



A collaborative approach for the identification of thermal hot-spots: from remote sensing data to urban planning interventions

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Abstract. This paper presents a novel methodology for enhancing urban planning in Frankfurt, Germany, through the identification of thermal hot-spots, i.e., areas of persistent high temperatures and thermal discomfort across multiple temperature parameters. Our approach integrates remote sensing and Geographical Information System (GIS) analyses to map thermal hot-spots, thereby highlighting target areas for urban planning interventions. We assess the efficacy of using remotely sensed Land Surface Temperature (LST) and the Physiological Equivalent Temperature (PET) thermal index, derived from simulations using the FITNAH model, for identifying thermal hot-spots at both the regional and city scales. Our findings highlight spatial discrepancies in hot-spot locations between LST and PET data, identifying areas where both indicators converge to signify thermal hot-spots. We explore the land cover contributing to these areas, laying the groundwork for future urban planning strategies. By incorporating visualisation tools tailored to the specific communication needs of urban planners, we provide actionable insights for developing maps which inform and guide the development of effective climate-adapted urban planning solutions.

Keywords. remote sensing, geo-visualisation, sustainable decision-making, land surface temperature, physiological equivalent temperature index

1 Introduction

In order to adapt to rising temperatures and mitigate overheating in urban areas, urban planning must be targeted towards areas which have consistently higher temperatures (Mavrakou et al., 2018). The use of satellite data to estimate Land Surface Temperature (LST) has emerged in the

last decade as a method for mapping Surface Urban Heat Islands (SUHI) at large geographical scales in the absence of ground data (Goldblatt et al., 2021; Chakraborty and Lee, 2019; Benz et al., 2021). As LST is widely available from remote sensing, planning authorities often use it for assessing regional and local climatic conditions and developing strategies and guidelines for climate adaptation. Despite Landsat LST data being the most commonly used remote sensing tool in this regard, its application in indicating thermal comfort conditions has been challenged and is not supported by many members of the scientific community (Patel et al., 2024; Venter et al., 2021). The distinction between LST and other heat indicators has not been given the care necessary; they are poorly correlated, particularly during daytime in urban environments and at high spatial resolutions (Coutts et al., 2016; Venter et al., 2021). LST data can give valuable insights into land cover and land management (Luyssaert et al., 2014), and they may give insight into long term, large scale heat exposure, but are not recommended for mapping actual temperature exposures and public health risk (White-Newsome et al., 2013).

The interpretation of information on urban heat becomes particularly important, as current planning approaches show the barriers of integrating climate considerations into decision-making (Boehnke et al., 2023). With substantial organisational or legal barriers, decision-makers require strong arguments to foster climate adaptation at the municipal scale. Urban planning, as an inter-disciplinary task, requires transparent approaches to integrate complex digital information into decision-making (Goodspeed, 2016). In this regard, remote sensing data pose particular challenges (De Groot-Reichwein et al., 2018).

According to a literature review of more than 250 scientific articles on urban heat indicators and mapping techniques by De Groot-Reichwein et al. (2018), the majority

of studies rely on air temperature and/or surface temperature. However, none of the articles they reviewed presented case studies where the indicators and mapping techniques were evaluated systematically based on their relevance for policy makers. In working with decision-makers to create geo-visualisations, they discuss the importance of considering both the information needs and communication needs in an iterative step-wise approach. The complexity of thermal data, especially when derived from remote sensing and GIS analysis, necessitates a translation into formats that are easily interpretable by non-specialists. This is where an iterative approach becomes particularly valuable, ensuring that the analysis is not only scientifically rigorous but also practically relevant and accessible to those involved in urban planning.

We address this gap by systematically evaluating heat indicators and mapping techniques for their applicability in planning and policy development. This study aims to identify and visualise thermal hot-spots - areas which are consistently experiencing high surface temperatures as well as thermal discomfort - for an urban context using remotely sensed Land Surface Temperature (LST) data and modeled PET, and to make this information available for planning and decision-making. We introduce a strategy which allows for the use of LST in a critical way at different urban planning scales, and highlight how LST data can contribute to informed sustainable urban planning decisions that effectively mitigate thermal discomfort and enhance urban livability. Based on the case of the City of Frankfurt, we describe and discuss a collaborative process involving actors and different state level administrations for developing an approach to identify thermal hot-spots and visualise climate data for urban and regional planning.

