

## Article

# Spatial Assessment of Heat Health Risk in Brussels Through GIS and Local Climate Zone Analysis

Dyna Chourouk Zitouni <sup>1,2,\*</sup>, Mohamed Akram Eddine Ben Ratmia <sup>2</sup>, Mohamed Elhadi Matallah <sup>1,2,3</sup> ,  
Djihed Berkouk <sup>2,4</sup> , Tianyi Wang <sup>1</sup>  and Shady Attia <sup>1,\*</sup> 

<sup>1</sup> Sustainable Building Design Lab, Department UEE, Applied Sciences, University of Liège, 4000 Liège, Belgium; elhadi.matallah@univ-biskra.dz (M.E.M.); tianyi.wang@uliege.be (T.W.)

<sup>2</sup> Department of Architecture, Mohamed Khider University, Biskra 07000, Algeria; akrameddine.benratmia@univ-biskra.dz (M.A.E.B.R.); dberkouk@dah.edu.sa (D.B.)

<sup>3</sup> Civil Engineering and Hydraulics Laboratory, Sustainable Development and Environment (LARGHYDE), University of Biskra, Biskra 07000, Algeria

<sup>4</sup> Department of Architecture, School of Engineering, Computing & Design, Dar Al-Hekma University, Jeddah 22246, Saudi Arabia

\* Correspondence: dczitouni@uliege.be (D.C.Z.); shady.attia@uliege.be (S.A.)

## Abstract

Climate change and rapid urbanization are increasing the frequency and intensity of extreme heat events, posing significant risks to public health in cities. Although numerous studies have investigated urban heat islands and heat vulnerability, spatially explicit assessments integrating environmental, demographic, and urban morphological characteristics remain limited, particularly in European cities. This study presents the first Heat–Health Risk Index (HHRI) assessment for the Brussels Capital Region, combining remote sensing, demographic information, and Local Climate Zone (LCZ) classification within a Geographic Information System (GIS) framework to evaluate the spatial distribution of heat health risk. The HHRI was developed by integrating three components (hazard, exposure, and vulnerability) derived from Landsat 8/9 imagery, WorldPop population data, and LCZ classification generated following the WUDAPT methodology. Hazard was represented by Land Surface Temperature (LST), exposure combined population density and built-up intensity (NDBI), while vulnerability incorporated vegetation (NDVI), surface water (MNDWI), and age-sensitive population groups. Principal Component Analysis (PCA) was applied to determine indicator weights, and the resulting HHRI was analyzed across different LCZs using zonal statistics. The results revealed pronounced spatial variability in heat health risk across Brussels, with the highest HHRI values concentrated within the densely urbanized central municipalities and the lowest values occurring in the vegetated southern and southeastern areas. LCZ analysis showed that Compact Low-Rise (LCZ 3) and Compact Mid-Rise (LCZ 2) exhibited the highest proportions of high and very high risk, whereas natural LCZs, particularly Dense Trees (LCZ A) and Low Plants (LCZ D), consistently functioned as urban cooling environments associated with low heat health risk. This study addresses an important research gap by providing the first LCZ-based HHRI assessment for Brussels and Belgium. The proposed open-data and reproducible methodology offer a transferable framework for identifying priority intervention areas and supporting evidence-based climate adaptation and urban planning in European cities.

**Keywords:** heat health risk index; local climate zones; urban heat island; remote sensing; geographic information system; Brussels; climate adaptation



Academic Editors: Tiziana Susca and Fabio Zanghirella

Received: 29 July 2026

Revised: 15 September 2026

Accepted: 30 September 2026

Published: 5 October 2026

**Copyright:** © 2026 by the authors.

Licensee MDPI, Basel, Switzerland.

This article is an open access article distributed under the terms and

conditions of the [Creative Commons](https://creativecommons.org/licenses/by/4.0/)

Attribution (CC BY) license.

## 1. Introduction

Climate change has intensified the frequency, duration, and severity of extreme heat events worldwide, making heatwaves one of the most significant environmental hazards affecting urban populations [1]. Rapid urbanization further exacerbates this challenge through the Urban Heat Island (UHI) effect, whereby dense built environments, impervious surfaces, and limited vegetation contribute to elevated temperatures compared with surrounding rural areas [2]. As a result, cities are becoming increasingly vulnerable to heat-related impacts, posing substantial challenges to public health, infrastructure, and urban sustainability. Addressing these impacts requires coordinated monitoring and early warning systems capable of supporting timely preventive measures and reducing heat-related risks across regions, particularly in economically vulnerable communities. Consequently, developing reliable spatial assessment frameworks has become essential for identifying priority intervention areas and supporting evidence-based climate adaptation and urban planning strategies [3].

Extreme heat has become one of the leading climate-related threats to human health, causing substantial increases in heat-related mortality, morbidity, and hospital admissions worldwide. Exposure to elevated temperatures can exacerbate cardiovascular, respiratory, and renal diseases, while prolonged heatwaves place additional pressure on healthcare systems and urban infrastructure [4]. However, the health impacts of extreme heat are not uniformly distributed across the population. Vulnerability varies according to demographic, socioeconomic, and environmental characteristics, with older adults, young children, individuals with pre-existing medical conditions, and socially disadvantaged populations experiencing disproportionately greater health risks. In addition, differences in housing conditions, access to green spaces, and the surrounding urban environment further influence the ability of communities to cope with extreme heat [5,6]. These spatial inequalities highlight the need for comprehensive approaches that assess not only thermal conditions but also the characteristics of exposed populations when evaluating urban heat-related health risks.

In recent years, European research has increasingly recognized the need to move beyond conventional Urban Heat Island (UHI) mapping toward more comprehensive assessments that integrate environmental and socioeconomic dimensions of heat-related risk [7,8]. Técher et al. (2023) developed a spatial methodology for the Montpellier metropolitan area (France) by combining urban planning indicators with measures of heat exposure and population sensitivity [9]. Their findings demonstrated that districts facing greater urban planning challenges were also the most vulnerable to urban overheating, highlighting the importance of integrating mitigation strategies such as increased green infrastructure, improved urban ventilation, and reduced anthropogenic heat emissions into planning policies.

A comparable approach was proposed by Pappalardo et al. (2023) in Padua (Italy), where satellite-derived thermal information was combined with demographic and socioeconomic indicators to develop a climate justice heat-related risk index [10]. Their results revealed that the greatest heat-related risks occurred in densely urbanized sectors where elevated temperatures coincided with higher concentrations of elderly residents, children, migrants, and low-income households, reinforcing the importance of considering social inequalities within climate adaptation planning.

Similarly, Alnajjar et al. (2025) investigated urban heat vulnerability in Seville (Spain) using a multidimensional framework integrating remotely sensed land surface temperature, vegetation and built-up indices, Space Syntax, and social vulnerability metrics [11]. Their study introduced the concept of Heat Boundaries (HBs) to identify thermally intense urban areas acting as barriers between vulnerable neighborhoods and emphasized the role of spatial configuration and environmental inequalities in shaping heat exposure patterns.

Expanding the analysis beyond individual cities, Sestito et al. (2025) performed the first dynamic heat vulnerability assessment at the European scale by integrating heat hazard, population exposure, and socioeconomic, demographic, and environmental indicators [12]. Their study identified urbanization and foreign citizenship as two of the most influential drivers of heatwave-related mortality and highlighted the need for sustainable urban planning and nature-based solutions to strengthen resilience across European cities.

Collectively, these studies demonstrate a clear shift in Europe toward multidimensional assessments of urban heat that combine environmental and socioeconomic factors. Nevertheless, most of these approaches primarily evaluate urban heat vulnerability or heat-related risk without explicitly incorporating standardized urban morphology classifications, leaving opportunities to further investigate how urban form influences the spatial distribution of heat health risk [13].

Recent advances in remote sensing and geographic information systems have considerably improved the spatial assessment of heat-related health risks by enabling the integration of environmental, demographic, and urban datasets [14]. Early studies primarily relied on satellite-derived thermal indicators combined with population characteristics to identify vulnerable communities. For instance, Zhang et al. (2019) assessed heat vulnerability among elderly populations in mountainous regions of China by integrating MODIS-derived land surface temperature with vegetation indices and demographic information [15]. Likewise, Estoque et al. (2020) developed a spatial heat-risk assessment for the Philippines using remotely sensed thermal data together with social and ecological indicators, demonstrating the importance of considering both environmental and human dimensions of heat exposure [16]. More recently, heat health risk assessments have expanded to other regions. In North Africa, Zitouni et al. (2025) conducted one of the first long-term heat health risk assessments for Algiers by integrating satellite observations, meteorological records, and census data within the IPCC framework [17]. Their study further coupled the Heat Health Risk Index (HHRI) with the Universal Thermal Climate Index (UTCI), demonstrating that combining multiple thermal indicators improves the identification of persistent heat-risk hotspots and provides a stronger basis for targeted climate adaptation and urban resilience planning.

Although this framework has demonstrated strong performance in urban risk assessments [18], relatively few studies have explicitly integrated it with the Local Climate Zone (LCZ) classification. Most existing applications have been conducted in China, where LCZs have been combined with environmental and demographic indicators to investigate the influence of urban morphology on heat health risk. These studies differ in terms of climatic indicators, spatial scales, and analytical approaches, yet collectively demonstrate the growing value of coupling standardized urban morphology with multidimensional heat-risk assessments.

In Belgium, research on heat-related health impacts has primarily focused on the epidemiological consequences of extreme temperatures. Demoury et al. (2022a) first quantified the effects of heat and cold on mortality across nine Belgian cities, demonstrating that mortality risks increase in highly urbanized municipalities and identifying older adults and women as particularly vulnerable to heat exposure [19]. In a second study, Demoury et al. (2022b) further investigated the influence of individual health conditions and residential environmental characteristics, showing that pre-existing diseases and air pollution can exacerbate heat-related mortality [20]. More recently, Ali et al. (2025) expanded the analysis to medically at-risk populations, reporting significantly higher heat-related morbidity and mortality among elderly individuals, patients with chronic diseases, urban residents, and low socioeconomic groups [21]. Despite these important contributions, existing studies remain largely health-oriented and do not provide a spatially explicit assessment of heat

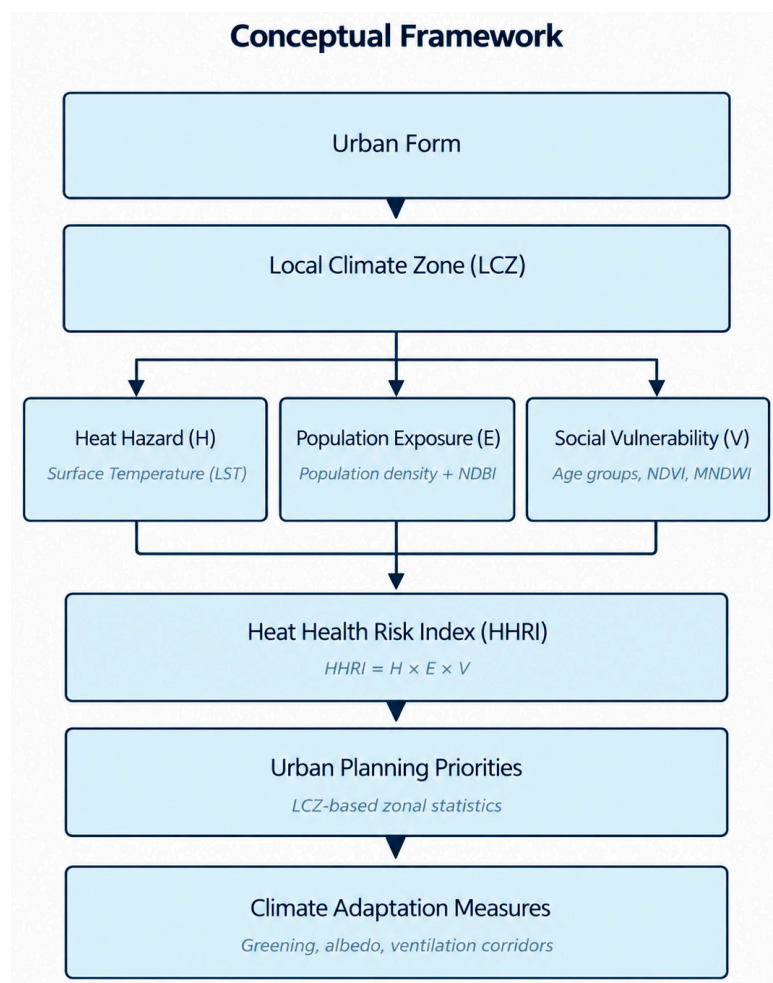
health risk. To the best of our knowledge, no study has developed a Heat–Health Risk Index (HHRI) for Brussels or Belgium, nor examined its spatial variability across Local Climate Zones (LCZs). Accordingly, the contribution of this study lies primarily in the integrated application of established heat health risk assessment methods to the Brussels Capital Region and in examining the resulting HHRI across LCZs, rather than in proposing a new methodological approach.

