THE HEAT DIVIDE

ASSESSING URBAN HEAT VULNERABILITY AND ITS SPATIALITY ACROSS BUDAPEST THROUGH GEOSPATIAL AND MULTIVARIATE ANALYSIS

By

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Abstract

As climate change is making heatwaves more frequent and intense in Central Europe, urban areas face a growing risk due to the heat-amplifying effect of urban land cover along with socio-economic and demographic vulnerabilities. However, robust analyses on the differential vulnerability of urban residents to extreme heat have been scarce. This study aims to fill this gap by developing a novel, spatially explicit, data-driven heat vulnerability index (HVI) for the subdistricts of one of the biggest Central European cities, Budapest, combining demographic, socio-economic and infrastructural indicators with spatially derived data on land cover, and temperature data from satellite observations. Using principal component analysis (PCA), six distinct vulnerability dimensions are identified, challenging the conventional integrated vulnerability assessment framework segmenting vulnerability to three components of exposure, sensitivity and adaptive capacity. To better understand vulnerability structures, cluster analysis was employed to identify areas with similar distinct vulnerability profiles, while a geographically weighted PCA (GWPCA) was applied to identify leading vulnerability factors in the subdistricts. While the findings clearly point to subdistricts where heatwave mitigation should take priority due to extreme vulnerability, the results also show that urban heat vulnerability is driven by a complex, spatially specific interaction of socio-economic, demographic, infrastructural and urban structural factors. By revealing the spatial complexities of heat vulnerability and identifying influential components, the study provides a more nuanced basis for designing heat adaptation policies tailored to the urban fabric and socio-economic geography of Budapest and other Central European cities.

Key words: HVI, principal component analysis, geographically weighted principal component analysis, PCA, GWPCA, urban climate, UHI, urban heat island, land surface temperature, geospatial analysis

AUTHOR’S DECLARATION

I, the undersigned, **Anna Eszter Kiszely**, candidate for the MSc degree in Environmental Sciences and Policy declare herewith that the present thesis titled “ The Heat Divide - Assessing Urban Heat Vulnerability and Its Spatiality Across Budapest Through Geospatial and Multivariate Analysis” is exclusively my own work, based on my research and only such external information as properly credited in notes and bibliography.
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I also declare that no part of the thesis has been submitted in this form to any other institution of higher education for an academic degree.

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1. Introduction

Due to human-induced climate change, the frequency and intensity of heatwaves has been increasing in the past decades and is projected to continue to do so in the next decades even if global CO2 emissions are stabilised (IPCC, 2021). While the frequency of extreme events is projected to increase larger-than-proportionally with warming globally, the growth in the intensity of heatwaves is predicted to increase most strongly in mid-latitude regions, including Central Europe (ibid.). Urbanisation has likely exacerbated the risk of heatwaves in cities in the past decades, especially regarding the growth in nighttime temperature extremes (Perkins et al., 2012). These growing temperature extremes in urban areas can greatly amplify the negative impacts of heatwaves as sustained and continuous exposure to high temperatures carries multiple health risks as well as lowers the life quality and productivity of the population. For example, Ballester et al. (2023) showed that during the one-week long heatwave of 2022, more than 11 000 people died of heat in Southern- and Central Europe alone, highlighting the special vulnerabilities of these regions regarding extreme heat. Aside from excess mortality, heatwaves also incur direct economic costs as the decreasing productivity is predicted to cost 0.5% of total GDP by the next decade in most European regions (Garcia-León et al., 2021). Risks of critical infrastructure failures furthermore amplify the potential damages, especially in the transport sector and public water network systems (Forzieri et al., 2018).

The negative impacts are particularly strongly felt in cities as land use and land cover forms in urban areas have heat-trapping properties due to low albedo, lack of impervious surfaces, greenery and water features, and reduced ventilation while heat emissions in cities from industrial and domestic sources further elevate local temperatures (IPCC, 2022). The resulting temperature difference between urban areas and surrounding rural land due to the combination of the aforementioned effects is defined as the urban heat island (UHI) effect (Oke, 1982). With increasing urban sprawl occurring in major cities, the UHI effect strengthens as ventilation between the urban cores and cooler rural surroundings lessens (World Bank, 2020, p.21). The UHI effect exacerbates heatwave risks as while in rural areas, the damage from the daytime temperature extremes might be mitigated by the better ability of surfaces to cool down during the night, urban building materials often prevent effective nighttime cooling due to the retention of heat, therefore driving a sustained exposure to high temperatures (IPCC, 2022). While water features can help reduce daytime extreme temperatures in their surroundings, it is predominantly green areas, especially those with dense vegetation, that might facilitate nighttime cooling (World Bank, 2020). On the other hand, poorly insulated buildings from materials with a high thermal mass can significantly exacerbate the effect on the city-level while also increasing the exposure to heat of their residents due to indoor temperatures (Zinzi et al., 2020). Additional to direct temperature differences, urban areas are more vulnerable to extreme heat due to high population density and the lower ability of residents to escape the heat.

In Central Europe, more frequent and more intense heatwaves are one of the most visible and detrimental impacts of climate change, with major cities increasingly preparing for a Mediterranean-like climate (Geletic et al., 2020, Huszár et al., 2016). As temperature extremes intensify, many Central European cities lag to adapt to the changing conditions as urban structures and urban planning in the region has formed with more temperate conditions in mind, historically omitting extreme temperature-adapting measures that are often historically rooted in Mediterranean cities such as light-coloured buildings or shading. The resulting vulnerabilities are amplified due to an aging population, making a higher share of the population sensitive to heat, and because of the structural inequalities that crowd sensitive or vulnerable populations in urban districts with higher temperatures and less cooling facilities. In the post-socialist countries like Hungary, the legacy of socialist residential policy of prefabricated housing block buildings also leaves its mark on heat vulnerability as panels built during the period and not retrofitted are often of poor material quality and create large heat-exposed surfaces, while the on-average large height of the buildings further exacerbates heat risk (Tirado Herrero and Ürge-Vorsatz., 2012, Brankovic et al., 2022). Heat vulnerability is further complexified with more sensitive populations such as low-income and elderly residents being more likely to live in such high-risk buildings. While substantial differences exist between major Central European cities in the progress towards heat adaptation and structural risk, there are many common heat vulnerability factors linked to the Central European urban structures, that imply that studies on heat risk and adaptation in major Central European cities can benefit urban planning in other urban areas in the region.

Budapest, the capital of Hungary is one of the largest Central European cities and faces a growing threat of extreme heat that is aggravated by the aforementioned structural vulnerabilities. Heatwave vulnerability has become extremely topical since the summer of 2024, during which the city experienced its most intense heatwave ever recorded from 07 July to 20 July, with temperatures mounting 38°C during the daytime peak and record high nighttime temperatures for an extended period of almost two weeks (Szabó and Pongrátz, 2024). While its impacts are yet to be quantified, this period of extreme heat is predicted to become regular in the next decades and thus, temperature patterns during the 2024 heatwave can inform urban planning on future heat risk.

The city is also a highly spatially diverse urban area with significant differences in both the thermal properties of urban structures and the vulnerability of residents to heatwaves. As the heatmap of the city in Figure 1 below shows, there are substantial temperature differences within the urban areas. The two main parts of the city on the two sides of the river Danube have foundationally different exposure to heat with the concrete-heavy, flat, and more populous Pest side being significantly more exposed to heat than the hilly, more scarcely populated and greener Buda side. Moreover, strong spatial disparities exist in the socio-economic and demographic characteristics of the population not only between the two sides of the city but also on a more local level within city districts. While these disparities alone imply a strong inequality in heat vulnerability across the city, these are further strengthened by the structural relationships that drive more sensitive or more vulnerable populations to live in urban areas that are exposed to more heat due to less greenery or poorer building materials, through for example housing pricing. These stark spatial differences imply that adaptation to heatwaves must follow a spatially diverse strategy which recognises the local drivers of heat vulnerability rather than treat Budapest as one unit in terms of heat vulnerability.

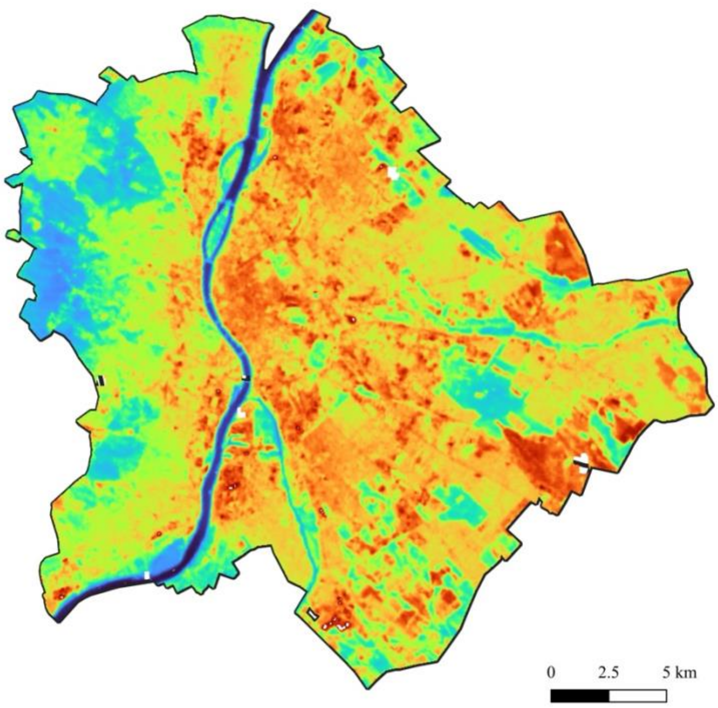


Figure 1: Heatmap of Budapest on the 12th of July, 2024 at 9:32 am. [2]

[2] Map created by author in QGIS, data sourced from LANDSAT-9 imagery through Google Earth Engine

Heat vulnerability itself is however a complex concept whose quantification requires the understanding of the components that make a system vulnerable to harm and assessing how these components might vary in different spatial contexts. While the concept is central in determining the risk of climate change-related hazards, it has been a term frequently debated in academia (Füssel, 2006). As discussed in the conceptual and theoretical framework section, this thesis employs the integrated vulnerability assessment framework that conceptualises vulnerability as the function how much a system is exposed to harm, its sensitivity and its capacity to adapt, as it offers a clear pathway to define vulnerability components and is in line with the majority of urban heat vulnerability literature. This framework has however been criticised for its reductionist understanding of vulnerability and implying the exogeneity of the exposure component, driving a significant conceptual development in the field allowing the recognition of complex components of vulnerability overarching these three dimensions. Data-driven methodologies can facilitate the building of vulnerability indices that move beyond the categorisation of variables based purely on the three pillars by recognising patterns in data structures that suggest the grouping of certain variables, together revealing dimensions of vulnerability related to multiple pillars, such as the characteristics of the built environment and the socio-economics of its dwellers, or heat-reducing household appliances in the buildings and their characteristic user groups.

1.1 Problem statement and research questions

Employing this holistic understanding of vulnerability and exploiting the potential benefits of data-driven vulnerability analysis, this research aims to examine the patterns of the danger from extreme heat in the city of Budapest, paying special attention to the spatiality of vulnerability and how accounting for this spatiality improves our understanding of what drives heat vulnerability in the city. As previous work on the spatially fine-level examination of heat vulnerability in Budapest and in Central European cities has been scarce, it aims to fill this gap by employing a robust, data-driven methodology to quantify heat vulnerability on the spatially fine subdistrict level, combining different spatially constant and spatially explicit methods of cluster analysis and principal component analysis (PCA). Specifically, the research aims to answer the following research question and sub-question:

RQ: How does the vulnerability of residents to extreme heat differ across the subdistricts of Budapest?

Sub-question 1: What vulnerability typologies can be identified across the city's subdistricts?

Sub-question 2: What relationships exist between the extreme heat vulnerability indicators of subdistricts, and how does this inform urban planning options to reduce heat vulnerability in the city?

1.2 Structure overview

The rest of the research proceeds as follows: the next section briefly discusses the theoretical and conceptual framework employed, explaining how the complex understanding of the concept of vulnerability facilitates the examination of local-level compound vulnerability factors. The third section then thoroughly reviews the current state of literature in the globally well-researched field of urban heat vulnerability and discusses in depth the breadth of research to date conducted in the Central European region. The literature review ends with a close look at heat vulnerability research in Budapest and identifies a significant research gap due to the shortcomings of previous publications. The fourth section details the methodology, including methods to acquire and process data, and methods of data analysis by employing cluster analysis, and global and geographically weighted principal component analysis, reflecting on the potential biases and shortcomings of the chosen methodologies. Section 5 presents the results of the analysis, starting with the groups identified by cluster analysis, through the PCA-derived heat vulnerability index answering the main research question, to presenting the results of the geographically weighted PCA in better explaining vulnerability patterns. Then, the discussion section follows, contextualising the most important results, relating findings to the literature, and discussing the implications for urban planning policy. The discussion also reflects on the limitations of the study and suggests path for future research before the conclusion summarises the paper.

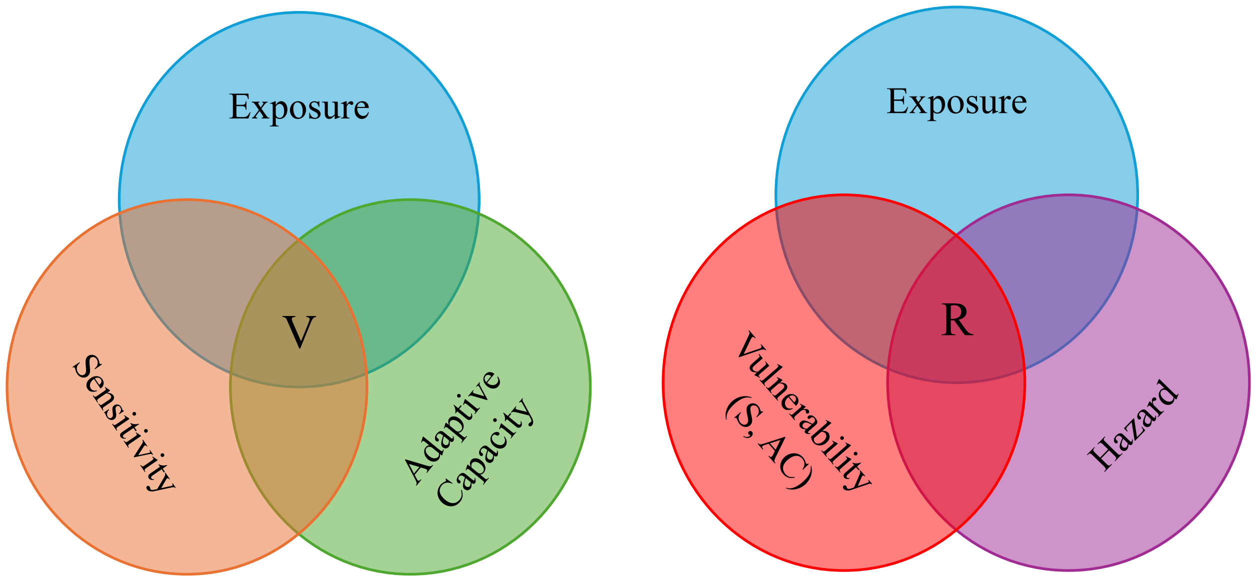
2. Theoretical and Conceptual Framework

With the aim of a robust analysis on the differential vulnerability of the residents of Budapest to extreme heat, this research adpots the Integrated Vulnerability Assessment (IVA) as its conceptual framework, while allowing for the adoption of more interconnected and multidimensional pillars to vulnerability than the traditional three factors of exposure, sensitivity, and adaptive capacity would suggest. The following paragraphs state the rationale for such a conceptual framework while reflecting on its theoretical grounding.

Climate change-related vulnerability is a complex term that encompasses a variety of theoretical lenses such as environmental justice, socio-ecolocial systems theory and resilience theory. At the start of the century, the IPCC defined vulnerability as "(…) a function of character, magnitude and rate of climate variation to which a system is exposed, its sensitivity and its adaptive capacity" (IPCC, 2001, 388.). Building on this definition, a standard method of determining vulnerability was developed by Wilhelmi and Hayden (2010) through the population vulnerability equation, quantifying vulnerability as the summation of exposure to harm and sensitivity, reduced by the adaptive capacity of the system to cope with it (Turner et al., 2003). Exposure in this framework captures to external environmental factors such as elevated temperatures, constrained access to greenspaces or buildings with poor thermal properties but also population density, while sensitivity is understood as the susceptibility of individuals due to health status, or cultural and behavioural patterns, potentially related to socio-economic status. Third, adaptive capacity refers to the adaptability of the residents to lessen the negative impacts, either through cooling their own homes using air conditioning, moving to nearby greenspaces or cooling centres, but the dimension can also capture the knowledge, awareness and practices of the population to cope with the dangers of extreme heat (Foroutan et al., 2024).

While these three pillars are permanent building blocks of vulnerability studies, the understanding of the interconnectedness and relationships between them has evolved significantly in the past decades. The IPCC's 2001 definition of the concept described the three factors as separate pillars, with exposure crucially understood as an exogeneous natural factor whose impact might be aggravated by sensitivity and/or alleviated by adaptive capacity (IPCC, 2001). This separation between the exogeneous natural hazard and the internal, anthropogenic dimensions of sensitivity and adaptive capacity however fail to integrate the three factors as co-contributors of vulnerability which might reduce or increase the impacts through a variety of complex interactions (Füssel and Klein, 2006).

The need for integrating the three dimensions thus led to the development of the intergated vulnerability assessment framework, moving towards an interdisciplinary approach, combining studies of impact and adaptation and harmonising the impacts of climate change with specific other environmental and socio-economic stressors forming vulnerabilities (Adger, 2006). Along with the fading exogeneity of the exposure factor, it was however also increasingly recognised how the impacts are triggered by partially exogeneous hazards whose chance and intensity of occurrence forms a risk that fundamentally defines the need for adaptation. The inclusion of the hazard element in the assessment of potential impacts therefore drove a paradigm shift from the vulnerability framwork to the risk triangle framework in which the exposure element is separated from vulnerability, and the three factors of hazard, exposure and vulnerability together form the systemic risk to be assessed (Estoque et al., 2023).



3 *Figure 2: Visualisation of the vulnerability and the risk frameworks.*

This shifting understanding was first signalled in the IPCC's 5th assessment report but was fundamentally unchanged in the revised vulnerability definition of the 6th assessment report: The 2022 definition states that vulnerability is " (…) The propensity or predisposition to be adversely affected. Vulnerability encompasses a variety of concepts and elements including sensitivity and susceptibility to harm and the lack of capacity to cope and adapt" (IPCC, 2022, 2927.), while they defined risk as the result of the "interaction of vulnerability, exposure, and hazard" (IPCC, 2022, 2921.), clearly implying a shift from the vulnerability to the risk framework where the exposure factor is separated and excluded from the concept of vulnerability. In this framework, exposure is independent of the environmental hazard and encompasses only the "presence of people, livelihoods, species or ecosystems, (…) in places and settings that could be adversely affected" (IPCC, 2022, 2911.). Estoque et al. (2023) show that this shift in the understanding of vulnerability has not been well adopted in academia and call for a clarification from the IPCC as to whether the new conceptualisation means a full nullification of the vulnerability framework.

[3] Source: own figure adopted from Estoque et al., 2023

In a study that aims to quantify vulnerability, it is however necessary to conceptualise the term in a pragmatic way that allows for the dimensions of vulnerability to encompass all theoretically plausible factors that might drive differential impacts of a climatic phenomenon. The need to account for hazard-specific characteristics is also recognised, as shown by Karanja et al (2025) who argued that the general nature of most heat vulnerability assessments significantly reduces their ability to accurately capture potential negative impacts during an extreme event. In the context local-level risk analyses however, the quantification of differential hazard frequency could easily become redundant when the area or region studied is not extensive and exogeneous climatic factors are feasibly assumed to be uniform. Furthermore, in the context of urban heat, the delineation of hazard and exposure can fundamentally be questioned on the intra-urban scale as hazard intensity, shown by temperature differences, it is not only anthropogenically triggered but directly modified through urban form and emissions, factors that are inseparable from socio-economic dimensions. Temperature differences within a city during a heatwave are therefore operationalised as differences in exposure. Because of this conceptualisation and the redundancy of the study of spatial variations in hazard intensity, it is argued that the vulnerability framework offers a more context-appropriate and pragmatic analytical lens to answer the research question.

The shortcomings of this three-pillared framework are however acknowledged, driving the study's methodology to enable the recognition of different key pillars of vulnerability that might encompass various elements of exposure, sensitivity, and adaptive capacity.

A nuanced conceptual understanding is however not yet sufficient to accurately capture differences in vulnerability without accounting for the inherently spatial nature of its contributing factors. As Tobler (1970, p. 236) defines in the first law of geography, phenomena are always related but those who are nearer will likely be more related than those distant from each other; on a fine spatial level in one urban area, such relations between the spatial units might become crucial in explaining vulnerability differences.

This spatial dependency is especially crucial to account for when considering physical geographical but also demographic or socio-economic factors as variables like temperatures, average age of the population or income is likely non-randomly distributed across space and might exhibit strong clustering or dispersal characteristics (Aldstadt, 2010). Analysing such spatially dependent variables using spatially constant methodologies might thus obstruct local-level variations in factors, and fail to explain locally important drivers of vulnerability, crucially hindering effective urban planning responses to reduce heat stress (Fotheringham et al., 2002). Inaccuracies from omitting spatial considerations may be especially pronounced at finer spatial scales, as assuming constant relationships between variables across the dataset effectively aggregates local-level variation to the city level (Rasanen et al., 2019). This can aggravate the Modifiable Areal Unit Problem (MAUP), which highlights that analysis results are highly sensitive to the spatial units used for data aggregation (Wong, 2009).

Incorporating spatially explicit methods in the analysis of vulnerability differences across the subdistricts of Budapest is thus a theoretically and conceptually crucial step at recognising the local drivers of vulnerability, adding another dimension to the IVA framework. While the fast-evolving family of geographically-weighted methodologies have been used in various contexts to analyse spatially dependent relationships (e.g. Harris, 2011, Lloyd, 2010, Graziano and Gillingham, 2014), there are few studies to date that explicitly employ spatial methods to assess heat vulnerability (Foroutan et al., 2024). Incorporating a geographically weighted principal component analysis methodology for the heat vulnerability assessment of Budapest subdistricts is therefore a significant step in the conceptual understanding of vulnerability as spatially non-uniform and dependent on local variations.

3. Literature review

The complexity of heat vulnerability calls for a structured review of relevant literature, covering key conceptual and methodological contributions and region-specific studies on urban heat and heatwave vulnerability. The literature review was conducted using a snowballing approach as referenced works and connected research to key studies of interest are reviewed; this approach also enables assessment of review completeness, as the appearance of new studies citing previously identified works indicates that key literature has been covered.

