DOI: 10.15201/hungeobull.73.1.2 Hungarian Geographical Bulletin **73** 2024 (1) 17–33.

Disproportionate exposure to urban heat island intensity – The case study of Győr, Hungary

Eszter SZEMERÉDI[1] and Sándor REMSEI[1]

Abstract

Extensive research has shown that urbanisation has a profound effect on the local climate system, leading to the formation of urban heat island. Exposure to urban heat islands poses a major health risk, and there is a growing body of literature recognising that urban population groups with particular demographic characteristics living in specific types of residential environments are disproportionately affected. By combining surface urban heat island data from the Global Surface Urban Heat Island Explorer with neighbourhood-level data on demographics and the type of housing, this study assesses disproportionate exposure to surface urban heat island intensity in the city of Győr, Hungary. Results of the study highlight the importance of targeted interventions for environmental justice, especially in areas characterised by housing estates, high population density and high ageing index.

Keywords: urbanization, residential environment, local climate, urban heat island, Győr, Hungary

Received September 2023, accepted February 2024.

Introduction

On a global scale, an increasing share of the population lives in cities, accounting for 57 percent in 2022 (World Bank, 2023a). Forecasts indicate a continued growth with nearly 68 percent of the world's population projected to live in cities by 2050 (UNCTAD, 2022). By 2030, growing urban land consumption is expected to increase the world's new urban built-up area by 1.2 million km² (World Bank, 2023b). The largely artificial materials that build up the urban surface lead to permanent changes in thermal characteristics. As a result, cities consistently experience higher temperatures compared to their rural surroundings, leading to the phenomenon known as the urban heat island (UHI) effect (Howard, L. 2007).

According to the World Meteorological Organization report, extreme weather and climate change has led to a five-fold rise in extreme weather events and disasters over the past 50 years (WMO, 2021). Prolonged extremely high temperatures, referred to as heatwaves, are becoming more extensive and intensive (WMO, 2023) and can intensify the urban heat island effect, leading to even higher local temperatures and impacting human health adversely (Yang, J. *et al.* 2016). Tong, S. *et al.* (2021) have shown that urban populations face more significant health risks during heatwaves compared to those living in rural or suburban areas. Furthermore, urban heat islands disproportionately affect vulnerable groups (Hsu, A. *et al.* 2021).

In Hungary, over the past two decades, urban-scale analyses based on local measure-

[1] Department of International and Applied Economics, Kautz Gyula Faculty of Business and Economics, Széchenyi István University of Győr. Egyetem tér 1. H-9026 Győr, Hungary. Correspondig author's e-mail: szemeredi.eszter@sze.hu

ments have been conducted predominantly focusing on the capital, and comparative analyses of Hungarian regional centres have been made using satellite imagery. The study of the urban heat island phenomenon from the perspective of environmental justice has only gained attention recently and, mainly in Budapest (Buzási, A. 2022). Consequently, this study aims to further understanding of the urban heat island phenomenon by linking socio-economic and housing data with urban heat island intensity metrics in Győr (Raab), which is one of the less studied cities concerning urban heat islands. Through analysing the spatial and social patterns of SUHII this study aims to answer how inequalities in exposure to SUHII emerge across various types of living environments, income and ageing index groups.

Literature review

The higher temperatures in a city compared to surrounding rural areas, referred to as the urban heat island (IPCC, 2007) is a microclimatic phenomenon influenced by several factors such as vegetation area, urban geometry and human activities. The difference in temperature measured by subtracting the average urban temperature from the average rural temperature is referred to as urban heat island intensity (UHII) (Hendel, M. 2020). The surface urban heat island intensity (SUHII) is derived from the differences in land surface temperature (LST), while the atmospheric urban heat island intensity (AUHII) is derived from the differences in air temperature (Gawuc, L. *et al.* 2020).

Although first mentioned in the early 19th century by Howard in his work on London's urban climate titled *The Climate of London* (first published in 1818) (Howard, L. 2007), the comprehensive study of the urban heat island phenomenon has gained research interest only from the early 1950s onward, using diverse methodologies, models, and simulation techniques (Wu, Z. and Ren, Y. 2019). Systematic reviews by Stewart, I.D. (2011), and Wu, Z. and Ren, Y. (2019) trace the development of approaches from local observations of daily and seasonal air temperature patterns through local measurement trips to incorporating satellite-based imagery to analyse land-surface temperature and to implementing machine learning techniques for UHI prediction.

Although it was not applied until the early 1970s (Krishna, R. 1972), modern studies on UHI predominantly use remote sensing. For instance, Cheval, S. *et al.* (2022) used MODIS data to analyse heat islands in Romanian cities with populations exceeding 30,000 inhabitants. In addition to MODIS, Landsat satellite is a frequently sutilised resource. Amindin, A. *et al.* (2021) used Landsat 4, 5, 7 and 8 satellite imagery to map land surface temperature, urban heat field variance index (UTFVI) and UHI index. Kopecká, M. *et al.* (2021) analysed land use/land cover change based on Urban Atlas data in three cities in Slovakia and their effect on temperature change. Apart from satellite imagery, urban-scale analyses typically rely on local measurements (e.g., Liu, L. *et al.* 2017).

Over the past two decades, urban-scale analyses have been conducted in Hungary for the cities of Budapest, Szeged, and Debrecen, primarily based on local measurements. Though not exhaustive, the UHI in Szeged has been studied by Bottyán, Z. *et al.* (2004), and Molnár, G. *et al.* (2017). Szegedi, S. and Kircsi, A. (2003) focused on the influence of different large-scale weather situations on the formation and spatial structure of the heat island in Debrecen, while László, L. (2017) examined long-term changes in meteorological conditions in the Debrecen region. Similarly, the UHI dynamics in Budapest have been studied by Pongrácz, R. *et al.* (2016), Additionally, Buzási, A. (2022) analysed the vulnerability of 23 districts of Budapest to heatwaves using a weighted indicator method.

In the last two decades, research interest has shifted towards studying the impacts of urban heat island (UHI). This shift encompasses the assessment of different exposures from the viewpoint of environmental justice and the exploration of mitigation strategies. Within the existing literature, the impacts of urban heat island can be broadly classified into two categories: impacts on human beings and impacts on the microclimate of an urban area (Khan, A. *et al.* 2021). Major impacts on human health include increased cardiovascular and pulmonary stress, heightened susceptibility to heat-related illnesses such as heat stroke and other cerebrovascular damage particularly among outdoor workers (Piracha, A. and Chaudhary, M.T. 2022). These symptoms are more pronounced in vulnerable groups such as children, the elderly and individuals with pre-existing medical conditions (Portier, C.J. *et al.* 2013).

Previous findings indicate that the factors possibly affecting exposure to urban heat islands include age, income, gender, housing tenure, and ethnicity (Mashhoodi, B. 2021). A number of techniques have been developed to study disproportionate exposure. Creating and mapping a vulnerability index for specific case study areas seems to be one of the most well-established methods. Wolf, T. and McGregor, G. (2013) created a heat vulnerability index (HVI) for London and have demonstrated that high vulnerability correlates with factors such as high-density housing, poor health status and welfare dependency. Morabito, M. *et al.* (2015), focusing on the elderly (people aged 65 or over), developed a heat-related elderly risk index (HERI) for major Italian cities. Their findings revealed that areas characterised by hazardous risk levels also have the highest total and elderly population densities.

