Science of the Total Environment 945 (2024) 173952

Contents lists available at ScienceDirect

Science of the Total Environment

journal homepage: www.elsevier.com/locate/scitotenv

Feeling hot is being hot? Comparing the mapping and the surveying paradigm for urban heat vulnerability in Vienna

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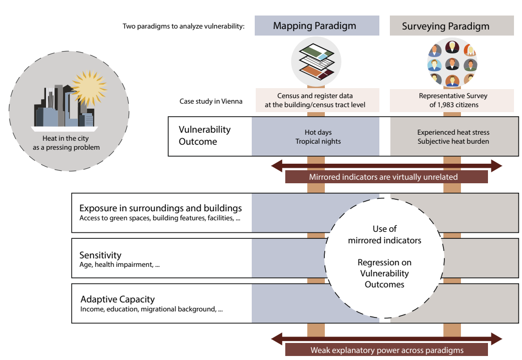
HIGHLIGHTS

- Considering mapping and surveying paradigms as equal may lead to ecological fallacy.
- We compare the paradigms in hierarchical regression models using a n = 1983 sample.
- Mirrored indicators have weak explanatory power across paradigms.
- The two paradigms do not seem to capture the same components of vulnerability.
- Heat vulnerability research should not center on just a single paradigm.

GRAPHICAL ABSTRACT



ARTICLE INFO

Editor: Scott Sheridan

Keywords:
Intra-urban vulnerability
Social vulnerability
Operationalisation
Adaptive behaviour
Urban heat island
Environmental justice

ABSTRACT

With rising global temperatures, cities increasingly need to identify populations or areas that are vulnerable to urban heat waves; however, vulnerability assessments may run into ecological fallacy if data from different scales are misconstrued as equivalent. We assess the heat vulnerability of 1983 residents in Vienna by measuring heat impacts, exposure, sensitivity and adaptive capacity with mirrored indicators in the mapping paradigm (i.e. census tract data referring to the geographic regions where these residents live) and the surveying paradigm (i.e. survey data referring to the residents' individual households). Results obtained in both paradigms diverge substantially: meteorological indicators of hot days and tropical nights are virtually unrelated to self-reported heat strain. Meteorological indicators are explained by mapping indicators (R^2 of 15–40 %), but mostly not by surveying indicators. Vice versa, experienced heat stress and subjective heat burden are mostly unassociated with mapping indicators but are partially explained by surveying indicators (R^2 of 2–4 %). The results suggest that the two paradigms do not capture the same components of vulnerability; this challenges whether studies conducted in the respective paradigms can complement and cross-validate each other. Policy interventions

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https://doi.org/10.1016/j.scitotenv.2024.173952
Received 23 December 2023; Received in revised form 10 June 2024; Accepted 10 June 2024
Available online 18 June 2024

should first define which heat vulnerability outcome they target and then apply the paradigm that best captures the specific drivers of this outcome.

1. Introduction

Urban areas face higher summer temperatures than rural areas, which relates to the urban heat island effect (Oke, 1982, 1995). Heat waves, such as recently 2021 in the USA, 2022 in India or 2022 and 2023 in Europe, have more pronounced effects on urban populations (Vescovi et al., 2005; Rinner et al., 2010; Rosenthal et al., 2014; Ho et al., 2018; Li et al., 2021). Summer temperatures in urban areas are projected to rise even further in the next decades (IPCC, 2022). The consequences of summer heat periods include substantial numbers of excess deaths and health-related impacts like psychological stress and hospital admissions (Reid et al., 2009; Xu et al., 2016; Niu et al., 2021). Vulnerable population segments, such as children, the elderly, outdoor workers, homeless people, people with pre-existing illnesses like diabetes, dependent drug users or those with lower socio-economic status, are more likely to be affected by adverse health impacts of heat waves (Reid et al., 2009; Rosenthal et al., 2014; Ho et al., 2018; Cheng et al., 2021). Heat waves also have economic impacts, such as reduced workforce productivity (Costa et al., 2016) and may have compound effects with air pollution, drought or other hazards (Ho et al., 2018; Zscheischler et al., 2018). These dynamics apply to cities all over the world as well as to Vienna, the capital of Austria and the case study of the present paper.

So far, numerous international and national policy documents acknowledge the increase of urban heat-related risks and discuss options for adaptation (e.g. EEA, 2020; WHO, 2021; BMNT, 2017; City of Vienna, 2022). Since, however, public budgets and resources are inherently limited, city administrations and planners need to focus their heat adaptation efforts where they are most effective or most needed (Filho et al., 2017). The unequal distribution of the heat load and the capacity to deal with heat are widely debated in the academic literature as well as in international and national policy documents. Thus, decision-makers need to understand the where and why of heat vulnerability, that is, the people and areas affected, as well as the characteristics which make some more vulnerable and have less coping and adaptive capacities than others (Filho et al., 2017; Kuras et al., 2017; Cheng et al., 2021). Building on a long-lasting discussion of how social vulnerability can be operationalised within disaster risk management and climate change adaptation (e.g. Burton et al., 1968; Chambers, 1989; Bohle et al., 1994; Cutter et al., 2003; Bogardi and Birkmann, 2004; Birkmann, 2006; IPCC, 2014), the present paper conceptualises heat vulnerability as comprising four components. The first three components represent sources of vulnerability: *exposure* as the presence of people in places that are adversely affected by heat; *sensitivity* as people's propensity or predisposition to be adversely affected by heat; and *adaptive capacity* as people's capacity to handle adverse effects by coping, recovering and adapting. The fourth component is the *vulnerability outcome*, as heat impacts that manifest in the physical and mental stress experienced by urban residents during extreme heat events. The regression framework adopted by the present paper translates these four components of vulnerability into a cause-effect logic, considering exposure, sensitivity and adaptive capacity as independent variables and vulnerability outcome as dependent variable.

Heat vulnerability is analysed by means of a wide range of approaches that use different data sources like surveys, census data or remote sensing and study different units of analysis, ranging from individuals or households to neighbourhoods, cities, catchments or entire nations (Reid et al., 2009; Ho et al., 2018; Ran et al., 2020). The present paper distinguishes between approaches following the mapping or the surveying paradigm. The *mapping paradigm* originated in North American environmental justice research and has become the dominant technique to identify the disproportionate presence of underprivileged groups in polluted, hot or otherwise environmentally hazardous areas (Locke and Grove, 2016; Banzhaf et al., 2019; Samuelson et al., 2020; Amorim-Maia et al., 2022). This paradigm uses geographical areas as the unit of analysis and is commonly termed 'hazards-of-place' (Cutter, 1996). Studies following the mapping paradigm join spatially explicit data from population census, city cadastre, meteorological measurement or satellite remote sensing. Maps are used to illustrate the vulnerability of geographical regions to natural hazards (Cutter et al., 2003; Ran et al., 2020), or to prioritise places for heat adaptation measures through creating more urban green and blue spaces (Anguelovski et al., 2022; EEA, 2022).

On the other hand, the *surveying paradigm* takes individual households as the unit of analysis and collects data on risk perception and protective behaviours by distributing questionnaires among heat-affected residents; it could thus be termed 'hazards-of-people' (Babcicky and Seebauer, 2021). Studies following the surveying paradigm relate perceived heat impacts to self-reported household and building attributes, motivations and heat-adaptive behaviours (Kabisch and Haase, 2014; Kunz-Plapp et al., 2016; Beckmann et al., 2021; Heidenreich et al., 2021).

The premise of the present paper is that the mapping and the surveying paradigm might be misconstrued as capturing heat vulnerability equally. For example, the review articles on heat vulnerability by Cheng et al. (2021) and Filho et al. (2017) suggest the surveying paradigm for validating the mapping paradigm, taking as given that both paradigms operationalise the same components of vulnerability because otherwise, the validation logic would not make sense. However, the mapping paradigm focuses on place-based characteristics as it "locates local vulnerability within the larger contexts that influence it" (Cutter et al., 2008:601), whereas the surveying paradigm focuses on the social and psychological attributes of people living in these places (Babcicky et al., 2021). The spatial and individual levels intersect in heat-related risk (Romero-Lankao et al., 2012); thus, equating mapping and surveying studies brings the risk of ecological fallacy; that is, confounding the units of analysis if the characteristics of individuals are inferred from the characteristics of the geographic unit in which they reside (Woodruff et al., 2018; Banzhaf et al., 2019).

Thus, the present paper tests empirically whether results obtained in the mapping paradigm conform with or diverge from results obtained in the surveying paradigm. We distinguish the paradigms by their most pronounced features: the use of secondary data and geographical regions as the unit of analysis in the mapping paradigm, versus the use of primary data and households as the unit of analysis in the surveying paradigm. The analysis applies both paradigms within the same context of heat vulnerability and to the same sample of 1983 Viennese households by measuring the same characteristics of heat impacts, exposure, sensitivity and adaptive capacity with mirrored mapping indicators on the one hand and surveying indicators on the other hand. Our findings pose a caveat to research centring on just a single paradigm, or, in the words of an early review on heat vulnerability, our findings remind researchers to consider that "what we know depends fundamentally on what questions we ask and how we go about answering those questions" (Romero-Lankao et al., 2012:680).