2.1 Urban microclimates and heatwaves

As the intensity and frequency of extreme heat events in urban areas is increasing, the importance of understanding the patterns of heat becomes indispensable to tackle the risks; there has been a significant effort in academia therefore to understand the relationship between the long-observed urban heat island (UHI) effect and extreme heat and how different urban forms might modify the geography of heat. The UHI has been shown to be induced by a number of factors including anthropogenic heat emissions from transport and buildings, and physical structures of the built environment such as street canyon geometry and impervious surface shares, making its interaction with exogeneous extreme heat conditions complex (Voogt and Oke, 2003). Several built environment typologies have been created with the aim of capturing the thermal properties of the built environment; as a notable example, Stewart and Oke (2012) developed the local climate zone classification, categorising urban forms into 17 groups based on land cover and land use, capturing building density and building height to capture spatial patterns of urban microclimates. Using this categorisation, Demuzere et al. (2019) created a publicly available dataset mapping European cities into local climate zones. The relationship between the local climate zones and temperatures have been studied extensively and in various regional contexts (Li et al., 2022); it has for example been shown by Gilabert et al. (2021) that the zone of large low-rise buildings is associated with the highest temperatures in Barcelona, and the same was shown by Olivares et al (2025) for Arica, Chile. In the context of Central Europe, Geletic et al. (2018) showed that the same zone, along with three other highly built up zones is associated with the highest level of thermal discomfort in Brno, Czechia. These findings point to the special relevance of the study of heat vulnerability in Budapest since the city's landscape is dominated by the large low-rise building zone, elevating exposure to heat (Demuzere et al., 2022). The potential of using the local climate zone mapping for heat vulnerability modelling and optimal urban planning has also been discussed as a tool to capture the thermal properties of the built environment, although this first requires a robust assessment of the LCZ-temperature relationships that might be highly time- and location-specific (Verdonck et al., 2018, Lehnert et al., 2021).

A wide range of research has considered specific urban forms and their effects on temperatures, especially those thought to reduce heat stress. Although blue infrastruture generally, and natural water bodies especially are important in mitigating extreme temperatures, the high thermal intertia of water causes inner city water bodies to increase the UHI effect because of their slow nighttime cooling and consequential release of heat during the night (Ward et al., 2016) Furthermore, while the influence of many single land cover types aggravating the UHI effect such as sealed surfaces and areas with high buildings is clear due to their thermal absorption and inability for nighttime cooling, the heat reducing effect of urban greenery is not unequivocal; on the one hand, Iungman et al (2023) estimated in 93 European cities that increasing tree cover to 30% would have a cooling effect of 0.4°C and could consequently prevent approximately 1.84% of all summertime premature deaths, and Marando et al (2022) found that green areas reduce the temperature by 1.07°C in the examined European cities. On the other hand, Dugord et al. (2014) showed non-forested urban greenspaces can in fact contribute to the UHI effect due to the possibility of drying grass which expose the area to unconstrained solar radiation. Jaganmohan et al (2016) also emphasise the importance of vegetation density, type and quality in the greenspace cooling effect, showing that smaller but high-quality, forested and densely vegetated greenspaces might have stronger and further reaching cooling effects than their larger but more sparsely vegetated counterparts. Delgado-Capel et al (2024) also highlight the different thermal properties of tree cover and patches of herbaceous vegetation or grass using empirical evidence from the Mediterranean, implying that the incorporation of tree planning in pedestrian areas and traditional urban squares would be able to reduce thermal stress, potentially to a greater extent than the forming of extensive urban parks with only grass cover. These findings, apart from having clear implications for urban policy, also point to the importance of accounting for various forms of greenery when analysing exposure differences. The relationship between UHI and heatwaves is furthermore a crucial and often overlooked aspect of heat vulnerability studies. Many estimate exposure differences using temperature data from summer days without considering whether the time of the observation was that of extreme climatic conditions, although the patterns of heat might be significantly different at times of heatwaves than in non-event days in the city (Li et al., 2011, Richard et al., 2021). This is not only due to the clear sky conditioning enabling an extreme trapping of heat by impervious and low-albedo surfaces and the increased heat emissions due to air conditioning use, but also due to the frequent co-occurrence of droughts that affect soils and greenspaces and their ability to mitigate the extreme heat (Possega et al., 2022). As an example in the context of Europe, Ward et al (2016) analysed the relationship between UHIs and heatwaves in 70 European cities using regional climatic data, landscape classifications and two population metrics, showing the compound effect of the UHI and the added heat stress due to extreme heat conditions compared to average summer days temperatures. A crucial finding of theirs is that cities with larger share of centrally located greenspaces seem to be affected by more additional heat during heatwaves compared to non-event days, while Southern European cities that are more frequently affected by heatwaves seem to be better adopted and experience lower additional heat during heatwaves than urban areas in cooler climates. Posega et al. (2022) furthermore show that the UHI intensity is aggravated during heatwaves especially during the night, forming extreme nocturnal heat islands, which points at the importance of analysing nighttime temperature patterns as well as daytime heatmaps when analysing vulnerability differences.

2.2 Urban heat vulnerability: a review of existing methodologies and concepts

Effects of the UHI on human discomfort, adverse health outcomes and productivity reudction have been extensively researched, as well as the impacts of added stress during heatwaves (Scherer et al., 2013, Kovats and Hajat, 2008). A large strand of literature has focused on the qualitative assessment of urban heat stress, studying the lived experiences of those working in heat-exposed occupations and live in low-income households (Palinkas et al., 2022, Dodd et al., 2023, Zografos et al., 2016), those with limited coping capacity (Guardaro et al., 2022, Kiarsi et al., 2022, Wolf et al., 2010), and those extremely sensitive to heat (Scorgie et al., 2023). Regarding the detrimental impacts, the estimation of the mortality effects of heatwaves in urban areas has been a key focus of quantitative studies since an accurate measurement is indispensable for the estimation of heat damage and is a complex task due to the potential mortality displacement effects (Cheng et al., 2018). Premature deaths due to heatwaves are also a key indicator for the validation and controlling of vulnerability studies as they can help confirm findings on the spatial differences in heatwave vulnerability (Li et al., 2022). Niu et al. (2021) for example critique existing heat vulnerability assessment methods on the grounds of a weak relationship between excess mortality and vulnerability results in thirteen samples studies. Due to the complexity of the negative impacts however, it is questionnable whether such a measure is capable of capturing vulnerability differences within cities (Zuo et al., 2015), and yet robust alternative methodologies for validating vulnerability assessments have not yet emerged (Niu et al., 2021).

Apart from the identification of impacts, the assessment of vulnerability differences has also developed to be a key research field, although Karanja et al. (2025) crucially notes that despite the number of empirical studies and conceptual reviews, no standardised methodology or framework to assess heat vulnerability exists yet. It was Reid et al (2009) who first outlined the heat vulnerability index (HVI) based on the population vulnerability framework, with its three pillars of exposure, sensitivity, and adaptive capacity. Quantifying vulnerability to extreme heat on the census tract level, the study highlighted priority areas for mitigation policies. Li et al (2022) provide a systematic review of heat vulnerability assessment methods and show that the past ten years have shown an upsurge of studies in the field, with the majority of assessments focuing on North America and Asia, but also a significant portion on Europe. Furthermore, they also highlight that studies have mainly centred on locations with warm temperate climate, to which Budapest is also often classified in new climate maps due to the changing climatic conditions (Beck et al., 2018). It is shown that vulnerability assessments mostly include a highly variable subjectively selected set of indicators, although these are largely overlapping across the studies; temperatures, and demographic and socio-economic characteristics such as elderly population and inocome status are the most frequently included while various other measures of health characteristics, and environmental factors related to the built environment or external weather conditions are considered depending on local contexts (Romero-Lankao et al., 2012).

Most vulnerability assessments aim for an index depicting local heat vulnerability, derived mostly through the vulnerability framework and less often by the risk triangle framework, while some built new indices using expert-based categorisation of factors (Li et al., 2022). For the index creation, one of the most crucial elements is the choice of the weighting method, as it substantially affects results and should reflect the variables' relative importance in driving vulnerability differences. The equal weighting method is often used due to the simple interpretability of the results, but requires the assumption that the factors all capture mutually independent and equally contributing factors of vulnerability . This assumption however has limited theoretical grounding and makes the resulting index extremely sensitive to the number of variables used in each category (Bao et al., 2015). A more theoretically robust method has been the weighting of indicators based on expert judgement through established methods such as the Delphi method (Rasanen et al., 2019). Another key methodology to evade the arbitrariness of equal weighting has been the principal component analysis (PCA), a statistical approach that derives weights from the data itself by identifying mutually uncorrelated dimensions – principal components – from the co-variance structure of the data, explaining the most of the variance in the dataset. This methodology has been found attractive due to its data-driven nature and consequential partial objectivity, although its input sensitivity still implies that careful selection of input variables is needed to deliver robust results. Furthermore, while it might address the theoretical weakness of equal weighting, it might shift the bias of weighting from arbitrary normative assumptions to the correlation structure of the data itself as variables are grouped into components that do not necessarily reflect theoretically grounded dimensions of vulnerability. Conlon et al. (2020) aimed to eliminate this bias by employing a supervised PCA method, where only variables that had significant correlation with mortality rates in Detroit, USA were included in the analysis, and only then performed the PCA, and found that the resulting heat vulnerability patterns differed significantly from the unsupervised (standard) PCA results, alhough the supervised PCA could only provide marginally better interpretable components. Through these results, the study posed a well-founded critique to the use of PCA for heat vulnerability assessments, highlighting the need for the careful interpretation of the resulting components to understand the factors of vulnerability. This might be a difficult task as studies employing PCA often found that the resulting components grouped together variables that might have been positively correlated with each other, but form fundamentally different factors of vulnerability; one example of the study of Johnson et al. (2012), who found that an important component of heat vulnerability in the USA is the most heavily influenced by temperatures and the proportion of black population, a finding that importantly shows the structural relationship between people of colour living in urban areas that experience more heat, but fails to explain how these two variables form one theoretically valid and coherent component of vulnerability.

In an attempt to compare the effectiveness and accuracy of the above methods, several studies have employed both equal weighting and PCA methods and analysed the differences in results. With regards to excess mortality due to heat, Liu et al. (2020) for example found that the HVI created with the EW method performed better than the PCA-created index. On the other hand, Tate (2012) found using a sensitivity analysis that PCA gave more precise results and gives better output stability than equal weighting. Studying heat vulnerability across local climate zones and census tracts in Arica, Chile, Olivares et al (2025) find that the EW- and PCA-derived HVI index together reveal the most heat vulnerable areas of the city but show significant differences in vulnerability patterns in other areas of the city, with both systematically overestimating vulnerability in distincts regions of the city. Guo et al. (2019) on the other hand found completely different heat vulnerability patterns using the two methods in Beijing, China, calling for caution in the interpretation of indices generated through one method. The findings resulting from these comparative studies have a crucial implication for the use of the PCA; while HVI indices generated through the PCA method might be harder to interpret due to components comprising of multiple variables, understanding how the individual component scores compare across the studied spatial units is key to reveal the potential biases in the allocation of high HVI values as certain components might cause large divergences in the HVI in case variables with extreme variation are weighted heavily.

Aside from weighting methods for the index, the spatiality of vulnerability assessment calls for an understanding of the spatial structure of data and the inclusion of spatial variables to the indicators. Surprisingly, geospatial methods have not been extensively used in the heat vulnerability literature, with Li et al. (2022) showing that less than 10% of their assessed studies used GIS techniques to assess and visualise heat vulnerability differences. Understandably, temperatures are the most commonly included GIS-derived variable, with the majority of studies using remote sensing data to derive land surface temperature averages on the chosen spatial unit for the temperature variable. GIS techniques have sometimes been used for the combination of the variables into the HVI index, such as by Sidiqui et al (2022), who assess heat vulnerability through an a combination of population mobility and accessibility to cooling facilities and greenspaces, urban heat island intensity maps, and sensitive populations. Based on expert weighting, the study overlays the variable layers in two steps to obtain the final HVI maps. In assessing heatwave vulnerability in Hangzhou, China, Sun et al (2022) combined census data with various spatially derived proxies such as nighttime light time intensity, green- and blue infrastructure coverage and medical infrastructure accessibility to calculate their socio-economic vulnerability index and conducted hotspot analysis to identify the spatial clustering characteristics of vulnerability. The study however used no explicit weighting methodology as variables were aggregated to the exposure, sensitivity, adaptive capacity pillars, implicitly assuming that the variables in each dimension contribute equally.

The consideration of spatial effects in heat vulnerability beyond the inclusion of spatial variables is crucial to capture the spatial patterns, as discussed in Section 2. Although geographically weighted methodologies have been extensively applied in studies of pollution exposure, land cover change, and urbanisation, heat vulnerability has not much applied these methods. An important exception is the work of Foroutan et al. (2024), which was the first to apply geographically weighted principal component analysis, using the method to understand the patterns of heat vulnerability in Philadelphia. Combined with an innovative geospatial big data approach that considered daily population mobility instead of constant population density metrics, the study employed a geographically constant PCA to derive a HVI, identifying components of exposure, sensitvity and adaptive capacity and aggregating them according to the population vulnerability equation, showing general patterns of heat vulnerability in the city. In the following, a geographically weighted PCA was applied which determines components locally, allowing for showing the variation in locally important drivers of vulnerability and showing where the PCA performs more accurately in analysing the data. Foroutan et al. (2024) found that vulnerability is driven by significantly different factors in different parts of the city, with exposure dominating in the central areas, and sensitivity leading vulnerability in the Western areas. Their findings are crucial in showing the importance of applying geographically weighted methods in order to understand heat vulnerability patterns beyond a hierarchical ranking and analyse which variables contribute, with important implications as to how strategic urban planning can introduce locally designed plans to reduce vulnerability. While the aggregation of components into the three components in the spatially constant PCA to derive the HVI can be criticised as a reductionist approach to understand the PCA results, the study's geographically weighted methodology serves as a key methodological reference for this study, likewise employing a spttially constant and a geographically weighted PCA to understand heat vulnerability patterns in Budapest, while aiming to conceptually develop the methods by allowing for more flexibility in the interpretation of PCA components beyond the traditional three-pillared framework.

2.3 The urban climate of Budapest

While the UHI effect in Budapest has been shown in the early 1970s, Probáld (2014) notes that not much research has considered the changes in the urban climate of the city since then. The study reviews changes in the UHI intensity in the past decades and shows that the anthropogenic heat generation due to cars and air conditioning has induced a temperature surplus of 1-1.5°C (ibid.). Probáld (2014) claims that the rigidity of the city's urban structure leaves little room for structural climate adaptation and argues that the best options to relieve the growing heat stress is the conservation of the city's natural cooling assets, mainly the bank and urban islands of the Danube ad the forested areas of the hills of Buda. Dian et al. (2020) analysed the UHI effect in more detail, along with its relationship to the local climate zones of Budapest, showing that the compact midrise built up zone – located in the city centre in an approximately 10 km^2 block – is associated with the highest UHI intensity, and UHI decreases continuously with building density (ibid.). Dezső et al. (2024) analyse the UHI during heatwaves and droughts, concluding that UHI intensity is more variable within the city in the summer months due to the larger amount of incoming solar radiation, highlighting the importance of within-city temperature disparities. The study's results furthermore reveal that summer temperatures show a moderate negative correlation with the UHI intensity, implying that as heatwaves warm the surrounding rural areas and potentially reduce their moisture, the difference between the urban and rural temperatures becomes smaller. This finding is crucial for heat vulnerability assessment because it shows that using generally calculated UHI intensity as exposure measures in an assessment can cause significant inaccuracies if aiming to account for temperature differences during heatwaves. The study furthermore underlines the importance of studying heat stress in Budapest, showing a rate of temperature increase of between 0.8 and 2 °C per decade (ibid.). Regarding the effect of vegetation on reducing temperatures, Molnár (2016) studied the relationship between land surface temperatures (LST) and normalised difference vegetation index (NDVI) in the local climate zones of Budapest, showing that densely vegetated urban areas can reduce temperatures by 5-15°C, but also noted that the temperature differences between vegetated and built up areas decreases with temperature, implying a diminishing cooling effect of vegetation during extreme heat, possibly because of frequently co-occuring drought conditions and resulting poor vegetation health. Another key contribution on the influence of the built environment on local climate is the study of Bakay (2011), who examined the thermal properties and vegetation attributes of housing estates in Budapest, that are key residential areas and typical urban forms of urban areas Post-Soviet legacy. While the high share of not yet retrofitted buildings in Budapest's housing estates, combined with a higher share of low-income and heat-sensitive residents such as elderly and chronically ill dwellers implies a higher heat vulnerability in these urban forms, Bakay (2011) shows that housing estates in Budapest have extensive vegetation due to large open spaces allowing for small size parks in between buildings, significantly ameliorating local climate conditions during the summer months.

2.4 Heat vulnerability studies on Budapest – identified research gap

While urban forms in Budapest and their relationships have been analysed thoroughly in literature, fewer studies exist on the heat vulnerability of the city. Buzási (2022) furthermore notes that there is a considerable hiatus of heat vulnerability assessments in the Central European region generally. However, The spatial patterns and correlations between human heat vulnerability factors and urban forms have mainly been examined through the aspect of green space access of residents of different income groups in Budapest. For example, Farkas et al. (2022) use the demand-supply composite index to map greenspace availability for the residents of Budapest, and find that young and middle aged dwellers have better access to greenspaces, along with those with higher income. The study highlights that interventions to increase greenspace availability are the most needed the city's outskirts, and note – echoing the findings of Bakay (2011) – that while housing estates show a relatively good availability of greenspaces, the changing demographics of these urban areas towards more elderly and less families with young children necessitates revisions in the facilities greenspaces in the area of housing estates have to offer (ibid.)

At the time of this research, there has been only one study published that attempted to reveal the spatial patterns of heat vulnerability in Budapest: the research of Buzási (2022) applied a weighted methodology to build a HVI for the 22 Budapest districts, further analysing the dimensions of heat vulnerability using Pearson correlation analysis and spatially constant principal component analysis. Buzási (2022) used a weighted indicator strategy where normalised socio-economic variables were first aggregated to sensitivity and adaptive capacity components, and were then weighted by exposure, calculated as the average land surface temperature measured in the district, and the resulting HVI index was then compared to its unweighted counterpart. The Pearson correlation analysis was then used to show some significant correlations between the variables, although the limited significance and extent of correlations suggested that the variables represented relatively independent dimensions of vulnerability (ibid.). This also explains why the PCA analysis, when applied to the dataset, did not result in considerably interpretable components of heat vulnerability, and was thus not used for the HVI construction.

However, in analysing the contribution of the research to the literature, limitations must also be mentioned, especially since the shortcomings of the assessment of Buzási (2022) form some of the key research gaps this research aims to address. Firstly, the used spatial unit of Budapest district meant that the analysis was done on 23 observations, largely preventing accurate assessment due to the considerable heterogeneity in key variables within the districts of Budapest. Contrastingly, due to data availability from the Hungarian census of 2022, this research is able to assess heat vulnerability on the subdistrict level, analysing 200 spatial units, allowing for significantly more robustness. Second, the weighted indicator methodology, while taking a step further from the equal weighting approach, still lacks the theoretical foundation as to the importance of the chosen variables, while the aggregation of the sensitiviy and adaptive capacity indicators to one dimension score are also somewhat arbitrary. The measurement of exposure furthermore suffered from shortcomings as temperatures were measured only on one summer day – not during a heatwave period – and might therefore reflect the temperature patterns of the city inaccurately. As Dezső et al. (2024) showed that temperature differences and the UHI effect differs significantly during heatwaves, it is argued that the examination of temperature patterns over a longer time period, using the example of the city's most intense and longest heatwave serves as a more robust measure of exposure differences in Budapest. Moreover, as only daytime temperature was included in the study, some further key exposure patterns might have been missed, as for example Ramamurthy and Bou-Zeid (2017) argued that nighttime temperatures are also crucial to include in heat vulnerability assessments due to the significantly increased heat risk in case of insufficient nighttime cooling. Regarding the included socio-economic factors included in the study, it is argued that the 12 included indicators might have failed to capture all relevant drivers; in particular, this research takes advantage of the Hungarian Census surveying the whole population about air conditioning equipment in their households for the first time 2022. Other factors such as those working in exposed occupations, building characteristics, and limited mobility and chronic illness are likewise omitted, posing a gap in literature that this research aims to fill. Lastly, the study of Buzási (2022) does not use any spatially explicit methods to reveal spatial relationships in the vulnerability structure of Budapest, possibly overlooking key differences in the drivers of vulnerability across the areas of the city. This paper aims to also fill this gap by applying geographically weighted PCA to analyse vulnerability in Budapest's subdistricts.

It can be concluded that the current state of literature on heat vulnerability assessments in Central Europe and Budapest specifically shows a considerable research gap, it is therefore hoped that the present paper can contribute significantly to academia by applying a complex and spatially explicit methodology to analyse heat vulnerability in one of Central Europe's biggest cities. The following section will thus detail the methodology employed to deliver robust results.

4. Methodology

In order to gain a comprehensive understanding of Budapest's heat vulnerability and its dimensions, the paper employs multiple methods which all serve the understanding of different aspects of the spatial patterns. First, a cluster analysis is conducted to show the groups of subdistricts with similar characteristics in exposure, sensitivity, and adaptive capacity. Second, a global principal component analysis is applied to the standardised data with the aim of identifying the key dimensions of vulnerability in the city and build a heat vulnerability index (HVI). Third, a geographically weighted modification of the PCA is conducted to better understand the spatial variations in the leading vulnerability drivers and understand the city's structural boundaries with regards to heat vulnerability. The following sections detail the methodological steps and principles applied during the analysis, after describing the processes of indicator selection, data collection, and preprocessing. Analysis was conducted using QGIS for geospatial data processing and R for data analysis using the Gwmodel, the FactoMineR, and the cluster packages.

