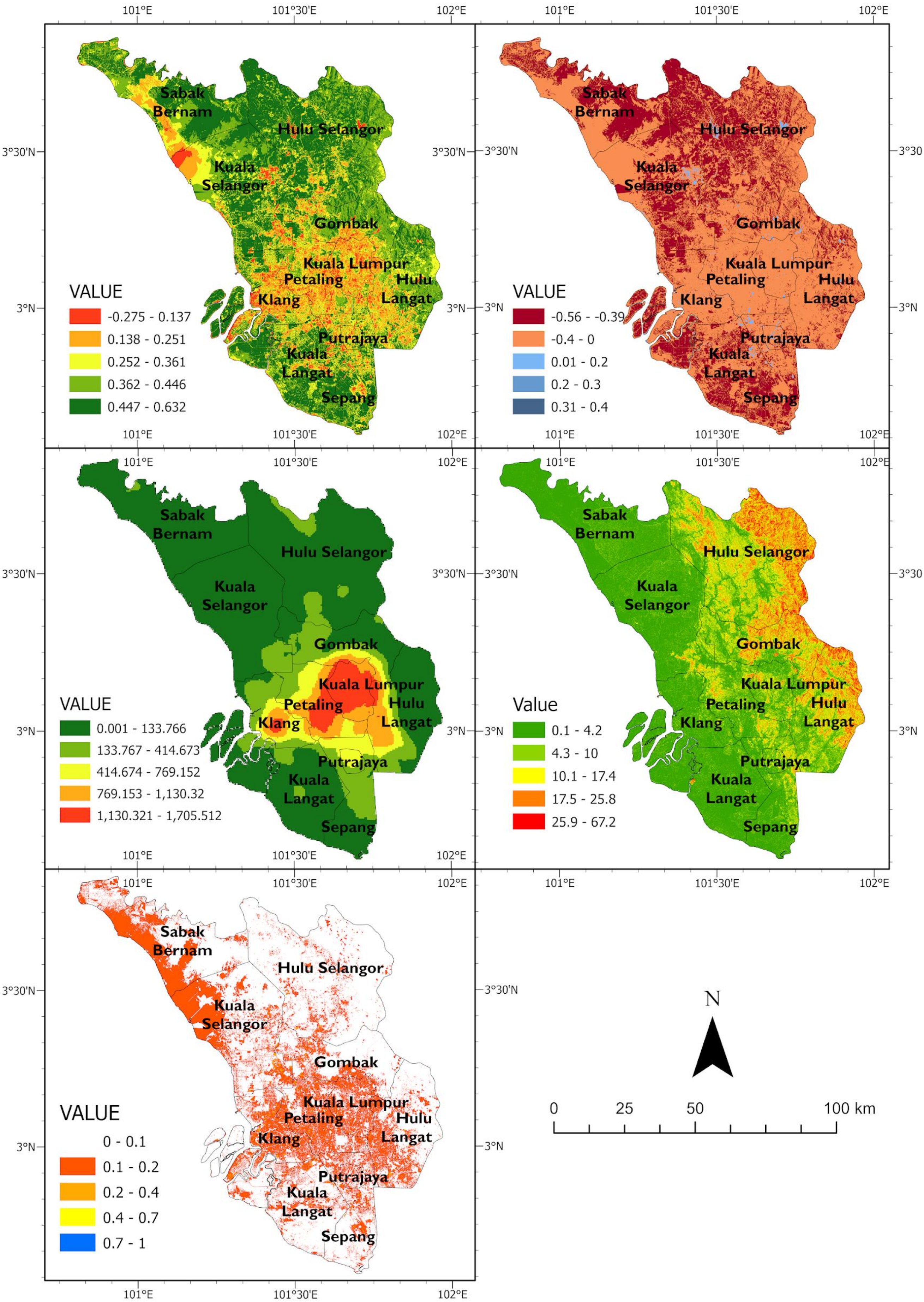

Figure 5. Variables of the Heat Vulnerability Index. a) NDVI, b) NDWI, c) road density, d) slope, and e) land surface albedo.