Similarly, Macintyre, H.L. *et al.* (2018) have shown that vulnerable groups such as the elderly and those with pre-existing health conditions are located in the hotter parts of their study region, the West Midlands. They highlighted the location of hospitals, care homes, schools, and childcare centres in areas with higher than the average air temperatures. Holec, J. *et al.* (2021) combined simulated temperature data of the MUKLIMO model with mobile phone data as a proxy for the population density of Bratislava. Their findings are consistent with existing research emphasising the heightened vulnerability of elderly, children and people with low income.

Research has also shown that ethnic minorities are more exposed to the urban heat island effect (Mitchell, B.C. and Chakraborty, J. 2015), and social conditions affect the urban surface heat distribution (Huang, G. and Cadenasso, M.L. 2016).

Local studies emphasise the significance of making a distinction between spatial scales to identify causes and construct effective strategies for mitigating adverse effects. (Mashhoodi, B. 2021). Environmental justice literature places increased emphasis on informed urban policies and strategies, as well. This requires bridging the knowledge gap and open communication between local communities, policymakers and researchers in a given area (Hsu, A. *et al.* 2021). This study aims to bridge the knowledge gap within the context of the case study of Győr, through analysing factors of disproportionate exposure to surface urban heat island intensity.

Methodology

To achieve the research aim identified earlier and to leverage research methods from previous studies on the topic (e.g., Hsu, A. *et al.* 2021; Mashhoodi, B. 2021) this study puts forward the following interconnected research questions:

a) What are the spatial intra-urban patterns of SUHII in the city of Győr? Do certain types of living environments experience elevated SUHII? What intra-urban inequalities emerge across various types of living environments?

b) Are certain socio-economic groups over- or underexposed to SUHII? Which socio-economic groups are over- or underexposed?

To answer these questions, this study first looks at the spatial and social patterns of SUHII in Győr, and analyses the variance of SUHII based on five independent variables. While creating a vulnerability index for the case study area is a common method to study this topic (e.g., Wolf, T. and McGregor, G. 2013; Morabito, M. *et al.* 2015), and would provide the most comprehensive characterisation of exposure to SUHII in Győr, this research elects instead to apply statistical analysis to a random selection of points in the city with the purpose of studying the phenomenon with a social science approach. In the next paragraphs, the methods used to select the case study city and analyse the exposure are presented.

Selection of the case study city

As of 2022, Budapest, the capital city of Hungary, had a population of 1,630,320 inhabitants. In addition to Budapest, the country has eight regional centres, with seven of them having a population of over 100,000 inhabitants each. These urban centres display unique economic, social, and human capital and infrastructural attributes distinct from their surroundings (Rechnitzer, J. and Berkes, J. 2021). The classification presented by Rechnitzer, J. and Berkes, J. (2021) offers a distinctive grouping of these regional centres. The authors categorised them into four groups: cities with a development path based on a new industrial base are Győr and Székesfehérvár; revitalised, traditional cities are Miskolc and Debrecen; cities in transition are Kecskemét and Nyíregyháza, while cities finding their path are Szeged and Pécs.

The grouping by Rechnitzer, J. and Berkes, J. (2021) holds significant merit in the selection process, given that the specific development trajectories of these regional centres have fundamentally determined their urban structure and land use, all of which are recognised as determining factors in the formation and intensity of the urban heat islands. Integrating the development trajectory of a city into the study adds a layer of context and understanding on the emergence and consequences of certain equilibria, a point often missing in studies, as pointed out by critics in the environmental justice literature (e.g., Noonan, D.S. 2008). Consequently, Győr, a city with a development path based on a new industrial base offers the opportunity to research exposure to surface urban heat island intensity within a regional centre characterised by higher levels of urbanisation, infrastructure development and a diverse urban landscape, which could result in more complex patterns of heat distribution.

Data processing

The dependent variables of this research are the average daytime and nighttime SUHII intensity for the year 2019. Leveraging the Google Earth Engine platform and the Global Surface UHI Explorer, SUHII intensity data at the neighbourhood level were retrieved and processed for a set of 100 randomised points within Győr. Using the MODIS 8-day TERRA and AQUA land surface temperature (LST) products, the Landscan urban extent database, the Global Multi-resolution Terrain Elevation Data 2010, and the European Space Agency (ESA) Climate Change Initiative (CCI) land cover data imagery, Chakraborty, T. and Lee, X. (2019) developed a simplified algorithm for estimating surface urban heat island intensity on a global scale. The algorithm was operationalised within the Google Earth Engine platform. The resulting database, the Global Surface UHI Explorer provides data for more than 9,500 urban clusters to calculate UHI intensity, making it one of the most comprehensive characterisations of the surface urban heat island intensity to date.

The variables are yearly mean daytime and nighttime SUHII at a resolution of 300 m × 300 m. According to Chakraborty, T. and Lee, X. (2019) the average 8-day per pixel LST retrieval is constrained to clear sky conditions, with an average LST error of less than or equal to 3 Kelvin (1 km x 1 km), as such it could significantly alter the estimated surface UHI. LST pixels are automatically resampled to 300 m x 300 m grids to match the resolution of the land cover data from the European Space Agency Climate Change Initiative (ESA

CCI). After calculating spatial mean LST for the subsets urban land use and other land use, their difference is the surface UHI. The data is then used to estimate LST at 0130, 1030, 1330, and 2230 local time (LT) through the algorithm developed by Chakraborty, T. and Lee, X. (2019). Mean daytime SUHII is derived from the mean LST values at 1030 and 1330 LT, while the mean nighttime SUHII is based on the mean LST at 0130 and 2230 LT.

The 100 points are uniformly random in the city and were generated using the ee.FeatureCollection.randomPoints function within the Earth Engine API. Following the specification of the city's geometry and the number of random points desired, the function generated a collection of 100 points subjected to further analysis.

As seen in the review of literature, variables representing lower socio-economic status are consistently associated with greater urban heat exposure. In this study, socio-economic neighbourhood-level data for the 100 randomised points at the highest resolution (100 m) were drawn from the GeoX database for the latest available year, 2019. It is important to note that the differences in resolution between the socio-economic and SUHII intensity data may impact the correlation analysis.

The independent variable "ageing index" showcases the typical age composition of people living in the area, thus, shows the ratio of groups, who are likely to be the most vulnerable to SUHII impacts. Variables representing population distribution and economic levels are "population density" and "per-capita income", while variables representing the housing status of the analysed points are the "type of living environment" and "type of residential area". The grouping of residential areas stems from the data source GeoX database, based on the classification of permanent population at the door-level in 100 x 100 cells and on how many dwellings there are. The type of living environment independent variable encompasses the type of residential area, the age composition of the population in the neighbourhood and estimated annual net income per capita.