2 Method

2.1 Data and Software availability

Land surface temperature data are publicly available from NASA and were prepared in Google Earth Engine's Python API. For nighttime LST, the Land Surface Temperature/Emissivity Daily L3 Global, Version 6.1 product MYD11A1 (band *LST_Night_1km*) was used Wan et al. (2021). It has a native resolution of 1 km at the equator and is observed daily, in the state of Hessen, at approximately 2 am local time. Data were aggregated over the summer months (June, July, August) for the ten-year time period 2013-2022. Based on the information provided in the band *QC_Night* only observations with an uncertainty <3 K are considered. For daytime LST this study relies on the Landsat 8 Collection 2 Level-2 Science Product (band *ST_B10*). In order to keep the number of images as constant as possible across the whole of Hessen, only tiles from WRS path number 195 are considered. Using the flags from band *QA_PIXEL* dilated cloud, cirrus (high confidence) and cloud are masked, in addition all data

with an uncertainty ≥ 3 K are disregarded (band *ST_QA*). While the thermal sensor has a resolution of 100 m, the final product is available at 30 m, the time of observation is 12:15 pm local time, and images are taken with a frequency of 16 days. Like for nighttime LST, the 10-year summer mean 2013-2022 is calculated. For both LST datasets we provide several bands of metadata including average uncertainty, standard deviation, number of observations, and average time of observation. All of this information is available per pixel, but proved to be difficult to include in the discussions with decision-makers.

The PET data used had been determined for the state of Hessen in a previous project paid for by local government, however this data is not currently publicly available (Ketterer et al., 2022). It is the result of a 200 m resolution FITNAH (Flow over Irregular Terrain with Natural and Anthropogenic Heat-Sources) model and represents values for a typically clear-sky summer day (August 1st) at 1:00 pm.

All described further processing steps were completed in RStudio and ArcGIS Pro 3.0.3 (ESRI, 2023) using built-in functions and tools.

2.2 Data analysis

To compare LST and PET, as well as identify thermal hot-spots, two different multidimensional visualisation approaches were tested, both of which work on the common spatial reference of the recommended 100 meter grid according to INSPIRE. This allowed for each grid cell to be uniquely coded and visualised, illustrating the distinct outcomes associated with every possible combination of variable classifications. The methodology was designed to analyse data at both the regional scale of Hessen and local levels. This dual-scale analysis allowed for a comprehensive understanding of thermal hot-spots, acknowledging that interventions may also differ significantly between broader regional strategies and localised, city scale actions.

The first approach follows a methodology recognised in spatial observation, similar to that used by the Federal Institute for Research on Building, Urban Affairs, and Spatial Development (BBSR) where two overlapping variables are collectively considered in order to identify planning action needs (Milbert, 2015). Individual variables are classified according to their distribution into classes. Thus, each value of a variable is assigned a class designation of 1 to 5 which can then be combined into an overall key to achieve 25 distinct combinations (Figure 1). For example, class 1 of the first variable and class 2 of the second variable yield an overall key of 12. In this process, for a multitude of individual variables, weightings can also be applied using a points system (Milbert, 2015). In the case of the intersection of two parameters applied here, weighting is omitted and the classified parameters are used directly.

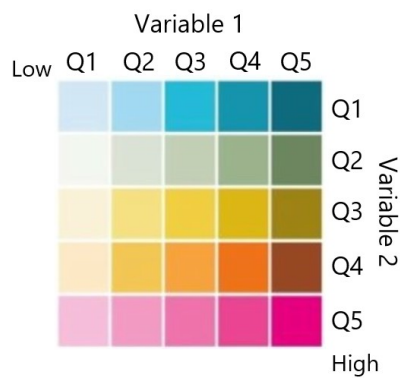


Figure 1. Scale for the method of intersecting two variables.

The second approach uses a three-variable intersection which makes use of the standard values in the RGB colour scheme, as often used in remote sensing (Hengl, 2003). Values of each variable are scaled within the ranges of the interval 0 to 255, with the colour channels red, green and blue assigned to one of the three variables.

2.3 From data to information

To ensure the effectiveness and applicability of our methodology, a collaborative framework was established with decision-makers. A series of regular meetings with two formats were crucial for understanding the specific needs, constraints, and objectives. The two formats were: meetings with experts from ministries responsible for the environment, urban and regional planning; and a broader group involving external experts and practitioners. Initial visualisations were reviewed in these collaborative sessions, where planners provided feedback on aspects such as clarity, relevance, and usability. This feedback was crucial in refining the visualisations to ensure they effectively conveyed the necessary information for decision-making. It was essential to strike a balance between the understandability and transparency of the information while still providing a detailed, albeit complex, description (Goodspeed, 2016). This ensured that the approach was not only scientifically robust but also aligned with the practical realities and priorities of urban planning. The validated methodology and visualisations were then finalised for use in guiding urban planning decisions.

In contexts where the immediacy of response is not critical, employing multi-colour maps can not only improve the precision of judgments but also enhance visual appeal and engagement (Barua et al., 2023). However, the three-layered RGB-based intersection methodology proved to be more challenging for decision-makers to interpret. The intricacy associated with images incorporating multiple hues was found to extend the time required to introduce them to a broader group of governmental actors.