The remainder of the paper is organised as follows: Section 2 presents the mapping and surveying paradigms in detail, discusses their respective methodological challenges and acknowledges previous attempts at reconciling the paradigms. The method Section 3 presents the mapping and surveying indicators used for the case of Vienna and outlines the hierarchical regression approach. The results Section 4 shows that mirrored indicators are virtually uncorrelated, and that mapping indicators have low explanatory power for surveying indicators of heat impacts and vice versa. Section 5 provides a critical discussion of the study's limitations and concludes with recommendations for future research to first specify policy needs and heat impacts and then select the applicable paradigm.

2. Theoretical background

2.1. Heat vulnerability in the mapping paradigm

The increase in heat vulnerability assessments brought about a diversification of conceptual models. Urban heat vulnerability assessments that follow the mapping paradigm frame heat impacts as the cumulative outcome of exposure, sensitivity and adaptive capacity (Cheng et al., 2021; Li et al., 2022; note that in the recent IPCC, 2022 risk framework, sensitivity and adaptive capacity are included as subcomponents of vulnerability). In addition to different frameworks being used, studies in the mapping paradigm differ regarding data availability and the selection of indicators and assessment methods; nevertheless, most of the studies reach similar results.

The vulnerability outcome (i.e., the manifest physical and mental stress experienced by residents) is measured via meteorological heat maps based on daily maximum temperatures or episodes of hot days, which are associated with heat-related excess mortality (Schuster et al., 2014, Vescovi et al., 2005; Benmarhnia et al., 2017; see also Section 3.1). More detailed integrated indices for measuring bioclimatic conditions for humans (e.g. the Universal Thermal Climate Index, UTCI) are difficult to apply in urban settings because they require meteorological data in very high spatial and temporal resolution (Blazejczyk et al., 2012).

As visualised in Table 1, the assessment of exposure influencing the vulnerability outcome mainly includes the (density of the) built environment and various land use and land cover variables (Ellena et al., 2020).Recent studies focus on spatially explicit Local Climate Zones (LCZ) by classifying the urban surface and spacing of buildings (Bechtel et al., 2015). However, LCZ usually exclude information about the vulnerability distribution within the cityscape (Verdonck et al., 2018). Lack of or unequal distribution of access to green spaces increases the exposure of individuals and communities to heat (Li and Liu, 2016). Exposure indicators in urban areas are often limited to the residential environment and under-represent building and dwelling characteristics such as thermal insulation, south-facing orientation or availability of air conditioning, mostly due to the unavailability of data with fine spatial resolution (Samuelson et al., 2020; Romero-Lankao et al., 2012).

Sensitivity indicators usually stem from a wide range of socio-demographic and economic variables. Sensitivity is measured as the composition of inhabitants regarding age, health and mental (pre-)

Table 1
Sources of heat impacts.

Vulnerability component	Indicator	Mapping studies	Surveying studies
Exposure in surroundings	Population density	Romero-Lankao et al., 2012 (7/54) Filho et al., 2017 Cheng et al., 2021 (18/52)	n/a
	Building/housing density	Romero-Lankao et al., 2012 (3/54) Filho et al., 2017 Ellena et al., 2020 Cheng et al., 2021 (5/52)	n/a
	Land cover and land use	Romero-Lankao et al., 2012 (3/54) Ellena et al., 2020 Cheng et al., 2021 (15/52)	n/a
	Vegetation cover	Romero-Lankao et al., 2012 (3/54) Ellena et al., 2020 Cheng et al., 2021 (26/52) Li et al., 2022 (23/76)	n/a
	Access (proximity) to blue and green space	Filho et al., 2017 (1/7) Cheng et al., 2021 (3/52) Niu et al., 2021	Franck et al., 2013 Borchers et al., 2020 Lai et al., 2020 Laranjeira et al., 2021
Exposure in buildings	Building age, insulation of the building envelope	Cheng et al., 2021 (6/52) Zuurbier et al., 2021	Beckmann et al., 2021
	Housing type	Romero-Lankao et al., 2012 (5/54) Cheng et al., 2021 (9/52)	Franck et al., 2013 Kunz-Plapp et al., 2016
	Top floor	Tomlinson et al., 2011 Zuurbier et al., 2021	Franck et al., 2013 Kunz-Plapp et al., 2016 Beckmann et al., 2021
	Housing attributes, dwelling facilities, garden	Filho et al., 2017 (2/7) Niu et al., 2021	Kunz-Plapp et al., 2016, Samuelson et al., 2020
	Air conditioning	Romero-Lankao et al., 2012 (6/54) Cheng et al., 2021 (10/52) Nazarian and Lee, 2021	Lai et al., 2020 Semenza et al., 1996 Wright et al., 2020
Sensitivity	Gender	Romero-Lankao et al., 2012 (14/54) Cheng et al., 2021 (6/52) Nazarian and Lee, 2021	Kunz-Plapp et al., 2016 Borchers et al., 2020 Lai et al., 2020 He et al., 2022a
	Age, in particular, the elderly and children	Romero-Lankao et al., 2012 (33/54) Filho et al., 2017 (5/7) Cheng et al., 2021 (50/52) Nazarian and Lee, 2021 Niu et al., 2021	Kunz-Plapp et al., 2016 Borchers et al., 2020 Lai et al., 2020 Beckmann et al., 2021 Chen et al., 2021 Laranjeira et al., 2021 He et al., 2022a
	Overcrowded living	Cheng et al., 2021 (2/52)	
	Health issues, in particular, chronic respiratory and cardiovascular diseases	Romero-Lankao et al., 2012 (6/54) Filho et al., 2017 (3/7) Cheng et al., 2021 (8/52) Nazarian and Lee, 2021 Niu et al., 2021	Kunz-Plapp et al., 2016 Beckmann et al., 2021 Borchers et al., 2020 Chen et al., 2021 He et al., 2022a Semenza et al., 1996
	Social isolation, living alone	Romero-Lankao et al., 2012 (5/54) Filho et al., 2017 (2/7) Cheng et al., 2021 (31/52) Niu et al., 2021	Semenza et al., 1996
Adaptive capacity	Level of education	Romero-Lankao et al., 2012 (10/54) Filho et al., 2017 (4/7) Cheng et al., 2021 (32/52) Niu et al., 2021	He et al., 2022a
	Income	Romero-Lankao et al., 2012 (8/54) Filho et al., 2017 (5/7) Gerrish et al. 2018 Cheng et al., 2021 (37/52) Niu et al., 2021	Chen et al., 2021
	Racial or ethnic minority	Romero-Lankao et al., 2012 (8/54) Filho et al., 2017 (3/7) Philipp and Chow, 2020 Cheng et al., 2021 (19/52) Niu et al., 2021	n/a
	Employment	Filho et al., 2017 (2/7) Philipp and Chow, 2020 Cheng et al., 2021 (15/52) Niu et al., 2021	Kunz-Plapp et al., 2016 Beckmann et al., 2021
	Home ownership	Shanahan et al., 2014 Cheng et al., 2021 (7/52)	Beckmann et al., 2021
	Social networks, relationships	Romero-Lankao et al., 2012 (4/54) Filho et al., 2017 (4/7) Klinenberg, 2002	Beckmann et al., 2021 Semenza et al., 1996

Numbers in brackets give, if available, how many of the studies included in the respective review used or confirmed the respective indicator.

conditions and household characteristics, mainly overcrowded living (Vescovi et al., 2005; Rinner et al., 2010; Rosenthal et al., 2014; Ho et al., 2018; Li et al., 2022). These variables often intersect; for instance, elderly residents are also more likely to live alone, thus their health risk may be exacerbated by insufficient social support during hot spells (Romero-Lankao et al., 2012; Filho et al., 2017; Cheng et al., 2021). Gender is, on the one hand, an indicator of sensitivity because women are physiologically more susceptible to heat (APCC, 2018), but on the other hand also touches on adaptive capacity as gender is associated with employment, income, access to heat-protective resources and social discrimination (Romero-Lankao et al., 2012; Amorim-Maia et al., 2022).

Adaptive capacity indicators similarly draw on census data of socio-economic status. Material deprivation is approximated by variables such as low income, unemployment, low education, single-householders or ethnic minorities (Mallen et al., 2019). The capacity to adapt the housing situation typically depends on the share of homeowners and renters (Cheng et al., 2021); for instance, owners realise more tree cover on private properties than renters (Shanahan et al., 2014). As above, indicators for adaptive capacity intersect; a particularly robust intersectionality is the persistent co-occurrence of race and income level in areas with pollution, gentrification or environmental burdens (Chakraborty et al., 2011; Banzhaf et al., 2019).