To analyse SUHII intensity distribution, the derived SUHII metrics were merged with neighbourhood-scale income, population and living environment data for the randomised points. Subsequently, the analysis had three stages: first, the analysis of the spatial distribution of surface urban heat islands in Győr; second, comparing median SUHII intensity across groups with different socio-economic features; and third, assessing vulnerability through correlation.

The case study city Győr

Győr is the centre of the West Transdanubia region, located at the confluence of three rivers. This geographical feature has played a significant role in the development of Győr, but also has determined the structure of the city. Its location made it an important distribution centre for grain and livestock trade. The transition from a trading town to an industrial city in the 19th century led to a twofold increase in population and to the emergence of a medium-sized (large), modern city (Balázs, P. 1980). Győr was characterised mainly by its manufacturing culture, the rapid revival of which contributed to the successful reception of foreign investment in the 1990s. The establishment of several large companies in the same decade led to increased migration and commuting to the city and a change in its image. This transformation reshaped the city's demographic landscape, giving rise to the phenomenon of suburbanisation (Rechnitzer, J. and Berkes, J. 2021).

The proportions of the functional belts have changed. Non-residential buildings have been built and their share is now higher than the share of residential buildings (Csapó, T. 2021).

Roughly half of the urban area (including green areas not classified as such by land use) is non-residential, but industrial in nature. As seen in *Figure 1* the urban fabric of Győr consists of large suburban areas. Single-family housing accounts for nearly 60 percent of the city's residential area as a result of the an-

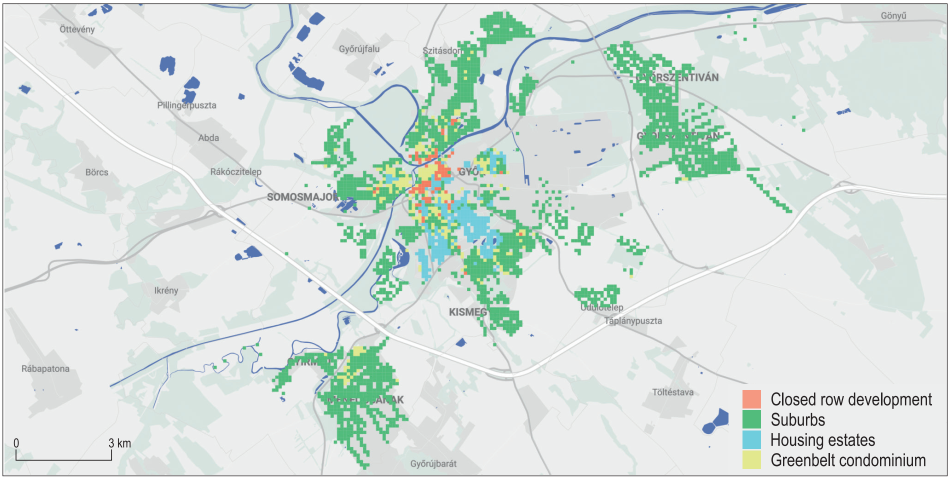

Fig. 1. Types of residential areas in Győr. *Source:* GeoX and TEIR. Authors' own elaboration.

nexation of nearby settlements. Multi-storey block development is also significant, accounting for 25–30 percent of the city's built-up area. Detached family houses are characteristic above all in the outer residential belt, while multi-storey blocks are concentrated in specific urban areas. Closed-row development is limited, covering mainly the historic core of the city (Lenner, T. *et al.* 2015).

The city has a continental climate. The average annual mean temperature in 2019 was 12,5 °C. The months of June to August experienced the highest temperatures, ranging from 22,6 to 23,2 °C. The average precipitation for the year amounted to 40 mm, with May having the highest precipitation. Based on the period of 2001 to 2020, the annual average global irradiance is 4,588 MJ/m², with over 650 MJ/m² in the months of June and July and the annual wind average is 1.96 m/s (HungaroMet, 2024).

The population is concentrated in the centre of the city, with densities as high as 100–1649 inhabitants per 0.01 km², while suburban areas register a lower average population density of 1–49 inhabitants per 0.01 km². The population of Győr demonstrates an ageing trend, particularly pronounced in the historical core of the city, with an ageing index of over 300 inhabitants aged 63 or older for every 100 people aged 0–14.

Certain areas of the city have a high concentration of residents with incomes above average, often situated near the riverbanks and green areas, which are cold spots of the city in terms of SUHII. Areas near the industrial parts of the city accommodate residents with incomes below average, aligning them with hotspots of the city in terms of SUHII. After providing an overview of statistics on the 100 random points, the next part of this study explores the interplays and provides a detailed analysis of the social and spatial patterns of SUHII in the city.

Analysis and results

First, descriptive of the sample points are provided to provide further context, focusing on the distribution of sample points across types of residential areas, living environments and demographic groups.

Descriptive statistics of the sample points

The spatial distribution of the 100 sampling points generated could not be influenced due to the Google Earth Engine platform's operating mechanism. The points in Győr were as follows (*Figure 2*). It can be observed that the distribution of the points is not uniform. Google Earth Engine distributes random sampling points over the entire city. For the research, area types specific to Győr were defined. Their names and the distribution of sampling points in each category are shown in *Table 1*.

The categorisation in *Table 1* also includes urban areas that are not considered residential (e.g., industrial), accounting for 34 percent of the 100 random sample points and are not subject to further analysis. The number of sampling points for the study of residential areas was determined according to the categorisation used by the data sources (GeoX and TEIR), based on the type of residential area and the type of living environment. The analysis of spatial patterns of SUHII was based on these variables.

The distribution of the points across types of residential areas (*Table 2*) is explained by the nature of the city's built-up area. As discussed, the dataset resulting from random point generation is more skewed towards suburban areas, which influenced the methodology used to analyse exposure to SUHII.

To conduct research, it is necessary to separate the different types of living environments,

*Table 1. Number of sample points found in the different categories of areas**

Type of area	Frequency	Percent
Riverside	3	3
Green area	6	6
Residential area	38	38
Downtown residential area	29	29
Service/business district	5	5
Industrial area	15	15
Roadside	1	1
Railway lines	3	3

*N = 100. *Source:* GeoX and Google Earth Engine Platform. Authors' own elaboration.

Table 2. Number of sample points found in the different types of residential areas

Type of residential area	Frequency	Percent
Garden suburbs	48	73
Greenbelt condominium	8	12
Downtown closed row buildings	6	9
Housing estate	4	6
Total	*66*	*100*

Source: GeoX and Google Earth Engine Platform. Authors' own elaboration.

Table 3 shows how many of the 100 sample points generated by Google Earth Engine fell into a type of living environment. Based on the categorisation determined by the data source GeoX, almost 40 percent of the residential

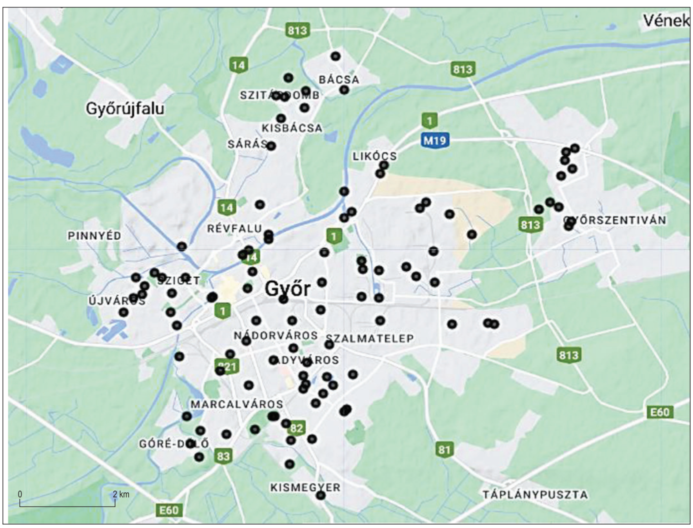

Fig. 2. The distribution of sample points across Győr. *Source:* Google Earth Engine Platform. Authors' own elaboration.

