How much Urban Green do Bavarian cities need to cool by 1 degree?

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Abstract

Urban environments are becoming increasingly susceptible to the adverse effects of climate change, with the urban heat island (UHI) effect amplifying temperature extremes and intensifying environmental challenges. This study examines the potential of urban greening to mitigate land surface temperatures (LST) across Bavaria's 44 largest cities by leveraging Landsat satellite data from 2013 to 2023 in conjunction with a spatial regression model. The research quantifies how green space, as measured by the Normalized Difference Vegetation Index (NDVI), influences LST. The spatial regression model, which accounts for spatial dependencies, explains approximately 87% of the variation in LST, outperforming traditional Ordinary Least Squares (OLS) regression. Notably, the study finds that an increase of 0.0243 in NDVI for the city and an increase of 0.0316 in NDVI in residential areas within the city is associated with a 1°C reduction in LST. These findings offer a clear, quantifiable benchmark for designing targeted greening strategies, particularly in areas with low NDVI. The insights generated by this research equip local authorities with actionable guidance to develop robust climate adaptation strategies tailored to the specific needs of urban areas, ultimately contributing to the creation of more resilient and sustainable cities in the face of climate change.

1. Introduction

Urban areas around the world are increasingly facing the challenges posed by climate change, particularly with the exacerbation of the urban heat island (UHI) effect (Voogt & Oke, 2003). The UHI effect refers to the observed increase in urban temperatures relative to their rural surroundings, primarily driven by the extensive coverage of impervious surfaces like asphalt and concrete. These surfaces absorb and retain heat, resulting in higher temperatures in cities, which in turn aggravates energy demand, public health risks, and environmental stresses. According to the Intergovernmental Panel on Climate Change (IPCC, 2022), these temperature increases are expected to become more pronounced in the coming decades, further intensifying the effects of climate change in urban areas. As cities continue to grow, their susceptibility to the negative impacts of high temperatures is expected to rise, affecting vulnerable populations, such as the elderly, low-income communities, and those living in densely built-up areas.
One of the most promising strategies to mitigate the UHI effect is the promotion of green spaces in urban environments. Green spaces, such as parks, gardens, and street trees, provide a natural cooling effect through processes like shading, evapotranspiration, and the absorption of solar radiation (Rötzer et al., 2019). By increasing the proportion of vegetation in urban areas, cities can significantly reduce land surface temperatures (LST), mitigate air pollution, enhance biodiversity, and improve overall quality of life for residents (Leichtle et al., 2023a). Moreover, the expansion of green spaces can offer additional ecological and social benefits, including enhanced recreational opportunities, improved mental health, and increased social cohesion. However, while numerous global studies have demonstrated the benefits of urban greening, the focus has primarily been on large metropolitan areas, with limited attention given to smaller cities or regional contexts. These smaller cities often face distinct challenges and opportunities that require tailored strategies for effective adaptation.
In recent years, remote sensing technologies, particularly satellite-based Earth observation, have become invaluable tools for monitoring and understanding urban heat dynamics. Remote sensing allows for the collection of large-scale, spatially detailed data on LST and vegetation cover, providing an efficient means of assessing urban thermal conditions over time. Satellites like Landsat, with their high spatial and temporal resolution, are widely used for monitoring urban environments, offering critical insights into surface temperature variations and changes in land cover. This technique is particularly useful for smaller communities and cities that may lack the resources or infrastructure for extensive ground-based temperature measurements. Remote sensing enables these areas to access valuable data that can guide urban planning and climate adaptation efforts without the need for expensive, on-the-ground temperature monitoring systems (Leichtle et al., 2023b).
The goal of this study is to address the gap in research regarding smaller urban areas by examining the relationship between green space and temperature reduction in the 44 largest cities in Bavaria, Germany, using remote sensing data. By modelling LST and assessing the potential of various adaptation strategies, particularly urban greening, this research aims to provide evidence-based insights into the effectiveness of these interventions. The findings of this study are intended to inform urban planners and policymakers in their efforts to develop localized, context-specific solutions for mitigating the UHI effect and addressing the urban heat challenges that many cities in Central Europe will face in the coming decades (Friesen & Taubenböck, 2024).