The mapping paradigm, however, comes with substantial methodological challenges. First, indicator selection is often driven rather by data availability than conceptual rigour, which impairs the validity of indicators. For instance, in the Hurricane Sandy assistance program, those who turned out to be vulnerable did not match up with the results created by the quantitative hazards-of-place models (Fekete, 2019; Rufat et al., 2019). Vulnerability studies use a wide range of different indicators; while some use only a handful, others include >20 indicators (Reid et al., 2009; Rosenthal et al., 2014; Ho et al., 2018; Mallen et al., 2019). The unharmonised use of indicators impedes comparison of heat vulnerability between different regions (Karanja and Kiage, 2021). Relying on socio-demographic indicators easily available from public data repositories often underestimates individual adaptive capacity, hence overestimating vulnerability. Elderly people, for instance, are usually classified as more vulnerable (Cutter et al., 2003) but they may have strong adaptive capacities from past experiences (e.g. in the case of volcano hazards, see Dibben and Chester, 1999). Further, census or cadastre data often do not cover relevant indicators of exposure at the building level, such as the equipment of apartment buildings with balconies or window blinds.

As a second major methodological challenge, the mapping paradigm critically depends on the definition of the size and boundaries of the analysed geographical units (Chakraborty et al., 2011, Banzhaf et al., 2019). Spatial analysis assumes that within a specific unit, the population is homogeneous and hazard exposure is distributed equally or that eventual heterogeneity within the unit can be treated as a negligible and unsystematic statistical error. The larger and more aggregated the geographical unit, however, the more likely this assumption is to be violated and the more prone the mapping paradigm is to ecological fallacy by inference of individual from area effects. For instance, ethnic or income inequity is more apparent when analysing smaller units (Banzhaf et al., 2019). Boundaries between geographical units usually follow statistical or political conventions instead of the actual spatial distribution of the hazard. Thus, if a hot spot is located close to the boundary, exposure in the adjacent unit may be underestimated (Banzhaf et al., 2019). Further, humans move across geographical boundaries (Philipp and Chow, 2020); thus, individuals may experience widely different heat impacts across the cityscape. Personal heat exposure depends on the share of time individuals spend indoors (Bernhard et al., 2015), not only at home but also at their workplace, at leisure locations, etc.

2.2. Heat vulnerability in the surveying paradigm

As illustrated in Table 1, the vulnerability indicators used in the mapping paradigm similarly appear in the surveying paradigm; however, the respective indicators are less established due to a lack of review studies and the under-researched area of psychological and social factors for thermal comfort (Lai et al., 2020). To the best of our knowledge, surveying studies include the exposure in surroundings only in terms of access to blue and green spaces and do not include residential density or land use as proxy indicators for the urban fabric. Vulnerability outcomes as the impacts of heat are typically measured via self-reports of perceived heat strain (Kunz-Plapp et al., 2016; Chen et al., 2021; Laranjeira et al., 2021; Shih et al., 2022), which in turn are a predictor for heat illness (Chakalian et al., 2019).

Households engage in a range of adaptive behaviours when they feel burdened by heat (Lai et al., 2020; Wright et al., 2020; Nazarian and Lee, 2021): changing everyday practices (e.g. wearing light clothes and a hat, regularly drinking water, seeking shade and cooler places), managing their dwelling (e.g. closing blinds during the day, ventilating only at night, installing and using air conditioning) and rearranging activity patterns (e.g. shifting work and sports to cooler times of day, visiting blue and green spaces outside the city). While research in the mapping paradigm tends to neglect that exposed households actively manage their thermal comfort and rather sees them as passive victims (Filho et al., 2017; Nazarian and Lee, 2021), many studies in the surveying paradigm address adaptive behaviours (e.g. Wolf et al., 2010; Laranjeira et al., 2021; Shih et al., 2022). Adaptive behaviours are conceptually different from adaptive capacity, as the former refer to actual coping whereas the latter refers to the ability to cope (Romero-Lankao et al., 2012). Adaptive behaviours are triggered by but also mitigate heat burden, thereby blurring the line between cause and effect (Esplin et al., 2019; Zuurbier et al., 2021). Cross-sectional analyses may only provide a snapshot of a situation that typically has evolved in the long run; most people who are approached for a heat vulnerability study have already experienced several heat episodes and have taken steps to remediate their burden. Thus, correlating heat impacts with adaptive capacity needs to account for adaptive actions that have been implemented before the time of data collection (see Section 3.3 on how the present study controls for adaptive behaviours).

The main methodological challenge of the surveying paradigm is that it relies on self-reports by affected households; thus, it is limited by the households' ability and willingness to give accurate answers. Perceived thermal comfort deviates from measured temperatures (see Section 2.3). Fragmentary memories and retrospective bias may colour reports of past events (Stopher and Greaves, 2007; Esplin et al., 2019). Respondents may draw on incomplete information, such as when giving proxy reports about other household members whose preferences and behaviours are not fully transparent to them (Seebauer et al., 2017, Hung, 2019). However, unreliable self-reports may also stem from a narrow perspective: respondents may refer to only those parts of their building or nearby parks they actually visit and consequently may omit less familiar elements of their residential surroundings, or may neglect how their home is nested within larger urban structures.

2.3. Cross-paradigm heat vulnerability research

The mapping and surveying paradigms diverge most visibly in how they operationalise heat impacts as the main vulnerability outcome, either based on temperature data or by self-reports of perceived heat strain. Previous research collected extensive evidence of discrepancies between metered and perceived temperature. Some considered these generally (Wang et al., 2017; Lai et al., 2020; Nazarian and Lee, 2021), others specifically indoors (Brager and Dear, 1998) and outdoors (Nikolopou et al., 2001; Klok et al., 2019), and yet others research them in workers (Nazarian and Lee, 2021) and passersby (Klok et al., 2019). Metered temperature does not necessarily correlate with self-reported heat illness symptoms (Quinn and Shaman, 2017), since many factors moderate the relationship between subjective and objective heat measures: perceived heat depends e.g. on meteorological characteristics like radiation, wind and humidity (van den Bosch and Ode Sang, 2017; Lai et al., 2020; Cheng et al., 2021; Nazarian and Lee, 2021), the extent of adaptive behaviours (Franck et al., 2013; Nazarian and Lee, 2021), individual and cultural heat preferences, expectations and habituation (Brager and Dear, 1998; Wang et al., 2017; Lam et al., 2018; Esplin et al., 2019; Klok et al., 2019). Furthermore, metered temperatures differ between indoor and outdoor spaces (Quinn et al., 2014; Bernhard et al., 2015; Kuras et al., 2017; Nazarian and Lee, 2021) and can be locally influenced for instance by cooling effects of shade, water bodies or grass (Esplin et al., 2019, Klok et al., 2019) or technical factors like climate-controlled buildings (Kuras et al., 2017). Thus, considering this breadth of moderating factors, it is open to question whether the mapping and surveying paradigms capture the same vulnerability outcome.

Methods from the mapping and surveying paradigms are frequently combined to close respective data gaps. Studies in the mapping paradigm distribute surveys to residents in order to assess building characteristics or adaptive behaviours that are not available from public registries (Reid et al., 2009; Quinn and Shaman, 2017; Zuurbier et al., 2021). Studies in the surveying paradigm identify heat-exposed areas from land use and meteorological information for targeted sampling of households at risk (Franck et al., 2013; Chen et al., 2021; Laranjeira et al., 2021) or for comparing survey responses between these areas (Harlan et al., 2006; Esplin et al., 2019; Borchers et al., 2020). Other studies in the surveying paradigm use in-home or mobile temperature loggers as supplementary measurements of thermal comfort (Franck et al., 2013; Wang et al., 2017; Beckmann et al., 2021; Bernhard et al., 2015). Review articles on heat vulnerability equivocally call for more combined methods (Romero-Lankao et al., 2012; Kuras et al., 2017; Karanja and Kiage, 2021; Nazarian and Lee, 2021). Combining mapping and surveying data needs to adjust for different units of analysis, however, which levels out variance and introduces ecological fallacy if individual survey responses are averaged over an entire district (e.g. in Tomlinson et al., 2011) or if all residents in a certain district are assigned identical values on census variables (e.g. in Esplin et al., 2019). More importantly, combining methods assumes that the combined data are valid and consistent (Wilhelmi and Hayden, 2010). Yet, this assumption need not hold; for instance, in a study on heat vulnerability and green space access, a variable as basic as the composition of visitors in the Berlin Tempelhof park by age and migratory background does not match between census and survey data (Kabisch and Haase, 2014).

3. Method

We apply a mirrored indicators approach to check the consistency assumption between the mapping and the surveying paradigm. In the present paper, mirrored indicators are understood as using the same variable in mapping and surveying data in an operationalization as similar as possible. The selection of indicators follows common methods and operationalisations used in previous research in the mapping or survey paradigm and thus underlies pragmatic requirements and inherent uncertainties. For instance, mapping studies are criticised for rarely considering humidity in heat monitoring (van den Bosch and Ode Sang, 2017; however, variations in atmospheric humidity across urban outdoor environments might be small). Similarly, differences in individual temperature perception are a common challenge in surveying studies (Wang et al., 2018). We mirror indicators according to the respective traditions in the mapping and surveying paradigm, being well aware of their associated limitations (see Section 5.2).

3.1. Mapping data

Mapping indicators are joined to the geo-located home addresses of survey respondents to create a set of indicators using a Geographic Information System (GIS). Table A1 in the Appendix lists the mapping indicators and gives reference year, spatial resolution and data source.

