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Research Paper

Optimizing urban greening and densification in the context of outdoor heat: Opportunities for AI-supported urban adaptation

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HIGHLIGHTS

- Weighing up urban greening and densification in established neighbourhood is complex.
- Urban land use and heat-based adaptation planning can be expedited with AI support.
- AI-supported methods are best combined, to balance different urban planning goals.
- Transdisciplinary methods can be used to test AI-supported methods for usability.

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ABSTRACT

Confronted with increasing urban heat stress risks, local governments need to reconcile expanding green infrastructure for urban cooling with urban densification goals. However, the impacts of incremental urban development in established neighborhoods on urban heat stress risks remain poorly understood. We demonstrate how decision support tools using Artificial Intelligence (AI) can assist complex urban land use and climate adaptation planning. Our findings are based on an inter- and transdisciplinary research project that developed and combined novel AI-supported simulation and prediction methods, namely 3D semantic models, AI-based outdoor thermal comfort models, and optimization and scenario-based AI models. Tool development was combined with transdisciplinary research to assess the real-world application potentials of AI-supported approaches in the City of Freiburg, Germany. The article demonstrates how AI-supported methods can aide and expedite urban land use and adaptation planning to support complex decision-making that needs to balance different strategic goals and interests.

1. Introduction

According to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change (IPCC AR6), extreme events will intensify due to climate change, with heatwaves becoming more frequent, more intense, and lasting longer (IPCC 2023a). Cities experience climate

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change risks in multiple and complex ways because climatic hazards, such as heat waves, heavy precipitation, and storms, interact with exposure, i.e. the presence of people or objects in places and settings that could be adversely affected and vulnerability, i.e. the propensity or predisposition of these people or objects to be adversely affected (IPCC 2023b). In addition, the risks of climate change to urban areas are compounded by local urban effects, such as urban heat islands (Oke 1973; 1982; Oke et al. 2017). Urban heat risks can thus be understood as 'the potential for adverse consequences for human or ecological systems' (IPCC 2023b) that result from increases in average temperatures, more frequent, more intense and prolonged occurrence of heatwaves in urban areas, and the associated, spatially and socially differentiated effects of exposure and vulnerability. According to a large modelling study by Zhao et al. (2021), between 2000 and 2019 around 489,000 heat-related excess deaths occurred globally each year, with heat-related mortality being highest in Europe and Oceania. By 2100, up to two-thirds of the global human population could be exposed to life-threatening climatic conditions arising from coupled impacts of extreme heat and humidity (Dodman et al. 2022), with substantial economic and social costs, such as increasing school closures due and lost working hours due to heat stress (United Nations 2024). The United Nations Secretary General's Call to Action on Extreme Heat considers dealing with urban heat by 'fostering nature-positive cities and climate-sensitive urban design and planning' (United Nations 2024: 18) areas of primary concern, due to the large number and high concentration of urban residents, commuters, and visitors whose health and well-being may potentially be affected by heat stress, adverse mental health effects, cardiovascular emergencies, and heat-induced death. Heat stress also affects human productivity, e.g., by reducing physical work capacity and motor-cognitive performance (Ebi et al. 2021). Extreme heat events have been shown to be particularly dangerous for city dwellers, resulting in high rates of mortality and morbidity (Norton et al. 2015). These effects are projected to increase with accelerating climate change (Guo et al. 2018; Ebi et al. 2018).

In built-up urban areas in Europe and elsewhere, heat-related urban planning requires maximizing urban greening while at the same time adhering to principles of sustainable and spatially efficient land use management is a challenge that can prove difficult both politically and technically (Erlwein et al. 2023; Verheij et al 2023). In established urban neighborhoods and in cities with limited options to expand, the need for densification and in-fill development (densification) to provide additional housing often clashes with the efforts to safeguard and expand urban greenspace and enhance thermal comfort (Erlwein and Pauleit 2021). Artificial Intelligence (AI) provides significant potentials for optimizing planning and decision-making at the intersection of urban greening and densification (Araújo et al. 2021; Othengrafen et al., 2025; Lartey and Law 2025), yet it also comes with its own limitations and challenges, including wide-ranging ethical concerns (Sanchez et al. 2025), questions regarding the anticipatory governance aspects (Cugurullo and Xu 2025) and the hidden politics of 'automated' urban planning (Peng et al. 2024) and AI urbanism (Cugurullo et al. 2024). The main objective of this paper is to demonstrate how AI and machine learning can substantially support urban heat risk analysis[1] and planning for heat adaptation in cities. We focus on the following research question: How can AI-supported approaches and workflows contribute to effective risk analysis and urban development planning aimed at reducing heat hazards in established urban neighborhoods? We draw on results from a 2021–2024 inter- and transdisciplinary research project called 'I4C – Intelligence for Cities' that developed novel approaches for AI-supported adaptation to urban climate risks and assessed their application potentials in a real-world setting. AI methods were used across the project for data assimilation, model input generation, model performance increases, and predictions. Unparalleled in its spatial (1x1m) and temporal (1hr) resolution, critical heat-related locations could be identified, visualized, and risks quantified using AI-based models and tools (Briegel et al., 2024). The project used an inter- and transdisciplinary approach where natural and social scientists worked with the City of Freiburg in southwestern Germany as the implementing partner in a real-world application lab. Through knowledge co-production, potential applications for the AI-based modelling and prediction tools for analyzing neighborhood-scale urban heat hazards developed in I4C were critically examined in transdisciplinary fashion. Using an established inner-city neighborhood as case study area, we demonstrated and critically reviewed the application potentials of AI-supported urban heat risk analysis (as defined above) for context-specific and scenario-driven urban heat adaptation planning and decision-making. While focused on heat risk analysis, the findings also have implications for other aspects of municipal climate risk assessment (broadly understood as 'the qualitative and/or quantitative scientific estimation of risks' (IPCC 2023b)) at the municipal scale.

2. Background

Cities are already experiencing extreme heat more often, more frequently, and for longer periods (Meehl and Tebaldi 2004; Dosio et al. 2018; Perkins-Kirkpatrick and Lewis, 2020), leading to increased health risks. By 2100, heatwave maximum temperatures in Central European cities are projected increase by up to 14 °C (Guerreiro et al. 2018). Many physical and non-physical urban parameters influence the heat-health nexus (Ellena, Breil, and Soriani 2020). In European cities, urban land use planning is a key lever for reducing heat hazards and future heat stress. However, urban planners face the dilemma of reconciling the need for urban greening to reduce heat-related risks with housing demand and pressures for densification and compact city development (Burton 2000) in order to minimize urban greenhouse gas emissions and land use change on the urban fringe (Haaland and Van Den Bosch 2015; Erlwein and Pauleit 2021). *Intelligent adaptation* supported by AI has the potential to play a major role in supporting such complex adaptation choices (Cheong, Sankaran, and Bastani 2022). It can help catalyze climate-sensitive urban planning by providing urban planners and decision-makers with precise and near real-time information that can deliver fine-grained analysis of heat hazards. Drawing on a range of potential development scenarios, such information can help urban planners and municipal adaptation managers identify entry points for heat-related climate adaptation interventions (cf. ISO International Organization for Standardization, 2021) and pave the ground for strategic, heat-sensitive urban planning and design. However, the interface between AI methods, workflows and their outputs on the one hand and the legal, regulatory and informational needs for making actual planning decisions on the other hand is crucial for such tools to be applicable in everyday urban planning and decision-making. In the following we critically examine current challenges for urban heat risk analysis and management to contextualize the tools developed and tested as part of our research.

2.1. Understanding outdoor human heat risk in urban areas

Outdoor human heat risk is the result of a dynamic interplay of heat hazard occurrence, exposure to heat, and individual and contextual vulnerabilities. Urban built form and urban vegetation can substantially influence heat hazard occurrence as well as human exposure to heat in cities. Heat exposure and a person's subsequent heat stress result from a complex interaction between different environmental factors (air temperature, radiation, humidity, wind), the human thermophysiology (Epstein and Moran 2006) as well as specific vulnerabilities, such underlying chronic illnesses or having limited mobility. Importantly, a physical-medical understanding of heat stress requires the prediction of

[1] 'Risk analysis' refers to the ISO 31000 process stage of risk assessment that follows risk identification and precedes risk evaluation (ISO, 2018). Its purpose is 'to comprehend the nature of risk and its characteristics including, where appropriate, the level of risk' (ibid: 12).

influencing atmospheric input variables that control a person's energy balance – variables that vary greatly in terms of space and time in cities and depending on the person's health condition (ibid.; Holst and Mayer 2011). For simplification, thermal indices are often used to describe and quantify the exposure of a standardized person to heat at any location and time (Coccolo et al. 2016; Staiger, Laschewski, and Matzarakis 2019). In human biometeorology, a number of thermal indices have been developed to describe heat stress (Potchter et al. 2018), including the Perceived Temperature (Staiger, Laschewski, and Grätz 2012), the Universal Thermal Climate Index (UTCI) (Jendritzky, De Dear, and Havenith 2012) or the Physiologically Equivalent Temperature (PET) (Höppe 1999). Maps of the distribution frequency of thermal indices are used in planning to identify areas of heightened heat risk (Matzarakis et al. 2008; Ketterer and Matzarakis 2015). For example, in their climate adaptation concept, the City of Freiburg blended maps of PET with the vulnerability of the population and identified 14 areas as heat 'hot spots' (Stadt Freiburg, 2019). Here, PET was calculated using numerical-physical models under a few theoretically-assumed case studies (extreme summer weather situations today and in the future).

