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Can spatial patterns mitigate the urban heat island effect? Evidence from German metropolitan regions

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Abstract

This study examines the efficacy of urban spatial patterns at alleviating the urban heat island (UHI) effect in Germany's city regions (*Großstadtregionen*) using multivariate and non-parametric regression methods. Urban spatial patterns are quantified using five landscape metrics that capture the spatial arrangement of urban footprints and greenspaces, along with a polycentricity index that measures the distribution of human activities. The results indicate that certain features of urban fabric, including fragmentation, mixed land use, and regular-shaped urban patches, have the potential to mitigate the UHI effect. Moreover, dispersing multiple smaller greenspaces throughout the urban area demonstrates a greater cooling effect compared to having a single large and more aggregated park. In addition, our analysis reveals that a doubling (100%) of the polycentricity degree corresponds to a significant decrease in both day- and night-time UHI effects, with reductions of 10.4% and 24.6%, respectively. This study confirms that polycentric development yields greater benefits in reducing urban heat for large-sized city regions compared to medium- and small-sized ones; and its effectiveness is mostly pronounced near urban center(s). These findings suggest that polycentric development represents an efficient and feasible strategy for urban thermal planning of large-sized city regions, surpassing other commonly discussed urban configurations, such as compact or dispersed urban development.

Keywords

Urban heat island effect, regional planning, urban spatial pattern, green space, polycentricity urban development

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Data Availability Statement included at the end of the article

Introduction

The urban heat island (UHI) effect refers to the thermal anomaly of higher temperature in urban areas compared with less densely populated rural areas. It is observed in human settlements of all sizes and varies in intensity across multiple dimensions, such as urban and rural areas, diurnal and nocturnal periods, and warm and cold seasons. The expansion of impervious surface, high population concentration, and reduced heat dissipation associated with urbanization are recognized as important contributors to urban heat (Oke, 1982). The adverse impacts of the UHI effect have been extensively well-documented, as it raises energy consumption, worsens air pollution, and increases risks of heat-related mortality by exacerbating the intensity of heatwaves (Debbage and Shepherd, 2015; Gago et al., 2013). Notably, low-income and marginalized communities are particularly vulnerable to high temperatures due to limited access to greenspaces and cooling resources.

City planners have engaged in ongoing debates concerning the potential of well-designed urban forms to diminish the UHI effect. On the one hand, studies have suggested that a high-density and compact urban development is positively correlated with high urban temperatures, as the mechanisms contributing to heat accumulation are amplified in densely populated urban areas (Debbage and Shepherd, 2015; Schwarz and Manceur, 2015). However, others have yielded paradoxical findings that sprawling configurations, characterized by low-density and fragmented urban development, may also exacerbate UHI intensity due to greater impervious surface coverage and higher per capita heat emission (Ewing and Rong, 2008; Shreevastava et al., 2019; Stone et al., 2010; Stone and Rodgers, 2001). The inconclusive relationship between density and urban heat has resulted in a dilemma over best management practices, highlighting the need for effective spatial strategies regarding urban thermal planning.

Moreover, the focus on examining the relationship between density and heat has been to the exclusion of broader questions linking the UHI effect with regional land-use patterns, as measured by, for instance, the degree of land-use mix, aggregation, and polycentricity. The spatial arrangement of land use and human activities, referred collectively to as urban spatial patterns, can directly influence the intensity and distribution of urban heat (Debbage and Shepherd, 2015; Schwarz and Manceur, 2015). Therefore, land-use and spatial planning policy may serve as an effective tool to mitigate the UHI intensity. This is particularly true for German metropolitan regions, where regional-scale planning and governance can have an outsized influence on the spatial structure of urban settlements and open spaces through regulatory policies and the coordination of land-use interests across multiple local municipalities and various sectoral plans in the spatial planning process (Schmidt et al., 2018, 2021; Siedentop et al., 2022).

In addition, within the German planning guidelines, regional polycentrism has been identified as integral to delivering more equitable opportunities and services (BMVBS, 2006, p7). It has also been adopted broadly as a normative goal to achieve more cohesive and sustainable territorial development across the EU (see, e.g., ESDP, 1999; EU Ministers, 2020; European Union, 2011). A polycentric urban system encompasses multiple centers, characterized by a more balanced distribution of employment and population, a less hierarchical spatial organization, and a network of interconnections among these centers (Davoudi, 2003). Polycentric regions distribute urban activities across multiple centers or cities rather than relying on a single center, resulting in lower densities in urban cores and reduced spatial aggregation in urban footprints. Meanwhile, the compact design of multiple centers helps curtail the excessive expansion of impervious surface and reduces energy consumption per capita compared with urban sprawling patterns. Given these considerations, polycentric spatial development is hypothesized to offer a more sustainable and efficient approach to urban thermal planning (Han et al., 2022; Yue et al., 2019).

While previous studies have explored the relationship between urban spatial patterns and the UHI effect in the US and China (Debbage and Shepherd, 2015; Liu et al., 2021; Stone et al., 2010), Germany-based investigations have mostly focused on case studies of specific cities (Schwarz et al., 2012; Straub et al., 2019), thus lacking universal conclusions that can be generalized to a wider range of metropolitan regions. The increasing number of deaths in Western Europe caused by severe heatwaves and drought in recent years highlights the urgency of implementing spatial planning policies to mitigate heat intensity and reduce heat-related costs. Furthermore, existing studies have primarily examined the mitigation of urban heat intensity through the lens of “compactness versus sprawl” utilizing “traditional” metrics of land use patterns. However, the effectiveness of polycentric urban configuration, which assumes to combine the advantages of compactness and disaggregation, has received limited empirical testing, particularly within the German context.

