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Predicting land surface temperature by different climate classification methods: A case study of Singapore

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Keywords: Land Surface Temperature, Urban Functional Zone, Local Climate Zone, Urban Form Indicator, Machine Learning Model.

Abstract

The urban thermal environment has become a challenge to humans in consideration of rapid urbanization and global warming. Various climate classification methods have been developed to analyze urban form and the urban heat island phenomenon. However, there is a lack of cross-comparison studies carried out to examine the accuracy of predicting land surface temperature by different climate classification methods (local climate zone, urban functional zone, and hybrid zone that integrates the strengths of local climate zone and urban functional zone), as well as their performance in statistical and machine learning models (ordinary least squares regression, geographically weighted regression, and random forest regression). Accordingly, this study focuses on comparing the performance and accuracy of predicting land surface temperature via different climate classification methods. In addition, the relative importance and marginal effect of factors on land surface temperature are discussed based on the approach with the highest accuracy. The results show that: random forest model performs best in predicting land surface temperature (average R^2: 0.72); hybrid zone is the most accurate approach to predict land surface temperature (R^2: 0.84); and urban functional zone (R^2: 0.80) performs slightly better than local climate zone (R^2: 0.76). This study helps urban planners and designers to assess which climate classification methods can more accurately predict and explain the influence of urban form on land surface temperature, and provides some insights into urban design strategies to improve the thermal environment.

1. Introduction

Urbanization refers to the flow of people from rural to urban areas (Chen et al., 2022). In recent years, under the process of rapid urbanization, though it promotes social and economic development, the natural environment of cities is gradually substituted by an artificial environment (Han et al., 2023; Lin et al., 2024). One of the most significant environmental challenges arising from urbanization and global warming is the urban heat island (UHI) effect (Jia et al., 2024). The UHI effect means that the urban areas experience higher land surface temperature (LST) or air temperature (AT) compared to the surrounding suburban and rural areas (Oke & Voogt, 2003). Mo et al. (2024) show that factors such as the solar radiation absorption capacity of the urban surface, the wind-blocking effect, and the anthropogenic heat have intensified the UHI effect. The increased UHI effect leads to the deterioration of the urban thermal environment, posing a huge threat to sustainable urban development (Zheng, Huang & Zhai, 2021; Zhang, Zhang, Chen & Su, 2022). It has been proven that the increased temperature not only has a negative influence on thermal comfort, public health, and vitality in outdoor space (Jia, Wang, Wang & Weng, 2025), but also has an impact on urban energy consumption for air-conditioning or mechanical ventilation.

Most studies show that the urban thermal environment does not only depend on the regional climate at a larger scale but is also associated with the urban built environment at a smaller scale (Deng, He & Dai, 2023). It is the urban form that is a key focus for implementing sustainable strategies to improve the urban thermal environment (Hou et al., 2023). Hence, there is an urgent need to understand the patterns of LST, comprehensively explore the correlation between urban thermal environment and urban form (e.g., building density, building height), find the dominant urban morphological features influencing the thermal environment and develop effective measures to mitigate UHI effect.

At present, there are two most widely used climate classification methods to study the relationship between urban form and the thermal environment: local climate zone (LCZ) and urban functional zone (UFZ). On the one hand, LCZ was proposed by Stewart and Oke in 2012, which is the first attempt to standardize and compare urban climatic studies across the world (Wang et al., 2018; Yin et al., 2022; Ng & Ren, 2015). It is applied to classify the morphology of cities for UHI studies in terms of land cover types and building forms (Zheng et al., 2018). Specifically speaking, the standard LCZs consist of ten built types describing compactness and building height (ranging from LCZ 1 to LCZ 10), and seven land cover types mainly including tree, rock, water, and other natural types (ranging from LCZ A to LCZ G) (Stewart & Oke, 2012). Generally speaking, the same type of LCZ usually displays similar thermal environmental characteristics. Recently, some studies have attempted to analyze urban morphology and the corresponding UHI effect via LCZs. For instance, Liu et al. (2022) applied an LCZ mapping method for urban thermal environment research, and acquired various LCZ types that coexist in irregular states. The results show that the AT demonstrates time-varying features and changes dramatically with LCZ types. In addition, the sky view factor and impervious surface fraction show a positive correlation with AT during daytime. Lin et al. (2023) used the random forest (RF) regression model to explore the relative importance and marginal effects of the influencing factors on seasonal LST based on the whole study area and the LCZ built type area of Fuzhou City. The results show that the level of LST of different spatial morphology rank as $open < compact$ and $high\text{-}rise < mid\text{-}rise < low\text{-}rise$.