The two-layered intersection method emerged as the preferred approach, striking an optimal balance between complexity, interpretability, and aesthetic engagement (Fig-

ure 2). However, the value ranges for the two variables were debated. In a first approach, the ranges were divided into quintiles, with each class representing 20 percent of the values. For the decision-makers the distribution highlighted by even quantiles proved to be too coarse as they required a more focused identification of areas where the combination of values would point to a need for planning interventions through adaptation measures. Hence, a 90th percentile quantile distribution was also tested. Regarding the regional and local scales relevant for spatial planning, the decision-maker further opted for the analysis at both scales.

3 Results

The intersection of daytime and nighttime Land Surface Temperature (LST) in comparison to Physiological Equivalent Temperature (PET) within the case study area of Frankfurt revealed significant variations in hot-spot delineation, contingent upon the chosen analysis method and scale of examination. This section presents the outcomes of these varied approaches, emphasising the impact of varying quantile distribution and scale, and a comparison of the LST data compared to the PET index for hot-spot identification.

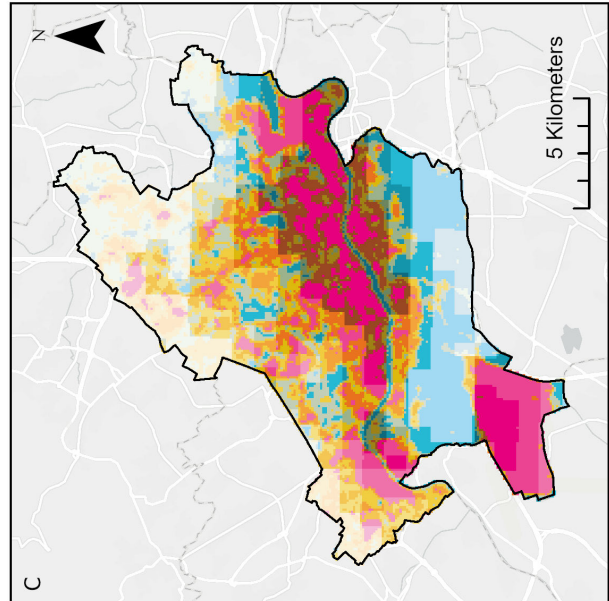
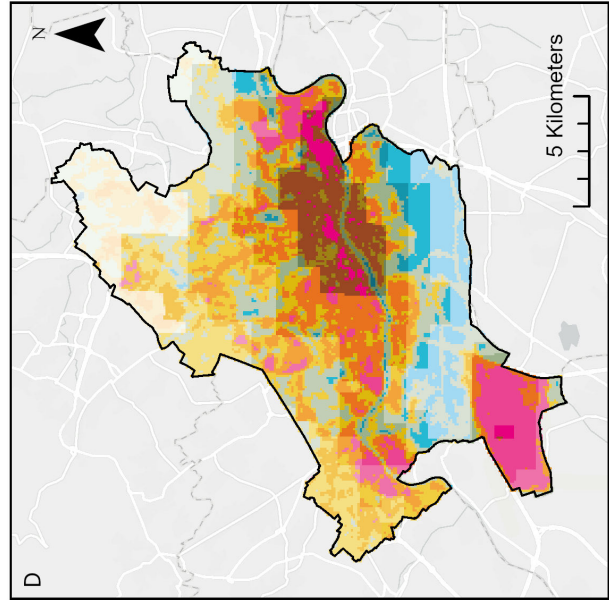
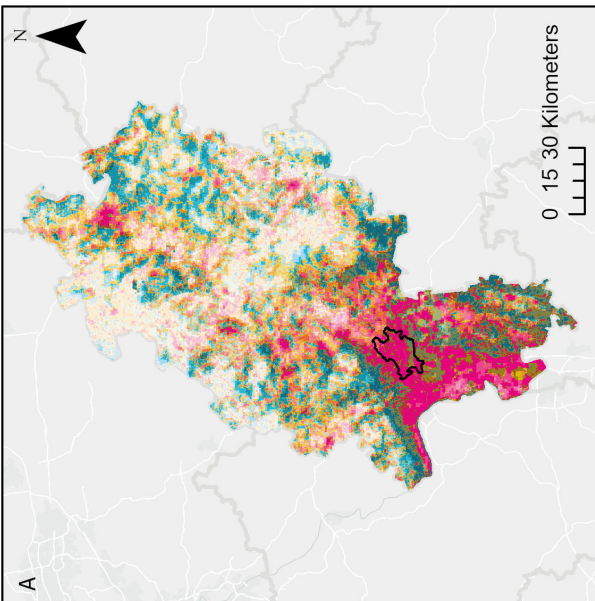
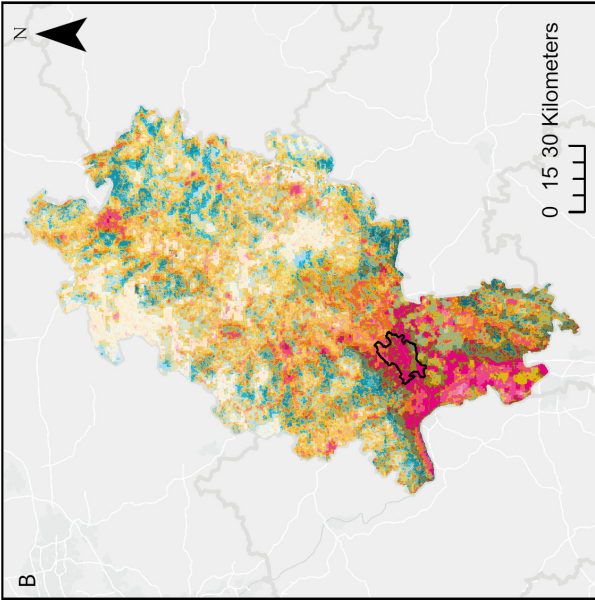
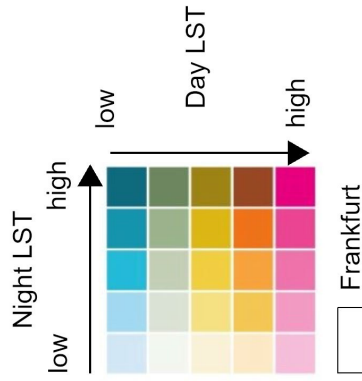
3.1 Impact of analysis scale and quantile distribution on LST hot-spot identification