With this as a point of departure, this study aims to achieve two objectives. First, we assess the impact of “traditional” land-use patterns, including measures of land-use composition, fragmentation, and shape complexity on the UHI effect. Second, we investigate the capacity of a polycentric spatial pattern to mitigate urban heat. As far as we know, the relationship between polycentricity and urban heat has not been empirically examined in Germany. Furthermore, previous studies have suggested that large (and denser) regions can effectuate greater benefits from adopting a polycentric configuration than small ones, primarily because polycentrism can alleviate the agglomeration diseconomies inherent to large regions, such as overcrowding and congestion (Han et al., 2020; Li and Liu, 2018). To this end, we explore the heterogeneous influence of polycentricity on the UHI effect, while controlling for population size. We hypothesize that polycentric development can more efficiently redistribute concentrated activities of larger compared with smaller regions, thereby mitigating the concentration and accumulation of human heat sources. Our analysis focuses on 50 city regions (*Großstadtregionen*) as the basic spatial units and relies on the MODIS land surface temperature (LST) dataset to calculate UHI intensities during the summer seasons (June, July, and August, JJA) of 2006 and 2012, considering both day- and night-time measurements. We quantify five traditional metrics of urban spatial pattern based on McGarigal and Marks (1995) and assess the degree of polycentricity by examining the distribution of population among multiple centers, following the works of Green (2007) and Liu and Wang (2016). Methodologically, we employ both naïve and multivariate OLS regressions to analyze the influences of urban spatial configuration on the UHI effect. Furthermore, we utilize nonlinear local weighted regression and kernel density estimates to compare temperature variations between polycentric and monocentric regions.

The paper is structured as follows. Section two describes the research area, data, and analytical methods employed in this study. Emphasis is placed on the measures of the UHI effect and urban spatial patterns, which are derived from satellite-based land surface temperature (LST) and land-use datasets. Section three investigates the relationship between landscape metrics and the UHI effects using naïve and multivariate regressions. Section four discusses the impact of polycentrism on the UHI effect, using both linear and nonlinear regression techniques. Finally, the last section summarizes the findings and discusses policy implications for future urban thermal planning.

Research area, data, and method

Regional delineation

The selection of appropriate regional delineation is of great importance for two crucial purposes: first, to accurately represent urbanized and rural areas for precise measurement of the UHI effect, and second, to provide a reliable approximation of functional urban areas for quantifying polycentric urban structure (Thomas et al., 2021). In this study, we chose 50 Germany city regions (*Großstadtregionen*) as the appropriate regional delineation. Each region, serving as the basic unit of analysis, comprises three hierarchical components (Milbert, 2016): one or multiple urban core(s) with a minimum population of 100,000, which serve as the regional employment center(s); a large core area characterized by a mix of urban and rural landscapes, exhibiting strong bi-directional commuting relations with the urban core(s); and a peripheral commuting zone where at least 25% of workers commute to the core areas, primarily displaying rural landscapes (see Figure 1 taking Berlin/Potsdam as an example). By incorporating both urban and hinterland areas and considering the extensive internal connectivity, our regional delineation ensures accurate measurement of the UHI effect and provides a robust approximation of functional urban areas.

Quantifying the urban heat island effect

The UHI effect is quantified as the temperature difference between the average surface temperature of urbanized area and rural area, as expressed by equation (1).

$$UHI = T_{U_{mean}} - T_{R_{mean}} \tag{1}$$

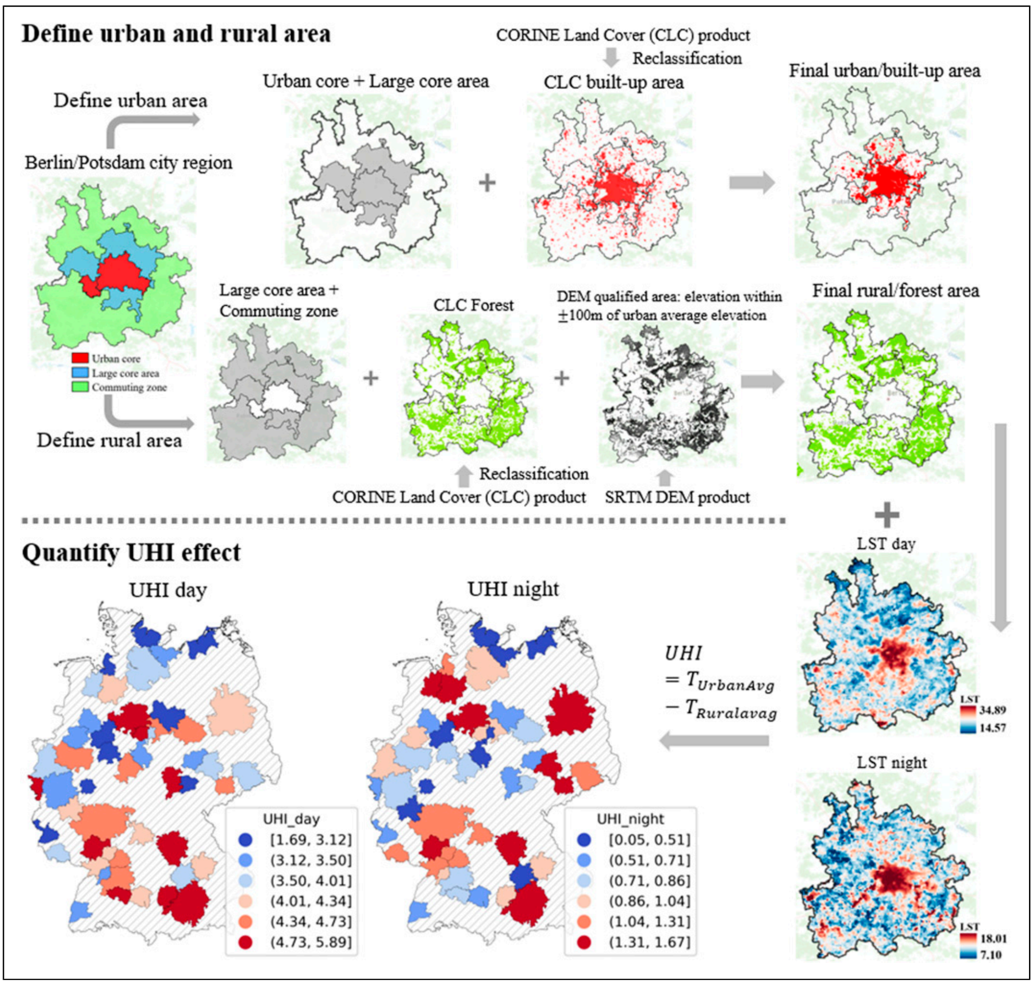

Figure 1. The illustrations of urbanized and rural areas delineation (step 1) and the quantification of the urban heat island (UHI) effect (step 2).