However, the LCZ classification does not fully take into ac-

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count human activities, such as residence, work, and entertainment, which account for a large amount of heat emission. On the other hand, the UFZ classification method extracts urban land use types, which can be applied to depict human activities (Zhang, Du & Wang, 2017). The features of the thermal environment in UFZs are different from those in LCZs (Yu, Jing, Yang & Sun, 2021). UFZs can also serve as the basic units for urban planning, which is practical for mitigating the urban thermal environment by urban planning authorities. Recently, some studies have tried to comprehensively investigate the impact of urban morphology on LST in UFZs. For example, Huang & Wang (2019) studied the effect of 2D/3D urban morphology on summer daytime LST in different UFZs in Wuhan, by adopting high-resolution remote sensing data and geographical information data. The results show that trees are the most influential factor in reducing LST, and the highest LST appears in commercial and industrial zones. Lin et al. (2024) reveal how UHI differs across UFZs by integrating remote sensing data with geospatial data. The results show that the 3D building form intensifies the UHI effect at a larger scale, while the 2D building morphology shows a higher intensity. Also, the 3D building distribution significantly impacts the UHI effect in administrative, business, and resident zones.

Numerous models have been developed to predict LST. Many studies were carried out to investigate the correlation between urban form indicators and LST by applying the ordinary least squares (OLS) model (Li et al., 2011; Guo et al., 2015). However, this model is unable to consider spatial heterogeneity. In response to this limitation, some studies used geographically weighted regression (GWR) as well as multiscale geographically weighted regression (MGWR) to better understand the spatial heterogeneity of multiple factors impacting the urban thermal environment. For example, Gao, Zhao & Han (2022) qualified the relationship between UHI effect and some influencing factors of block morphology using the GWR model. The results show that compared to OLS model, the GWR model improves the modeling fit by means of capturing spatial heterogeneity. Yin, Liu & Han (2022) explored the correlation between urban morphology and LST using the MGWR model. The results show that the MGWR model can accurately reflect the impact of urban green space, road, building height and building density on LST, with a superior fitting effect over the GWR model. Nevertheless, these models face challenges in capturing the complicated relationship between variables. Subsequently, to address these limitations, machine learning models have been applied to explore the relationship between various influencing factors and LST. The RF model is one of the models that has been applied to predict LST. It has the ability to capture complicated non-linear relationships and interactions between factors, thereby improving the accuracy of prediction (Liu, Gou & Yuan, 2024). For instance, Shen et al. (2022) conducted a prediction of surface urban heat island using the RF model at the base of future landscape distribution. The results show that the RF model has a better performance than a stepwise multiple linear regression model.

Research on predicting LST is rapidly increasing, and a variety of climate classification methods have been developed. However, there exist limited cross-comparison studies to examine the accuracy of predicting LST by different climate classification methods, as well as their performance in statistical and machine learning models. Given this observation, this study aims to compare the performance of estimating LST through different climate classification methods. The specific objectives of this study are: (1) To comprehensively investigate the distribution of built-up LCZs, built-up UFZs, LST and urban form indicators. (2) To compare the accuracy of predicting LST by different climate classification methods in different models. (3) To analyze the relative importance and marginal effects of variables on LST in the classification method with the highest predictive accuracy. (4) To propose some urban design strategies that can create a comfortable thermal environment. The study provides a comparable framework to help urban planners and designers evaluate which climate classification method can more accurately explain the relationship between LST and urban morphology. This systematic framework can be applied to other areas for comparing the performance of climate classification methods in predicting LST.

2. Methodology

2.1 Study Area

Singapore, as the economic, scientific, and cultural center of Southeast Asia, is a typical high-density city. It is located at the southern tip of the Malay Peninsula (Figure 1). The urban area was about 735.2 square kilometers and the population was about 5.9 million in 2023. Singapore's proximity to the equator gives it a typically tropical rainforest climate (Koppen climate classification Af) (Kottek et al., 2006), with abundant rainfall, high and uniform temperatures, and high humidity all year round. Singapore has been warming up twice as fast compared to the rest of the world because of the global warming effects and densely built environment. 2023 was the hottest recorded year in Singapore, which significantly had an impact on the physical and mental well-being of the local residents. All in all, in light of Acero, Koh, Ruefenacht & Norford (2021), the increase of population density with limited land for further urban development will increase the UHI effect and reduce the thermal comfort of outdoor open space. Singapore Government's (2021) Singapore Green Plan 2030 aims to achieve the goal of island-wide sustainable climate resilient development. Thus, optimizing the urban thermal environment is of particular importance.