Heat impacts are measured as hot days and tropical nights, that is, days and nights when the minimum temperature does not drop below 30 °C and 20 °C, respectively. While these indicators do not directly measure heat strain as self-reported experiences do, they serve as viable proxies for the vulnerability outcome in the mapping paradigm. Such high temperatures are outside of most people's thermal comfort range (Nikolopou, 2011) and were found to negatively effect physical health, in terms of mortality and physical morbidity (e.g. Niu et al., 2021; He et al., 2022b; Wang et al., 2019; Kim et al. 2023), as well as mental health (Mullins and White, 2019; Thompson et al., 2023). The association between hot days and mortality was also recently explicitly established for Vienna (Hagen and Weihs, 2023). However, the epidemiological data available in Austria are of insufficient quality to be (additionally) used in the regression analysis (see Section 5.2). The heat impacts are calculated as the yearly average number of hot days and tropical nights in the period 2011–2020, in the 100*100 m grid cell the household lives in, derived from the 'MUKLIMO_3' urban climate model (Sievers, 2016; Žuvela-Aloise et al., 2016). Furthermore, the number of hot days and tropical nights from May to September 2022 is derived from the weather station closest to the household's home address.

For heat exposure in residential surroundings, data availability allows the use of distance-based buffer indicators because these are superior to spatial units used in the unit-hazard-coincidence approach (Chakraborty et al., 2011). The data stem from the land use cadastre of Vienna. The straight line distance from the home address to the centre point of the next green area is calculated in GIS, categorising parks by their size of >1, > 3 and > 10 ha. Furthermore, for an urban green space index, the total green area within a buffer of 250 m surrounding the home building in residential areas is summed up. From these individual values z-scores are calculated to create a relative indicator of greenness in the neighbourhood.

Indicators for exposure in buildings comprise the building period and housing type dominant in the respective census tract. Census tracts or 'Zählgebiete' are statistical units that comprise 2 to 20,500 persons, or 1 to 8560 households, and cover areas of 0.006 to 18.8 km^2. Sensitivity and adaptive capacity indicators are based on census data and are calculated as the share of the respective group among the residential population in the census tract of the home address. Indicators for sensitivity include age and care benefit payments as a proxy for health pre-conditions, whereas adaptive capacity indicators refer to income, social benefit or unemployment payment receivers, education, migratory background (i.e. non-Austrian-born residents) and rental dwellings. Gender was not included because this indicator has a uniform 50 % share across all census tracts and offers no explanatory value because of minimal variance.

3.2. Surveying data

Standardised online questionnaires were distributed to two cross-sectional survey samples in Vienna in May and September 2022. Already starting in May, the summer of 2022 featured frequent high daytime and night-time temperatures; thus, the issue of urban heat waves was presumably salient in the survey population. A market research company contacted Viennese residents who had preregistered as panel participants. Each of the two samples of 1100 and 1081 residents representatively reflects the socio-demographic distribution in Vienna's population in terms of gender, level of education and city district, and within the age span of 18 to 69 years. Panel participants are, however, presumably trained in completing questionnaires because the panel remuneration scheme incentivises regular completion of surveys. On the one hand, this makes misunderstanding of complex question formats less likely and mitigates respondent burden of questionnaire length but on the other hand, responses may be biased towards higher internal consistency and compliance with what the respondents surmise to be the underlying research aim. The present analysis uses a pooled sample of $n = 1983$ respondents for whom a home address was available. The sample of the survey is evenly distributed over the Vienna cityscape and includes 823 out of 1276 census tracts, with an average of 2.4 survey respondents living in the same census tract. Listwise deletion of missing values reduces the sample in some regression analyses, since hierarchical regression analysis requires complete information on all indicators for each respondent.

With the first 100 respondents in each sample, the data were checked for implausible patterns that might point to questionnaire design shortcomings or implementation errors; as no unusual data were detected, data collection continued unchanged for the remainder of the sample. Items were presented in mixed order in the questionnaire, so that it was not transparent to the respondents which item was assigned to which index. All items were originally worded in German. A summary of all items including wording, unit of measurement or response scale, and descriptive statistics is available in Table A2 for indicators of exposure, sensitivity and adaptive capacity, and Table A3 for adaptive behaviours.

Heat impacts are measured as self-reports of experienced heat stress (index of five items, e.g. 'On hot days during this summer, how often were your living quarters much warmer than 25°C during the day?') and subjective heat burden (index of 6 items, e.g. 'In recent years, I have been burdened by the increase in very hot days in Vienna'). The full number of items on experienced heat stress was only assessed in the second September 2022 sample; thus, for the other half of the sample, this index relies on the single item how hot the living quarters are perceived on a summer day. Heat adaptive behaviours are grouped by principal component analysis into outdoor activities (index of 4 items, e.g. 'Make day trips outside Vienna'), adapted practices (index of 6 items, e.g. 'Eat light food'), air conditioning (index of 2 items, e.g. 'Turn on the air conditioning') and indoor temperature management (index of 2 items, e.g. 'Ventilate my dwelling at night'). All indices are calculated as mean indices that use the same response scale as the underlying items and are coded so that higher values indicate more stress, stronger burden, more frequent behaviours and more green in the neighbourhood.

Surveying indicators mirror their counterpart mapping indicators, wherever possible using the same or equivalent units of measurement. For instance, in exposure in surroundings, the self-reported walking time in minutes to the next park mirrors the GIS-calculated straight line distance to the next park in metres. The relative greenness of the neighbourhood is measured with an index of three items (e.g. 'My urban quarter is greener than most other parts of Vienna'). In exposure in buildings, additional surveying indicators capture whether the dwelling is on the top floor or under the roof of the building; whether the dwelling has a garden; as well as the number of cooling facilities on the inside of the dwelling (e.g. air conditioning, window blinds) and the number of items of cooling features on the outside of the building (e.g. trees, shading by adjacent buildings). In sensitivity, health pre-conditions are measured as the presence of cardiovascular disease, overweight or similar impairment. To additionally capture sensitivity, the living area per household member indicates the extent of overcrowded living. In adaptive capacity, income is measured both in euro and in how far the household considers its income sufficient to cover living expenses.

3.3. Analytical approach

The unit of analysis is households, which are assigned values of mapping indicators according to their home address and values of surveying indicators from their survey responses. Correlations between mirrored mapping and surveying indicators illustrate the discrepancy between the two paradigms. A series of hierarchical regression models analyses the determinants of heat impacts in the respective paradigm. Mapping and surveying heat impacts are regressed separately on exposure in surroundings, exposure in buildings, sensitivity and adaptive capacity. Each of these regressions uses as predictors a set of mirrored mapping and surveying indicators. The dependent variable in the regressions in the mapping paradigm are hot days and tropical nights because this is the best available proxy for not only deaths as the most extreme effects of heat waves but more comprehensively the physical and mental load on heat-affected households. The counterpart dependent variables in the regressions in the surveying paradigm are experienced heat stress, which mirrors the prevalence of hot temperatures at the place of living given by hot days and tropical nights; and subjective heat stress, which reflects the heat morbidity of households. While the assignment of indicators to the specific components of vulnerability of exposure, sensitivity and adaptive capacity is to some degree arbitrary (Romero-Lankao et al., 2012; Filho et al., 2017; Cheng et al., 2021), it helps to structure the analyses.

Predictors enter the regression models stepwise in three blocks: Block 0 includes adaptive behaviours; this block controls for individual adaptation processes that had been accomplished prior to the survey data collection and that may have already reduced the heat impacts the respondents experienced when they participated in the cross-sectional survey. Block 0 regression results are only reported in Table 3 because they are redundant across all regression models. Block 1 includes mapping indicators. Block 2 includes the respective counterparts as surveying indicators; thus, Block 2 shows the additional variance explained by the surveying paradigm above and beyond the mapping paradigm (as suggested in Cheng et al., 2021, Karanja and Kiage, 2021). The differences in the adjusted R^2 values represent the additional explained variance in each block while correcting for the increasing overall number of predictors. The F values indicate how well the model fits the data; in the Block 0 model, F compares to the null, intercept-only model. All coefficients are tested against a $p < .05$ significance level.

4. Results

4.1. Correlating mapping and surveying indicators

Correlations between indicators for heat impacts are much higher within than between paradigms (Table 2). Within the mapping paradigm, hot days and tropical nights correlate highest when both indicators refer to the same time period ($r = 0.79$ in 2011–2020; $r = 0.78$ in 2022). However, the 2022 hot days and tropical nights indicators consist of only ten discrete values from ten weather stations across Vienna; due to this low variance, the 2022 indicators are not used as dependent variables in the following regression analyses. Within the surveying paradigm, experienced heat stress and subjective heat burden show a moderate correlation of $r = 0.47$.

The associations of heat impacts between paradigms are, however, exceptionally weak: hot days and tropical nights correlate at only $r =$

Table 2
Correlations of mapping and surveying indicators for heat impacts.