To calculate the UHI effect, the first step involves delineating urbanized and rural areas, followed by computing the mean land surface temperature, $T_{U_{mean}}$ and $T_{R_{mean}}$. Figure 1 provides an illustrative example of these processes using Berlin/Potsdam as a reference. To delineate urbanized areas, we employed the approach proposed by Debbage and Shepherd (2015), which first establishes an urban boundary for each region, and second, extracts artificial surfaces[1] within the boundary based on the CORINE land cover (CLC) imagery. Two definitions of the urban boundary were adopted. The first one comprises the urban core(s) and large core area for each region, ensuring that the identified areas are either part of the urban core(s) or closely associated with them. The second definition of urban boundary is used to specifically examine the influence of polycentricity on the UHI effect, which substitutes the extended core area with a smaller area restricted to only the urban core(s), allowing for a more precise representation of heat intensity in the most densely populated areas. The CLC dataset provides land cover classification at a spatial resolution of 100 m, covering all Western Europe and is updated every six years. Consequently, the final delineation of the qualified urbanized area encompasses all areas (pixels) classified as artificial surfaces within the defined urban boundary.

Rural areas in the existing literature are typically defined as comprising all types of rural landcovers in the hinterlands, excluding urban settlements and water bodies (Debbage and Shepherd, 2015; Liu et al., 2021). However, satellite-derived LST measurements may present significant variations across different rural landcovers, such as forests, agriculture, and bare rock, owing to differences in solar albedo and the evaporative cooling effect detected by satellite sensors. To address potential measurement errors resulting from the heterogeneous composition of rural landcovers, we defined rural areas as specifically consisting of forested landcover, which exhibits relatively homogeneous features in remote sensing monitoring, following the approach by Chen et al. (2006). Accordingly, we confined the rural domain to forests within a defined rural boundary, comparising the large core area and the commuting zone of a city region. Additionally, to eliminate temperature variations caused by elevation differences between urbanized and rural areas, we imposed an elevation criterion, which ensures that the elevations of selected areas (pixels) remain within ±100 m of the average elevation of the corresponding urbanized area.

In the subsequent step, we derived the mean LST of urbanized and rural areas for each region from the MODIS Aqua LST product (MYD11A2 Version 6.1)[2] with a 1 km spatial resolution. Urban geometry and the correction of atmospheric and surface emissivity effects are essential for extracting accurate surface temperatures (Coutts et al., 2016). The LST was retrieved from the thermal infrared band of MODIS through the generalized split-window algorithm, leveraging an accurate radiative transfer model and a set of multi-dimensional look-up tables derived via radiative transfer simulation to transfer band radiance (observed by bands 31 and 32) to land surface temperature (Li, 2013). A series of validation studies confirms that the product accuracy is better than 1k at all sites except for arid regions.[3] Utilizing the Aqua sensor enables us to acquire LST measurements at approximately 1:30pm, corresponding to the time when urban temperatures reach the maximum, as well as around 1:30am at night. To eliminate measurement errors due to cloud cover, we collected a series of LST imageries covering three consecutive summer seasons to ensure the coverage of the entire study areas and compute their average to obtain the final LST measurement. This implies that the LST measurement for 2012 represents the average value derived from a series of LST imageries obtained during the summers of 2011, 2012, and 2013. Data processing was conducted on the Google Earth Engine (GEE) platform, and the sample code was obtained from the NASA's Applied Remote Sensing Training Program (ARSET)[4]. Subsequently, for each region, we calculated the mean LST values for urbanized and rural areas by averaging the LST values of all pertinent areas (pixels). Equation (1) is then employed to quantify the UHI effect for both day- and night-time as illustrated in Figure 1.

Quantifying urban spatial patterns

We choose five "traditional" landscape metrics and a polycentricity index to investigate the association between the UHI effect and urban spatial patterns, following previous works by Debbage and Shepherd (2015), Liu et al. (2021), and Stone et al. (2010). The equation and definition for each metric can be found in Table 1. The landscape metrics are calculated using the R package "landscapemetrics," which provides reimplementation of the majority of metrics originally developed by McGarigal and Marks (1995) in "Fragstats." We create metrics for both urban land cover and greenspaces.[5]

The percentage of like adjacencies (PLADJ) quantifies the degree of spatial aggregation of a specific landcover by measuring the frequency of adjacent pixels between the focus class and other classes. Increasing PLADJ values indicate a more aggregated pattern for pixels of the focus class, eventually reaching maximum aggregation when all pixels merge into a single patch. We calculate the PLADJ for both the urban footprint and urban greenspace within the large core area of each region. By evaluating the PLADJ of greenspaces, we assess whether an aggregated or fragmented spatial arrangement of greenspaces contributes more effectively to urban cooling. Patch density (PD) evaluates the degree of fragmentation of urban footprint by measuring the number of urban patches per region. PD is considered the opposite of PLADJ, as higher PD values indicate a patchier and more fragmented landscape pattern. The inclusion of these variables is a nod to a long-standing debate in the field of landscape ecology and conservation biology over whether a "single large" or "several small" (SLOSS) preserves were more effective in protecting habitat and biodiversity in an otherwise fragmented landscape (Diamond, 1975).