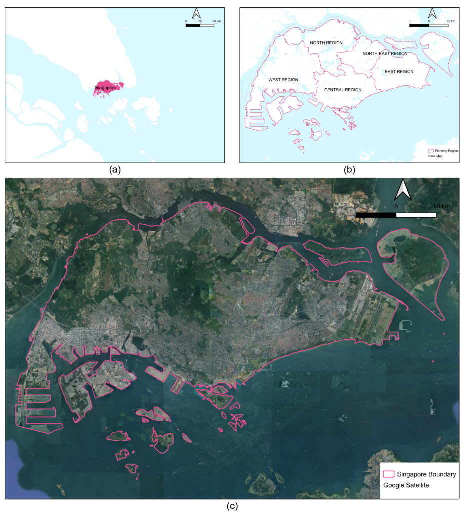

Figure 1. Location of the study area: (a) Map of Singapore; (b) Map of planning region; (c) Satellite image of Singapore. (Source: Google Maps, 2024)

2.2 Research Data

This study utilized multi-source data (Figure 2). The Master Plan 2019 of Singapore from the Urban Redevelopment Authority (URA) was chosen as land use data. Building data containing information on footprints and heights was obtained from National University of Singapore (NUS). Urban form indicators were calculated through QGIS from both land use data and building data. LST was retrieved from Landsat 8 remote sensing image data in 2016 with a resolution of 30m (downloaded from the official website of the United States Geological Survey (USGS)). There was little cloud cover over the study area, with high atmospheric visibility. The images were dealt with in ENVI via the fast line-of-sight atmospheric analysis of hypercubes (FLAASH) module to reduce the impact of the atmosphere and get the accurate LST in Singapore.

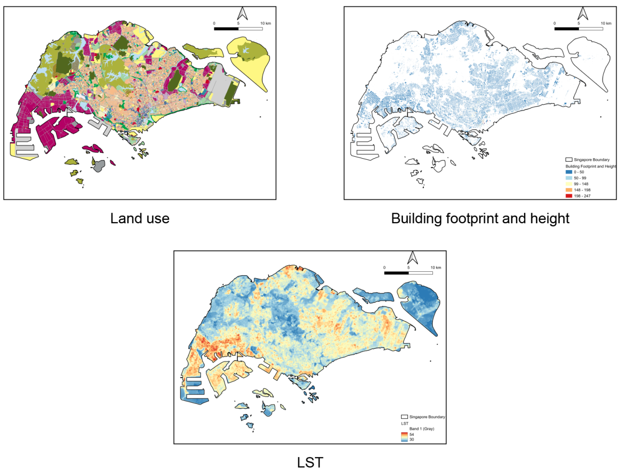

Figure 2. Multisource data.

2.3 Research Methods

2.3.1 Research Framework Figure 3 shows the framework of this study. This framework comprises three key modules: (1) Setting up built-up UFZs and built-up LCZs from urban function and urban form data, respectively, with a spatial scale of 200m, and analyzing the spatial distribution of LST and urban form indicators; (2) Applying multiple models, including OLS, GWR, and RF to identify the best-performing climate classification method for LST prediction, including no-zone, UFZ, LCZ, and hybrid zone; (3) Identifying major contributing factors to LST prediction and discussing the marginal effect of the indicators on LST for the zone classification with the highest predicting performance.

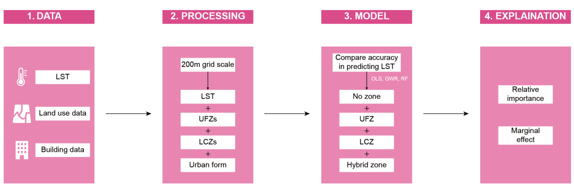

Figure 3. Research framework.

2.3.2 Mapping Built-up Urban Functional Zones and Built-up Local Climate Zones Firstly, according to the analytical units used in the previous studies (Lu, Yue, Liu & Huang, 2021), the study area was divided into grid cells of 200m by 200m. Considering that LST data is available at a resolution of 30m, on the one hand, it may cause large errors if the size of the grid cells is similar to the size of the image pixels. On the other hand, if the size of the grid cells is too large, the number of grid cells will be too small and overfitting will easily happen in a model such as RF. Consequently, a 200m grid cell was chosen as the analytical unit in this study.

Secondly, for built-up UFZ, this study utilized land use data to identify the urban functional types. Based on the Long-Term Plan of Singapore, nine land use types, i.e., Residential, Commercial, Industry, Open Space/Recreation/Agriculture, Infrastructure, Institution, Special Use, Reserve Site, and Waterbody, were selected to characterize the urban functions. Afterwards, these land use types were classified into five urban functional types based on the similarity of the functions, such as residential, commercial, industry, service, and open space. Subsequently, the ratio of each urban functional type area in each grid cell was calculated. If an urban functional type is the largest ratio in a grid cell, the grid cell is defined as the corresponding UFZ. Finally, this resulted in four types of built-up UFZ, i.e., residential, commercial, industry, and service.

