A Revisit of the Fifteen-minute City Model

Exploring the trade-off between urban accessibility and thermal environment using interpretable machine learning

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Global warming continues to threaten urban residents, and trends have intensified in recent years. The Fifteen Minute City (FMC) framework has been recognised as an important solution to the urban environmental challenge and has met the needs of residents. However, recent studies have found that FMC can negatively impact the thermal environment in cities and may disrupt constructed systems. The value of FMC has been widely debated in recent years, and consensus has not been reached due to the influence of binary assessments in the past. Therefore, to further explore the relationship between FMC and the urban thermal environment, this study introduces an interpretable machine learning approach to quantitatively investigate the relationship between FMC scores and Land Surface Temperature (LST) in Greater London. The study uses the XGBoost model and the SHAP tool to build analyses for LST and accessibility indicators based on a 500 m grid (n = 5567). The training results explained 76% of the LST phenomena. The results show that overall accessibility and distance to services are non-linearly related to LST. High accessibility may lead to a higher industrial density and a more compact urban layout, thus worsening the thermal environment. In the FMC framework, a reasonable distance (500-1000m) for residents to reach services can achieve a trade-off with the thermal environment. This study revisits the FMC framework from new techniques and perspectives to provide further theoretical support rather than rejecting it. The FMC framework shows strong potential in urban environmental and social service issues and can be further enhanced in the future.

Keywords: *15-Minute City, Accessibility, Urban thermal environment, Interpretable machine learning, Trade-off.*

INTRODUCTION

Global warming has shown an intensifying trend in recent years, and it poses a significant threat to public health (Lenton et al., 2023). Research warns that the current trend of temperature increase is already failing to meet the target set at the 2015 Paris Climate Conference to limit the increase to less than 1.5°C (Polya, 2023). The most obvious consequence of global warming is that it raises temperatures in cities and strengthens the intensity of Urban Heat Islands (UHI), exposing residents to more frequent overheating (Nazarian et al., 2022). Globally, almost 55% of the population lives in cities, and this ratio is expected to reach 68% by 2050 (Liu et al., 2021). Mitigating urban overheating and reducing residents' heat exposure is urgent and has been widely discussed in recent years. The relatively typical study discusses the significant impact of Land Use and Land Cover (LULC) on the existing thermal environment in cities (Karakuş, 2019). Studies have concluded that chaotic urban planning is an important factor that potentially exacerbates urban overheating and that industries, businesses, and residences in cities contribute to the thermal environment (Kardinal Jusuf et al., 2007; Xu et al., 2024). Therefore, developing land use strategies in cities becomes an important way to optimise the thermal environment.

As an emerging urban planning framework, the 15-minute city (FMC) suggests that residents can fulfil their physical, safety and social needs within 15 minutes by walking or cycling (Moreno et al., 2021). The FMC concept has become widely discussed after the COVID-19 pandemic, where it was seen as a solution to reduce traffic congestion and improve environmental quality (Nieuwenhuijsen, 2020). Recent studies discuss the contribution of FMC in dealing with urban thermal environment problems (Shartova et al., 2024). One of the most important aspects is the discussion of the threat of environmental overheating to residents, with the central aim of reducing their heat exposure (Hu et al., 2019). Heat exposure of residents generally involves two core factors: exposure duration and background temperature (Sadeghi et al., 2021). Therefore, when the study discusses whether FMC can solve the overheating problem, the total heat exposure of residents can be recognised as an important evaluation indicator. Firstly, as a positive aspect, the FMC framework relatively reduces the time people spend outdoors, thus reducing overheating exposure. However, the comparison is based on scenarios with the same background temperature. Shartova's study found that urban areas that met the FMC criteria tended to accumulate more heat than those that did not. Despite the benefits of FMC, residents living in urban centres suffer more heat than those living in rural areas. On the other hand, FMCs are potentially encouraging increased urban compactness (Di Marino et al., 2023). Compact urban layouts were also promoted following the COVID-19 pandemic (Ninivaggi and Cutrini, 2025). Past studies have demonstrated that a compact and concentrated urban form has an enhanced effect on heat concentration, i.e. the formation of an urban heat island effect (UHI) (Li et al., 2020). Several studies have suggested that FMC creates a multiple city centre layout that can relatively avoid the heat concentration problem (Han et al., 2022). However, Guzman criticised that FMC is not of equal quality and the urban layout still tends to prefer single centres (Guzman et al., 2024). Furthermore, studies worry that multi-centric urban layouts expand the extent of regional heat accumulation (Yang et al., 2016). Overexploitation of FMC standards also risks destroying existing green infrastructure and enhancing UHI instead (Chen and He, 2024). It is worth emphasising that the study is not a comprehensive denial of the contribution of FMC to optimising urban environments; instead, the FMC framework has the potential to solve the UHI problem. The different ideas, methods and technologies in the world nowadays are in a state of confluence and collision. When multidisciplinary convergence and innovative approaches are driven, FMC, as a typical urban planning theory, should be revisited rather than based on a binary division.