To address these research gaps, this study aims to develop a spatially explicit Heat–Health Risk Index (HHRI) for the Brussels Capital Region by integrating remote sensing, demographic data, and urban morphology within a Geographic Information System (GIS) framework. Specifically, the study (i) maps the spatial distribution of hazard, exposure, vulnerability, and the composite HHRI at a high spatial resolution, (ii) investigates the relationship between heat health risk and Local Climate Zones (LCZs) to identify urban morphologies associated with elevated risk, and (iii) provides a reproducible methodology based exclusively on open-access datasets to support climate adaptation planning.

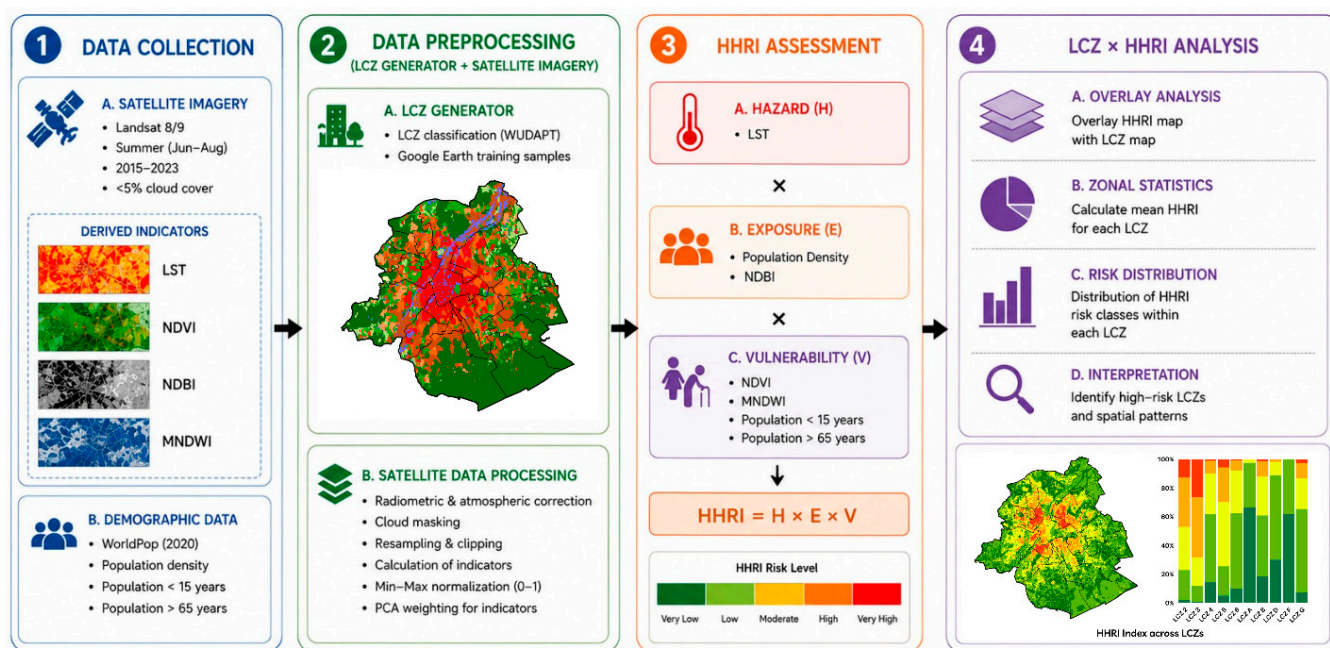
This study makes four principal contributions to the heat health risk literature. First, it provides one of the first empirical integrations of a Heat Health Risk Index with Local Climate Zone classification for a Belgian, and more broadly a temperate Western European, urban context, extending an approach previously applied mainly in Asian cities to a new climatic and urban-morphological setting. Second, the framework prioritizes methodological transparency by deriving component weights through the Principal Component Analysis procedure rather than expert judgement, and by relying exclusively on openly accessible satellite and census datasets, allowing the workflow to be audited and potentially transferable. Third, by combining hazard, exposure, and vulnerability within a fine-resolution, LCZ-linked spatial framework, the study provides a direct spatial decision-support tool that identifies not only where heat health risk is highest, but which urban morphological characteristics are associated with that risk, enabling morphology-specific rather than generic adaptation planning. Fourth, the explicit separation between universal and locally calibrated framework components (Section 4.4) demonstrates the transferability of the methodology to other temperate European cities, positioning this study as a reproducible template for comparative, cross-city heat health risk assessment.

## 2. Materials and Methods

The conceptual framework underpinning this study (Figure 1) highlights the relationships between urban morphology, represented by the Local Climate Zone (LCZ) classification, environmental conditions, and the Heat Health Risk Index (HHRI). It shows how variations in urban form influence thermal conditions and contribute to the hazard, exposure, and vulnerability components of the HHRI, ultimately supporting the identification of priority areas for climate adaptation and urban planning. Building upon this conceptual basis, the methodological workflow adopted in this study is presented in Figure 2. The proposed workflow follows a structured sequence, beginning with data collection and preprocessing, followed by the development of the Heat Health Risk Index (HHRI), and concluding with the assessment of heat health risk across Local Climate Zones (LCZs). The framework relies exclusively on standardized, open-access datasets and reproducible GIS and remote sensing techniques, ensuring methodological transparency and facilitating its application to other cities. The different stages of the methodology are described in detail in the following section.



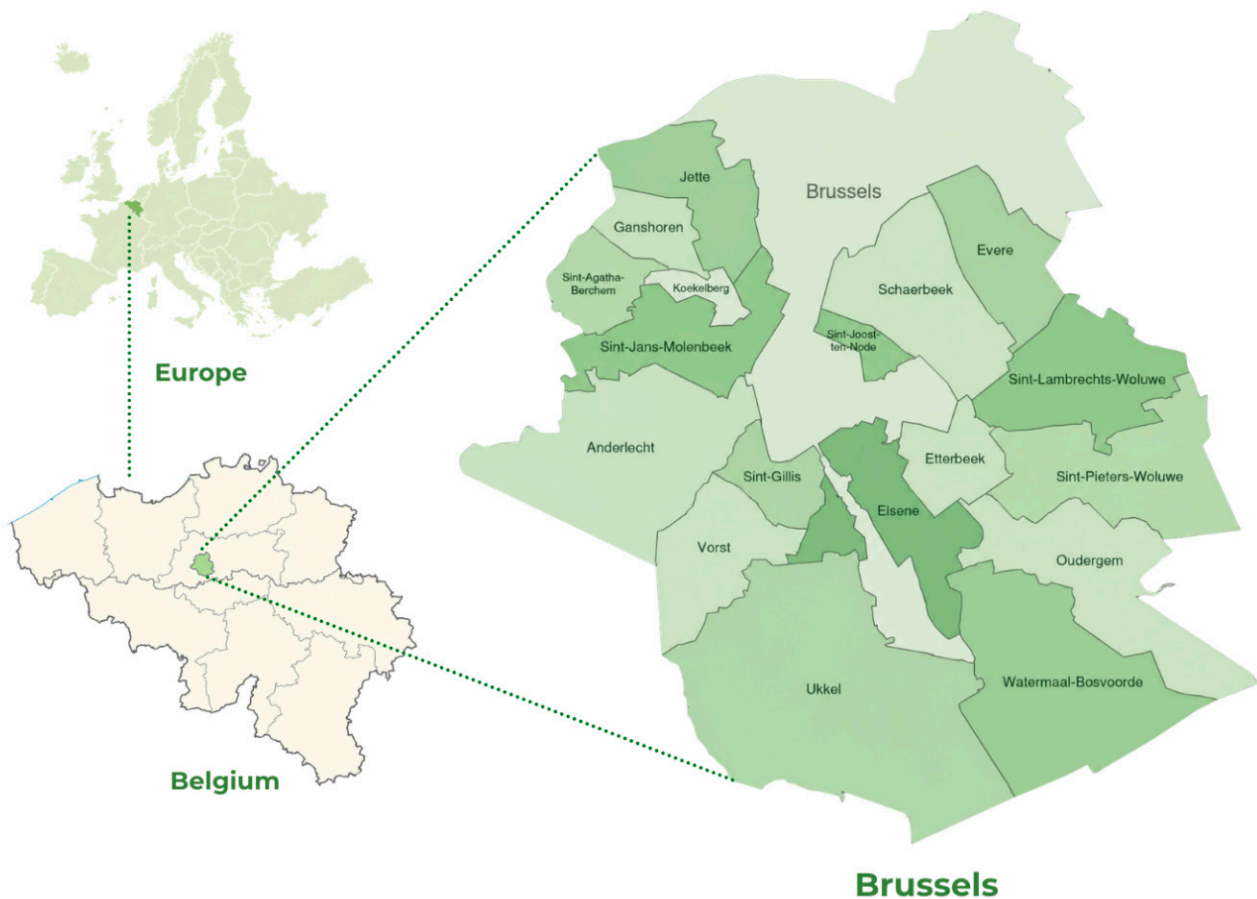
**Figure 1.** Conceptual framework linking urban form and Local Climate Zones to surface temperature, the hazard-exposure-vulnerability structure of the HHRI, and downstream urban planning and climate adaptation priorities.



**Figure 2.** Methodology framework.

### 2.1. Case Study

The Brussels Capital Region, located in central Belgium, was selected as the study area for this research (Figure 3). As the political and economic center of Belgium and the headquarters of several European institutions, Brussels is characterized by a dense urban fabric, a heterogeneous land-use structure, and a population exceeding one million inhabitants distributed across nineteen municipalities.



**Figure 3.** Case study (Brussels).

Brussels experiences a temperate oceanic climate characterized by mild winters and moderate summers. However, recent decades have witnessed an increasing frequency and intensity of heatwave events across Europe, raising concerns regarding the impacts of extreme heat on urban populations [22]. The combination of urbanization, population concentration, and climate change has heightened the need to identify areas most vulnerable to heat-related risks and to support the development of targeted adaptation strategies.

The urban landscape of Brussels exhibits considerable spatial variability, ranging from densely built historical districts and commercial centers to residential neighborhoods, parks, and forested areas. This diversity in urban morphology makes Brussels particularly suitable for investigating the spatial distribution of heat health risk and its relationship with different urban forms. The selection of Brussels is further motivated by the limited number of heat health risk assessments conducted in Belgium. Applying the proposed Heat Health Risk Index (HHRI) framework in a temperate European city provides an opportunity to evaluate its applicability beyond similar environments and contributes to the growing body of research on urban heat risk assessment in Europe.