4.1 Data acquisition and preprocessing

As Li et al. (2022) notes, the selection of indicators considered in the construction of HVIs is essential, and the imbalance in the representation of the different dimensions can lead to inaccuracies in the weighting of variables. Due to data availability, – especially on the level of census tracts and administrative areas – demographic and socio-economic indicators are often more heavily used in vulnerability assessments than features of the built environment or natural factors, leading to an overestimation in their importance in many HVIs. Aiming to alleviate this problem, this analysis not only uses readily available census data or aggregated indicators on the subdistrict level, but also collects various data from remote sensing and spatial databases to derive indicators of geographical factors on the subdistrict level using geospatial analysis. Factors were chosen based on literature and the characteristics of Budapest, making some frequently used indicators such as water/electricity supply or internet availability redundant due to little variation and almost complete access. Regarding most demographic, health- and socio-economic factors, data was acquired from the Hungarian National Statistical Office from the database of the 2022 census (KSH, 2022). One exception is per capita income, an indicator which is not included in the census questionnare; in the absence of available subdistrict-level data on income, the paper used the study of Farkas et al. (2022) who presented a map of four income groups in Budapest. Averaging the group value on the subdistrict level, the study thus uses the mean income group as the indicator for financial wellbeing. It is furthermore worth noting that the 2022 census was the first one to assess the air conditioning availability at the household level, providing crucial insights to the preparedness of households to extreme heat. Other factors, such as building characteristics of the subdistricts, were constructed considering the urban structural characteristics of the city, with the share of panel buildings approximating for poor thermal characteristics of the buildings while the share of new buildings (built after 2000) were chosen to proxy the heat-mitigating effect of better insulated buildings with newer technologies in the subdistricts. It is recognised that this operationalisation of the indicators is limited as high-quality reconstruction and retrofitting of the housing estates in Budapest have led to some panel buildings offering better thermal comfort, while a high number of newly built houses have poor thermal properties. However, due to the aggregation of the data to subdistrict level, it is argued that these indicators can capture the general thermal comfort levels of building types in the city.

High-quality and accurate temperature data is indispensable when accounting for differences in heat vulnerability, and many studies quantify exposure differences based on limited temperature data from remote sensing sources (e.g. Buzási, 2022). In order to gain a heatwaespecific and accurate understanding of the temperature differences, this study uses the MODIS observations' 8-day land surface temperature (LST) measure between 13/07/2024 and 20/07/2024, capturing LST exclusively during the heatwave period. As the 8-day product averages data from the 8 daily observations, common limitations such as obstructing cloud cover becomes less severe of a problem. Moreover, a strong advantage of using the MODIS data is that the satellite does not only provide daytime LST data but also nighttime LST, a crucial contribution to the understanding of temperature differences across the city including not only daytime temperature maximums but also the inability of nighttime cooling.

While greenery is often captured by the share of designated greenspaces in a city, this study addittionally includes an indicator of tree cover in the greenery category, making sure that it is not only public green areas that contribute to the heat-mitigating effect of green infrastructure, but also forested pavements, private gardens and small treepatches in city squares. Finally, geospatial analysis is also used to derive indicators of the urban infrastructure, with distance to the nearest hospital providing a direct easure of healthcare acessibility in case of emergencies, whle road density serves as a proxy of transport accessibility and therefore human mobility in the subdistricts.

After the acquisition of data and processing of geospatially derived indicators, the process of data cleaning had to include the harmonisation of subdsitricts from the statistical and from the geospatial data sources, and the fixing of no value data fields due to the data sensitivity of the analysis. Alhtough Budapest consists of 203 subdistrict in total, three were removed due to no statistical data, resulting from lack of population in the subdistrict: Infopark, and the two in-city islands Óbudai-sziget and Margit-sziget. The resulting dataset thus contains 200 subdistricts.

Due to minor mismatches between the subdistrict list used by the statistical office and the subdistrict map of openstreetmap, some re-categorisations of the statistical office-derived data were necessary, in order to retain spatial information for all the subdistricts in the analysis. No data values occurred predominantly in subdistricts where population counts were extremely low, leading to data unavailability due to data protection concerns. With regards to indicators with shares, no value fields were filled with the district average value as a close approximation, while in the case of missing population or household counts, the latest available statistical information was used, in most cases from the census of 2011.

Subdistricts with extremely low populations posed another problem of extreme outliers due to the low sample size, heavily diverging the analysis. Following a commonly employed method to mitigate such outliers, for the 19 subdistricts with lower than 500 capita population, the statistical indicator values were capped. Using indicator values from the rest 181 subdistricts, the 1st and 99th percentile of the values are used as the maximum and minimum values for the indicators in the low population subdistricts. Across the 18 variables derived from data from the statistical office, and 19 subdistricts, the maximum and minimum values had to be used more than 50 times, showing the importance of the fixing of outliers.

Diverging indicator scales pose a severe problem for statistical analysis, making the standardisation of variables crucial; the study employs z-score standardisation to better capture divergences from the mean values both in the positive and the negative direction (Foroutan et al., 2024).

Lastly, it is important to note that not all variables chosen have vulnerability-exacerbating effects; many indicators capture vulnerability-mitigating factors – to name a few, greenery, new buildings, income and high education. In the analysis of correlations in the data and the cluster analysis, this bidirectionality does not cause a problem if the interpretation of results remain cautious of the differing signs of impact. However, the PCA analysis requires unidirectionality in the dataset. The z-score standardisation makes it simple to change the directionality by flipping signs for indicators where larger values mean less vulnerability for the PCA and GWPCA analysis.

Table 1 below offers a summary of the chosen indicators, their theoretical connection to heat vulnerability, data sources, and preprocessing steps, with underlined variable names indicating that the variable values are flipped in the analysis for unidirectionality.

Category	Variable/indicator	Rationale	Data acquisition/calculation steps	Data source
Temperature	Median daytime LST	Outdoor exposure	MODIS data derived through Google Earth Engine, median calculated in QGIS using zonal statistics	MODIS
	Median nighttime LST	Outdoor exposure	MODIS data derived through Google Earth Engine, median calculated in QGIS using zonal statistics	MODIS
Population exposed	Population density	Exposed population, dense urban structure	-	Hungarian National Statistical Office (KSH), Census 2022
Demographics	Share of population over 65	Age-related heat sensitivity	-	KSH, Census 2022
	Share of households with only elderly dwellers	Age- and isolation-related added sensitivity	-	KSH, Census 2022
	Share of population under 4	Age-related heat sensitivity	-	KSH, Census 2022
	Share of one-person households	Isolation related sensitivty	-	KSH, Census 2022
Socio-economic status	<u>Mean income group</u>	Socio-economic adaptive capacity	Data on income categories derived from income map in Farkas et al (2022) using georeferencing, mean calculated in QGIS using zonal statistics	Farkas et al. (2022)
	Unemployment	Socio-economic sensitivity	-	KSH, Census 2022
	Share working in heat-exposed occupations	Socio-economic-related exposure	Sum of number of employed persons in heat-exposed occupation categories (e.g. construction	KSH, Census 2022

		workers) divided by total employed population	
	Share of inactive population, receiving care	Socio-economic (health- and age-) related sensitivity	-	KSH, Census 2022
	Share of high education attainment population	Socio-economic adaptive capacity	Number of residents with university degree divided by total population	KSH, Census 2022
	Share of households with low space per person	Socio-economic sensitivity and exposure	-	KSH, Census 2022
Health	Share of population living with chronic illness	Health-related sensitivity	-	KSH, Census 2022
	Share of population with limited mobility	Health-related sensitivity and lack of adaptive capacity	-	KSH, Census 2022
Greenery	Greenspace cover share	Urban infrastructure related exposure mitigation and adaptive capacity	Indicator derived through geospatial analysis in QGIS using the urban greenspace and forest classes of the Urban Atlas	Copernicus Urban Atlas 2018
	Tree cover	Urban infrastructure related exposure mitigation	Indicator derived through geospatial analysis in QGIS using the treepatch dataset of the Urban Atlas 2018	Copernicus Urban Atlas
Urban infrastructure	Distance to the nearest hospital	Infrastructural adaptive capacity	Indicator derived through geospatial analysis in QGIS using dataset of healthcare facilities of Openstreetmap	Humanitarian Data Exchange, Openstreetmap, 2023
	Road density	Infrastructual adaptive capacity, transport accessibility proxy	Indicator derived through geospatial analysis in QGIS using the road network data of Openstreetmap	Humanitarian Data Exchange, Openstreetmap, 2023
Buildings and household infrastructure	Share of panel buildings	Building-related exposure, instrument for thermal mass of buildings	-	KSH, Census 2022

Share of new buildings	Building-related exposure mitigation	Number of buildings built after 2000 divided by total number of buildings	KSH, Census 2022
Share of households with air conditioning	Household-level adaptive capacity	-	KSH, Census 2022

Table 1: Summary of indicators, data sources, and processing steps.

4.2 Cluster Analysis

The understanding of Budapest's heat vulnerability patterns necessitates more than a hierarchical analysis of high-to-low vulnerability levels, and the complexity of the concept of vulnerability calls for an examination of the vulnerability typologies that exist across the city's subdistricts. Cluster analysis is a frequently used method to show groups in a dataset and identify dominant patterns and correlations in the data; conducting a cluster analysis on the compiled vulnerability dataset can thus show the subdistricts that resembe each other the most in their vulnerability factors. MacQueen (1967) was the first who outlined the process of k-means clustering, a form of cluster analysis which aims to group the observations to a predefined number of clusters to create non-overlapping, flat groups based on similarity in the data, minimising within-cluster variance. The analysis is spatially constant, therefore not taking into account the geographical distance between subdistricts and potential resulting relationships in data. The input variables used for the cluster analysis are the bi-directional set of standardised variables in order to avoid the overweighting of larger scale indicators in the clustering process.

A crucial decision in cluster analysis is that of the choice of the number of clusters to use. Rather than arbitrarily determining the cluster number, various tests can be conducted to derive the optimal count of clusters based on the data structure. First, the elbow method is applied (Thorndike, 1953), measuring the inertia – the within-cluster sum of squared errors - for 1 to 10 number of clusters and plotting the result with the cluster number on the x axis and the inertia on the y axis. The optimal number of clusters is indicated at the 'elbow point'; after which the rate of decrease in inertia sharply slows down, indicating that adding further clusters to the analysis does not improve the results much anymore. Results of the elbow test indicate that the optimal number of clusters is 4 or 6, but the result is not decisive as no sharp decline in the steepness of the curve can be identified at a single point (see Appendix 1.1). In cases when the results of the elbow method are unclear and to improve the robustness of the testing, the silhuette method is also frequently used (Rousseeuw, 1987). In contrast to the elbow method where errors are plotted, the silhuette score measures how well-separated and compact the clusters are with a given number, with a score close to 1 indicating an exceptionally good assignment and a score close to -1 indicating a bad performance. The silhuette score method is likewise plotted, with the cluster number on the x axis and the average scores on the y axis, and the chosen number of clusters should be that where the average score is the highest. Plotting the silhuette scores for the observations, it is shown that either 2 or 5 clusters result in the clearest distinction between clusters (see Appendix 1.2); it is however noted that even these two numbers exhibit an average silhuette score of 0.198, indicating significant heterogeneity within clusters and less-than-perfect distinction between them. Based on the results of the two tests, 5 is chosen as the number of clusters for the sake of theoretical validity and interpretability along with the highest possible explanatory power.

4.3 Principal Component Analysis (PCA)

As discussed in the literature review section, the principal component analysis, although with its limitations, still stands as the most robust weighting method in the construction of heat vulnerability indices. Originally introduced by Pearson (1901) and formalised into algebra form by Hotelling (1936), the PCA is a dimension reductionality tool that aims to form mutually uncorrelated linear combinations - principal components- of the original data by rotating the data structure, aiming to keep the maximum amount of variation from the dataset.

The number of resulting components equals the number of variables in the dataset with all components loading on every variable but to a different extent: the loadings of variables for the individual components reflect their weight in the component. The index of the component reflects its relative importance as the first component explains the most variation in the dataset. The eigenvalues of the components serve as indicators of the absolute amount of variance explained by the component. It is thus an underlying principle in the use of PCA for an index creation that the variables with high loadings in the certain components should form theoretically interpretable 'dimensions' of vulnerability; most aim to categorise the components into the three pillars of exposure, sensitivity, and adaptive capacity (e.g. Foroutan et al., Wolf and McGregor, 2013), but it can be argued that such a categorisation might be forced if using variables that represent factors overarching these three pillars (Li et al., 2024): indeed, a key advantage of the PCA analysis can be to reveal locally specific dimensions of vulnerability based on the data structure, offering a better explanation of vulnerabilities than the globally applicable but reductionist exposure, sensitivity, adaptive capacity framework.

It is first advisable to test the fit of the data for such an analysis as datasets with completely random structures are likely to lead to poor PCA performance. The paper employs two frequently performed tests of PCA fit; first, the Kaiser-Meyer-Olkin (KMO) test is conducted, measuring the sampling adequacy of the dataset. As a general rule, a test result of above 0.8 is considered great while a result of 0.6 is considered acceptable for the PCA (Kaiser and Rice, 1974). For the used dataset, the KMO test shows an average result of 0.76 (See Appendix 2.1), indicating a more-than-adequate fit for PCA. As the KMO test is conducted separately for all variables, it can also be seen that only greenspace cover shows a considerably lower score of 0.5, but the variable is kept for the analysis due to its theoretical importance. Second, the Bartlett test is frequently used to test the hypothesis that the correlation matrix of the dataset is significantly different from an identity matrix, making the dataset suitable for PCA, where a significant p-value indicates satisfactory suitability. With an extremely large chi-squared vale of 3086, resulting in a p-value of 0, the test confirms the dataset suitability on all confidence levels (see Appendix 2.2). The two test results together indicate that the data is highly suitable for PCA analysis.

A further consideration with the use of PCA for index construction is the criteria for the number of components to keep for the weighting, as the method can only serve its aim of reducing data dimensionality in the dataset if fewer components are retained than the number of variables. When determining components to keep, this paper adheres to the following criteria: as per the Kaiser criterion, components with eigenvalues greater than 1 are retained, resulting in 6 components. Second, a scree plot is used and similarly to the elbow method in the cluster analysis, the number of components from where the additional explained variance decreases significantly is chosen as the number of retained components. Based on the scree plot, the optimal number of components to keep is 4. Third, the total explained variance of the components is inspected, aiming for the retained omponents to explain at least 60-70% of variation in the dataset; this technique indicates that at least 4, more optimally 5 components need to be retained. Lastly, as the theoretical interpretation of the components has to be clear for the construction of the index, the loadings in in all components are inspected to make the final decision to the number of components to keep. As a result, 6 components are retained due to their very clear distinction of vulnerability dimensions in the dataset, which are then used to construct the final HVI index. The 6 component scores that are summed for the HVI are computed as weighted sums of standardised input variables, using their respective loadings and the component's eigenvalue as weighting factors.

Due to the often difficult interpretability of the PCA loading structure, the varimax rotation of the PCA is often used to ensure that the components are adequately distinctive and each variable loads strongly in only few components (e.g. Wolf and McGregor, 2013). Building on the PCA analyis , this rotation of the original PCA components offers a clearer structure to the loading table by maximising the variance of squared loadings within each component (Kaiser, 1958). The varimax rotation of the PCA can only be conducted after determining the number of components to retain. In order to ensure that the dimensions represented by the components are clearly recognisable, the paper uses the varimax rotation with 6 components to build the HVI.

The HVI resulting from the combination of the 6 component scores varies highly in value and the resulting scores have no absolute implications, making their raw visualisation and interpretation redundant. As the aim of the developed HVI index is to compare the vulnerability of subdistricts to each other, the HVI result, as well as the individual component scores are normalised using min-max normalisation, making result visualisations and interpretations more understandable and straightforward with values ranging from 0 to 1 in each component score and the final HVI.

4.4 Geographically Weighted PCA (GWPCA)

As Harris (2011) argues, spatial structures such as cities cannot be analysed using purely spatially constant methods as this implies the risk of overlooking the spatial variance in the data – as detailed in the Theoretical and Conceptual Framework section of the paper, spatially explicit methods can help identify these spatial patterns and gain a more comprehensive undertsanding of vulnerability differences across the city. The geographically weighted extension of the PCA serves this purpose by allowing for spatial variation in the detemination of the components. Thus, instead of running the analysis for the whole dataset, the GWPCA runs separately for all observations, and variances in the data are weighted with how far the observations are from each other using a kernel's weighting approach, resulting in different components and their loading structure in all subdistricts. Therefore, a value in a vulnerability aggravating variable that differs substantially not only from the average of all subdistricts but specifically from the values of nearby subdistricts will be identified as a key local factor of vulnerability. The results of the GWPCA can thus inform about the local drivers of vulnerability and structural boundaries in the city where the component composition shifts significantly.

To make sure that the addition of the geographical analysis is not redundant, the Moran's I index can be calculated for the variables, testing whether the variables are distributed spatially randomly, or whether they have spatial clustering or dispersal tendencies. A positive and significant Moran's I value indicates a strong clustering characteristic of the variable, implying that spatially constant models would significantly misinterpret their structure. The Moran's I statistics from the 22 used variables in the analysis are all significant but range between 0.05 and 0.4, indicating a detectable but subtle spatial autocorrelation (See Appendix 3.1). As the GWPCA is a robust addition to the data if the individual variables, or their correlations with each other have significant spatial patterns, the data is considered fit for the GWPCA.

To implement GWPCA, each subdistrict must be georeferenced, and a spatial weighting function must be defined. The kernel's bandwidth determines the spatial extent over which nearby observations influence each local PCA, with two main options: fixed or adaptive. A fixed bandwidth includes all observations within a certain radius, whereas an adaptive bandwidth includes a fixed number of nearest neighbours, regardless of their distance (Harris et al., 2015). In urban settings with large variation in subdistrict sizes, adaptive bandwidths are preferable, as they ensure each local PCA includes a comparable number of observations, avoiding distortion due to uneven spatial density.

This study uses an adaptive bi-square kernel, where spatial weights decrease continuously with distance and drop to zero beyond the defined bandwidth threshold (Harris et al., 2015). This type of kernel ensures that closer subdistricts receive higher weights in the local PCA, while distant subdistricts have no influence. The optimal number of neighbours to include in the adaptive kernel is determined through cross-validation, which selects the bandwidth that minimises the local reconstruction error of the principal components (Harris et al., 2011). For this dataset, cross-validation indicates an optimal bandwidth including the 86 nearest subdistricts, suggesting that substantial local variation exists in the data. This relatively large neighbourhood size helps capture both local specificity and regional structure in vulnerability dimensions.

In contrast to the global PCA, the number of components to generate has to be determined in advance in the GWPCA process. Although in the global PCA, 6 components were retained due to theoretical interpretability, the heightened complexity of the GWPCA calls for a simplification; therefore, following the previously described Scree plot, the GWPCA is run to generate the first 4 components. Although this might make the comparability of GWPCA results to the global PCA results more difficult due to the different number of components, retaining six components in GWPCA would require a large bandwidth (196 nearest neighbours) based on the cross-validation method, suggesting spatial homogeneity — which undermines the very purpose of GWPCA. Therefore, keeping 4 components in the GWPCA minimises the risk of overfitting the data which might result in theoretically invalid results.

Figure 2 below offers a comprehensive visual summary of the methodological components and how they serve the research in answering its research questions. The next section proceeds to present the results of the study.

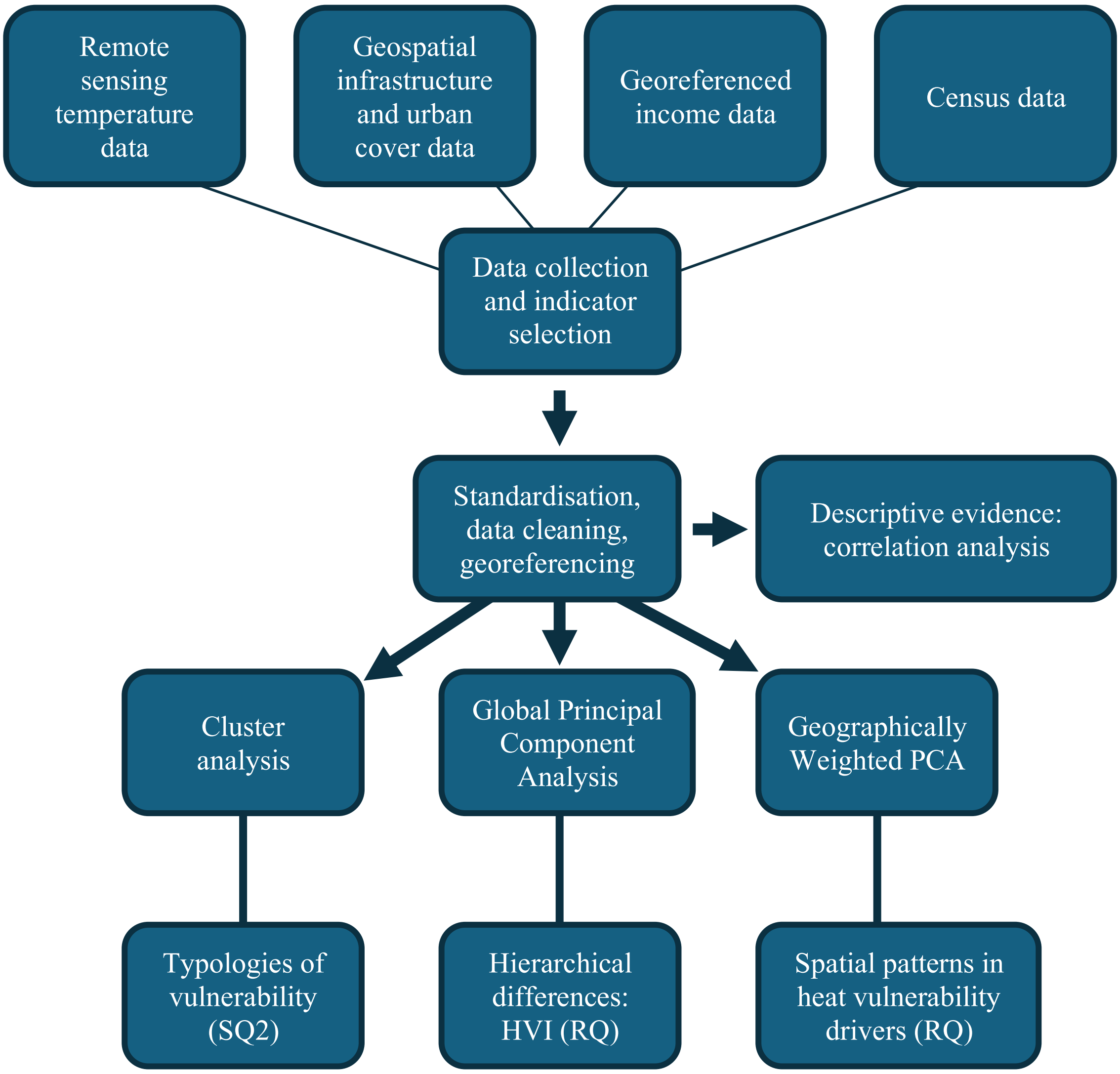


Figure 3: Summary of the methodological workflow.