2. Methods

In this study, building on the approach of Massaro et al. (2023), we developed a spatial framework to investigate the factors influencing surface temperature in the 44 largest Bavarian cities. City rankings were derived from the latest German census (Zensus, 2024), and official administrative boundaries were used to define the study areas. Landsat LST data from the summer months (June–August, 2013–2023) provided information on average thermal patterns during the hot season and can be considered a robust proxy for urban thermal conditions (Massaro et al. 2023).

Initially, we examine the relationship between LST and land use by computing median LST values for each city across several land use categories based on OpenStreetMap: Commercial, Residential, Industrial, Forest, and the aggregated urban area.

To quantify these observations, we implemented regression analyses that relate green space coverage—as measured by the Normalized Difference Vegetation Index (NDVI)—to LST. NDVI was calculated using Landsat data using the mean NDVI value in the time series. Specifically, we estimated two types of models for both the overall urban area and for residential zones: ordinary least squares (OLS) and spatial regression models.

In the spatial regression framework, we examined how the proportion of green spaces influences LST. The model is expressed as:

$$\mathbf{LST} = \rho W \mathbf{LST} + \mathbf{X}\beta + \epsilon$$

Here, ρ represents the influence of neighboring areas' LST on the LST of a given area, W represents the spatial weights matrix, $\mathbf{X}$ describes the input variables (NDVI), β the contribution of the independent variables and ϵ the error.

We then developed a secondary model that focuses solely on residential areas, again using OpenStreetMap classifications. We focus on residential areas for further analysis, as reducing thermal stress in these places is critical for mitigating risks to human health. This model allows us to estimate the increase in green space (in terms of NDVI) required to achieve a one-degree reduction in average urban temperature. For a specific target reduction in LST (ΔLST), the corresponding NDVI increase (ΔNDVI) is calculated as:

$$\Delta\text{NDVI} = \frac{\Delta\text{LST}}{\beta^*_{NDVI}}$$

with

$$\beta^*_{NDVI} = \beta_{NDVI} \times \frac{1}{1-\rho}.$$

This approach provides clear, quantitative insights into how enhancing green space can mitigate urban heat. The results form a solid foundation for the design of targeted urban heat mitigation strategies in the face of climate change.

3. Results

3.1 Distribution of LST and relation to landuse

The distribution of LST values for the cities investigated is shown in Figure 1. In our analysis of median LST across the study area, substantial spatial variability was observed, highlighting the influence of land cover and urban morphology on local thermal regimes. Overall, the total area exhibited a broad range of median LST values, with cooler urban districts such as Geretsried registering medians around 28.67 °C, while warmer cities like Regensburg reached medians of approximately 35.23 °C. This gradient reflects the heterogeneity of urban fabric and the differential distribution of impervious surfaces, vegetation, and built-up structures but also regional differences.

When disaggregated by land use, distinct thermal signatures emerged. Industrial zones displayed the most pronounced thermal extremes, with median LST values peaking at nearly 41.92 °C in Schweinfurt and reaching as low as 29.46 °C in Germering. Commercial areas also exhibited considerable variability; for instance, Lindau (Bodensee) showed medians as low as 30.74 °C (probably related to the proximity of the city to a large water body), whereas Bamberg recorded values close to 39.69 °C.