The contagion index (CONTAG) quantifies the degree of mixed land use at the landscape level by measuring the probability of adjacent pixels belonging to the same landcover. We expect that a higher CONTAG value, suggesting a higher degree of homogenous land cover, is associated with higher urban heat intensity. The area-weighted mean shape index (AWMSI) quantifies the degree of patch irregularity. Increasing AWMSI value suggests a greater departure from a squared shape for urban patches, reflecting increased irregularity and complexity in the overall shape. The ratio of vegetated area (ROV) represents the proportion of all types of vegetated coverage, excluding agriculture, within a city region. Higher ROV values are expected to be associated with a lower UHI effect.

The polycentricity index quantifies the extent to which inhabitants are evenly distributed throughout a city region, using a modified morphological polycentricity approach based on Green (2007) and Liu and Wang (2016). The calculation of the polycentricity index involves two steps, outlined in Table 1. In the first step, we determine the degree of polycentricity by benchmarking the standard deviation (SD) of municipality populations against the SD of a hypothetical region characterized by the highest degree of monocentricity, while considering a fixed number of centers. In the second step, we compute the final polycentricity index for each region by averaging the polycentricity indices derived from the top two, three, and four centers, following the method employed by Meijers and Burger (2010) and Ouwehand et al. (2022).

Regression analysis

Multiple confounding factors may exert influence on the UHI effect, including the inherent attributes of cities, such as population and landcover composition, as well as the external influences from climate, weather, and seasons (Oke, 1982; Stewart, 2011). To account for the presence of these factors, we adopt a multivariate OLS regression approach to estimate the impacts of urban spatial patterns for the years 2006 and 2012, respectively, while controlling for population and climate variables. The basic model is as follows

Table 1. The equation and definition of land-use pattern metrics and polycentricity index following McGarigal and Marks (1995).

Metric	Equation	Definition
Percentage of like adjacencies (PLADJ)	$PLADJ_i = \frac{g_{ii}}{\sum_{k=1}^{m} g_{ik}} * 100$	g_{ii} = number of adjacent pairs of pixels in land-use class i g_{ik} = number of adjacent pairs of pixels between land-use class i and k m = number of land-use classes in the landscape
Patch density (PD)	$PD_i = \frac{n_i}{a_i} * 10000 * 100$	n_i = number of patches in class i a_i = total area of class i
Contagion index (CONTAG)	$CONTAG = \left\{1 + \frac{1}{2\,ln(m)}\left[\left(\sum_{i=1}^{m}\sum_{k=1}^{m} p_i \frac{g_{ii}}{\sum_{k=1}^{m} g_{ik}}\right) - ln\, p_i \frac{g_{ii}}{\sum_{k=1}^{m} g_{ik}}\right]\right\} * 100$	g_{ik} = number of adjacent pairs of pixels between class i and k All pairs of pixels in the adjacency matrix are double counted
Area-weighted mean shape index (AWMSI)	$AWMSI_i = \sum_{j=1}^{n}\left[\left(\frac{0.25 p_{ij}}{\sqrt{a_{ij}}}\right)\left(\frac{a_{ij}}{\sum_{j=1}^{n} a_{ij}}\right)\right]$	P_{ij} = perimeter of patch j in class i a_{ij} = area of patch ij n = total number of patches in class i
Ratio of vegetated area (ROV)	$ROG = \frac{a_g}{A}$	a_g = total area of vegetated spaces within a metropolitan area, including urban greenspace, rural shrub, and forest
Polycentricity index (POLY)	Step 1: $P_i(n) = 1 - \frac{\sigma_n}{\sigma_{max}}, (n = 2, 3, 4)$	Step 2: $POLY_i = \frac{P_i(2) + P_i(3) + P_i(4)}{3}$
	Step 1: $P_i(n)$ = degree of polycentricity for region i incorporating the top n centers. σ_n = standard deviation of population for the top n centers. σ_{max} = the maximum standard deviation of population of an absolute monocentric two-center scenario, namely one center with zero population and another with the maximum population in the region Step 2: $POLY_i$ = the average degree of polycentricity considering $P_i(2), P_i(3)$, and $P_i(4)$	

$$UHI_i = c + \beta_1 SPM_i + \boldsymbol{\mu} \boldsymbol{Z_i} + \epsilon_i \tag{2}$$

where UHI_i represents the UHI effect for region i. SPM_i is one of the urban spatial pattern measures for region i. The vector $\boldsymbol{Z_i}$ contains a set of UHI control variables, including population density,[6] day-time or night-time windspeed during the summer season, and a drought index derived from gridded temperature and precipitation datasets. The sources for these datasets and descriptive statistics for all variables in 2012 are provided in Table 2.

Previous studies have demonstrated that the impact of polycentric development on socio-economic outcomes varies across cities and regions of different sizes (Meijers and Burger, 2010; Ouwehand et al., 2022). We propose that the influence of polycentric development on the UHI effect may vary contingent upon the size of regions, with large regions potentially reaping greater benefits. This assumes that a polycentric configuration can effectively redistribute concentrated activities among multiple urban cores of large-sized regions, thereby mitigating the concentration and accumulation of human heat sources. To test this hypothesis, we interact the variable of polycentricity with region size, measured by total population, and the equation is expressed as

$$\mathrm{UHI}_i = c + \gamma_1 POLY_i \times PopSize_i + \boldsymbol{\delta} \boldsymbol{Z_i} + \epsilon_i \tag{3}$$

where *PopSize* is a categorical variable, classifying regions into three equal-sized groups based on population size. The coefficient γ_1 captures the varying effects of polycentricity on the UHI effect, moderated by population size of the region i.

Table 2. Descriptive statistics and data sources of variables collected for the year 2012 (N = 49).