5. Results

5.1. Descriptive evidence: Differences in temperatures and correlation matrix

To start understanding the spatial variations of heat vulnerability in Budapest, this section first explores the spatial distribution of land surface temperatures during the 2024 July heatwave. Figure 3 presents the daytime and nighttime land surface temperatures across the city's subdistricts, derived from MODIS data. Complementing the temperature maps, Figure 4 shows the locations of forests and urban greenspaces in the city to better understand how vegetation mitigates temperatures. Temperature patterns offer an initial picture of where heat exposure is most severe and how it varies between different areas.

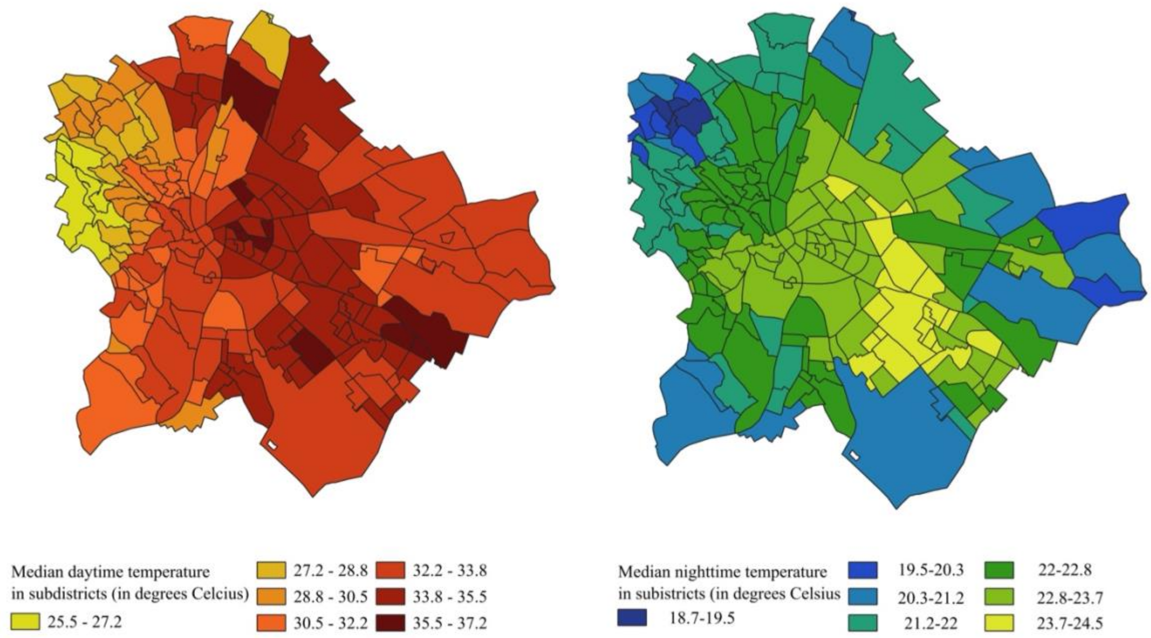


Figure 4: Median temperature map in Budapest subdistricts during the 2024 July heeatwave period, between 13/07 and 20/07.[3]

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[4] *Map created by author in QGIS using MODIS 8-day satellite data derived from Google Earth Engine.*

The maps reveal substantial heterogeneity in temperatures across Budapest, with a 12 °C difference in the daytime median temperatures between the coolest and the hottest subdistricts. The importance of including both daytime and nighttime temperature data is clearly indicated by the fact that the two temperature maps differ significantly; it is not necessarily the subdistricts that heat up the most during the day which are the least able to cool down during the night.

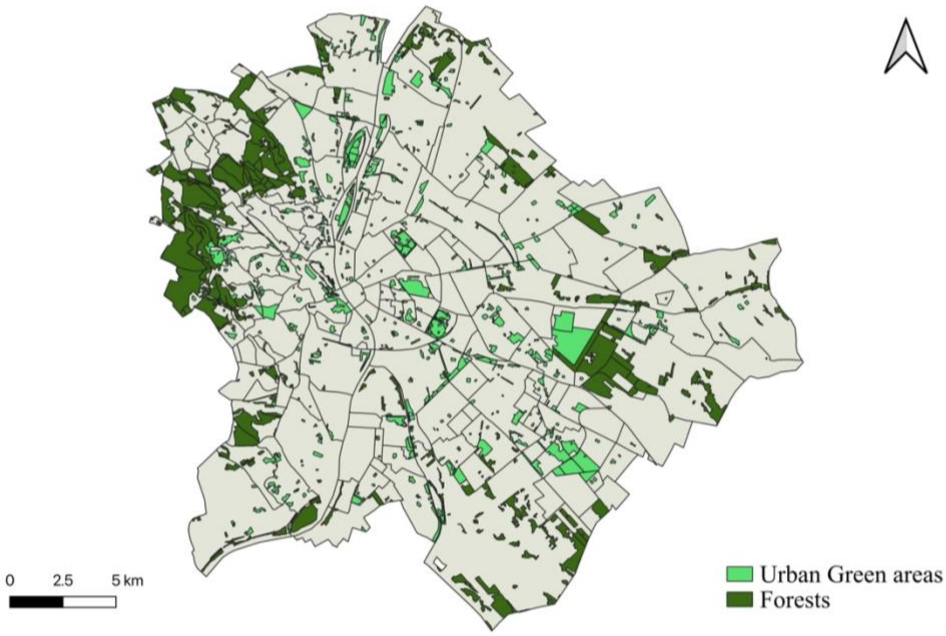

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Figure 5: Map of urban greenspaces and forests in Budapest.[6]

There is a clear indication on the map of the Buda hills on the western side of the city, where the frequently forested, higher altitude areas contribute to significant cooling. It is visible that subdistricts on the city's outskirts might heat up to a similar extent than the densely built central subdistricts during the day but due to their proximity to the more scarcely built agglomeration areas, their nighttime temperature average is significantly lower than in the city centre.

[6] *Map created by author in QGIS from data from the Urban Atlas 2018 of Copernicus.*

Interestingly, the highest nighttime temperatures are detected not in the exact city centre but rather in central subdistricts of the Pest side, possibly due to the lack of vegetation and dense building structures, as well as the added distance from the Buda hills and the Danube compared to the central subdistricts along the river. Another surprising pattern is that of the extreme heat detected in the subdistrict of the City Park, one of the largest urban green areas in Budapest which spans almost an entire subdistrict. Located near the city centre and recently having undergone significant development with cultural venues and museums built in the park (Liget Budapest, n.d.), the City Park shows no evident sign of cooling its own, or its nearby areas. In contrast, the other large urban greenspace in the city, the People's Park – located more in the outskirts, on the Pest side – shows significantly lower temperatures than its surroundings both during the day and at night. This park, less well-kept than the City Park, is also much more densely vegetated, raising its ability to moderate high temperatures during a heatwave.

The analysis of spatial disparities in heat vulnerability are thus justified firstly because of the significant temperature differences. However, the uneven distribution of heat exposure moreover likely interacts with socio-demographic and built-environment characteristics, forming dominant spatial patterns. It is also predicted that the variables used in the analysis show some correlation patterns with each other. Before turning to the results of the vulnerability indices, the remainder of this subsection therefore presents a correlation matrix of the variables used in the principal component analyses, shown below in Table 2.[7] This helps identify collinearity between variables and provides descriptive insight into the structure of the dataset.

[7] Statistical significance of the correlations is indicated by stars with *, **, *** indicating significance at the 90%, 95%, and 99% respectively. Dark green shading indicates a correlation stronger than 0.5 and significant at the 99% level, while light green a correlation stronger than 0.25 and significant at the 99% level

	Population density	Daytime median temperature	Nighttime median temperature	Tree cover	Exposed occupations	Panel buildings	New buildings	Low space per person	Unemployment	Inactive, receiving care	Chronic illness	Limited mobility	One person households	Elderly households	Income	Population under 4 years	Population over 65 years	High education	Air conditioning	Greenspace cover	Distance to nearest hospital	Road density
Population density	1***	0.35***	0.28***	-0.19**	0.09	0.34***	-0.25***	0.31***	0.44***	0.04	0.13	0.19**	0.55***	-0.01	-0.02	-0.23***	-0.09	0.02	-0.2**	-0.31***	-0.38***	0.46***
Daytime median temperature		1***	0.47***	-0.25***	0.58***	0.21**	-0.13	0.48***	0.53***	0	0.3***	0.35***	0.3***	-0.2**	-0.53***	-0.23***	-0.29***	-0.51***	-0.11	-0.42***	-0.03	0.24***
Nighttime median temperature			1***	0	0.23***	0.13	-0.11	0.26***	0.25***	0.04	0.12	0.16*	0.37***	-0.01	-0.03	-0.13	-0.1	-0.16*	0.01	-0.16*	-0.28***	0.21**
Tree cover				1***	-0.24***	-0.06	-0.1	-0.14*	-0.19**	0.15*	-0.03	-0.05	0.05	0.27***	0.28***	-0.01	0.14*	0.25***	-0.05	0.33***	-0.11	0.03
Exposed occupations					1***	0.29***	-0.13	0.63***	0.59***	-0.01	0.39***	0.4***	0.03	-0.3***	-0.71***	-0.27***	-0.37***	-0.88***	-0.26***	-0.16*	0.16*	0.01
Panel buildings						1***	-0.24***	0.51***	0.22**	0.18*	0.27***	0.28***	0.17*	0.04	-0.29***	-0.12	0.03	-0.32***	-0.07	-0.09	-0.07	0.41***
New buildings							1***	-0.21**	-0.26***	-0.54***	-0.46***	-0.55***	-0.28***	-0.51***	0.11	0.59***	-0.42***	0.12	0.57***	0.01	0.22**	-0.21**
Low space per person								1***	0.53***	-0.07	0.2**	0.3***	0.38***	-0.21**	-0.4***	-0.25***	-0.34***	-0.56***	-0.39***	-0.18*	-0.17*	0.23**
Unemployment									1***	-0.05	0.24***	0.32***	0.31***	-0.24***	-0.38***	-0.31***	-0.3***	-0.44***	-0.39***	-0.15*	-0.15*	0.29***
Inactive, receiving care										1***	0.62***	0.7***	0.11	0.69***	-0.09	-0.32***	0.7***	-0.09	-0.3***	0.05	-0.02	0.08
Chronic illness											1***	0.8***	0.1	0.4***	-0.37***	-0.38***	0.34***	-0.36***	-0.22**	-0.21**	0.06	0.13
Limited mobility												1***	0.23**	0.46***	-0.3***	-0.44***	0.38***	-0.35***	-0.32***	-0.24***	-0.07	0.19**
One person households													1***	0.15*	0.24***	-0.39***	-0.04	0.13	-0.29***	-0.13	-0.64***	0.47***
Elderly households														1***	0.28***	-0.12	0.75***	0.39***	-0.15*	-0.07	-0.17*	0.05
Income															1***	0.2**	0.2**	0.8***	0.12	0.11	-0.38***	0.06
Population under 4 years																1***	-0.1	0.33***	0.49***	-0.04	0.2**	-0.18*
Population over 65 years																	1***	0.29***	-0.11	-0.05	-0.07	0.02
High education																		1***	0.29***	0.06	-0.3***	0.05
Air conditioning																			1***	-0.05	0.14	-0.16*
Greenspace cover																				1***	0.03	-0.06
Distance to nearest hospital																					1***	-0.39***
Road density																						1***

Table 2: Correlation matrix of the dataset.

The correlation matrix reveals several important relationships that inform our understanding of spatial heat vulnerability in Budapest. First, population density shows a positive but non-deterministic correlation with land surface temperature**,** indicating that while denser areas tend to be hotter, other urban characteristics significantly mediate this relationship. The share of one-person households, although perhaps unintuitively, is positively correlated with population density due to one-person households being strongly concentrated in the inner districts. However, these inner subdistricts—often characterized by older building stock and limited vegetation—may differ from high-density housing estates, where other socio-economic patterns emerge.

Importantly, daytime and nighttime median temperatures are only moderately correlated, highlighting that the spatial distribution of heat exposure is not uniform across time. Daytime temperatures are strongly associated with lower income, higher unemployment, and lower educational attainment, suggesting that poorer and more socially deprived subdistricts experience higher daytime heat**.** In contrast, nighttime temperatures do not follow this socio-economic pattern as clearly. A potential explanation is the persistent heat retention in inner-city areas, which are relatively affluent and have limited capacity to cool overnight due to dense built-up surfaces and scarce vegetation. This is reflected in the observed positive correlation between nighttime temperatures and the share of one-person households—a demographic prevalent in central districts.

Vegetation indicators provide further insight. The share of tree patches correlates moderately with income and high education, aligning with expectations that greener areas tend to be more affluent. It also shows a moderate positive correlation with households composed only of people aged 65 or older. Interestingly, the correlation between tree patch cover and designated greenspace share is only modest, justifying the inclusion of both variables in the analysis: the official designation of green areas does not necessarily reflect the actual greenness or shading potential offered by tree patches on streets or in pivate gardens.

Social vulnerability is further reflected in the relationships between exposed occupations and other variables. Subdistricts with a high share of heat-exposed occupations correlate strongly with low income, lower education, smaller dwelling space per person, and higher unemployment—typical indicators of social deprivation. These areas also tend to have an older population and poorer health indicators, including higher shares of people with chronic illness or limited mobility. Notably, exposed occupations are negatively correlated with air conditioning availability, suggesting that those most exposed to occupational heat stress are also least likely to benefit from cooling at home.

Panel housing estates reflect many of these vulnerability patterns. Residents in these areas tend to have lower income and education levels and less living space. On the other hand, no correlation is shown between air conditioning access and the share of panel buildings. Conversely, subdistricts with a higher share of new buildings tend to have younger populations, more children, higher air conditioning rates, and less social deprivation.

Aggravating vulnerability on the household level, subdistricts with a higher share of people with limited mobility and chronic illness, who are likely to spend more time indoors and have less access to outdoor cooling, are also less likely to have air conditioning.

In central districts, one-person households also tend to coincide with low cooling access, which can be explained by the regulations not allowing for the equipment of air conditioning in the case of buildings under monument protection or where the residential community prohibited its installation (Szecskő and Horváth, 2024).

Interestingly, districts with a higher share of 65+ households also exhibit higher income and education levels, particularly in the more affluent areas of Buda. As expected, income and high education are very strongly correlated. Lastly, subdistricts with more children are generally better educated and better equipped with air conditioning, suggesting that the share of young children is unlikely to be a major driver of vulnerability in the PCA due to its positive correlation with vulnerability reducing factors. In contrast, older age groups generally appear more strongly associated with both exposure and deprivation indicators.

5.2. Cluster Typology of Vulnerability

The above descriptive analysis already hints at the fact that the strong correlation structure of the data would likely form groups of subdistricts which have similar values in most of the indicators. The cluster analysis is used to formalise this, with the number of clusters chosen to be 5 based on the tests outlined in section 4.2. Figure 5 below presents the result of the analysis with the legend indicating the approximate exposure, sensitivity and adaptive capacity values that the group falls in, based on the mean value of the indicators.

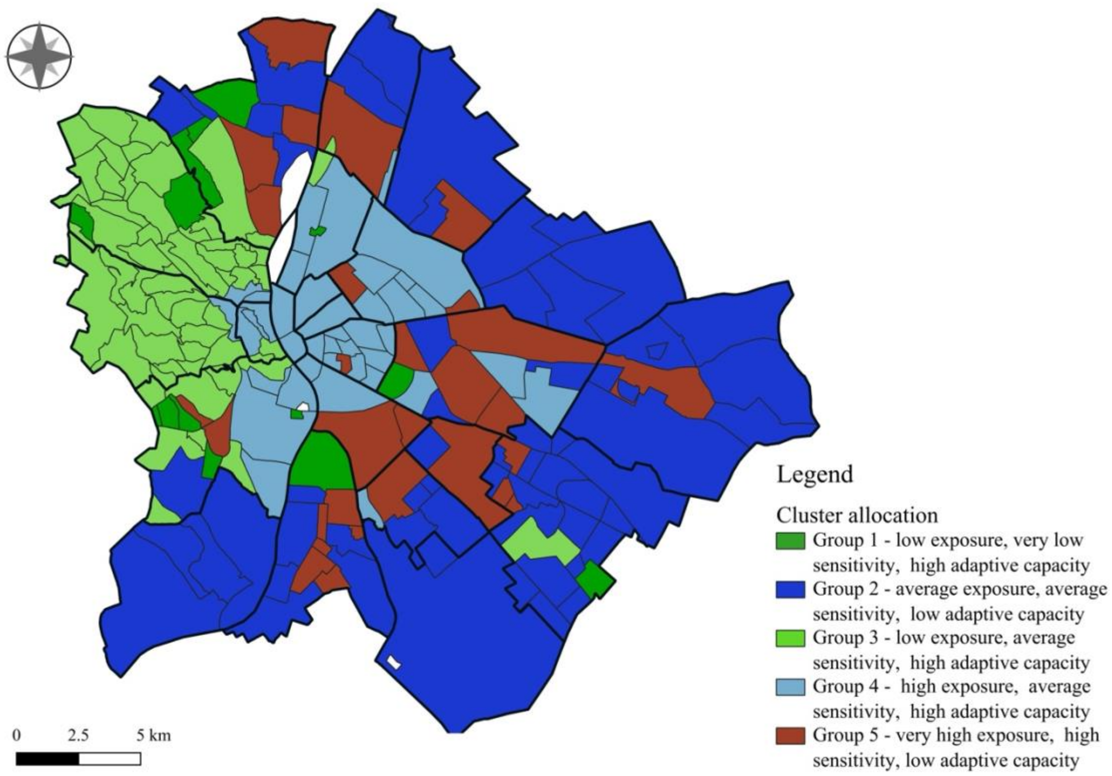

Figure 6: Results of the cluster analysis.

The cluster analysis results show clear patterns of vulnerability typologies across the city, and already gives an early evidence to the highest- and lowest vulnerability districts. Groups 1 and 3, overwhelmingly concentrated in the hilly areas of Buda, face low vulnerability in two out of three dimensions: low exposure and high adaptive capacity. The distinction between the two groups is their average sensitivity: as discussed in section 5.1, the affluent and cooler-than-average subdistricts of Buda have a high share of elderly residents, with higher sensitivity resulting from chronic illnesses or limited mobility. Group 3 represents these subdistricts, showing average, rather than low sensitivity to heatwaves, while group 1 consists of the more spatially dispersed, consistently low vulnerability districts. In contrast, group 5 could very well serve as a prediction as to which subdistricts would score the highest in their vulnerability: with very high exposure to high temperatures, high sensitivity and low adaptive capacity, these subdistricts would clearly experience the most negative impacts from heatwaves. Subdistricts in the 5th cluster have a broad spatial pattern of being located in the highest nighttime temperature zones in central and semi-peripheral Pest, with some subdistricts in Northern Buda. Subdistricts in group 5 mostly concentrate higher-than-average social and economic deprivation, driving the high sensitivity and low adaptive capacity as well as exposure through a higher share working in heat-exposed occupations.

The cluster analysis however also reveals spatial patterns that go beyond hierarchical indexing, showing groups that face different kinds of vulnerabilities to heatwaves although their ranking would not be possible based on this grouping. Groups 2 and 4 reveal crucial types of subdistricts regarding heat vulnerability: while group 4 mostly concentrates the inner city subdistricts on both sides of the Danube, group 2 almost exclusively contains subdistricts on the very outskirts of the city. The inner city group faces vulnerability challenges due to high exposure and considerable sensitivity but these risks can partially be mitigated by the high adaptive capacity detected in the subdistricts. In contrast, the outskirts subdistricts show average exposure and sensitivity values but a lower capacity to adapt to heat. While the considerable difference in exposure is intuitive due to the temperature patterns observed in the city, the large difference in adaptive capacity can be more difficult to understand given the low air conditioning access in the central subdistricts which in contrast showed high adaptive capacity; this difference can be explained by the differences in socio-economic adaptive capacity indicators such as education or income, significantly higher in the centre, while the access to greenspaces is similarly low in both groups, as indicated by figure 4, showing greenspaces in the city. While significant differences exist within the clusters in many indicators, groups 2 and 4 clearly justify the use of the cluster analysis as a preparatory step to understand the structure of heat vulnerability in Budapest.

5.3. Principal Component Analysis (PCA)

Having examined the subdistrict level vulnerability structure in detail through the descriptive evidence and the cluster analysis, the results of the principal component analysis are presented, showing the key vulnerability dimensions identified in the data, and the final HVI index. As outlined in the methodology section, the PCA was conducted and 6 components were kept, which were than rotated using the varimax rotation for better interpretability. Table 3 below presents the results of the analysis in the form of a loading table, showing how heavily and with what sign each variable loads into the 6 components. The inspection of the loading table subsequentially allows the identification of the key components from the group of variables with strong loadings in the components.

The first rows of the table inform about the explanatory power of the components, showing that the first component explains 20% of the total variation in the dataset, while the following components explain continuously less of the variation. The 6 components together explain 75% of variation, suggesting that the PCA performs well in reducing dimensionality but keeping the original source of variation, the vulnerability differences across the subdistricts.