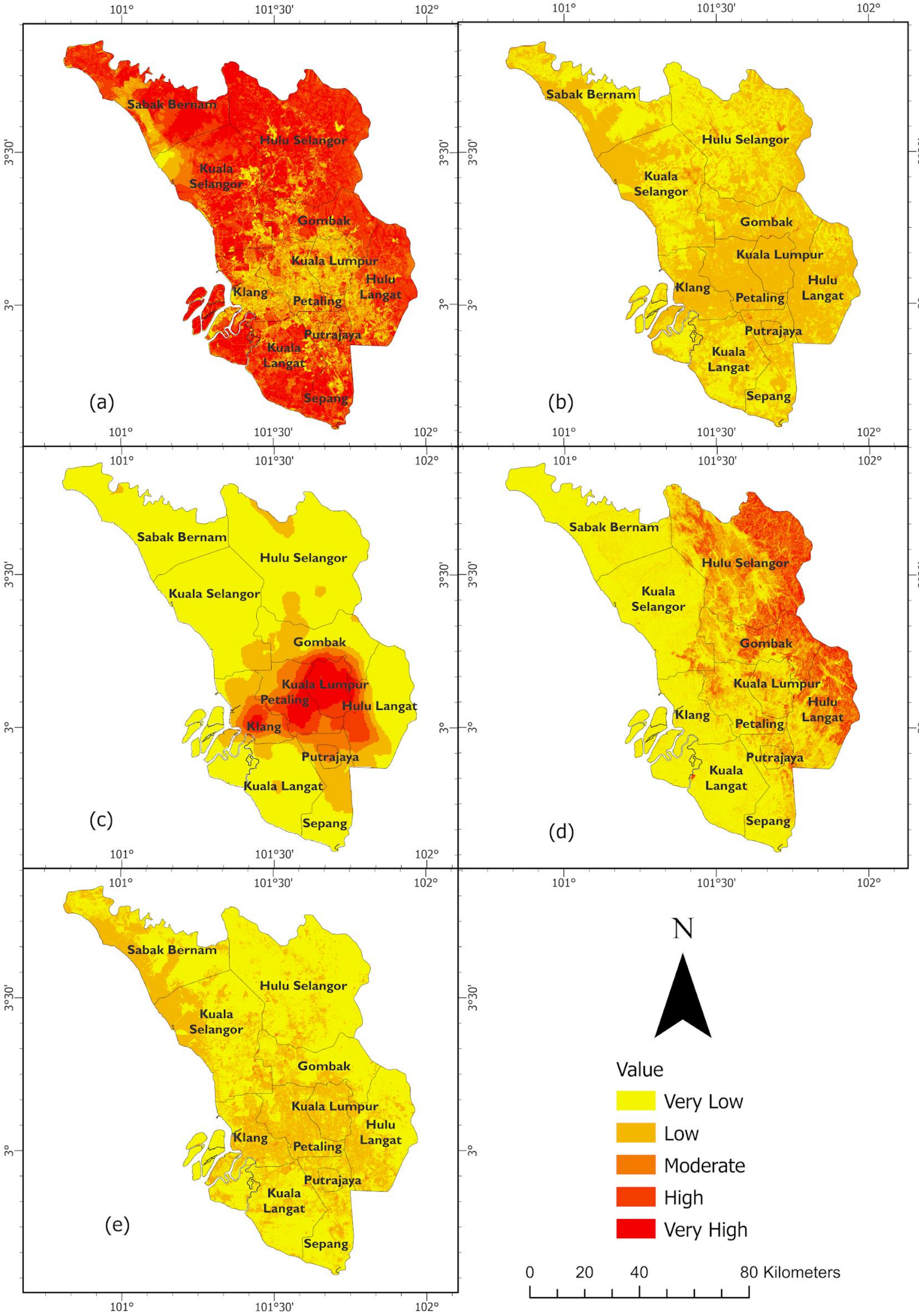

Figure 6. Classified variables of the Heat Vulnerability Index. a) NDVI, b) NDWI, c) road density, d) slope, and e) land surface albedo.

Table 4. The Classification of the Parameters of the Adaptive Capacity Variable.

Parameters	Classification	Classification Method	Ranges
Normalized Difference Vegetation Index (NDVI)	1 - Very Low	Natural Jenks	-0.26 – 0.14
	2 - Low		0.14 – 0.25
	3 - Moderate		0.25 – 0.36
	4 - High		0.36 – 0.45
	5 - Very High		0.45 – 0.63
Normalised Difference Water Index (NDWI)	1 - Very Low	Manual Interval (Szabó *et al.*, 2016)	-0.60 - -0.40 (Drought)
	2 - Low		-0.40 – 0.00 (Moderate Drought)
	3 - Moderate		0.00 – 0.20 (Water)
	4 - High		0.20 – 0.30 (Water)
	5 - Very High		0.30 – 0.40 (Water)
Slope	1 - Very Low	Natural Jenks	0.00 – 4.21
	2 - Low		4.22 – 10.01
	3 - Moderate		10.01 – 17.38
	4 - High		17.38 – 25.81
	5 - Very High		25.81 – 67.16
Road Density	1 - Very Low	Natural Jenks	0.001 – 133.766 km^2
	2 – Low		133.77 – 414.673 km^2
	3 – Moderate		414.65 – 769.15 km^2
	4 – High		769.13 – 1130.32 km^2
	5 - Very High		1130.32 – 1705.51 km^2
Land Surface Albedo	1 - Very Low	Manual Interval	0 – 0.10
	2 - Low		0.10 – 0.20
	3 - Moderate		0.20 - 0.40
	4 - High		0.40 – 0.70
	5 - Very High		0.70 – 1.00