This study aims to revisit the 15-minute city framework using advanced machine learning techniques and discuss whether it benefits the thermal environment. Therefore, a hypothesis is proposed that the FMC framework is not an absolute binary (benefit or detriment) to the urban thermal environment, but instead that FMC and the urban thermal environment are a non-linear relationship with trade-offs where designers can find the best strategies. The study chose the Greater London area of the UK for the study and acquired the necessary data.

DATA AND METHODS

Data

For the urban temperature data, this study uses global sequential surface temperature data recorded from satellites, which has also been commonly used in past studies. Remote sensing satellites convert received electromagnetic digits into spectral radiance and can detect any electromagnetic energy emitted above absolute zero (K) (Ziaul and Pal, 2018). The LST dataset is a series of images taken by the United States Geological Survey (USGS) every 15 days for each global region using the Landsat8 Earth-orbiting surround satellite. The study acquired Landsat8 data from Google Earth Engine (GEE), which can have a 30m spatial resolution (Ermida et al., 2020).

For the FMC maps, the study used data provided by City Access Map (CAM) (Nicoletti et al., 2023). The FMC data were computed from two key data sources: first, urban pedestrian infrastructure and Point-Of-Interest (POI) data were obtained from Open-Street-Map. The CAM summarises fifty types of POIs into seven categories, including Mobility, Active Living, Entertainment and Nightlife, Food Choices, Community Space, Education, and Health. The study created homogeneous (100m × 100m) grids and calculated the closest distance from the grid centroid to each service. The second step was to obtain the population density from the Global Human Settlements Layer (GHSL) 2020 published by the European Commission. CAM measures the accessibility of each type of service facility at the neighbourhood level by walking time and assigns human density as a weight to the grid. The final FMC map is a 100m x 100m grid that contains the closest distance (m) to 7 types of services and an overall accessibility score.

Past studies have noted that physical form in cities can significantly impact microclimate (Yin et al., 2018). The Local Climate Zone (LCZ) framework proposed by Demuzere (Demuzere et al., 2019) was chosen for the study. The LCZ is an approach for describing the local microclimate, replacing the long-term climatic context at the global scale (generally the whole city or region) (Aslam and Rana, 2022). The LCZ framework is based on the urban form (height, density), Sky View Factor (SVF), and surface cover (permeable and impervious) at a 100 m resolution. The LCZ is divided into 17 standard categories, 10 of which are building clusters categories, and 7 are vegetation categories. Figure 1 shows the distribution of LCZs. In the study area, LCZ6 (Open low-rise) is the dominant LCZ type (43.14%), in which the building form is commonly residential buildings of no more than three storeys with an open sky view (SVF=0.6-0.9). High-rise LCZ1s and LCZ2s (building heights >25m) are found in the city centre, but the total number of LCZs is lower (3.18%). The LCZ maps provided by Demuzere do not show any LCZ7s (Lightweight low-rise) or LCZCs (Bush, scrub) in the Greater London area (Figure 1).