	RC1	RC2	RC3	RC4	RC5	RC6
Eigenvalues	4.39	3.77	2.51	1.67	2.25	1.97
Proportion of total variance explained	0.20	0.17	0.11	0.08	0.10	0.09
Cumulative proportion of total variance explained	0.20	0.37	0.48	0.56	0.66	0.75
Loadings						
Daytime median temperature	0.57	0.00	0.08	0.37	0.12	**0.53**
Nighttime median temperature	0.16	0.05	0.05	-0.01	0.05	**0.84**
Population density	-0.06	-0.02	0.30	0.44	**0.58**	0.26
Share working in exposed occupations	**0.89**	-0.03	0.18	0.09	0.04	0.16
Share of panels	0.37	0.20	-0.12	-0.05	**0.81**	-0.10
Share of area covered with treepatches	0.21	-0.15	0.02	**0.75**	0.00	-0.20
Share of population under 4 years	-0.21	-0.26	**-0.72**	0.04	-0.02	-0.13
Share of households with only elderly dwellers	-0.38	**0.82**	0.06	-0.06	0.02	0.03
Share of population over 65 years	-0.36	**0.81**	-0.01	-0.01	-0.03	-0.17
Share of population with chronic illness	0.41	**0.74**	0.11	0.12	0.06	0.11
Share of population with limited mobility	0.36	**0.75**	0.24	0.15	0.12	0.17
Share of inactive, care-receiving population	0.04	**0.89**	0.15	-0.11	0.03	-0.02
Share of one person households	-0.21	0.02	0.47	0.10	0.44	**0.56**
Share of households with low space per person	0.58	-0.12	0.30	0.05	0.45	0.20
Share of unemployed population	0.48	-0.14	0.47	0.22	0.25	0.24
Income	**0.87**	0.07	0.00	0.13	-0.01	-0.13
Share of population with high education	**0.94**	0.00	0.15	0.01	-0.02	-0.01
Share of households with air conditioning	0.16	0.16	**0.82**	-0.07	0.07	-0.10
Share of new buildings	0.06	0.57	**0.61**	-0.04	0.17	0.01
Share of area covered with greenspace	0.07	0.15	-0.13	**0.79**	0.05	0.23
Road density	0.07	-0.06	-0.13	-0.02	**-0.76**	-0.20
Distance to the nearest hospital	0.41	0.03	-0.35	0.01	-0.38	-0.47

Table 3: Loadings of the 6-component varimax rotation of GPCA[8]

In all components, the strongest loadings are highlighted in bold, showing that the components all capture distinct dimensions of vulnerability. The first component – which has the most explanatory power and thus the highest importance in explaining vulnerability differences – has particularly high loadings in a set of socio-economic dimensions: the share of population working in heat-exposed occupations, income, and the share of population with high education attainment. It is worth noting again that the positive sign of the loadings for income and high education are due to having flipped the standardised variable values so that all variables would

[8] Variables in italic indicate that the variable was flipped so that higher values indicate higher vulnerability for unidirectionality.

theoretically increase vulnerability; the sign of loadings therefore aligns with the theoretical expectations of a higher income subdistrict being associated with lower vulnerability. Given the high loadings for these variables, component 1 of the PCA can be understood as the dimension of vulnerability of socio-economic capital, the vulnerability differences resulting from socio-economic status. The dimension overarches the three pillars of exposure, sensitivity, and adaptive capacity, as socio-economic status differences can modify both exposure through occupation, and adaptive capacity.

In contrast, the second most important component 2 clearly captures the dimension of sensitivity; with high loadings for elderly age- and health-related variables: the share of elderly population and the share of households with only elderly dwellers, the share of people with chronic illness and the share of population with limited mobility, and the share of inactive population. Component 2 can therefore be directly understood as the indicator of lower physiological resilience to heat and resulting heightened heat risk.

Component 3 uncovers a more latent dimension of vulnerability: with the strongest loading in air conditioning access but strong loadings in the share of new buildings and the share of young children, this dimension can be understood as the household-level technological and infrastructural adaptive capacity pillar of vulnerability reduction. The share of young children appears with a negative loading, implying a vulnerability reducing factor, likely because of the higher prevalence of air conditioning and newer building stock in younger subdistricts with a high share of family households.

Component 4 shows, similarly to component 2, an extremely clear dimension of vulnerability: the strong loadings for the greenspace cover and tree cover form this component to be an indicator of ecological heat buffering. With an explained variance of 0.08, the PCA suggests that greenery explains a bit less than 10% of vulnerability differences across the subdistricts: a considerable, but partial role.

The 5th component again captures a more latent dimension: the share of panel buildings, road density and population density having strong loadings suggests that the component captures the heat-trapping effect of densely built and populated environments with buildings of poorer thermal properties and the resulting enhanced vulnerability. The negative loading of road density – due to the flipping of the standardised variable values for unidirectionality – suggests that the higher the road density, the more vulnerable the subdistrict is, contrasting the theoretical expectations of transport accessibility's role in raising adaptive capacity. This is likely due to the fact that highly heat-exposed, densely built housing estates, as well as other densely built subdistricts also have a denser road network.

It is the 6th principal component which captures the vulnerability aggravating effect of high temperatures the most strongly – especially nighttime temperatures, but also daytime temperatures have a high loading in the component. Additionally, the share of one-person households having a moderately high loading indicates that the temperature dimension allocates the highest vulnerability to the central districts of the city, where one-person households are more prominent. The 6th component thus reflects the vulnerability-aggravating effect of persistent heat stress due to the inability of nighttime cooling, compounded with compact urban structure and a higher level of social isolation.

The dimensional coherence of the extracted principal components offers strong support for the suitability of PCA in this analysis. Each component represents a theoretically interpretable pillar of vulnerability, combining variables to components that align well with established understandings of how vulnerability forms. This internal consistency suggests that the underlying covariance structure of the data effectively captures the multi-dimensional nature of urban heat vulnerability in Budapest. However, a critical reflection is necessary regarding a few notable deviations from theoretical expectations. For instance, the share of population under 4 loads negatively on component 3—implying a vulnerability-reducing rather than risk-enhancing role—despite the theoretical assumption that young children are particularly heat-sensitive. Similarly, road density – flipped for unidirectionality, appears to increase vulnerability based on the PCA results, in contrast to the theoretical expectation that transport accessibility and resulting enhanced mobility in well-connected districts decreases vulnerability. These inconsistencies can be traced back to the covariance structure of the dataset: the share of young children is positively correlated, and road density negatively correlated, with several vulnerability-reducing factors such as air conditioning prevalence, modern building stock, and lower daytime and nighttime temperatures. Consequently, these variables – with different directions - align with the statistical patterns as other protective factors, even if their theoretical vulnerability status suggests otherwise. This underscores a fundamental aspect of PCA: it captures statistical rather than normative relationships, reflecting the empirical covariance structure rather than theoretical causality. Nonetheless, the general alignment between the PCA results and theoretical expectations reinforces the value of this approach in uncovering latent dimensions of vulnerability that are both data-driven and theoretically meaningful. This multidimensionality highlights the limitations of strictly segmenting vulnerability into exposure, sensitivity, and adaptive capacity, as many variables inherently overlap these boundaries and co-vary in complex, context-dependent ways.

Figure 6 below shows how the subdistricts perform across the 6 components through mapping the normalised component scores. It is important to note that like the complete indexing process, the component scores shown on the map are for between-subdistrict comparative purposes only – the min-max normalisation used to deliver easily interpretable maps was conducted separately for all components, implying that the component scores across the components cannot be compared to each other.

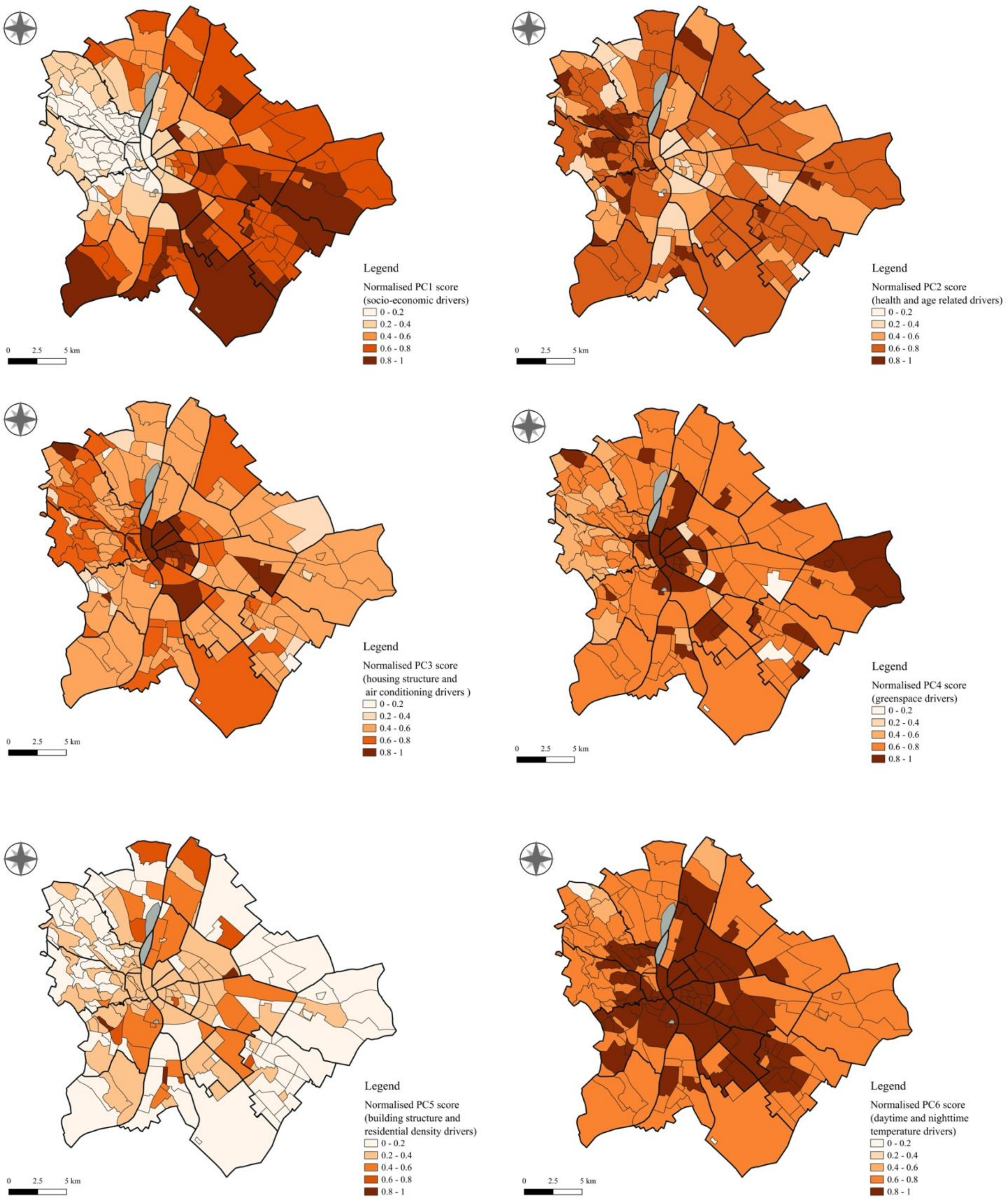

Figure 7: Scores in the 6 heatwave vulnerability dimensions according to the PCA analysis.

The six component maps clearly show the diversity in vulnerability structure across the subdistricts through the diverse spatial patterns. In the first component – socio-economic capital - , the Southern Pest subdistricts clearly emerge as the most vulnerable areas, with the Buda hills showing the least vulnerability, as well as the most central subdistricts. PC2 shows a completely different picture: as mentioned previously, the high share of elderly population in the Buda hills causes this component to show the highest vulnerability scores in these subdistricts, along with a dispersed set of subdistricts of Pest. The city centre shows considerably lower vulnerability in this dimension due to the younger population structure and better health indicators. As for the 3rd dimension of cooling technology access and new buildings, the central districts however clearly emerge as the most vulnerable, due to their extremely low air conditioning equipment, and the high share of old buildings. It is generally the city's outskirt subdistricts which show lower vulnerabilities in this dimension, with the exception of the outskirts in Western Buda where the high share of old buildings and likewise low air conditioning access drives higher vulnerability. The ecological buffering dimension of PC4 shows some extreme outliers almost entirely covered by greenspaces which make the differentiation between the other districts more difficult due to the min-max normalisation. It is however clearly noticable that the city centre has the least access to greenery, and the outer subdistricts of Buda have higher ecological buffering from heat. It is also important to note that the easternmost outskirt subdistricts of Pest show a limited greenspace cover just like the centre of the city, implying a considerable lack of vegetation in the otherwise not-so-dense urban area. Component 5 shows a pattern in which the housing estate subdistricts distinctively stand out with the highest vulnerability scores, while most of the outskirts of the city show lower vulnerability scores in the dimension due to less urban density. Lastly, variations in component 6 scores are also less detectable due to some extreme outliers with the coolest temperatures across the city. A clear pattern of growing vulnerability in the direction of the city centre is however noticeable in this dimension of temperature differences determining vulnerability.

As described in the methodology section, the HVI index is constructed from the PCA results using the 6 component scores, which are composed not only of the variable values multiplied by their loadings, but also the explained variance by the given component – reflecting the components' importance in determining vulnerability. For this reason, the summation of the component scores for all subdistricts delivers a well-comparable index of heat vulnerability in the city. Due to the arbitrary scale of the values, this summed index is also normalised using min-max normalisation to arrive at a final HVI, ranging from 0 to 1. Figure 7 presents the map with the final HVI values, providing a direct answer to the study's research question of how vulnerability to extreme heat differs across the city's subdistricts. It is again noted that the index is purely comparative and carries no absolute information on the level of vulnerability the index categories represent; it rather conveys the difference in the level of risk the residents of the subdistricts face during heatwaves.

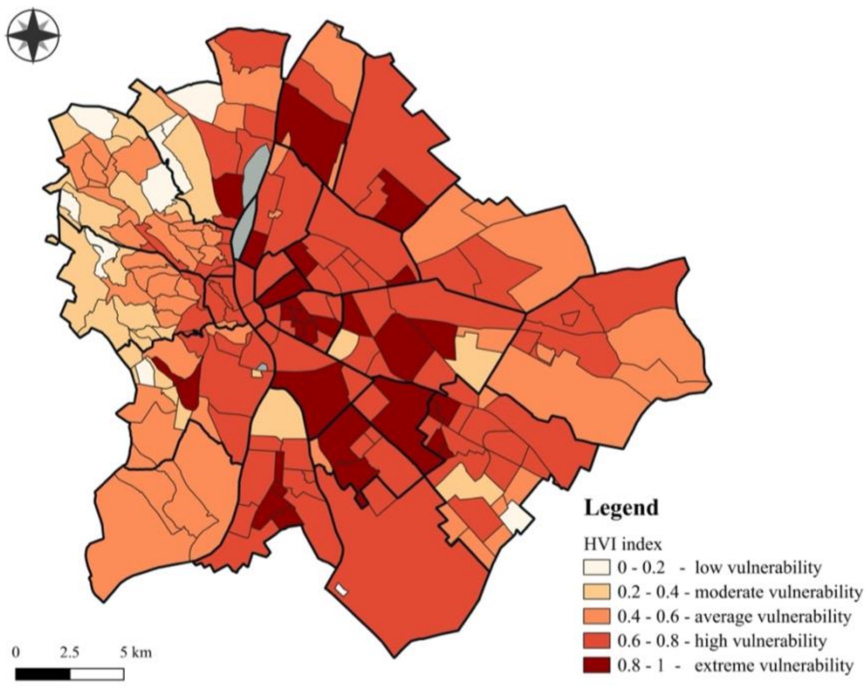

Figure 8: HVI index results.

It is visible that heat vulnerability in Budapest shows a clear Buda-Pest distinction: 28 of the

30 highest vulnerability subdistricts are located on the Pest side, most commonly in the central or semi-central areas of the city. The extreme vulnerability category greatly overlaps with the group 5 of the cluster analysis, suggesting that the cluster analysis mostly successfully predicted the vulnerability ranking, although multiple extreme vulnerability subdistricts are in clusters 2 or 4. Cluster 1 also served as a predictor as the subdistricts in that cluster almost perfectly align with the low vulnerability subdistricts, mostly on the outskirts of Buda in the areas with younger demographic structure. On the Pest side, subdistricts with moderate vulnerability are only those where the share of greenspace is extremely high, resulting in a outstandingly low vulnerability score in PC4, the greenery dimension. In contrast, the high or extreme vulnerability subdsitricts on the Buda side are overwhelmingly the ones with a high share of panel buildings due to the presense of housing estates, combined with a high age- and health-related vulnerability as signalled by a high score in PC2, the age- and health dimension. The index clearly challenges the notion that heat vulnerability is only dependent on temperatures and thus concentrates the highest vulnerability districts in the city centre, as multiple central subdistricts fall into the high, but not extreme vulnerability category.

Before turning to the discussion of what implications the results of the vulnerability index show for the focus of climate resilient urban planning, it is however necessary to examine in more depth the localities in the vulnerability structure – and while the global PCA assumes that the same dimensions form vulnerability in the whole city, the GWPCA method allows the recognition of locally important drivers of the vulnerability differences. The following section thus presents the results of the GWPCA, concluding the results on the spatial patterns of heat vulnerability in Budapest.

5.4. Geographically Weighted Principal Component Analysis (GWPCA)

As the GWPCA generates the predetermined number of principal components separately for all subdistricts, the presentation of a single loading table or component score maps is infeasible: in contrast, it is the core intuition of the GWPCA that how important the indicators are in driving the differences in vulnerability between the nearby subdistricts differs for all spatial units, and the loading tables for each subdistrict therefore show separate leading indicators.

As the first step of analysing the results of the analysis, it should be established whether, and where the GWPCA method elevated the ability of the data analysis to explain the variation in the dataset. This can be shown using the proportion of explained variation of the components, particularly the cumulative explained variance by the 4 components. Mapping this value helps highlight how variable the vulnerability structure in the subdistricts is, and how well the analysis performs in explaining the vulnerability differences, indirectly signalling how reliable the discussion and takeaways about comparative local vulnerability can be. The below map thus shows the cumulative variance explained by the GWPCA.

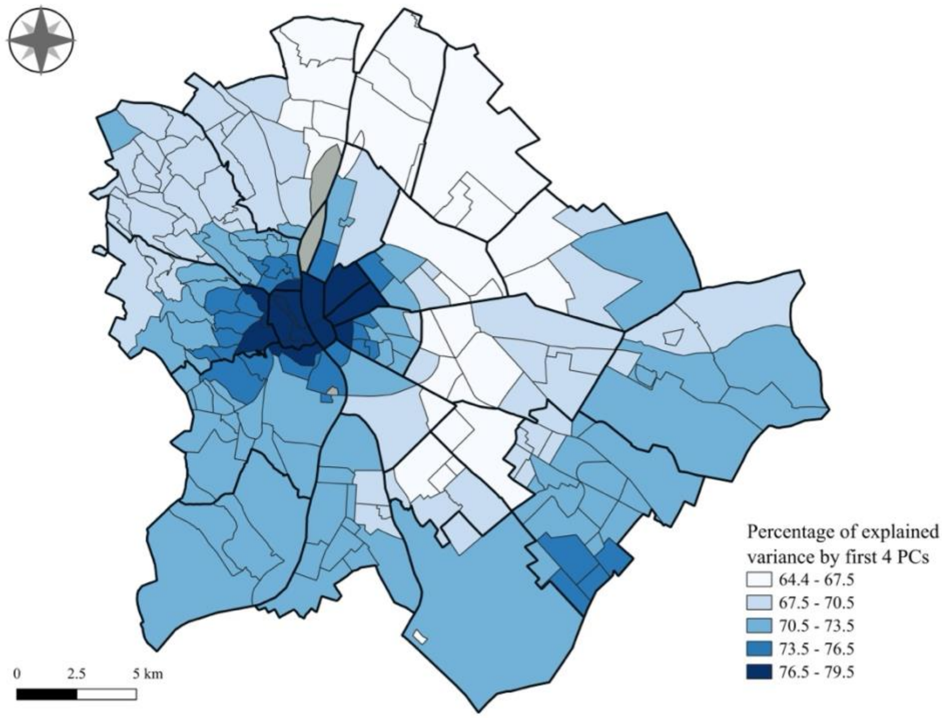

Figure 9: Cumulative variance explained by the 4 PCs in the GWPCA.

Before delving into the spatial differences, it can first be highlighted that the GWPCA raised the explanatory power of the analysis in all subdistricts compared to the global PCA first 4 components – which together explained 56% of variation in the dataset. The choice of 4 components for the GWPCA is due to the complexity in the interpretation of the method and because it was expected that when accounting for variations locally, fewer dimensions will dominate the vulnerability patterns: it can be concluded that this assumption was only partially right as in many subdistricts 4 GWPCA components can capture significantly less variation than the 6 components in the Global PCA, and only in the centre of the city did the GWPCA perform better with 4 components than the global PCA with 6 components. This spatial heterogeneity in the performance also indicates that in the city centre, vulnerability structure is more homogeneous, and thus can be well captured with the 4 dimensions, while the North of the city and the Pest-side semi-periphery, which also concentrate most extreme vulnerability districts, show more diverse vulnerability patterns that can be less captured by the 4 components. This is a crucial result because it implies that the most vulnerable subdistricts of Budapest are at higher risk of heat-related damages not because of one of few factors but because of a complex combination and interactions of vulnerability indicators. This furthermore underscores the takeaway from the global PCA analysis, that the dimensions of vulnerability are multiple and its segmentation to the exposure, sensitivity, and adaptive capacity might oversimplify the reasons behind vulnerability differences.

To extract the value of findings of the GWPCA analysis, a different approach is needed due to the complexity of the separate loading structures; a common method outlined by Harris et al. (2011) is to map the winning variables of the components in the GWPCA. A winning variable of a component is defined as the variable with the highest absolute loading value. For each subdistrict, the variable with the highest absolute loading in each component was recorded, producing one 'winning variable' per component per subdistrict, resulting in 200 times 4 winning variables in the analysis due to the 4 components. As it is always the first component that has the most explanatory power and thus weight in the vulnerability analysis, it can be concluded that the winning variable of PC1 can be understood as the most important driver of vulnerability differences between the given subdistrict and its neighbours. In the case of the winning variables of PC2, 3, and 4, this is less clear as other strong variables in PC1 might have a stronger weight; they can however also be understood as significant drivers of cross-neighbour vulnerability differentiating factors.

Figures 9-13 show the winning variables of the 4 first components in each subdistrict respectively. While the 6-component GWPCA model suggested spatial homogeneity – see section 4.4 - , the 4-component model instead reveals spatially clustered dominant drivers. This supports the choice of a lower-dimensional model to preserve local variation**.** Limited mobility emerges as the winning variable in PC1 in 50 of the 200 subdistricts, suggesting its considerable weight in defining across-subdistrict differences in vulnerability. As in the GWPCA, each subdistrict's PCs are calculated using the variance between the subdistrict and its 86 nearest neighbours, weighted by their distance from it, this does not necessarily mean that the share of people with limited mobility is an objectively more important factor in defining vulnerability than the other measures, rather it suggests that the indicator either has large values, or varies greatly in the nearby area and thus drives the differential vulnerability the subdistrict faces compared to their neighbours. Limited mobility being a variable in close correlation with multiple age- and health-related vulnerability, it can be therefore concluded that health status and demographics are key in shaping local vulnerability differences in the South and in the North of Budapest, two regions which diverge greatly in their HVI from moderate to extreme vulnerability. A similar pattern shows in the West of Buda and the four most central subdistricts of the city, where elderly households emerges as the winning variable, suggesting that in these areas the age sructure of the population is dominant in driving vulnerability differences. Other common winning variables are the share of new buildings and air conditioning, likewise theoretically justified dominant drivers in the centre of Pest and in the Southern areas of Buda.

A highly variable building stock on the Buda side and a number of monument-protected buildings in the centre of Pest warrants the importance of building structure and air conditioning access in terms of indoor heat exposure.. Distance to the nearest hospital being a winning variable in the outermost subdistricts of Pest is also highly understandable given the peripheral location of the area, where differences in spatial access to healthcare might be more important in changing vulnerability than in central districts with universally better spatial connection to health facilities.

