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Comparing land surface temperature and air temperature for assessing socio-demographic inequalities in urban heat exposure: evidence from Germany

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Abstract

Urban heat exposure is a growing public health concern, exacerbated by climate change and rapid urbanization. While the drivers of urban heat are well-studied, social disparities in exposure—a core environmental justice (EJ) concern—remain understudied. Existing EJ studies in urban heat typically rely on either land surface temperature (LST) or air temperature, although these two capture different aspects of urban heat. In this study, we compare both metrics to assess socio-demographic inequalities in heat exposure, across multiple spatial contexts and diurnal periods, using Germany as a national case study. We combine temperature data with census information to quantify disparities across urban, suburban, and rural districts and examine whether specific population groups are disproportionately exposed to higher temperatures. Our analysis reveals consistent inequalities associated with nationality, with foreigners disproportionately residing in hotter neighborhoods. More than 84% of cities show significantly higher night time air temperatures in districts with higher shares of foreigners, while more than 50% of cities exhibit significant disparities against foreigners for both LST and air temperature. Differences between daytime and night-time patterns and between LST and air temperature highlight the importance of metric choice when assessing heat exposure and EJ. Our findings highlight areas of heightened vulnerability and provide insights for targeted mitigation strategies, contributing to equitable urban planning in the face of rising temperatures.

1. Introduction

Climate change and rapid urbanization are intensifying heat risks across the globe [1–3]. Heat exposure is associated with a range of adverse outcomes, including impaired cognitive performance, heightened anxiety, reduced overall well-being, and in severe cases, long-term health impacts [4, 5]. As urban areas expand and pervious surfaces decline, cities increasingly experience the urban heat island (UHI) effect, whereby temperatures are elevated relative to surrounding rural areas [6, 7]. Major contributors to urban heat include weather and location, as well as urban design that impact the thermal characteristics and hence the surface energy balance. Furthermore

anthropogenic activities such as energy use associated with air conditioning, industrial activity, and emissions from private vehicles result in urban warming [8, 9].

Despite considerable knowledge about the drivers of urban heat, less is known about which population groups are disproportionately exposed—a question central to environmental justice (EJ) research. EJ is the notion that the environmental burden on which our growing civilization is built should be distributed equally among all its citizens [10]. However, in reality, this is often not the case. And, with more than 50% of the population living in an urban environment and numbers projected to increase [11], disparities in urban heat extremes are becoming increasingly

relevant [12–14]. Studies in the United States have shown that socially disadvantaged groups, including low-income residents and minorities, tend to experience higher levels of heat exposure as compared to census tracts with low share of these population groups within the same city [15, 16]. In Zhengzhou, China, a disparity consistent with the US pattern is observed where lower-priced housing is associated with higher land surface temperatures (LST) due to differences in green space and urban form [17]. In contrast, in several cities across the Global South the pattern is reversed, with wealthier neighborhoods experiencing greater heat hazard than poorer ones [18]. These studies suggest the relationship between heat and socio-economic disparities is not universal; however, similar analyses are lacking for many parts of the world, including Germany. This gap reflects several reinforcing factors. The EJ framework originated in the United States within civil rights and regulatory contexts [10] and has gradually gained increasing attention within European policy discourse comparatively recently, i.e. over the past two decades [19]. In addition, fine-grained, spatially referenced demographic data have been available for the US for a considerably longer period than for many European and Global South contexts. As a result, most existing research is concentrated in regions where high-resolution census data are readily accessible and where the EJ framework aligns closely with national policy priorities, leading to a geographic bias towards studied urban contexts.

Moreover, many existing studies rely only on LST to assess heat exposure [12]. While LST is statistically correlated with air temperature, particularly at night [20], it does not directly represent the thermal conditions experienced by humans and is highly sensitive to land-cover characteristics [21, 22]. Air temperature, although more indicative of human heat exposure, is often unavailable due to the sparse distribution of ground-based measurements [23]. With the recent publication of a gridded hourly air temperature data set resolving cities by the German weather service [24], we are now able to fill this research gap in Germany.

Accordingly, in this study, we quantify urban heat justice in Germany by investigating if certain sections of society—namely foreigners, elderly, and low income residents (using ‘rent per resident’ as a proxy variable) are disproportionately exposed to elevated temperatures. We quantify exposure in terms of LST, air temperature as well as both simultaneously, enabling a comparison of heat disparities across indicators, spatial contexts, and diurnal periods. We use census data to study the distribution of different population groups in districts and also evaluate how patterns of heat injustice differ among cities, towns/suburbs and rural districts of the country. We also explore the relation between population density and heat exposure disparities.

2. Data and methods

2.1. Overview

This study combines remote sensing, meteorological, and socio-demographic datasets to quantify UHI Intensities (UHII) and assess temperature exposure disparities within individual districts across Germany. To do so we follow the pipeline shown in figure 1. Data preprocessing takes place in Google Earth Engine [25] and Python. All analysis was conducted at the 1 km × 1 km INSPIRE grid [26]. The INSPIRE grid is a harmonized, multi-resolution geographical grid system developed by the European commission, allowing compatible mapping, integration and analysis of spatial data across national borders [27].

2.2. Socio-demographic data

Socio-demographic variables were obtained from the 2022 Census, conducted by the Federal Statistical Office (Statistisches Bundesamt, Destatis) [28]. The data is available open access and provides information on various variables including population, education, and housing. We analyze three socio-demographic variables:

- **Share of foreigners (%)**: percentage of foreign residents relative to total population per 1 km grid cell.
- **Share of people aged 65+ (%)**: percentage of residents aged 65 and above.
- **Rent per resident (€)**: calculated as a product of the available variables ‘living space per resident (square meter)’ and ‘rent per square meter (€ per square meter)’.