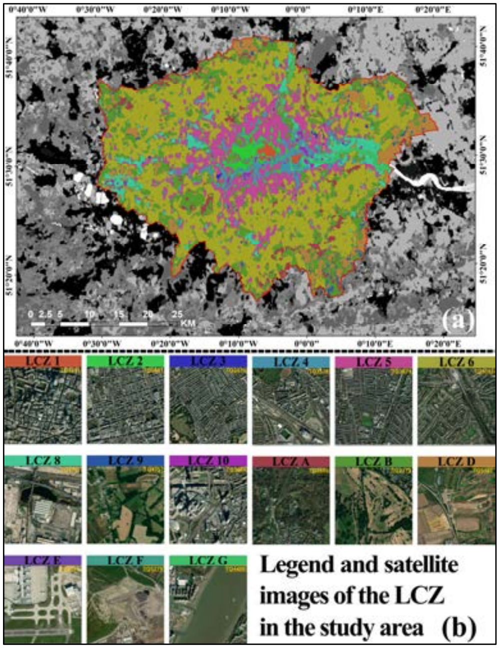

Figure 1
(a) Map of LCZ distribution in the study area, (b) legend and satellite images of each typical LCZ in the study area.

Methods

Figure 2 shows the workflow of the study, which is organised into three main steps.

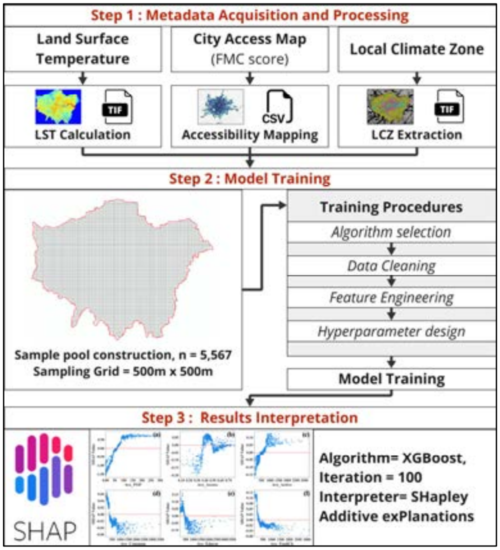

Figure 2
The workflow of the study

Step 1: Data acquisition and processing

The first step of the study had three data sets to be processed: surface temperature, city accessibility score map (FMC score), and LCZ map. For LST, past research has provided a standardised process for extracting Landsat data from GEE, allowing data retrieval commands to be entered and data downloads to be performed at the GEE interactive console (Ermida et al., 2020). However, studies need to check the quality of Landsat products, which frequently have missing data (Tang et al., 2021). As with prevalent satellite products, Landsat's products are subject to missing data due to return period constraints and cloud cover. Landsat cannot record all the data in a long time series for a region like ground-based monitoring stations, which typically have a data period of 15 days (Loveland and Irons, 2016). Secondly, the weather in the Greater London area of the UK tends to have a cloudy climate, with cloudiness weakening the results of LST calculations. Therefore, in this study, the average LST data for the summertime of the last five years (2015-2019) were used to avoid the negative effects of missing data.

The study for the urban accessibility score maps was mapped in a GIS system based on the coordinates of the centre points of the grid in the data table. Each point was used as a centre to create a 100 m square buffer. Demuzere provided data for the LCZ maps and stored it using raster graphics (.tif). To calculate the distribution and area of LCZ categories in each sample, the study converted the raster image into a vector graphic and separated the study area.

Step 2: Model training

After extracting the data, the study creates the sample pool for model training. For this study, the samples were defined as map tiles split at the neighbourhood scale using a square grid. For the sample scale, the study chose a square grid with a side length of 500m. The selection of the sampling scale is highly relevant to the research question, and street and neighbourhood scales have typically been limited to 1km in past studies (Ferreira et al., 2021). After completing the sample production, the study created a machine learning model using the eXtreme Gradient Boosting (XGBoost) algorithm. The feature values of the samples were the accessibility metrics of the area in which they were located and the mean values of the sub-items (transport stops, parks, community services, restaurants, education, healthcare, and entertainment). Furthermore, the study also inputs urban environmental parameters (LCZ configurations) within the sample grid as feature values for model training. The five-year average summer surface temperature was then used as the target value.