4.4. Heat Vulnerability Index (HVI): Principal Component Analysis (PCA) and Equal-Weighted Index (EWI)

1. Principal Component Analysis (PCA): HVI-PCA

The Heat Vulnerability Index (HVI) for the Klang Valley is calculated using Principal Component Analysis (PCA). The computation has two tiers: the first-tier PCA examines exposure, sensitivity, and adaptive capacity parameters. To produce maps showing the regional exposure, sensitivity, and adaptive ability, each parameter's weightage is determined.

The weight of 100% is given to the Land Surface Temperature (LST) as the only parameter that determines exposure. Various parameters related to sensitivity, such as population density, are analyzed using PCA. Most heavily weighted among these is Population Density at 98.172% (Table 5).

Table 5. The Results of the Parameters of the Sensitivity Variables.

Parameters	Weight (%)
Population Density	98.17
Elderly Population Density	0.86
Very Young Population Density	0.76
Median Age Population Density	0.21
Female Population Density	0.00
Male Population Density	0.00
Citizen Population Density	0.00
Non-Citizen Population Density	0.00

Factors like NDVI, NDWI, Slope, Road Density, and LSA are analyzed, with NDVI having the highest weightage at 49.607% (Table 6).

Table 6. The Results of the Parameters of the Adaptive Capacity Variables.

Parameters	Weight (%)
Normalized Difference Vegetation Index (NDVI)	49.61
Normalized Difference Water Index (NDWI)	29.14
Slope	13.62
Road Density	24.75
Land Surface Albedo (LSA)	2.88

A complicated analysis shows how variables are weighted in the HVI, namely exposure, sensitivity, and adaptive capacity. Every variable carries a different percentage that reflects its importance in vulnerability (Table 7).

Table 7. The Results of the PCA of the Variables.

Parameters	Weight (%)
Exposure Variable	68.70
Sensitivity Variable	23.40
Adaptive Capacity Variable	7.90

The resulting HVI map is an exhaustive representation of the susceptibility of heat-related issues in Klang Valley. It indicates diverse levels of susceptibility distributed across multiple locations, which offer critical insights into spatial vulnerability patterns (Figure 7).