In the intersection of daytime LST and nighttime LST, based on the scale applied, four categories were defined separating the hottest and hot areas from the cool and medium areas (Figure 3). The hottest areas (Q5/Q5) were then considered as LST hot-spots, where both daytime LST and nighttime LST are high. Depending on the method of quantile distribution used and scale at which the analysis is conducted, the size of the areas identified as LST hot-spots in Frankfurt varies, as do the proportions of areas included in the different heat categories (Figure 2, 4).

When employing a regional-scale analysis that encompasses the entire Hessen region, followed by a focused examination of Frankfurt, the results define nearly the entire city area as a hot-spot (Figure 2, A/B). This extensive classification underscores the influence of scale on hot-spot identification, with the regional analysis predisposing to a broader, less discriminating identification. Furthermore, the adoption of different quantile distributions alters the threshold for what constitutes a hot-spot, thereby impacting the spatial extent of areas identified under this category (Figure 2, C/D).

Intersections of Summer day LST vs. Summer night LST

Based on the highest category of 90th percentile calculation and even quantile calculation of nighttime land surface temperature from MODIS at a 1000 m resolution, and daily land surface temperature from Landsat 8 at a 100 m resolution.



- A: Even quantiles calculated at the scale of Hessen
- B: 90th percentile calculated at the scale of Hessen
- C: Even quantiles calculated at the scale of Frankfurt
- D: 90th percentile calculated at the scale of Frankfurt

Map basis:
 HVBG, Esri, HERE, Garmin, Foursquare, GeoTechnologies, Inc, METI/NASA, USGS

Data basis:
 LST MODIS, ca. 2:00, 1000 m resolution, Average for Summer 2013-2022
 LST L8, ca. 12:00, 100 m resolution, Average for Summer 2013-2022

Figure 2. Hot-spots highlighted by the highest intersection category of Summer day LST vs. Summer night LST using the 4 methods of analysis.

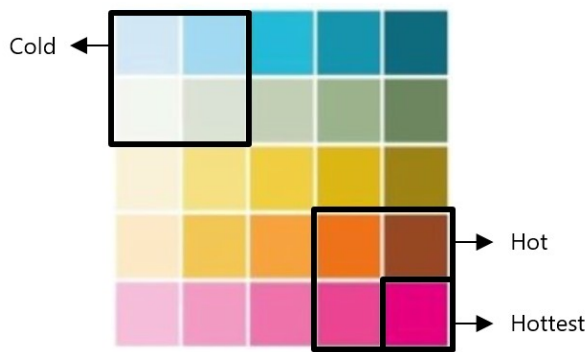


Figure 3. Legend depiction of categories "cold", "hot", and "hottest"

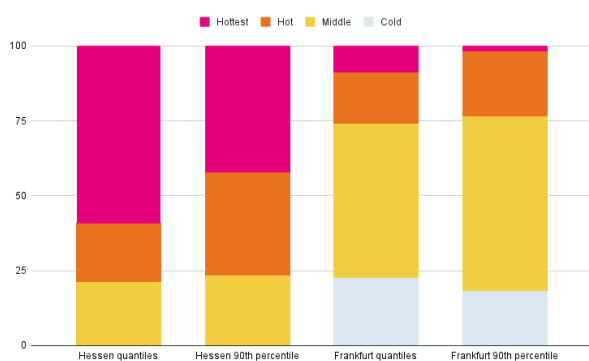


Figure 4. The distribution of each category hottest, hot, middle, and cold using the four different analysis methods for the City of Frankfurt area.