Winning variables of the remaining 3 PCs can be interpreted similarly. Elderly households emerges as a key driver in the second most important principal component in the subdistricts of the Buda hills to the east of where the same indicator was winning variable in component 1. Air conditioning drives vulnerability differences most strongly in the second component in the centre of the city, and population density is the winning variable in a number of subdistricts near the centre in Pest and the outskirts of Buda, implying significant differences in density among these subdistricts. Greenspace and vegetation clearly shows to be the leading driver of vulnerability differences in the third component in most of Buda and the South and East of Pest, while population density dominates in the central areas of the city, making the third component one of the most coherent in terms of drivers across subdistricts. Vegetation indicators are likewise common as winning variables in the fourth component, but the share of panel buildings emerges as the winning variable the most commonly, mostly in the North of the East of Pest.

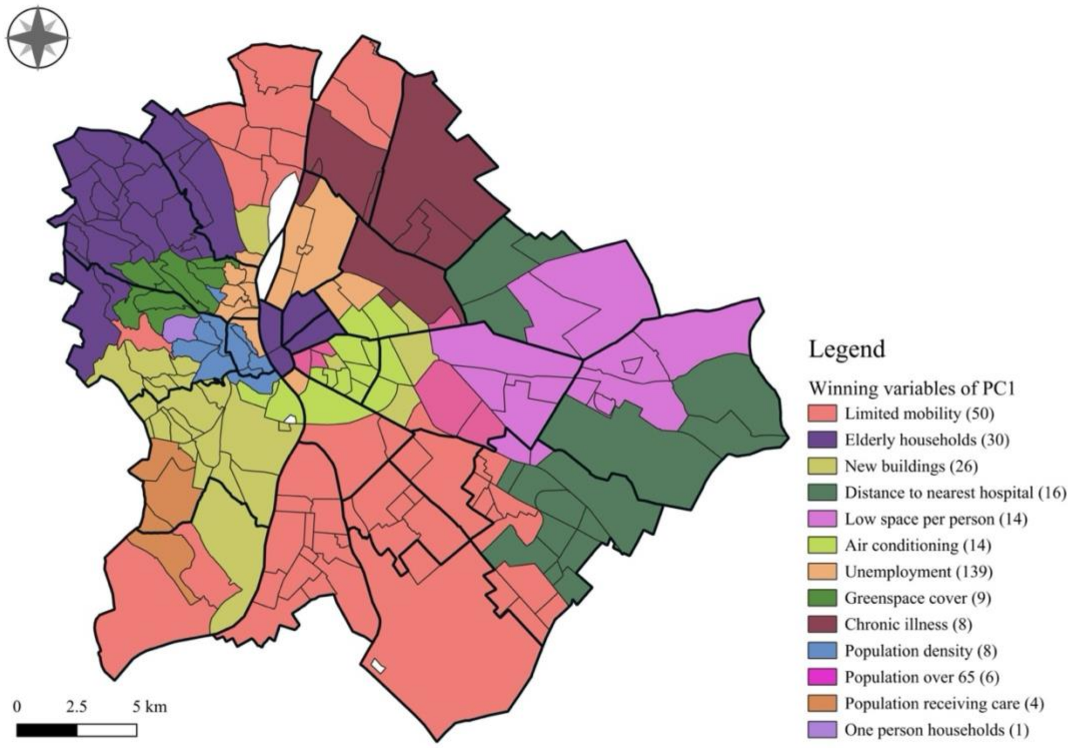

Figure 11: Winning variables of PC1.

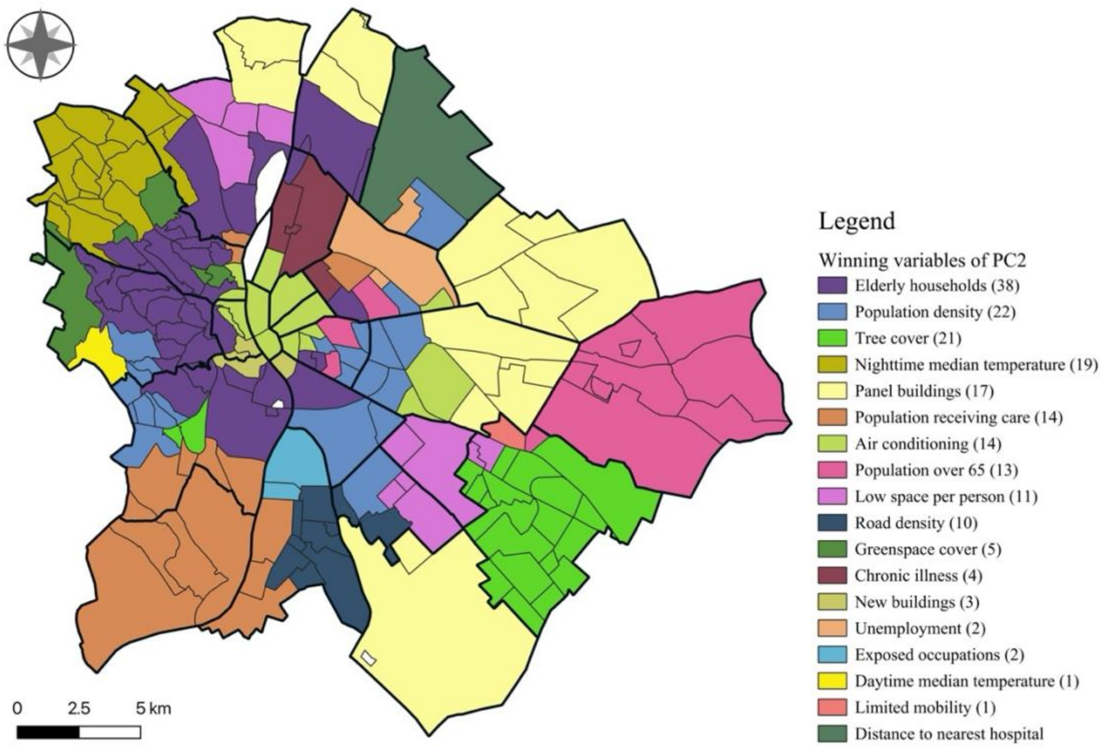

Figure 10: Winning variables of PC2

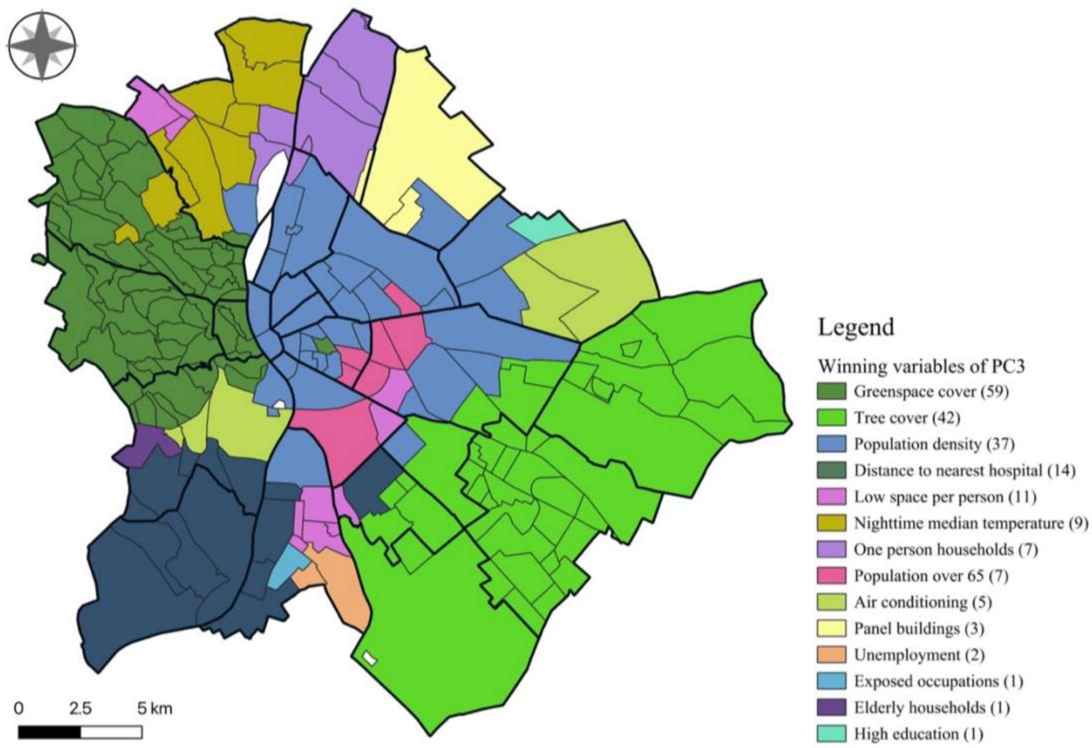

Figure 12: Winning variables of PC3.

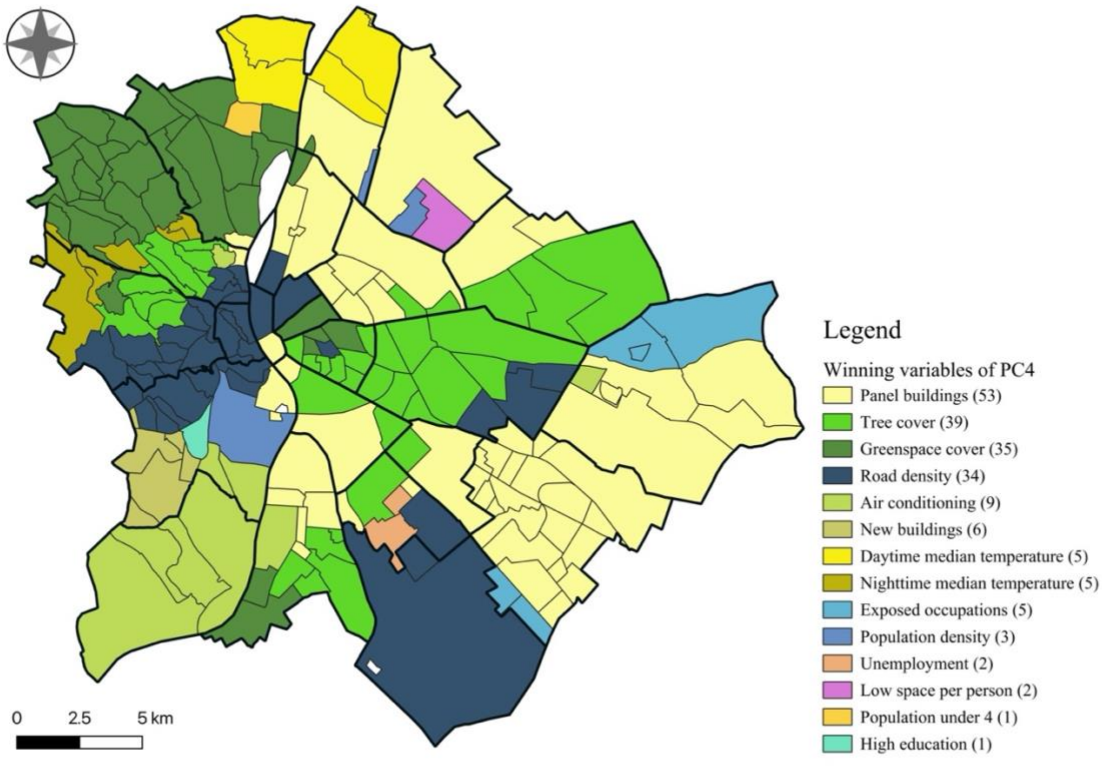

Figure 13: Winning variables of PC4.

The value of the GWPCA winning variable maps however is not only the variables themselves, but also the boundaries along which the winning variables change. These dominant drivers are not randomly dispersed across the city but rather are spatially clustered, with each variable dominating mostly in one or two areas. As the GWPCA principal components in two neighbouring subdistricts are calculated based on variance in almost, but not entirely the same set of neighbours, the subdistrict borders where the winning variable changes can be interpreted as structural boundaries in the vulnerability patterns and dominant drivers. As an example, in the case of the previously mentioned Southern Pest area with limited mobility as a winning variable and the more central subdistricts of Pest in the 8th, 9th and 10th district with air conditioning being the winning variable, the boundary is clearly a marker line in the 9th district, dividing the district into the outer area where health and age are key in driving vulnerability differences, and the more central region where a great variability and low values in air conditioning access define vulnerability more strongly. Several other such structural boundaries can be identified on the map, with implications for prioritizing vulnerability drivers in policy responses.

The four winning variable maps together clearly show the structural boundaries in the vulnerability patterns of the city, with approximately the same subdistrict borders being the winning variable boundaries that divide the city into areas of vulnerability typologies. Where these boundaries overlap borders in the spatial patterns discovered in the cluster analysis and the global PCA analysis, a more comprehensive understanding can be gained by synthesising these findings, showing the detected vulnerability typologies and spatial units, and the comparative urgency of adaptation shown by the HVI. The next section will thus structurally discuss the results, along with suggesting their implications for local-specific and targeted urban planning.

6. Discussion

As this study aimed to answer its research question of how vulnerability to heatwaves differs across the subdistricts of Budapest using both descriptive evidence on correlations and distincts methodologies which all offered differential insights, the discussion aims to harmonise the results of the analysis, through the lens of explaining spatial patterns, finding implications for urban planning priorities, and conceptual contributions to vulnerability studies.

While the study of correlations and the cluster analysis showed patterns in how vulnerability-aggravating factors group in the subdistricts, the PCA analysis was used to form a comparative, hierarchical index of heat vulnerability. Lastly, a next step was taken with the GWPCA analysis to understand the spatial heterogeneity in the patterns and understand how the drivers of vulnerability differences disperse across space. Implications for urban planning and policy responses are offered not only by identifying the highest vulnerability areas but also by examining the source of extreme vulnerabilities and the agency of urban planning and policy to mitigate risks directly or indirectly. The results also offer various reflections to contribute to the conceptual thinking on vulnerability and how it should be assessed for urban heat, especially by emphasising the need for local- and context-specific analysis and segmentation.

This section therefore aims to do a cross-methodological synthesis of the results to explain these various implications. It first details the findings on the spatial typologies of vulnerability, including the most vulnerable subdistricts and key areas where spatially coherent vulnerability drivers dominate. It will then move to the implications and recommendations on urban planning and policy to mitigate heatwave-related risks that were specifically identified by the study. Third, the values of the used methodologies and the resulting conceptual findings are discussed, along with how the paradigm of vulnerability might benefit from local- and context-specific frameworks. The discussion closes by reiterating the multi-dimensionality of the vulnerability concept.

6.1 Spatial Typologies of Vulnerability

6.1.1 The most vulnerable subdistricts: Housing estates and the city centre

The HVI index results clearly show the priority areas for policy interventions to mitigate heatwave damages. Subdistricts in the extreme vulnerability category should not only be the focus of urban climate adaptation because of their hierarchical comparative vulnerability but also because they ehibit a complex vulnerability structure that necessitates a layered approach to minimise heat risk, ranging from direct interventions to reduce heat to support for individual-level risk minimisation. For reference to which subdistricts belong to this group, the 15 subdistricts with the highest overall HVI values are shown in table 4 below.

Subdistrict	Final HVI
Havanna-lakótelep	1
Csepel-Erdőalja	0.993
Csepel-Belváros	0.971
Magdolnanegyed	0.963
Szent Lőrinc-lakótelep	0.952
Rákosfalva	0.934
Gazdagrét	0.934
Losonci negyed	0.913
Lakatos-lakótelep	0.894
Csepel-Csillagtelep	0.890
Óhegy	0.890
Csarnok negyed	0.889
Külső-Ferencváros	0.886
Újpalota	0.885

Table 4: The 15 most vulnerable subdistricts based on the global PCA results

Within the extreme vulnerability category, two distinct groups of subdistricts can be identified: First, the (semi-)peripheral housing estate areas exhibiting what can be termed as multi-dimensional, cumulative vulnerability, and second, the centrally located subdistricts with more homogenous, persistent vulnerabilities.

The first group consists of the predominantly Southern- and Northern Pest subdistricts, almost exclusively categorised into group 5 in the cluster analysis with very high exposure, high sensitivity, and low adaptive capacity values. In this group, concentrating all of the 10 highest vulnerability subdistricts, the highest vulnerability values allocated predominantly to subdistricts entirely consisting of housing estates which tend to house an ageing population with a lower socio-economic status, making them more sensitive and exposed to heat. The subdistrict with the highest overall HVI score, the Havanna-lakótelep [Havanna housing estate] subdistrict exemplifies the characteristics of these extreme vulnerability areas. With above average population density, extremely high temperatures, a generally low share of greenspaces, high share of elderly population and only-elderly households, high levels of social and economic deprivation, and lower-than-average access to air conditioning, these subdistricts face cumulative disadvantages resulting in a multidimensional vulnerability with high scores in most of the 6 shown vulnerability dimensions. The multi-dimensional vulnerability structure in these districts is shown by the proportion of explained variance by the first 4 principal components in the GWPCA analysis: in these subdistricts, the proportion of explained variance is relatively low, suggesting that the vulnerability data structure is more complex than in other areas of the city and can be less accurately captured by 4 components. This is also underscored by the winning variable maps of the GWPCA, which show that the most influential drivers of vulnerability differences vary greatly, the winning variables changing even between neighbouring extreme vulnerability subdistricts.

This result emphasises the complexity of heat vulnerability in these high-risk subdistricts and suggests that no single policy- or planning solution can be successfully applied to mitigate the negative impacts of heatwaves. Rather, the complex vulnerability structure highlights the need for context-specific identification of key factors and their interactions which might substantially aggravate the risks; in the case of the most economically deprived subdistricts with limited green infrastructure, for example, the lack of access to greenspaces might be a considerably more severe problem due to limited capacity to travel and spend time in local cooling centres such as shopping malls or other public institutions. These cumulative disadvantages aggravate individual vulnerabilities and can limit the effectiveness of risk mitigation policies if they only target infrastructural vulnerability reductions.

These characteristics show a large contrast with the second group of extremely vulnerable subdistricts, which are located more centrally - the 6th district consisting of a single subdistrict, multiple subdistricts in the 8th district, and the City Park subdistrict of the 14th district. The vulnerability variation in these areas are shown to be the best explained by the components in the GWPCA analysis, suggesting a less complex vulnerability data structure, which can be captured with the 4 components in the geographically weighted analysis. This implies that it is largely the same factors and covariance patterns that differentiate these extreme vulnerability districts from their neighbours rather than a wide set of variable indicators, showing that the high vulnerability scores in this area result from a more constant set of vulnerability factors, such as extremely low air conditioning access, high nighttime temperatures, and lack of greenspaces.

Interestingly, these subdistrict belong predominantly to group 4 of the cluster analyis – a cluster characterised by a more ambiguous set of characteristics with high exposure and average sensitivity being partially counterbalanced by high adaptive capacity. This higher than average adaptive capacity can be attributed to the area's good transport- and infrastructural connectivity, as shown by the healthcare access and road density variables, as well as a generally higher socio-economic status as shown by income. As a result, risk mitigation in these subdistricts could potentially happen more directly through interventions such as the supporting of air conditioning installation, and urban planning solutions to reduce temperatures and facilitate nighttime cooling. These subdistricts thus clearly represent how historic urban cores, even if in less socio-economically deprived, remain some of the most vulnerable areas of a city with a persistent vulnerability resulting from constant high temperatures due to the central location, an ageing building stock and lack of cooling technologies.

Notably, several central subdistricts similarly in group 4 of the cluster analysis but falling in the high, rather than extreme vulnerability category, share most characteristics with the above group. The key differentiating factors between the vulnerability scores of these central areas are the socio-economic indicators, particularly in the share of the population working in heat exposed occupations, and high education attainment.

6.1.2 The Buda Hills: Limited, but age- and health-related vulnerability dominance

Perhaps the most spatially consistent vulnerability typology is formed by the Buda hills subdistricts, clearly shown by group 3 – and to a lesser extent, by group 1 - of the cluster analysis and categorised into similar vulnerability scores in most components of the GPCA analysis. Although some heterogeneity within the area exists mostly in the sensitivity values, it can be seen that these subdistricts are overwhelmingly the ones with low or moderate heat vulnerability. This result is notably in line with the patterns of heat in the city as the hilly areas of Buda exhibit much lower daytime maximum temperatures and better ability of nighttime cooling.

Furthermore, component 1 – the dimension with the most explanatory power – clearly shows that the area is the least socio-economically deprived, with a low share of the population working in heat-exposed occupations, and an extremely high average education attainment. These socio-economic indicators, along with the temperature values are the most important drivers of the low vulnerability scores in the area. This importantly overscores the structural relationship – also shown in the correlation matrix of the data - that socio-economic status and temperature is negatively correlated within the city, a phenomenon that has been shown for multiple urban areas frequently affected by heatwaves (e.g. Harlan et al., 2006).

The area furthermore enjoys a better-than-average – although variable - greenspace accessibility due to the proximity to the largest forested areas of the city and a relative abundance of urban greenspaces, also forming a key dimension in which the low vulnerability scores contributed to the low HVI values. It is also important to note that the comparatively low population density and large living spaces per capita is paired with a relatively good infrastructural accessibility in the subdistricts, further lowering heat vulnerability.

Between the subdistricts in the Buda hills area, the key factor differentiating vulnerability values is the dimension of age- and health-related sensitivity, as shown by the Component 2 of the GPCA analysis. Sensitivity is also the factor that separates groups 1 and 3 of the cluster analysis, both of which are dominantly located in the area. The inner subdistricts of the area concentrate some of the highest shares of elderly populations in the city, which also show extremely strong correlations with the share of those living with chronic illnesses and limited mobility. The importance of the variability in this dimension is underscored by the winning variable results, which show that in components 1 and 2, the GWPCA winning variable is the share of elderly population in a dominant part of the area. With these high age- and health-related vulnerabilities, household-level, indoors thermal comfort provision becomes extremely important due to potentially lower physical access to cooling centres or greenspaces. Indeed, the highest vulnerability subdistricts within the area are those which also showed relatively high vulnerability scores in dimension 3 of the GPCA analysis –housing structure and air conditioning drivers. From this analysis, it can be estimated that greenspace cover in these subdistricts might be of lower qualitative importance to heat vulnerability from the aspect of greenspace access raising adaptive capacity; this therefore points at a key limitation of the analysis as the relatively large variance in greenspace cover between the district means that the greenspace variables gain considerable weight in the GWPCA analysis, being frequent winning variables in components 2-4. As the HVI index was built from the GPCA analysis that formed spatially invariant dimensions, this unintuitively large weight of greenspace cover in the area is not reflected in the composite vulnerability score; it is however an important takeaway from the results that the examination of the locally specific individual drivers of heat vulnerability might reveal that the importance of certain dimensions can qualitatively differ from what is suggested in the data structure.