The variables determining thermal indices at any point and time can be calculated with numerical-physical models considering current weather conditions and the local geospatial environmental context. Examples of such numerical-physical models are building-resolving radiation models such as SOLWEIG (Lindberg, Holmer, and Thorsson 2008), building-resolving urban wind models such as Large Eddy Simulations (LES, (Giometto et al. 2017)), or urban climate models that predict neighborhood-average temperature and humidity (e.g., SUEWS, (Järvi, Grimmond, and Christen 2011)). Also, integrative models such as PAML-4U (Maronga et al. 2020) or ENVI-met (Sinsel et al. 2022) provide calculations of all above variables. Combined, this allows for the calculation of maps of thermal indices at any time based on atmospheric input variables (air temperature, radiation, humidity, wind) and the complex 3D form (morphology, trees, and materials). However, running such physical simulations is complex, computationally demanding, and hence only affordable for short periods, and small subsets of a city. Although simulations with physical models are effective, there is a need to develop more efficient statistical and AI-based methods (Matzarakis et al. 2018; Masson et al. 2020; Meyer et al. 2022) directly interfacing with widely available geospatial data. Only in this way can long-term statistics of heat hazards (i.e., data on an hourly basis over ten to 30 years in the past or future) be simulated. When modelling efficiency is enhanced using statistical and AI-based methods, this also facilitates simultaneous analysis of heat hazards for a large number of incremental development scenarios, which in turn allows for selecting the best available adaptation planning options with reasonable and affordable computing time.

2.2. Planning to minimize urban heat risk and maximize potentials for cooling

Urban land use planning facilitates processes with direct implications for heat-related climate risks and adaptation, such as densifying cities and promoting green infrastructure. Measures to reduce outdoor urban heat risks can readily be taken into account when planning new suburbs, e.g., by including ample green and blue infrastructure to increase shading and evaporative cooling and by aligning buildings to minimize solar radiation exposure and maximize naturally occurring air flows (Santos Nouri et al. 2018). However, in already developed urban areas, land use planning usually takes effect through a multitude of small-scale and incremental planning interventions, such as by granting individual building permits for in-fill development, building extensions or by planting additional street trees. Even in cities where heat risk reduction is a priority, these micro-scale interventions are then assumed to add up to cumulative positive urban cooling effects, although the complex interplay of urban form, wind patterns and solar radiation exposure renders generalizable statements regarding the actual effects of such measures impossible a priori. Therefore, for urban land use planning interventions to result in effective urban cooling, fine-grained analyses of urban heat hazards and cooling potentials down to the neighborhood, streetscape and even the building levels are required. To date, such analyses have been based on physical modelling methods, which are costly and time-consuming, especially if different climate change scenarios are to be considered (Weeding et al. 2023).

2.3. Current challenges and limitations with urban heat risk analysis

In built-up areas not undergoing substantial urban redevelopment, the strategies available for reducing land-use-based urban heat hazards are limited. They include changes to building form and materials, sealed surfaces, increasing vegetation (Venter, Krog, and Barton 2020), and blue infrastructure to increase evapotranspiration (Aminipouri et al. 2019). Tree planting in public spaces is a critical nature-based adaptation solution (Seddon et al. 2020) employed by many cities, including those that are investing massively in green infrastructure by creating 'urban forests' (Jones and Instone 2016; Esperon-Rodriguez and Harrison 2021; Rötzer et al. 2023). Trees primarily decrease heat occurrence during daytime due to an increased fraction of shading (Middel et al. 2016). They also help cool cities through evapotranspiration (ref.). However, trees also increase heat retention during the night and the effect on thermal comfort varies also depending on ground cover (Middel et al. 2021). Finding an optimized trade-off between day-time shading and night-time cooling can be complex. De-sealing and revegetating surfaces are another strategy at the hands of urban planners (Parison et al. 2023; Vieillard et al. 2024). At a small scale, de-sealing can readily be incorporated into urban planning, e.g., along light railway tracks and in marginal urban streetscapes that pedestrians and other traffic do not heavily frequent, and greening even small patches of sealed land can result in measurable heat mitigation (Morel et al. 2025). In heavily used and dense public spaces, large-scale de-sealing is more challenging and requires, for example, re-thinking existing urban land uses, such as the conversion of street parking into green spaces (Croeser et al. 2022). In light of the need to balance urban greening with other present challenges, such as providing additional housing, mitigating urban greenhouse gas emissions and improving accessibility in the compact city, it is evident that densification needs to be optimized, in particular in the context of growing urban populations (Artmann, Inostroza, and Fan 2019; Wicki, Hofer, and Kaufmann 2022). This means deciding on the optimal, thermally most effective ways of adding new buildings and trees. AI-supported methods promise to support such complex decision-making for effective urban heat mitigation (Ketterer and Matzarakis 2016; Shahrestani et al. 2023; Briegel et al., 2024). If long-term simulations of urban heat amplifiers and mitigation potentials under multiple development scenarios were readily available, urban planners and decision-makers could effectively and more efficiently select options that optimize and balance between densification requirements on the one hand and reducing day and night time heat hazards on the other. Eventually, some scenario-based optimizations could even be done automatically. Through such substantial improvements, urban heat risk analyses could evolve into a precise, real-time planning tool for identifying urban areas suitable for densification and those prioritized for ventilation and urban heat reduction (Chaturvedi and De Vries 2021; Nagappan and Daud 2021).

In summary, a series of challenges that are currently limiting applications of urban heat risk analyses can be identified: (1) they are complex and costly to carry out as they rely on the time-consuming physical-numerical modelling of context-specific micro-climatic conditions for selected scenarios (Weeding et al., 2023). Therefore, (2) municipal administrations usually outsource them to planning consultancies, resulting in substantial transaction costs, including time lags. Due to costs, such heat-related and other forms of municipal climate risk assessments are (3) usually only carried out for large urban developments or redevelopments and usually for selected periods, but not for smaller changes, and for already developed areas, e.g., established local neighborhoods. Urban heat risk analyses are thus (4) currently not applied for capturing small-scale, incremental changes to the urban form, which can have a cumulative impact on urban heat over longer time frames. Such small-scale changes are particularly relevant in safeguarding sustainable spatial development, which focuses on minimizing urban spatial expansion through densification of existing neighborhoods (Wicki, Hofer, and Kaufmann 2022).

With current approaches, simulation and prediction, the required level of detail at the meter scale and over long periods cannot be achieved with reasonable computational effort and cost allowing optimization efforts that are feasible for use by municipal administrations. However, recent advances in AI increasingly facilitate the performance of complex computations on spatial and temporal fields quickly and at a fraction of the computational costs (Middel et al. 2022). AI-based models could provide information to urban planners and decision-makers in near real-time and for iterative optimizations. To push the frontier of AI-supported urban heat risk analysis, the I4C project developed and implemented a workflow that combined precise semantic 3D models of urban form with weather and environmental data to model building-resolved heat stress (Fig. 1). Furthermore, we explored using AI-supported design optimizations, e.g., to effectively select tree planting locations to mitigate heat at the pedestrian level.

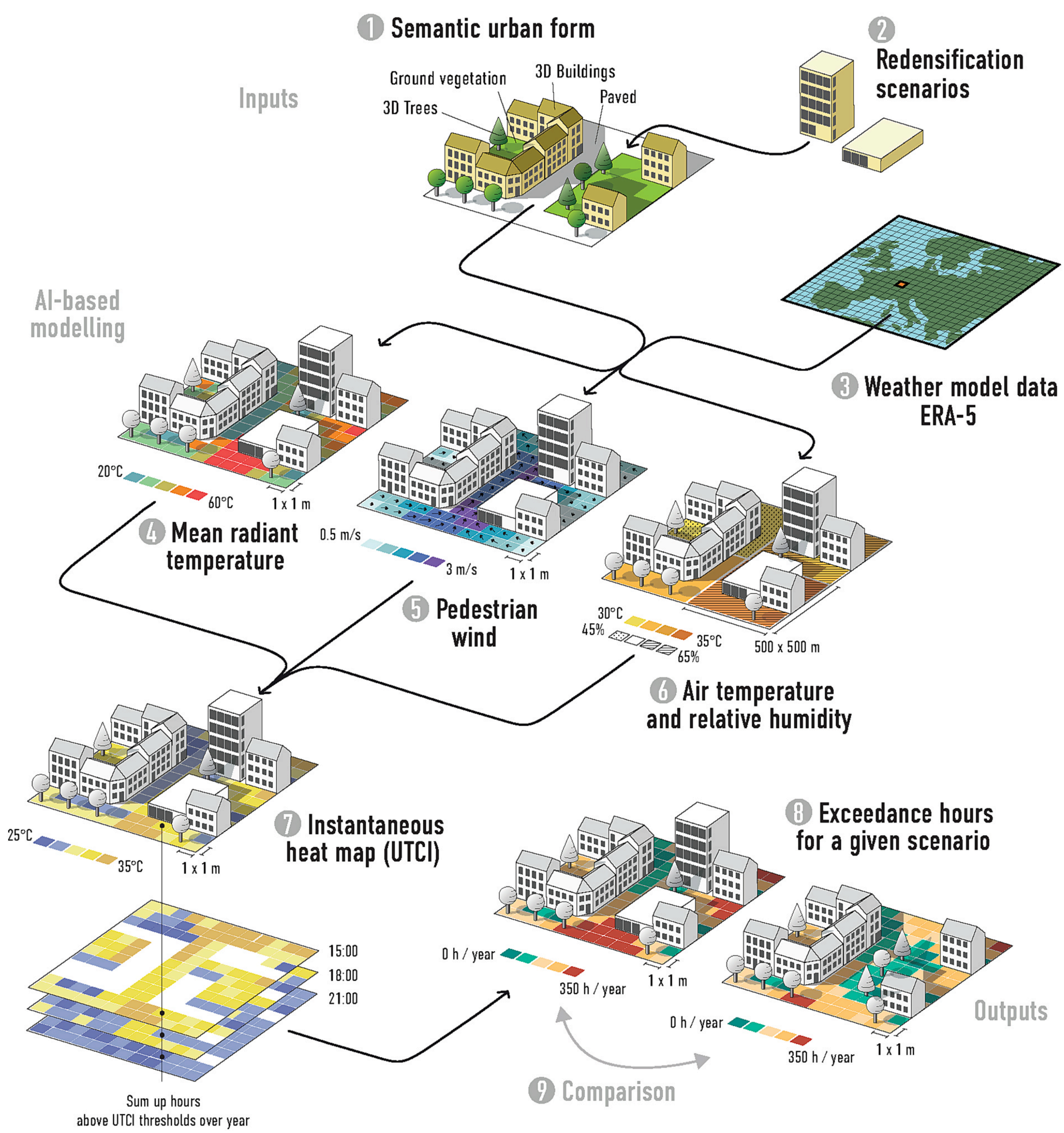

Fig. 1. Schematic representation of the proposed work flow. As inputs we use urban form LIDAR and AI-semantics (A), complemented by different development scenarios (B) and past weather data from meteorological reanalysis models (C). In a first step three separate AI-based models are run that predict high-resolution mean radiant temperature (D), pedestrian-level wind (E) and air temperature / humidity (F) for every hour over 10 years. Based on the three models, for each hour the spatial distribution of thermal comfort (UTCI) is calculated (G). Summing up all cases over the 10 years of simulation when UTCI is exceeding thresholds for heat stress, we calculate average annual exceedance hours for each pixel (H). The exceedance hours from a baseline scenario can then be compared to maps produced the same way for another scenario (I) to assess microclimatic impacts.