Table 3. Number of sample points found in the different types of living environment

Type of living environment	Frequency	Percent
Rich-suburban-adult	17	26
Rich-suburban-with children	4	6
Rich-green zone-adult	13	20
Rich-downtown-adult	26	39
Rich-residential complex-with young children	2	3
Average-low-price condominium-adult	2	3
Average-downtown-adult	2	3
Total	***66***	*100*

Source: GeoX and Google Earth Engine Platform. Authors' own elaboration.

sample points fall within the rich-downtown-adult category, which means that these points are found in inner-city areas characterised by higher than average income, higher population density and the dominant age group is adults.

By pairing the categories in *Table 3* with the suburban and downtown residential area subcategories, a new distribution of measurement points was created, which refines the analysis results. As seen in *Table 4*, suburban residential areas in the city cover a wide variety of built-up areas and living environments for all types of income ranges and age groups. The numbers in *Table 4* reveals that the classification of living environments does not always align with the type of residential area expected for that particular living environment in the city. For instance, the rich-suburban-adult quality of life and living environment could also emerge in downtown residential areas, as it falls into this category. The reverse is also true for rich-downtown-adult living environment and suburban residential area.

A summary of the socio-demographic data from the measurement points is shown in *Table 5*. Description of estimated annual net income per person reveals that almost 60 percent of the measurement points fall within the highest income brackets (over 1,400 thousand HUF) and the lowest income bracket has the smallest percentage in the dataset. It can also be seen that there is an ageing population in 76 percent of the neighbourhoods of the measurement points. The population density correlates with data for Hungarian cities of similar size.

Table 6 shows the data for the demographic categories studied (see *Table 5*) for the number of measurement points in different types of residential areas. Most of the measurement points are in the garden suburbs section,

Table 4. Number of sample points found in different types of living environment within the subcategories of suburban and downtown residential areas

Type of living environment/type of area	Suburban residential area	Downtown residential area	Total
Rich-suburban-adult	16	16	17
Rich-suburban-with children	4	0	4
Rich-green zone-adult	12	1	13
Rich-downtown-adult	2	24	26
Rich-residential complex-with young children	1	1	2
Average-low-price condominium-adult	2	0	2
Average-downtown-adult	0	2	2
Total	*37*	*29*	***66***

Source: GeoX and Google Earth Engine Platform. Authors' own elaboration.

Table 5. Demographic data of the analysed sample points

Indicators	Categories	Frequency	Percent
Estimated annual net income per person, in thousand HUF	< 1,000	1	2
	1,100–1,199	5	8
	1,200–1,299	4	6
	1,300–1,399	18	27
	1,400–1,499	20	30
	> 1,500	18	27
Ageing index, persons	0	16	24
	1–99	10	15
	100–199	20	30
	200–299	14	21
	> 300	6	9
Population density, number of persons per 0,01 km²	1–24	29	44
	25–49	15	23
	50–99	12	18
	100–199	7	11
	> 200	3	5

Source: GeoX and Google Earth Engine Platform. Authors' own elaboration.

Table 6. Demographics of people living in different types of residential areas

Indicators	Categories	Garden suburbs	Greenbelt condominium	Downtown closed-row buildings	Housing estate	Total
Estimated annual net income/ person (1000 HUF)/types of residential areas	< 1,000	1	0	0	0	1
	1,100–1,199	4	1	0	0	5
	1,200–1,299	3	1	0	0	4
	1,300–1,399	13	1	1	3	18
	1,400–1,499	13	3	3	1	20
	> 1,500	14	2	2	0	18
Total		*48*	*8*	*6*	*4*	***66***
Ageing index, number of people aged > 63 per 100 people aged 0–14	0	16	0	0	0	16
	1–99	8	1	1	0	10
	100–199	11	3	3	3	20
	200–299	9	3	1	1	14
	> 300	4	1	1	0	6
Total		*48*	*8*	*6*	*4*	***66***
Population density, number of people /0.01 km²	1–24	26	3	0	0	29
	25–49	13	2	0	0	15
	50–99	8	3	1	0	12
	100–199	0	0	5	2	7
	> 200	1	0	0	2	3
Total		*48*	*8*	*6*	*4*	***66***

Source: GeoX and Google Earth Engine Platform. Authors' own elaboration.

with the number of measurement points for the other categories being significantly fewer. The obvious reason for this is the predominance of the suburban character of the city. *Table 6*, similarly to *Table 4*, shows that residents from all types of income brackets and age groups choose to live in the suburban residential areas of the city.

Spatial and social patterns of SUHII

In order to develop an understanding of SUHII in Győr, first, we looked at patterns of average daytime and nighttime SUHII across various types of areas, residential areas and living environments. This provided us with a comprehensive overview. Subsequently we analysed the relationship between SUHII and socio-economic variables, as these variables are recognised in the body of literature as determining factors for residents' choices of living locations (Mashhoodi, B. 2021).

Based on the patterns of annual daytime SUHII (*Figure 3*), industrial areas tend to have an intensity as high as 4.5 °C, while green areas on the outskirts of the city had temperature differences of 0 to -1.5 °C compared to the surrounding rural areas. The map of the annual daytime SUHII for 2019 also suggests that areas in the inner residential belt had a wider distribution of SUHII values, with possible localised heat islands or hotspots in areas of the city core. Patterns of annual nighttime SUHII suggest that heat retention in downtown areas leads to a more pronounced heat island effect during the night.

Literature on disproportionate exposure to UHII often compares subgroups within the population, usually through comparing the means of the top and bottom deciles. In the case of the surface urban heat island data we processed, we took into account the spatial heterogeneity and the attributes of the sample used. Areas characterised by housing estates are underrepresented, and areas characterised by garden suburbs are overrepresented, leading to a skewed, not normal distribution. Given this distribution, we compared medians of average daytime and nighttime SUHII values across various types of living environments and socio-economic groups, as the median is less affected by outliers, rendering it more suitable for analysing variations. As seen in *Figure 9*, the median daytime SUHII ranged from 0.8 to 2.1 °C in 2019, whereas the night time SUHII ranged from 0 to 1 °C.

The visual comparison of medians (*Figure 4*) indicates that the garden suburbs within the city experience a lower heat island effect during both daytime and nighttime compared to other types of residential areas. Among these, areas characterised by housing estates had the highest temperature differences in 2019. It is in these types of residential areas, particularly in districts like Gyárváros or Újváros, where lower-educated and older neighbourhoods are concentrated (Municipality of Győr, 2014).