6.1.3 The outskirts: Greenspaces and economic factors dominate diverging capacity to adapt

Although a diverse area ranging from the South of Buda to the Northeast of Pest, the city's outskirts except for the Buda hills can be broadly categorised into a similar vulnerability typology where greenspace and infrastructural access, along with socio-economic indicators majorly dominates vulnerability differences. While daytime temperature averages might reach similarly high levels to those in the central areas of the city, nighttime cooling is much stronger in the area due to the proximity to the city boundaries, with nighttime temperature averages similar to the Buda hills in some of the outer subdistricts.

These subdistricts overwhelmingly fall into group 2 of the cluster analysis, with an average exposure and sensitivity but with low adaptive capacity. The area is unified by a low average residential density and a generally newer building stock with a high share of children-family households and a higher rate of air conditioning access compared to the city centre. On the other hand, greenspace cover, especially the share of public greenspaces, is lower than average, and larger distances to medical infrastructure and lower transport accessibility undermines the capacity of the population to adapt beyond the household level appliances. HVI scores in the area largely range from moderate to high vulnerability, with the leading socio-economic drivers component showing considerable differences across the districts; in a spatially clustered pattern, the Southern Pest side and the South-East of Pest, two areas are characterised by higher lebels of social deprivation, a higher share of those working in exposed occupations and lower incomes, while the majority of the outskirts shows a moderate-to-high vulnerability in this component. Age- and health related drivers also significantly affect the across-subdistrict differences, and greenspace cover shows a considerable variation, as shown by component 4 of the GPCA analysis; the Easternmost end of Pest shows a greenspace access rate that is in the same category as the most densely built city centre subdistricts. These dominant drivers of HVI variability are underscored by the winning varible results of the GWPCA, which show that limited mobility, elderly households and care-receiving persons largely dominate in the Southern areas, while distance to the nearest hospital emerges as the winning variable in component 1 in many Eastern Pest subdistricts, indicating a high variation in the spatial access to healthcare among the outskirt districts. Regarding greenspace cover, interestingly, only tree cover emerges as a winning variable dominantly, mainly in components 2 and 3, indicating that public greenspace cover is less variable in the area than smaller-scale vegetation cover. Building structure is also suggested to be a locally important driver with the share of panel buildings emerging as winning variable in component 2 and 4 in multiple outskirt areas – a result that is not surprising given the variability between housing estate subdistricts in the nearby central Pest area and the detached-housing areas in the outskirts.

6.2 Implications for urban planning and policy

Due to a combination of vulnerability factors of a dominantly ageing population, higher-than-average levels of socio-economic deprivation, and a dense housing sctructure, the central Pest subdistricts consisting mainly of housing estates dominate the extreme vulnerability category. This suggests that even after the considerable development projects and building retrofit programmes, housing estates should remain the focus of urban heat adaptation. This stands in a significant contrast to current discourse on urban heat and mitigation options, which has largely centred on Budapest's downtowns where temperatures are often the highest (e.g.

Baranka et al., 2015; Ghira and Heilemann, 2025). Socio-economic capital having emerged as the most important dimension of heat vulnerability based on the PCA analysis, the ability of interventions to address socio-economic inequalities rather than reinforce them should become the key focus of heat resilient urban planning.

It is however important to note that this study focused on residential vulnerability on the subdistrict level without considering mobility, and can therefore offer implications for policy with considerable limits: local hotspots that should take priority in heat mitigation, such as tranport hubs where a large number of the population is exposed to the outdoor heat, cannot be recognised. Therefore, the recognition of priority areas for heatwave adaptation, along with any intervention recommendations is purely intended to guide interventions aimed at reducing the overall, multi-dimensional vulnerability of the residents, considering the interactions between the vulnerability factors, in a general manner rather than specific cooling plans for neighbourhoods.

In the following sections, key principles and directions for urban planning and policy emerging from the analysis are outlined. These recommendations are grouped into five categories: promoting heat-resilient urban forms that reduce exposure at the neighbourhood scale; increasing infrastructural access and introducing cooling centres in vulnerable areas; enhancing household-level cooling access and support building retrofits as a critical pillar of adaptive capacity; supporting individual-level risk mitigation strategies to protect vulnerable groups during heat events; and ensuring that heatwave adaptation efforts contribute to spatially just outcomes, addressing unequal vulnerabilities across the city.

6.2.1 Heat resilient urban forms

Urban forms play a critical role in determining the exposure of residents to heat as well as their ability to adapt, and thus urban planning solutions for heat resilient urban transformations can go a long way of reducing heat vulnerability, especially if done in a locally targeted manner. Lack of vegetation coupled with the heat-exacerbating characteristics of dense building structures, with high buildings and street limited ventillation substantially increases temperatures and heat perception. The HVI results indicating the highest vulnerability subdistricts to be those of housing estates and the central areas of the city reflect these environmental and urban structure-based exposure factors and indicate the highest priority areas for interventions.

Green infrastructure is key in raising the adaptive capacity of residents to heat as well as reduce local temperatures and facilitate nighttime cooling (Zölch et al., 2016), with green and blue infrastructure provision suggested to be the only method of reducing the UHI effect in Budapest by Oláh (2012). Component 4 of the global PCA analysis clearly signals where greenspace is scarce, with the inner city showing the lowest values in greenspace and tree cover, and with some outskirt subdistricts exhibiting an exceptionally low share of public greenspaces, paired with a near average tree cover value resulting from private gardens and tree patches along residential streets. Greenspace provision to reduce heat vulnerability should thus be adapted to these heterogeneous deficits in access to vegetation: larger-scale, public greenspaces in the outskirts might substantially raise the adaptive capacity of residents to extreme heat not only by providing access to cool outdoor areas but also by facilitating community engagement among the dwellers (Lan et al., 2022). In the city centre where space is largely constrained, pocket parks and street greening can help alleviate the lack of access to vegetation on a smaller scale; it however remains crucial that the greening initiatives do not happen without conscious planning and in isolation of each other as fragmented greening might not be successful in providing substantial thermal comfort unless integrated to a connected green infrastructure network (Gill et al., 2007; Iafortezza et al., 2013).

Vegetation provision in greenspace-scarce subdistricts can also be facilitated by incorporating modular greening such as green facades and green roofs on buildings, enhancing the permeability of the urban surfaces and thermal comfort through evapotranspiratory cooling. Although found to be considerably less effective for cooling than tree planting in dense urban environments (Zölch et al., 2016), multiple initiatives for introducing intensive green roofing are underway, mostly in the central subdistricts such as the Green House office building in the 13. District, multiple central shopping mall roof terraces, and within the Liget Budapest project in the City Park (Liget Budapest, n.d.). Tree planting along the streets however remains the most effective method to improve thermal comfort in the central areas. The space constraints however not only prevent the planting of new vegetation but might also substantially damage the existing vegetation due to the limited soil availability and the sorrounding concrete. This results in an elevated tree mortality in urban areas especially in the case of young trees, making planting initiatives less effective; Hilbert et al. (2019) found that 6-7% of urban trees die within 5 years of planting, suggesting a considerable need to enhance vegetation health along with its quantity. The Stockholm tree pit method, a specialised soil and stone mixture developed in the Swedish capital to improve the breathability of tree soils in the city, are now spread across Europe including Budapest in the city centre's partially pedestrianised areas (Pocsai, 2021). This is especially important as urban trees are found to be especially effective at reducing land surface temperatures in Central European cities compared to other European regions (Schwaab et al., 2021). The method not only enhances tree health but also allows for a better water runoff interception, which is essential for the quality and heat properties of the soil during heatwave events to mitigate the UHI effect (Abidli et al., 2024).

It must also be considered in greenspace planning that vegetation cover does not necessarily equal access to greenery; especially in the case of sensitivie populations with limited mobility, proximity and easy access to greenspaces is extremely important to mitigate heat-related health impacts (Klemm et al., 2015). This need offers an important caveat to the results of the analysis which showed that the subdistricts of the Buda area are some of the most well-equipped with greenspace cover in the city, while the hilly, forested areas might not offer a feasible cooling space for the elderly and/or chronically ill residents in this highly sensitive area.

Furthermore, an unequal distribution of greenspaces is apparent in many urban areas, including Budapest. Farkas et al (2022) showed that socio-economic indicators have a considerable relationship with greenspace availability, with the most socially deprived populations lacking access to green areas. The correlation matrix of the study's data however shows no evidence of such relationships, which can be attributed to the greenspace indicators and some unique features of the urban structures in Budapest: while the greenspace cover variables are imperfect measures of greenspace access, it can also be argued that the most socio-economically deprived, predominantly post-socialist housing block-dominated subdistricts are better equipped with green areas than more affluent central areas, or even the residential, terraced-house outskirts where only small scale private gardens are present. Indeed, housing blocks often have more vegetation than modern residential park projects where the aim of maximising profit from the building investment causes many of the new residential parks to only focus on building the maximum number of dwellings at the expense of designing public spaces such as green areas in the parks (Carbera, 2024). These modern residential blocks often house higher-income populations with a high share of families with small children, substantially modifying the pattern of inequalities in greenspace access in the process of urban development.

The unequal distribution of greenspaces is however not only detectable in quantities, but also in the quality and maintenance of public green areas. Kabisch and Haase (2013) discuss that in post-socialist urban settings, large public greenspaces are often undermaintained, preventing the use of the spaces for recreation or as a cooling hub for nearby residents and giving rise to anti-social behaviour which reinforces a downward spiral of lack of greenspace use and maintenance. This is an especially relevant observation in the context of the People's Park, Budapest's largest public greenspace, which has been largely neglected in city planning in the past decades, leading to considerable infrastructural demise and overgrown vegetation in the park and a decreasing perception of safety by the park's visitors (Balázs and Bardóczi, 2008). New plans to improve the park's quality have been developed in the past years and 2024 marked the publishing of the vision on the spatial structure of the park, indicating an intent to make it better maintained (Office of the mayor of Budapest, 2024a). This is especially important as the People's Park location makes it a crucial potential hub that could provide better access to greenspace to some of the most socially deprived subdistricts of the city on the Pest side, which could substantially elevate the adaptive capacity of residents against extreme heat events. This development, along with efforts to ensure that greenspace provision interventions are planned with the aim of ensuring socially equitable access, are in line with the fundamental theoretical framework of just climate adaptation, emphasising the need for greening interventions to enhance thermal justice rather than reinforce existing socio-spatial inequalities through green gentrification – the potential displacement of socio-economically deprived populations due to rising rents and real estate prices following urban greening initiatives (Ufara et al., 2023; Xu et al. 2022). Hamstead (2023) emphasises the importance of such considerations by showing that current discourses around urban heat and urban climate adaptation through greening are largely detached from their distributional aspects, presenting the problem of urban heat as a technical and environmental, rather than socially and institutionally determined problem.

Urban planning solutions to mitigate high temperatures during heatwaves do not stop at greening initiatives, however. Huszar et al (2014) note that the role of increasing the albedo of road surfaces and buildings to cool down surfaces has been significantly underresearched in Central Europe, while use of lighter colours could bring significant temperature reductions- especially during the daytime temperature peaks - where greening and shading is unfeasible

(Gál, 2015). As the urban canyon effect causes temperatures to soar in densely built neghbourhoods, especially in case of high buildings, ventilation and shading in narrow streets is also key to enhance thermal comfort (Georgakis and Santamouris, 2006). Local cooling can also be achieved by micro-scale blue infrastructure interventions such as misting tunnels heat (Ulpiani et al., 2020), especially in local transport hubs where residents are often exposed to the outside heat; such solutions have already been put in place in some frequented squares of in Budapest such as Baross square and Móricz Zsigmond square: the local cooling island projects have combined green walls, shading, albedo and misting interventions to improve thermal comfort in the squares (Office of the mayor of Budapest, 2024b). However, the presence of such solutions remains limited outside of the downtown subdistricts with multiple key transport hubs in central Pest lacking basic shading and vegetation, making the implementation of urban cooling solutions imperative in the most vulnerable, outer subdistricts.

6.2.2 Building retrofits and insulation, cooling access at home

While literature on urban heat and vulnerability often focuses on outdoor temperatures, it is important to recognise that the thermal conditions in homes are crucial to consider as indoor exposure to heat might substantially differ from LST patterns across the city. Indeed, it has been argued by many that building characteristics are much more important than outdoor temperatures in determining indoor thermal comfort and related health outcomes (Oneill et al., 2009; White-Newsome et al., 2012). The findings of the analysis show that building characteristics such as the share of newly built dwellings and the share of panel housing are key determinants of heat vulnerability, dominating 2 out of 6 principal components along with air conditioning access.

The share of panel houses clearly emerged as a key indicator of heat vulnerability in the 5th principal component of the PCA, with the GWPCA showing it as a winning variable in a high number of subdistricts in principal components 2-4, suggesting the importance of building characteristics in determining exposure to heat. It must be noted here that the share of panel buildings, along with the included share of new buildings, are imperfect indicators of the thermal properties of homes as retrofitting efforts and different building types form significantly more heterogeneity in heat properties than the two variables would suggest. For a comprehensive analysis of how residential buildings in Budapest behave during heatwaves, a minimum of a block-level analysis should be applied, considering exact measures of shading, wall thickness and type, and window placements to arrive at accurate results on how indoor thermal comfort varies across households in the city. The analysis however aimed to capture a part of this variation by including the two building characteristics variables to complement data on outdoor LST values.

Improving indoor thermal comfort remains a key intervention to mitigate the detrimental impacts of heatwaves, especially where poor insulation and limited cooling access intersects social deprivation reducing the adaptive capacity of residents. The results of the analysis show that most housing estate districts face such multidimensional vulnerability, making indoor thermal comfort a key priority.

Post-socialist housing estates are relatively more affected by heatwaves than other buildings in the city, owing to the poor thermal properties of the prefabricated panel buildings, such as lack of shading and poor insulation (Hermelink, 2005, in Tirado Herrero and Ürge-Vorsatz., 2012). Tirado Herrero and Ürge-Vorsatz (2012) argue that this structural exposure might be an indication of fuel poverty as residents are unable to afford adequate cooling of their homes due to the inefficiency of cooling appliances because of the building structure and because of their economic constraints (Healy, 2004). This phenomenon, termed by Herrero and Ürge-Vorsatz (2012) as summertime fuel poverty, can be interpreted from the analysis results as the share of panel buildings in the subdistricts shows strong negative correlations with the measures of economic status.

Panel retrofits are therefore crucial in the adaptation to heatwaves in Budapest, alongside many other benefits such as reduced energy costs. The past decades have seen some significant progress in efforts to insulate the post-socialist housing estates, such as in the framework of the Staccato project in Óbuda and Békásmegyer on the Buda side (Smart cities marketplace, n.d.). The programme achieved up to 50% in energy savings due to the retrofits, signalling a significant improvement in the thermal properties of the buildings; however, the project was implemented only for a fraction of the buildings with most panels remaining underinsulated. The nationwide panel programs likewise aimed to target the problem by offering up to 60% state financing for building retrofits; with the program's three phases running intermittently since 2001, approximately 25% of housing estate panel buildings were insulated by 2017, although early projects had lower insulation thresholds than current expectations. However, around 55% of panel buildings remained unretrofitted as of 2017, signalling a limited progress (Szabó and Bene, 2019). In Budapest, 2025 marks another significant milestone in retrofit efforts as the council launched the Green Panel Program, providing a total of 5 billion HUF non-refundable financial support for climate-friendly retrofits, which is expected to be complemented by possibilities for long-term credit arrangements with subsidised interest rates for the residents to initiate retrofits (Budapest Climate Agency, n.d.). Related to self-initiated retrofits, it is important to recognise another challenge of housing estates: that of a large number of households living in a single building, resulting in a more difficult building governance in housing estates where building-scale retrofits and investments might be harder to negotiate, especially when households have significant financial constraints (Patkós et al., 2019).

Air conditioning access is yet another key determinant of vulnerability, dominating the 3rd principal component and proving to be the winning variable in the GWPCA analysis in the central subdistricts, suggesting its importance in the city downtowns. As mentioned before, building regulations do not always allow the installation of AC on historical or unfit buildings, a key constraint to AC access in the city centre, necessitating the implementation of other methods of building cooling described in 7.2.1. In addition to the above measures, it must be highlighted that courtyards, an apparent feature of many buildings in the central subdistricts, provide an opportunity for cooling homes through forming courtyard microclimates by dense vegetation and targeted cooling in the small, enclosed areas (Lizana et al., 2022).

In the most vulnerable districts, air conditioning penetration is however also significantly lower than in the relatively newly built detached housing outskirt subdistricts. Installation subsidies are important due to the large upfront costs, but as mentioned above, in poorly insulated buildings, the costs of using AC might pose another financial constraint to households, necessitating targeted energy subsidies if AC is installed before retrofitting (Jessel et al., 2019). The conscious planning of cooling solutions is important with regards to the emissions as excessive use of air conditioning might be necessary in poorly insulated buildings to achieve adequate temperatures, causing significant emissions and heat release from the buildings and further strengthening the UHI effect (Tremeac et al., 2012).

Lastly, the correlation matrix clearly showed evidence for the common perception that low income individuals are more likely to live in thermally insufficient buildings and lack access to cooling (O'Neill et al., 2009). Rising rents and real estate prices due to retrofits and AC installations might cause interventions to reinforce, rather than ameliorate, inequalities in heat exposure (Kontor et al., 2025; Anguelovski et al., 2019).

6.2.3 Infrastructural access and cooling centres

Beyond the home, the residents' adaptive capacity to extreme heat crucially depends on the urban infrastructure and the availability of local cooling centres. As shown in the cluster analysis, group 5 concentrating the most vulnerable subdistricts and the outskirt areas exhibit the lowest adaptive capacities, partially due to infrastructural inaccessibility. In these areas especially, the the implementation of affordable and accessible cooling centres and the strenghtening of heat-related urban infrastructure might significantly reduce the negative impacts of heatwaves.

Healthcare access - proxied by distance to the nearest hospital in the analysis – was found to be a key driver of heat-related vulnerability in many urban settings, but the analysis results suggest that it is only a significant variable in determining vulnerability variations in the outskirt districts. This is hardly a surprising result, firstly due to the imperfect proxy used as the distance to the nearest hospital cannot accurately capture all dimensions of healthcare access, including social or financial: higher income residents for example might have the resources to access private healthcare where faster treatments might significantly reduce the potential negative impacts of heatwaves. However, the proxy indicator does measure an important factor in healthcare access, which is the availability and distance to places of treatment in case of heat-related emergency healthcare situations; in this aspect, the dominance of the variable in the outskirts is also understandable as the subdistricts on the Easternmost side of the city are the only ones with a larger distance from the nearest hospital.

Infrastructural inequality generally is a key determinant of heat vulnerability (Reid et al., 2009), but its measurement on the subdistrict level remains challenging. Road density was used to proxy for transport accessibility in the subdistricts, but cooling centres were not included due to data unavailability: furthermore, commonly used cooling infrastructure sucha s shopping malls or swimming pools are often the least used by the most vulnerable populations who might not have the financial resources to comfortably access these spaces (Wilhelmi and Hayden, 2010). This necessitates a conscious design for public cooling centres which are adequately integrated into the community and accessible to all income levels (Santamouris and Cartalis, 2015). Hondula et al (2015) discuss that the use of community cooling hubs remains low unless the residents actively participate in the design of spaces, highlighting the need for integrating the residents into decision-making; the use of public spaces with other functions such as libraries, schools or community health centres as cooling hubs during heatwaves could also facilitate larger uptake due to the possible familiarity with the public space.

6.2.4 Individual-level risk mitigation

While urban planning interventions such as greening and infrastructure developments stay at the core of damage minimisation, individual-level risk mitigation remains crucial, especially in the case of sensitive populations and those who might not be able to access public cooling spaces. The results of the analysis show that the Buda hill subdistricts are some of the most affected in this regard, with a high share of chronically ill and elderly population. This is combined with a more difficult-than-average mobility in the subdistricts due to the hilly geography, meaning that a high share of elderly and/or ill residents stay at home during heatwaves and potentially lack access to public mitigation measures. Protecting these residents through public interventions is especially important for those living alone, as isolation forms one of the key risk factors for heat-related health hazards as untimely treatment might result in more adverse health outcomes (Klinenberg, 2015, Kovats and Hajat., 2008). Due to the high share of population living alone in the central subdistricts, these areas should also be in the focus of such measures, even if the younger population structure in the downtown districts makes these areas less sensitive to heat.

Knowledge on how to mitigate damages was found to be lacking particularly with elderly populations in many study settings, rendering effective communication and risk awareness campaigns key (Abrahamson et al., 2009). When family members are not available to regularly check in with heat-sensitive residents, community-based initiatives can help provide regular visits and inquire about the residents' needs. In order to ensure timely treatment in case of heat-related health problems, cooperation between the social and healthcare services is crucial.

There is however a key constraint to such public interventions which might undermine the effectiveness of any individual-level risk mitigation options beyond family support: that of public trust. Klinenberg (2002) shows in the context of Chicago that social heat resilience – the neighbourhood level social infrastructure, trust, and outreach determined heat-related mortality more than income, but also more than LST. Sampson et al (2013) also discusses that the role of informal support networks and relationships in the neighbourhood should not be underestimated in supporting heat-resilient urban transformations. As such, supporting the building of trust and reducing misinformation through social and behavioural interventions can greatly help individual-level risk mitigation, especially among the most vulnerable populations who often exhibit the lowest amount of trust in any support system beyond family networks (Hondula et al., 2015).

6.2.5 Towards spatially just adaptation

The previous three sections detailed policy interventions informed by the analysis results to combat the damages of heatwaves in the city. A key principle emerging from best practices to minimise urban heat vulnerability is the need to address underlying patterns of socio-spatial inequalities and not only outdoor temperatures, a takeaway that is often failed to be adequately considered in urban heat planning discussions which mainly derive priority areas for heat mitigation from satellite-sourced heatmaps (Hamstead, 2023). The consideration of the relationships between temperature exposure and socio-economic status is necessary for sustained heat resilience in the warming city, and this is where climate justice and urban heat adaptation meet to emphasise the need for spatially just urban adaptation (Aguelovski et al., 2016). The importance of socio-economic drivers in the analysis informs of how vulnerability stems from intersecting social, economic, and infrastructural disadvantages beyond just temperature differences, and the HVI ranking clearly shows that the most vulnerable subdistricts emerged where multiple overlapping dimensions of risk were identified. This corresponds strongly with Cutter's (2003) hazard of place framework where the multiple risk factors clustering in single locations causes a concentration of vulnerability to climate change and weather extremes.