## 2.2. Data Collection and Preprocessing

The assessment of heat health risk in Brussels was based on the integration of environmental, demographic, and urban morphology datasets within a GIS framework. To ensure consistency and reproducibility, all datasets were obtained from openly accessible sources and harmonized to a common spatial resolution of 100 m. The collected data supports the characterization of the three HHRI dimensions (hazard, exposure, and vulnerability) while also enabling the investigation of heat-risk patterns across different Local Climate Zones (LCZs). A summary of the datasets used in this study is provided in Table 1.

**Table 1.** Dataset summary.

| Type               | Description                                                     | Period    | Resolution | Source                       |
|--------------------|-----------------------------------------------------------------|-----------|------------|------------------------------|
| LCZ Classification | Local Climate Zone map used for urban morphology analysis       | 2023      | 100 m      | WUDAPT/Google Earth Pro [23] |
| Population Data    | Total population and age-group distribution (<15 and >65 years) | 2020      | 100 m      | WorldPop [24]                |
| Satellite Imagery  | Landsat imagery used to derive LST, NDVI, NDBI and MNDWI        | 2015–2023 | 30 m       | USGS Earth Explorer [25]     |

### 2.2.1. Urban Morphology Data: Local Climate Zones

Urban morphology was characterized using the Local Climate Zone (LCZ) classification system proposed by Stewart and Oke (2012) [26], which provides a standardized framework for classifying urban and natural landscapes according to their building structure, surface cover, land use, and thermal characteristics. The LCZ scheme enables a detailed representation of urban form and has been widely adopted for investigating the influence of urban morphology on local climate and thermal environments.

The LCZ map of the Brussels Capital Region was generated following the World Urban Database and Access Portal Tools (WUDAPT) Level 0 methodology (Bechtel et al., 2015). A total of 60 representative training areas for each LCZ class were delineated using high-resolution imagery in Google Earth Pro. These training samples were selected to capture homogeneous urban and natural surfaces representative of the different LCZ categories. The delineated training areas were subsequently used within a supervised classification workflow to produce the final LCZ map of Brussels. Following classification, the LCZ map was harmonized with the 100 m analysis grid used for the HHRI assessment.

### 2.2.2. Environmental and Demographic Data

Environmental and demographic datasets were integrated to characterize the hazard, exposure, and vulnerability dimensions of the Heat Health Risk Index (HHRI). More than 80 Landsat 8 and Landsat 9 Level-2 scenes acquired during the summer period (June–August) between 2015 and 2023 were selected, applying a scene-level cloud-cover threshold of <5%. More than 80 scenes satisfying these criteria were included in the analysis. LST, NDVI, NDBI, and MNDWI were calculated individually for each available scene following the procedures described below. The resulting scene-level raster layers were subsequently combined by calculating the pixel-wise arithmetic mean across all selected summer scenes over the 2015–2023 period, producing the final multi-year mean LST, NDVI, NDBI, and MNDWI layers used in the HHRI assessment. This compositing approach was adopted to characterize representative summer conditions over the study period rather than conditions associated with a single acquisition date.

Demographic information was obtained from the WorldPop database [27], which provides gridded population estimates at a spatial resolution of 100 m. The dataset included

total population counts as well as two age groups recognized as particularly vulnerable to extreme heat, namely individuals younger than 15 years and those aged 65 years and above. The population rasters were clipped to the Brussels Capital Region and spatially aligned with the environmental datasets using a 100 m analysis grid. This preprocessing ensured spatial consistency among all indicators prior to their integration within the HHRI framework, where population density represented the exposure component, while the age-specific datasets were incorporated as demographic vulnerability indicators.

### 2.2.3. Software, Processing Environment, and Reproducibility

All geospatial processing was conducted in ArcGIS Pro 3.2.0 [28], with satellite image preprocessing and spectral index calculations performed using the Spatial Analyst extension and the Raster Functions/Map Algebra tools available in ArcGIS Pro. Landsat 8 and Landsat 9 Collection 2 Level-2 products were used to derive the satellite-based environmental indicators. Surface reflectance was obtained from the Level-2 spectral bands using the following scaling Equation (1):

$$\rho = (DN \times 0.0000275) - 0.2 \quad (1)$$

where  $\rho$  represents surface reflectance and  $DN$  is the Level-2 pixel value. The Normalized Difference Vegetation Index (NDVI) was calculated using Equation (2):

$$NDVI = \frac{B5 - B4}{B5 + B4} \quad (2)$$

where  $B5$  represents the near-infrared (NIR) band and  $B4$  the red band. The Normalized Difference Built-up Index (NDBI) was calculated using Equation (3):

$$NDBI = \frac{B6 - B5}{B6 + B5} \quad (3)$$

where  $B6$  represents the short-wave infrared (SWIR1) band. The Modified Normalized Difference Water Index (MNDWI) was calculated using Equation (4):

$$MNDWI = \frac{B3 - B6}{B3 + B6} \quad (4)$$

where  $B3$  represents the green band and  $B6$  the SWIR1 band.

Land Surface Temperature ( $LST$ ) was derived from the Landsat Collection 2 Level-2 ST\_B10 product using the scale factor and offset in Equation (5):

$$LST_K = (ST\_B10 \times 0.00341802) + 149.0 \quad (5)$$

where  $LST_K$  is the surface temperature in Kelvin. The resulting temperature was converted to degrees Celsius using Equation (6):

$$LST\ ^\circ\text{C} = LST_K - 273.15 \quad (6)$$

All raster and vector datasets were projected to a common coordinate reference system, Belgian Lambert 2008 (EPSG:3812), and resampled to a common 100 m analysis grid described in Section 2.2 using nearest-neighbor resampling for categorical datasets (LCZ) and bilinear resampling for continuous raster datasets ( $LST$ ,  $NDVI$ ,  $NDBI$ ,  $MNDWI$ , and population layers). The complete processing workflow, comprising image preprocessing, indicator derivation, min–max normalization, PCA-based component derivation, HHRI

computation, and zonal statistics by LCZ, followed the sequential structure illustrated in Figure 2.

### 2.3. Heat Health Risk Index Assessment

The Heat Health Risk Index (HHRI) was developed to quantify the spatial distribution of heat health risk across the Brussels Capital Region. The framework follows the risk concept proposed by Crichton (1999) and adopted by the IPCC Sixth Assessment Report (IPCC, 2021) [29,30], where heat health risk is considered the combined effect of hazard, exposure, and vulnerability. Each component was represented by a set of environmental and demographic indicators selected according to their relevance to urban heat risk and processed within a GIS environment. Prior to integration, all variables were standardized using min–max normalization to ensure comparability despite differences in units and value ranges. To minimize subjectivity in the weighting process, Principal Component Analysis (PCA) was employed to derive weights for each indicator based on their statistical contribution.

#### 2.3.1. Hazard Assessment

The hazard component represents the spatial intensity of urban heat and was characterized using Land Surface Temperature (LST) derived from Landsat imagery. LST was selected as the primary hazard indicator because it provides a spatially continuous representation of surface thermal conditions and has been widely recognized as a reliable proxy for assessing urban heat intensity and identifying heat accumulation patterns.

Landsat 8 Operational Land Imager (OLI) and Thermal Infrared Sensor (TIRS), together with Landsat 9 imagery, were acquired from the USGS Earth Explorer platform for the summer months (June to August) over the period 2015–2023. Only cloud-free or low-cloud-cover scenes (<5% cloud cover) were retained to minimize atmospheric interference and ensure the reliability of the retrieved thermal information. The selected images were radiometrically and atmospherically corrected prior to processing.

Land Surface Temperature was retrieved from the thermal infrared bands using the standard radiative transfer procedure. The processing workflow involved the conversion of digital numbers to top-of-atmosphere spectral radiance, followed by the calculation of brightness temperature and the estimation of land surface emissivity based on vegetation cover. Before integration into the HHRI framework, the LST values were standardized using min–max normalization to eliminate differences in measurement scales.

#### 2.3.2. Exposure Assessment

The exposure component represents the degree to which populations and the built environment are subjected to hazardous heat conditions. In this study, exposure was characterized using two complementary indicators: population density and the Normalized Difference Built-up Index (NDBI). Population density reflects the spatial concentration of individuals potentially affected by extreme heat, whereas NDBI was included as a proxy for the intensity of the built-up environment in which this exposure occurs. Population density data were obtained from the WorldPop database, which provides gridded population estimates at a spatial resolution of 100 m. The dataset was clipped to the Brussels Capital Region, projected to the common coordinate system adopted in this study.

The NDBI was derived from Landsat 8 and Landsat 9 imagery acquired during the summer months (June–August) between 2015 and 2023. Following radiometric and atmospheric preprocessing, the index was calculated using the shortwave infrared (SWIR) and near-infrared (NIR) spectral bands according to the standard formulation. Higher NDBI values indicate a greater proportion of built-up and impervious surfaces, which are associated with increased heat retention and reduced surface cooling.

Prior to integration into the HHRI framework, both population density and NDBI were standardized using min–max normalization to ensure comparability between indicators. A Principal Component Analysis (PCA) was then performed in ArcGIS Pro using the standardized indicators to derive the exposure component. The resulting PCA raster output was used directly as the exposure layer in the HHRI calculation; no manually assigned indicator weights were applied.

### 2.3.3. Vulnerability Assessment

The vulnerability component represents the susceptibility of populations and the urban environment to the adverse impacts of extreme heat. In this study, vulnerability was characterized using two demographic indicators, namely the proportion of the population aged 65 years and above and 15 years and below, together with two environmental indicators: the Normalized Difference Vegetation Index (NDVI) and the Modified Normalized Difference Water Index (MNDWI). These indicators were selected to capture both the sensitivity of exposed populations and the capacity of the urban environment to mitigate heat stress.

Age-specific population data were obtained from the WorldPop database at a spatial resolution of 100 m. Elderly individuals and young children were considered vulnerable population groups due to their increased sensitivity to heat-related illnesses and reduced physiological capacity to cope with extreme temperatures.

The environmental indicators were derived from Landsat 8 and Landsat 9 imagery acquired during the summer months (June–August) between 2015 and 2023. Following radiometric and atmospheric preprocessing, the Normalized Difference Vegetation Index (NDVI) was calculated to quantify vegetation density, while the Modified Normalized Difference Water Index (MNDWI) was derived to identify the presence of surface water bodies. Vegetation and water features play a key role in regulating urban microclimates by enhancing evapotranspiration and reducing surface temperatures, thereby mitigating heat exposure.

Since higher NDVI and MNDWI values indicate greater cooling potential and consequently lower vulnerability, both indicators were inversely normalized before their incorporation into the HHRI framework. The demographic and environmental indicators were subsequently standardized using min–max normalization and subjected to a separate PCA in ArcGIS Pro. The resulting PCA raster output was used directly as the vulnerability layer in the HHRI calculation, without manually assigning indicator weights.

### 2.3.4. HHRI Computation

Following the preparation of the hazard, exposure, and vulnerability components, the Heat Health Risk Index (HHRI) was computed by integrating the three normalized and weighted dimensions within a GIS environment. Prior to aggregation, all indicators were standardized using the min–max normalization method to transform their values into a common dimensionless scale ranging from 0 to 1, thereby ensuring comparability among variables with different units and magnitudes.

The three weighted components; Hazard (H), Exposure (E), and Vulnerability (V), were subsequently combined according to the conceptual risk framework proposed by Crichton (1999) and adopted by the IPCC (2021), as expressed in Equation (7):

$$\text{HHRI} = H \times E \times V \quad (7)$$

The multiplicative formulation was adopted following the risk-triangle concept and established HHRI approaches, reflecting the principle that heat health risk emerges from the combined interaction of hazard, exposure, and vulnerability rather than from their inde-

pendent additive contributions. Using the Jenks Natural Breaks classification method the resulting HHRI raster was classified into five categories: Very Low, Low, Moderate, High, and Very High. This data-driven classification technique minimizes variance within classes while maximizing differences between classes, enabling the identification of meaningful spatial clusters of heat health risk across the Brussels Capital Region.