3. Study area and methods: Heat hazards in an urban neighborhood under different development scenarios

A part of the I4C project involved developing novel AI-supported workflow for modelling and predicting outdoor heat hazard occurrence and related risks of heat stress occurrence. For this paper, we use the central part of the inner-city urban neighborhood of *Wiehre*, a residential and mixed-use area located immediately to the south of the city center of Freiburg.

Wiehre was primarily developed in the late 19th and early 20th century and, in December 2022, was home to 24.640 inhabitants (Stadt Freiburg, 2024). The neighborhood is inhabited mainly by members of middle and upper socioeconomic strata, with an exceptionally high percentage of academics (Stadt Freiburg, 2024). The built form is dominated by heritage-listed urban villas dating from the 18th, 19th and early 20th centuries, which originally featured large, park-like courtyards that, in recent decades, have become a focus of densification (Fig. 2). Densification has mainly occurred through incremental in-fill development and, to a lesser extent, urban re-development of non-heritage-listed buildings. These measures for densification have largely focused on providing additional residential space that is high in demand in this inner-city neighborhood situated within the broader context of a city that has continued to attract new residents. These in-fill developments have been driven mostly by individual planning applications of building owners.

Situated in the Upper Rhine Valley, Freiburg and its neighborhood of *Wiehre* experience a warm temperate climate, making it one of the hottest areas in Germany. Based on long-term climate data (1991–2020), the Freiburg region has an average annual air temperature of 11.0 °C and a monthly mean air temperature of 20.1 °C in July. It also experiences on average 19 days per year with maximum air temperatures exceeding 30 °C (CDC, 2025). The average annual temperature over the past decade (2015–2024) in the Freiburg area increased to 11.9 °C. almost 1 K above the long-term mean. The region is particularly vulnerable to strong heat, with the Upper Rhine Valley currently experiencing the highest levels of heat stress in Germany – a trend expected to worsen in the future (Briegel et al., 2024; Hundhausen et al., 2023). In a shorter-term study in 2022/23, the neighborhood of *Wiehre* has been identified to experience elevated annual average air temperatures by + 0.5 °C, and 19 tropical nights per year − nights when the minimum air temperature does not drop below 20 °C. This is indicative of a significant nocturnal heat island effect, as compared outside the city at the official weather station only 4 tropical nights were recorded per year (Plein et al., 2025).

Within *Wiehre*, a 1400 x 700 m subset of the neighborhood with primarily residential / mixed-use was selected, referred to as study area The study area has a population density of 88.4 inhabitants per hectare of populated area (Stadt Freiburg, 2024: 12). The plan area in the study areas is 22 % paved, 32 % occupied by building footprints, and is covered by 44 % vegetation (Fig. 3).

We applied AI-supported models to (1) characterize and map the neighborhood for modelling, (2) develop scenarios for this area with the goal to identify and to assess climate-sensitive densification options and heat mitigation options, and finally also, (3) optimizing mitigation options through AI-supported tools.

This paper highlights four different methodological steps carried out as part of the I4C project:

1) Developing a 3D semantic model using LIDAR data and AI segmentation to characterize highly detailed inputs on urban buildings, structures, and vegetation needed in the subsequent heat hazard modelling;
2) Developing an AI-based model for heat stress risk mapping at high temporal (hours to years) and spatial resolution (resolving buildings and trees) based on the 3D semantic model and varying weather data.
3) Applying the AI-based model to numerous planning scenarios in the study area, in particular, also using AI to 'do the planning' for optimization of planning interventions for urban heat hazard mitigation at the urban densification/urban greening dilemma using predefined (simplified) criteria, and
4) Elaborating and assessing how the AI-supported models and their outputs can best be incorporated into urban planning and decision-making using participatory methods, such as scenario-based simulation games.

4. Results: Tools for AI-supported heat adaptation planning in urban areas

High-resolution heat risk modelling is an increasingly important decision-support tool for planning heat mitigation options at or below the urban neighborhood scale. In the following, we present the results of the four steps outlined above. Our core aim in discussing the findings from our developmental research is not to explicate the technical methods used in detail (readers interested in this aspect are encouraged to refer to Appendices A1 to A3 and references therein) but to highlight

Fig. 2. Aerial view of parts of the Wiehre neighborhood with typical block perimeter buildings and park-like courtyards featuring large trees in a near-original state (left) and a densified precinct with in-fill development and less green infrastructure. .
Source: Google Earth 2024

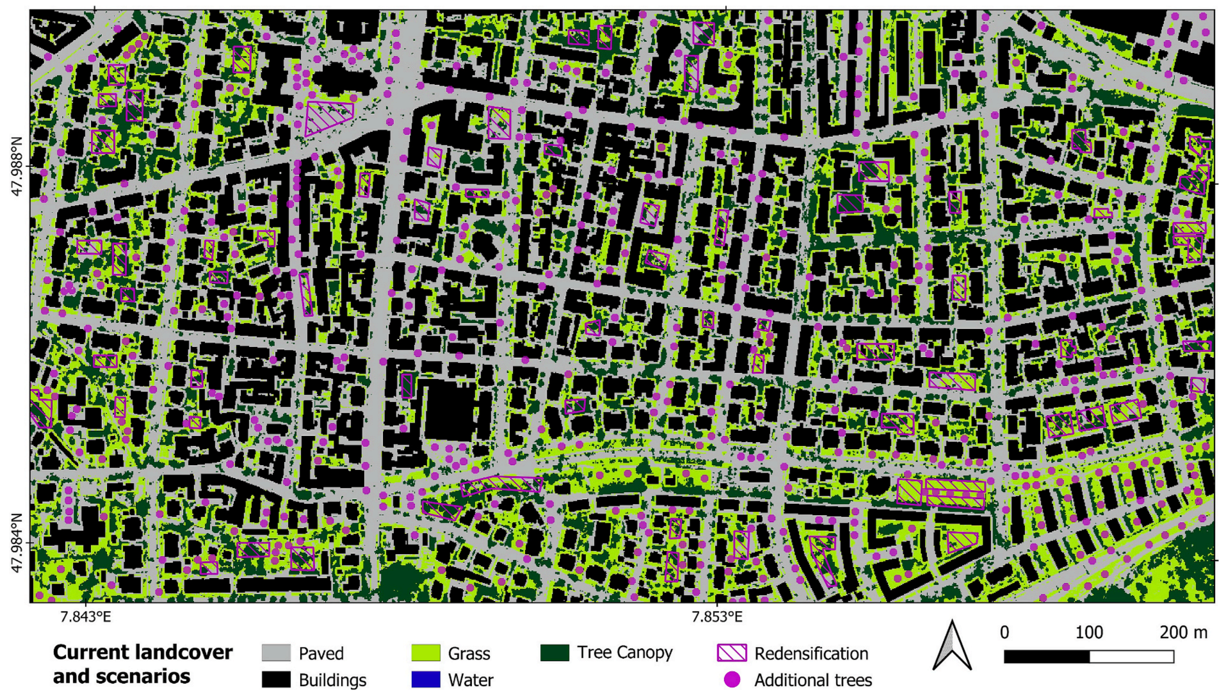

Fig. 3. Map of the Wiehre study area in Freiburg including modifications to built form and vegetation considered in the AI-based simulations. Current land cover is shown in colors, while added buildings (in-fill in scenarios 5–8) are shown as hashed purple outlines. The locations of new tree plantings considered in scenarios 2, 4, 6, and 8 (Table 1) are purple dots. The sites for additional tree locations are possible available spaces. The plausibility of such tree placements must be established using ground-truthing on site.

key developmental steps that bear direct relevance for AI-supported adaptation to urban heat risks. Key opportunities and limitations regarding the application of AI-based models and tools and their application in urban heat adaptation planning are then critically reviewed in the Discussion section.

4.1. Characterizing urban form using LIDAR and AI segmentation

Describing, georeferencing, and quantifying urban form is one of the main starting points for developing strategies for mitigating human heat risks in densely populated urban areas. Urban form is also a crucial determinant at the neighborhood scale when considering potentially contradictory urban planning goals, such as the need to densify established inner-urban residential areas through infill development, while at the same ensuring public acceptance of such development and allowing for urban cooling by, for example, retaining mature trees (Wicki, Hofer, and Kaufmann 2022). In urban outdoor spaces, this requires detailed and timely information on the urban form (in particular buildings and vegetation) to consider shading, thermal radiation, surface energy exchanges, and wind. Although, digital surface models exist for many cities, they may be incomplete and, for instance, rarely include all vegetation, which is critical in shading and cooling cities through evapotranspiration (Krayenhoff et al. 2021).