	Av. tropical nights 2011–2020	# Hot days 2022	# Tropical nights 2022	Exp. heat stress	Subj. heat burden
Yearly average of hot days in 2011–2020	**0.79**	**0.33**	**0.30**	**0.14**	**0.05**
Yearly average of tropical nights in 2011–2020	1	**0.48**	**0.45**	**0.13**	**0.05**
Number of hot days in 2022		1	**0.78**	**0.10**	0.03
Number of tropical nights in 2022			1	**0.11**	0.04
Experienced heat stress				1	**0.47**

Pearson correlation coefficients. $p < .05$ printed bold.

0.10 to 0.14 with experienced heat stress, and even lower, at $r = 0.03$ to 0.05, with subjective heat burden. Previous studies report much higher consistency between mapping and surveying indicators for heat impacts: for instance, $r = 0.68$ (Ueberham et al., 2019), an odds ratio of 2.8 (Quinn and Shaman, 2017), and $\eta^2 = 0.038$ (Heidenreich et al., 2021); however, these previous studies analyse small and self-selective survey samples in specific contexts ($n = 66$ urban cyclists, $n = 40$ urban homes, $n = 306$ visitors at a garden show, respectively).

Correlations between the mirrored mapping and surveying indicators for exposure, sensitivity and adaptive capacity are given in Tables A4 to A7 in the Appendix. The correlations between paradigms also turn out rather low, not least because they refer to park polygons, building blocks or census tracts on the one hand and households on the other hand. In exposure in surroundings, the mapping- or surveying-based distances to the next green area are associated at $r < 0.20$. In exposure in buildings, the building period and type of house conform fairly well ($r = 0.45$, $r = 0.36$), pointing to homogenous housing structures within Vienna's districts. In sensitivity and adaptive capacity, the correlations regarding age, health impairment and migratory background do not exceed $r = 0.14$, highlighting the diversity of the Viennese residential population even within the same census tracts as the result of a century-long social housing policy (Hatz, 2009; Friesenecker and Kazepov, 2021). Slightly higher correlations appear in renter status ($r = 0.28$), presumably because of the general dominance of renting on the Viennese housing market, and in level of education ($r = 0.28$), presumably because of Vienna's status as the nation's capital and as a university town.

4.2. *Explaining heat impacts with mapping and surveying indicators*

Adaptive behaviours, in other words, personal strategies for coping with heat by wearing light clothing, keeping the dwelling cool or shifting activities to cooler times and places, strongly affect subjective heat burden ($\beta = -0.12$ to 0.31) and to some degree experienced heat stress ($\beta = -0.06$ to 0.16), but, as can be expected, have practically no association with hot days and tropical nights ($\beta = -0.09$ to 0.03; see Block 0 in Table 3). The mostly positive coefficients with surveying indicators of heat impacts demonstrate that a certain level of subjective heat burden and experienced heat stress remains even when adaptive behaviours are performed, underscoring the need to control statistically for earlier adaptation processes.

Regarding explained variance by exposure in surroundings (Table 3), the models on mapping heat impacts reach an R^2 of around 30 %, whereas the explanatory power is much lower for surveying heat impacts at $R^2 < 16$ % that mainly stems from adaptive behaviours. Hot days and tropical nights are influenced by green space availability, both in absolute terms as the distance to nearby parks ($\beta = 0.07$ to 0.21) and in relative terms as the greenness compared to other parts of Vienna ($\beta = -0.34$ and $\beta = -0.30$). Surveying indicators have little explanatory power for mapping heat impacts; this applies vice versa, as mapping indicators hardly contribute to the explanation of surveying heat impacts. The only exception is the relative greenness of the residential area which is associated with mapping as well as surveying heat impacts ($\beta = -0.11$ to -0.31).

In the influence of exposure in buildings on heat impacts, the previous predictor pattern reappears (Table 4): R^2 is higher in mapping than surveying heat impacts; surveying indicators only marginally contribute to the explanation of mapping impacts and vice versa. Hot days and tropical nights are less frequent in areas with more modern, better-insulated buildings ($\beta = -0.56$ and -0.63) and a higher share of single-family houses ($\beta = -0.19$ and -0.23); these areas typically feature more greenery and improved shading between buildings. From the surveying indicators, the presence of a garden ($\beta = -0.05$ and -0.10) and of cooling building features (e.g. trees in front of the building or in the courtyard; $\beta = -0.05$ and -0.06) further buffer the number of hot days and tropical nights. For experienced heat stress and subjective heat burden, mapping indicators and their surveying counterparts have weak influences, but cooling building features reduce heat stress and burden ($\beta = -0.14$ and -0.11). The overarching influence of cooling building features resonates with Quinn et al.'s (2014) observation of considerable between-home variability in indoor heat under the same outdoor conditions. Living on the top floor of the building has the weak but contrary effect of increasing heat stress ($\beta = 0.05$), presumably because attic apartments and penthouses absorb heat through the roof or directly through windows and because hot air may rise through stairwells, but decreasing heat burden ($\beta = -0.05$), possibly because these apartments tend to have a balcony or terrace with a view.

In the influence of sensitivity on heat impacts, again the familiar pattern emerges (Table 5): higher R^2 in mapping than surveying heat impacts (though less pronounced), and mostly absent effects of surveying indicators on mapping impacts and vice versa. The Block 1 effects on hot days and tropical nights reflect the population distribution in Vienna where predominantly older people and families live in the cooler outer districts ($\beta = -0.34$ to -0.40). This effect, albeit weaker, also extends to the experienced heat stress ($\beta = -0.10$). Age and number of elderly household members reduce experienced heat stress ($\beta = -0.13$) and subjective heat burden ($\beta = -0.12$ and -0.11). Older people seem to be under a coping illusion – they are particularly vulnerable but consider themselves insensitive to heat (Wolf et al., 2010; Lai et al., 2020). Health impairment increases heat stress and burden ($\beta = 0.09$ and 0.15, respectively).

In the mapping regression models on adaptive capacity (Table 6),

Table 3
Regression of heat impacts on mapping and surveying indicators on exposure in surroundings.

Block	Indicators	Av. hot days 2011–2020			Av. tropical nights 2011–2020			Experienced heat stress			Subjective heat burden		
0	Outdoor activities	−0.01	−0.04	−0.05	0.03	−0.01	−0.02	−0.06	**−0.07**	**−0.08**	**−0.12**	**−0.12**	**−0.12**
	Adapted practices	−0.07	−0.01	0.01	−0.04	0.01	0.03	**0.11**	**0.13**	**0.14**	**0.31**	**0.31**	**0.31**
	Air conditioning	0.03	−0.00	−0.02	−0.00	−0.03	−0.04	**0.08**	**0.08**	0.06	**0.15**	**0.15**	**0.14**
	Indoor temperature management	−0.06	−0.04	−0.03	**−0.09**	−0.06	−0.05	**0.16**	**0.17**	**0.18**	**0.17**	**0.17**	**0.18**
1	Straight line to next park of size >1 ha		**0.19**	**0.17**		**0.17**	**0.14**		−0.03	−0.05		−0.01	−0.03
	Straight line to next park of size >3 ha		**0.21**	**0.19**		**0.09**	0.07		0.04	0.03		0.00	−0.01
	Straight line to next park of size >10 ha		0.07	0.05		**0.15**	**0.13**		0.01	−0.00		−0.01	−0.02
	Z-score of green areas within 250 m		**−0.34**	**−0.31**		**−0.30**	**−0.26**		**−0.14**	**−0.11**		−0.02	0.00
2	Walking distance to small park			−0.06			−0.04			0.01			0.01
	Walking distance to large park			0.03			−0.01			−0.04			−0.01
	Walking distance to large green			−0.01			−0.02			−0.02			0.01
	Greener neighbourhood			**−0.19**			**−0.25**			**−0.16**			**−0.13**
	F	2.3	**47.4**	**36.5**	2.2	**33.7**	**29.3**	**11.0**	**7.9**	**7.0**	**38.7**	**19.3**	**14.4**
	adj. R^2	0.6 %	30.8 %	33.8 %	0.6 %	23.9 %	28.9 %	4.6 %	6.2 %	8.0 %	15.3 %	14.9 %	16.1 %

Standardised regression coefficients. $p < .05$ printed bold. Block 0: Adaptive behaviours as control variables. Block 1: Mapping indicators. Block 2: Surveying indicators. Degrees of freedom: Block 0 models df = 4/831, Block 0 + 1 models df = 8/827, Block 0 + 1 + 2 models df = 12/823.

Table 4
Regression of heat impacts on mapping and surveying indicators on exposure in buildings.