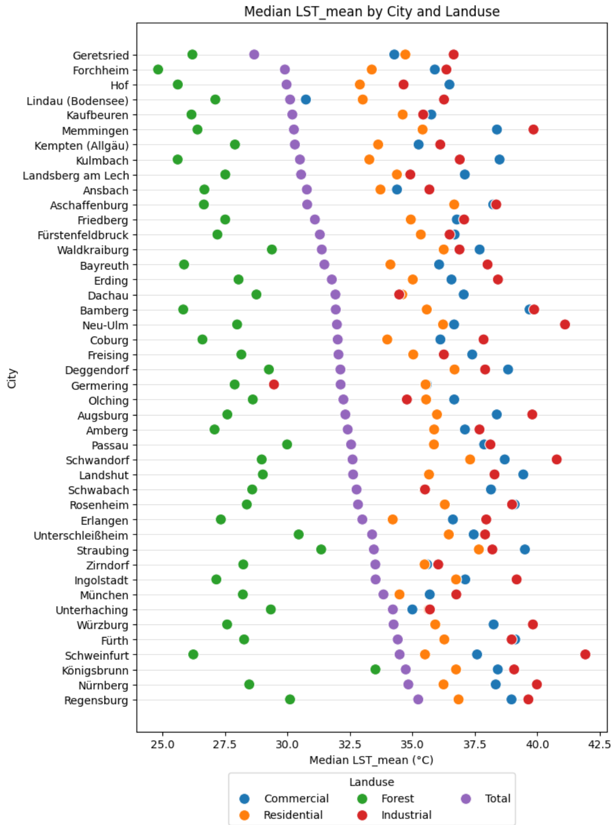

Figure 1: Median LST for the cities investigated and differences for various land uses.

Residential zones, meanwhile, tended to fall in the intermediate range, with median values spanning from 32.90 °C in Hof to 37.66 °C in Straubing. Notably, forested areas consistently exhibited the lowest temperatures, with medians ranging from approximately 24.82 °C in Forchheim to 33.52 °C in Königsbrunn, underscoring the mitigating effect of vegetation on urban heat.

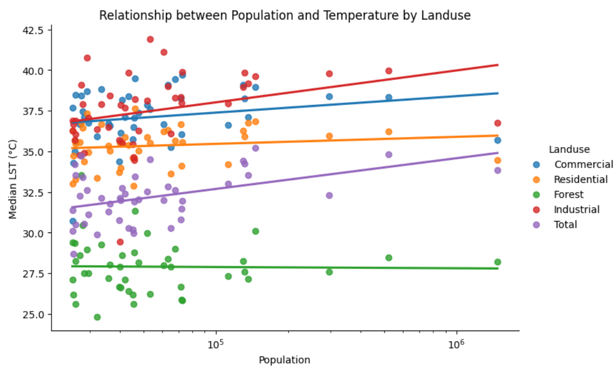

Figure 2: Relationship between Population and Temperature by Landuse.

Analysis of the relationship between median LST and land use reveals distinct patterns across urban categories. According to Figure 2, forested areas show little to no impact on median temperatures in relation to city size, suggesting that the cooling effects of vegetation prevail regardless of urban scale. Residential zones also exhibit only a modest association between city size and median LST, indicating that population density or built-up area has a limited influence on thermal conditions in these neighbourhoods. In contrast, both the overall urban fabric and industrial areas show a clearer relationship, with larger cities tending to exhibit higher median LST values, which underscores the amplified urban heat island effect in more extensive and industrially active settings.

3.2 Modelling LST

The spatial regression model demonstrates a markedly superior fit compared to the ordinary least squares (OLS) approach. Specifically, the spatial model yields a (pseudo) R^2 of 0.96, indicating that 96% of the variance in median LST is explained - substantially higher than the 37% explained by the OLS model (Table 1). Moreover, the mean absolute error (MAE) is considerably lower for the spatial model (0.55 versus 2.21), highlighting its enhanced predictive accuracy. The spatial model also incorporates a substantial spatial lag effect (ρ = 0.91), underscoring the significant influence of neighbouring temperatures on local LST. Although NDVI exhibits a negative relationship with LST in both models, the spatial model estimates a coefficient of -3.75 compared to a much steeper -23.88 in the OLS model, emphasizing that accounting for spatial dependencies is critical in accurately capturing urban thermal dynamics.

Table 1: Model outputs for the general model comparing spatial regression to OLS regression.