Airborne or ground-based Light Detection and Ranging (LiDAR) data can provide up-to-date and complete information on urban form including buildings and vegetation. The resolution, however, is often limited, and it can be challenging to obtain vegetation data at the pedestrian scale due to the geometric limitations of overhanging trees and roofs. Therefore, cities also use car-based surveys with terrestrial laser scanning. This data provides point clouds of laser returns that must first be translated into 3D datasets. To use this data as input for heat stress models, the data needs to be further converted into objects, identifying relevant forms (buildings, types of trees) and discarding dynamic objects (cars, garbage bins.). The process of translating LIDAR point clouds into objects is called *semantic segmentation*. In the case study, we tested an AI-based approach to transform the LIDAR point clouds in the area of *Wiehre* into geometric objects.

The AI-based segmentation results in an automated 3D object classification per LiDAR point of the Wiehre area are shown in Fig. 4. Details on the AI-based approach can be found in Appendix A1. This approach serves as a baseline input, providing geospatial data on urban form in the subsequent heat modelling (Fig. 1, A). In particular, it separates stiff and non-transparent objects like buildings from partially translucent vegetation. We show that segmentation using AI-based 3D neural network approaches can efficiently generate meaningful, realistic digital models of urban form (buildings, vegetation) that can be used for various specialized urban planning applications due to the high-resolution semantic representation. As our study showed, they could serve as a key decision-support tool for municipalities with limited financial resources that, in the near future, could be applied in-house without relying on specialized planning and spatial data consultancies.

4.2. Ai-supported heat stress and mitigation mapping

AI-based methods have tremendous potential to help address urban heat stress and to overcome some of the main challenges with urban heat stress analysis outlined above. As part of the I4C project, we developed a novel and efficient AI-based model chain that accurately predicts maps of thermo-physiological stress based on the type of geospatial data outlined above and weather data (Fig. 1). In summary, the model framework consist of three different AI-based emulators of numerical-physical models that predict pedestrian-level mean radiant temperature (Fig. 1, D), wind (Fig. 1, E) as well as air temperature and relative humidity (Fig. 1, F) based on fixed urban form and constantly changing weather data. Mean radiant temperature and wind are modelled at 1 x 1 m spatial resolution because they depend on shadow patterns and three-dimensional pressure fields around buildings, respectively. Air temperature and humidity change less in space, so they were modelled at 500 x 500 m resolution. All models were run at an hourly resolution over 10 years. From the three model outputs, UTCI was calculated for every hour

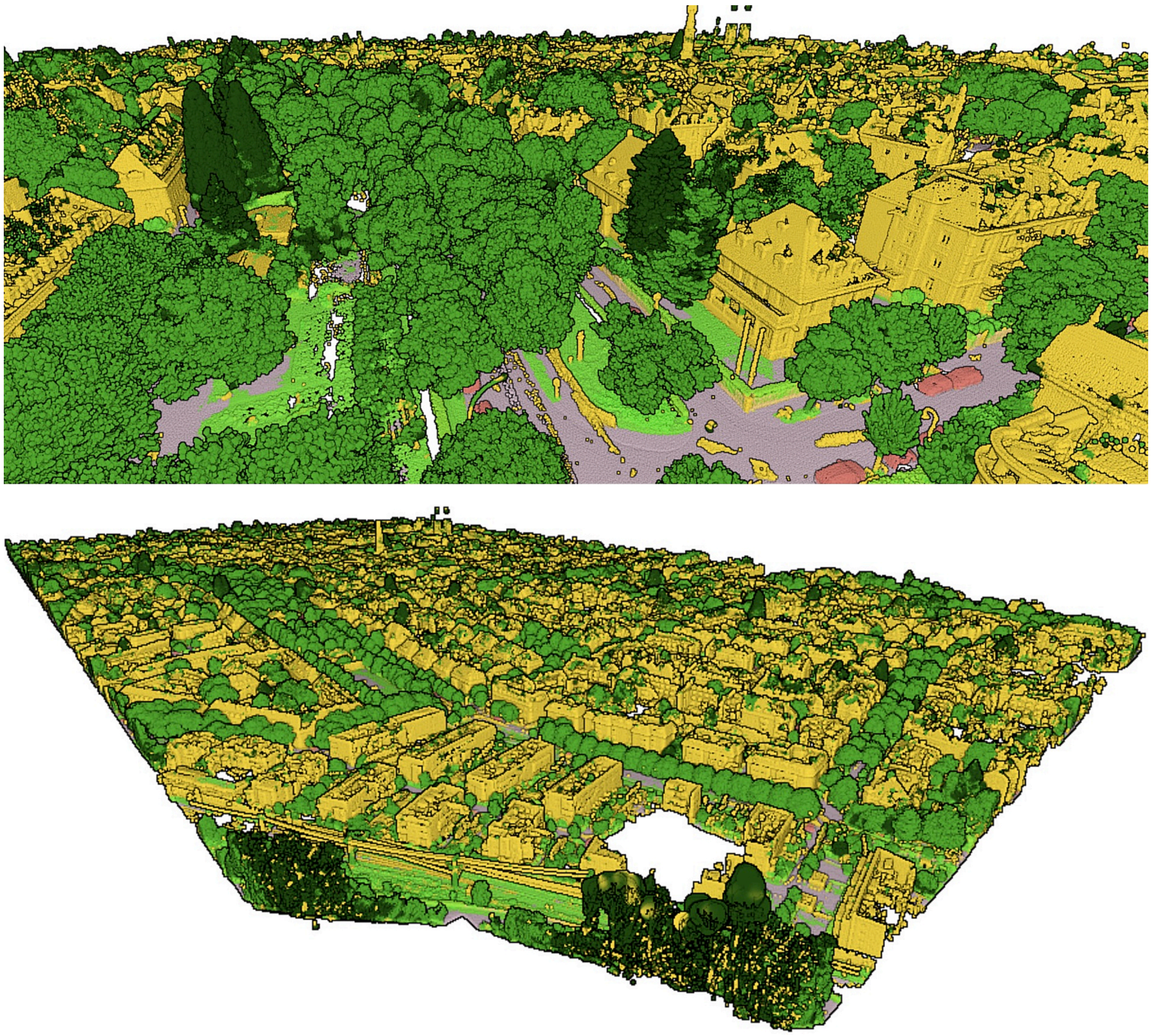

Fig. 4. AI-based segmentation of the Wiehre Area, including urban vegetation.

at 1 x 1 m resolution (Fig. 1, G). Summing up all daytime hours in any pixel when the UTCI value was greater than a threshold for *moderate* (UTCI > 26 °C), *strong* (UTCI > 32 °C), *very strong* (UTCI > 38 °C) and *extreme* (UTCI > 46 °C) heat stress enabled the calculation of average daytime exceedance hours for each class. Similarly, summing up all nocturnal hours when the UTCI value was greater than 20 °C led to nocturnal exceedance hours for heat (Fig. 1, H). A more detailed technical description of the model framework and how UTCI and the necessary variables for its calculation (air temperature, relative humidity, wind speed, and mean radiant temperature) were obtained can be found in Appendix A2, as well as in Briegel et al. (2023) and Briegel et al. (2024). The calculated UTCI values has a comparable accuracy as the numerical-physical models which it is based on with a mean absolute error of 2.3 K compared to a dense urban sensor network (see Appendix A2 and Briegel et al., 2024).

The model was first run for a baseline scenario (SC1), representing the urban area in its current (2021) state, including today's built form and vegetation. Then, different heat mitigation options were considered, including adding 5 % more trees (SC2), desealing all inner courtyards (SC3), as well as a combination of SC2 and SC3 (SC4). The additional trees are considered mature, with a maximum height of 12 m and a spherical crown with a diameter of 9 m. To simulate the impact of additional densification, 65 additional (hypothetical) detached buildings were added as infill (+3% plan area), primarily on courtyards and currently open spaces (SC5). This scenario was again combined with additional trees (SC6), desealing of the remaining courtyard areas (SC7), and the combination of additional trees and desealing (SC8). Finally, two sensitivity scenarios were run. These assess the maximum potential impact on ecosystem services. In SC9, all surfaces, including major roads, are desealed, in SC10, all trees are removed. Each scenario (SC1-10) was run for 36,720 time steps covering all summers (May – September) from 2010 to 2019. From the output, the average exceedance hours per year for *moderate*, *strong*, *very strong* or *extreme* heat stress were extracted for each 1 x 1 m pixel.

Fig. 5 shows a map of the study area with the number of hours experiencing *strong* heat stress (UTCI > 32 °C) for the study area in its current form. Blue colors show areas with few hours of *strong* heat stress, located mainly on the northern side of buildings and underneath clusters of mature tree crowns. Orange and red delineate areas with more hours of *strong* heat stress, mostly found on unshaded South-facing walls, on large open areas, and along paved traffic infrastructure.

