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Scale-dependent and season-dependent impacts of 2D/3D building morphology on land surface temperature

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Abstract

Urbanization has caused significant changes of urban morphology in three-dimensional (3D) space. Although previous studies found a close association between 2D/3D urban morphology and land surface temperature (LST), the conclusions are various and the reasons lie in three fundamental components of urban morphology: physical form, resolution and time. Beijing's old city includes massive vernacular and modern architecture, which provides an ideal laboratory for the studies. In a new approach, 3D landscape metrics were applied to analyze built forms from aspect of composition and configuration, and explain their contributions ~~in~~ LSTs together with tree height data across scales and seasons. The selected metrics explained over 80% variations of LST across seasons at large scales. Tree height contributed most during the hot season. Compared to composition, configuration metrics were less efficient for cross-scale LST changes. The relative importance of building features is scale-dependent. At small scales (under 105m), 3D composition features contributed more to LST, while 2D composition features ~~turned to be~~ dominant at larger scales (over 180m). At intermediate scales, 2D and 3D composition metrics together affect the LSTs. These variations indicate the scale and seasonal dependencies of how urban morphology affects LST, which provide important support for future urban transformation.

Keywords: 3D landscape metrics, urban built forms, land surface temperature, scales, seasons, tree height

1. Introduction

Urban morphology refers to the physical form of a city, which transforms and replaces continuously under the process of urbanization (Moudon, 1997; Oke et al., 2017; Song et al., 2020). Buildings and their neighboring environment are dominant components of urban morphology, ~~that~~ buildings can alter the reflection and absorption of solar radiation, as well as the proliferation of heat in urban area (Huang and Wang, 2019). One of well-documented environmental risks is urban heat island (UHI), defined as the temperature difference~~s~~ between urban and rural regions. The hazards related to urban heat island are various, including air pollution accumulation, vegetation phenology variations, sustainability of water supplies, and extreme heat events (Gober et al. 2011; Connors et al., 2013). In this case, studying the influence of urban morphology on urban heat environment is of great importance for future urban transformation and resilient cities.

Satellite remote sensing (RS) provides high-resolution urban building data and spatially explicit land surface temperature (LST) with higher coverage than in-situ observations (Yu et al., 2020; Guo et al., 2021). In the past decade, identification of the relationship between urban morphology and LST is increasingly found in the literature, aiming to reveal in-depth influencing mechanism and supply detailed scientific suggestions. Particularly, the influence of 3D urban morphology on urban heat has achieved great progress, due to the development of RS technology (Alexander et al., 2009; Wang and Wang, 2009; Awrangjeb et al., 2010) and introduction of 3D morphology metrics (Kedron et al., 2019; Guo et al., 2021). Most of these researches followed a very similar mode. LST-morphology data pairs were fistly created using moving window method, and then apply linear (e.g., Pearson correlation coefficient) or nonlinear models (e.g., random forest, and eXtreme gradient boosting) to discuss their correlation and contribution to LST. However, the conclusions are various, even contradictory. Positive, negative, important and nonimportant are well documented in literature (Huang and Wang 2019; Guo et al., 2021; Lu et al., 2021; Li and Hu, 2022). This is related to three ~~important~~ fundamental components for urban morphology research: resolution, physical form, and time (Moudon, 1997).

Resolution/scale involves ~~the aspect looking a~~t the arrangement of buildings, streets, public spaces, and land use (Moudon, 1997). For urban planning, scale represents the plan unit that knead the buildings, open space, lots and vegetation together. In this case, the cohesive and adjacent relationship of these elements vary with size of unit or scale. Scale usually refers to the size of moving window ~~in literature~~ (Yang et al., 2019; Li and Hu, 2022). To study the relationship between 2D/3D urban morphology and LST, various sizes have been selected: 25 m (Yang et al., 2019), 60 m (Hu et al., 2020), 150 m and 540 m (Qiao et al., 2020), and 1 km (Wu et al., 2022). The dominant building features may change with ~~sizes~~, and the corresponding influence on LST may change. ~~For a~~ 25 m window size~~, it~~ corresponds to ~~the~~ single or limited buildings, the building spacing cannot be well displayed and spatial configuration of multi-building layouts is neglected. The dominant feature might be building height, and the influence on LST origins from building shade. ~~For a~~ 1 km window ~~size, it~~ corresponds to the street/block, which covers various styles of buildings. The vertical fluctuation of buildings tends to be stable, and the dominant morphological might be building coverage ratio, building spacing and openness. These features affect LST through heat accumulation and ventilation. In addition, the amplitude of incoming solar radiation and corresponding sensible heat flux and heat storage would vary more significantly over scales. The differences of urban morphology among scales are objective existence, therefore, studying multiscale relationship is conducive to ~~have a cubic~~ understanding on how urban morphology affects LST.