Variables	Mean	Std. Dev	Median	Min	Max
Dependent variables					
UHI_day[a]	3.994	.859	4.066	2.013	5.885
UHI_night[a]	.911	.404	0.875	.053	1.668
Variables of interest					
PLADJ_urban[b]	87.489	2.208	87.513	82.022	91.983
PD[b]	.439	.2	0.366	.177	.958
CONTAG[b]	48.45	4.854	47.701	38.222	62.99
AWMSI[b]	5.154	2.057	4.432	2.635	11.002
PLADJ_Green[b]	76.762	3.266	77.024	70.142	82.143
ROV[b]	.535	.159	0.534	.156	.8
POLY[c]	.615	.296	0.546	.218	1.597
Control variables					
Popdensity[c]	2952.19	673.606	2714.156	1817.403	4567.669
Windspeed_day[d]	1.432	.256	1.452	1.051	2.24
Windspeed_night[d]	.989	.25	1.043	.477	1.713
Drought index[e]	8.367	1.764	8	5	14

Data sources.
[a]The MODIS LST product to measure the UHI effect: https://lpdaac.usgs.gov/products/myd11a2v061/.
[b]Land-use dataset to generate landscape metrics: https://land.copernicus.eu/pan-european/corine-land-cover.
[c]Municipality population to quantify polycentricity index (POLY): INKAR (https://www.inkar.de/).
[d]ERA5 monthly averaged data for day- and night-time windspeed in summer (June, July, and August): https://cds.climate.copernicus.eu/cdsapp#!/dataset/reanalysis-era5-land-monthly-means?tab=fo.
[e]Drought index in summer: Deutscher Wetterdienst, https://opendata.dwd.de/climate_environment/CDC/grids_germany/.

The influence of landscape metrics on the urban heat island effect

This section investigates the influence of “traditional” landscape metrics on the UHI effect. We estimate both the effects of urban land use patterns and green space patterns on the UHI effect. The analysis begins with the naïve regression models (Figure 2), followed by multivariate OLS regression models that control for population, weather, and climate variables (Table 3). Figure 2 illustrates the relationship between each landscape metric and the daytime UHI effect, with p-values denoting the level of statistical significance. Green represents green spaces and red represents urban land covers. To address skewness and improve interpretability, all variables are log-transformed, except for PLADJs of urban and greenspace patches, as these follow a normal distribution.

The results suggest a positive and statistically significant association between the PLADJ of urban patches and the UHI effect, indicating that a higher level of aggregation and contiguity in urban patches contributes to increased urban heat intensity. Similarly, the relationship between PD and the UHI effect supports this finding, indicating a mitigation effect by increasing fragmentation and patchiness in urban landcover. The CONTAG, which measures the level of mixed land use, exhibits a positive and significant trend, implying that a higher degree of mixed landcover (lower index value) is associated with a cooler urban environment. As urbanized land becomes more contiguous and less mixed, UHI increases. Furthermore, a higher proportion of vegetated coverage (ROV) can reduce urban heat intensity. However, there is no significant relationship between the UHI effect and the urban shape index (AWMSI) and PLADJ of greenspace patches. According to Debbage and Shepherd (2015), the lack of significance in the naïve models does not necessarily indicate a definitive absence of association, as the existence of omitted variables may bias the estimates. Therefore, we present multivariate regressions for both day- and night-time UHI effects in 2012, including population density, windspeed, and drought index as control variables (Table 3). Robust standard errors are reported to account for heteroskedasticity.

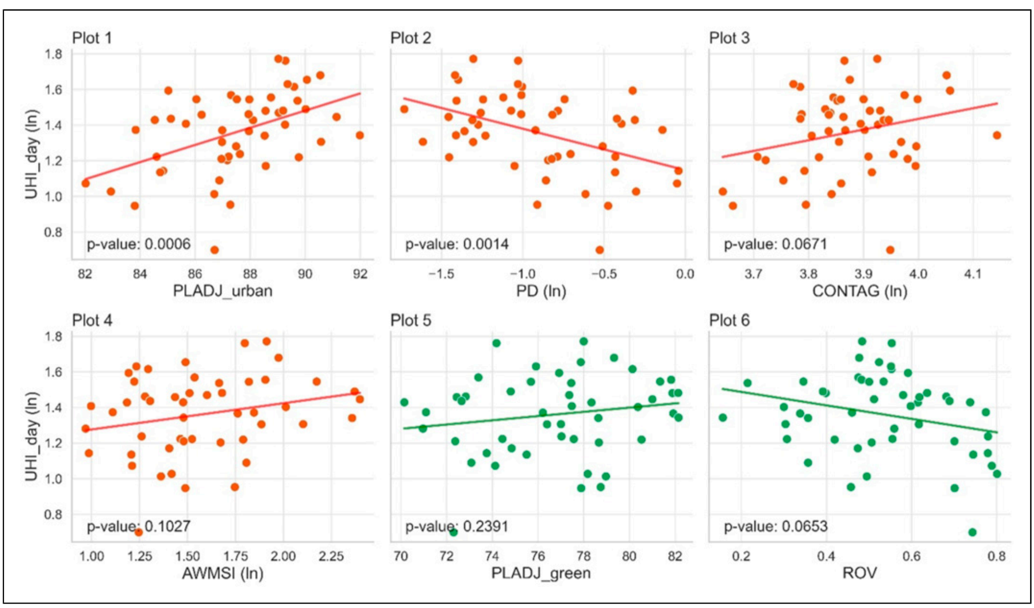

Figure 2. Scatterplots and fitted lines presenting the relationships between urban heat island (UHI) effects and landscape metrics.

Table 3. Regressions investigate the effects of land-use patterns on the day- or night-time urban heat island (UHI) effects in 2012.