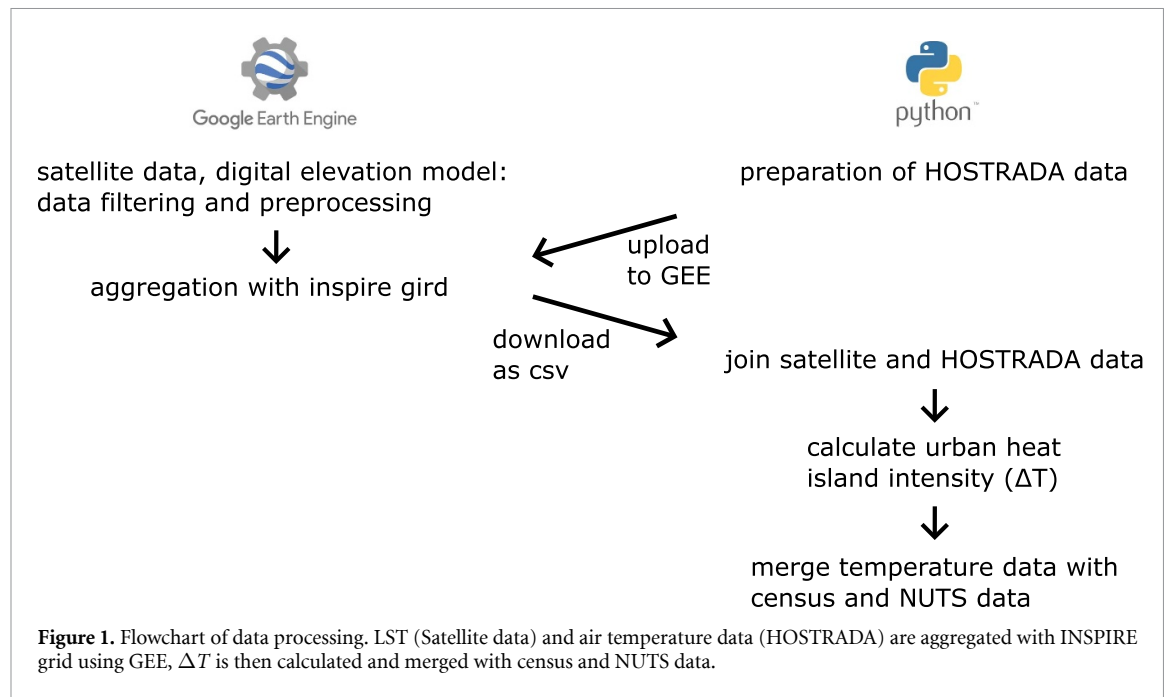
2.3. Preparation of temperature data

2.3.1. LST and air temperature data

For this study, two different temperature datasets are used namely 90th percentile summer (June, July, and August) LST and air temperature of the three years 2021–2023, i.e. centering around the year of the census.

LST is obtained from the moderate resolution imaging spectroradiometer product MYD11A1 (Aqua) ([29]). It captures LST of Germany daily at around ~13:30 in the early afternoon and ~01:30 at night, when UHI are more extreme as compared to Terra. Only pixels with an average LST error < 3 K are considered. For daytime and nighttime separately, 90th percentile LST is determined for all valid observations.

Air temperature data, measured at a height of 2 m, are obtained by the German weather service (Deutscher Wetterdienst). These data form part of the publicly available high-resolution hourly raster dataset (HOSTRADA) [24]. Air temperature is



recorded at ~ 250 synop stations supplemented with station data from neighboring countries to improve the precision in areas close to the border. They calculate the Air temperatures for the 1 km^2 grid cells with the help of digital elevation models (DEM) and land cover data. From the hourly values the 90th percentile of daily minimum and maximum are determined. The maximum and minimum air temperatures correspond with daytime and nighttime temperature respectively.

2.3.2. Calculating UHII (ΔT)

Absolute LST and air temperature values are strongly influenced by regional climate, elevation, and terrain characteristics, which complicates direct comparisons between different geographical locations. UHI intensity provides a robust framework to identify the temperature increase caused by urbanization by comparing urban areas with nearby rural areas under similar topographic conditions. Therefore, we quantify UHI intensity using the temperature difference ΔT between each grid cell and its corresponding rural reference, following the methodology published by [30] and expressed as

$$\Delta T_{i,j} = T_{i,j} - \text{median}(T_{\text{rural}})_{i,j} \quad (1)$$

where $T_{i,j}$ is the temperature at grid cell i,j and it is corresponding rural background temperature $T_{\text{rural}})_{i,j}$. Rural is hereby described by a lack of nighttime light (NL) and background is defined as all topographically similar location within 100 km. To maintain statistical reliability, a minimum number of 50 rural background cells is required for each calculation.

We base topographic similarity to the grid cell i,j on elevation and terrain aspect, i.e, if a location is facing south or north. Thresholds are set following previous studies [15, 30]:

- orientation: $\pm 90^\circ$
- elevation difference: $\pm 100\text{ m}$

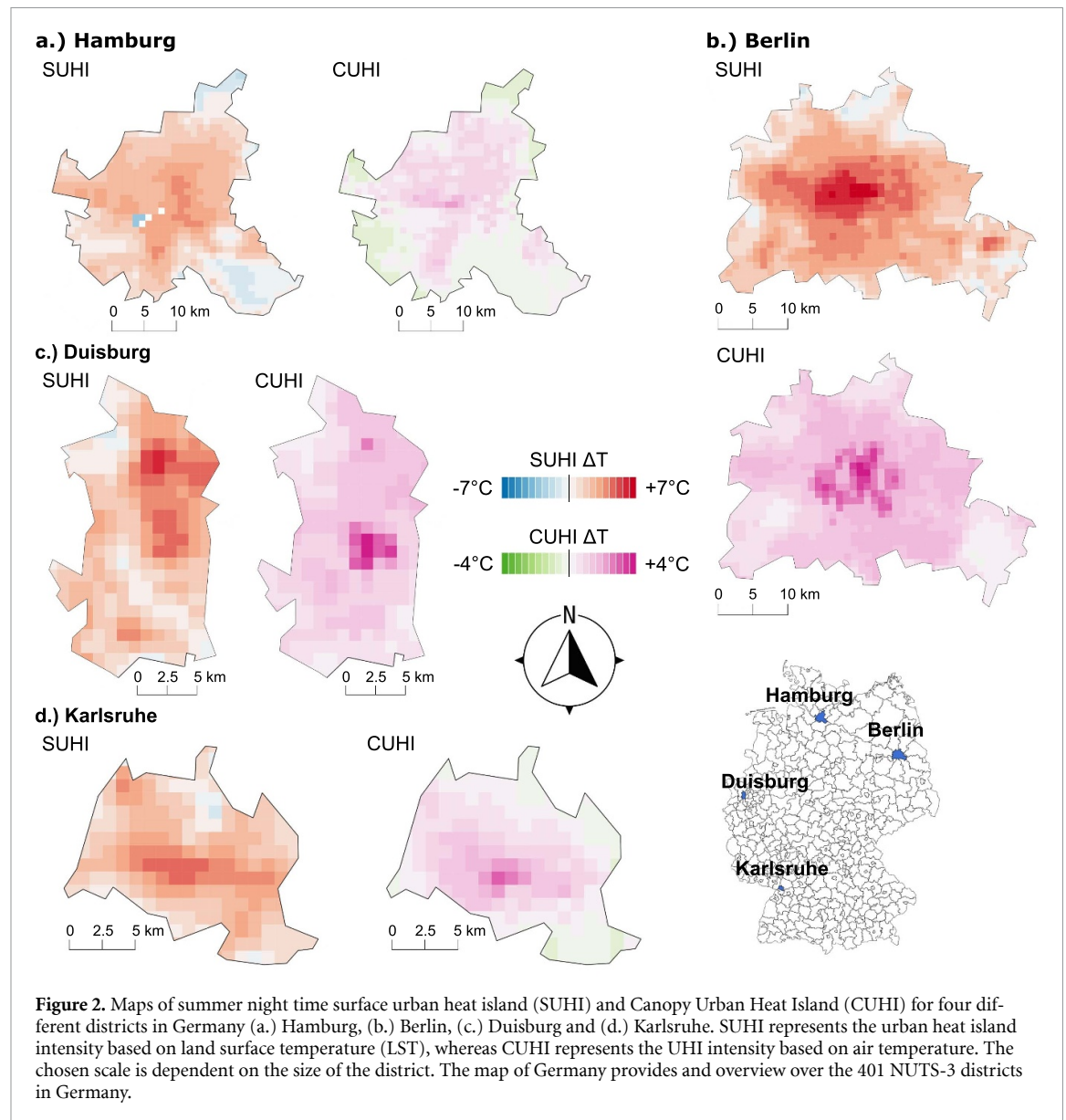
We use Copernicus DEM GLO-30 [31], provided by the European Space Agency in a 30 m resolution and derive the terrain aspect from it using QGIS.