Thirdly, for built-up LCZ, building data were used to develop a building surface fraction (BSF) map and building height (BH) map. BSF is the fraction of land surface covered by the buildings and BSF is one of the key parameters for classifying built-up LCZ, distinguishing between compact ($BSF > 0.4$) and open ($BSF < 0.4$). BH is defined as the mean building height of a grid cell. BH is also one of the key indicators for LCZ classification in built-up areas, identifying high-rise ($BH > 25m$), mid-rise ($BH = 15 - 25m$) or low-rise ($BH < 15m$). Finally, two urban morphology analysis maps were spatially merged to create six types of built-up LCZ, including Compact High-rise, Compact Mid-rise, Compact Low-rise, Open High-rise, Open Mid-rise and Open Low-rise.

2.3.3 Retrieval of Land Surface Temperature In this study, LST was retrieved using the atmospheric correction method. This process includes evaluating the influence of the atmosphere on the surface thermal radiation, reducing this atmospheric influence from the total thermal radiation observed by the satellite sensor, acquiring the surface thermal radiation intensity, and then transforming this thermal radiation into the corresponding LST. Then, the mean LST for each grid cell was determined.

2.3.4 Urban Form Indicators Urban form describes the shape and distribution of urban spaces. It can significantly influence the urban thermal environment. Therefore, based on the principles of theoretical and practical importance, and being easily understood and calculated, the following urban form indicators were selected to analyze the effect of the urban morphology on LST: gross plot ratio (GPR), height variance (HV), building height to street width ratio (BH / SW), percentage of waterbody (P_Waterbody), and percentage of park (P_Park)) (Yang et al., 2021). These indicators mainly include 2D/3D building morphology indicators and land cover, and they have been confirmed to be related to LST (Xu et al., 2017). From a 2D perspective, waterbody and park are the main factors reducing LST via evaporation and shading, while building is the main factor raising LST because of low albedo, low evaporation, and high heat capacity. From a 3D perspective, the building form factors may have a complicated relationship with LST, since they can determine the absorption of solar radiation, the formation of wind flow and the generation of anthropogenic heat.

2.3.5 Statistical Analysis OLS, GWR, and RF models were utilized in this study to compare the performance of predicting LST by different climate classification methods (no-zone, LCZ, UFZ, and hybrid zone integrating LCZ and UFZ). The root-mean-square error (RMSE) and R-squared (R^2) were used to evaluate and compare the accuracy of the models. R^2 indicates the squared correlation between observed and estimated values. RMSE presents the average difference between the observed values and the predicted values. A higher R^2 and a lower RMSE indicate a more accurate model.

For the climate classification methods, five basic factors were used as continuous variables, including *GPR*, *HV*, *BH/SW*, *P_Park*, and *P_Waterbody*, while *LCZ label*, *UFZ label*, and *hybrid zone label* were used as categorical variables to distinguish them (Table 1).

Table 1. Methods for predicting LST.

Methods	Models
No zone	LST ∼ GPR+HV+BH/SW+P_Waterbody+P_Park
LCZ	LST ∼ GPR+HV+BH/SW+P_Waterbody+P_Park+LCZ label
UFZ	LST ∼ GPR+HV+BH/SW+P_Waterbody+P_Park+UFZ label
Hybrid zone	LST ∼ GPR+HV+BH/SW+P_Waterbody+P_Park+Hybrid zone label

The OLS model is a traditional linear regression model, which is usually used to fit the correlation model between the urban form indicators (independent variables) and LST (dependent variable) from a global perspective, widely used in urban planning and design.

The GWR model is a local regression model. It assumes that a non-stationary relationship exists between the response variable and the explanatory variables. The regression parameters were estimated in each location separately to reflect the spatial heterogeneity of the influence of urban morphology parameters on the LST.

The RF algorithm is a common machine learning model that is used in regression and classification (Breiman, 2001). A variety of machine learning models were compared, and the RF model proved to be the most accurate one (Logan, Zaitchik, Guikema & Nisbet, 2020). It has been widely used since it can accommodate nonlinearities. This model integrates multiple decision trees through an ensemble learning method, and obtains the results through randomly selecting features from each decision tree, finally adopting majority voting or averages. The number of decision trees in this study was 1000.

The RF model was also applied to analyze the relative importance and marginal effect of urban morphology indicators on LST. On the one hand, it can calculate a quantitative weight for each variable without considering the interaction of the variables. That is, it can illustrate which component can best estimate LST change. On the other hand, partial dependency plots were applied to analyze the correlation between urban form indicators and LST.