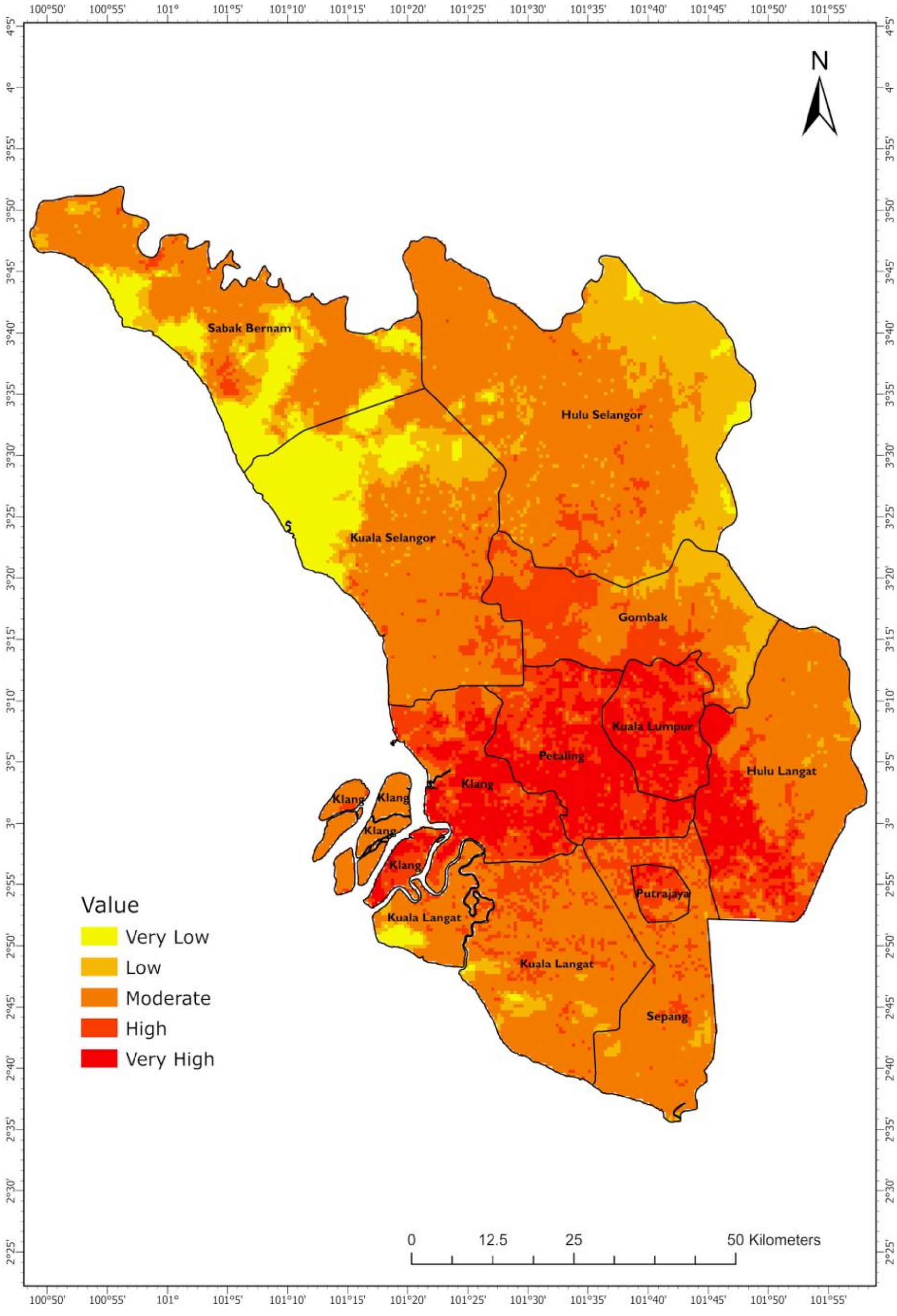

Figure 7. The Heat Vulnerability Index (HVI) of Klang Valley using the PCA Method.

1. Principal Equal-Weighted Index (EWI: HVI-EWI)

In this method, all parameters within the Exposure, Sensitivity, and Adaptive Capacity Variables receive equal weight under EWI. This approach aims to achieve balance by considering all factors involved in heat vulnerability. Land Surface Temperature weighs and occupies 100%. This map is further partitioned into five divisions, which explicitly demonstrates the extent of heat exposure within the Klang Valley region, which serves as an excellent reference for the vulnerability assessment (Figure 8).