#### *2.4. Heat Health Risk Analysis Across Local Climate Zones*

To investigate the influence of urban morphology on heat health risk, the computed Heat Health Risk Index (HHRI) was analyzed in relation to the Local Climate Zone (LCZ) classification. The LCZ map and the HHRI raster were integrated within the ArcGIS Pro environment using a common 100 m spatial grid, ensuring spatial correspondence between both datasets.

A zonal statistics analysis was performed to calculate the mean values of the HHRI as well as its three components for each LCZ class. This approach enabled a quantitative comparison of heat health risk across different urban forms while preserving the spatial characteristics of the LCZ classification. In addition to average values, the spatial distribution of HHRI classes within each LCZ was examined to identify urban typologies associated with elevated heat health risk.

To further characterize the relationship between urban morphology and heat health risk, the proportion of each LCZ occupied by the five HHRI classes (Very Low, Low, Moderate, High, and Very High) was computed. This analysis provides shows how heat health risk is distributed among compact, open, industrial, vegetated, and water-related urban environments. Finally, descriptive statistics and graphical visualizations were generated to compare HHRI patterns among LCZ classes and to identify the urban forms most susceptible to elevated heat health risk.

#### *2.5. Spatial Consistency Assessment*

The proposed HHRI framework was evaluated through a spatial consistency and plausibility assessment, examining whether the spatial distribution of the index is consistent with established environmental and urban characteristics associated with heat health risk. Direct epidemiological validation using heat-related morbidity or mortality data was not possible because spatially disaggregated health records are not currently available for the Brussels Capital Region. This limitation is common in heat health risk research, where initial framework evaluation often relies on comparisons with independent environmental and spatial evidence. Accordingly, this assessment should be interpreted as an evaluation of the spatial plausibility of the resulting HHRI patterns rather than as an independent validation of the index.

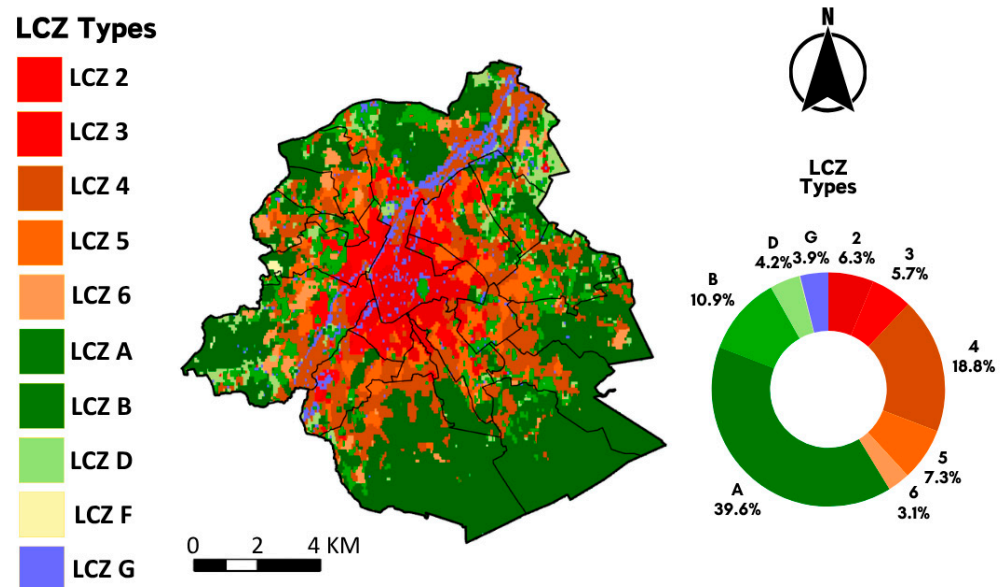
The HHRI was assessed against four complementary sources of information: (i) the Land Surface Temperature (LST) distribution derived in this study, (ii) the Local Climate Zone (LCZ) classification, (iii) the official urban heat island mapping published by Bruxelles Environnement [31], and (iv) previously reported heat-risk patterns in Brussels [32,33]. The agreement among these independent datasets supports the spatial consistency and plausibility of the proposed HHRI framework.

Future work should focus on validating the HHRI against spatially resolved health datasets, including heat-related mortality, morbidity, and hospital admissions, as these become available, enabling formal assessment of its predictive performance.

### 3. Results

#### 3.1. Local Climate Zone Distribution in Brussels

The LCZ classification was generated using the LCZ Generator based on representative training areas defined for the LCZ classes present within the study area. Classification performance was assessed using the accuracy assessment provided by the LCZ Generator, which yielded an overall accuracy (OA) of 0.89. No separate independent validation dataset was used; therefore, the reported OA should be interpreted as an internal estimate of classification performance rather than an independent external validation of the final LCZ map. Potential differences in classification performance among LCZ classes are considered as a source of uncertainty in the subsequent LCZ-based analysis. The resulting LCZ map (Figure 4) reveals a heterogeneous urban landscape composed of compact, open, industrial, and natural land-cover classes.



**Figure 4.** Brussels LCZ spatial distribution and proportions (2023).

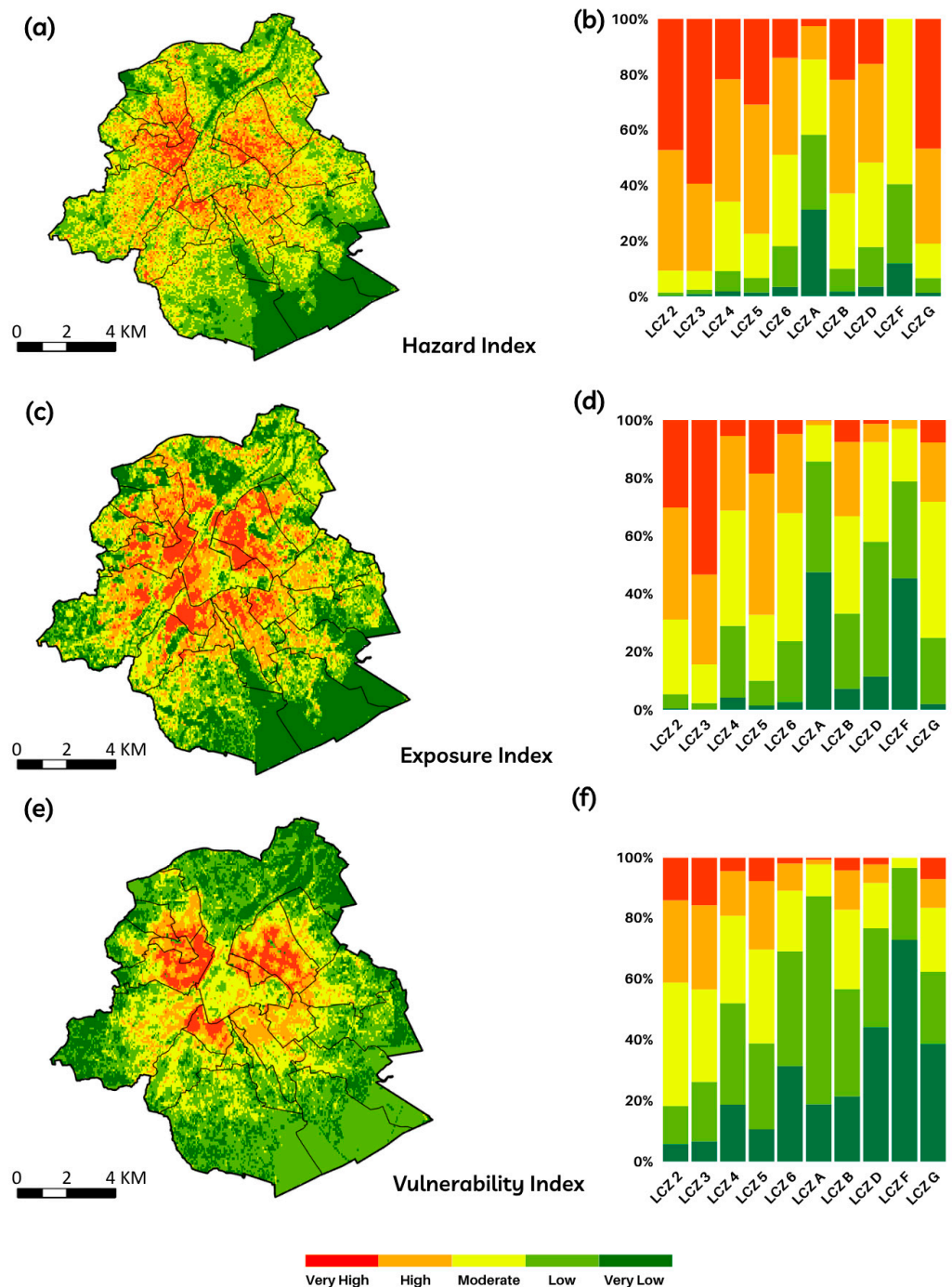
Among all LCZs, Dense Trees (LCZ A) represent the dominant land-cover class, accounting for 39.6% of the total study area, highlighting the substantial presence of urban forests, parks, and wooded green spaces within the region. The second largest class is Open High-Rise (LCZ 4), occupying 18.8%, followed by Scattered Trees (LCZ B) (10.9%). Open Mid-Rise (LCZ 5) and Compact Mid-Rise (LCZ 2) account for 7.3% and 6.3% of the study area, respectively, while Compact Low-Rise (LCZ 3) represents 5.7%. Smaller proportions are occupied by Low Plants (LCZ D) (4.2%), Water (LCZ G) (3.9%), and Open Low-Rise (LCZ 6) (3.1%). Bare Soil or Sand (LCZ F) is almost absent, representing only 0.1% of the Brussels Capital Region.

Spatially, compact and open built-up LCZs are predominantly distributed throughout the central municipalities, including the City of Brussels, Saint-Josse-ten-Noode, Schaerbeek, Etterbeek, Ixelles, Saint-Gilles, and Molenbeek-Saint-Jean, whereas the largest vegetated LCZs are mainly concentrated in the southern and southeastern municipalities, particularly Uccle, Watermael-Boitsfort, Auderghem, and Woluwe-Saint-Pierre. This spatial heterogeneity provides a suitable framework for examining how heat health risk varies among contrasting urban morphologies across the Brussels Capital Region.

#### 3.2. Hazard Distribution Across Local Climate Zones

The spatial distribution of the hazard component, represented by normalized Land Surface Temperature (LST) in Figure 5a and the distribution of hazard classes across the

different LCZs in Figure 5b reveal a heterogeneous thermal pattern across the Brussels Capital Region. High and very high hazard levels are primarily concentrated within the central municipalities, particularly Molenbeek-Saint-Jean, Schaerbeek, Saint-Gilles, Koekelberg, Saint-Josse-ten-Noode, and parts of the City of Brussels, forming a continuous belt of elevated surface temperatures. In contrast, the southern and southeastern municipalities, including Uccle, Watermael-Boitsfort, Auderghem, and portions of Woluwe-Saint-Pierre, are predominantly characterized by low hazard levels. Moderate hazard conditions occupy a large proportion of urban fabric and are mainly distributed across municipalities such as Anderlecht, Forest, Ixelles, Etterbeek, Jette, Evere, and Woluwe-Saint-Lambert, creating a gradual transition between the highest and lowest hazard zones.



**Figure 5.** Spatial distribution of the Hazard (a), Exposure (c), and Vulnerability (e) in Brussels and their stacked columns of LCZ at different levels (b,d,f).