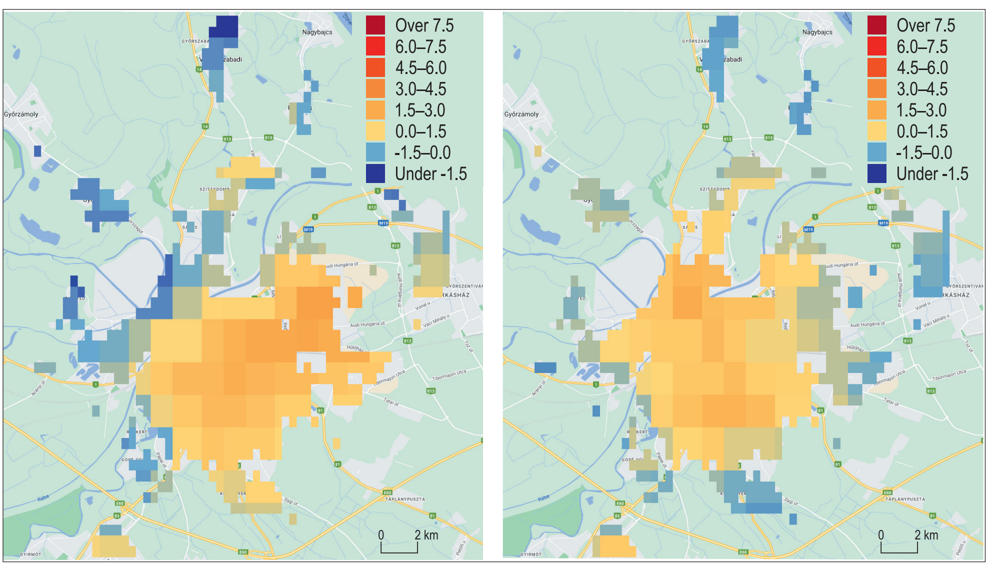

Fig. 3. Patterns of annual daytime (left) and nighttime (right) SUHII. *Source:* Global Surface UHI Explorer database provided by Yale Center for Earth Observation. Authors' own elaboration.

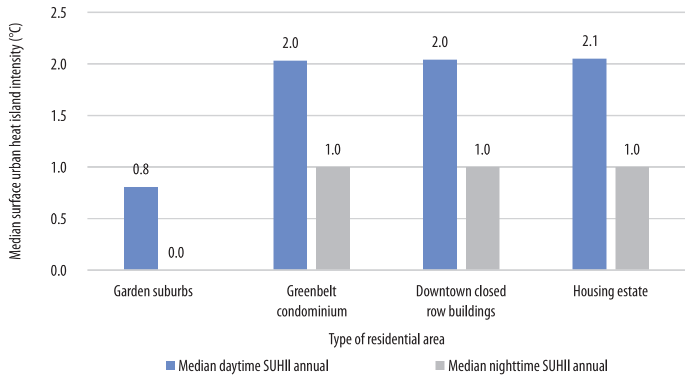

Fig. 4. Median SUHII across types of residential areas, 2019. *Source:* Authors' analysis.

Neighbourhoods characterised by garden suburbs are diverse in terms of year of construction, condition and size (Lenner, T. *et al.* 2015). The effect size calculation for the Kruskal-Wallis test we ran reveals that approximately 17.3 percent of the total variability in daytime SUHII scores can be attributed to the differences between residential areas and 21.6 percent of the total variability in nighttime SUHII scores.

Providing further context, *Figure 5* on median daytime and nighttime SUHII across types of living environments shows that rich suburban and average green-belt condominium neighbourhoods experienced lower daytime SUHII intensities, ranging from 0.4 to 0.9 °C. In contrast, regardless of the income situation of the people living there, downtown neighbourhoods experienced higher temperature differences, exceeding 2 °C. While other areas registered median nighttime SUHII values at 0 °C, downtown areas experienced a median nighttime SUHII value of 1 °C. This suggests that these neighbourhoods experience a more noticeable heat island effect during both daytime and nighttime hours. The effect size of eta2 = 0.119 indicates that approximately 11.9 percent of the total variability in daytime SUHII scores and 23.1 percent of the total variability in nighttime SUHII can be attributed to differences between the types of living environments. These results suggest that there are clear differences in exposure based on the type of residential area, but income might not be a determining factor of disproportionate exposure in Győr. However, understanding which socio-demographic factors are associated with higher SUHII requires further analysis.

The visual comparison of median SUHII across income groups suggests that in the case of Győr, a higher income level does not presuppose lower exposure to SUHII. As shown in *Figure 6*, the median daytime SUHII intensity ranges from 0.6 to 1.8 °C, whereas nighttime SUHII values range between 0 and 1 °C. We observed that neighbourhoods falling within the lower quantile of the income bracket experienced 0.7 °C higher intensities during daytime and 1 °C higher during nighttime, in comparison to neighbourhoods in the upper quantile of the income group. Notably, top-quantile neighbourhoods experienced a moderate surface urban heat island intensity, while those with an income between 1,100 and 1,399 thousand HUF had lower median SUHII intensities. From observing the data, it is not possible to deduce a general trend of decreasing SUHII with increasing income and the application of the Spearman's correlation revealed no statistically significant association ($p = 0.824$) between income and daytime SUHII scores, nor between income and nighttime SUHII scores ($p = 0.929$).

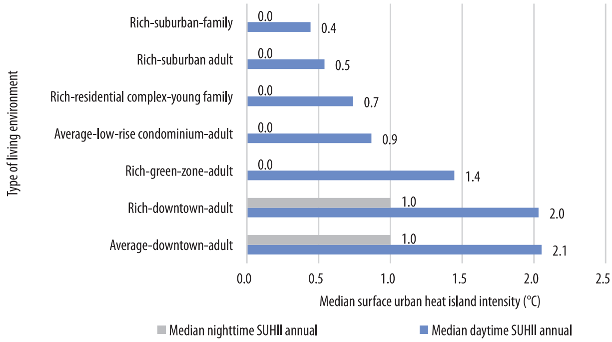

Fig. 5. Median SUHII across types of living environments, 2019. *Source:* Authors' analysis.

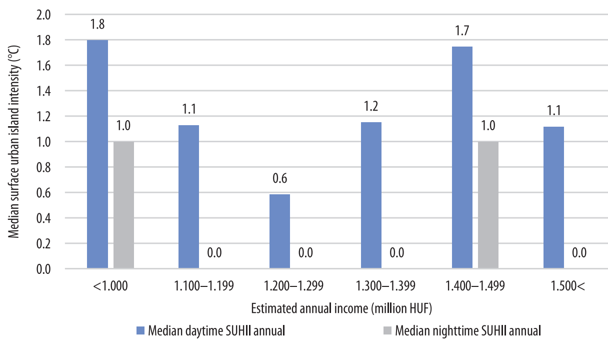

Fig. 6. Median SUHII across income groups, 2019. *Source*: Authors' analysis.