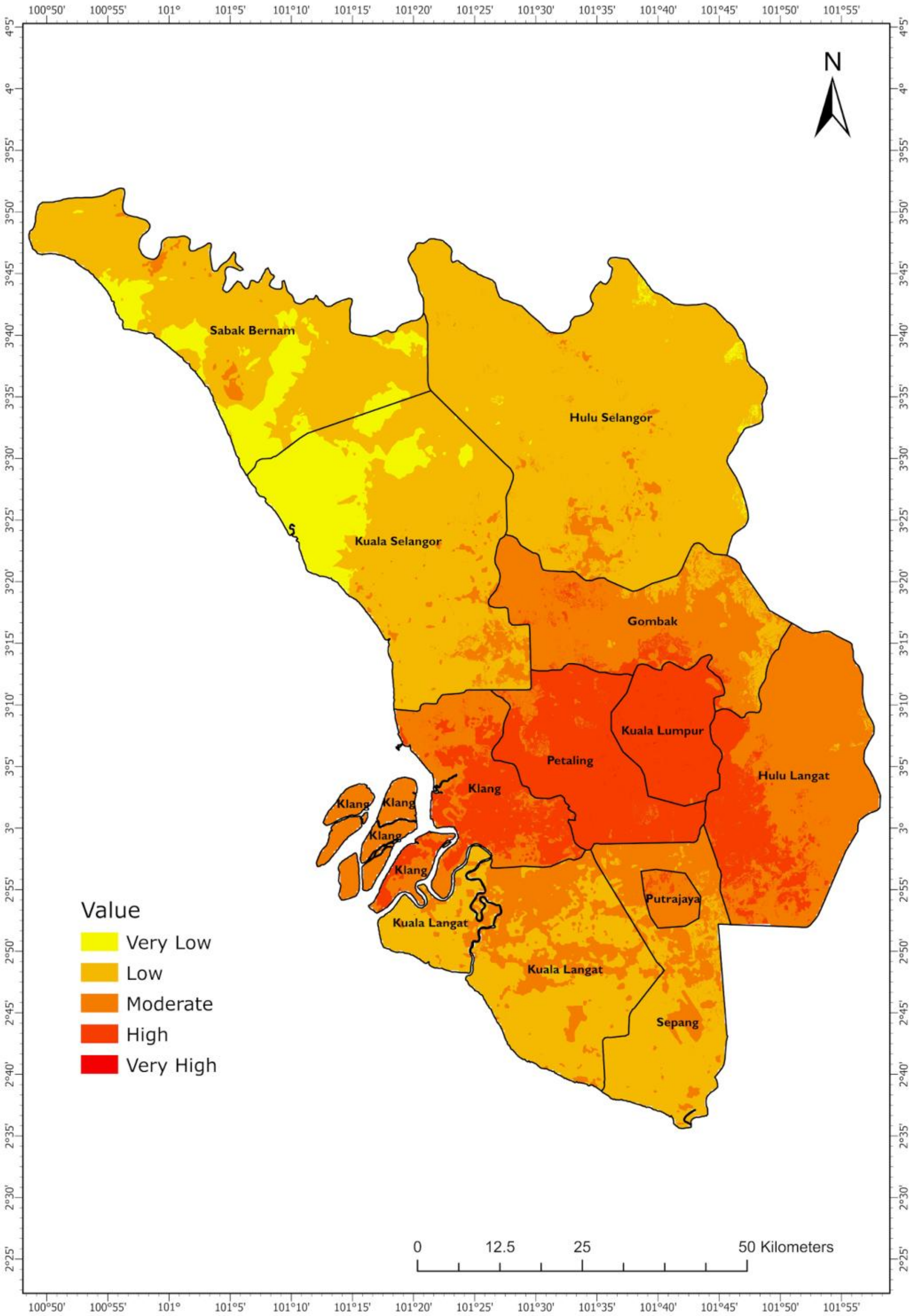

Figure 8. The Heat Vulnerability Index (HVI) of Klang Valley using the Equal-Weighted Index (EWI) Method.

In this uniformity of weighting of the demographic parameters, the Sensitivity Map provides a global view of the sensitivity levels prevailing in that area (Table 9).

Table 8. The Weightage Distribution for Sensitivity Variable.

Parameters	Weight (%)
Population Density	12.50
Elderly Population Density	12.50
Very Young Population Density	12.50
Median Age Population Density	12.50
Female Population Density	12.50
Male Population Density	12.50
Citizen Population Density	12.50
Non-Citizen Population Density	12.50

The following variable shall now be presented under the caption of Adaptive Capacity Variables. This variable coincides with the allocation of assistance known as equal-weightage and details how well it adapts to heat stressors within a particular district or subdistricts, if any exist (Table 9).

Table 9. The Weightage Distribution for the Adaptive Capacity Variable.

Parameters	Weight (%)
Normalised Difference Vegetation Index (NDVI)	20
Normalised Difference Water Index (NDWI)	20
Slope	20
Road Density	20
Land Surface Albedo (LSA)	20

HVI-EWI is arrived at through the proportionate allocation of weight among Exposure, Sensitivity, and Adaptive Capacity Variables (Table 10). The HVI map resulting from the overlay classification only allows to distinguish six categories of potential vulnerabilities of the Quelimane urban area, depicting not only the focal hot spots of Kuala Lumpur Himalayan Peninsular Geosites in Petaling and Klang but other regions such as Sabak Bernam, Hulu Selangor low in vulnerability levels; this integrative assessment underlined while extenuation of climate change vulnerability is the exposure, sensitivity and adaptive capacity aspect risk towards climate change (Figure 8).

Table 10. The Weightage Distribution of the Heat Vulnerability Index Component.

Parameters	Weight (%)
Exposure Variable	33.33
Sensitivity Variable	33.33
Adaptive Capacity Variable	33.34

4.5. Heat Vulnerability Index (HVI): Comparative Analysis of Principal Component Analysis (PCA) and Equal-Weighted Index (EWI)

Figure 9 presents a comparison between the Heat Vulnerability Index (HVI) as calculated using Principal Component Analysis (PCA) and the Equal-Weighted Index (EWI). The percentage area covered by each methodology for the five vulnerability categories is illustrated in Table 11.