The LCZ-based analysis further demonstrates that thermal hazard is unevenly distributed among different urban morphologies. Compact Low-Rise (LCZ 3) exhibited the highest proportion of Very High hazard, accounting for 59.41% of its total area, followed by Compact Mid-Rise (LCZ 2) (47.27%), Water (LCZ G) (46.78%), and Open Mid-Rise (LCZ 5) (30.86%). Likewise, the High hazard class occupied more than 40% of Open Mid-Rise (46.59%), Open High-Rise (44.08%), Compact Mid-Rise (43.47%), and Scattered Trees (LCZ B, 40.97%), indicating that elevated thermal conditions are not restricted to a single urban form but occur across several LCZ categories.

Conversely, natural LCZs were generally associated with lower hazard levels. Dense Trees (LCZ A) recorded the largest proportion of Very Low hazard (31.25%) and the smallest proportion of High hazard (12.08%), reflecting the lower surface temperatures typically observed within densely vegetated environments. Open Low-Rise (LCZ 6) presented a more balanced distribution, with 32.90% of its area classified as Moderate hazard and only 14.01% as Very High hazard. Bare Soil or Sand (LCZ F) was dominated by the Moderate (59.52%) and Low (28.57%) hazard classes and did not contain pixels classified as either High or Very High hazard.

The observed hazard distribution is consistent with the thermal characteristics represented by the LCZ framework. Compact built-up LCZs are characterized by a larger proportion of high and very high hazard classes due to the greater capacity of impervious urban materials to absorb and store heat during summer daytime conditions. In contrast, densely vegetated LCZs exhibit predominantly low hazard levels owing to the cooling influence of vegetation through shading and evapotranspiration. The relatively high hazard observed within LCZ G (Water) reflects the thermal response of water surfaces during the daytime satellite overpass, where stored heat can result in elevated land surface temperatures despite their different thermal behavior compared with built-up environments.

### 3.3. Exposure Distribution Across Local Climate Zones

Figure 5c shows the spatial distribution of the exposure component, while Figure 5d presents the distribution of exposure classes across the different LCZs, revealing a pronounced urban–peripheral gradient throughout the Brussels Capital Region. The highest exposure levels are concentrated within the central municipalities, particularly the City of Brussels, Schaerbeek, Molenbeek-Saint-Jean, Saint-Josse-ten-Noode, Saint-Gilles, and parts of Ixelles and Etterbeek, where extensive areas are classified as high or very high exposure. In contrast, the lowest exposure levels are predominantly observed in the southern and southeastern municipalities, including Uccle, Watermael-Boitsfort, Auderghem, and Woluwe-Saint-Pierre, while moderate exposure is widely distributed across the intermediate urban belt, particularly within Anderlecht, Forest, Jette, Evere, and Woluwe-Saint-Lambert.

The LCZ analysis reveals clear differences in exposure among the various urban morphologies. Compact Low-Rise (LCZ 3) recorded the highest proportion of Very High exposure, with 53.31% of its total area classified within this category, followed by Compact Mid-Rise (LCZ 2) (30.17%) and Open Mid-Rise (LCZ 5) (18.46%). Similarly, the High exposure class was most prevalent within Open Mid-Rise (48.77%), followed by Compact Mid-Rise (38.68%) and Compact Low-Rise (31.01%), indicating that these urban forms contain the greatest concentration of highly exposed areas.

Conversely, natural LCZs were predominantly associated with lower exposure levels. Dense Trees (LCZ A) exhibited the highest proportion of Very Low exposure (47.50%) and only 0.15% of its area was classified as Very High exposure. Bare Soil or Sand (LCZ F) also displayed predominantly low exposure conditions, with 45.45% of its area classified as Very Low exposure and no pixels belonging to the Very High class. Open Low-Rise

(LCZ 6) was largely characterized by Moderate exposure (44.19%), whereas Water (LCZ G) presented a distribution concentrated within the Moderate (46.93%) and Low (22.86%) exposure classes.

The observed exposure pattern reflects the spatial distribution of the indicators used to construct this component, namely population density and the Normalized Difference Built-up Index (NDBI). LCZs characterized by compact and open urban development contain a greater proportion of high and very high exposure classes due to the simultaneous concentration of built-up surfaces and resident populations. In contrast, vegetated and sparsely occupied LCZs are dominated by low exposure classes, reflecting their comparatively lower population density and reduced built-up intensity.

### 3.4. Vulnerability Distribution Across Local Climate Zones

The spatial distribution of the vulnerability component as presented in Figure 5e, and the distribution of vulnerability classes across LCZs in Figure 5f, show that compared with the hazard and exposure components, vulnerability exhibits a more heterogeneous spatial pattern across the Brussels Capital Region. High and very high vulnerability levels are primarily concentrated within the central municipalities, particularly Molenbeek-Saint-Jean, the City of Brussels, Schaerbeek, and Saint-Gilles, where localized hotspots are clearly identifiable. Moderate vulnerability extends across much of the intermediate urban belt, including Anderlecht, Forest, Etterbeek, Ixelles, and Evere, whereas the southern and southeastern municipalities, notably Uccle, Watermael-Boitsfort, Auderghem, and Woluwe-Saint-Pierre, are largely characterized by low to very low vulnerability.

The LCZ analysis reveals distinct differences in vulnerability among the various urban forms. Compact Low-Rise (LCZ 3) exhibited the highest proportion of Very High vulnerability (15.92%), closely followed by Compact Mid-Rise (LCZ 2) (14.33%). These LCZs also recorded the greatest proportions of the High vulnerability class, representing 27.58% and 26.92% of their respective areas. Open Mid-Rise (LCZ 5) presented an intermediate distribution, with 22.44% of its area classified as High vulnerability and 30.79% as Moderate, while Open High-Rise (LCZ 4) was dominated by the Low (33.23%) and Moderate (28.70%) vulnerability classes.

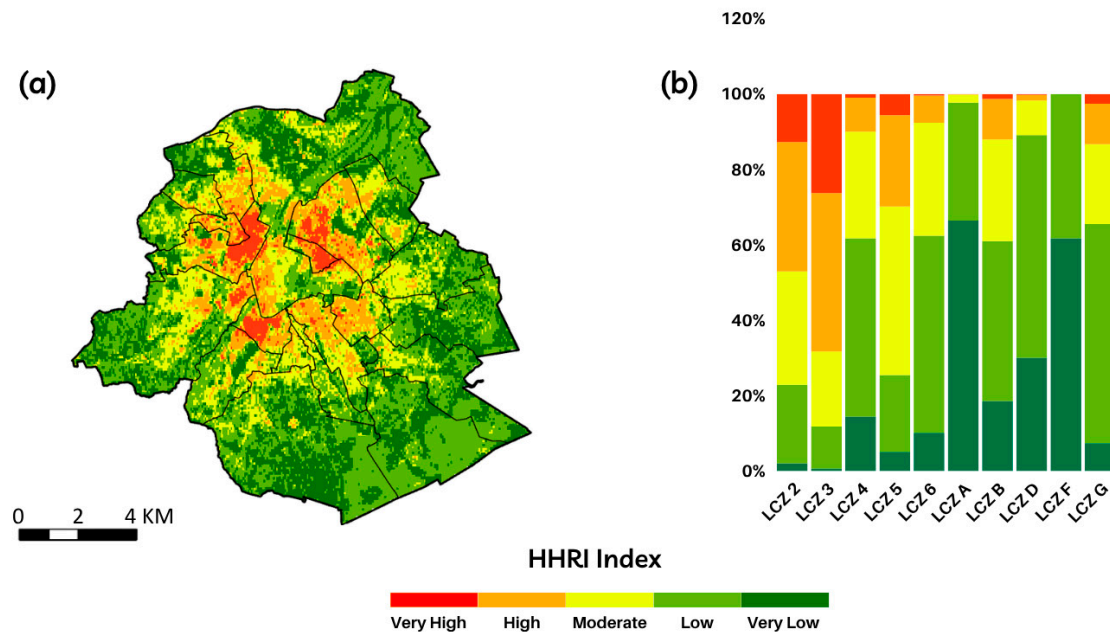
Natural LCZs were consistently associated with lower levels of vulnerability. Dense Trees (LCZ A) was primarily characterized by Low vulnerability (68.23%), with only 1.58% and 0.66% of its area classified as High and Very High, respectively. Similarly, Bare Soil or Sand (LCZ F) exhibited the lowest overall vulnerability, with 72.73% of its area belonging to the Very Low class and no pixels classified within either the High or Very High categories. Water (LCZ G) and Scattered Trees (LCZ B) also displayed predominantly low vulnerability levels, while Open Low-Rise (LCZ 6) showed a relatively balanced distribution, although nearly 69% of its area remained within the Very Low and Low classes.

The observed vulnerability pattern reflects the combined spatial influence of demographic sensitivity and environmental characteristics incorporated within the vulnerability component. Urban LCZs containing larger proportions of vulnerable population groups and lower environmental cooling capacity exhibit a greater share of high vulnerability classes, whereas vegetated and less densely occupied LCZs are predominantly associated with low and very low vulnerability levels. This spatial differentiation complements the hazard and exposure analyses and provides the final component required for the computation of the composite Heat Health Risk Index.

### 3.5. Heat Health Risk Index Across Local Climate Zones

The spatial distribution of the composite Heat Health Risk Index (HHRI) presented in Figure 6a, with the distribution of HHRI classes across the different LCZs in Figure 6b reveal

pronounced spatial variability across the Brussels Capital Region, highlighting localized heat health risk hotspots primarily within the central municipalities. The highest HHRI levels are concentrated in Molenbeek-Saint-Jean, the City of Brussels, Schaerbeek, and Saint-Gilles, with additional high-risk pockets extending into Koekelberg, Saint-Josse-ten-Noode, and parts of Ixelles and Etterbeek. In contrast, the southern and southeastern municipalities, including Uccle, Watermael-Boitsfort, Auderghem, and Woluwe-Saint-Pierre, are predominantly characterized by very low and low HHRI values, while intermediate risk levels form a transitional belt surrounding the urban core.



**Figure 6.** Spatial distribution of the HHRI in Brussels (a) and its stacked columns of LCZ at different levels (b).

The LCZ-based assessment demonstrates substantial differences in the distribution of heat health risk among urban morphologies. Compact Low-Rise (LCZ 3) exhibited the highest proportion of Very High HHRI, representing 26.28% of its total area, followed by Compact Mid-Rise (LCZ 2) with 12.71%. These two LCZs also recorded the largest proportions of the High HHRI class, accounting for 41.98% and 34.32%, respectively. Open Mid-Rise (LCZ 5) displayed a predominantly Moderate risk distribution (44.69%), with approximately one-quarter (24.17%) of its area classified as High HHRI, whereas Open High-Rise (LCZ 4) and Open Low-Rise (LCZ 6) were largely dominated by the Low and Moderate categories.

Natural LCZs consistently exhibited the lowest heat health risk levels. Dense Trees (LCZ A) recorded 66.45% of its area within the Very Low HHRI class, with only 0.12% and 0.04% classified as High and Very High, respectively. Likewise, Bare Soil or Sand (LCZ F) was almost entirely associated with Very Low (61.76%) and Low (38.24%) risk, with no pixels belonging to either the High or Very High categories. Low Plants (LCZ D) also remained predominantly within the lower HHRI classes, confirming a markedly different risk profile from the compact urban LCZs. The relatively high proportion of Very High hazard in LCZ G (46.8%) is consistent with the LST observations, in which water surfaces did not systematically exhibit the lowest temperatures across the analyzed summer scenes. This pattern may reflect the thermal inertia of water and its slower daytime thermal response relative to surrounding surfaces. Nevertheless, the LCZ G result should be interpreted cautiously, particularly considering the spatial resolution and potential influence of mixed pixels along water–land boundaries.

Compared with the individual hazard, exposure, and vulnerability components, the composite HHRI demonstrates a more spatially constrained distribution of high-risk areas. While elevated hazard or exposure may occur independently in several LCZs, the highest HHRI values are concentrated only where the three dimensions coincide, resulting in more localized yet more pronounced heat health risk hotspots. This integration emphasizes that elevated heat health risk is governed by the combined interaction of thermal conditions, population exposure, and vulnerability rather than by any individual component alone.