	Spatial Model		*Ordinary Least Squares*
LST (mean)		32.44	
LST (std)		3.74	
(Pseudo) R^2	0.960	R^2	0.373
MAE	0.553	MAE	2.21
Constant	4.035	Constant	39.32
β (NDVI)	-3.751	β (NDVI)	-23.88
$\rho W\boldsymbol{LST}$	0.90871	-	-

An examination of the residuals in Figure 3 reveals subtle spatial patterns. Cities in northern Bavaria - such as Forchheim (–0.269), Hof (–0.254), and Kulmbach (–0.225) - tend to exhibit more pronounced negative residuals, indicating that the model slightly underpredicts LST in these areas. In contrast, several cities located in southern and eastern Bavaria, including Deggendorf (0.133), Kempten (Allgäu) (0.216), and Straubing (0.234), show positive residuals, suggesting a modest overprediction of temperatures. Major urban centers like Munich (0.017), Augsburg (–0.024), and Ingolstadt (0.115) display minimal residuals, likely reflecting their larger pixel counts and more stable estimations.

Overall, although the magnitude of residuals is small - generally within ±0.3°C - these patterns hint at regional differences in model performance. The systematic underprediction in some northern cities and overprediction in certain southern and eastern areas may be linked to regional variations in temperature, underscoring the need for further refinement to capture these effects.

Figure 4 presents the measured LST alongside NDVI values for Aschaffenburg – a city in northern Bavaria, clearly illustrating the spatial variability of urban heat. In this figure, the urban core, characterized by low NDVI and limited vegetation, exhibits notably higher temperatures. In contrast, the outer zones with abundant greenery show significantly lower temperatures, and the river Main stands out as a distinct cooling feature. These observed patterns underline the strong association between vegetation density and thermal conditions in the city.

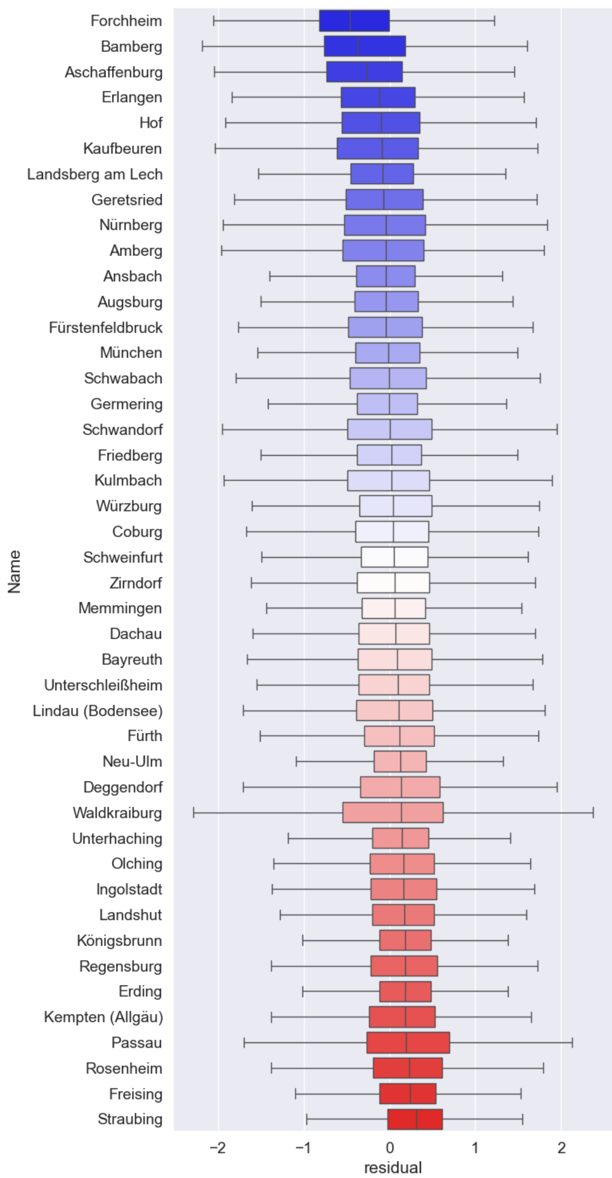

Figure 3: Residuals of the general spatial model.