3. Results

3.1 Spatial Distribution of Built-up Urban Functional Zones and Built-up Local Climate Zones

Figure 4 describes the distribution of built-up UFZs and built-up LCZs. As for UFZ, large residential areas are located along the Central Water Catchment, Western Water Catchment, and Paya Lebar. These zones consist of HDB flats, condos, and landed properties, providing homes for the population. Industrial areas are mainly distributed in the West Region. This region is home to several industrial parks, including Jurong Industrial Estate, Jurong Innovation District, and International Business Park, which supports a wide range of economic activities like research & development and manufacturing. Commercial areas are primarily located in the Central Area where leading international businesses, financial institutions, and corporate headquarters are located. Service areas are primarily distributed in the East Region and West Region including Changi Airport and Tuas Port, which are important for supporting Singapore's transportation and logistics.

As to LCZ, Open Low-rise and Open Mid-rise mainly appear in residential areas with landed properties, and old HDB flats, and industrial areas. Open High-rise and Compact High-rise are primarily distributed in the Central Business District and some new towns, such as Punggol, where high-rise commercial buildings and new residential buildings are covered, respectively. The numbers of Compact Mid-rise are relatively limited in Singapore, while Compact Low-rise is mainly distributed in industrial areas.

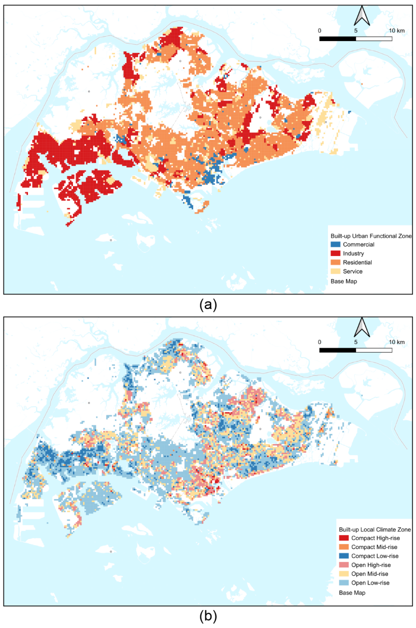

Figure 4. Built-up UFZ (a) and Built-up LCZ (b).

3.2 Spatial Distribution of Land Surface Temperature and Urban Form Indicators

Figure 5 shows the spatial distribution of LST. From the perspective of UFZ, the low-value areas of LST are mainly concentrated in residential areas close to the Central Water Catchment, by virtue of the cooling effects of vegetation and waterbody. The Central Water Catchment is an important cool island within the city. In contrast, the high-value areas of LST are mainly located in the industrial areas such as Jurong Industrial Estate, where industrial activities consume a lot of energy and release a large amount of waste heat.

From the point of LCZ, it shows that Open High-rise has low LST, reflecting that tall buildings can create shaded space while open space between them allows for better natural ventilation and heat dispersion. By contrast, Compact Low-rise has high

LST, meaning that less shade and reduced airflow can result in a higher temperature.

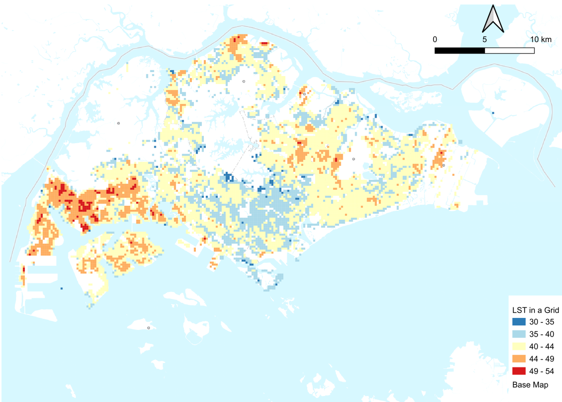

Figure 5. LST in a grid.

The spatial distribution of urban form indicators is shown in Figure 6. The values of building surface fraction are relatively low in the study area, with the exception of some industrial and service areas in the West and East Regions. These areas exhibit higher building surface fraction values, indicating the concentration of large-scale industrial or public buildings. High values of building height, gross plot ratio, height variance, and building height to street width ratio are mainly concentrated in the Central Area and some new towns such as Punggol. The high values of waterbody and park are scattered without any high concentrated areas. This spatial pattern reflects the integration of the natural environment with the built environment, contributing to the livability of the study area.