## 4. Discussion

### 4.1. Spatial Patterns of Heat Health Risk in Brussels

The results demonstrate that heat health risk is not uniformly distributed across the Brussels Capital Region but exhibits distinct spatial concentrations associated with the combined influence of thermal conditions, population exposure, and vulnerability. Unlike the hazard component, which primarily reflects the spatial distribution of land surface temperatures, the composite HHRI highlights areas where elevated thermal conditions coincide with highly exposed and vulnerable populations. Consequently, the highest HHRI values are concentrated within the central municipalities, particularly Molenbeek-Saint-Jean, the City of Brussels, Schaerbeek, and Saint-Gilles, whereas the southern and southeastern municipalities, including Uccle, Watermael-Boitsfort, Auderghem, and Woluwe-Saint-Pierre, consistently exhibit lower heat health risk.

The spatial differences observed between the hazard and HHRI maps highlight the importance of adopting a multidimensional assessment framework. Several locations characterized by elevated surface temperatures do not necessarily correspond to the highest heat health risk zones because heat hazard alone does not determine risk. Instead, the HHRI reflects the interaction between environmental conditions, the spatial distribution of the population, and demographic susceptibility. Areas exhibiting high hazard, but relatively limited population exposure or lower demographic vulnerability therefore display lower overall HHRI values, whereas municipalities where these three components overlap emerge as the principal heat health risk hotspots.

This distinction illustrates one of the main advantages of the HHRI framework over conventional temperature-based assessments. While land surface temperature provides valuable information regarding the spatial intensity of urban heat, it does not alone account for the spatial distribution of population exposure and vulnerability that contribute to potential heat health risk. By integrating hazard, exposure, and vulnerability within a single spatial framework, the HHRI enables the identification of priority intervention areas where the combined effects of thermal stress, population concentration, and susceptibility are greatest. Consequently, the resulting risk map provides a more comprehensive spatial representation of potential urban heat health risk than analyses based solely on thermal indicators.

The spatial pattern identified in Brussels also reflects the marked intra-urban variability that characterizes large metropolitan areas. Rather than exhibiting a simple center-to-periphery gradient, heat health risk is organized into localized hotspots surrounded by areas of moderate and lower risk. Such heterogeneity demonstrates the necessity of conducting analyses at fine spatial resolutions, as municipal-scale averages may mask substantial variations occurring within individual neighborhoods. The use of a 100 m analysis grid in the present study therefore provides a more detailed representation of local heat health conditions, allowing the identification of fine-scale priority areas that would remain undetected using coarser spatial resolutions. These findings demonstrate that the spatial distribution of heat health risk in Brussels is governed by the interaction of multiple environmental and demographic factors rather than by surface temperature alone. This

integrated perspective provides a spatial evidence base for identifying potential priority areas for climate adaptation and public health interventions and highlights the value of multidimensional heat health risk assessments for supporting urban resilience planning.

#### 4.2. Comparison with Previous Studies

Although no previous study has evaluated the Heat Health Risk Index (HHRI) across Local Climate Zones (LCZs) in Brussels, the spatial distribution observed in the present study is largely consistent with previous investigations of urban heat patterns in the Brussels Capital Region. Recent research has consistently identified the densely urbanized city center as the area most affected by elevated thermal conditions, while the extensive vegetated areas in the southeastern part of the region, particularly the Sonian Forest, act as important cooling zones [33]. These broad spatial gradients closely match the HHRI distribution obtained in this study, where the highest risk values were concentrated within compact urban LCZs and progressively decreased towards vegetated and less urbanized zones. This agreement suggests that the proposed HHRI framework successfully captures the underlying thermal structure of Brussels while extending previous work by incorporating population exposure and vulnerability into a single spatially explicit indicator.

Similarly, Verdonck et al. (2019) developed a heat-risk assessment for the Brussels Capital Region using the UrbClim model under different urban planning and greenhouse gas emission scenarios [32]. Their results showed that the highest heat stress and heat risk occurred in densely built urban areas, whereas lower-risk conditions were associated with vegetated zones and green corridors. They also demonstrated that compact LCZs consistently experienced higher thermal stress than natural LCZs and highlighted the mitigating role of vegetation in reducing urban heat exposure. The spatial patterns identified in the present study closely resemble these findings despite important methodological differences. While Verdonck et al. focused on future scenario modelling based on Heat Wave Degree Days (HWDD) and projected vulnerability, the present study provides a detailed, observation-based HHRI assessment using remotely sensed land surface temperature, demographic exposure, and vulnerability indicators at the LCZ scale. Consequently, the current research complements previous modelling efforts by offering the first empirical HHRI map for Brussels under present climatic conditions and demonstrates that the highest heat health risks remain concentrated within compact urban neighborhoods.

The spatial distribution of HHRI obtained in this study is consistent with the official urban heat island map produced by Bruxelles Environnement for the Brussels Capital Region [31]. The map identifies the densely built city center as the principal heat island, while the extensive vegetated areas, particularly the Sonian Forest in the southeast, constitute the main urban cooling zones. This agreement provides additional confidence in the ability of the proposed methodology to capture the spatial variability of heat exposure across Brussels.

The findings of this study are consistent with previous European research demonstrating that urban heat exposure is not solely controlled by temperature patterns but is also strongly influenced by demographic and environmental vulnerability. Similar to the study of Bhattacharjee et al. (2019) in Milan, areas characterized by greater social vulnerability exhibited higher levels of heat-related risk, reinforcing the importance of integrating socioeconomic indicators into urban heat assessments [34]. However, while the Milan study primarily relied on exposure, sensitivity, and adaptive capacity indicators at the district level, the present study extends this approach by incorporating LCZ and environmental variables within a unified HHRI, enabling a more detailed representation of how urban morphology contributes to spatial variations in heat health risk. Our results also support those reported by Ziliaskopoulos et al. (2024), who found that socioeconomic characteristics,

including ageing populations and housing conditions, are among the strongest determinants of heat vulnerability in Greece [35]. Likewise, the present study identifies population vulnerability as a major contributor to heat health risk. Nevertheless, unlike the Greek study, which focused predominantly on socioeconomic predictors using machine-learning techniques, our framework integrates environmental hazard and urban form alongside vulnerability, providing a more comprehensive assessment of heat health risk.

More recently, Alnajjar et al. (2025) demonstrated in Seville that socially disadvantaged neighborhoods experience substantially higher land surface temperatures than affluent areas and highlighted the combined influence of vegetation, built-up intensity, and spatial configuration on urban heat vulnerability [11]. The present findings are in agreement with these observations, as areas characterized by dense urban development and limited vegetation generally corresponded to higher heat health risk levels. However, whereas the Seville study employed Space Syntax to investigate spatial segregation and introduced the concept of Heat Boundaries, the present research adopts the LCZ framework to characterize urban morphology. Furthermore, while the Seville study focused primarily on urban heat vulnerability, the HHRI developed in this research explicitly integrates thermal hazard, environmental conditions, and population vulnerability into a single spatial indicator that directly supports urban planning. These comparisons suggest that although recent European studies increasingly recognize the importance of combining environmental and demographic dimensions of urban heat, the present study advances this body of research by integrating LCZ-based urban morphology, environmental indicators, and population vulnerability within a unified heat health risk framework.

#### *4.3. Influence of Local Climate Zones on Heat Health Risk*

The LCZ-based analysis demonstrates that urban morphology plays a fundamental role in shaping the spatial distribution of heat health risk in Brussels. Although all built-up LCZs exhibited varying degrees of heat health risk, the highest proportions of High and Very High HHRI were consistently observed in Compact Low-Rise (LCZ 3) and Compact Mid-Rise (LCZ 2), whereas Open Mid-Rise (LCZ 5) was predominantly characterized by moderate risk levels. Conversely, natural LCZs, particularly Dense Trees (LCZ A), Low Plants (LCZ D), and Bare Soil or Sand (LCZ F), were overwhelmingly associated with very low and low HHRI classes, confirming their important role in moderating urban heat health risk.

These findings are generally consistent with previous LCZ-based heat health risk studies, which have shown that compact urban morphologies tend to experience greater heat accumulation and consequently higher heat health risk than vegetated environments. Ma et al. (2023) and Yu et al. (2024) similarly reported that densely built LCZs exhibited the greatest heat health risk due to the combined effects of elevated surface temperatures, limited vegetation, and high population concentrations [36,37]. Likewise, Su et al. (2024) demonstrated that compact and mid-rise urban forms are particularly susceptible to the combined influence of thermal hazard and population exposure, emphasizing that urban morphology directly affects the spatial distribution of heat health risk [38].

A comparison with our previous assessment conducted in Algiers, Algeria [39] reveals both similarities and differences in the relationship between LCZs and heat health risk. In both cities, natural LCZs consistently exhibited the lowest HHRI values, confirming the important cooling function of vegetated environments regardless of climatic context. However, while Open High-Rise (LCZ 4) represented the highest-risk urban morphology in Algiers, the Brussels analysis identified Compact Low-Rise (LCZ 3) and Compact Mid-Rise (LCZ 2) as the most vulnerable LCZs. These differences likely reflect the contrasting urban structures, climatic conditions, and demographic distributions between the two cities.

Algiers, characterized by a hot Mediterranean climate and extensive high-rise residential developments, experiences stronger thermal stress within open high-rise environments. In contrast, Brussels exhibits a more compact historical urban fabric where dense low- and mid-rise neighborhoods coincide with higher population concentrations, resulting in greater composite heat health risk despite lower absolute temperatures.

The contrasting heat health risk patterns observed among LCZs can largely be explained by their morphological and biophysical characteristics. Compact urban forms, particularly LCZ 2 and LCZ 3, are characterized by dense building configurations, extensive impervious surfaces, and limited vegetation, which collectively enhance heat storage while reducing evapotranspirative cooling. Their relatively low sky-view factor further restricts nocturnal radiative heat loss, whereas reduced ventilation within dense street canyons limits convective heat dissipation. These processes promote the persistence of elevated surface temperatures and, when combined with higher population concentrations, contribute to increased heat health risk. In contrast, vegetated LCZs such as LCZ A and LCZ D provide effective cooling through shading and evapotranspiration, while their more open structure facilitates radiative and convective heat exchange, explaining their consistently lower HHRI values.

The comparison further demonstrates that the relationship between LCZs and heat health risk is not universal but depends on the interaction between urban morphology, climatic conditions, and the demographic and environmental characteristics incorporated within the HHRI framework. While the specific LCZs exhibiting the highest risk differ between Brussels and Algiers, both case studies consistently show that compact urban environments concentrate a larger proportion of high-risk areas, whereas vegetated LCZs remain effective urban cooling environments. This consistency across two climatically distinct cities supports the reliability and transferability of the proposed LCZ-based HHRI methodology.

#### *4.4. Urban Planning and Policy Implications for Heat Health Risk Adaptation*

The spatially explicit HHRI developed in this study provides a practical decision-support framework for climate adaptation by identifying not only where heat health risk is greatest but also the urban characteristics contributing to this risk. Unlike conventional heat maps that primarily depict thermal conditions, the HHRI simultaneously considers hazard, exposure, and vulnerability, enabling urban planners and public health authorities to prioritize interventions in neighborhoods where elevated temperatures coincide with highly exposed and vulnerable populations. This integrated perspective supports a more efficient allocation of adaptation resources and contributes to evidence-based urban resilience planning.