Fig. 6a shows a map of the difference in hours with *strong* heat stress between SC5 (additional densification with infill buildings) and SC1 (baseline). This difference estimates the impact of the densification on pedestrian-level outdoor heat stress. The densification increases the spatially averaged number of hours with *strong* heat stress only

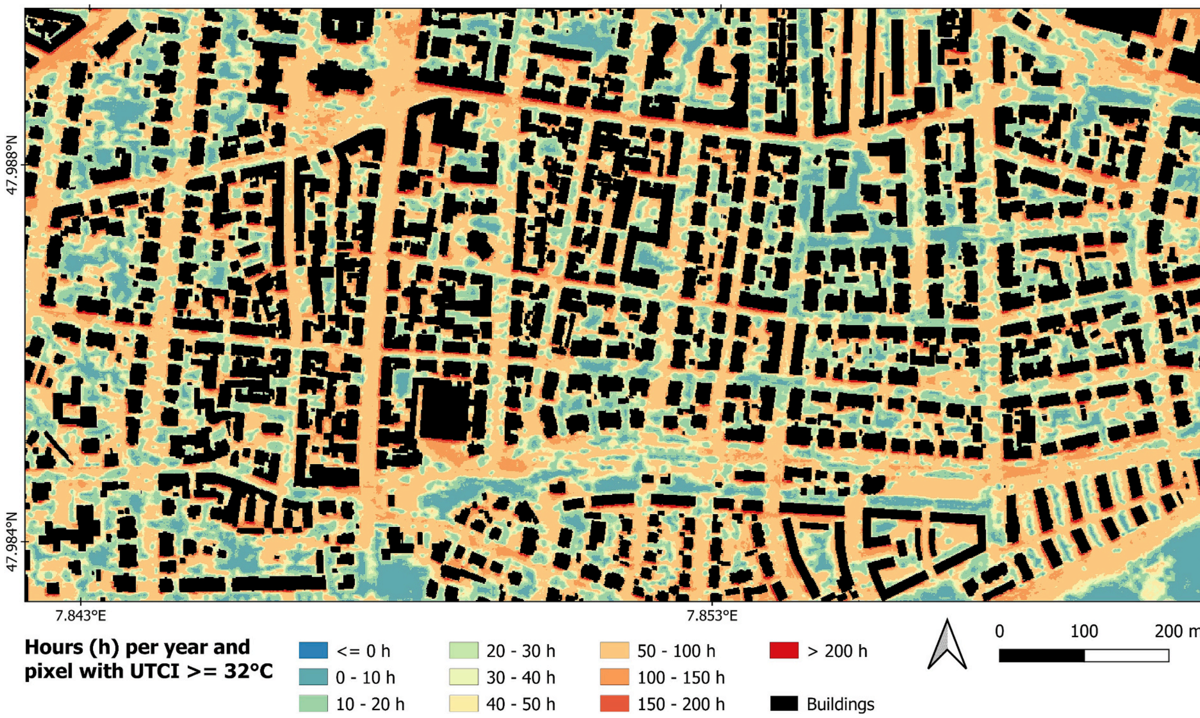

Fig. 5. AI-based modelling of heat stress in the baseline scenario 1. The map shows hours per year with strong heat stress (UTCI > 32 °C) calculated based on hourly weather data from the period 2010–2019.

minimally, from 53.1 to 54.1 h per year. The area that would experience at least 66 h of strong heat stress increases by 1.1 % due to the densification. Average air temperatures would not change significantly. However, minimum nocturnal air temperatures would increase by 0.5 °C. Overall, the impact of the re-densification on heat stress and air temperature is minor, with a pattern that in-filled buildings generally increase heat stress on their south side but decrease heat stress to the north, due to their shadows. Fig. 6b shows a map of the difference in hours with *strong* heat stress between SC6 (densification plus 5 % additional trees) and SC1 (baseline). Hence, this is an attempt to estimate the impact of additional densification while mitigating heat by tree planting at the same time. The 5 % additional trees have a significant effect, reducing the number of hours with *strong* heat stress from 54.1 to 45.1 h per year, the area affected by at least 66 h of extreme heat stress would be reduced by 32 %. Average air temperature would increase by 0.1 °C and minimum nocturnal air temperature by 0.4 °C. The impact of an additional 5 % trees on average air temperature is limited as the small number of trees only produce a marginal effect, mainly through shading.

Tab. 1 summarizes the same spatial statistics for all scenarios from SC1 to 10 for the entire study area. From the different AI-based simulations, several planning-relevant findings can be derived: For example, unsealing all inner courtyards has an impact that is about half as effective (−3.2 h / year or −6% reduction in *strong* heat stress) compared to adding 5 % mature trees (−8.8 h / year or −17 % reduction in *strong* heat stress). Combining the two will further cool the city, but it is not simply the addition of the two effects (−10.9 h / year, −21 %). However, it is also notable from Tab. 1 that planting trees causes an increase in night-time heat hours with UTCI > 20 °C by about 5 % and an increase of nocturnal air temperatures due to radiation trapping at night. This effect is rarely reported because, due to computing constraints, most assessments only consider and simulate daytime conditions. The effect of densification on 24-hour average air temperatures is negligible for all scenarios except the sensitivity SC10, removing all trees, which would cause an overall air temperature increase of 1 °C across the neighborhood. In other words, the current mature tree canopy in the neighborhood decreases heat stress hours by 46 % and cools the neighborhood by 1 °C, which highlights an imperative to maintain mature trees during and despite densification.

4.3. Optimizing adaptive planning interventions for urban heat hazard mitigation

In addition to AI-based modelling of current and future user-defined urban densification options, we also explored the potential of AI-based methods to automatically select greening options that optimize specific climate adaptation goals, e.g., reducing urban heat hazards. For example, urban planners may want to identify optimal placements for trees and buildings for any given densification scenario, in a way that minimizes avoids creating additional heat hot spots and minimizes any reduction or degradation of existing thermally comfortable outdoor space. The optimal placement depends on ground land cover (e.g., grass vs. paved) as well as on areas already areas by buildings or trees.

To explore the potential of such an optimization-based AI approach to reduce urban heat, we used two scenarios of additional trees to mitigate mean radiant temperature, a main determinant of daytime thermal discomfort, using an AI-based optimization (Schrodi et al., 2023). The output map of such an AI-generated tree-planting option is visualized in Fig. 7, which shows the location and impact of generated trees to most efficiently mitigate heat at the pedestrian level by adding of four trees/ha and ten trees/ha within a subset of the study area. Through optimal placement of trees, the mean radiant temperature can be reduced on daily average by 0.33 K and 0.66 K for four trees/ha and ten trees/ha, respectively (Fig. 7b,c). This relatively low decrease is due to the spatial averaging across the entire study area, as well as the averaging of the effects of the trees across the day. The nocturnal effects of the trees are rather an increase in T_{mrt} due to radiation trapping. Nevertheless, locally observed decrease in T_{mrt} is up to 8 K.

4.4. Examining real-world application potentials in urban planning and decision-making

To examine the potential applicability of enhanced heat risk

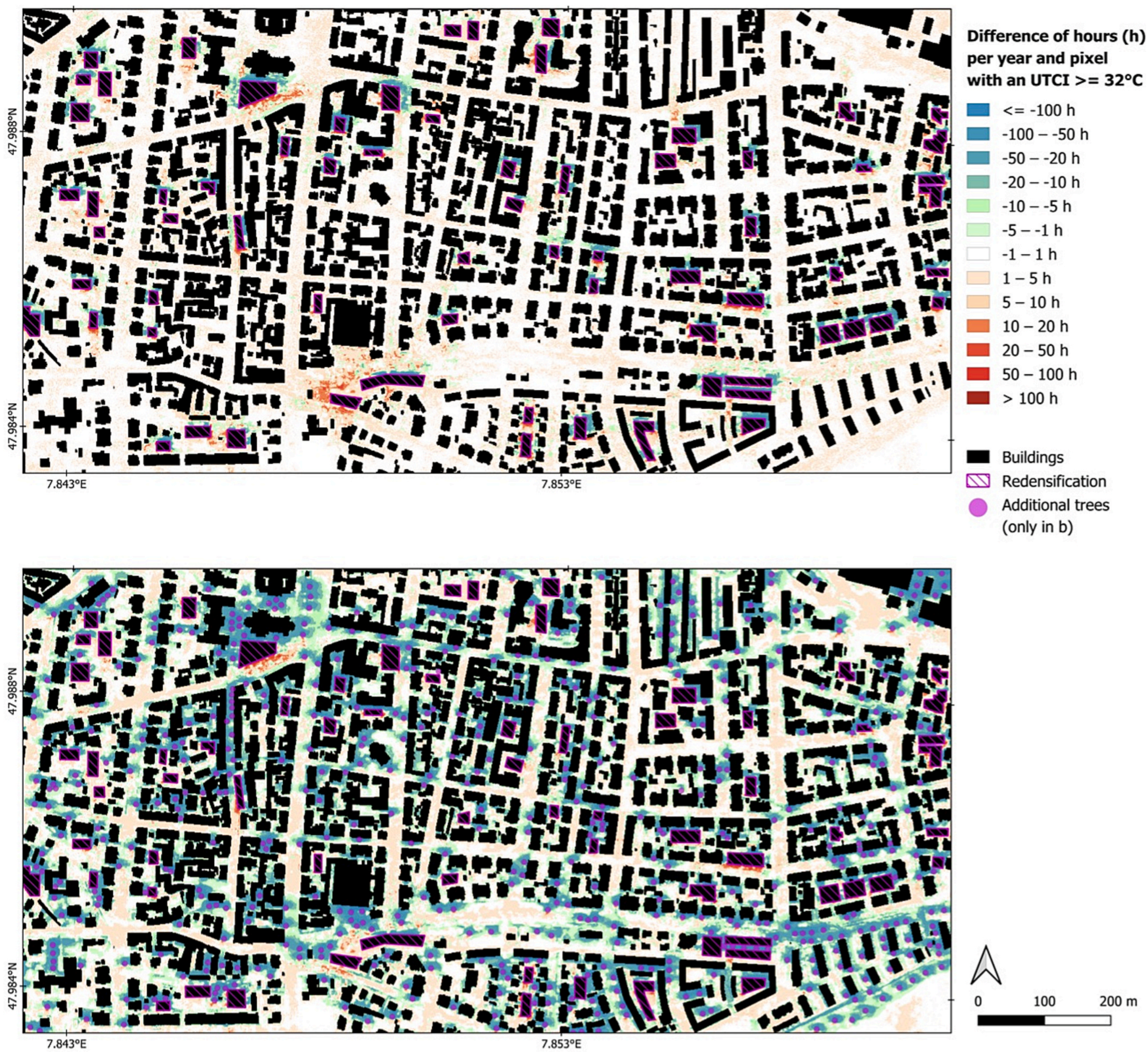

Fig. 6. Changes in heat stress due to (a) densification with 10 % more buildings (new buildings hashed) and (b) 10 % more buildings plus 5 % more mature trees and all backyards de-sealed in the study area. The maps show the differences in hours per year with strong heat stress (UTCI > 32 °C) between (a) scenario 4 and 1, and (b) scenario 8 and 1 for the period 2010–2019.

management using the AI-based models and tools discussed above, we worked with City of Freiburg officials in the Office of Environmental Protection, the Office of Urban Planning, the Surveying Office and the Digital and IT Office. We used qualitative and participatory methods to assess the real-world requirements of AI-supported climate change adaptation planning and decision-making. A participatory and scenario-based planning exercise was implemented in October 2023, where ten local government officials and seven researchers discussed key decision points in heat-related statutory land use planning and explored the potentials and implications of AI-supported models and their map-based outputs. The scenario-based planning exercise was set in the year 2030 (i.e. the near future) and assumed that the AI-based decision-support tools for reducing urban heat risks discussed above work without any technical flaws. The exercise centered on the map-based application using AI-based modelling of heat stress through densification (as highlighted in Fig. 5 and 6a,b) and on the automatic tree placement optimization tool (Fig. 7, see above). These two tools were used to identify key decision points for urban heat risk reduction in statutory urban land use planning and strategic climate change adaptation.