NL is used to separate urban areas, with high emissivity of artificial light at night, and rural areas. The initial introduction of ΔT was based on the Operational Linescan System of the Defense Meteorological Satellite Program of the U.S. air force. As this dataset has been discontinued we adapted the approach to data from the visible infrared imaging radiometer suite with a rural threshold of $< 2.2255 \frac{\text{nW}}{\text{cm}^2}$, defined empirically by testing different cut-off values and selecting the one that best separated known urban and rural areas. This annual data has a resolution of 463.83 m., here we take the mean of the years 2021–2023.

Within this study ΔT is determined for LST and air temperature for daytime (i.e. max air temperature) and nighttime (i.e. min air temperature) separately.

2.4. Quantifying temperature exposure disparities within districts

Administrative district information for Germany was incorporated using the Nomenclature of Territorial Units for Statistics (NUTS) level 3, which includes all districts (e.g., ‘Landkreise’ and ‘Kreisfreie Städte’). Functionally, these districts are comparable to



counties in the United States or local authority districts in the United Kingdom. Germany has 401 NUTS-3 districts in total, as shown in the general overview in figure 2.

For each of them, the populated 1 km INSPIRE grids (900 ± 750) are sorted into quartiles for each of our socio-demographic variables (i.e. share of foreigners (%), share of people older than 65 (%), and rent per resident (€)). Then, for the part of district within each quartile, the mean ΔT values are calculated for daytime and nighttime and for LST and air temperatures. To assess exposure disparities the temperature difference between the highest (Q_4) and lowest (Q_1) quartiles ($Q_4 \Delta T - Q_1 \Delta T$) of each socio-demographic variable is determined for each district. A two sample t -test is run with a value of $P < 0.05$ to identify significant differences between the temperature distributions in Q_1 and Q_4 . The test is run separately for daytime and nighttime LST as well as air temperature differences.

District-level results were subsequently aggregated according to the Eurostat's Degree of Urbanisation (DEGURBA) categories—cities, towns/suburbs, and rural areas [32]. This standardized classification ensures comparability with other European studies and aligns with official EU statistical definitions. This categorization is mainly based on population and population density. In Germany 95 districts are cities, 196 towns/suburbs, and 110 are rural.

Within each region type, we calculated the share of districts showing statistically significant temperature disparities for LST based disparities, air temperature based disparities, and cases where both LST and air temperature disparities were significant. This comparison was carried out separately for daytime and nighttime observations.

LST and air temperature (T_a) provide complementary insights into urban heat exposure and its implications for human well-being. LST represents

the radiative skin temperature of the land surface, which strongly responds to land cover, built materials, and solar radiation during the day [33]. In contrast, air temperature reflects the conditions within the atmospheric boundary layer and is more directly linked to thermal comfort and human health [34].

Daytime LST is particularly sensitive to differences in vegetation, albedo, and impervious surfaces, and thus indicates how strongly certain urban areas heat up under solar radiation [35]. Nighttime LST, on the other hand, reflects the thermal inertia of materials and the capacity of built-up areas to retain heat after sunset—crucial for understanding how well cities cool down at night [36]. Meanwhile, air temperature captures the heat stress actually experienced by residents, with elevated nighttime air temperatures shown to increase mortality during heat events [37, 38].

Hence, analyzing both variables across day and night offers a comprehensive view of the diurnal heat environment—from surface heating to human exposure—and allows the identification of areas where socio-demographic groups experience disproportionate thermal burdens.

To quantify the degree of spatial correspondence between LST and air temperature disparities, we employ the Jaccard Index, also known as the Jaccard similarity coefficient. It measures the similarity between two sets and is defined as the size of their intersection divided by the size of their union [39]. Mathematically, it is expressed as:

$$J(A, B) = \frac{|A \cap B|}{|A \cup B|}$$

where A and B represent the districts showing significant disparities in LST and air temperature, respectively. The index ranges from 0 (no overlap) to 1 (complete overlap). In this context, higher Jaccard values indicate that disparities in surface and air temperature coincide spatially.

We also analyze the relation of population density with temperature disparities. Population Density data were sourced from Eurostat for the year 2022 [40].

3. Results and discussion

3.1. UHI intensity for LST and air temperature

Nighttime results of UHI intensity (ΔT) are shown for example districts in Germany: Hamburg, Berlin, Duisburg, and Karlsruhe, in figure 2. As is also done in comparable publications, UHI measured with LST is referred to as surface UHI (SUHI), and if air temperature is used, as Canopy UHI (CUHI).

The intensity difference between SUHI and CUHI, is clearly visible. As expected the SUHI is much more pronounced than the CUHI [22, 41]. Though air temperature is comparatively homogeneous it still shows up to 4 degrees high ΔT

forming nighttime CUHI in city centers. LST on the other hand forms nighttime UHI with ΔT as high as 7 degrees in the city centers.

The overall heat distribution pattern generally agrees in the two parameters but some differences remain. For example, in Northern Duisburg we see hotspots in LST which are not evident in air temperature and in Karlsruhe cold spots in air temperatures are not evident in LST.