3.2 Comparison with Physiological Equivalent Temperature index categories

Hot-spot areas identified through the top intersection category of daytime LST and nighttime LST (Q5/Q5) were compared to areas categorised under the highest category of the PET index of "extreme discomfort" (PET >41°C), according to the standardised scale (Matzarakis et al., 1999). This revealed a significant spatial discrepancy between the identified LST and PET hot-spots across all methods of analysis (Figure 5 and 6). The Hessen-wide analysis of LST (Figure 6, A/B), encompassing a larger regional scale, more accurately reflects areas of "extreme discomfort" as per the PET index, suggesting a broader criterion for hot-spot identification at this scale.

As shown in Figure 5, with a state-wide analysis using even quintiles, 74 percent of the total area of Frankfurt is in agreement between LST and PET either as hot-spot areas (green) or with the absence of hot-spot areas (empty). However, high LST is predicted without the presence of high PET (purple) in 25 percent of the total study area, and PET without LST (red) in the remaining 1 percent of cases.

This distribution changes dramatically when the analysis is carried out at the city scale and shows a reduced accuracy of LST data for the identification of hot-spots (Figure 6, C/D). Areas of agreement represent 68 percent of the total study area when using even quintiles for Frankfurt. Areas with high LST without high PET only represent 1 percent, and the areas where PET predicts hot-spots without LST hot-spots represents 31 percent of the total area. At this scale, the differences between both parameters are most prominent and this is further emphasised when using a 90th percentile categorisation.