The higher values observed in neighbourhoods with incomes under 1 million HUF, and between 1.4 and 1.5 million HUF can be explained by the urban characteristics and land use in these income brackets. Nearly 50 percent of neighbourhoods with these income ranges are found in downtown areas, within the inner city, characterised by medium to high population densities exceeding 50 inhabitants per 0.01 km². These areas are predominantly closed-row buildings, housing estates and green-belt condominiums.

The observation of differences among ageing index groups indicates certain inequities. Notably, there is a difference of 1.6 °C between groups with the highest ageing index and groups with the lowest ageing index (*Figure 7*). The graphical depiction of the relationship between the two variables shows that as the ageing index increases, median daytime and nighttime SUHII values increase, as well. Specifically, neighbourhoods with an ageing index of 300 or greater had a SUHII of 2.1 °C. These findings align with existing literature (e.g., Hsu, A. *et al.* 2021), which highlights that older populations are more vulnerable to the surface urban heat island phenomenon.

Within Győr, neighbourhoods with the highest ageing index primarily comprise the city-core characterised by closed-row developments, a mix of multi-storey blocks, condominiums, and semi-detached or detached family houses. The Spearman's rho correlation coefficient of 0.289 evidences a weak positive relationship between daytime SUHII intensity and ageing index. However, it is important to note that there is no statis-

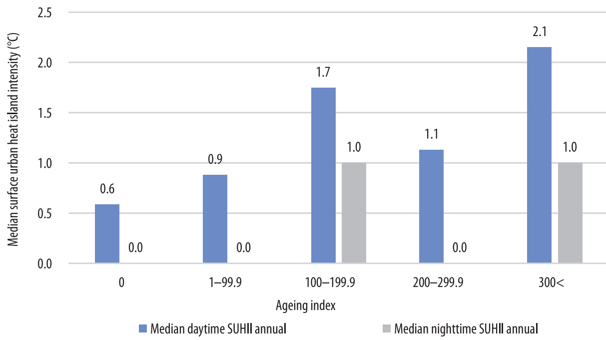

Fig. 7. Median SUHII across ageing index groups, 2019. *Source*: Authors' analysis.

tically significant relationship between the nighttime SUHII and the ageing index. It can be concluded that areas with a higher concentration of people aged 63 and above experienced higher daytime SUHII (0.462, $p < 0.01$), and areas with a higher concentration of people aged 0–14 experienced lower daytime SUHII (0.364, $p < 0.01$).

Likewise, the graphical depiction of population density shows a trend, wherein areas with a higher population density tend to have elevated daytime SUHII values compared to neighbourhoods with lower population density (*Figure 8*). Notably, areas with the highest population density had a daytime SUHII of 2.1 °C, which is 1.5 degrees hotter than areas with a population density of 1 to 24 inhabitants within a 100 × 100-meter cell. Moreover, areas with a population density exceeding 50 inhabitants similarly experienced temperatures 1 °C hotter than low-density neighbourhoods. The Spearman's rho correlation analysis shows a statistically significant relationship, the coefficients of 0.525 and 0.540 show that among the socio-demographic variables, population density has the strongest positive relationship with daytime and nighttime SUHII.

Discussion

Using established methods, this research analysed the relationship of SUHII with socio-economic and urban living environment factors based on random points generated

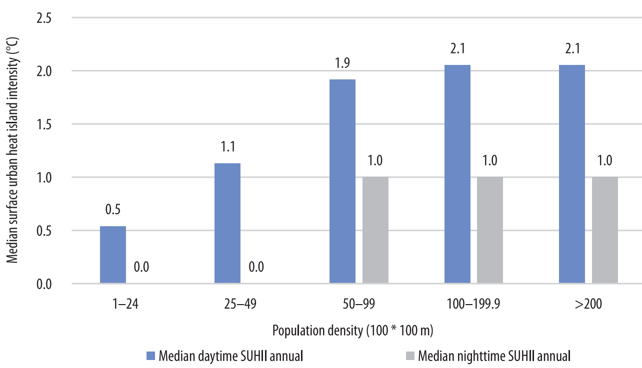

Fig. 8. Median SUHII across population density groups, 2019. *Source:* Authors' analysis.

using the Google Earth Engine platform. The study identified distinct daytime and night-time SUHII patterns across various types of residential areas and living environments. Notably, sample points in suburban areas of Győr experienced comparatively lower temperature differences compared to other residential areas, whereas areas with housing estates had the highest surface urban heat island intensity. These findings coupled with the data on living environments, emphasise the significance of urban layout in influencing patterns of SUHII. Our results align with the works of Wolf, T. and Mcgregor, G. (2013), Morabito, M. *et al.* (2015) or Macintyre, H.L. *et al.* (2018) linking increased vulnerability with higher ageing index and greater population density. However, the current study's findings do not support results indicating a correlation between lower income and increased vulnerability.

The results align with the results of Buzási, A. (2022) who also identified a high ratio of elderly people as a common vulnerability in the districts of Budapest. It is important to note that in the literature, these socio-economic groups are often seen to be contributing to exaggerating SUHII, as they may lack the resources or knowledge to mitigate the urban heat island effect (Dialesandro, J. *et al.* 2021). Moreover, neighbourhoods with high population density may lack the adequate ratio of greenery and impervious surfaces to mitigate the SUHII effect. While the age composition of Győr is more favourable than the national average, making it less vulnerable to summer heat waves, with the ageing population, the elderly population density will increase in the future. This highlights the importance of incorporating these findings when planning strategies of mitigation.

Győr, in its climate strategy (Municipality of Győr, 2021), emphasises climate protection awareness raising among the population, however, this may not fully be sufficient for socio-economic groups with limited resources. While the strategy recognises the existence of urban heat island hotspots in downtown areas, comprehensive mapping of the phenomenon is lacking. Although these downtown areas are seen as green space deficit zones and are subject to foreseen greening initiatives such as green roofs, roof gardens or green walls, we recommend identifying neighbourhoods with cumulative vulnerability based on population density and ageing index and formulating targeted interventions accordingly.

In addition to exploring grants that can be used to support community green spaces, we recommend providing communities with better opportunities to maintain existing green spaces and exploring how the benefits and costs of various mitigation initiatives are distributed across different neighbourhoods in the city.

While our study focuses on Győr, other middle-sized cities in Hungary may show different patterns of SUHII. Therefore, further research is required across other regional centres of Hungary and incorporating additional socio-demographic and building variables. These efforts will provide a more comprehensive understanding of disproportionate exposure and the ways SUHII patterns developed based on distinct development paths of various middle-sized cities. Additionally, this study has certain limitations as it relies on the Global Surface UHI Explorer, which measures land surface temperature differences and as such offers only a one-sided description of the urban heat island phenomenon (Wu, Z. and Ren, Y. 2019).

Furthermore, the algorithm by Chakraborty, T. and Lee, X. (2019) was developed to create a globally consistent UHI database, leading to a generalised selection of the rural reference, which calls for caution when analysing SUHII in urban clusters. SUHII data is estimated using the average 8-day per pixel LST, but retrieval is constrained to clear sky conditions only, which influences the reliability of the SUHII data. Thus, air temperature measurements or estimation through modelling is important for an in-depth analysis.