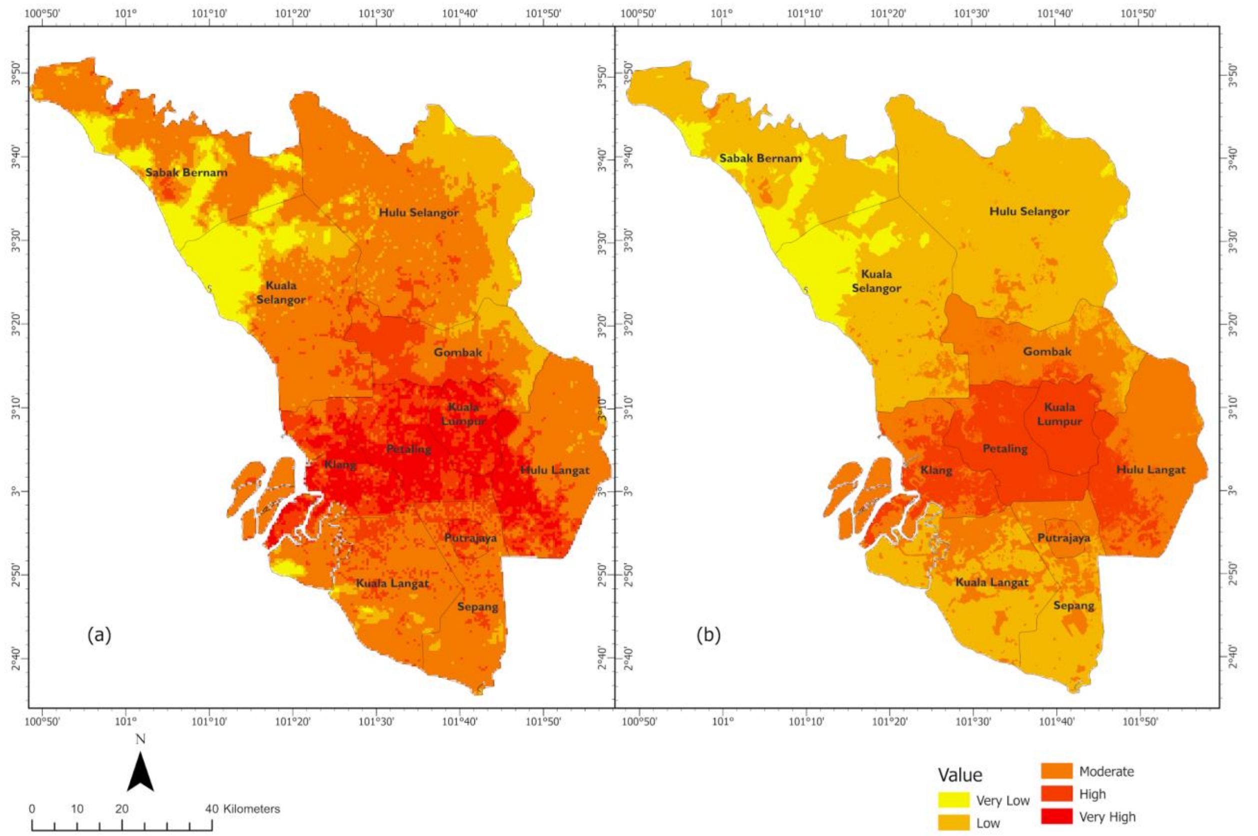

Figure 9. Comparison of EWI and PCA for HVI Analysis. a) HVI-EWI b) HVI-PCA.

Table 11. The Area Percentage Covered by Each Methodology.

Method	Value	Percentage Area Covered (%)
HVI-PCA	1 - Very Low	7.07
	2 - Low	12.87
	3 - Moderate	54.82
	4 - High	14.99
	5 - Very High	10.26
HVI-EWI	1 - Very Low	6.62
	2 - Low	51.29
	3 - Moderate	26.85
	4 - High	15.22
	5 - Very High	0.024

The resulting HVI map is a detailed representation of Klang Valley's heat-related vulnerability landscape. The illustration of different levels of susceptibility spread across several places in order to provide useful indicators for understanding spatial vulnerability patterns is what makes this figure important. The paper provides an overview of the process and outcomes that go into calculating the Heat Vulnerability Index for Klang Valley, which include exposure, sensitivity, adaptive capacity, among others, and finally the HVI overall.

Principal Component Analysis (PCA) and Equal-Weighted Index are two different methods used to assess heat vulnerability, with each being unique. In Table 12, we bring out the differences between PCA and EWI based on their methodological approach, impact on the estimation of heat vulnerabilities, as well as data characteristics.

Table 12. The Reason for the Differences between PCA and EWI.

Aspect	Principal Component Analysis (PCA)	Equal-Weighted Index (EWI)
Approach	Dimensionality reduction, identifying integrated variables from multiple indicators.	Measures the distribution of variables, distinguishes the direction of influence, and adds variations with equal weights for the index.
Impact on Heat Vulnerability Estimation	The absolute values of the coefficients may differ due to incorporating many variables into the model for dimensionality reduction.	Equal weighting of variables may influence results.

In addition, it also brings out other factors when discussing how to choose between PCA or EWI, including considerations such as data characteristics influencing the choice of PCA or EWI and its use in the development of an HVI (Table 13).

Table 13. The Dependence of Choices between Both Approaches.

Aspect	Principal Component Analysis (PCA)	Equal Weighted Index (EWI)
Data characteristics	This is particularly useful when dealing with a large number of variables, aiming to identify the most critical components and explain variance.	Gives equal importance to all variables in the index without emphasizing statistical characteristics.
Application in the Heat Vulnerability Index	Identifying key factors contributing to heat vulnerability by reducing dimensionality and identifying common factors.	Creating an index that gives equal weight to all contributing factors without emphasizing statistical characteristics.
Decision Factors	Depends on the need to reduce dimensionality and identify integrated variables.	Depends on the need to create an index with equal weight.
Considerations	Useful for large datasets and identifying key components.	Appropriate for cases where equal weight to all variables is desired.
Overall dependence	The choice between PCA and EWI depends on specific analysis objectives and the nature of the data being assessed.	