Panel A: The effect of urban land-use patterns on the UHI effects	UHI (ln) at day				UHI (ln) at night			
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
PLADJ_Urban	.059*** (.009)				.113*** (.031)			
PD (ln)		−.305*** (.06)				−.672*** (.191)		
CONTAG (ln)			.521** (.243)				1.604** (.646)	
AWMSI (ln)				.238*** (.079)				.443** (.191)
Control variables[a]	Yes				Yes			
Observations[b]	48	48	48	48	49	49	49	49
R-squared	.517	.52	.346	.405	.314	.369	.229	.222

Panel B: The effects of greenspace patterns on UHI effects	UHI (ln) at day		UHI (ln) at night	
	Model 1	Model 2	Model 3	Model 4
PLADJ_Green	.023** (.009)		.053*** (.018)	
ROV (ln)		−.314*** (.083)		−.639*** (.208)
Control variables[a]	Yes		Yes	
Observations[b]	48	48	49	49
R-squared	.381	.48	.238	.307

Robust standard errors are in parentheses; ***$p < .01$, **$p < .05$, *$p < .1$.
[a]Observations removed due to the extremely low UHI (ln) values: the regions of Siegen and Erfurt in daytime models, and the region of Ingolstadt in night-time models.
[b]All models include population density, windspeed, drought level as control variables.

As shown in Panel A of Table 3, a unit increase in the degree of aggregation (PLADJ) of urban patches corresponds to a 5.9% increase in the daytime UHI effect (Model 1). The R-squared value (0.517) is one of the highest among all other models, suggesting the significant impact of urban aggregation and contiguity on intensifying urban heat. The coefficient estimated of the PD metric is consistent with this finding, implying that a percentage increase in the degree of fragmentation (PD) can lead to a 0.287% decrease in the UHI effect (Model 2). These metrics remain statistically significant and align with expectations in the night-time UHI models (Models 5 and 6). A percentage increase in mixed land-use (CONTAG) contributes to a 0.521% and 1.604% decline in the day- and night-time urban heat intensity, respectively. After controlling for confounding variables, the coefficients of urban shape index (AWMSI) display statistical significance, indicating that a higher level of irregularity in the shape of urban patches exacerbates both day- and night-time urban heat intensity.

We further present the cooling effects of greenspace in Panel B of Table 3. After incorporating the control variables, the coefficient of PLADJ for greenspace becomes significant. This indicates that a fragmented and disaggregated distribution of urban greenspace performs better in reducing urban heat than an aggregated greenspace arrangement (see Models 1 and 3). Put differently, dispersing multiple smaller greenspaces throughout the urban area demonstrates a greater cooling effect compared to having a single large and more aggregated park.

We conduct a robustness check by applying the same models using variables collected for the year 2006. The regression results are in the supplementary material. Models in 2006 and 2012 produce similar results, except for the variable PLADJ for greenspace. The absence of significant coefficients in these models, for both day- and night-time, suggests that we should be cautious regarding the cooling effect of greenspace arrangement, and further studies are necessary to gain a more conclusive understanding.

The influence of polycentric development on the urban heat island effect

This section investigates the efficacy of polycentric development in mitigating the UHI effect during both day and night periods and explores whether this effect varies across regions of different sizes. A conventional approach for distinguishing between polycentric and monocentric patterns is to analyze the population and/or employment density gradient from the CBD(s) to the urban periphery. Considering the significant influence of anthropogenic heat sources on urban heat distribution (Oke, 1982), we hypothesize that the heat gradient may display similar features to the population density gradient, allowing us to identify variations in heat distribution between polycentric and monocentric regions.

Panel A of Figure 3 illustrates a comparison of surface temperature gradients during both daytime (solid line) and nighttime (dotted line) for polycentric and monocentric regions. The city regions are classified into three equal-sized groups, and further categorized as either polycentric or monocentric depending on whether their polycentricity index exceeds the mean value or not. We visualize the fitted surface temperature gradients using local weighted regression, wherein the temperature at each distance level is regressed against the distance to urban center(s). The dependent variable, ΔT, represents the differences in land surface temperature (LST) between the urbanized area at each distance level and the rural area. The starting point(s) of the temperature gradient, known as urban center(s) or CBD(s), are determined as the pixel(s) with the highest population density within each urban core.[7] Notably, certain polycentric regions, such as Essen/Bochum/Dortmund/Hagen, may possess multiple urban centers due to their multiple urban cores.

Panel A of Figure 3 displays the significant differences in temperature gradients between large-sized regions and small- and medium-sized regions, irrespective of day or night. Urban centers in large polycentric regions have notably lower temperatures, and the temperature gradient changes more gradually compared to their monocentric counterparts. Moreover, as the distance from the urban center(s) increases, the temperature gap between monocentric and polycentric regions diminishes until 13.2 km, where the temperature of polycentric regions slightly exceeds that of monocentric ones. Similar patterns are also observed in night-time gradients of large-sized regions. In contrast, during the daytime, the temperature gradients between polycentric and monocentric regions in medium-sized are minimal, indicating that polycentric configuration has limited impact on reducing the UHI effect in the urban core(s) of medium-sized regions. Discernible distinctions emerge beyond 7.0 km, where the temperature of polycentric regions exceeds that of monocentric regions. This may reflect the more decentralized human activities within polycentric regions that contribute to rising temperature. The nighttime temperature gradients generally follow the same pattern as the daytime gradients in medium-sized regions. For small-sized regions, we conclude that polycentric development cannot effectively mitigate the UHI effect, as the temperature gradients between monocentric and polycentric regions overlap significantly.