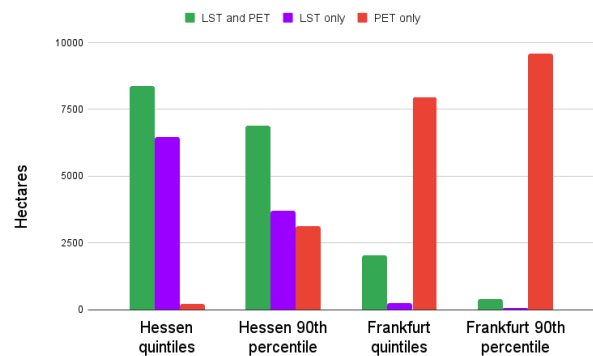


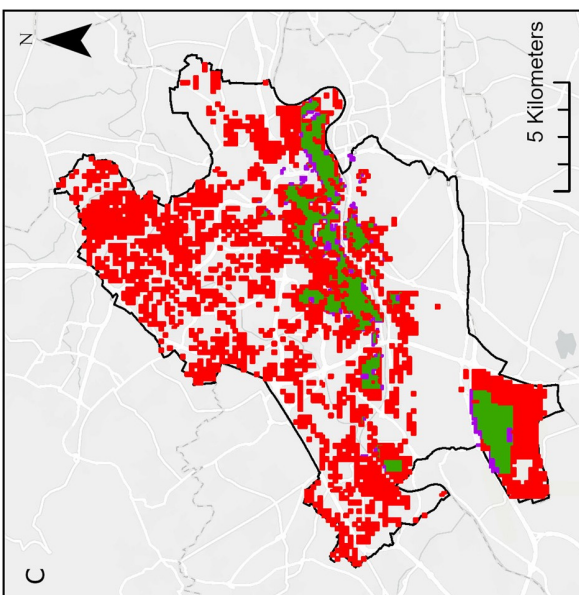
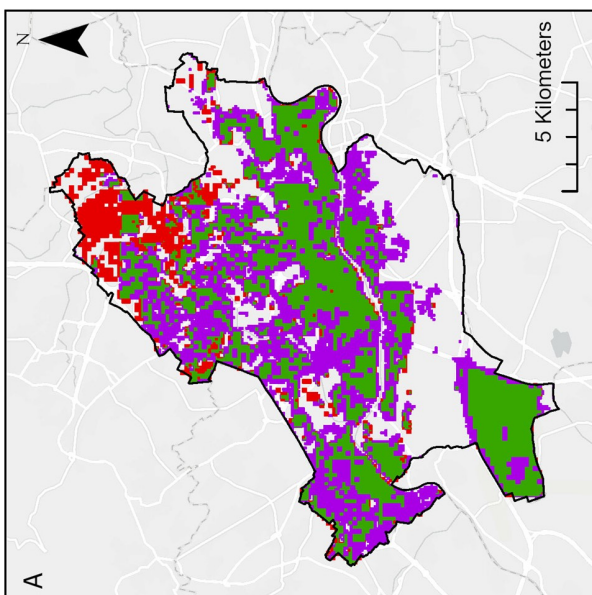
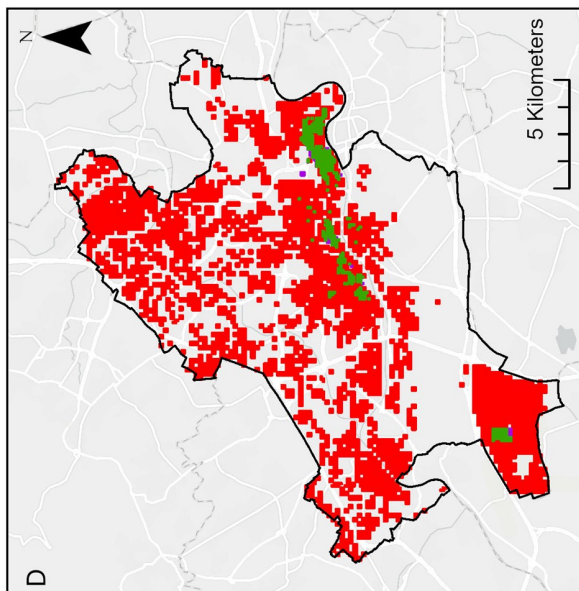
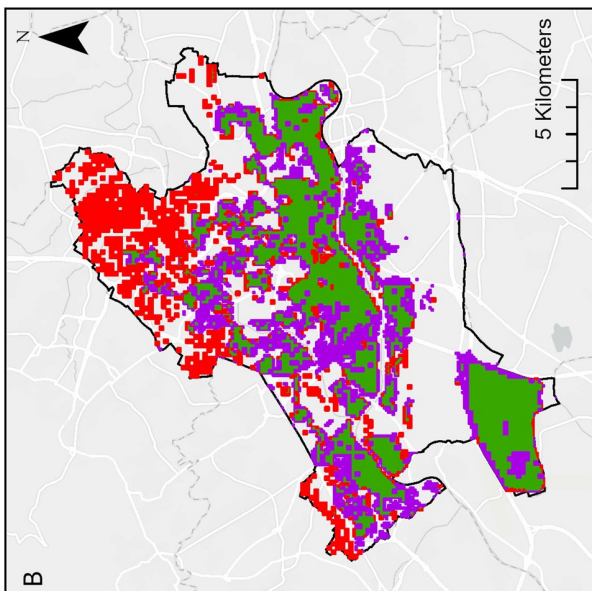
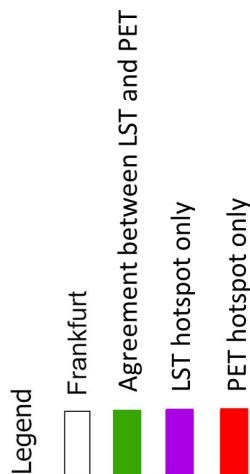
Figure 5. Sums of areas highlighted as hot-spots [ha] in Frankfurt (25529 hectares) for the Frankfurt and Hessen-wide analyses using even quintiles and 90th percentile: In green are areas that are identified as a hot-spots by daytime and nighttime LST, as well as by PET; purple identifies areas where daytime and nighttime LST are in the highest category but PET is not; red indicates areas where PET is in the highest category but LST is not.

3.3 Land cover characteristics of thermal hot-spots

The examination of areas where the LST hot-spots either cover a greater area or lesser area in comparison to PET hot-spots provides insight into the influence of land cover on thermal comfort predictions (Figure 7). Notably, areas where the LST category is lower than PET are predominantly fields and farmlands. This is attributed to the inherently lower land surface temperatures of grassy areas, caused by evapotranspiration and a high latent heat flux. PET instead is high due to the high intensity of incoming radiation with little to no shading. As a result, agricultural lands, are a hot-spot for heat stress, which is not the case for LST. In contrast, LST in urban areas with greenery are higher than PET. Satellite derived LST often cannot depict temperatures in the street canyon due to the viewing angle and instead measures LST of buildings and/or roofs with little relevance to human health.

LST vs. PET areas for planning intervention

Based on the highest category of 90th percentile calculation and even quantile intersection of nighttime land surface temperature from MODIS at a 1000 m resolution, and daily land surface temperature from Landsat 8 at a 100 m resolution in comparison to the highest category of Physiological Equivalent Temperature (PET in °C) (Matzarakis et al., 1999).



- A: Even quantiles calculated at the scale of Hessen.
- B: 90th percentile calculated at the scale of Hessen.
- C: Even quantiles calculated at the scale of Frankfurt.
- D: 90th percentile calculated at the scale of Frankfurt.