The dual method approach demonstrates the value of both simplicity (EWI) and statistical rigor (PCA). EWI offers ease of interpretation and policy communication, while PCA enhances the accuracy and analytical strength of the index. The application of PCA in the Klang Valley provides a novel contribution by empirically identifying weight structures aligned with regional variability. This study contributes to the literature by:

a. Introducing a comparative methodological analysis in a Southeast Asian context.

b. Integrating triadic vulnerability components into a spatially explicit HVI.

c. Demonstrating the relevance of PCA for detailed and refined urban climate risk profiling.

Both PCA and EWI offer complementary strengths for HVI development. PCA is best when data quality and availability are high, allowing for detailed and refined data-driven insights. EWI excels in settings requiring simplicity, stakeholder inclusiveness, or when data limitations exist. Choosing the appropriate method depends on your goals, audience, data availability, and context of application. In addition, the PCA technique also has the advantage of managing large datasets efficiently, which is crucial in handling complex data involving the Klang Valley. Apart from this, it enables the identification and prioritization of essential indicators by assigning unique weights based on their contribution to variance, thereby ensuring that major factors are duly stressed. Hence, the PCA method is aligned with the purposes of this study and serves as a strong one, backed up by an evidence-based approach to depicting vulnerability levels, rightly comparing them across various locations.

On the contrary, the EWI Method is more straightforward compared to PCA; nonetheless, it cannot determine which indicator is more important. This will lead to an over-simplification of results, hence not capturing the varying degrees of impact each factor has on HVI. Given the uniform distribution of weights used in developing such an index, it may yield less accurate results. Therefore, this research will prefer PCA as its most suitable method.

5. Discussion

This study presents a context specific Heat Vulnerability Index for the Klang Valley using EWI and PCA approaches. While EWI facilitates straightforward application, PCA offers a more refined analysis of regional vulnerability dynamics. The integration of exposure, sensitivity, and adaptive capacity provides a comprehensive understanding of heat risks, supporting targeted climate adaptation and urban planning strategies. To summarize, this study successfully assessed the Heat Vulnerability Index (HVI) in Malaysia's Klang Valley region using both Principal Component Analysis (PCA) and Equal Weighted Index (EWI) approaches. The findings showed the importance of variables such as Land Surface Temperature (LST), population density, NDVI and NDWI, slope analysis, road density maps, and land surface albedo in evaluating heat vulnerability for both HVI-PCA and HVI-EWI. Weighted Overlay Analysis comprehensively investigated regional variations in exposure, sensitivity, and adaptive capacity across the Klang Valley.

This study has several limitations. First, the availability and resolution of data constrained the selection of indicators, particularly for adaptive capacity and real-time health outcomes. Some socioeconomic data were only available at aggregated levels, which may mask intraurban variability. Methodologically, while PCA effectively reduces dimensionality, its reliance on statistical variance may overlook the context-specific relevance of certain indicators. Similarly, EWI assumes equal importance of all variables, which might not reflect the actual weight of each factor in influencing heat vulnerability.

To reiterate, the original objectives of this study were to construct a heat vulnerability index for the Klang Valley using both EWI and PCA, and to compare the spatial outputs to identify vulnerable populations and regions. These objectives have been addressed through a systematic evaluation of vulnerability indicators and comparative mapping, yielding insights into regional heat risk dynamics and the applicability of both methodologies in urban Malaysian contexts.

Based on the Exposure Variables of the HVI in the Klang Valley Area, temperatures range from 15°C to 33.2°C, with the middle section having the greatest temperatures due to urbanization, and the northwest experiencing lower temperatures due to less urbanization. In terms of population density, female population density generally follows overall population density patterns, with higher concentrations in central locations. Male population density, on the other hand, follows a similar trend, albeit with significant variances, especially in the south. Furthermore, noncitizen population density is particularly concentrated in central regions, whereas Malaysian citizen density varies by district. Other considerations can certainly be valued added to the study, like the inclusion of existing or recurrent natural disasters (Dewa *et al.*, 2023), indoor thermal comfort and air quality (Muhamad *et al.*, 2024).

NDVI values indicate lower vegetation density in the center regions and higher density in the northern parts, while color-coded maps provide a more nuanced picture of greenery distribution. NDWI values demonstrate that center regions are represented in blue, indicating water presence, while the peripherals appear in red, indicating drier conditions, emphasizing vulnerability to water-related difficulties. Slope study reveals topographic differences, with the northeast having greater elevations and steeper slopes than other places. Road density maps provide insight into the infrastructure network, with key sections having higher densities than outlying places. This understanding is critical for determining mobility and access during extreme heat occurrences. For Land Surface Albedo, the middle region demonstrates multiple albedo ranges, reflecting distinct surface materials and their thermal properties, thus influencing heat vulnerability.