The incorporation of the Local Climate Zone (LCZ) framework further strengthens the operational value of the assessment by linking heat health risk to specific urban morphologies. The results indicate that compact urban forms, particularly Compact Low-Rise (LCZ 3) and Compact Mid-Rise (LCZ 2), consistently exhibit the highest heat health risk in Brussels. Consequently, adaptation measures within these LCZs should focus on reducing heat storage and improving outdoor thermal conditions through interventions such as increasing street tree cover, expanding pocket parks and green corridors, implementing green roofs and façades, and replacing conventional pavements with high-albedo or permeable materials. Such measures can reduce surface temperatures while simultaneously improving pedestrian thermal comfort.

In contrast, LCZs characterized by extensive vegetation, including Dense Trees (LCZ A) and Low Plants (LCZ D), were consistently associated with the lowest HHRI values. These areas therefore represent important urban cooling resources whose ecological and climatic

functions should be preserved within future urban development strategies. Protecting existing green infrastructure, limiting the conversion of vegetated land into built-up areas, and strengthening ecological connectivity between parks and urban forests may help maintain these cooling benefits while enhancing the resilience of surrounding neighborhoods.

Based on the observed heat health risk patterns, Table 2 summarizes the principal adaptation priorities for each LCZ, together with recommended mitigation strategies and their expected benefits. These recommendations are intended to support evidence-based urban planning by linking spatially explicit risk assessment with targeted climate adaptation measures.

**Table 2.** LCZ-specific heat health adaptation priorities.

| LCZ                            | Priority            | Recommended Adaptation                                                                                   | Expected Benefit                                                                      |
|--------------------------------|---------------------|----------------------------------------------------------------------------------------------------------|---------------------------------------------------------------------------------------|
| LCZ 3—Compact Low-Rise         | Very High           | Pocket parks and green corridors; permeable/reflective pavements; shading over pedestrian routes         | Lowered surface and near-surface temperatures in the highest-risk residential fabric  |
| LCZ 2—Compact Mid-Rise         | High                | Green roofs and façades; tree-lined street retrofits; high-albedo pavement replacement                   | Reduced daytime heat storage and improved nocturnal radiative cooling                 |
| LCZ 5—Open Mid-Rise            | Moderate            | Street tree planting; courtyard greening; preservation of ventilation corridors between blocks           | Enhanced convective heat removal and reduced peak exposure                            |
| LCZ 4—Open High-Rise           | Moderate–Low        | Reflective roofing; façade greening; shaded public space design                                          | Reduced building-scale heat gain and improved outdoor comfort                         |
| LCZ A/D—Dense Trees/Low Plants | Protective priority | Preservation of existing canopy cover; restriction of green-to-built conversion; ecological connectivity | Maintained cooling ecosystem service and UHI mitigation for surrounding neighborhoods |
| LCZ G—Water                    | Contextual          | Maintain riparian vegetation buffers; account for daytime thermal signature in hazard interpretation     | Preserved cooling function while avoiding hazard misclassification of water bodies    |

Beyond identifying adaptation priorities for individual LCZs, the proposed framework provides a practical interface between urban climate science and policy implementation. By explicitly linking heat health risk to urban morphology, the HHRI-LCZ approach enables municipalities to move beyond city-wide heat mitigation strategies toward spatially targeted interventions. This allows planners to prioritize neighborhoods where compact urban form, high population exposure, and social vulnerability coincide, thereby maximizing the effectiveness of limited adaptation resources. Such evidence-based prioritization is particularly relevant for the development of local Heat Action Plans, urban regeneration programmers, green infrastructure strategies, and climate adaptation policies within the Brussels Capital Region.

The proposed adaptation measures also contribute to the broader objectives of the urban energy transition. Increasing urban vegetation, expanding green roofs and façades, improving building envelopes, and introducing high-albedo materials not only mitigate urban overheating but can also reduce cooling energy demand during summer periods. By lowering outdoor and indoor temperatures, these interventions contribute to improved building energy performance, reduced electricity consumption for air conditioning, and enhanced urban resilience under future climate change. Consequently, the HHRI-LCZ

framework supports integrated planning approaches that simultaneously address public health, urban climate adaptation, and sustainable energy transitions.

Beyond its application in Brussels, the proposed methodology demonstrates considerable potential for transfer to other cities. Because the HHRI relies primarily on widely available satellite imagery, gridded population datasets, and standardized LCZ classification, the framework has the potential to be reproduced and applied in different geographical contexts without requiring extensive local datasets.

#### *4.5. Strengths, Limitations and Future Perspectives*

This study presents several methodological and practical strengths. First, to the best of our knowledge, it constitutes the first Heat Health Risk Index (HHRI) assessment conducted for Brussels and Belgium, providing a spatially explicit evaluation of heat health risk at a fine spatial resolution. Second, the integration of remotely sensed environmental indicators, demographic characteristics, and LCZs within a unified GIS framework enables a comprehensive representation of the multiple factors influencing heat health risk. Unlike conventional urban heat assessments based solely on temperature, the proposed framework simultaneously accounts for hazard, exposure, and vulnerability, allowing the identification of priority intervention areas rather than simply thermal hotspots. Furthermore, the use of standardized datasets and open-source spatial information enhances the reproducibility and transferability of the methodology to other urban environments.

Despite these strengths, several limitations should be acknowledged. The hazard component was represented using Land Surface Temperature derived from satellite imagery, which, although widely adopted in urban climate research, does not fully capture the thermal conditions experienced by individuals at pedestrian level. Another important limitation concerns the validation of the Heat Health Risk Index. Ideally, HHRI results should be evaluated against spatially detailed records of heat-related mortality, morbidity, or hospital admissions to verify their ability to identify populations experiencing adverse health outcomes. However, such health datasets are rarely available at appropriate spatial resolutions because of data privacy restrictions, limited accessibility, and inconsistencies in health reporting systems. Accordingly, the comparisons performed in the present study should be interpreted as a spatial plausibility and consistency assessment rather than as a formal epidemiological validation of the HHRI, since no observed heat-related health outcome data were available for Brussels. This limitation is shared by the majority of spatial heat–health risk assessment studies.

Additional limitations should nevertheless be acknowledged. The HHRI integrates datasets with different temporal references, including multi-year Landsat observations (2015–2023), population data from 2020, and the LCZ classification from 2023, and therefore does not represent a strictly contemporaneous snapshot or capture temporal variations in heat health risk across individual heatwave events or future climate conditions. Second, although the 100 m spatial resolution provides a detailed representation of intra-urban variability, resampling the original 30 m LST and LCZ datasets to the common 100 m analysis grid inevitably introduces spatial aggregation and smoothing, which may obscure fine-scale thermal and morphological patterns, particularly at LCZ boundaries and at the street or building scale. Finally, uncertainties associated with satellite-derived environmental indicators, gridded population datasets, and LCZ classification may propagate into the composite HHRI, as potential collinearity among LST, NDBI, and NDVI may introduce some redundancy because these indicators partly reflect common urban-form and land-cover characteristics; therefore be interpreted as a spatial decision-support tool rather than an exact prediction of heat health outcomes. Accordingly, the HHRI should be interpreted as a spatial indicator of potential heat health risk based on the combined

conditions of thermal hazard, exposure, and vulnerability, rather than as a direct measure of observed health impacts or individual-level thermal exposure.

Future research should focus on strengthening the proposed framework through the integration of additional environmental, demographic, and socioeconomic indicators. Variables such as household income, poverty rate, educational attainment, housing quality, employment status, social isolation, and access to healthcare services could further improve the representation of social vulnerability and provide a more comprehensive understanding of heat health risk. Incorporating dynamic population datasets and higher-temporal-resolution environmental observations would also allow a better representation of population exposure throughout the day.

As more detailed health datasets become available, future studies should prioritize the validation of HHRI using observed heat-related mortality, morbidity, emergency department visits, or hospitalization records, enabling a direct evaluation of the predictive capability of the index. Finally, applying the methodology across additional Belgian and European cities would facilitate comparative analyses of urban heat health risk, contributing to the development of standardized approaches for climate adaptation planning.

#### 4.6. Uncertainty Assessment

Beyond the qualitative limitations discussed in Section 4.5, several sources of uncertainty affect the quantitative outputs of the HHRI framework and should be considered when interpreting the results. Table 3 summarizes the main sources of uncertainty, their likely direction of influence, and their expected impact on the reported HHRI patterns.

**Table 3.** Sources of uncertainty in the HHRI framework.

| Source of Uncertainty                                               | Potential Influence                                                                                                                          | Expected Impact on Results                                                                                                                                                                                  |
|---------------------------------------------------------------------|----------------------------------------------------------------------------------------------------------------------------------------------|-------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| Satellite-derived LST (Landsat, ~30 m, single time-of-day overpass) | Captures only mid-morning/early-afternoon surface conditions; sensitive to atmospheric correction and emissivity assumptions                 | May underrepresent nocturnal heat-retention differences between LCZs; HHRI values should be interpreted as relative rather than absolute risk magnitudes                                                    |
| WorldPop census-derived population resolution (100 m, modelled)     | Redistributes census counts using ancillary predictors rather than direct enumeration                                                        | Localized over- or under-estimation of exposure, e.g., in high-rise or non-residential areas                                                                                                                |
| Raster resampling to the common 100 m grid                          | Aggregation/resampling of 30 m LST and native-resolution LCZ layers introduces smoothing                                                     | Sharp boundaries between adjacent LCZs may be blurred, moderating extreme values at LCZ edges                                                                                                               |
| Spatial aggregation of zonal statistics by LCZ                      | Mean values are calculated per LCZ, masking within-class heterogeneity                                                                       | Reported LCZ-level averages may obscure local variability within large or mixed LCZ patches                                                                                                                 |
| PCA-derived component weighting                                     | Weights reflect statistical variance in the sampled indicator set, not an independent measure of health relevance                            | Weights may shift if additional or alternative indicators are introduced, affecting the relative ranking of borderline LCZs                                                                                 |
| LCZ classification accuracy (OA = 0.89)                             | Classification performance may vary among individual LCZ classes, particularly between spectrally and morphologically similar urban classes. | Class-specific classification uncertainty may propagate into LCZ-based zonal statistics and affect comparisons among LCZ types; LCZ-level results should therefore be interpreted with appropriate caution. |

## 5. Conclusions

By combining PCA-weighted, multidimensional risk index with a standardized urban morphology classification, the proposed framework moves beyond conventional temperature-based heat mapping to support the identification of priority intervention areas where thermal hazard, population exposure, and social vulnerability coincide. The universal hazard-exposure-vulnerability structure and reliance on openly available datasets make the workflow potentially transferable to other temperate European cities, even though the specific indicators, weights, and thresholds should be recalibrated to local conditions. Beyond its scientific contribution, the HHRI-LCZ framework provides a practical decision-support tool for integrating heat health considerations into urban planning, climate adaptation strategies, and sustainable urban development policies. By linking heat health risk to urban morphology, the framework enables targeted interventions that can simultaneously improve public health resilience, enhance urban livability, and contribute to broader urban climate and energy transition objectives. Future work should prioritize epidemiological validation against observed heat-related health outcomes as such data become accessible, together with the extension of the framework to additional Belgian and European cities to support comparative, evidence-based climate adaptation planning.

**Author Contributions:** Conceptualization, D.C.Z., D.B., M.E.M. and S.A.; Data curation, D.C.Z.; Methodology, D.C.Z. and M.A.E.B.R.; Software, D.C.Z. and M.A.E.B.R.; Visualization, D.C.Z. and M.A.E.B.R.; Writing—original draft, D.C.Z.; Writing—review & editing, D.C.Z., M.E.M., D.B., T.W. and S.A. All authors have read and agreed to the published version of the manuscript.

**Funding:** This research received no external funding.

**Institutional Review Board Statement:** Not applicable

**Informed Consent Statement:** Not applicable.

**Data Availability Statement:** The data that support the findings of this study are available from the corresponding author upon reasonable request due to the large volume of the datasets and their ongoing organization and documentation as part of related research.