These findings, along with the takeaways from the HVI map indicating the most vulnerable subdistricts to range mainly in the central Pest areas, have several implications for the focus of heat-resilient policies. While high-profile downtown areas and tourist spots have received considerable attention to mitigate summer heat through conscious urban planning, the HVI analysis shows that these efforts should not come at the expense of more vulnerable and more peripheral subdistricts. Furthermore, the intersection of socio-economic deprivation and heat vulnerability suggests that the monitoring and evaluation of heat resilient interventions should not only focus on achieved temperature reductions but also on equity outcomes, preventing the reinforcement of existing inequalities through urban development because of green gentrification.

Lastly, the constraint of public trust in interventions highlights the need to involve vulnerable communities directly in the design of heat-resilience interventions, since participatory planning might substantially increase the takeup of new facilities. Giving voice to the vulnerable communities on how to mitigate negative impacts can make interventions more effective due to recognising the priorities and individual constraints of dwellers, and sets the direction towards spatially just adaptation by practising procedural justice in the planning of interventions.

Ghira and Heilemann (2025) show a key example of how participatory planning and co-design can facilitate heat adaptation in the city through the example of the central 8th district

Józsefváros, a socio-economically highly heterogeneous district, and its "CoolCo's" project [Cooling corners and corridors], a co-design project following the European New Bauhaus principles. The project, inolving small-scale interventions such as modular greening and urban furniture provision, and the design of heat-resilient public spaces, engaged families and elderly residents who are the most sensitive to heat in the education and design process, which led to the resulting spaces being better used and maintained. The small-scale interventions could achieve highly substantial local cooling ranging from 12 to 19 °C, essentially providing cooling escapes in the heat of the city centre. The key principles of the New European Bauhaus movement, sustainability, beauty, and inclusion, reflect on the mutual importance of environmental and social outcomes. Lastly, the struggles regarding the integration of the project into municipal frameworks for long-term maintenance signal the importance of institutional support and integration that is necessary to make local-level, potentially self-initiated heat resilience projects effective and sustainable in the long term.

6.3 Methodological and conceptual reflections and limitations

In order to accurately understand the implications of the analysis results for conceptual thinking on heat vulnerability and heat-resilient urban planning, it is necessary to reflect on how the applied methodologies guided the research, and what limitations exist. The key conceptual and methodological approach of this study was to apply data-driven tools to understand the vulnerability data structure, thereby preventing the arbitrariness resulting from self-determined weighting and grouping of variables. The multiple layers of the methodology, including the cluster analysis, the global PCA and the GWPCA process, have helped to form a comprehensive picture of vulnerability patterns across the city, and overarching patterns in the cluster analysis and PCA methods showed robust evidence of where high vulnerability subdistricts are located. The cluster analysis served as a successful tool to answer the study's subquestion 3 – what vulnerability typologies can be identified across Budapest's subdistricts. The PCA remains the most robust and commonly used method in heat vulnerability assessments (Li et al. 2022), however, the advantages of using this data-driven tool to construct a novel HVI for the subdistricts of Budapest extend beyond its academic foundations. The global PCA allowed the study to overcome the often oversimplifying conceptual segmentation of vulnerability into exposure, sensitivity, and adaptive capacity, and showed dimensions of ulnerabiity specific to Budapest which would have remained hidden in absence of such a data-driven method recognising the co-variance patterns of the vulnerability dataset. The theoretically coherent loading structure of the global PCA results serves as a key affirmation of the method's appropriateness for the vulnerability assessment, as the lack of theoretical validity is one of the most widely encountered problem with using PCA for HVI index creation (Li et al., 2022). The emphasis should furthermore be on the fact that the recognised dimensions are city specific; they were identified based on co-variance in the specific dataset of Budapest, thereby highly adhering to the previously discussed imperative of local- and context-specific studies on climate change vulnerability, formulated by Karanja et al.(2025). The interplay of seemingly completely different factors in the dimensions, such as young children and newly built buildings, or one-person households and nighttime temperatures, show crucial city-specific patterns in the vulnerability structure, like the higher share of those living alone in the city centre or the high share of young family households in newly built residential areas. Furthermore, the GWPCA results showed even more locally specific patterns as variations between neighbouring subdistricts were considered in how they form vulnerability differences, showing clustering patterns of leading drivers of vulnerability which do not conform to the city-wide ranking of vulnerability drivers.

As such, the analysis produced a set of results that are not merely reproducible steps of a vulnerability assessment in other urban areas, and findings can only be undertood in the context of the urban development patterns and recent heat-adaptive projects in Budapest.

Closely tied to this context-specificness and the data-driven characteristic of the methodology lie however the study's key limitations. The cluster analysis and the PCA tool crucially relies on data input as it is an entirely atheoretical data analysis method. The choice of input variables - constrained to some extent by data availability and the spatial scale applied – happened based on a robust analysis of the literature on relevant drivers, but as the results show, factors always remain context specific; thus, the use of international heat vulnerability assessments to derive relevant drivers might result in an imperfect recognition of which variables to include. Even if relevant drivers are correctly identified – such as with regards to the special importance and context of post-socialist housing estates and the thermal characteristics of their buildings -, the operationalisation of the variables remains challenging. On the subdistrict level, limited information is available that could accurately capture the heterogeneity of building characteristics or infrastructural access. In absence of direct measures, this study relied on self-designed proxies for these variables, which might hide more accurate patterns of how thermal comfort and vulnerability builds based on these factors. Socio-economic and demographic indicators are easier to account for, especially on the subdistrict level where census data is available; this also highlights a key and common limitation of heat vulnerability literature as Li et al (2022) discuss that the availabiity bias regarding these factors makes them more heavily featured in vulnerability analyses, which can cause an overestimation of their impact, especially in data-driven methodologies where expert-based weighting of indicators cannot account for the bias. This study strived to eliminate this potential problem to the fullest extent by considering a variety of sources to derive indicator values from beyond the census results – multiple measures of greenery derived rom geospatial databases, a multi-faceted examination of temperature patterns including daytime and nighttime LST, and geospatially derived infrastructural variables were used to capture all factors. Lastly, spatial aggregation of the data always poses key challenges to the accuracy of results due to the previously discussed modifiable areal unit problem – results might have substantially differed if data was segmented to block- or household level. Current data availability only allowed the examination of vulnerability on the subdistrict level, which already signals a major step in spatially explicit analyses, as heat vulnerability in the city had only been analysed on the district level before. However, it is a recognised shortcoming of the study that especially spatial variables and building characteristics might have substantial within-subdistrict heterogeneity, and as data is segmented baed on administrative units which do not necessarily align with geographical- or other structural boundaries, the units might cause inaccuracies in estimating the local importance of the factors.

As mentioned previously in the policy implications section, assuming a spatially constant population is one of the most crucial shortcomings of the study. A key methodological reference to the analysis, Foroutan et al. (2024) remain one of the few who integrated the considerations of human mobility into vulnerability assessments, using mobile network data to quantify where people resided during the hottest hours of the day. Due to lack of available data, this study failed to incorporate such measures and thus has to assume that the residents' vulnerability to extreme heat is defined by the characteristics of their home area – this approach allows for several key takeaways with respect to how residential areas should adapt to heat, but also prevents the recognition of key daytime vulnerability hotspots. The inclusion of heat-exposed occupations aimed to capture to some extent the vulnerability variability resulting from workplace exposure to heat, but it is recognised that such a variable is not sufficient in capturing the effect of mobility and daily activities on heat vulnerability.

Lastly, it must also be noted that the temperature variables might not accurately capture variations in thermal comfort or perceived temperatures, even outdoors. The remotely sensed LST is a widely used indicator of temperature patterns due to its availability, and spatial and temporal resolution and continuity, but land surface temperatures do not equal air temperature, nor do they capture factors that crucially modify perceived heat and its damages, such as wind speed, air humidity, or UV intensity. Budapest currently has 8 operating temperature measurement stations which produce hourly data on air temperature values; these however are not nearly sufficient to estimate city-wide temperature patterns. As LST is not used in the analysis to draw exact temperature measurements but rather it is examined to recognise subdistrict-level patterns, it is argued that this satellite-derived measure was the best way to capture heat variations specific to heatwave events throughout the city.

Some words of caution are warranted regarding the PCA methodology as well. Partially discussed in the results section, it must again be emphasised that the PCA is fundamentally atheoretical and thus cannot recognise the importance of vulnerability indicators; it merely analyses the co-variance structure of the data and identifies highly correlating factors to reduce dimensionality and show mutually uncorrelated components of vulnerability. This is the reason why the global PCA results implied that the share of young children is a vulnerability-reducing factor as it showed a strong correlation with other positive indicators such as the share of newly built houses and air conditioning access. Similarly, road density, a measure aiming to capture transport accessibility and its adaptive capacity-increasing properties, was found to be a vulnerability-exacerbating factor due to its strong co-occurrence with densely built,, high-exposure subdistricts. These results contradict theoretical expectations and show key pieces of evidence why data-driven tools must always be interpreted in their context in order to avoid drawing inaccurate conclusions from the results. It remains a fundamental question whether the importance of vulnerability factors can accurately be derived from their covariance with other variables – which implies that theoretically relevant but spatially more random factors might be substantially underrepresented in the analysis.

Given these limitations, the need of integrating data-driven assessment tools with qualitative research on the lived experiences of heat in the city strongly shows; the combination of top-down approaches like the PCA and bottom-up methods integrating individual perspectives on heat vulnerability could offer the most comprehensive insight on heat vulnerability in Budapest.

Finally, another key concern identified by Li et al (2022) must be noted: that of the lack of index validation. Studies that validate results do so almost exclusively using heat-related mortality or morbidity data. Heat vulnerability assessments often lack any measures to validate the index results, mainly due to data constraints as even if heat-related mortality is recorded in statistics, the location of residency of patients on a fine spatial scale is rarely available. This is the case with this research as well, as subdistrict-level heat-related mortality data based on residency is not available in healthcare databases. In fact, due to the relatively recent timing of the heatwave event considered in this paper, hardly any exact information is available on the impacts the heatwave has caused on health- or economic outcomes.

It is however also important to question whether heat related mortality is a sufficient measure to validate the HVI. The effects of heatwaves extend way beyond mortality, but even beyond healthcare impacts, with damages including economic losses due to reduced productivity, and more importantly, decreased life quality and comfort levels due to heat. While healthcare impacts, and possibly economic damages, are relatively easy to measure with statistical data, life quality and comfort are extremely difficult to quantify and would certainly require direct contact with a high number of residents to arrive at representative results. The multiple dimensions of heatwave impacts beyond mortality however also crucially show how the assessment of heat vulnerability and design of interventions has to consider a complex system of urban heat resilience that extends beyond mortality rates and consider the lived experiences of heat.

6.4 Towards a new vulnerability paradigm

The paper's analysis results and conceptual results might be interpreted to guide future research on urban heat vulnerability, suggesting a revised vulnerability paradigm that offers a more locally tailored approach to HVI ranking and vulnerability analysis than standardised methods. The IPCC's recent definition of vulnerability already recognises that it results from the complex interaction of sensitivity, adaptive capacity and exposure, but the way in which vulnerability assessments use the framework – and the population vulnerability equation quantifying the relationship – still widely relies on a simplistic understanding of mutually independent factors whose summation can give an accurate indication of vulnerability. The results of this analysis however crucially highlight the shortcomings of such analytical framework because the recognised dimensions of the PCA analysis overarch the three components and show fundamentally different segmentations of vulnerability factors. The results show that vulnerability cannot be quantified by universally weighting globally determined factors but is deeply tied to local social, infrastructural, and environmental contexts, necessitating the examination of local characteristics for an adequate choice of variables and methodologies.

The previously discussed limitations of the research imply definitive routes for further research to folow the agenda of spatially just urban transformations. Building comprehensive vulnerability studies that consider spatial patterns of how heat is perceived, and how it is affecting the lives of residents across the city can help identify sources of structural inequalities that remain hidden in statistical and quantitative analyses. The examination of mobility patterns might also show key patterns in where working places and activity spaces of residents of different socio-economic backgrounds are located.

One pattern that emerges throughout the results is the importance structurally determined patterns of spatial inequalities, the most vulnerable subdistricts showing a consistent cluster of areas with high levels of socio-economic deprivation, low access to greenspaces, high building density and higher-than-average temperatures. This finding underscores that urban heat vulnerability is inherently linked to socio-economic inequalities and suggests that building heat-resilient cities can only be successful if structural social inequalities in heat are addressed. It is only through spatially just adaptation that the growing risk of heatwaves in cities can be mitigated, and future research should therefore emphasise the role of inequalities in recinforcing vulnerability patterns and evaluate interventions regarding their implications on equity.

7. Conclusion

The 2024 July heatwave in Budapest showed residents a snapshot of how climate change is shifting the intensity and frequency of hot temperature extremes. The vulnerability of the city became apparent as the constrained greenspaces, dense built-up areas and often insufficiently insulated building stock led to a trapping of the extreme summer heat, causing significant damages to the health and life quality of dwellers. It is unequivocal that the vulnerability of residents to heat across the Budapest is not uniform because of the unique geographical characteristics and non-uniform spatial distribution of sensitive populations and infrastructure to adapt to heat. Yet, while international literature has long considered the assessment of heatwave vulnerability on fine spatial scales within urban areas, little previous work has been conducted in Budapest to examine how vulnerability differs across the city's neighbourhoods. Building on temperature data from during the 2024 heatwave, this study thus aimed to conduct a robust analysis on the factors of heat vulnerability across the city's 200 populated subdistricts, posing the research question of how the vulnerability of residents to extreme heat differs across the subdistricts of Budapest.

The study built an analysis using a variety of data derived from satellite observations, geospatial databases, and census and statistical resources. Indicators were chosen based on previous research and empirical evidence on the key drivers of heat vulnerability.

Using a three-pillared data-driven research design, the paper conducted a comprehensive examination of vulnerability patterns both hierarchically and structurally. A cluster analysis resulted in five theoretically coherent spatial clusters in the city regarding the vulnerability dataset, already showing a key indication of where extreme vulnerability might concentrate.

Using principal component analysis, the paper built a novel heat vulnerability index for the subdistricts of Budapest, revealing a clearly identifiable group of extreme vulnerability subdistricts, mainly located in central Pest. The analysis also resulted in the identification of 6 theoretically comprehensive, distinct vulnerability dimensions that are specific to the city's characteristics and that overarch the often-used conceptual segmentation of vulnerability into exposure, sensitivity, and adaptive capacity. Based on the global principal component analysis, socio-economic capital, age- and health-related sensitivity, infrastructural and technological cooling access, greenspace density, built environment density, and temperatures can be understood as the 6 key pillars of vulnerability, forming a key conceptual contribution to the vulnerability literature as most PCA-reliant analyses segment principal components into the three pillars and do not allow the recognition of multi-dimensional vulnerability factors. The geographically weighted principal component analysis was then applied to question the uniformity of driving factors across the city, and the winning variable maps showing the most influential vulnerability variable clearly indicated that substantial spatial variability in the importance of factors prevails, with locally important drivers of across-subdistrict vulnerability variations emerging as added values of the geographically weighted methodology.

Synthesising the results, the discussion identified four fundamental vulnerability typologies in the city, including the highest vulnerability housing estate subdistricts, the downtown areas, the Buda hill subdistricts and the city's outskirts. These typologies also helped to identify appropriate policy responses to mitigate the impacts of heatwaves, and policy implications were discussed across the fields of heat-resilient urban planning, building retrofits and air conditioning access, infrastructural adaptation, and individual-level risk minimisation. All results and policy implications crucially highlighted the importance of spatially just adaptation as socio-economic inequalities showed to be deeply intertwined with heat vulnerability. The limitations of the study were discussed to lead to suggestions for future research in the field, also emphasising how the monitoring and evaluation of equity outcomes should go hand in hand with vulnerability research, moving beyond only a technical approach of temperature analyses and infrastructural cooling solutions.

The study contributes to literature on urban heat vulnerability in various ways. First, the geographical coverage of Budapest, a previously understudied city which is predicted to be highly affected by heatwaves due to climate change in the near future might be useful not only for academia, but also for decision-makers who aim to alleviate heat vulnerability in Budapest. Second, with a novel HVI construction method and a combined use of distinct quantitative methodologies to assess heat vulnerability, the study contributes to methodological and analytical development in the fast-emerging field of urban heat vulnerability assessments. Lastly, the paper offered a novel way to quantify vulnerability while allowing for understanding it as a multi-dimensional concept resulting from the interaction of various environmental, social, and infrastructural factors. The recognised dimensions identified in the analysis hopefully highlights how heat vulnerability should always be understood in its own local-specific context rather than strictly segmenting it to a predetermined set of components.

It is seldom questioned that extreme heat will be one of the most severe climate change-related risks urban areas will have to face in the coming years, and successful adaptation crucially requires a deep understanding of the patterns of residents' vulnerability to it. This research took a key step in this direction by conducting a multi-layered assessment of heat vulnerability across Budapest's subdistricts. However, quantifying and indexing vulnerability can only help bring about better urban futures if future planning and policies recognise the importance of informed, spatially sensitive, and equity driven adaptation approaches that leave no resident behind.

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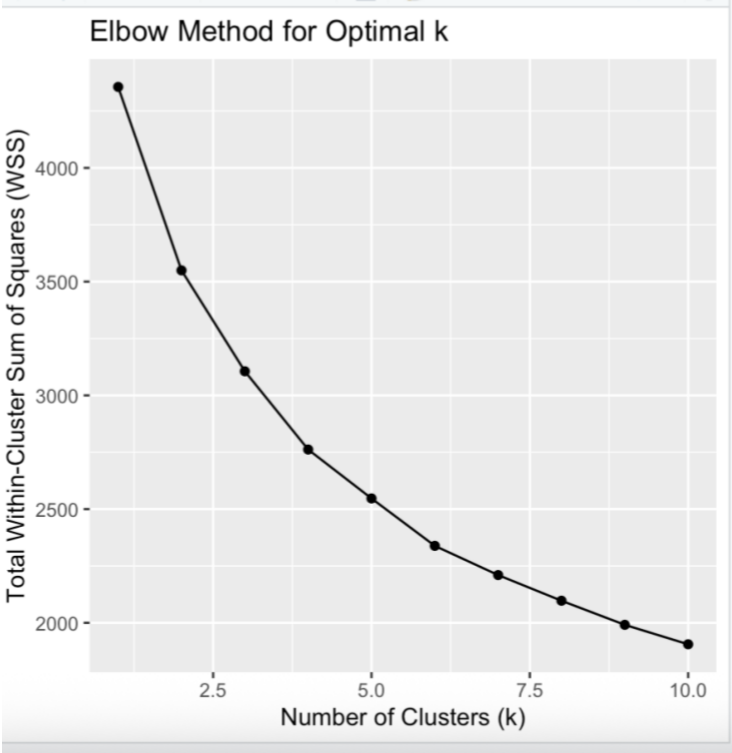
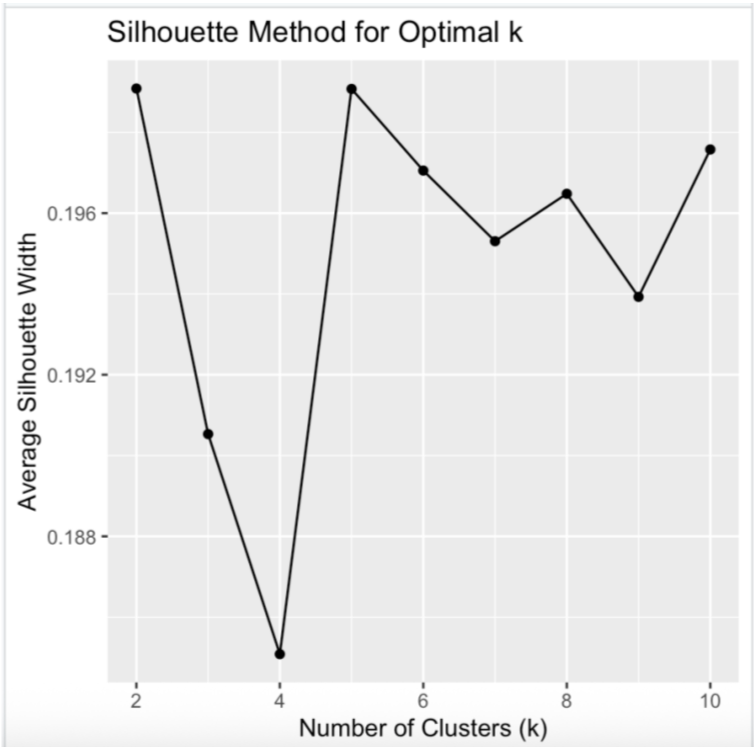
Appendices

Appendix 1.1: Elbow method for optimal number of clusters



Appendix 1.2: Silhuette method for optimal number of clusters



Appendix 2.1: Kaiser-Meyer-Olkin factor adequacy test

Kaiser-Meyer-Olkin factor adequacy			
Overall MSA = 0.76			
MSA for each item =		Road density 0.76	Distance to nearest hospital 0.84
Population density 0.77	Daytime median temperature 0.80	Nighttime median temperature 0.71	Share of inactive population 0.66
Tree cover 0.82	Share working in exposed occupations 0.74	Share of panel buildings 0.64	Share living with chronic illness 0.89
Share of new buildings 0.83	Share of households with low space per person 0.78	Unemployment 0.83	Share living with limited mobility 0.82
Share of one person households 0.72	Share of households with only 65+ dwellers 0.69	Income 0.83	Share of population under 4 0.77
Share of population over 65 0.83	Share with high education attainment 0.66	Share of air conditioning access 0.69	Greenspace cover 0.50

Appendix 2.2: Barlett test of sphericity

chisq
[1] 3086.478

$p.value

[1] 0

$df

[1] 231

Appendix 3.1: Moran’s I test results

	Moran's I	**p-value<**
Median daytime LST	0.273	0.000047
Median nighttime LST	0.119	0.000028
Population density	0.090	0.000046
Share of population over 65	0.092	0.000047
Share of households with only elderly dwellers	0.094	0.000047
Share of population under 4	0.056	0.000046
Share of one-person households	0.182	0.000047
Mean income group	0.313	0.000047
Unemployment	0.123	0.000047
Share working in heat-exposed occupations	0.274	0.000047
Share of inactive population, receiving care	0.027	0.000046
Share of high education attainment population	0.287	0.000047
Share of households with low space per person	0.121	0.000047
Share of population living with chronic illness	0.067	0.000046
Share of population with limited mobility	0.049	0.000047
Greenspace cover share	0.034	0.000046
Tree cover	0.037	0.000046
Distance to the nearest hospital	0.196	0.000047
Road density	0.084	0.000046
Share of panel buildings	0.028	0.000046
Share of new buildings	0.034	0.000046
Share of households with air conditioning	0.023	0.000046