Figure 5 compares the predictions from both the ordinary least squares (OLS) and spatial regression models. Although both models generally capture the inverse relationship between NDVI and temperature - predicting cooler temperatures in greener areas - the OLS model exhibits substantial discrepancies. It overpredicts temperatures in areas with high vegetation (including along the river) and severely underpredicts temperatures in the sparsely vegetated urban center, with errors often exceeding 5°C. In contrast, the spatial model, which accounts for spatial autocorrelation, yields predictions that closely align with the observed data, typically with errors below 2°C. This stark difference in performance highlights the critical importance of incorporating spatial dependencies in accurately modeling urban thermal dynamics.

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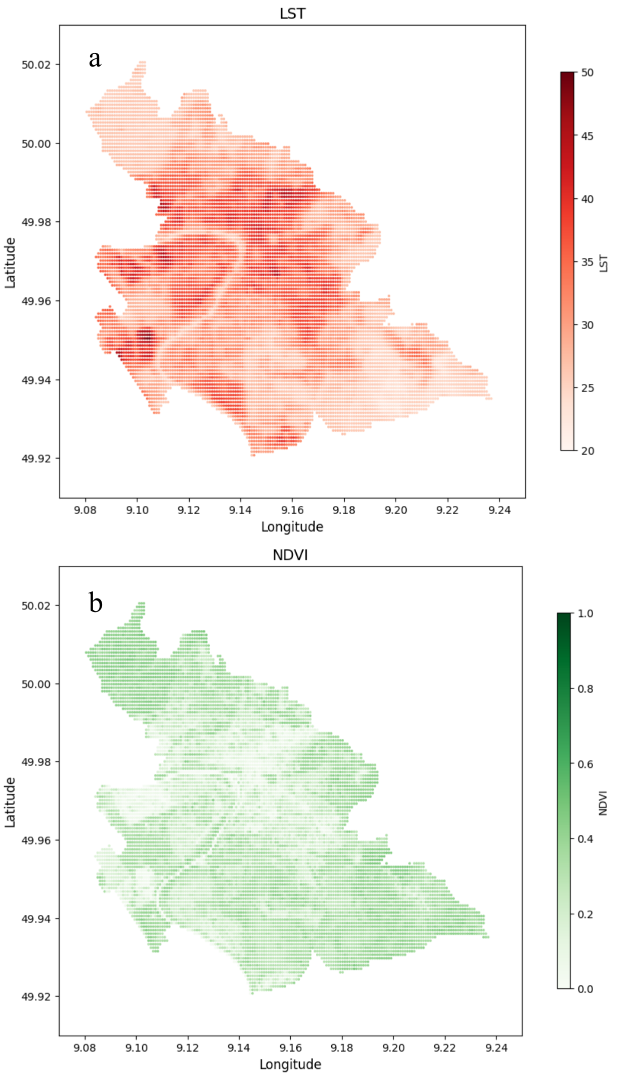

Figure 4: LST (a) and NDVI (b) in the city of Aschaffenburg in northern Bavaria.

For the residential areas, the spatial regression model again outperforms the ordinary least squares (OLS) approach (Table 2). The spatial model achieves a (pseudo) R^2 of 0.894 – more than double the 0.402 from the OLS model - indicating that it explains approximately 89% of the variability in median LST, compared to just 40% by the OLS model. In addition, the spatial model's mean absolute error (MAE) is 0.55 compared to 1.32 for the OLS model, highlighting its greater predictive accuracy. The spatial lag parameter (ρ = 0.734) confirms a substantial influence of neighbouring residential temperatures on local conditions. Moreover, while both models show a significant negative relationship between NDVI and LST (reflecting the cooling effect of vegetation), the spatial model estimates a less steep coefficient (β = -7.99) than the OLS model (β = -20.73). These findings underscore the importance of accounting for spatial dependencies in modelling urban thermal environments, particularly in residential settings.