The analysis of temperature gradients across regions of varying sizes reveals two key findings. First, polycentric development is more effective in mitigating the UHI effect than monocentric development, particularly in large-sized regions. Second, this mitigation effect is most pronounced

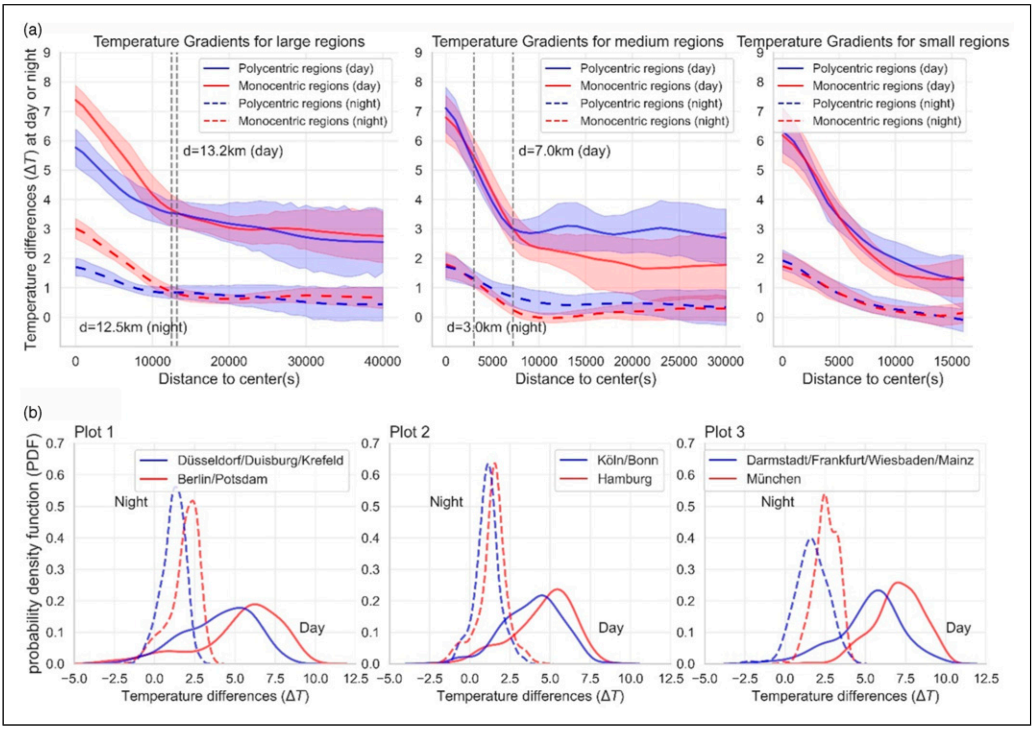

Figure 3. Panel A: day- and night-time temperature gradients in large-, medium-, and small-sized regions estimated by local weighted regression. Panel B: day- and night-time kernel density estimates (KDE) for three representative region pairs using Gaussian kernel. Red depicts monocentric regions and blue polycentric regions.

closer to the urban center(s), where the UHI effect is most severe, and gradually diminishes as the distance from the urban center(s) increases.

To further explore the temperature variations between polycentric and monocentric regions, Panel B of Figure 3 visualizes the temperature distributions of three selected pairs of regions using kernel density estimates, with temperature difference as the x-axis and density probability as the y-axis. To ensure comparability between the two regions within each pair, it is necessary to maximize their differences in the degree of polycentricity while maintaining the highest similarity in other attributes influencing urban heat. Accordingly, for each pair, a representative monocentric region (red) is selected and then is matched with its polycentric counterpart (blue) based on a Euclidean distance method that maximizes the similarity of population density, urbanized area, windspeed, and precipitation between the two regions. The three representative pairs are Berlin and Düsseldorf/Duisburg/Krefeld/Mönchengladbach; Hamburg and Köln/Bonn; and München and Darmstadt/Frankfurt/Wiesbaden/Mainz. As depicted in Panel B of Figure 3, the daytime temperature distributions of the three monocentric regions exhibit a left-skewed pattern, with visibly higher peak values shifted towards the right. This suggests that monocentric regions have a greater proportion of high-temperature areas and a lower proportion of medium to low temperature areas compared to their polycentric counterparts. During night-time, the distribution curves become steeper and more pronounced than during daytime, primarily due to the dense clustering of urbanized areas within a narrow temperature range. Although the nighttime curves display a similar shape between the monocentric and polycentric regions, the monocentric regions demonstrate a distinct shift toward higher temperatures. These findings highlight the advantage of polycentric regions in mitigating urban heat compared to monocentric ones, thus further reinforcing, and validating the conclusions from the previous section.

The preceding discussion suggests that polycentric development is particularly advantageous in mitigating the UHI effect for larger regions. To explore this further, we utilized regression analysis to validate our finding using the 2012 variables presented in Table 4. This analysis includes models using different definitions of the UHI effect, with Models 1–4 defining UHI as the temperature difference between the urban fabric within the extended large core area and rural area, the same definition as in the previous section. For Models 5–8, we redefine the UHI by substituting the extended large core area with a smaller area restricted to only the urban core(s). See Figure 1 for a comparison of urban core and large core area. This substitution allows a more precise representation of heat intensity in the most densely populated areas, as the urban core(s) specifically delineate the urban domain of regional central cities.

The utilization of different UHI definitions introduces different regression outcomes. Models 1–4 demonstrate that the variable representing polycentric development, denoted as POLY, exhibits no statistically significant impact on the UHI effect in any models. In contrast, for Models 5–8 that represent the UHI effect of urban core(s), POLY displays statistical significance in both day- and night-time models (Model 5 and 7), implying that polycentric development is more efficient in reducing heat intensity within the urban core(s) rather than the extended large core area. Specifically, a doubling of the degree of polycentricity (a 100% increase) leads to a 10.47% reduction in the UHI effect during the daytime and a 24.61% decrease at night. Moreover, the interaction term, defined large-sized regions as benchmark, is statistically significant (Model 6), indicating that polycentric development is more effective in mitigating the UHI effect in larger regions compared to smaller ones, similar to the observed pattern illustrated in Figure 3. We employ the same models and variables collected for 2006 to ensure the robustness of our findings and present the results in the supplementary material. The variable, POLY and the interaction term capturing large-sized regions

Table 4. Regressions examine the impacts of polycentric development on the day- and night-time UHI effects in 2012.