The simulated planning process highlighted the substantial potential of AI-supported methods for enhancing and expediting urban heat-related climate risk management at different planning stages, particularly during exploratory phases of developing binding land use plans. Key potential benefits identified were overall cost and time efficiencies, the ability to produce many variations for land use plans at limited expense, and the potential for using AI-supported maps as additional evidence base in the political process and in discussing adaptation options with the general public (Tab. 2). However, the evaluation of the exercise also highlighted that some decision-makers found the complexity of the AI-based tools difficult to understand, in particular regarding which aspects of the tools and the output maps generated

Table 1
Metrics of the different planning scenarios.

	Interventions			Daytime heat stress		Nocturnal heat stress		Other climate impacts			
Scenario (SC)	Additional buildings (%)	Additional unsealing (%)	Additional trees (%)	Number of exceedance hours > 32° UTCI per year (mean per pixel)	Fraction of area with exceed-ances > 32° UTCI (at least 66 h)[2] (%)	Number of exceedance hours > 20 °C UTCI per year (mean per pixel)	Fraction of area with exceed-ances > 20 °C UTCI (at least 108 h)[3] (%)	Mean air temperature (°C all pixels)[3]	Mean maximum air temperature (°C, all pixels)[4]	Mean minimum air temperature (°C, all pixels)[5]	Mean relative humidity (all pixels)[3]
1	–	–	0	53.1	33.4	100.2	33.2	16.2	21.0	5.7	78.3
2	–	–	+5%	44.3	23.0	104.8	36.6	16.2	21.0	5.6	78.4
3	–	+100 %	0	49.9	29.9	97.7	31.5	16.2	21.0	5.0	78.8
4	–	+100 %	+5%	42.2	20.4	102.2	34.3	16.2	21.0	4.9	78.8
5	+10 %	–	0	54.4	34.5	104.7	37.5	16.3	21.0	6.2	78.1
6	+10 %	–	+5%	45.1	23.4	109.6	41.0	16.3	21.1	6.1	78.1
7	+10 %	+100 %	0	51.3	31.2	102.0	35.9	16.2	21.0	5.5	78.6
8	+10 %	+100 %	+5%	42.9	20.9	106.8	39.0	16.2	21.0	5.5	78.6
9	–	All surfaces unsealed	–	45.9	22.4	94.9	29.7	16.1	21.0	4.2	79.4
10	–	–	All trees removed	98.4	86.3	82.0	22.1	16.3	21.1		77.6

[2]The 67. Percentile of the UTCI > 32 °C distribution of the status-quo is used a threshold.
[3]The 67. Percentile of the UTCI > 20 °C distribution of the status-quo is used a threshold.
[4] Mean values are weighted SUEWS 500 x 500 m tiles based on proportion within Study Area (redensificated area).
[5] Mean values are weighted SUEWS 500 x 500 m tiles based on proportion within Study Area (redensificated area).

were based on AI. The planners involved in the exercise also voiced concerns regarding AI-based tools potentially limiting creative freedoms necessary for achieving high-quality urban planning outcomes amidst unclear legal liabilities for AI-based planning decisions. In addition, multiple practical challenges were identified, such as aligning AI-supported and scenario-based modelling with a diverse array of planning time frames and the need to keep physical building and climate and weather-related data up to date on an at least annual basis.

5. Discussion

Using AI-supported approaches for analyzing and optimizing land use and adaptation planning promises tangible improvement for addressing urban outdoor heat risks in cities. However, at present, AI-supported approaches and workflows require establishing preliminary pieces of data collection and training work, while also addressing data availability, technical as well as legal and ethical challenges that are likely to emerge during the process. In the following, we discuss the potentials and possible challenges of integrating AI-supported approaches and methods into real-world urban planning and adaptation processes.

5.1. 3D data availability and requirements

As our case study showed, data acquisition to generate 3D semantic models that serve as a basis for effective and useful AI-based modelling is a crucial step upon which all subsequent urban heat hazard and heat stress analyses are built. Even in data-rich environments such as in the City of Freiburg, data acquisition can be a challenge and remains constrained by cost and broader feasibility constraints: 3D data collection can be carried out by mounting sensor platforms to different vehicles such as cars, drones, or airplanes, but each of these data collection methods comes with different strength and weaknesses. In our example, a car mounted sensor was able to collect very accurate and dense data at limited cost, but the collection process was still cumbersome and some parts of the urban morphology (e.g., gardens, roof tops) could not be fully observed. LiDAR + RGB-based measurements collected via airplanes, which are relatively expensive, are typically more affected by a low signal-to-noise ratio that renders data less reliable. Therefore, decisions regarding the approach(es) to data collection will need to be guided by weighing up costs, legal and regulatory constraints (see below) and specific data requirements. In the case of semantic segmentation, the performance of the neural network is directly linked to the amount and suitability of training data and therefore highly susceptible to training data limitations. In our study, different methods for reducing the required training data were explored. One promising direction is using Active Learning, where a neural network is trained with a very small base of labelled examples. The network then queries a human for more labels on those samples it is most uncertain about. This allows improving network performance while not requiring a complete annotation of the data. In the future, fusing aerial and car-based data collection methods can help further automatize creating homogeneous 3D data baselines where all relevant signals are best represented.

5.2. Limitations of the UTCI AI model

Despite the positive trade-off between accuracy and computational cost, there are limitations to the AI-based UTCI model framework for simulating pedestrian-level outdoor heat stress. While the numerical models SUEWS (T_a/RH) and SOLWEIG (T_{mrt}) incorporate time lag effects, the emulators do not consider previous time step states. Although the emulator predictors are set to incorporate this by applying lag effects (e.g. T_a of previous time steps), time-dependent processes such as the gradual heating of buildings may not be fully represented.

Although the AI-based model framework was carefully tested against a wide variety of urban environments, caution should be taken when applying it to other cities or climates. The model can only capture urban environments and climates that have the same building and vegetation morphologies, and the same meteorological data, as those covered by the training data. Therefore, this model should only be transferred to similar climates and cities.

Also, the AI-based model framework uses mean values for each spatial area (i.e., tile), irrespective of the area's diverse use types. For example, a sealed area in a private courtyard used as a parking lot is

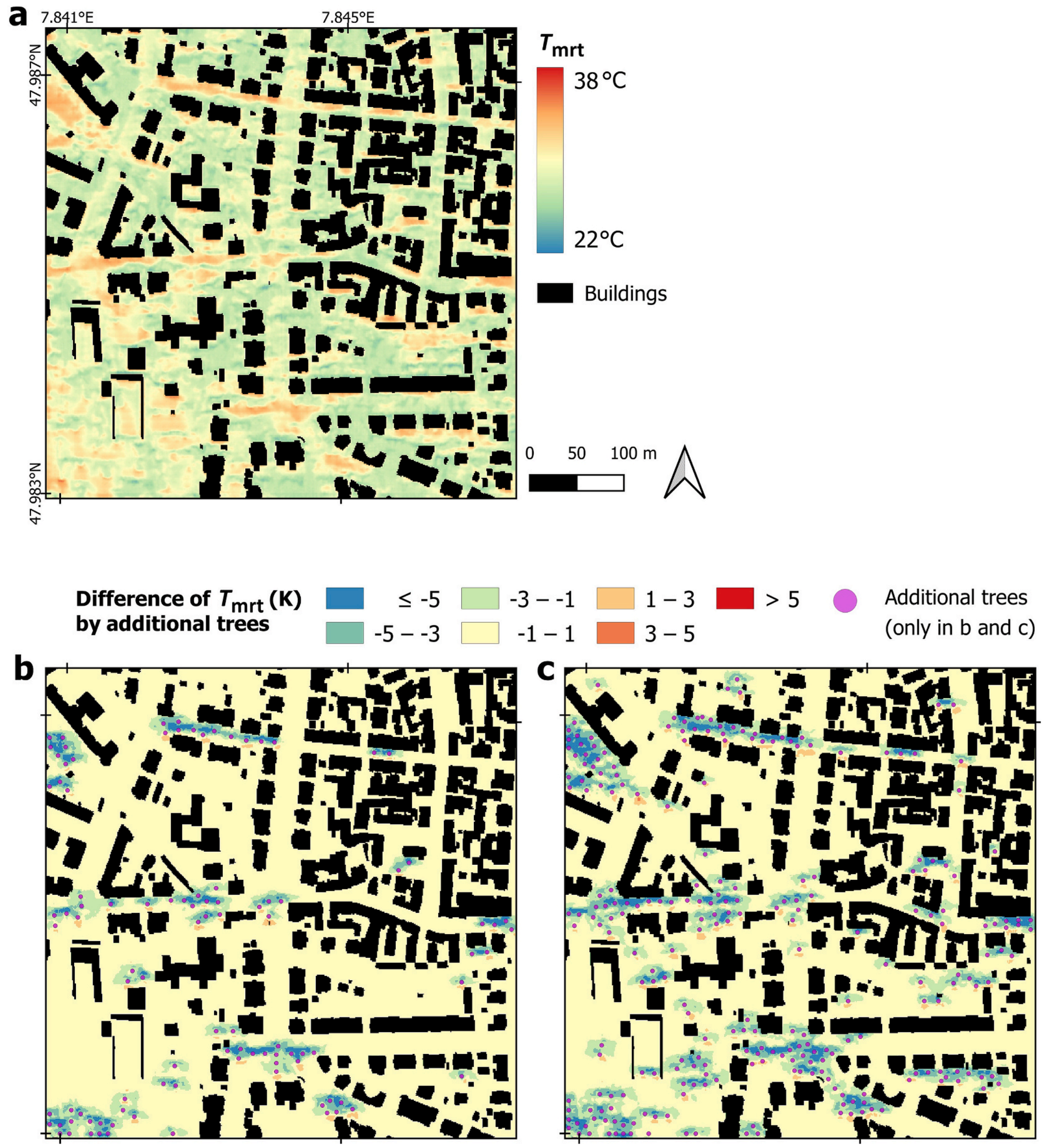

Fig. 7. AI-based tree planting in the Wiehre area with 4 and 10 additional trees/ha (b,c). The study area has an extent of 500 x 500 m.

weighted equally in the model as a busy footpath on the roadside outside a string of local shops. Also, the model cannot distinguish between different user groups, e.g., whether or not a public sealed area is used by people particularly vulnerable to heat, e.g., a footpath outside a nursing home or a kindergarten.