3.2. Sociodemographic heat disparities within selected German districts

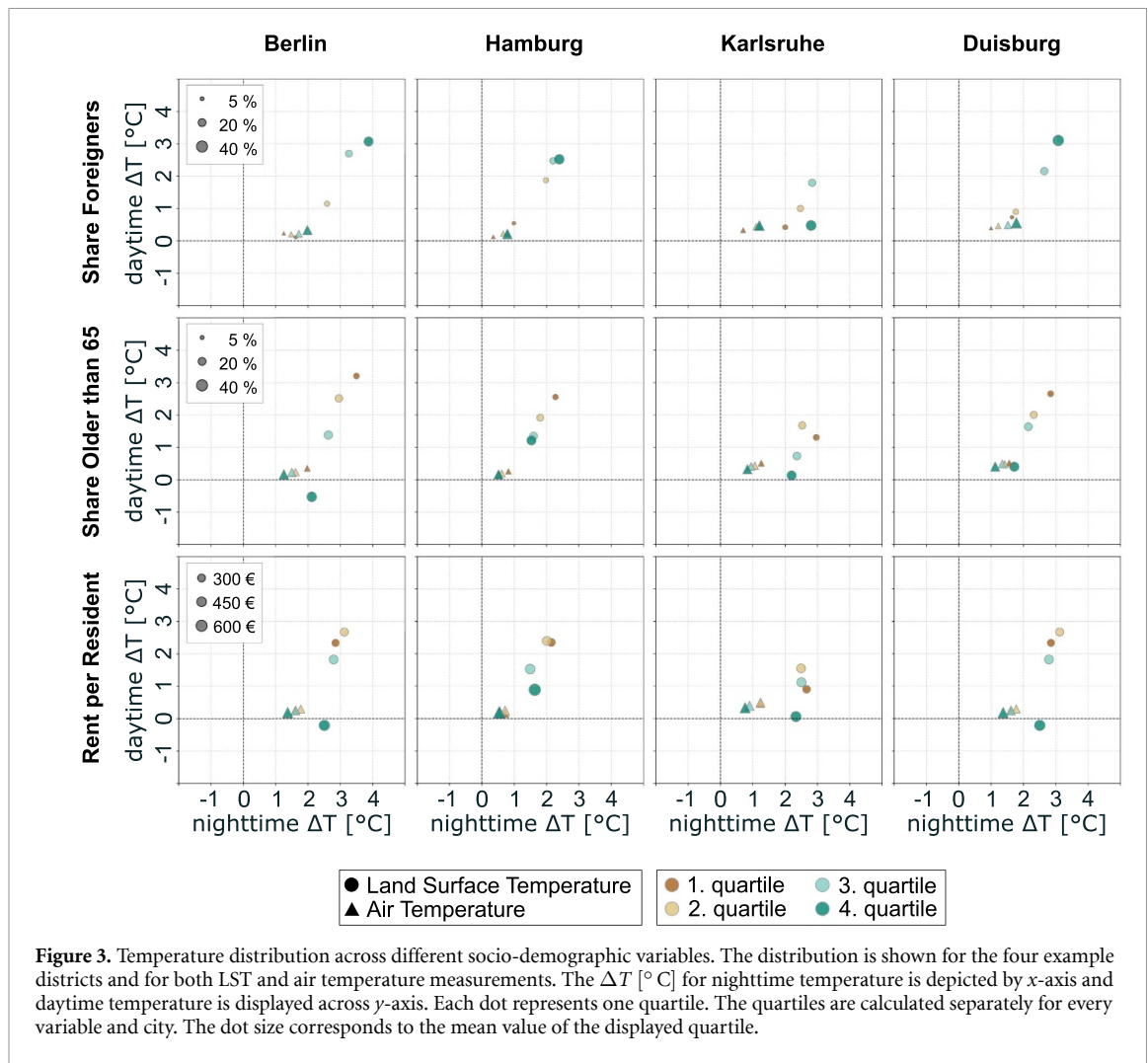
In order to understand disparities in heat experienced by different communities within a district, we quantified mean LST and air temperature across four quartiles of selected socio-demographic variable. Results are exemplarily depicted for four districts in figure 3, key characteristics of selected example districts can be found in supplementary table S1. Results of all districts can be found in our accompanying interactive web application *EJ Heat Germany* (www.ipf.kit.edu/GRUSS/EJ_Heat_Germany/).

For most of our example districts, we observe a generally linear relationship between socio-demographic quartiles and summer extreme temperature—indicating that higher shares of certain population groups correspond to systematically higher or lower temperature exposures. However, notable exceptions occur, particularly in Karlsruhe, the smallest of them. Here observed disparities are less structured along the quartiles across all three variables examined. This pattern raises the question of whether city size and population density play a role in shaping heat exposure inequalities, which we examine in more detail below.

For all example districts interesting contrasts emerge among the socio-demographic indicators: areas with a higher share of foreigners consistently experienced higher temperatures across all districts. Conversely, the highest quartile for elderly population tended to have lower average temperatures across all the four example districts. Similarly, areas with higher rent per resident were generally associated with lower temperatures. Both the highest quartile of elderly population and the highest quartile of rent per resident correspond to comparatively lower ΔT —suggesting that elderly populations and people paying high rents (i.e. potentially high income) live in cooler areas. This may suggest a correlation between age demographics and net wealth [42] with the ability to reside in cooler, more vegetated urban areas.

3.3. Nationwide patterns of district-level heat exposure disparities

To provide a nationwide overview of EJ in urban heat exposure, we summarize district-level disparities across Germany by plotting the temperature differences between the lowest and highest quartiles across the selected socio-demographic variables



for each district for both LST and air temperature (figure 4). Districts are furthermore sorted based on their level of urbanization and population density. LST exhibits higher disparity magnitudes, as compared to air temperatures (aligning with the previous figures 2 and 3). Still, air temperature disparities show greater spread along the x-axis (nighttime), whereas LST disparities dominate the y-axis (daytime), reflecting stronger diurnal contrasts in disparities as per the two temperature variables.

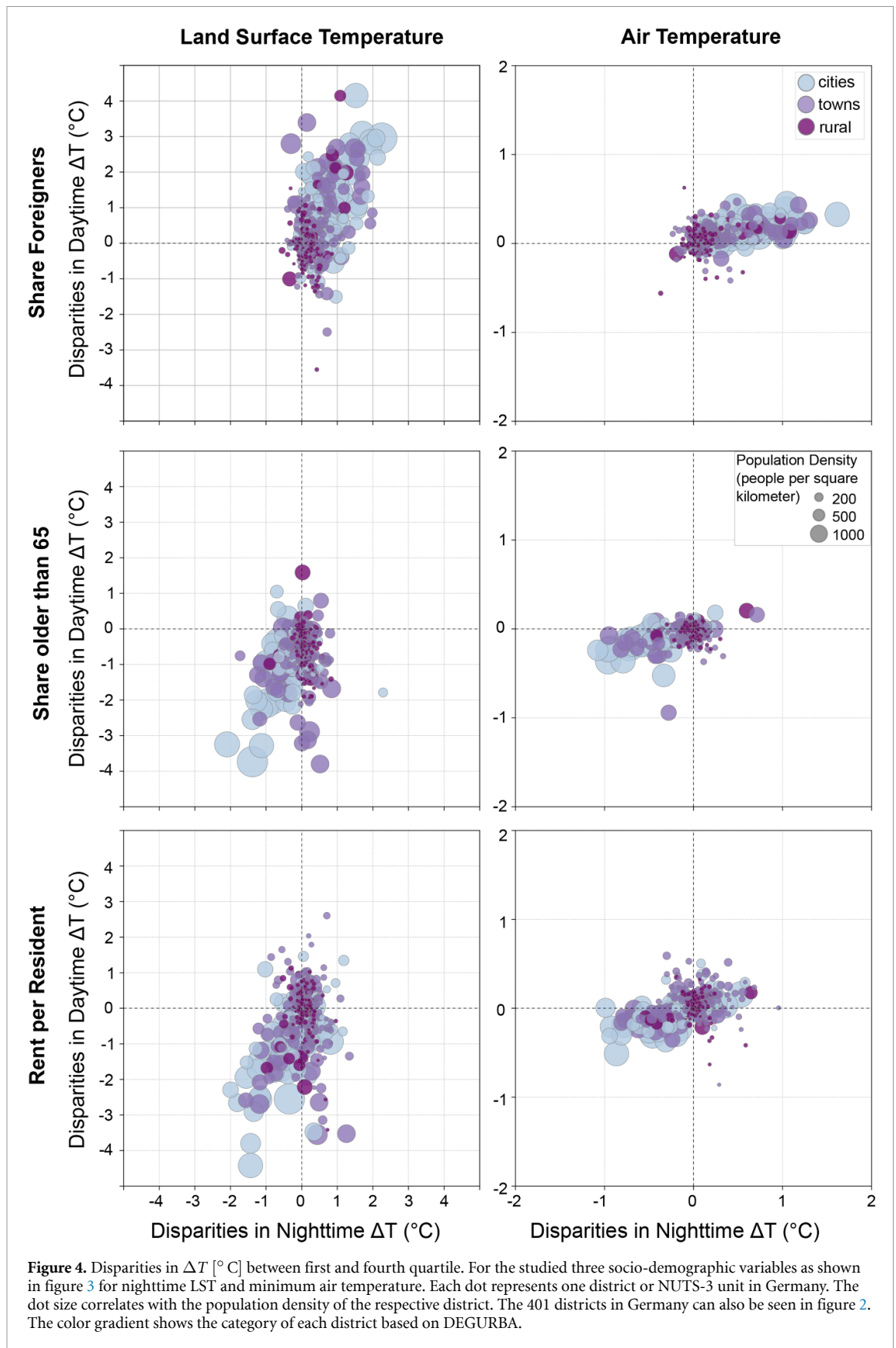
We observe that foreigners are consistently living in hotter areas, with more than 50% of the cities reflecting significant disparities during both day and night. Towns/suburbs exhibit similar but less intense patterns, while rural areas show comparatively minor disparities. These results likely reflect social or economic housing inequalities: foreigners may face limited housing choices due to shortages or socioeconomic constraints, and are therefore more often located in less desirable, hotter neighborhoods. Previous studies support these mechanisms, highlighting that immigrants often have lower income levels or reduced access to high-quality housing [43, 44].