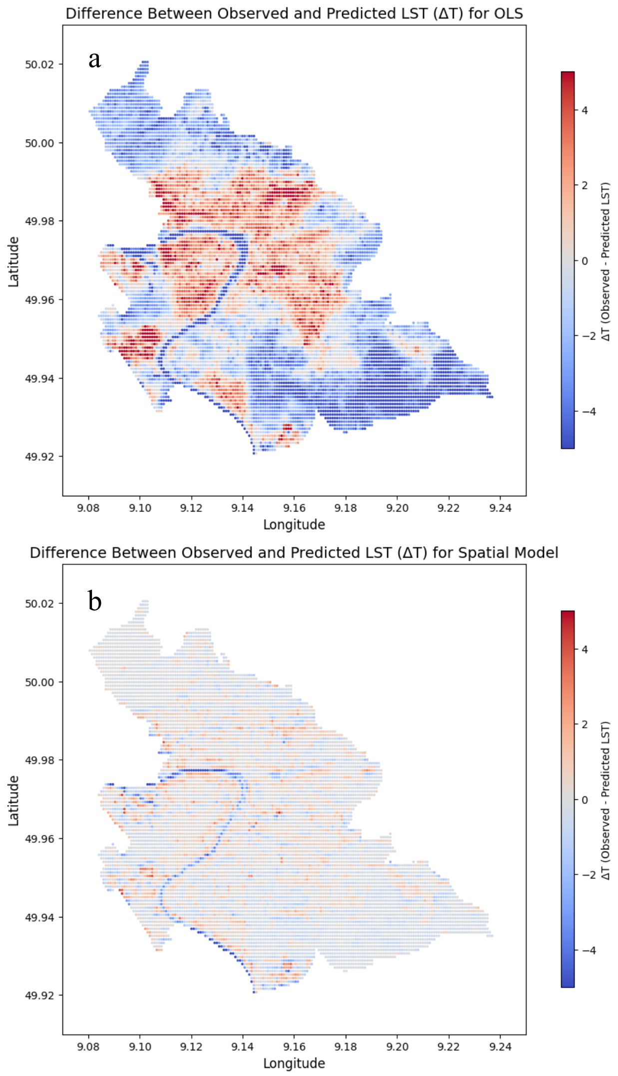

Figure 5: Differences between observed and predicted LST for the general model based on OLS regression (a) and spatial regression (b) in Aschaffenburg in northern Bavaria.

Table 2: Model outputs for the residential model comparing spatial regression to OLS regression

	Spatial Model		*Ordinary Least Square*
LST (mean)		35.21	
LST (std)		2.17	
(Pseudo) R^2	0.894	R^2	0.402
MAE	0.545	MAE	1.32
Constant	10.673	Constant	39.94
β (NDVI)	-7.992	β (NDVI)	-20.73
$\rho W\boldsymbol{LST}$	0.73383	-	-

3.3 Estimation of NDVI increase to reduce LST

Using the model outputs for the general model (Table 1), we calculate the $\Delta NDVI$=0.0243 required to achieve a 1°C reduction in LST. Using the residential model (Table 2), we calculate the $\Delta NDVI$=0.0316 required to achieve a 1°C reduction in LST.
When applying the increased $NDVI_{new=}NDVI + \Delta NDVI$ and running the model with the new parameter using iterative computation to account for spatial effects

$$LST^{k+1} = \rho W LST^{k} + X_{new}\beta$$

we find a significant predicted reduction in LST in the residential areas. Although a mean reduction of 1°C in LST was aimed for, it can clearly be seen, that in the exemplary city of Aschaffenburg, a higher reduction would be achieved, especially outside of the center of the city.