5.3. *Enhanced performance and efficiency gains through AI support*

As infill urban developments in existing neighborhoods occur incrementally, detailed and highly context-sensitive heat risk analyses are necessary. One of the key benefits of AI-based models vis-à-vis physical models is that, once the modelling data has been obtained and the model has been set up, many different planning scenarios can be calculated for a local urban precinct at low cost and in reasonable time: such models do not rely on high-performance computing capabilities, and once a suitable user interface has been generated, they can be run using a few mouse clicks. In addition to 'testing' different planning scenarios (i.e., where exactly a new building or a tree of a specific shape and height could be placed), the AI-based model can also simulate seasonally changing conditions across large time frames, as the models can be run for specific days of the year, for the near or the far future. Therefore, one of the key benefits of AI-supported heat risk analyses is the ability to process very large quantities of data in a near real-time fashion. The outputs of such model runs can be produced as maps, which can then serve as a basis for goal-orientated planning discussions (including participatory deliberation). Such decision-making could take technical and qualitative aspects into account that are currently not included in the model, such as underground infrastructure, aesthetics, and intended beneficiary groups.

Nevertheless, it should be noted that AI-based models are developed and tested for specific and targeted applications and are not generally valid, as physics-based models are. This means, while current AI-based models are valuable tools for assessing heat risks in specific environments, they cannot reproduce the full complexity of physical-numerical urban climate models.

5.4. *Legal and ethical implications for AI-supported urban heat adaptation*

At present, AI systems merely serve as decision-support tools, to provide input into decision-making. However, there is potential for (generative) AI systems to independently suggest optimization decisions

Table 2
Opportunities and challenges of using AI-supported methods in statutory land use planning and climate change adaptation, as identified by participants in a scenario-based simulation exercise, 19 October 2023.

AI-supported methods in urban heat-related planning and adaptation: Opportunities	Challenges
Cost and resources savings (when compared to using physical models)	High initial and maintenance costs (e.g., for maintaining data quality and currency)
Increased time efficiencies	Lack of transparency and plausibility of AI-based modelling results
Optimizing urban land use planning from the outset	Focus on quantitative assessments potentially sidelines qualitative aspects
Enhanced evidence base for data-driven deliberation and decision-making	Unclear legal liabilities for AI-based urban planning and decision-making
Developing a broad range of planning options, leading to more open-minded planning	Too many planning options may become politically instrumentalized, making it difficult to reach consensus
Supporting the increased need to develop multi-functional urban spaces	Understanding the limitations of AI-supported tools and communicating these appropriately to stakeholders
Fostering sensitization and awareness raising for urban heat issues across departments/offices	

Table 3
Guidelines for structurally embedding AI-supported decision-support. The bullet points represent key findings from a best practice review summarizing current state of the art with regard to including AI-supported processes in municipal climate adaptation and land use planning. Key sources are: Berryhill et al. 2019; Engstrom et al. 2020; Hein and Volkenandt 2020; Wulf and Egli 2021, Campion et al. 2022.

Planning	Implementation	Governance
• Determining specific requirements (data, decision-making needs,…) · Identifying specific tasks and administering • associated processes • Identifying beneficial and limiting aspects • Comparing goals vs. feasibility and constraints • Appraising legal framework conditions • Garnering support from upper management • Identifying suitable actors, e.g., 'champions', relevant departments etc.	• Developing AI strategy papers to determine the appropriate and intended use of AI-based tools • Ensuring appropriate technical infrastructure • Piloting (e.g., experiments, learning processes) • Establishing a multidisciplinary team with clearly defined responsibilities • Promoting AI acceptance through information campaigns (citizens) • Offering training courses (staff) • Inter-municipal cooperation	• Establishing a supervisory/control body for monitoring and evaluation of AI-supported processes • Regular, comprehensive testing for quality control • Updating / further development of data sources and methods • Institutionalized training and development options

in the future, which can then significantly influence planning decisions, e.g., by visualizing options and thus making them much more tangible and more easily accessible to decision-makers and the wider public alike (see Cugurullo and Xu 2025). As a basis for decision-making, AI-based predictions are typically incorporated into informal planning instruments such as city concepts and strategies, which in turn prepare decisions within the framework of formal legal instruments (development plans and land use plans). Regardless of the specific legal integration of AI-based predictions in procedures and decisions, there are legal challenges, such as (1) uncertainties resulting from limited technical possibilities or limited knowledge; (2) challenges under certain data protection laws of safeguarding personal rights and data protection when recording local data as part of semantic models; (3) risks of discrimination in the selection of modelling and training areas, which may exacerbate urban inequalities; and (4) ethical challenges of transparency, as AI-based methods as the precise 'intelligence' of AI is grounded in neuronal networks' machine and deep learning processes that are practically incomprehensible. On the other hand, AI-based methods are highly efficient and therefore allow for in-depth analyses down to the level of streets and individual buildings. As such, their potential for in-depth analysis of existing and potential future urban form and its heat risks can also support evidence-based urban planning and decision-making, e.g., by treating politically contested objects of the urban form (such as buildings with historical meanings, street trees of particular local significance, or sealed car parking areas) in the same way as less controversial ones. This in turn can support more nuanced deliberation on different options for urban redevelopment and improve the legitimacy of planning decisions.

5.5. *Enhancing adaptive capacities in municipalities using AI-supported approaches*

A range of measures can be taken to implement AI-supported decisions in local governments (Tab. 3). There are low-threshold opportunities for using AI-based tools effectively, e.g., for gaining an overview of different planning scenarios and for identifying the range of technically or politically feasible land use and adaptation planning options, or to elaborate the most cost-effective options and thus save limited public funds. Such 'decision options tests' can be conducted in-house or awarded to external contractors; also incremental in-fill developments can be assessed for their heat-related implications, e.g., by running AI-based simulations for individual construction permits.

Shifts in predictive technology can produce efficiency gains with potentially transformative effects in municipal administrations and the local governance of urban heat. Using AI-based methods, larger municipalities may soon be able to run parts of the simulations of the heat impacts of buildings and other urban infrastructure in-house (i.e., in municipal planning offices). In that case, however, urban planning departments will need to substantially upskill their planners to develop the skills to effectively and appropriately use AI-support decision support tools. Far from relinquishing 'control' to AI (a commonly held fear also expressed in our participatory research with the City of Freiburg), municipal planners who are trained to use tools supported by AI may be able to effectively steer a larger proportion – or perhaps the entire – process of generating evidence bases for planning in-house, to expedite planning processes on the whole while maintaining total quality oversight. Ultimately, using AI-supported simulation and prediction methods is likely to result in a need for more technically skilled planning personnel or a shift towards an institutionalized interface between urban planning departments and urban digital data hubs, where AI-based modelling and prediction tools can be housed and maintained. With regard to political decision-making, elected councilors will need to be trained in understanding the basic challenges and pitfalls of AI-based methods – yet this may add additional demands on already heavily burdened lay decision-makers.

6. Conclusions

AI-supported, locally contextualized and highly specific forecasts of urban heat discussed here directly support the New Urban Agenda's and other international policy frameworks' calls for ramping up the use of 'smart' digital technologies for improving evidence-based decision-making with methods and approaches that are both ubiquitously applicable and affordable. As we were able to demonstrate, AI-based modelling and prediction methods have the potential to radically transform urban planning and decision-making in climate change adaptation. More efficient and finer-grained climate modelling using statistical-numerical processes can reduce the costs of establishing the evidence base for heat-resilient urban development and help select or pre-select the most effective options for mitigating heat. As shown in our case study of the City of Freiburg, the need for expensive and time-consuming heat exposure and sensitivity analyses can be reduced by drawing on AI-supported methods, in particular AI-trained 3D semantic models and deep learning UTCI models. The possibilities of calculating heat-related effects of urban greening and densification under different climate change projections are promising here because this facilitates cost-effective and rapid assessment of how urban greening and densification interventions will perform under different climate futures.

In addition, generative high-resolution AI can assist in virtual experiments at early stages of planning processes, e.g., at the precinct scale, when new green infrastructure options are being considered. For example, if a brownfield is to be redeveloped, high-resolution and scenario-based AI modelling can rapidly produce spatially explicit representations of future buildings, sealed surfaces, and green and blue infrastructure (e.g., the location of trees and water fountains) and their respective positive or negative impacts on urban heat. Moreover, high-resolution modelling can also assist in the assessment of the ecosystem functions and value of existing green infrastructure. For instance, AI-supported modelling can highlight the value of preserving and maintaining mature trees in urban cooling: the mature tree canopy in our study area reduces annual heat stress hours by half, cooling the neighborhood by an average of 1 °C.