Areas with higher proportions of elderly residents are generally cooler, particularly in cities and towns/

suburbs. This suggests that older populations tend to reside in greener, suburban or less densely built neighborhoods. This pattern is consistent with previous findings showing that elderly people in Germany are more likely to live in peripheral areas though this is good from a health perspective these peripheral areas are often characterized by lower population density and greater living space per person, although such locations often provide more limited access to health-care and everyday infrastructure [45].

Rent was used as a potential proxy for income as it might reflect an aspect of socioeconomic status. However, the results show mixed patterns. High-rent areas may be either cooler for example due to higher green space or high-rent areas might be hotter such as in dense city-center locations or mixed used neighborhoods. Thus, rent appears to be a complex indicator that does not linearly correlate with heat exposure. Although studies from other countries including Australia [46], China [17] and U.S [15, 16, 47, 48] have found clearer income-based disparities in heat exposure, low-income neighborhoods are consistently exposed to higher heat risks.

We also checked these disparities based on absolute temperature along with ΔT , the distributions



suggest similar findings (supplementary figure S1). Overall, these patterns reinforce the notion that urban heat exposure is not evenly distributed within cities. In other countries such as the US [15] or Australia

[46], these disparities have been attributed to disparities within the physical drivers of local temperature variability such as land cover, building density and vegetation density. In addition political drivers

such as urban planning decisions, shaping residential patterns and housing conditions, can influence how heat exposure and impacts are distributed across populations. Such systematic biases have been exposed e.g. for air pollution in California [49] or in historic housing policies of the US, i.e. redlining [50]. In Germany, several city-scale studies have identified socio-spatial inequalities in environmental conditions, particularly with respect to access to urban green spaces and exposure to multiple environmental burdens. For example, distributive injustices in green space provision have been documented in individual cities such as Berlin [51] as well as in comparative analyses across major German cities [52]. Studies in Dortmund show that socio-economically disadvantaged neighborhoods are disproportionately exposed to combined environmental burdens such as poor air quality, noise and limited green space [53, 54]. However, unlike the extensive literature linking urban heat exposure to historical and political drivers in other countries, comparable analyses explicitly addressing systematic planning or policy-driven heat exposure inequalities remain scarce for Germany.

3.4. Disparities by settlement type

To further assess how urbanization influences heat exposure disparities, we analyzed the distribution of temperature differences (ΔT), by testing if disparities in each district are significant; separately for all three settlement types, i.e. across cities, towns/suburbs and rural districts in Germany (table 1). For more convenient visualization, figure 5 also shows the distribution of nighttime disparities across all socio-demographic variables for each settlement type, while Supplementary figure S2 shows the distribution of daytime disparities and Supplementary figure S3 provides a detailed spatial mapping of ΔT across every district in Germany. We find no clear large scale spatial patterns, such as an East–West divide in Germany; instead, disparities are primarily structured along the urban–rural gradient.

Cities are positioned further from the central axis, meaning that they consistently exhibit the largest temperature disparities across all socio-demographic groups, suggesting that higher levels of urbanization amplify thermal inequality (figures 5 and 4). Towns/suburbs show moderate disparities, while rural areas display narrow distributions centered near zero, reflecting more homogeneous thermal conditions of heat exposure across various population groups.

This pattern is further supported by the relationship between nighttime temperature disparities and population density (figure 6). Generally, districts with a higher population densities tend to exhibit larger temperature disparities. Across the studied socio-demographic variables, Pearson's correlation

coefficients (r) are calculated. The results indicate that temperature disparities are most strongly associated with population density for the share of foreigners and elderly. Positive correlations are observed between disparities and population density for the share of foreigners, while negative correlations are found for the share of elderly. The relationships for rent per resident are comparatively weaker. These associations are stronger for air temperature as compared to LST for all studied variables.

The relationship between population density and daytime disparities is shown in supplementary figure S4. The direction of correlations remains consistent with nighttime results, with positive associations for the share of foreigners and negative associations for the share of elderly and rent per resident. However, the strength of these relationships differs: during daytime the strongest association is observed for foreigners, followed by rent per resident and elderly. In contrast to nighttime patterns, LST shows stronger associations than air temperature for all variables during daytime.

3.5. LST vs air temperature disparities

The overlapping areas (where significant disparities exist simultaneously for both LST and air temperature, table 1) indicate districts where vulnerable socio-demographic groups are simultaneously exposed to hotter surfaces and higher air temperatures, amplifying potential heat stress. Conversely, lower overlaps suggest that physical heat patterns do not fully translate into air temperature differences—possibly due to localized cooling effects such as advection; and vice-versa, meaning that air temperature disparities can also arise in areas where LST shows little or no contrast, likely due to canopy-layer processes unrelated to surface heating.

Across Germany, disparities are more pronounced during the daytime, particularly for LST, highlighting the role of built environment characteristics and land cover in shaping surface heat accumulation. The correspondence between LST and air temperature disparities is moderate, consistent with previous work showing that LST typically exaggerates temperature contrasts among urban surfaces, compared to air temperatures [55, 56]. Also, air temperature is affected by various other processes in the canopy layer including advection and shading [57].