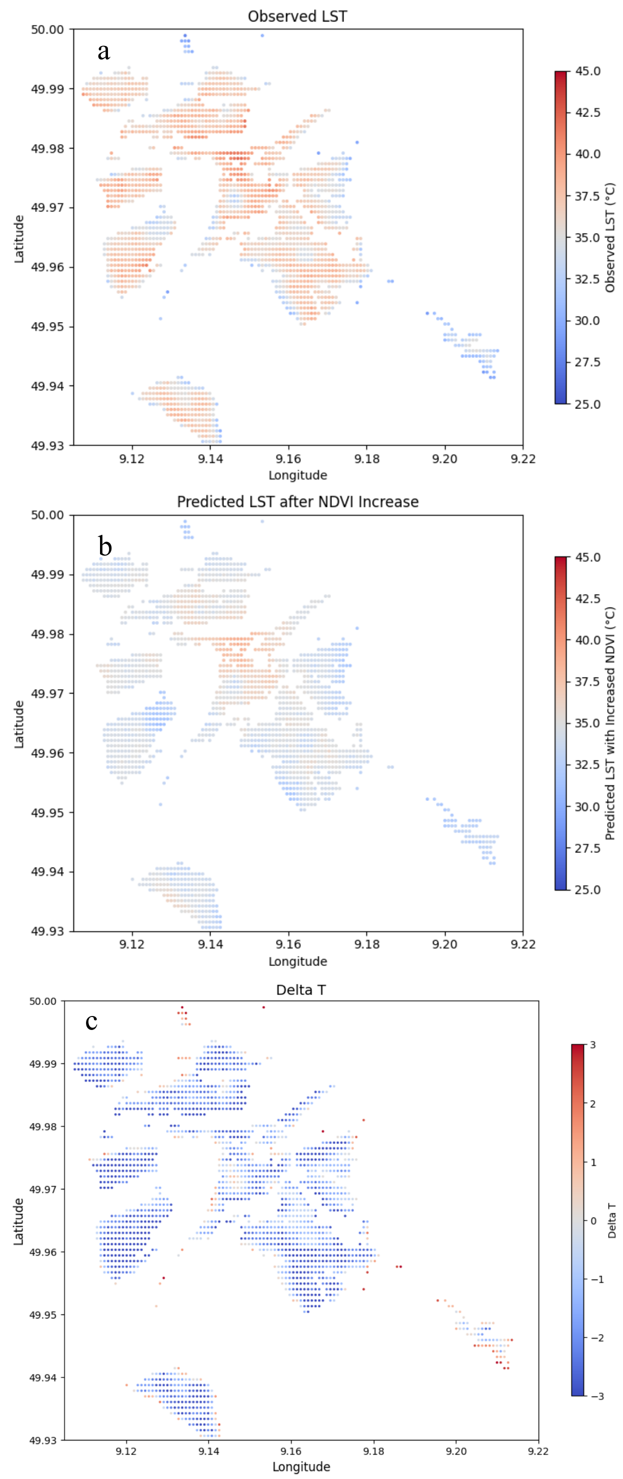

Figure 6: Observed LST in residential areas (a), predicted LST after NDVI increase based on the residential model (b) and the difference between the observed and the newly predicted LST (c).

4. Discussion

The results highlight the substantial impact of vegetation quality on urban thermal conditions. The urgent need to adapt cities to climate change and especially cities in Central Europe in the coming decades has been shown (Taubenböck et al., 2024).

The calculated requirement of a NDVI increase to reduce LST by 1°C in Bavarian cities provides a general actionable guidance for decision makers. These findings emphasize the importance of targeted greening efforts, particularly in areas with low initial NDVI values where promotion of vegetation can have disproportionately large cooling effects.

To maximize the benefits of urban greening, it is crucial to identify specific locations within cities that are particularly vulnerable to heat, such as neighbourhoods with high population density, limited existing green space, and socioeconomically disadvantaged communities (cf. Massaro et al., 2023). By integrating these results with census data, planners can prioritize interventions in areas where the need is most urgent and where vulnerable populations are most affected.

A detailed examination of the methods used in this study reveals several key insights. Two modelling approaches were employed—a general urban model and a residential model—to capture the relationship between NDVI and LST. Although both models exhibited similar mean absolute errors (MAE), the residential model was chosen for further analysis, as reducing thermal stress in residential areas is critical for mitigating risks to human health. Residential areas are where human exposure to high temperatures is most consequential, making the slight advantages in model performance particularly relevant.