Our findings offer a limited understanding of vulnerability as we primarily focused on age, income and population density. Previous findings suggest that health status, ethnicity and welfare dependency represent additional risk factors. Due to the data's availability only at the neighbourhood level (100 x 100 m) in groupings, the analysis makes assumptions regarding the variance of socio-economic data, presuming homogeneity inside a given neighbourhood. Furthermore, income data retrieved from the GeoX database is an estimate downscaled from municipal data to the neighbourhood level, thereby impacting the reliability of our results. Due to the differences in resolution between the socio-economic (100 x 100 m) and SUHII intensity data (300 m x 300 m), the results of the correlation analyses could be inflated and should be interpreted with caution.

Other influencing factors such as building height and proportion of vegetation, are not captured in our research. Despite the limitations of our research, focusing on social and economic variables furthers our understanding of the urban heat island phenomenon in Hungary. The combination of methods and the inclusion of other influencing factors offers a direction for future research expansion. An aspect to follow-up is how greening initiatives outlined in the city's climate strategy may mitigate the urban heat island effect.

Conclusions

This study set out to better understand how certain socio-economic and urban living environment factors influence exposure to surface urban heat island intensity in a city with a development path based on a new industrial base. Leveraging the Google Earth Engine platform and the Global Surface UHI Explorer, SUHII intensity data at the neighbourhood level were retrieved and processed for a set of 100 randomised points within Győr. Although the methodology of this study and the data used call for caution, the results are in line with previous studies and show that population density has the strongest relationship with daytime and nighttime SUHII, and that neighbourhoods with an ageing index of 300 or greater experience the highest urban heat island intensity.

The findings of this research highlight the importance of identifying neighbourhoods with cumulative vulnerability and formulating targeted interventions to mitigate the adverse effects of urban heat islands in the city of Győr. Despite its limitations, the insights gained from this study may be of assistance to formulating these targeted interventions. Further research is needed to investigate other factors, such as building and vegetation characteristics influencing vulnerability to SUHII in the city of Győr. In addition, future work should be extended to other major cities in Hungary.

REFERENCES

Amindin, A., Pouyan, S., Pourghasemi, H.r., Yousefi, S. and Tiefenbacher, J.P. 2021. Spatial and temporal analysis of urban heat island using Landsat satellite images. *Environmental Science and Pollution Research* 28. 41439–41450. https://doi.org/10.1007/s11356-021-13693-0

Balázs, P. 1980. *Győr a feudalizmus bomlása és a polgári forradalom idején* (Győr during the disintegration of the feudalism, and at the time of bourgeois revolution). Budapest, Akadémiai Kiadó.

Bottyán, Z., Unger, J., Szegedi, S. and Gál, T.M. 2004. A városi hőmérsékleti többlet területi eloszlásának statisztikus modellezése a beépítettségi paraméter alapján, Szegeden és Debrecenben (Modelling spatial distribution of urban temperature surplus statistically based on the built-up area parameter in Szeged and Debrecen). In *A magyar földrajz kurrens eredményei: II. Magyar Földrajzi Konferencia*. Szeged, SZTE TTK Természeti Földrajzi és Geoinformatikai Tanszék.

Buzási, A. 2022. Comparative assessment of heatwave vulnerability factors for the districts of Budapest, Hungary. *Urban Climate* 42. 101127. https://doi.org/10.1016/j.uclim.2022.101127

Chakraborty, T. and Lee, X. 2019. A simplified urban-extent algorithm to characterise surface urban heat islands on a global scale and examine vegetation control on their spatiotemporal variability. *International Journal of Applied Earth Observation and Geoinformation* 74. 269–280. https://doi.org/10.1016/j.jag.2018.09.015

Cheval, S., Dumitrescu, A., Irașoc, A., Paraschiv, M.g., Perry, M. and Ghent, D. 2022. MODIS-based climatology of the surface urban heat island at country scale (Romania). *Urban Climate* 41. 101056. https://doi.org/10.1016/j.uclim.2021.101056

Csapó, T. 2021. Nagyvárosok területfelhasználásának alakulása (Change of landuse in large cities). In

Nagyvárosok Magyarországon. Eds.: Rechnitzer, J. and Berkes, J., Budapest, Ludovika Kiadó, 99–107.

Dialesandro, J., Brazil, N., Wheeler, S. and Abunnasr, Y. 2021. Dimensions of thermal inequity: neighborhood social demographics and urban heat in the Southwestern US. *International Journal of Environmental Research and Public Health* 18. (3): 941. https://doi.org/10.3390/ijerph18030941

Gawuc, L., Jefimow, M., Szymankiewicz, K., Kuchcik, M., Sattari, A. and Struzewska, J. 2020. Statistical modeling of urban heat island intensity in Warsaw, Poland using simultaneous air and surface temperature observations. *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing* 13. 2716–2728. https://doi.org/10.1109/JSTARS.2020.2989071

Hendel, M. 2020. Cool pavements. In *Eco-efficient Pavement Construction Materials*. Eds.: Pacheco-Torgal, F., Amirkhanian, S., Wang, H. and Schlangen, E., Sawston, Woodhead Publishing, 97–125. https://doi.org/10.1016/B978-0-12-818981-8.00006-0

Holec, J., Šveda, M., Szatmári, D., Feranec, J., Bobáľová, H., Kopecká, M. and Šťastný, P. 2021. Heat risk assessment based on mobile phone data: Case study of Bratislava, Slovakia. *Natural Hazards* 108. (3): 3099–3120. https://doi.org/10.1007/s11069-021-04816-4

Howard, L. 2007. *The climate of London: Deduced from meteorological observations, made at different places in the neighbourhood of the metropolis.* London, IAUC International Association for Urban Climate. https://urban-climate.org/documents/LukeHoward_Climate-of-London-V1.pdf

Hsu, A., Sheriff, G., Chakraborty, T. and Manya, D. 2021. Disproportionate exposure to urban heat island intensity across major US cities. *Nature Communications* 12. (1): 2721. https://doi.org/10.1038/s41467-021-22799-5

Huang, G. and Cadenasso, M.L. 2016. People, landscape, and urban heat island: Dynamics among neighborhood social conditions, land cover and surface temperatures. *Landscape Ecology* 31. (10): 2507–2515.https://doi.org/10.1007/s10980-016-0437-z

HungaroMet 2024. *Győr éghajlati jellemzői* (Climate characteristics of Győr). Budapest, Magyar Meteorológiai Szolgáltató Nonprofit Zrt. https://www.met.hu/eghajlat/magyarorszag_eghajlata/varosok_jellemzoi/Gyor/

IPCC 2007. *IPCC Fourth Assessment Report: Climate Change 2007*. Intergovernmental Panel on Climate Change. https://archive.ipcc.ch/publications_and_data/ar4/wg1/en/ch3s3-2-2-2.html

Khan, A., Chatterjee, S. and Weng, Y. 2021. Characterising thermal fields and evaluating UHI effects. In *Urban Heat Island Modelling for Tropical Climates*. Eds.: Khan, A., Chatterjee, S. and Weng, Y., Amsterdam, Elsevier, 37–67. https://doi.org/10.1016/B978-0-12-819669-4.00002-7

Kopecká, M., Szatmári, D., Holec, J. and Feranec, J. 2021. Urban heat island modelling based on MUKLIMO: Examples from Slovakia. *AGILE: GIScience Series* 2. (5) https://doi.org/10.5194/agile-giss-2-5-2021

Krishna, R. 1972. Remote sensing of urban heat islands from an environmental satellite. *Bulletin of the American Meteorological Society* 543. 647–648.