Block	Indicators	Av. hot days 2011–2020		Av. tropical nights 2011–2020		Experienced heat stress		Subjective heat burden	
1	Building period	**−0.56**	**−0.54**	**−0.63**	**−0.58**	**−0.08**	−0.03	**−0.07**	−0.04
	Single-family house dominated	**−0.19**	**−0.18**	**−0.23**	**−0.21**	**−0.06**	−0.04	−0.03	−0.02
2	Year of construction		−0.02		**−0.08**		−0.05		**−0.05**
	Single-family house		−0.01		−0.01		**−0.08**		−0.04
	Top floor		0.00		−0.01		**0.05**		**−0.05**
	Garden		**−0.05**		**−0.10**		−0.05		−0.04
	Cooling dwelling facilities		0.01		0.01		0.00		0.01
	Cooling building features		**−0.05**		**−0.06**		**−0.14**		**−0.11**
	F	**125.9**	**64.5**	**183.6**	**98.6**	**18.9**	**15.5**	**56.6**	**31.9**
	adj. R^2	31.5 %	31.8 %	40.2 %	41.8 %	6.2 %	9.7 %	17.0 %	18.5 %

Standardised regression coefficients. p < .05 printed bold. Block 1: Mapping indicators. Block 2: Surveying indicators. Regression model includes Block 0 adaptive behaviours (coefficients as in Table 3); R^2 refers to the explained variance including Block 0. Degrees of freedom: Block 0 + 1 models df = 6/1627, Block 0 + 1 + 2 models df = 12/1621.

Table 5
Regression of heat impacts on mapping and surveying indicators on sensitivity.

Block	Indicators	Av. hot days 2011–2020		Av. tropical nights 2011–2020		Experienced heat stress		Subjective heat burden	
1	Share of >65 years old	**−0.39**	**−0.39**	**−0.37**	**−0.37**	**−0.12**	**−0.10**	−0.01	0.02
	Share of 0–6 years old	**−0.34**	**−0.34**	**−0.40**	**−0.40**	**−0.09**	**−0.10**	−0.01	−0.01
	Share of care benefit receivers	−0.04	−0.04	−0.01	−0.01	0.02	0.01	−0.02	−0.03
2	Age		−0.03		−0.04		−0.00		**−0.12**
	Female		−0.02		0.01		0.02		0.01
	Household members >60 years		−0.02		−0.01		**−0.13**		**−0.11**
	Household members 0–6 years		**−0.05**		**−0.05**		−0.00		−0.03
	Living area per household member		−0.00		**0.05**		−0.03		0.01
	Health impairment		0.02		0.01		**0.09**		**0.15**
	F	**52.2**	**29.0**	**54.0**	**30.2**	**18.3**	**13.5**	**55.8**	**40.0**
	adj. R^2	15.5 %	15.6 %	15.9 %	16.2 %	5.8 %	7.6 %	16.4 %	20.6 %

Standardised regression coefficients. p < .05 printed bold. Block 1: Mapping indicators. Block 2: Surveying indicators. Regression model includes Block 0 adaptive behaviours (coefficients as in Table 3); R^2 refers to the explained variance including Block 0. Degrees of freedom: Block 0 + 1 models df = 7/1954, Block 0 + 1 + 2 models df = 13/1948.

Table 6
Regression of heat impacts on mapping and surveying indicators on adaptive capacity.

Block	Indicators	Av. hot days 2011–2020		Av. tropical nights 2011–2020		Experienced heat stress		Subjective heat burden	
1	Share of higher educated	**0.42**	**0.42**	**0.55**	**0.56**	0.05	**0.07**	0.05	**0.06**
	Share of migratory background	**0.43**	**0.43**	**0.48**	**0.48**	**0.12**	**0.12**	0.05	0.04
	Share of rental dwellings	**0.21**	**0.20**	**0.28**	**0.27**	**0.09**	**0.06**	0.05	0.03
2	Income		−0.04		−0.04		−0.04		−0.05
	Income considered sufficient		−0.02		−0.03		**−0.12**		**−0.15**
	Employed		0.03		0.01		0.03		**0.09**
	Higher educated		0.01		−0.01		−0.01		0.03
	Migratory background		−0.03		**−0.04**		**−0.06**		−0.04
	Renter		0.03		0.01		**0.07**		0.03
	F	**88.4**	**48.5**	**159.3**	**87.2**	**18.3**	**14.1**	**45.5**	**30.6**
	adj. R^2	27.6 %	27.8 %	40.9 %	41.2 %	7.0 %	9.6 %	16.3 %	19.4 %

Standardised regression coefficients. p < .05 printed bold. Block 1: Mapping indicators. Block 2: Surveying indicators. Regression model includes Block 0 adaptive behaviours (coefficients as in Table 3); R^2 refers to the explained variance including Block 0. Degrees of freedom: Block 0 + 1 models df = 7/1595, Block 0 + 1 + 2 models df = 13/1589.

Block 1 includes a reduced set of indicators because of multicollinearity: average net income, share of social benefit receivers, share of unemployment payment receivers and share of migratory background intercorrelate at $r = 0.57$ to 0.83. Apparently, low income, social transfers, unemployment and not being born in the country go together in Austria just as they do in other parts of the world (Gerrish and Watkins, 2018, Philipp and Chow, 2020). Thus, for the purpose of the present analysis, we retain only the share of migratory background as mapping predictor because it represents the European counterpart to the race characteristic, which plays a crucial role in North American environmental justice research (Wilson, 2020).

The influence of adaptive capacity on heat impacts repeats the pattern of higher R^2 in mapping than in surveying heat impacts and the weak influence of surveying indicators on mapping impacts and vice versa (Table 6). In the mapping regression models, the number of hot days and tropical nights is associated with the level of education (β = 0.42 and 0.55) due to an over-proportional share of university graduates in the hotter inner city districts; by migratory background (β = 0.43 and 0.48) due to restricted market access for housing in cooler residential districts; and by renter status (β = 0.21 and 0.28). In the surveying regression models, the influences of mapping indicators carry over to some extent. Higher income decreases heat stress and burden, because of broader options for moving in or refurbishing to cooler homes, but interestingly, this effect applies only to self-assessed affluence (β = −0.12 and − 0.15) but not to actual income. Renter status increases heat stress due to the tenant-landlord dilemma in building refurbishment (Seebauer et al., 2021). Some surveying indicators have a negative sign and thus the opposite direction of influence to that of their mirrored mapping indicators. For instance, while the mapping indicator for migratory background increases experienced heat stress (β = 0.12), the corresponding surveying indicator decreases heat stress (β = −0.06), possibly pointing to different individual practices for coping with heat waves. Being employed increases subjective heat burden (β = 0.09), possibly because heat burden at the workplace spills over to the home.

5. Discussion and conclusions

5.1. Divergence between the mapping and the surveying paradigm

The results paint an overarching picture of divergence between mapping and surveying indicators in the context of heat vulnerability in Vienna. Mapping and surveying heat impacts are virtually unrelated ($r < 0.14$). Mapping heat impacts are explained by mapping indicators for green space access, building characteristics, age and socio-economic background (unique explained variance ΔR^2 of 15–40 %) but mostly not by surveying indicators. Surveying heat impacts are hardly associated with mapping indicators but are explained to some degree by surveying indicators on building characteristics, age, health impairment and income insufficiency (ΔR^2 of 2–4 %). When controlling for adaptive behaviours, spatial patterns, in particular those of socio-economic variables, influence heat impacts in the mapping paradigm. Nonetheless, the effect of these spatial patterns on individual heat strain is attenuated by characteristics of the building and the personal living situation. The results strongly suggest that the mapping and surveying paradigms do not capture the same components of vulnerability. Considering the two paradigms as interchangeable and equivalent may lead to ecological fallacy because the aggregated spatial effects generated by urban heat islands or spatial patterns in social variables do not match individual heat vulnerability. However, the results of the present study should be replicated in other cities and with a broader range of heat vulnerability indicators.

For heat vulnerability research, this finding calls into question the degree to which studies conducted in the two paradigms can complement each other. Researchers call for cross-validating mapping with surveying methods in order to overcome their respective shortcomings (see Section 2.3; Wilhelmi and Hayden, 2010, Chakraborty et al., 2011); however, the marginal overlap between the two paradigms observed here renders expectations for cross-validation questionable. We thus recommend validating heat vulnerability results within rather than between paradigms. Quasi-experimental field studies could offer clearer causal inference than the common practice of correlating indicators. For instance, to validate within the surveying paradigm, several longitudinal survey waves could monitor a specific urban quarter that is to be greened whether subjective heat burden actually decreases: a baseline survey wave establishes the initial level of burden and controls for pre-existing adaptive behaviours; a subsequent survey wave shows whether burden changes more than in neighbouring, similar quarters that are not greened; a follow-up survey wave checks whether the observed changes persist in the long run. Comparing the levels and changes in subjective heat burden between socio-economic groups could point to relevant indicators of sensitivity and adaptive capacity.

Nevertheless, we caution against playing off the mapping versus the surveying paradigm as providing ‘objective’ versus ‘subjective’ data. Mapping data can be less accurate than they seem because they may be outdated, fragmentary or impaired by undercoverage of private properties. Temperature data from weather stations or climate models do not necessarily reflect the individual scale of the heat impact (Hu et al., 2023). Surveying data need not be biased by nature; for instance, self-reports of building characteristics or household composition can be justifiably taken as correct (Hadler et al., 2022).