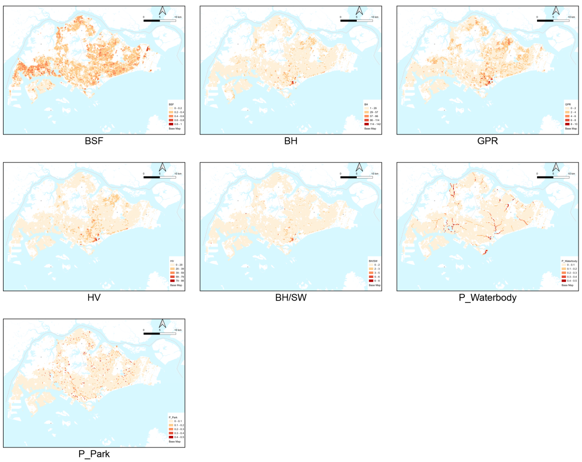

Figure 6. Urban form indicators.

3.3 Statistical Analysis Results

3.3.1 Model Performance in Land Surface Temperature Prediction The model performances are shown in Table 2. In general, RF model accuracy is highest (average R^2 value is 0.72), indicating a strong predicting ability by right of capturing the nonlinear relationship between various factors and LST. And the R^2 value of GWR model (average: 0.48) is higher than that of OLS model (average: 0.26), suggesting that it can capture the spatial heterogeneity of variables impacting the urban thermal environment and improve the estimation accuracy.

Table 2. Overall model performance of OLS, GWR and RF.

	OLS		GWR		RF	
Zone type	R^2	RMSE	R^2	RMSE	R^2	RMSE
No zone	0.10	2.94	0.44	2.32	0.46	2.40
LCZ	0.23	2.72	0.51	2.16	0.76	1.66
UFZ	0.31	2.58	0.49	2.22	0.80	1.46
Hybrid zone	0.39	2.42	0.47	2.25	0.84	1.30
Average	0.26	2.67	0.48	2.24	0.72	1.71

In the RF model, LCZ, UFZ, and hybrid zone all show a better performance of predicting LST when compared to no-zone, (Figure 7). The R^2 value is the highest and the RMSE value is the lowest when applying hybrid zone to predict LST. 84% of LST can be estimated by those selected influencing factors. This is because hybrid zone integrates the strengths of both LCZ (urban form) and UFZ (urban function), allowing the RF model to better understand the correlation between a variety of factors and LST. In addition, the performance of UFZ is slightly higher than that of LCZ. That is because UFZ mainly describes urban functional characteristics, which are less collinear with other urban form indicators in the model, providing more independent variables for estimating LST. Reversely, LCZ primarily shows urban morphological features, such as building surface fraction and building height, which may overlap with other factors in the model and thereby reducing prediction accuracy. UFZ not only reflects urban functional layout, but also reflects dynamic human activities, which have a direct and significant influence on the urban thermal environment. Human activities are often closely related to other variables like energy consumption, heat emission, and traffic flow, which are also important drivers of LST and are less correlated with urban form indicators. Instead, LCZ only reflects on urban form, which may not fully capture the temporal factors influencing LST.

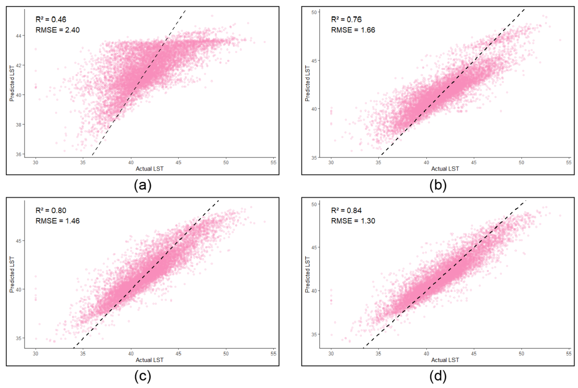

Figure 7. The RF model accuracy among different climate classification methods for predicting LST: (a) no-zone; (b) LCZ; (c) UFZ; (d) hybrid zone.

3.3.2 Relative Importance and Marginal Effect of Urban Form Indicators on Land Surface Temperature Figure 8 shows the relative importance of urban form indicators to LST for hybrid zone classification. Overall, the gross plot ratio shows the strongest influence on LST (over 30%). The reason is that a higher value for gross plot ratio indicates a denser building layout, which can lead to heat accumulation and reduced ventilation. Both contribute to a rise in LST. Height variance also shows a strong impact on LST (over 20%). The reason is that varying building heights can create complex urban canyons that affect solar radiation absorption and wind flow, contributing to temperature variations. Other urban morphology indicators, such as building height to street width ratio, percentage of waterbody, and percentage of park, have a lower importance of influencing LST in this context.

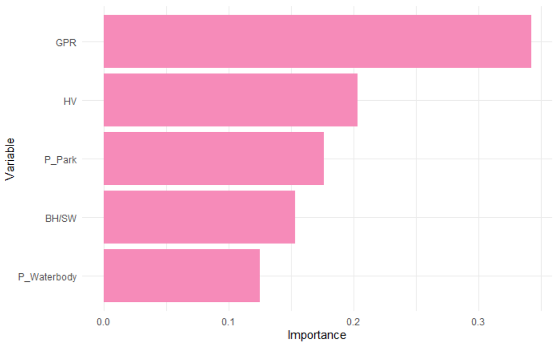

Figure 8. The relative importance of urban form indicators to LST in hybrid zone.