When it comes to implementing AI-supported urban land use and adaptation to mitigate heat, there are still many challenges issues to be resolved, in particular in relation to the development of appropriate technical interfaces that can be integrated with existing geodata portals and digital models; the skillset required by urban planners; and the governance and quality assurance of AI-supported planning, including legal and ethical ramifications. However, with the rapid advances in machine learning, deep learning, and generative AI, technological capabilities are likely to become rapidly available for everyday planning situations. These technologies can expedite urban planning processes while making them more affordable – once specific preliminary requirements regarding data, IT infrastructure as well as ethical and governance challenges have been addressed.

CRediT authorship contribution statement

Hartmut Fünfgeld: Writing – review & editing, Writing – original draft, Supervision, Project administration, Conceptualization. **Andreas Christen:** Writing – review & editing, Writing – original draft, Supervision, Project administration, Methodology, Conceptualization. **Ferdinand Briegel:** Writing – original draft, Visualization, Methodology, Formal analysis, Data curation. **Simon Schrodi:** Writing – original draft, Visualization, Methodology, Formal analysis, Data curation. **Alexandra Speidel:** Writing – original draft, Methodology, Investigation. **Christiane Felder:** Writing – review & editing, Project administration. **Jasper Hoffmann:** Writing – original draft, Visualization, Methodology, Formal analysis, Data curation. **Lina Irscheid:** Writing – original draft, Methodology, Investigation, Formal analysis. **Dominik Merkle:** Writing – original draft, Methodology, Investigation, Formal analysis. **Johannes Meyer:** Writing – original draft, Visualization, Formal analysis, Data curation. **Dirk Schindler:** Writing – original draft, Supervision, Methodology, Formal analysis, Conceptualization. **Jonas Wehrle:** Writing – original draft, Visualization, Formal analysis, Data curation. **Cathrin Zengerling:** Writing – review & editing, Supervision, Project administration, Methodology, Investigation.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix

Appendix A. 1 – technical description of the AI-based urban form segmentation and annotation

For our study area, data collected in a recent ground-based LiDAR survey of the City of Freiburg using a car-based mobile mapping platform was available. Before its use in heat hazard models, the dataset required substantial processing. The ground-based LiDAR dataset contained GPS coordinates, with the intensity of return points in space being complemented by visual 360-degree images. The ground-based data for the entire City of Freiburg contained 31.040 point cloud tiles with a spatial dimension of 50 x 50 m each. Manual semantic segmentation of ground-based LiDAR data would be very labor- and cost-intensive, and therefore, not economical for urban neighborhoods or complete cities. For example, manually annotating all data in Freiburg would take 760 days, with a person working 24 h/day. Although 3D neural networks for segmentation tasks exist (Thomas et al. 2019), the main labor-intensive part is the training and optimization for a defined number of object classes.

As part of the I4C project, an AI-based segmentation method was developed to identify objects within the LIDAR point cloud data with the following categories: buildings (walls, roofs), sealed surfaces, vegetated surfaces, leaf trees, needle trees, bushes, hedges, other vegetation, and dynamic objects (e.g., cars, bicycles, garbage bins). With the segmentation, relevant objects such as buildings, hedges, or trees are used as inputs in the heat risk model, while mobile and unresolved objects, such as cars, power lines, or street lights, are discarded. Therefore, we developed, implemented, and tested an AI-based neural network approach for automated 3D data segmentation of urban form data. As part of this work, a subset of data outside the study area was manually labelled by human annotators into the above categories to serve as training data using the software CloudCompare (Girardeau-Montaut). The annotation of a 50 x 50 m tile typically took 3 to 8 h. The process was repeated for 17 training tiles covering typical urban forms. A semantic segmentation network (KPConv, Thomas et al. 2019) was trained on labelled data. The training of the network took about 24–36 h. The network was then applied to all LiDAR data within the study area, providing an annotated dataset of buildings and different vegetation types, as illustrated in Fig. 4.

Appendix A. 2 – technical description of the AI-based model chain to map spatial heat stress

This study used the AI-based model framework presented by Ronneberger et al. (2015), Briegel et al. (2024, 2023), Wehrle et al. (2024), where all details on model development and evaluation can be found. The proposed framework by Briegel et al. (2024) introduced a novel and computationally efficient machine learning framework for modeling outdoor human thermal comfort at a fine spatial resolution of 1 × 1 m in complex urban environments. This approach, referred to as the Human

Thermal Comfort Neural Network (HTC-NN), enables high-resolution prediction of outdoor thermal comfort by downscaling numerical weather prediction or reanalysis data, while explicitly accounting for urban geometry and functional characteristics. The HTC-NN is composed of four submodels and all submodels were developed, trained, and tested by using state-of-the-art numerical-physical urban climate models:

(i) A building-resolved U-Net (Ronneberger et al. 2015) is used for modeling mean radiant temperature (T_{mrt}) by emulating the numerical model SOLWEIG (Lindberg, Holmer, and Thorsson 2008). Details on the emulator can be found in Briegel et al. (2023).

(ii) Two neighborhood-scale multilayer perceptrons (MLPs) are used for predicting air temperature (T_{a}) and relative humidity (RH) based on the numerical urban climate model SUEWS (Järvi, Grimmond, and Christen 2011; Ward et al. 2016). Details on the emulator can be found in Briegel et al. (2024);

(iii) A building-resolved statistical wind field emulator based on random forest (RF) regression trained on large-eddy simulations (LESs – Albertson & Parlange, 1999a,b). Details on the emulator can be found in Briegel et al. (2024) and Wehrle et al. (2024).

The U-Net emulates the SOLWEIG model to predict T_{mrt} at 1.1 m a.g.l. with 1 × 1 m resolution. The MLPs emulate the surface energy balance model SUEWS at a 500 × 500 m scale to estimate T_{a} and RH at 2.0 m above ground level (a.g.l.). The wind fields, resolved at 10 m a.g.l. and 1 × 1 m resolution within the urban canopy layer, are derived from x ,y, and z wind components, using RF models trained on LES output for four cardinal wind directions. This integrated framework enables rapid, high-resolution assessments of human thermal comfort in urban areas with limited computational overhead, making it suitable for operational use or climate adaptation planning.

Each submodel in the model chain was evaluated independently using simulation data from its parent numerical model that had not previously been used, as well as measurement data from a dense urban sensor network in Freiburg that recorded all the variables required to calculate UTCI (Briegel et al., 2024, 2023; Wehrle et al., 2024). The sensor network is organized into two categories: Tier-I (biometeorological) stations and tier-II stations, comprising 7 and 30 stations, respectively (Feigel et al., 2025; Plein et al., 2025). Tier-I stations provide comprehensive meteorological and biometeorological observations, including T_{a}, RH, wind speed, and black-globe temperature, which allows the calculation of T_{mrt} (Feigel et al., 2025). In contrast, the Tier-II stations offer a more limited set of measurements, recording only T_{a} and RH (Plein et al., 2025). The final UTCI results were additionally tested against UTCI measurements from the Tier-I stations in the sensor network (Briegel et al., 2024; Plein et al., 2025). A detailed table for each of the four variables as well as for UTCI can be found in Table 4 of Briegel et al. (2024). The MLPs can predict T_{a} and RH with a level of accuracy comparable to that of the SUEWS model. Both achieve a Root Mean Square Error (RMSE) of around 1.5 K and 8 %, respectively. The U-Net model for T_{mrt} closely matches SOLWEIG, achieving RMSEs of 6.18 and 5.86 K, respectively. Despite the lower R^2 values, wind speed predictions from the RF model significantly reduce the RMSE compared to the forcing data. Overall, the HTC-NN accurately estimates UTCI (RMSE ∼ 3 K, $R^2 = 0.92$), performing similarly to SOLWEIG but lower computational costs (e.g. U-Net is 130 times faster than SOLWEIG).

The hourly spatial UTCI output data of the model chain over ten years is much too large to be stored in files. Therefore, in the model, all data were aggregated into 1 °C bins for UTCI from which for each pixel, the number of hours per year could be calculated which experience moderate (UTCI > 26 °C), strong (UTCI > 32 °C), very strong (UTCI > 38 °C) and extreme (UTCI > 46 °C) heat stress. In addition, the number of hours was aggregated separately in the model and output for day and night (based on actual sunrise and sunset times). Data were then transferred to a Geographic Information System (QGIS Development Team 2024) where data were mapped and analyzed spatially and separately for each scenario.

Appendix A. 3 – technical description of the AI-based tree placement optimization tool

We summarize our approach below and refer interested readers to (Schrodi et al., 2023). The goal of the optimization tool is to automatically find the best tree planting sites for a given number of trees and a given time period, e.g., a week, month, year, or decade. We based our optimization tool on the mean radiant temperature (T_{mrt}) modelling approach of (Schrodi et al., 2023); refer to Appendix A2 for details. However, while estimation of T_{mrt} is faster than for physical models, we still found them too slow for our optimization tool. Note that we want to automatically plant trees so that they reduce T_{mrt} for a time period. That is, we want to reduce the overall T_{mrt} for that time period. To obtain this aggregated result, we need to estimate T_{mrt} for all timesteps of that time period and finally aggregate (e.g., average) it. However, this is computationally very costly. Thus, we learn a *meta*-network that directly predicts the average T_{mrt} of that time period in a single step. This effectively reduces the computational cost of the estimation of the average T_{mrt} by a factor that scales with the number of timesteps of that time period (Schrodi et al., 2023).

Having a fast approximation of average T_{mrt} for a time period at our hands, we use a classical iterated local search approach (Lourenço, Martin, and Stützle 2003) for our optimization. Specifically, we initialize the optimization based on a greedy heuristic and iteratively (1) perturb the current best tree planting sites with a genetic algorithm and (2) refine the best candidate from the previous perturbation by a hill climbing algorithm. For the greedy heuristic, we place the trees at the sites, in which each individual tree yields the largest reduction in Tmrt. For the perturbation, we used a genetic algorithm that applies random mutations and single-point crossovers to the current best tree site configurations, interleaved with few random tree site configurations. Subsequently, we refine the best-found tree site configurations with a classical hill climbing algorithm.

Data availability

Data will be made available on request.

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