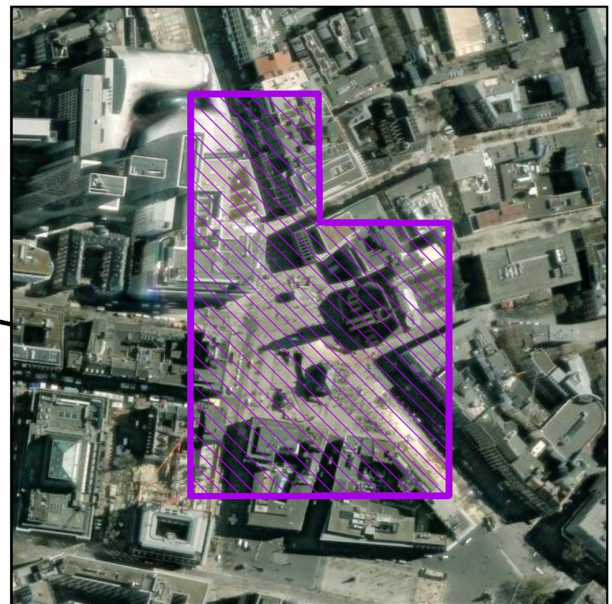
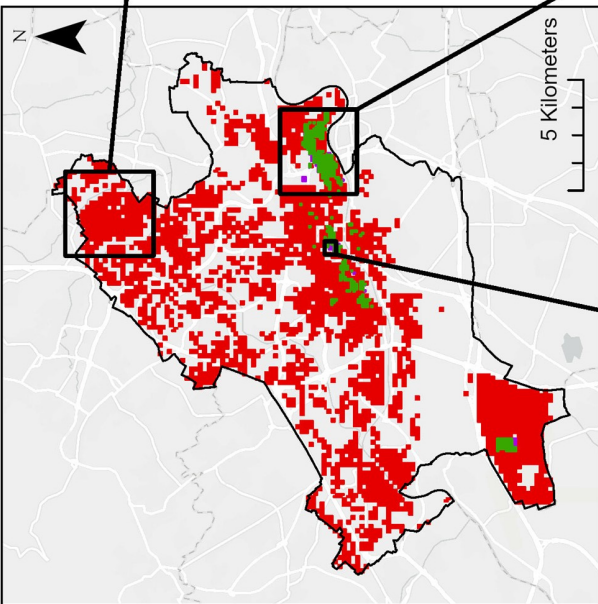
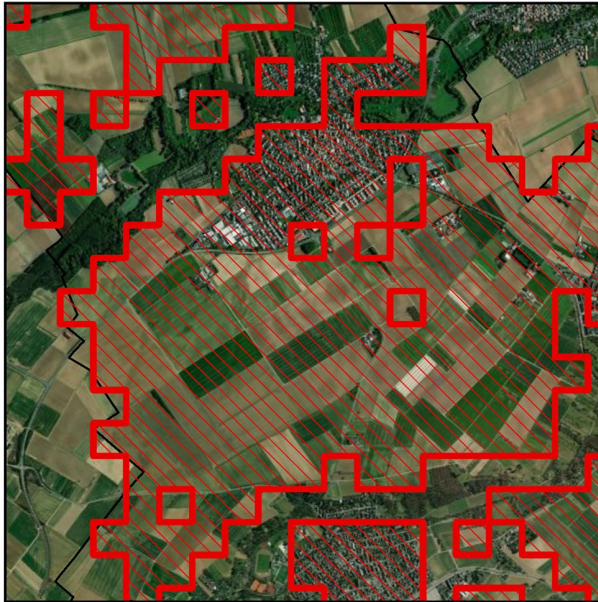
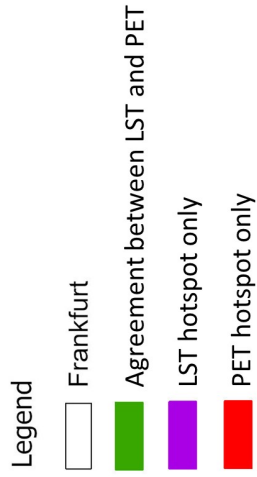
Map basis:
 HVBG, Esri, HERE, Garmin, Foursquare, GeoTechnologies, Inc, METI/NASA, USGS

Data basis:
 LST MODIS, ca. 2:00, 1000 m resolution, Average for Summer 2013-2022
 LST L8, ca. 12:00, 100 m resolution, Average for Summer 2013-2022
 PET FITNAH model, 200 m resolution, clear-sky summer day (August 1st) at 13:00

Figure 6. Areas highlighted for planning intervention by thermal hot-spots: In green are areas that are identified as a hot-spot by the intersection of daytime and nighttime LST, as well as PET; purple identifies areas where daytime and nighttime LST are in the highest category but PET is not, and red indicates areas where PET is in the highest category but LST daytime and nighttime are not.