During nighttime, we observe the overlaps between air temperature disparities and LST are generally higher, suggesting that LST and air temperature are more aligned and consistent at night as observed in other studies [20, 58]. The Jaccard index, measuring the overlap between LST and air temperature based exposure disparities, was highest in cities, particularly at night. Relying only on daytime LST may therefore introduce bias when identifying daytime heat disparities. Ideally, combining both datasets

Table 1. Socio-demographic disparities in daytime and nighttime LST and air temperature across Germany. The table shows the percentage of each socio-demographic group experiencing higher or lower LST and air temperature, as well as overlapping disparities, for all areas combined and by settlement type (cities, towns/suburbs, and rural areas). (−) or (+) behind the Socio-demographic variable indicates whether the disparity value shown e.g. in figure 4 is positive or negative for the given statement. The bold values highlight percentages above 50, italic values highlight percentages between 30 and 49.9. The gray column represents the Jaccard index, a higher number indicates higher overlap in LST and air temperature disparities.

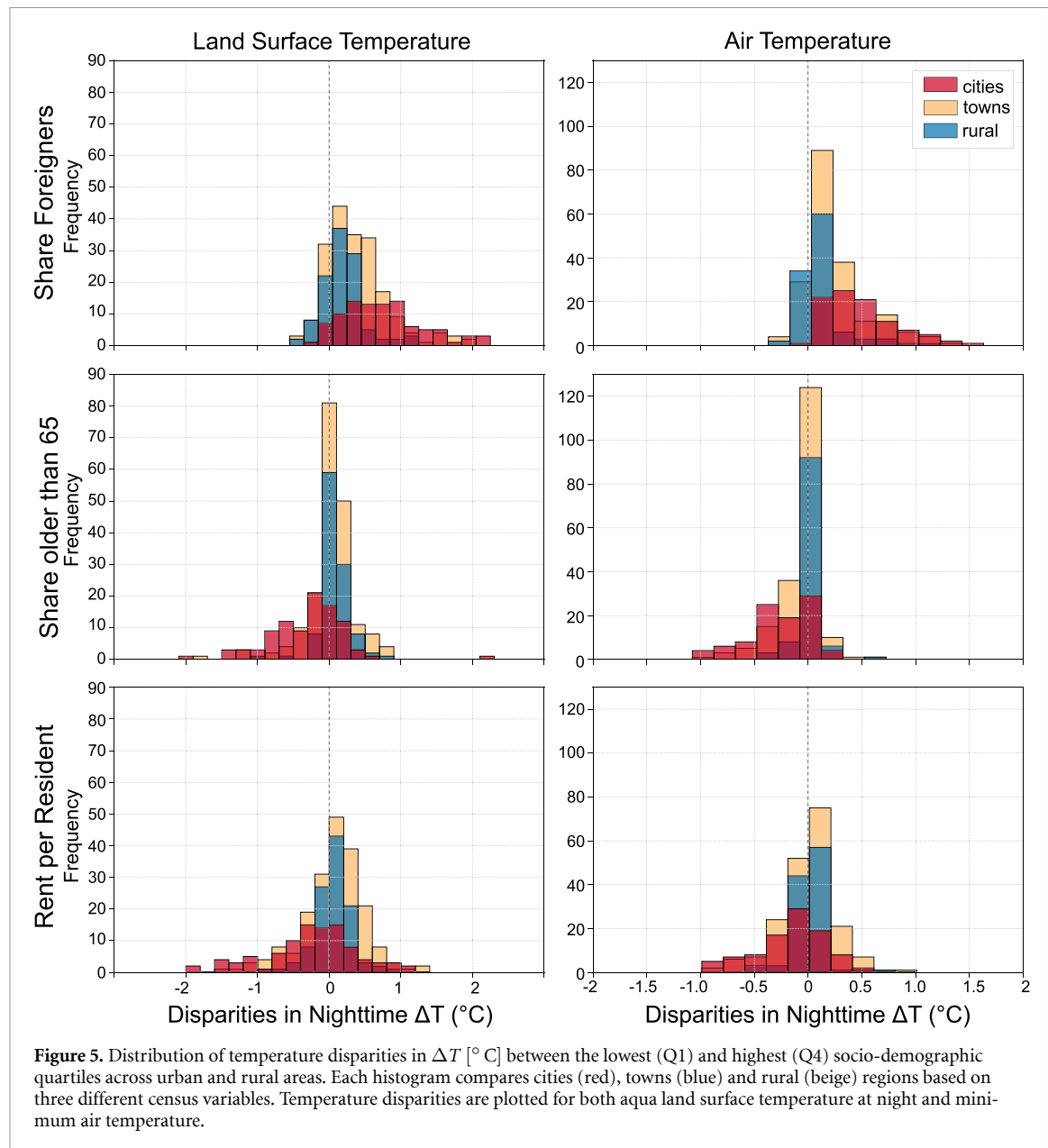
Socio-demographic variable	Day time				Night Time			
	LST	Air temp.	Both LST & Air temp.	Jaccard Index	LST	Air temp.	Both LST & Air temp.	Jaccard Index
Germany (All 401 NUTS-3 units)								
Foreigners in cooler areas (−)	8.70%	3.20%	0.25%	0.02	1.50%	2.00%	0.50%	0.17
Foreigners in hotter areas (+)	33.20%	44.90%	22.90%	0.23	47.40%	59.90%	37.25%	0.53
Elderly in cooler areas (−)	49.60%	26.20%	18.75%	0.33	12.70%	23.90%	9.75%	0.36
Elderly in hotter areas (+)	0.20%	3.50%	0.00%	0.00	12.20%	7.50%	2.00%	0.11
Low rent in hotter areas (−)	27.20%	15.70%	8.75%	0.26	17.20%	20.00%	10.00%	0.37
Low rent in colder areas (+)	16.20%	28.90%	8.47%	0.23	25.20%	24.40%	12.50%	0.34
CITIES (95 NUTS-3 units)								
Foreigners in cooler areas (−)	4.20%	1.10%	0.00%	0.00	0.00%	0.00%	0.00%	0.00
Foreigners in hotter areas (+)	64.20%	68.40%	50.52%	0.62	69.50%	84.20%	63.15%	0.70
Elderly in cooler areas (−)	53.70%	43.20%	33.68%	0.53	33.70%	49.50%	28.40%	0.52
Elderly in hotter areas (+)	1.10%	1.10%	0.00%	0.00	3.20%	5.30%	1.05%	0.14
Low rent in hotter areas (−)	47.40%	29.50%	23.15%	0.43	34.70%	33.70%	25.26%	0.59
Low rent in colder areas (+)	7.40%	18.90%	5.26%	0.25	13.70%	15.80%	11.57%	0.65
TOWNS (196 NUTS-3 units)								
Foreigners in cooler areas (−)	7.70%	3.10%	0.51%	0.05	1.50%	2.00%	0.51%	0.17
Foreigners in hotter areas (+)	28.60%	40.80%	17.30%	0.33	45.40%	57.10%	35.71%	0.53
Elderly in cooler areas (−)	50.00%	22.40%	15.30%	0.27	9.20%	18.90%	6.12%	0.11
Elderly in hotter areas (+)	0.00%	4.60%	0.00%	0.00	12.80%	7.70%	2.04%	0.28
Low rent in hotter areas (−)	24.00%	12.80%	4.08%	0.13	13.80%	18.90%	7.67%	0.31
Low rent in colder areas (+)	20.40%	34.70%	10.71%	0.24	32.10%	30.10%	16.32%	0.36
RURAL (110 NUTS-3 units)								
Foreigners in cooler areas (−)	14.50%	5.50%	0.00%	0.00	2.70%	3.60%	0.90%	0.17
Foreigners in hotter areas (+)	14.50%	31.80%	9.10%	0.24	30.90%	42.70%	16.40%	0.29
Elderly in cooler areas (−)	44.50%	18.20%	11.81%	0.23	0.90%	10.00%	0.90%	0.00
Elderly in hotter areas (+)	0.00%	3.60%	0.00%	0.00	19.10%	9.10%	0.00%	0.11
Low rent in hotter areas (−)	14.50%	8.20%	4.50%	0.05	8.20%	10.00%	0.90%	0.05
Low rent in colder areas (+)	16.40%	27.30%	7.30%	0.20	22.70%	21.80%	6.40%	0.17