	$UHI(\ln) = T_{LargeCore(mean)} - T_{R(mean)}$				$UHI(\ln) = T_{Core(mean)} - T_{R(mean)}$			
	Model 1 Day	Model 2 Day	Model 3 night	Model 4 night	Model 5 Day	Model 6 Day	Model 7 night	Model 8 night
Poly (ln)	−.065 (.0387)	−.067 (.1155)	−.157 (.1377)	.002 (.3001)	−.1047** (.0426)	.0452 (.1064)	−.2461* (.1287)	.1109 (.2511)
Poly (ln)* Medium		.1088 (.1603)		−.1627 (.508)		−.1551 (.1992)		−.599 (.4251)
Poly (ln)*Large		−.0188 (.1297)		−.1473 (.3539)		−.1913* (.1123)		−.3439 (.2962)
Control variables[a]	Yes				Yes			
Observations[b]	48	48	49	49	48	48	49	49
R-squared	.5397	.5463	.3698	.4398	.3597	.388	.2815	.4875

Robust standard errors are in parentheses; ***p < .01, **p < .05, *p < .1.

[a]All models include population density, windspeed, drought level, PLADJ for urban fabric, and contagion index as control variables.

[b]Observations removed due to the extremely low UHI (ln) values: The regions of siegen and erfurt in daytime models, and the region of ingolstadt in nighttime models.

are both statistically significant in the daytime regressions, thereby confirming the robustness of our findings.

Conclusion and policy implication

This study examines the effectiveness of urban spatial patterns in alleviating the UHI effect in German city regions (*Großstadtregionen*) in the years of 2006 and 2012 utilizing multivariate regression and non-parametric methods. The urban spatial patterns are quantified using five landscape metrics that capture the spatial arrangement of urban footprint and greenspace, as well as a polycentricity index that measures the distribution of human activities.

The regression analysis of the landscape metrics suggests that a more spatially fragmented urban footprint, mixed land use, and regular-shape urban patches have the potential to effectively mitigate the UHI effect. These findings are consistent with the conclusions drawn by Debbage and Shepherd (2015), who emphasized the adverse impact of contiguous urbanized area on intensifying urban heat in metropolitan areas across the United States. Similar effects of spatial contiguity have also been corroborated by Liu et al. (2021) in their studies on urban clusters in China. Furthermore, our analysis suggests that incorporating more vegetated areas helps reduce urban heat. Importantly, more dispersed and fragmented patterns of green spaces demonstrate greater effectiveness in reducing the UHI effect compared to more aggregated and contiguous greenspace. In addition, we provide empirical evidence that polycentric spatial development can effectively ameliorate the UHI effect across German metropolitan regions. But notably, polycentric configuration is particularly advantageous in cooling large-sized regions compared to medium- or small-sized ones, and its effectiveness is mostly pronounced near urban center(s) with the highest population density. These results support our hypothesis that a polycentric configuration may serve as a more efficient approach to address the UHI effect for large-sized regions. Such a configuration not only helps reduce the density of the urban core and facilities disaggregated urban development, but also serves to curb the excessive expansion of impervious surface.

These conclusions offer important policy insights for land use and greenspace planning within the German context. Specifically, regional-scale governance, widely recognized as the most experimental and varied, plays an important role in coordinating federal, state (*Länder*), and municipal planning (Schmidt et al., 2018) and can incorporate urban heat mitigation as a regional policy objective. Collaboration between multi-level planning authorities can prevent excessive aggregated, homogeneous, and contiguous urban development. One feasible spatial strategy to achieve this is to facilitate consolidated green infrastructure planning and governance (Pauleit et al., 2019), as the spatially targeted distribution of greenspace can reduce urban development density while offering an extra cooling effect. According to the Federal Spatial Planning Act (*Raumordnungsgesetz*), regional plans include specifications about the spatial structure of settlements and open spaces (Schmidt et al., 2018; Siedentop et al., 2022). Consequently, regional planning institutions should coordinate with state and local governments to plan for more greenspaces and, importantly, distribute multiple smaller greenspaces throughout the urban fabric rather than planning for a single large park, as “several small” yields greater benefits in reducing urban heat than a “single large.”

Finally, our findings suggest that regional polycentricism is not a one-size-fits-all spatial solution for all metropolitan regions; rather it is particularly beneficial for larger ones characterized by high-density urban cores and aggregated urban patterns. The potential climate and environmental advantages of polycentric development for small- and medium-sized regions remain uncertain. These regions should be cautious to adopt polycentric development as a regional planning goal and take into consideration a range of potential impacts of polycentric spatial development, including its potential to effectuate regional cohesion and economic competitiveness simultaneously (Li et al., 2023). Federal-level planning should acknowledge this and offer differentiated guidelines that consider the varying sizes and geographical contexts of different regions.

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Data Availability Statement

The datasets generated during and/or analyzed during the current study are available from the corresponding author on reasonable request.

Supplemental Material

Supplemental material for this article is available online.

Notes

1. Urbanized area is defined as pixels classified as class 1: artificial surfaces. Find the detailed nomenclature guideline at https://land.copernicus.eu/user-corner/technical-library/corine-land-cover-nomenclature-guidelines/html.
2. MYD11A2.061 Aqua Land Surface Temperature and Emissivity (LST&E) 8-Day Global 1 km.
3. See the general accuracy statement at: https://modis-land.gsfc.nasa.gov/ValStatus.php?ProductID=MOD11.
4. The sample code is available at: https://code.earthengine.google.com/63c37316806efa35321f7e8651429bb2.
5. We define urban greenspace as the class 1.4 of the CLC dataset, which includes all artificial, non-agricultural vegetated areas, within large urban core area.
6. To calculate the population density, we divide the total population within the large urban core area by the total area of urban footprint extracted from the CLC dataset.
7. We rely on the LandScan 1 km global population grid dataset to select the pixels with the highest population.

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