To further explore the nonlinear association between urban form indicators and LST for hybrid zone classification, partial dependency plots are applied to examine their marginal effects (Figure 9). That is, partial dependency plots can explain how the predicted variable changes when a predictor variable is changed while others remain constant. The percentage of waterbody, percentage of park, height variance, and building height to street width ratio are all negatively correlated with LST, while the gross plot ratio is positively correlated with LST. To be specific, a strong positive impact of gross plot ratio on LST occurs when its value reaches 1.2, while a strong negative impact of height variance on LST occurs when its value reaches 30. On the one hand, a compact building layout prevents the loss of heat so that building materials with high heat absorption can capture more heat to lower the quality of the urban thermal environment. On the other hand, a high value of height variance means that the area has higher buildings, creating larger shadow areas when compared to buildings with the same height. Also, the height variance of building groups has an impact on the wind speed and direction, forming mechanical turbulence and reducing heat. Hence, an appropriate gross plot ratio and height variance can create mutual shading effects between buildings and promote ventilation. The marginal effect of building height to street width ratio implies a complicated relationship with LST. The response curve of it to LST initially rapidly increases and then sharply decreases, followed by a moderate increase and a significant decrease. The effect of building height to street width ratio on LST increases gradually when the value exceeds 4. When the ratio is small, although it can help to enhance airflow, the streets receive more solar radiation, leading to a rise in temperature. When the ratio is large, the urban canyon enhances shading, resulting in a fall in temperature. Thus, both positive and negative relationships can be observed in building height to street width ratio.

For green & blue, the relationship between waterbody, park, and LST is almost linear. Although waterbody and park contribute to cooling, the cooling effect of waterbody is not as strong as that of park, with a maximum temperature range of only 1.58°C. This is because the thermal capacity of water is higher than that of vegetation.

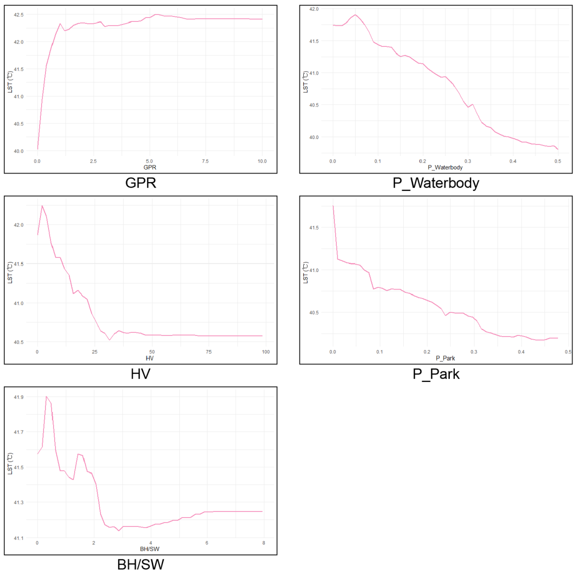

Figure 9. Marginal effects of urban form indicators on LST in hybrid zone.

4. Discussion

4.1 Hotspot Map and Mitigation Strategies

Industry Compact Low-rise, Industry Compact Mid-rise, Service Compact Low-rise, Residential Compact Low-rise, Industry Compact High-rise, and Industry Open Low-rise are the top six zones that demonstrate high LST. The mean LST values of these zones are higher than $43°C$, indicating significant heat stress. Hotspot areas are observed in various locations, including industry zones mainly in the West and North Region, and residential zones mainly in the East and North-East Region (Figure 10). These can be attributed to several factors. Firstly, as for anthropogenic heat, heat emissions from machines and vehicles in the industry zone contribute to high LST. Similarly, high population density and associated activities in the residential zone generate waste heat, resulting in high LST. Secondly, as to urban form, the compact building layout reduces natural ventilation and prevents heat dispersion. And mid-rise and low-rise buildings limit shading opportunities and exacerbate heat accumulation. In summary, industry zones in the West Region and residential zones in the East Region need to be paid special attention.

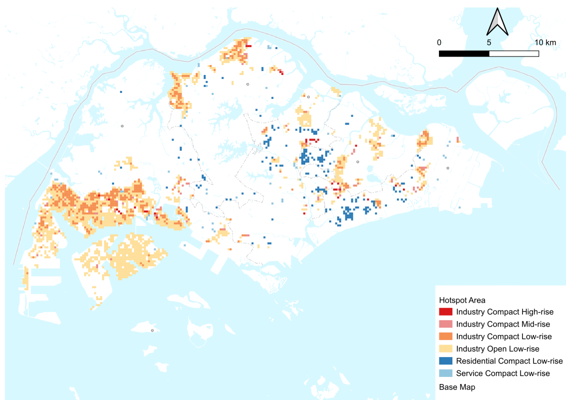

Figure 10. Hotspot area.