For heat adaptation policy, this finding means city governments need to be more specific on the exact vulnerability outcome they wish to minimise. Hence, a clear terminology that names the underlying paradigm should be stressed. Heat-vulnerable locations are best represented in the hazards-of-place perspective of the mapping paradigm. In this paradigm, the number of hot days and tropical nights (or, preferably, thermal comfort indices that also account for radiation, wind and humidity) reflects health impacts on the overall population in terms of heat-induced mental and physical symptoms or even deaths. Heat-vulnerable locations might be tackled preventively at the scale of city quarters or districts. By contrast, heat-vulnerable groups are best represented in the hazards-of-people perspective of the surveying paradigm. Here, experienced heat stress reflects the role of individual housing conditions as filters for personal well-being; subjective heat burden reflects the feeling of being overburdened by heat despite efforts at adaptive behaviours. Preventive efforts addressing heat-vulnerable groups should deploy at the scale of individuals or neighbourhood community groups. Mapping and surveying vulnerability outcomes do not go hand in hand and have different drivers; therefore, we recommend tackling each vulnerability outcome separately. Policy interventions for mitigating urban heat-related risks should first define which vulnerability outcome they address and then target the specific drivers of this particular outcome. If city governments aim to reduce heat-related medical admissions and negative mental health effects, they should apply the mapping paradigm and, for instance, expand green public spaces in hot districts. If city governments aim to improve the perceived well-being of their electorate, they should follow the surveying paradigm and, for instance, foster heat-resilient homes and promote risk awareness among elderly residents.

5.2. Limitations and directions for future research

As in any other empirical study, the design of the present study implies certain limitations, which at the same time provide directions for future research. Because of restricted data availability, the mapping and surveying indicators of vulnerability outcomes are not perfectly mirrored. As discussed in Section 3.1, while the surveying indicators of experienced heat stress and subjective heat burden directly assess the heat impacts on individuals, the mapping indicators hot days and tropical nights are only a proxy of the physical and mental load of heat-affected households. Including data from health statistics on heat-induced physical symptoms such as dizziness, nausea, fainting or muscle cramps and on the mental impact of high temperatures would more accurately capture the vulnerability outcome in the mapping paradigm. However, epidemiological data in Austria are only available for hospital stays at the city district level and are biased by the diagnostic habits of attending doctors; the low incidence of just 1 in 100,000 Viennese inhabitants being diagnosed with heat-induced symptoms during the summer months suggests severe under-reporting (Brugger et al., 2022).

In a similar vein, the hot days and tropical nights indicators do not include wind and humidity, which play a role in thermal comfort (van den Bosch and Ode Sang, 2017; Cheng et al., 2021; Nazarian and Lee, 2021) and capture outdoor, not indoor, temperatures. The association between outdoor and indoor temperatures is, however, well confirmed (Quinn et al., 2014; Zuurbier et al., 2021). Thus, while the indicators of hot days and tropical nights may not be optimal, they seem sufficiently valid and may address the multidimensionality of heat effects better than a single health outcome variable could, even if it were available at an appropriate spatial resolution. Furthermore, the current building register data do not allow mirroring of all surveying indicators on exposure in buildings and sensitivity. If these building data were available, we would expect that explained variance in the regression models for the mapping paradigm increases.

Both mapping and surveying indicators consistently refer to the residents' place of living, either by geo-located home addresses or by phrasing survey items in terms of their house or the place where they sleep. Urban heat does, however, affect people also in their workplace, at leisure locations, etc. (Karanja and Kiage, 2021). People perceive less thermal discomfort if they can decide freely whether to stay in or leave a hot place (Lai et al., 2020); presumably, personal autonomy is higher at home than at work. Future research could analyse whether our observed discrepancies between mapping and surveying data hold for other activities of urban residents than at home.

To some extent, the low explained variance found in our regression models could also result from omitted variable bias. For example, socially isolated individuals suffer more from heat because they cannot draw on informal social structures for care and support (see Table 1). Due to the lack of adequate information on survey respondents' social relationships and the lack of a properly mirrored indicator in the mapping paradigm, we could not include this factor. We would however welcome future research to replicate our consistency analysis of the mapping and the surveying paradigm with additional indicators of heat vulnerability.

Spatial autocorrelation between neighbouring census tracts (Chakraborty et al., 2011, Gerrish and Watkins, 2018) may violate the regression requirement of independent predictors. Checking the spatial autocorrelation by using the Global Moran's I with several bandwidths shows that modest spatial autocorrelation exists for the higher educated and persons with a migratory background (values ≈ 0.4). Other mapping indicators show no spatial autocorrelation. However, as spatial autocorrelation inflates effect sizes, at least the models for experienced heat stress and subjective heat burden do not seem biased since there, the effects of mapping indicators are already very small.

Finally, we would raise as a point for reflection whether the frequent practice in the mapping paradigm of using land use variables to explain temperature indicators derived from microclimate models might be prone to circular reasoning or might reflect mismatching scales. Microclimate models have the advantage over weather stations that they provide long-term average temperatures in a high spatial resolution; however, the model algorithms account for the distribution of sealed structures and green surfaces over the cityscape – the very land use variables used as exposure indicators to explain the modelled temperature estimates. The MUKLIMO_3 urban climate model used here to operationalise heat impacts in the mapping paradigm already accounts for the cooling effect of very large green areas; thus, the effect of the exposure indicator 'straight line to next park of size > 10 ha' (up to $\beta = 0.15$; see Table 3) could be biased by the circular reasoning of explaining climate model output with climate model input parameters. The 100*100 m grid resolution of MUKLIMO_3 is consistent with the spatial resolution of the other mapping indicators. However, this scale could introduce uncertainties if the associated cooling effect does not represent the scale where it affects humans in their daily life. Recent urban climate research aims to capture on a more fine-grained scale where e.g. pedestrians in urban public space are affected, such as the mean radiant temperature or the average temperature of road and façade surfaces or under tree canopy (Hu et al., 2023; Stewart et al., 2021). Thus, future research could attempt to disentangle heat impact from heat exposure by using temperature measurements or Local Climate Zones typologies which better represent the heat impacts on humans, possibly at different times of the day.

CRediT authorship contribution statement

Sebastian Seebauer: Writing – review & editing, Writing – original draft, Methodology, Formal analysis, Conceptualization. **Michael Friesenecker:** Writing – original draft, Data curation. **Thomas Thaler:** Writing – original draft. **Antonia E. Schneider:** Writing – review & editing. **Stephan Schwarzinger:** Writing – review & editing.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Sebastian Seebauer, Michael Friesenecker, Thomas Thaler, Antonia E. Schneider, Stephan Schwarzinger reports financial support was provided by Vienna Science and Technology Fund (WWTF). If there are other authors, they declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

Acknowledgements

We thank Claudia Hahn and Maja Zuvela-Aloise for providing the microclimate data. This work has been funded by the Vienna Science and Technology Fund (WWTF) [10.47379/ESR20011].

Appendix A

Table A1
Descriptive statistics of mapping indicators.

Vulnerability component	Indicator	Reference year	Spatial resolution	Unit of measurement	N	Mean	SD	Data source
Heat impacts	Yearly average of hot days in 2011–2020	2011–2020	100 × 100 m grid cell	Count	1983	28.1	5.5	GeoSphere Austria
	Yearly average of tropical nights in 2011–2020	2011–2020		Count	1983	27.8	5.6	
	Number of hot days in 2022	2022	Closest out of 10 weather stations in Vienna	Count	1983	33.2	5.9	
	Number of tropical nights in 2022	2022		Count	1983	16.6	7.6	
Exposure in surroundings	Straight line to next park of size >1 ha	2020	Park polygons	m	1983	375.9	212.0	Own calculation based on data.wien.gv.at
	Straight line to next park of size >3 ha	2020	Park polygons	m	1983	652.6	395.1	
	Straight line to next park of size >10 ha	2020	Park polygons	m	1983	1160.5	531.0	
	Z-score of green areas within 250 m of the home building block	2020	Building blocks	Number of standard deviations from the citywide average	1983	0.0	0.98	

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Table A1 (*continued*)

Vulnerability component	Indicator	Reference year	Spatial resolution	Unit of measurement	N	Mean	SD	Data source
Exposure in buildings	Building period	2016	Census tract	Midpoint calendar year of the dominant building period	1773	1950.9	41.3	data.wien.gv.at
	Single-family house dominated	2011	Census tract	Dummy: 1 = yes, 0 = no	1968	0.12	0.33	
Sensitivity	Share of >65 years old	2020	Census tract	% of population	1983	16.2	6.0	Statistics Austria
	Share of 0–6 years old	2020	Census tract	% of population	1983	6.2	1.8	
	Share of care benefit receivers	2019	Census tract	% of population	1982	5.8	4.6	
Adaptive capacity	Average net yearly income	2019	Census tract	Average in Euro over the midpoints of five income groups	1982	26,404	4760	Statistics Austria
	Share of social benefit receivers	2019	Census tract	% of population	1982	5.2	2.5	
	Share of unemployment payment receivers	2019	Census tract	% of population	1982	9.2	3.1	
	Share of higher educated	2020	Census tract	% of population	1983	53.3	14.8	
	Share of persons with a migratory background (i.e. non-Austrian-born residents)	2020	Census tract	% of population	1983	41.6	12.2	
	Share of rental dwellings	2011	Census tract	% of all dwellings	1968	73.1	19.0	

Table A2
Descriptive statistics of surveying indicators.