**Conflicts of Interest:** The authors declare no conflicts of interest.

## References

1. Klingelhöfer, D.; Braun, M.; Brüggmann, D.; Groneberg, D.A. Heatwaves: Does global research reflect the growing threat in the light of climate change? *Glob. Health* **2023**, *19*, 56. [\[CrossRef\]](#) [\[PubMed\]](#)
2. Huang, L.; Dong, Q.; Song, Y.; Tao, Y.; Shi, L.; Zhao, X.; Qi, J.; Song, Z.; Zheng, Z.; Zhang, G. Joint effects of urban heat island and global warming on heatwave risk. *Sustain. Cities Soc.* **2026**, *141*, 107270. [\[CrossRef\]](#)
3. Belkhiri, K.; Onescu, I.; Szitar-Sirbu, M.-A. Integrating Sustainability into Urban Planning: A Systematic Review of Policies Addressing Hazard Risks and Climate Change. *Sustainability* **2026**, *18*, 2068. [\[CrossRef\]](#)
4. Ebi, K.L.; Capon, A.; Berry, P.; Broderick, C.; de Dear, R.; Havenith, G.; Honda, Y.; Kovats, R.S.; Ma, W.; Malik, A. Hot weather and heat extremes: Health risks. *Lancet* **2021**, *398*, 698–708. [\[CrossRef\]](#) [\[PubMed\]](#)
5. Gabbe, C.J.; Mallen, E.; Varni, A. Housing and Urban Heat: Assessing Risk Disparities. *Hous. Policy Debate* **2023**, *33*, 1078–1099. [\[CrossRef\]](#)
6. Anderson, C.C.; Olafsson, A.S.; Romelli, C.; Albert, C. Assessing the equity of urban public green space visitation for cooling off from extreme heat: A public participation GIS (PPGIS) survey. *Urban For. Urban Green.* **2025**, *112*, 128989. [\[CrossRef\]](#)
7. Rohat, G.; Flacke, J.; Dosio, A.; Pedde, S.; Dao, H.; van Maarseveen, M. Influence of changes in socioeconomic and climatic conditions on future heat-related health challenges in Europe. *Glob. Planet. Change* **2019**, *172*, 45–59. [\[CrossRef\]](#)
8. Slesinski, S.C.; Matthies-Wiesler, F.; Breitner-Busch, S.; Gussmann, G.; Schneider, A. Social inequalities in exposure to heat stress and related adaptive capacity: A systematic review. *Environ. Res. Lett.* **2025**, *20*, 033005. [\[CrossRef\]](#)
9. Técher, M.; Haddou, H.A.; Aguejdad, R. Urban Heat Island's Vulnerability Assessment by Integrating Urban Planning Policies: A Case Study of Montpellier Méditerranée Metropolitan Area, France. *Sustainability* **2023**, *15*, 1820. [\[CrossRef\]](#)

10. Pappalardo, S.E.; Zanetti, C.; Todeschi, V. Mapping urban heat islands and heat-related risk during heat waves from a climate justice perspective: A case study in the municipality of Padua (Italy) for inclusive adaptation policies. *Landsc. Urban Plan.* **2023**, *238*, 104831. [\[CrossRef\]](#)
11. Alnajjar, S.; García-Martínez, A.; López-Cabeza, V.P.; Al-Azhari, W. A Multidimensional Approach to Mapping Urban Heat Vulnerability: Integrating Remote Sensing and Spatial Configuration. *Smart Cities* **2025**, *8*, 137. [\[CrossRef\]](#)
12. Sestito, B.; Reimann, L.; Mazzoleni, M.; Botzen, W.J.W.; Aerts, J. Identifying vulnerability factors associated with heatwave mortality: A spatial statistical analysis across Europe. *Environ. Res. Lett.* **2025**, *20*, 044025. [\[CrossRef\]](#)
13. Zhou, B.; Rybski, D.; Kropp, J.P. The role of city size and urban form in the surface urban heat island. *Sci. Rep.* **2017**, *7*, 4791. [\[CrossRef\]](#) [\[PubMed\]](#)
14. Yao, Y.; Lu, L.; Guo, J.; Zhang, S.; Cheng, J.; Tariq, A.; Liang, D.; Hu, Y.; Li, Q. Spatially explicit assessments of heat-related health risks: A literature review. *Remote Sens.* **2024**, *16*, 4500. [\[CrossRef\]](#)
15. Zhang, W.; Zheng, C.; Chen, F. Mapping heat-related health risks of elderly citizens in mountainous area: A case study of Chongqing, China. *Sci. Total Environ.* **2019**, *663*, 852–866. [\[CrossRef\]](#) [\[PubMed\]](#)
16. Estoque, R.C.; Ooba, M.; Seposo, X.T.; Togawa, T.; Hijioka, Y.; Takahashi, K.; Nakamura, S. Heat health risk assessment in Philippine cities using remotely sensed data and social-ecological indicators. *Nat. Commun.* **2020**, *11*, 1581. [\[CrossRef\]](#) [\[PubMed\]](#)
17. Zitouni, D.C.; Berkouk, D.; Matallah, M.E.; Ratmia, M.A.E.B.; Attia, S. Advancing Heat Health Risk Assessment: Hotspot Identification of Heat Stress and Risk Across Municipalities in Algiers, Algeria. *Atmosphere* **2025**, *16*, 484. [\[CrossRef\]](#)
18. Ye, J.; Yang, F. Towards multi-scale and context-specific heat health risk assessment—A systematic review. *Sustain. Cities Soc.* **2025**, *119*, 106102. [\[CrossRef\]](#)
19. Demoury, C.; Aerts, R.; Vanderinden, B.; Van Schaeybroeck, B.; De Clercq, E.M. Impact of short-term exposure to extreme temperatures on mortality: A multi-city study in Belgium. *Int. J. Environ. Res. Public Health* **2022**, *19*, 3763. [\[CrossRef\]](#) [\[PubMed\]](#)
20. Demoury, C.; De Troeyer, K.; Berete, F.; Aerts, R.; Van Schaeybroeck, B.; Van der Heyden, J.; De Clercq, E.M. Association between temperature and natural mortality in Belgium: Effect modification by individual characteristics and residential environment. *Sci. Total Environ.* **2022**, *851*, 158336. [\[CrossRef\]](#) [\[PubMed\]](#)
21. Ali, E.A.; Aerts, R.; Vaes, B.; Scheeren, C.; Beerten, S.G.; Van De Vel, K.; Duarte, E.; Van Pottelbergh, G. Health impacts of extreme heat in medically at-risk populations: A space-time stratified case-crossover analysis in Belgium. *BMC Public Health* **2025**, *25*, 3701. [\[CrossRef\]](#) [\[PubMed\]](#)
22. Dosio, A.; Migliavacca, M.; Maraun, D. How fast is climate changing? One generation is sufficient for unfamiliar heatwave characteristics to emerge in Europe. *Clim. Change* **2025**, *178*, 26. [\[CrossRef\]](#)
23. Ching, J.; Mills, G.; Bechtel, B.; See, L.; Feddema, J.; Wang, X.; Ren, C.; Brousse, O.; Martilli, A.; Neophytou, M. WUDAPT: An urban weather, climate, and environmental modeling infrastructure for the Anthropocene. *Bull. Am. Meteorol. Soc.* **2018**, *99*, 1907–1924. [\[CrossRef\]](#)
24. Open Spatial Demographic Data and Research, WorldPop. Available online: <https://www.worldpop.org/> (accessed on 2 May 2025).
25. USGS. Earth Explorer. 2024. Available online: <https://earthexplorer.usgs.gov/> (accessed on 1 March 2024).
26. Stewart, I.D.; Oke, T.R. Local climate zones for urban temperature studies. *Bull. Am. Meteorol. Soc.* **2012**, *93*, 1879–1900. [\[CrossRef\]](#)
27. Bondarenko, M.; Priyatikanto, R.; Garavito, N.T.; Zhang, W.; McKeen, T.; Cunningham, A.; Woods, T.; Hilton, J.; Cihan, D.; Nosatiuk, B. Constrained Estimates of 2015–2030 Total Number of People per Grid Square at a Resolution of 3 Arc (Approximately 100m at the Equator) R2025A Version v1. 2025. Available online: <https://eprints.soton.ac.uk/508534/> (accessed on 14 July 2026).
28. Esri. ArcGis Pro. 2023. Available online: <https://www.esri.com/fr-fr/arcgis/products/arcgis-pro/overview> (accessed on 10 March 2026).
29. Crichton, D. The risk triangle. *Nat. Disaster Manag.* **1999**, *102*, 102–103.
30. IPCC. Sixth Assessment Report. 2021. Available online: <https://www.ipcc.ch/assessment-report/ar6/> (accessed on 28 August 2024).
31. Îlot de Chaleur | Citoyen—Bruxelles Environnement. Available online: <https://environnement.brussels/citoyen/documentation-et-outils/etat-des-lieux-de-lenvironnement/ilot-de-chaleur> (accessed on 14 July 2026).
32. Verdonck, M.-L.; Demuzere, M.; Hooyberghs, H.; Priem, F.; Van Coillie, F. Heat risk assessment for the Brussels capital region under different urban planning and greenhouse gas emission scenarios. *J. Environ. Manag.* **2019**, *249*, 109210. [\[CrossRef\]](#) [\[PubMed\]](#)
33. Matallah, M.E.; Boulkaibet, A.; Arrar, H.F.; Wang, T.; Amaripadath, D.; Ahriz, A.; Amer, M.; Attia, S. Data-driven characterization of urban heat island intensity, heat wave, and heat stress interactions in Brussels: A field measurement study. *Sustain. Cities Soc.* **2025**, *135*, 106974. [\[CrossRef\]](#)
34. Bhattacharjee, S.; Gerasimova, E.; Imbert, C.; Tencar, J.; Rotondo, F. Assessment of different methodologies for mapping urban heat vulnerability for Milan, Italy. In *IOP Conference Series: Earth and Environmental Science*; IOP Publishing: Bristol, UK, 2019; p. 012162. Available online: <https://iopscience.iop.org/article/10.1088/1755-1315/290/1/012162/meta> (accessed on 14 July 2026).
35. Ziliaskopoulos, K.; Petropoulos, C.; Laspidou, C. Enhancing sustainability: Quantifying and mapping vulnerability to extreme heat using socioeconomic factors at the national, regional and local levels. *Sustainability* **2024**, *16*, 7603. [\[CrossRef\]](#)

36. Ma, L.; Huang, G.; Johnson, B.A.; Chen, Z.; Li, M.; Yan, Z.; Zhan, W.; Lu, H.; He, W.; Lian, D. Investigating urban heat-related health risks based on local climate zones: A case study of Changzhou in China. *Sustain. Cities Soc.* **2023**, *91*, 104402. [[CrossRef](#)]
37. Yu, W.; Yang, J.; Sun, D.; Xue, B.; Sun, W.; Ren, J.; Yu, H.; Xiao, X.; Xia, J.C.; Li, X. Shared insights for heat health risk adaptation in metropolitan areas of developing countries. *Iscience* **2024**, *27*, 109728. [[CrossRef](#)] [[PubMed](#)]
38. Su, R.; Yang, C.; Xu, Z.; Luo, T.; Yang, L. Assessment of Fine-Scale Urban Heat Health Risk and Its Potential Driving Factors Based on Local Climate Zones in Shenzhen, China. *ISPRS Int. J. Geo-Inf.* **2024**, *13*, 367. [[CrossRef](#)]
39. Zitouni, D.C.; Berkouk, D.; Matallah, M.E.; Ratmia, M.A.E.B.; Sharifi, A.; Attia, S. Machine Learning-Driven Mapping of Heatwave Health Risks Across Local Climate Zones in a Mediterranean Context. *Earth Syst. Environ.* **2026**, *10*, 4463–4482. [[CrossRef](#)]

**Disclaimer/Publisher’s Note:** The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.