LST vs. PET areas for planning intervention

Based on the highest category of 90th percentile intersection of nighttime land surface temperature from MODIS at a 1000 m resolution, and daily land surface temperature from Landsat 8 at a 100 m resolution in comparison to the highest category of Physiological Equivalent Temperature (PET in °C) (Matzarakis et al., 1999).



Map basis:
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 LST MODIS, ca. 2:00, 1000 m resolution, Average for Summer 2013-2022
 LST L8, ca. 12:00, 100 m resolution, Average for Summer 2013-2022
 PET FITNAH model, 200 m resolution, clear-sky summer day (August 1st) at 13:00

Figure 7. Examples of land cover in areas with high LST, high PET, and both high LST and PET

4 Discussion

4.1 Limitations of remote sensing data in identifying urban hot-spots

The application of LST in urban planning, specifically for identifying target areas for climate adaptation, underscores the complexity of translating remote sensing data into practical interventions. While LST has the potential to serve as a valuable tool for delineating broad areas of urban heat at the regional level (Guillevic et al., 2017), it cannot reliably indicate thermal comfort levels. It does not incorporate the multifaceted factors influencing human thermal comfort, such as air temperature, humidity, wind speed, and human activity (Höppe, 1999). This limitation emphasises the necessity of integrating more comprehensive indicators such as PET, which account for a wider range of environmental and physiological factors for detailed local-scale planning and urban design aimed at enhancing livability.

4.2 The role of land cover in determining thermal hot-spots

Our findings also emphasise the significant role of land cover in determining thermal hot-spots. Urban areas with dense construction and limited vegetation consistently emerge as areas of concern, being highlighted as thermal hot-spots across all heat parameters. This correlation highlights the importance of incorporating land use planning and green infrastructure as key components of climate adaptation strategies, aligning interventions with broader environmental objectives to mitigate urban heat effectively (Zölch et al., 2016; Bowler et al., 2010).

4.3 Barriers to climate adaptation in planning

Municipal planning requires technically relevant data and maps for decision-making, some of which are not yet available - especially for new planning tasks (Boehnke et al., 2023, 2022). Maps generated for this purpose require suitable quality, certainty, resolution and informative value for the desired governance. Ideally, the data and generated maps can be used to identify areas with a particular need for action, which can be clearly differentiated from one another using suitable parameters and/or indicators. In the case of thermal hot-spots, areas with high heat stress should be identified for which planning interventions in the form of targeted heat reduction measures is necessary. This study thus provides the necessary basis for the next step of developing suitable and meaningful indicators for climate adaptation. The study points to the open questions of whether the necessary data accuracy is yet to be achieved to promote climate adaptation and if the limitations can be adequately communicated in decision-making processes.

4.4 Recommendations for indicator use in urban planning

For actors and decision-makers in urban planning, adopting a two dimensional approach that leverages both LST for broad hot-spot identification and PET for detailed thermal comfort assessments proved to be suitable to meet the communication and information needs of the involved actors (De Groot-Reichwein et al., 2018). This dual-indicator strategy can enhance the planning of climate adaptation measures, ensuring they are both scientifically grounded and aligned with the specific thermal comfort needs of urban populations. The developed collaborative geo-visualisation approach is considered to be well-suited to assist planning actors in integrating urban heat challenges into planning decisions in a scientifically informed and practically feasible way (Boehnke et al., 2023). We thus emphasise the importance of collaboration, adaptability, and clear communication in addressing complex environmental issues.

5 Conclusion

This study has examined the use of Land Surface Temperature (LST) maps and the Physiological Equivalent Temperature (PET) index for identifying urban hot-spots in order to aid the formation of climate adaptation strategies. Our findings highlight the critical role of scale, data interpretation, and the integration of more comprehensive heat indicators in urban planning. The investigation of the role of land cover in determining thermal hot-spots underscores the importance of strategic urban planning in mitigating heat stress in urban environments, thereby enhancing city livability and climate resilience. Our collaboratively formed methodology and geo-visualisation approach exemplifies a model for integrating scientific research with practical urban planning, promoting evidence-based and feasible decision-making. Future research should refine these approaches and explore new thermal data integration methods, thereby enriching the toolkit for sustainable and climate adapted urban planning.

Author contributions. Claire Gallacher, and Mathias Jehling designed the study and developed the methodology. Susanne Benz prepared all input data. Claire Gallacher prepared all data and code for analysis, and designed figures. All authors wrote the manuscript, interpreted results and edited the manuscript together.

Competing interests. The authors declare no competing interests.

Acknowledgements. We would like to thank Stefan Hinz, Karlsruhe Institute of Technology, for initiating this research on the thematic integration of geospatial and spatial planning approaches to address climate adaptation.

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