Step 3: Interpretation of results

After training, the study created an explanator using the SHapley Additive exPlanations (SHAP) approach to explain the relationship between

FMC scores and the urban thermal environment (Li, 2022). The use of SHAP interpreters and XGBoost models is a more common approach for interpretable machine learning in recent years (Vega García and Aznarte, 2020). Firstly, the explainer predicts a baseline based on background samples without features. As feature values are added, the model output values will change, defining the output prediction deviation from the baseline as the contribution of this feature (Ponce-Bobadilla et al., 2024). In this study, the horizontal axis (X) is the scores of the sample FMCs and the vertical axis (Y) represents the contribution of each score to the LST (SHAP value). When the vertical axis is negative (Y<0), it represents that the score of this FMC negatively contributes to the LST; conversely (Y>0), it represents that the FMC score positively contributes to the LST.

RESULTS AND DISCUSSIONS

Results

After 100 rounds of iterations, the model achieves to explain 76% of the LST phenomena (training R^2 = 0.77, training MAE = 0.95°C; test R^2 = 0.76, test MAE = 0.99°C). Figure 3 shows the dependent scatterplot using the SHAP.

Score ranges from 0.35 to 0.50, its contribution to LST is significantly positive, meaning that surface temperatures tend to be higher at moderate to high levels of accessibility. As accessibility continues to increase or decrease, its impact on temperature tends to weaken or even turn negative, indicating a trend of marginal diminishing or reversing effects. This non-linear relationship suggests that the interaction between service facility layout and thermal environment is not a simple linear relationship but is highly sensitive to comprehensive factors such as spatial density, service overlap, and surface cover features.

The study found that various service facilities reveal that facilities of different types have a predominantly positive impact on LST when located near residential areas (typically within 500 metres). This phenomenon is particularly significant for facilities such as educational institutions, healthcare facilities, transportation hubs, and nightlife venues. The concentrated layout of service facilities is commonly associated with larger building volumes, denser pedestrian traffic, and more complex transportation systems, all of which exacerbate the release of anthropogenic heat.

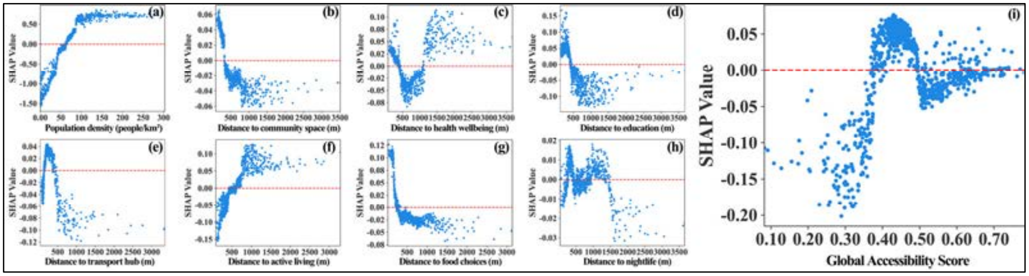

Figure 3
Feature dependent scatterplot

The SHAP feature dependency plot reveals a complex and non-linear relationship between the accessibility of urban services and surface temperature. Within the framework of the 15-Minute City (FMC), when the Global Accessibility

Meanwhile, to ensure the efficiency of functional layout, these areas frequently sacrifice green space ratios and ventilation areas, leading to poor heat dissipation and thereby elevating local surface temperatures.

However, when service facilities are more than approximately 1 km away from residential areas, the impact of most facilities on LST gradually becomes negative, and urban heat stress is expected to be alleviated. A potential explanation is that as functional facilities become more dispersed, the intensity of urban space utilisation decreases, leading to a reduction in heat source density. Facilities located at greater distances are more likely to be situated in non-core areas, which generally have higher surface greenery rates and better natural ventilation conditions, facilitating heat dispersion and regulation.