provides the most complete picture: LST helps to understand surface and urban fabric contributions, while air temperature directly links to human thermal exposure.

To examine whether these low to moderate overlaps reflect different exposure mechanisms rather than random statistical effects, we compared the p -values of the t -tests for both variables. Since foreigners consistently emerged as the most heat-exposed group, we focused this comparison on their disparities for nighttime. We found that districts showing significant disparities in LST frequently had high p -values (non-significant) for air temperature, and vice versa. This inverse relationship confirms that the two indicators identify distinct thermal exposure patterns, not merely artifacts of statistical thresholds. In particular, few edge cases were observed, meaning that only a small number of data points lie close to the

chosen significance cutoff ($p = 0.05$). This suggests that the overall pattern is robust and would remain largely unchanged under slight shifts in the threshold. The distribution of these p -values for both indicators is illustrated in figure 7. Similar observations are made for daytime, shown in the supplementary figure S5

It should however be noted that while LST and air temperature provide valuable information on the spatial distribution of urban heat exposure, neither fully represents human heat stress, which is also influenced by humidity, wind, and radiation. Recent work from Germany showed that heat stress estimated using Humidex exhibits stronger UHI effect than LST or air temperature alone, suggesting that these temperature based indicators may underestimate physiological heat stress. Nevertheless, LST has been shown to correlate moderately with thermal comfort indices,



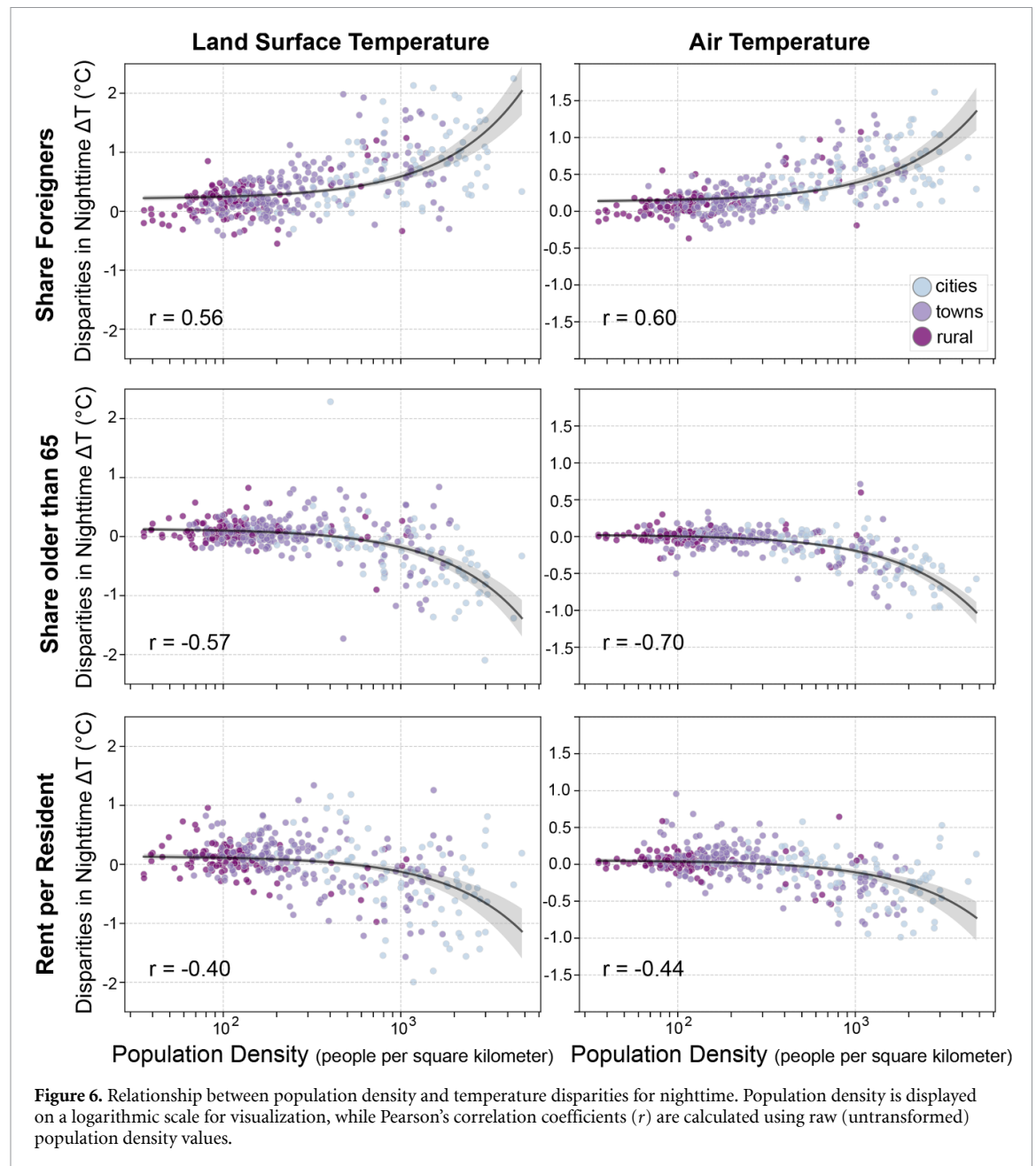
including the physiological equivalent temperature during the day and Humidex at night [59], indicating that it remains a useful proxy for identifying spatial patterns of heat exposure.