The weighting of the parameters for HVI-PCA and HVI-EWI differs; for HVI-PCA, LST is the only parameter that affects exposure, while population density has the highest weighting for sensitivity. NDVI is the factor with the most weight in adaptive capacity. All in all, it shows different degrees of vulnerability dispersed throughout different places in the Klang Valley, providing crucial information about patterns of spatial vulnerability. On the other hand, HVI-EWI prioritises land surface temperature, giving it a weight of 100%. It also provides a detailed picture of the sensitivity levels in the region and equally distributes the weight of adaptive capacity to explain how adaptable the region is to heat stressors. Based on the HVI-EWI computation, core regions like Klang, Petaling, and Kuala Lumpur become hotspots of susceptibility, whereas Sabak Bernam and Hulu Selangor show lower degrees of exposure. The comparison between the outcomes of PCA and EWI methods underscored the differences in vulnerability assessments and the factors influencing these variations. However, PCA is the most appropriate for the HVI in the Klang Valley because it can handle big datasets, find important indications, and assign unique weights to each indicator, all of which are in line with the assessment's goals. To progress, maximal representativeness of indicators, consideration of social and behavioral characteristics, utilization of advanced analytical techniques, and interaction with the society in order to improve accuracy and inclusivity of the Klang Valley heat vulnerability assessments are necessary.

This research contributes to the emerging field of proactive planning for heat waves as well as enhancing urban resilience by unveiling complexities surrounding human health under urbanization and climate change. For future research endeavors in this area, there is need to continue exploring innovative ways (Cresswell, 2023; Bayomi & Fernandez, 2023), long term (Kasihairani *et al*, 2024) and strategies that can help mitigate the challenges from extreme heat events and climate change so that ultimately promotes sustainable and healthy cities (Akbari *et al*, 2024). Future studies could also expand on this framework by incorporating real-time climate data and validating the HVI with health outcome records to further enhance policy relevance. This study lays the groundwork for future undertakings in relation to heat vulnerability assessment. It highlights the significance of interdisciplinary partnerships between researchers together with community members for countering negative impacts of global warming on public health in cities.

6. Conclusion

This study developed and compared Heat Vulnerability Indices (HVI) for Malaysia's Klang Valley using Equal Weighted Index (EWI) and Principal Component Analysis (PCA) approaches, offering new insights into how urbanization shapes heat risk. Both methods consistently identified land surface temperature, population density, vegetation cover, water availability, slope, road networks, and surface albedo as key drivers of vulnerability. The results show that urbanized districts such as Klang, Petaling, and Kuala Lumpur experience heightened susceptibility to heat, while less urbanized areas like Sabak Bernam and Hulu Selangor are less exposed. Among the two methods, PCA proved particularly effective in handling complex datasets and assigning context-specific weights to indicators, producing a more nuanced understanding of spatial vulnerability patterns than the uniform weighting assumed by EWI. At the same time, the study acknowledges its limitations. Data availability and resolution constrained indicator selection, particularly for adaptive capacity and health outcomes, while methodological assumptions may have simplified real-world dynamics. These findings highlight the need for future research to integrate real-time climate and health data, apply more advanced analytical techniques, and engage directly with local communities to ensure assessments reflect lived experiences. By providing a robust, context-sensitive picture of heat vulnerability, this research contributes to proactive urban planning and climate adaptation in Malaysia. It underscores that addressing heat risk is not only a technical exercise but also a social and collaborative endeavor that one that benefits from interdisciplinary partnerships, policy relevance, and public engagement to build healthier, more resilient cities in the face of climate change..

Acknowledgements

The author would like to acknowledge and express their incredible gratitude to the Universiti Teknologi MARA for the financial support provided under the Strategic Research Partnership Grant Scheme 100-RMC 5/3/SRP (084/2022).

Author Contributions

Conceptualization: Salleh, S. A., Yaman, R; **methodology**: Khalid, N., Saraf, N. M.; **investigation**: Rueda, G., Samsuddin, N.; **writing—original draft preparation**: Samsuddin, N., Salleh, S. A.; **writing—review and editing**: Khalid, N., Salleh S. A., Pintor, L.; **visualization**: Samsuddin, N., Yaman, R., Saraf, N. M. All authors have read and agreed to the published version of the manuscript.

Conflict of interest

The authors reported no potential conflicts of interest.

Data availability

Data is available upon Request.

Funding

This research is funded by Universiti Teknologi MARA, Malaysia under the Strategic Research Partnership Grant Scheme 100-RMC 5/3/SRP (084/2022).

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