To further explore the influence of variables on LST, the relative importance of the factors to LST among the top six hybrid zones is shown in Figure 11. The following urban design strategies are proposed from the perspective of the hybrid zone classification: (1) The results of Industry Compact Low-rise and Industry Compact Mid-rise indicate that reducing gross plot ratio, especially reducing building density, can allow more wind flow and lower heat accumulation. (2) The results of Industry Compact High-rise and Industry Open Low-rise indicate that natural landscapes such as waterbodies and parks can be integrated into the built-up area to provide a cooling effect to decrease LST and enhance the outdoor thermal comfort. (3) The results of Service Compact Low-rise and Residential Compact Low-rise indicate that improving height variance and optimizing gross plot ratio can enhance airflow and mitigate UHI. These urban design strategies can help the local government address the UHI effect in different locations by considering urban function and form.

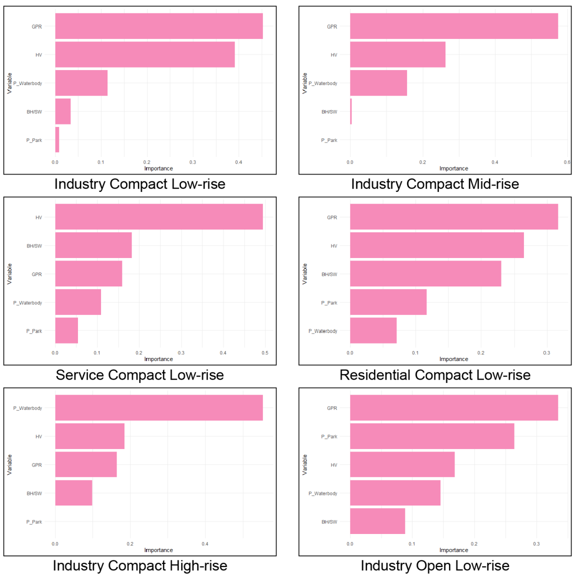

Figure 11. The relative importance of urban form indicators to LST among top 6 hybrid zones.

4.2 Limitations and Future Work

There are still some limitations to this study. Firstly, the research is carried out in Singapore, a high-density tropical city, which may limit the application of the findings to other cities with different climate conditions, latitude, urban morphology, population density, and urban planning policy. Urban design strategies to improve the thermal environment may also vary by location. Secondly, additional variables may have an influence on LST (e.g. population density, latitude, longitude, elevation, building orientation, distance to waterbody, distance to park, etc.), which will further improve the prediction accuracy. Future research can address these limitations by including more diverse case studies and a broader range of indicators.

5. Conclusion

This study compared the performance of predicting LST through different climate classification methods, including no-zone, LCZ, UFZ and hybrid zone. Three different models for estimating LST were also used and compared, including OLS, GWR and RF models. The high-density tropical city of Singapore was selected as a study area, and the analysis unit was at the resolution of 200m. One important contribution of this research is the development of a new climate classification method: hybrid zone that integrates the strengths of LCZ and UFZ. Specifically, hybrid zone classification can not only describe urban morphology, but can also reflect the intensity of human activities. It is scientifically proven that this method provides the best performance in estimating LST in Singapore, providing urban planners and designers with a deeper understanding of how urban form and human behavior interact with local climate. The main findings are: (1) The highest LST appears in the industrial zone (from the perspective of UFZ) and Compact Low-rise zone (from the point of LCZ). (2) The RF model performs better than the OLS and GWR models in predicting LST, with the average R^2 equal to 0.72. (3) Different climate classification methods show better performance to no-zone. Hybrid zone that combines the advantages of LCZ and UFZ is the most accurate approach to predict LST (R^2: 0.84). UFZ (R^2: 0.80) performs slightly better than LCZ (R^2: 0.76). (4) Urban morphology plays an important role in the urban thermal environment, with the gross plot ratio showing the most significant impact on LST for hybrid zone classification. The gross plot ratio is positively correlated with LST, while height variance, building height to street width ratio, percentage of waterbody, and percentage of park are negatively correlated with LST for hybrid zone. This study contributes to the field of urban planning and design by providing a comparable framework for urban planners and designers to evaluate which climate classification methods can perform well in explaining the relationship between LST and urban form. The findings can support decision-making and effective measures to improve the urban thermal environment.

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