4. Conclusion and Outlook

This study provides a comprehensive picture of urban heat exposure in terms of LST and as well air temperature during both daytime and nighttime among cities, towns/suburbs and rural districts of Germany. We quantify EJ by examining disparities in heat exposure associated with the share of foreigners, elderly and rent per resident using two sample t -tests to identify districts with significant disparities. We find consistent and statistically significant disparities, particularly with respect to nationality. Across Germany, 59.90% of districts show

significantly higher nighttime air temperatures and 47.40% show significantly higher nighttime LST in areas with higher shares of foreigners; when considering cities only, these numbers increase to 84.20% and 69.50%, respectively. As income data are not available, we cannot assess whether the observed differences in temperature exposure reflect underlying socioeconomic inequality or environmental racism. The results therefore describe differences in exposure across population groups rather than mechanisms driving these differences.

Our research fills in the gap in existing researches on urban heat exposure disparities in Germany. Also, beyond a national case study, our analysis highlights the importance of metric choice in EJ assessments of heat exposure. LST and air temperature capture different aspects of the urban thermal environment and can reveal distinct patterns of inequality. The findings also highlight that socio-demographic disparities in

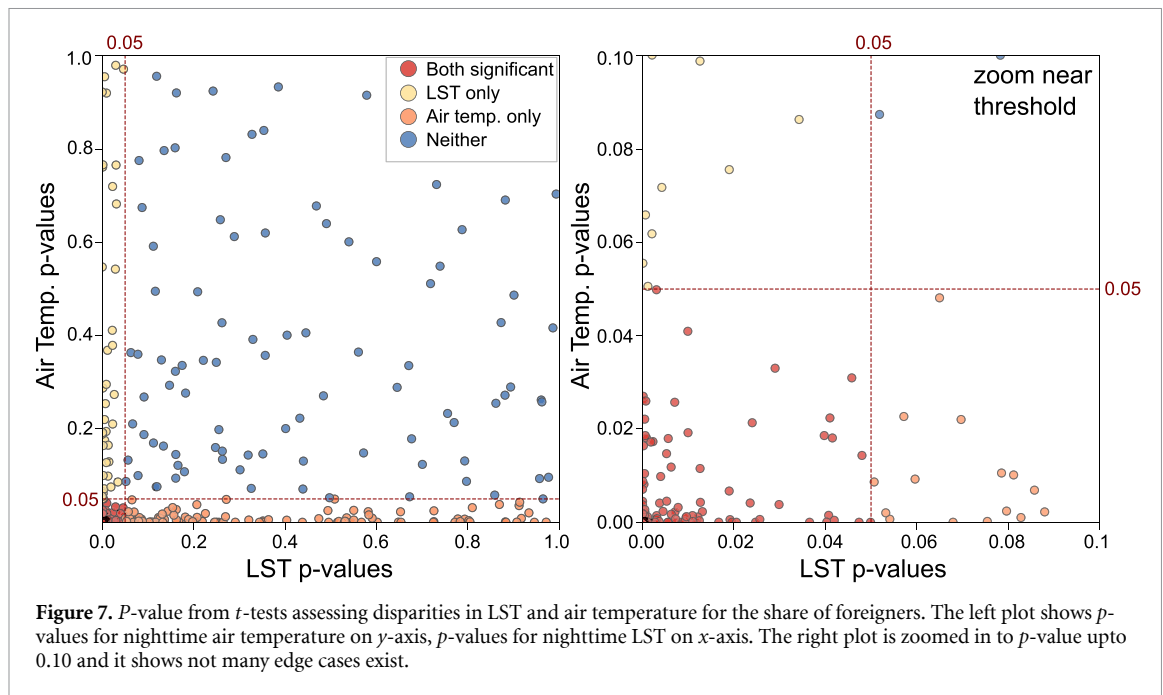


heat exposure are not limited to cities but extend into towns/suburbs and, to a lesser degree into rural districts. The consistent differences observed between daytime and nighttime and between LST and air temperature emphasize that mitigation strategies must address both surface-level processes (e.g. increasing vegetation, reflective materials) and microclimate conditions that affect human heat exposure, especially during the night when physiological recovery from heat stress is critical. Combining the two datasets i.e. LST and air temperatures can help us target the most vulnerable areas for heat mitigation and adaptation policies.

Although LST and air temperature reliably capture the direction of heat exposure disparities, the magnitude of these disparities varies depending on the indicator used [60]. Therefore, future research should incorporate more comprehensive thermal

comfort metrics, such as Humidex or the universal thermal climate index, to further improve assessments of heat exposure inequalities and their implications for EJ.

Our findings further suggest that urban heat exposure is not evenly distributed within cities. While physical factors such as land cover and building density are the main drivers of temperature differences, prevailing urban planning practices often overlook social dimensions. As a result, urban morphology can inadvertently amplify or mitigate heat exposure across different population groups. Groups with social advantage often live in greener, and cooler neighborhoods, while vulnerable populations are more likely to live in denser and hotter parts of the city. In this way, socio-demographic characteristics are associated with people's exposure to heat through the neighborhoods they occupy. This suggests



that current planning systems do not provide equitable thermal environments for all residents and there exists a need to examine why such city planning blind spots persist and how they can be addressed in future urban design and policy. This disconnect between environmental inequalities and their systematic consideration in planning practice has also been highlighted in recent reviews on climate resilience and EJ in Germany, which point to persistent gaps between research insights and implementation [61].

While countries like Germany are often regarded as having more equitable social structures due to their extensive welfare programs and labor regulations, our study indicates that environmental disparities particularly along nationalities can still exist in nuanced-complex social factors, and spatially embedded ways likely as a result of long-term planning decisions. The disparities observed in Germany are not necessarily obvious or uniform but rather subtle, context-dependent, and influenced by overlapping factors like migration history, housing policies, or land use planning. It might be interesting to look at a finer detail, to understand the drivers of these disparities. The existence of these disparities opens many more research questions, for example if disparities exist only in terms of heat exposure or also in neighborhoods in terms of infrastructure, building typology, green areas and income. Due to the unavailability of income data we could not quantify how many of these disparities are actually class based and how many race based. We can also get a clearer perspective on race based disparities if we have the data of origin of people—including migrants and refugees, right now we only know if these people are natives or foreigners. Though we understand that there are historical reasons to preserve the identity of different

groups; information about their background might allow a deeper understanding to see if there are disparities even within the passport holders depending upon where they come from.

More broadly, this study provides a framework that can be applied to other national contexts where both remotely sensed surface temperatures and meteorological data are available. Applying similar analyses across different countries and climatic regions would help determine whether the patterns observed here represent broader structural dynamics in urban development or reflect country-specific factors. Expanding such analyses globally would contribute to a more systematic understanding of EJ in a warming climate and support the development of equitable urban heat adaptation policies.

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Data availability statement

All codes are available at Zenodo with development hosted on GitHub [62]. All data used in the paper is available at: Zenodo [63]. Results for all districts in

Germany is also viewable as an interactive site under (www.ipf.kit.edu/GRUSS/EJ_Heat_Germany/).

Supplementary data 1 available at: <https://doi.org/10.1088/1748-9326/ae929e/data1>.

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