Crucially, the spatial regression model demonstrated markedly superior performance relative to the ordinary least squares (OLS) approach. By incorporating spatial dependencies through a spatial lag term, the spatial model captured the influence of neighboring temperatures more accurately than the OLS model. This improved performance was reflected in dramatically higher (pseudo) R^2 values and lower MAE. The spatial model's capability to account for spatial autocorrelation not only results in more reliable estimates of NDVI's impact on LST but also underscores the interconnected nature of urban thermal conditions. Given these significant improvements in predictive accuracy and model robustness, the spatial approach should be adopted in future applications.

The analysis of the modelled NDVI requirements further elucidates the sensitivity of urban thermal conditions to green space interventions. Notably, the general model suggests that a ΔNDVI of 0.0243 is needed for a 1°C LST reduction, while the residential model indicates a higher threshold of 0.0316. This discrepancy underscores the greater sensitivity of residential areas to thermal mitigation efforts - a critical insight given the higher stakes for human health in densely populated neighbourhoods.

While the study demonstrates the potential of promotion of green space to mitigate urban heat, it also underscores the need for a nuanced approach. The calculated requirement of a NDVI increase to reduce LST by 1°C in Bavarian cities is a general value from the modelling and of course varies locally depending on the city and structure and has to linked with specific measurements - like the amount of additional trees, shrubs, and grass, as these contribute differently to NDVI and cooling effects (cf. Pauleit et al., 2022). Future planning should consider the relative effectiveness of these vegetation types and prioritize those that provide the greatest thermal benefits, such as trees and shrubs.

It is important to note that the data used in this study, derived from Landsat satellite observations, offers only a preliminary

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proxy for surface temperatures and green space coverage. Landsat's temporal resolution, with a revisit period of 16 days, limits its ability to capture dynamic and short-term changes in urban surface temperatures or vegetation health. Consequently, the results may not fully reflect day-to-day or seasonal variability, particularly during periods of rapid environmental change. Incorporating higher-frequency satellite data, such as from MODIS, or integrating ground-based measurements could improve the temporal granularity and accuracy of future analyses.

Furthermore, while surface temperature serves as a valuable proxy, it does not directly account for air temperature variations or human thermal comfort, which are critical for understanding urban heat impacts. Still, high correlations between surface temperature and air temperature have been shown in the German context (Leichtle et al., 2023b). However, as such, the findings presented here should be considered as a first approximation to inform strategic planning. Future studies are suggested to combine surface temperature data with finer-scale, higher-resolution datasets and consider additional environmental variables, such as humidity and wind patterns, to create a more comprehensive understanding of urban heat mitigation potential.

In conclusion, the findings provide a foundation for implementing localized urban greening strategies. By translating NDVI changes into specific green space requirements, the study bridges the gap between modelling outcomes and practical planning applications. However, planners and researchers should be mindful of the limitations posed by the temporal and spatial resolution of the data and strive for further refinement of methods. Future research should explore seasonal variations, integrate real-time vegetation and temperature monitoring, and combine greening strategies with other adaptation measures, such as reflective surfaces and urban water features, to develop holistic approaches to urban heat mitigation.

5. Conclusion

In conclusion, this study lays a robust foundation for implementing localized urban greening strategies to mitigate the urban heat island effect. The quantification of the NDVI increase needed to achieve a 1°C reduction in LST provides practical benchmarks, particularly in residential areas where reducing exposure to heat is vital for safeguarding public health. The significant improvements provided by the spatial regression model - reflected by its superior fit and lower prediction error - underscore the importance of incorporating spatial dependencies in urban thermal assessments. Moving forward, future applications should prioritize the use of spatial models, ensuring that urban heat mitigation strategies are informed by the most accurate and robust predictive tools available. Despite inherent limitations related to data resolution and temporal frequency, the insights gained here represent a crucial first step toward developing holistic, actionable solutions for urban climate adaptation. Further research should explore seasonal dynamics, real-time monitoring, and the integration of multiple adaptation measures to enhance urban resilience against climate change and improve overall environmental quality and public well-being.

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