Except for the distance between service facilities and residential areas, the population density within residential areas also plays a significant role in the thermal environment. Population density exhibits a typical rapid growth trend in its impact on LST, especially after exceeding 100 people/km^2, at which point the SHAP value rises sharply. There is a strong correlation between population density and anthropogenic heat emissions. More importantly, an increase in population density may lead to a greater demand for basic services, resulting in an expansion of service facilities. This is a key factor contributing to the worsening thermal environment in cities.

Therefore, this study proposes an important corrective perspective for FMC: while emphasising functional convenience, urban planning must also consider the need to optimise the thermal environment. Uncritically adopting a layout model that prioritises the 'shortest service distance' may improve travel efficiency but could also induce new thermal environmental burdens. Urban design should transition from a single functional logic to an integrated perspective that synergises ecology and climate, encouraging medium-scale facility layout strategies and strengthening the integration and penetration of green spaces to achieve a dynamic balance between accessibility and thermal comfort. Thus, the FMC concept can truly move toward a sustainable and climate-resilient future urban form while ensuring social equity and living convenience.

Discussion

Conflict between thermal environment and accessibility

This study reveals an environmental paradox within the Fifteen-Minute City (FMC) framework: while the FMC concept aims to improve quality of life and reduce reliance on motor vehicles by encouraging residents to live near essential services, this functionally oriented spatial organisation may inevitably exacerbate the worsening urban heat environment. The findings also confirm Shartova's suggestion in previous research that the background temperature increase caused by functional clustering may negate the environmental benefits provided (Shartova et al., 2024). Criticisms in the past have also referred to the fact that FMCs tend to be over-ambitious in achieving assessment criteria in practical situations and that unequal infrastructure does not effectively break down the single urban centre layout (Guzman et al., 2024).

From a critical perspective, the implementation of FMC often falls into a 'evaluation-oriented' binary governance logic, where FMC objectives in urban planning are simplified to whether they meet the '15-minute accessibility' quantitative indicators. Therefore, we advocate viewing FMC as an adaptable, multi-objective urban governance framework and promoting its evolution toward multi-objective optimisation (MOO), so that while improving urban service efficiency, it also places greater emphasis on the coordinated achievement of thermal environment regulation, ecological resilience, and social equity.

Limitations and future directions

It is important to realise that SHAP is a novel approach to exploring black box models, but it does not promise to explain causality (Hamilton and Papadopoulos, 2024). Therefore, the study discusses the trend of FMC parameters on urban LST and explains its potential relevance. The results of SHAP do not guarantee or imply that changing specific FMC parameters will be beneficial (or harmful) in mitigating UHI. In the future, researchers still need to explore the relationship between the FMC framework and the environment further.

Furthermore, it is recommended that future studies expand the focus from LST to quantifying 'actual heat exposure,' that is, not only focusing on overheated areas but also on when and how residents are exposed to heat. This will provide a more comprehensive tool for synergising FMC strategies with environmental equity and climate adaptation goals.

CONCLUSION

This study uses interpretable machine learning (SHAP) techniques to revisit the 15-minute urban framework and discuss whether it benefits the urban thermal environment. It was found that the FMC framework is not an absolute binary relationship (benefit or damage) to the urban thermal environment; instead, they are a non-linear relationship and have trade-off points. A high density of facilities in the city potentially raises the LST, whereas a reasonable distance (500-1000m) can achieve a trade-off between accessibility and the thermal environment. The study highlights that abundant emerging technologies bring new possibilities for urban management and design. The extreme simplifying binary divisions of any design concept should be avoided. The study revisits the FMC framework from new technologies and perspectives to provide further theoretical support rather than a complete denial. The FMC framework has demonstrated strong potential in urban environmental and social issues, and it can be further enhanced in the future.

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