László, L. 2017. *A városi hősziget-intenzitás jellemzése, statisztikus modellezése Debrecen és Beregszász példáján* (The characterization and statistical modelling of urban heat island intensity in Debrecen and Berehove). Doctoral Thesis, Debrecen, Debreceni Egyetem, Földtudományok Doktori Iskola.

Lenner, T., Kozma, K. and Csapó, T. 2015. Győr településmorfológiája (Settlement morphology of Győr). *Településföldrajzi Tanulmányok* 4. (1): 17–34.

Liu, L., Lin, Y., Liu, J., Wang, L., Wang, D., Shui, T., Chen, X. and Wu, Q. 2017. Analysis of local-scale urban heat island characteristics using an integrated method of mobile measurement and GIS-based spatial interpolation. *Building and Environment* 117. 191–207. https://doi.org/10.1016/j.buildenv.2017.03.013

Macintyre, H.L., Heaviside, C., Taylor, J., Picetti, R., Symonds, P., Cai, X.M. and Vardoulakis, S. 2018. Assessing urban population vulnerability and environmental risks across an urban area during heatwaves – Implications for health protection. *Science of the Total Environment* 610. 678–690. https://doi.org/10.1016/j.scitotenv.2017.08.062

Mashhoodi, B. 2021. Environmental justice and surface temperature: Income, ethnic, gender, and age inequalities. *Sustainable Cities and Society* 68. 102810. https://doi.org/10.1016/j.scs.2021.102810

Mitchell, B.C. and Chakraborty, J. 2015. Landscapes of thermal inequity: Disproportionate exposure to urban heat in the three largest US cities. *Environmental Research Letters* 10. (11): 115005. https://doi.org/10.1088/1748-9326/10/11/115005

Molnár, G., Gyöngyösi, A.Z. and Gál, T.M. 2017. A városi hősziget vizsgálata meteorológiai modell segítségével Szegeden (Analysis of urban heat island with meteorological forecast model in Szeged). *Légkör* 62. (3): 130–135.

Morabito, M., Crisci, A., Gioli, B., Gualtieri, G., Toscano, P., Di Stefano, V., Orlandini, S. and Gensini, G.F. 2015. Urban-hazard risk analysis: Mapping of heat-related risks in the elderly in major Italian cities. *PLoS One* 10. (5): e0127277. https://doi.org/10.1371/journal.pone.0127277

Municipality of Győr 2014. *Megalapozó vizsgálat Győr Megyei Jogú Város Településfejlesztési Koncepciójához és Integrált Településfejlesztési Stratégiájához* (Feasibility study for the Urban Development Concept and Integrated Settlement Development Strategy of the city of Győr). Győr, Városi Önkormányzat. https://gyor.hu/easy-docs/5dc9829cb6d4c

Municipality of Győr 2021. *Győr Megyei Jogú Város klímastratégiája 2021–2023 közötti időszakra* (Climate strategy of Győr for the period 2021–2023). Győr, Universitas-Győr Nonprofit Kft. https://gyor.hu/easy-docs/615ffdac205c3

Noonan, D.S. 2008. Evidence of environmental justice: A critical perspective on the practice of EJ research and lessons for policy design. *Social Science Quarterly* 89. (5): 1153–1174. https://doi.org/10.1111/j.1540-6237.2008.00568.x

Piracha, A. and Chaudhary, M.T. 2022. Urban air pollution, urban heat island and human health: A review of the literature. *Sustainability* 14. (15): 9234. https://doi.org/10.3390/su14159234

Pongrácz, R., Bartholy, J., Dezső, Z. and Dian, C. 2016. Analysis of the air temperature and relative humidity measurements in Budapest-Ferencváros. *Hungarian Geographical Bulletin* 65. (2): 93–103. https://doi.org/10.15201/hungeobull.65.2.1

Portier, C.J., Tart, K.T., Carter, S.R., Dilworth, C.H., Grambsch, A.E., Gohlke, J., Hess, J., Howard, S.N., Luber, G., Lutz, J.T., Maslak, T., Prudent, N., Radtke, M., Rosenthal, J.P., Rowles, T., Sandifer, P.A., Scherage, J., Schramm, P.J., Strickman, D., Trtanj, J.M. and Whung, P.Y. 2013. A human health perspective on climate change: A report outlining the research needs on the human health effects of climate change. *Journal of Current Issues in Globalization* 6. (4): 621.

Rechnitzer, J. and Berkes, J. 2021. *Nagyvárosok Magyarországon* (Large cities in Hungary). Budapest, Ludovika Egyetemi Kiadó.

Stewart, I.D. 2011. *Redefining the Urban Heat Island*. Vancouver, University of British Columbia.

Szegedi, S. and Kircsi, A. 2003. The effects of the synoptic conditions on development of the urban heat island in Debrecen, Hungary. *Acta Climatologica et Chorologica Universitatis Szegediensis* 36. (37): 111–120.

Tong, S., Prior, J., Mcgregor, G., Shi, X. and Kinney, P. 2021. Urban heat: An increasing threat to global health. *British Medical Journal* 375. 2467. https://doi.org/10.1136/bmj.n2467

UNCTAD 2022. *Handbook of Statistics 2022 – Total and urban population*. Geneva CH, UNCTAD. https://hbs.unctad.org/total-and-urban-population/

Yang, J., Wong, N.H. and Lam, H.K. 2016. Modelling the mitigation effect of various heat mitigation measures on building energy consumption and the impact on urban air quality. *Environmental Modelling & Software* 84. 235–243.

Wolf, T. and Mcgregor, G. 2013. The development of a heat wave vulnerability index for London, United Kingdom. *Weather and Climate Extremes* 1. 59–68. https://doi.org/10.1016/j.wace.2013.07.004

World Bank 2023a. *Urban population (% of total population).* Washington, D.C., World Bank. https://data.worldbank.org/indicator/SP.URB.TOTL.IN.ZS

World Bank 2023b. *Urban development. Overview*. Washington, D.C., World Bank. https://www.worldbank.org/en/topic/urbandevelopment/overview

WMO 2021. *Weather-related disasters increase over past 50 years, causing more damage but fewer deaths*. Geneva CH, World Meteorological Organization. https://wmo.int/media/news/weather-related-disasters-increase-over-past-50-years-causing-more-damage-fewer-deaths

WMO 2023. *Heatwaves show importance of health early warnings and action plans*. Geneva CH, World Meteorological Organization. https://wmo.int/media/news/heatwaves-show-importance-of-health-early-warnings-and-action-plans

Wu, Z. and Ren, Y. 2019. A bibliometric review of past trends and future prospects in urban heat island research from 1990 to 2017. *Environmental Reviews* 27. (2): 241–251. https://doi.org/10.1139/er-2018-0029