Vulnerability component	Indicator and item wording	Unit of measurement	N	Mean	SD	Item-total correlation	Cronbach's α
Heat impacts	Experienced heat stress	Mean index of 5 items	2181	3.80	0.82		0.80
	On hot days during this summer, how often was the street in front of your house much warmer than 30 °C during the day?	Five-step response scale, 1 = never, 5 = always	1081	3.72	0.91	0.50	
	On hot days during this summer, how often was the street in front of your house much warmer than 25 °C during the night?		1081	3.22	0.95	0.58	
	On hot days during this summer, how often were your living quarters much warmer than 25 °C during the day?		1081	3.69	1.09	0.70	
	On hot days during this summer, how often were your living quarters much warmer than 25 °C during the night?		1081	2.87	1.16	0.67	
	On a hot summer day at 30 °C or more, are your living quarters during the day…	Five-step response scale, 1 = much too cold, 5 = much too hot	2181	4.10	0.78	0.51	
	Subjective heat burden	Mean index of 6 items	2181	3.70	0.91		0.89
	In recent years, I have been burdened by the increase in very hot days in Vienna.	Five-step response scale, 1 = fully disagree, 5 = fully agree	2181	3.56	1.20	0.77	
	Outside temperatures of over 30 °C make me feel uncomfortable in everyday life.		2181	3.70	1.24	0.72	
	Heat has a negative impact on my health.		2181	3.46	1.15	0.71	
	I sleep worse during very hot nights (does not cool down below 20 °C).		2181	3.72	1.19	0.69	
	Summer temperatures in Vienna are too hot for my taste.		2181	3.71	1.18	0.75	
	Compared to the other seasons, how well do you sleep at high summer temperatures, that is at nighttime outdoor temperatures of 20 °C or more?	Five-step response scale, 1 = much better, 5 = much worse	2181	4.02	0.83	0.62	
Exposure in surroundings	How long does it take you to walk from your home to the nearest small park?	min	1994	5.4	4.1		
	How long does it take you to walk from your home to the nearest large park?	min	1627	10.5	8.1		
	How long does it take you to walk from your home to the nearest large green or recreational area? (e.g. Prater, Schönbrunn, Donauinsel, Wienerwald)	min	1070	17.0	13.8		
	Greener neighbourhood	Mean index of 3 items	2181	3.58	1.04		0.77
	My urban quarter is greener than most other parts of Vienna.	Five-step response scale, 1 = fully disagree, 5 = fully agree	1689	3.80	1.27	0.71	
	Most other parts of Vienna have more green areas and parks than the urban quarter where I live. (reverse-coded)		2181	3.49	1.20	0.48	
	My urban quarter has more green streets (with trees and bushes) than most other parts of Vienna.		1619	3.75	1.28	0.62	

(continued on next page)

Table A2 (*continued*)

Vulnerability component	Indicator and item wording	Unit of measurement	N	Mean	SD	Item-total correlation	Cronbach's α
Exposure in buildings	When was your building constructed?	Midpoint calendar year of the periods 1945 or earlier, 1945–1980, 1981–2000, 2001 or later	2015	1974.0	31.9		
	What is the type of your building?	Dummy: 1 = Single-family house, 0 = others	2181	0.15	0.36		
	Is your dwelling on the top floor or under the roof?	Dummy: 1 = yes, 0 = no	2181	0.15	0.36		
	Has your dwelling a personal garden?	Dummy: 1 = yes, 0 = no	2181	0.17	0.38		
	Has your dwelling any of the following facilities to keep it cool? Ventilator, air conditioning in some rooms, air conditioning in all rooms, external window shading (blinds, shutters), internal window shading (blinds, curtains), wall insulation	Sum score of 6 dummies 1 = yes, 0 = no	2181	2.09	1.07		
	Has your building any of the following features to keep it cool? Green façade, green courtyard, shading by trees, shading by other buildings, cross-ventilation	Sum score of 5 dummies 1 = yes, 0 = no	2181	1.80	1.01		
Sensitivity	What is your age?	Years	2181	42.8	14.0		
	What is your gender?	Dummy: 1 = female, 0 = others	2181	0.51	0.50		
	How many people, including yourself, live in your household that are … Adults older than 60 years	Count	2181	0.35	0.85		
	… Children aged 0 to 6 years	Count	2181	0.19	0.70		
	What is the size of the living area of your dwelling? (excluding outdoor areas or balconies)	m^2 divided by number of all household members	2149	43.0	26.5		
	Do you suffer from any of the following health impairments? Cardiovascular disease, high blood pressure, overweight, respiratory disease, renal insufficiency	Dummy: 1 = yes, 0 = no	2181	0.37	0.48		
Adaptive capacity	Please state the monthly net income of your household.	Midpoint in Euro of the categories <850, 851–1000, 1001–1250, 1251–1650, 1651–2000, 2001–2500, 2501–3200, 3201–4000, 4001–4650, >4650	1801	2998	1902		
	How easy or difficult is it for you to cover your household's living expenses with your household income?	Six-step response scale, 1 = very difficult, 6 = very easy	2181	3.71	1.35		
	What is your current employment status?	Dummy: 1 = employed, in training, student; 0 = unemployed, housewife, retired, on maternal/paternal leave	2135	0.76	0.43		
	What is your level of education?	Dummy: 1 = school leaving exam or university degree, 0 = compulsory school or apprenticeship	2181	0.63	0.48		
	In which country were you, your mother and your father born?	Dummy: 1 = migratory background, 0 = no migratory background	2181	0.26	0.44		
	Do you rent or own your dwelling?	Dummy: 1 = renter, 0 = owner	2181	0.74	0.44		

Table A3
Descriptive statistics of adaptive behaviours.

Indicator and item wording	Unit of measurement	N	Mean	SD	Item-total correlation	Cronbach's α
What did you do during the last heat wave? Outdoor activities	Mean index of 4 items	2181	2.80	0.80		0.67
Leave Vienna for several days	Five-step response scale, 1 = never, 5 = always	2181	2.40	1.16	0.41	
Make day trips outside Vienna		2181	2.67	1.07	0.54	
Spend more time in green areas in Vienna		2181	3.16	1.09	0.44	
Go swimming in public pools, rivers or lakes		2181	2.99	1.21	0.43	
Adapted practices	Mean index of 6 items	2181	3.25	0.71		0.61
Spend less time in hot/unshaded streets and squares	Five-step response scale, 1 = never, 5 = always	2181	3.84	1.05	0.36	
Eat light food		2181	3.52	1.03	0.44	
Wear light clothing when outside		2181	3.82	1.09	0.33	
Wear a hat when outside		2181	2.58	1.37	0.27	
Shift work hours to cooler times of day		2181	2.57	1.31	0.34	
Shift sports activities to cooler times of day		2181	3.15	1.38	0.38	
Air conditioning	Mean index of 2 items	2181	1.86	1.19		0.76
Buy (additional) air conditioning	Five-step response scale, 1 = never, 5 = always	2181	1.66	1.23	0.62	
Turn on the air conditioning		2181	2.06	1.41	0.62	
Indoor temperature management	Mean index of 2 items	2181	4.36	0.78		0.40
Ventilate my dwelling at night	Five-step response scale, 1 = never, 5 = always	2181	4.45	0.89	0.26	
Close blinds and curtains during the day		2181	4.27	1.07	0.26	

Table A4
Correlations of mapping and surveying indicators for exposure in surroundings.

	Walking distance to small park	Walking distance to large park	Walking distance to large green	Greener neighbourhood
Straight line to next park of size >1 ha	**0.08**	**0.10**	**0.07**	**−0.29**
Straight line to next park of size >3 ha	0.04	**0.09**	**0.15**	**−0.31**
Straight line to next park of size >10 ha	0.03	**0.10**	**0.20**	**−0.34**
Z-score of green areas within 250 m	−0.01	**−0.08**	**−0.13**	**0.22**

Pearson correlation coefficients. $p < .05$ printed bold. Mapping indicators in rows, surveying indicators in columns.

Table A5
Correlations of mapping and surveying indicators for exposure in buildings.

	Year of construction	Single-family house
Building period	**0.45**	0.05
Single-family house dominated	**0.17**	**0.36**

Pearson correlation coefficients. $p < .05$ printed bold. Mapping indicators in rows, surveying indicators in columns.

Table A6
Correlations of mapping and surveying indicators for sensitivity.

	Household members > 60 years	Household members 0–6 years	Health impairment
Share of >65 years old	**0.09**	−0.03	0.01
Share of 0–6 years old	**−0.07**	**0.07**	−0.01
Share of care benefit receivers	0.03	0.02	0.02

Pearson correlation coefficients. $p < .05$ printed bold. Mapping indicators in rows, surveying indicators in columns.

Table A7
Correlations of mapping and surveying indicators for adaptive capacity.

	Higher educated	Migratory background	Renter
Share of higher educated	**0.28**	−0.03	**−0.16**
Share of migratory background	**−0.05**	**0.14**	**0.09**
Share of rental dwellings	**−0.14**	0.03	**0.28**

Pearson correlation coefficients. $p < .05$ printed bold. Mapping indicators in rows, surveying indicators in columns.

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