One challenge for ~~the~~ multiscale analysis is to find the turning point. Lots of literature is struggling for this, but needs more work (Peng et al., 2016; Lu et al., 2021; Li and Hu, 2022). The restricted availability of methods describing the built forms is one limit. The types and number of selected morphology metrics not only affect the accuracy of regressed LST, but also affect the final conclusion (Li and Hu, 2022). In addition to traditional two-dimensional (2D) features (e.g., building density, building number and building spacing), 3D building features (e.g., building height, building volume and sky view factor) that are closely related to surface roughness and surface energy balance, are arousing more and more interest ~~in literature these years~~ (Yang et al., 2019; Li and Hu, 2022). Although Li and Hu (2022) have applied 3D shape and fractal index to explain urban LST, systematic and pointed metrics for spatial configuration of buildings layouts and other composition characteristics are so far insufficiently involved. Based on a land mosaic model and a surface gradient model, Guo et al., (2021) proposed a suite of 2D/3D landscape metrics that perform well in comparing urban morphology in China and Europe (Guo et al., 2022). The present study applies their metrics for measuring the composition and configuration characteristics under different scales, and then links them to LST. In built-up landscape, vegetation also needs to be considered for a higher accuracy in predicting LST. Although some vegetation indexes, such as NDVI, ~~has~~ been widely applied, they focus on describing whether a region has vegetation. However, trees affect LST more by their shade that reduces incoming solar radiation, which is why tree height might be a more efficient indicator (Wu et al., 2022).

Impacts of urban morphology are dependent on seasons. The thermal demands of cities vary with climate zones and seasons from the aspect of thermal management (Ewing and Rong, 2008; Guo et al., 2021). In the northeast and northwest during winter, cold winds may carry away urban surface heat, and generate additional heating energy consumption and corresponding greenhouse gas emissions (Ewing and Rong, 2008). The increase in building density helps create a warm city environment, and can save a large amount of heating costs. During summer in tropical or subtropical regions, higher temperature within dense built environment leads to local abnormal airflow and even diseases related to ~~heat pressure~~, which threaten the health of urban dwellers. Therefore, studying the association and relative importance of morphological features on seasonal LST is important for seeking an efficient urban heat management policy. An encouraging trend in the literature is that more and more ~~researches focus~~ on seasonal influence in different cities (Hu et al., 2020; Li et al., 2021), however, they usually select one RS ~~imagine~~ to represent the season, and the conclusions in this case might be biased by confounding factors (e.g., local weather condition). To address these problems, this study selected LST data extracted from Landsat 8 remote sensing imagery over 12 months in Beijing's old city, applied a suite of 3D landscape metrics to compare the urban morphology at different scales, and assessed the contribution of different factors on LST. We aimed to determine which building characteristic at which scale affect the LST significantly over seasons.

2. Study area and Data

2.1 Study area

Beijing is the capital of China, covers approximately 16000 km^2 with more than 20 million urban ~~populations~~, and has a humid continental monsoon climate with severe dry winters, hot summers and strong seasonality. Our study focuses on Beijing's old city (Fig. 1), which is located at the center of metropolitan area, ~~with a~~ covering area over 40 km^2. There are lots of traditional architecture buildings (e.g., courtyard houses) and royal buildings (e.g., the Forbidden city). Since 1950s, giant changes of building~~s~~ styles are witnessed due to significant urbanization, mainly the demolition of traditional buildings and the introduction of high-rise modern architectures along the main street (e.g., Chang'an street and Second Ring road). The courtyard houses, royal buildings and modern buildings shape the typical multiple-building landscape, which make Beijing's old city an ideal laboratory for the studies of multiscale relationship between urban morphology and LST.

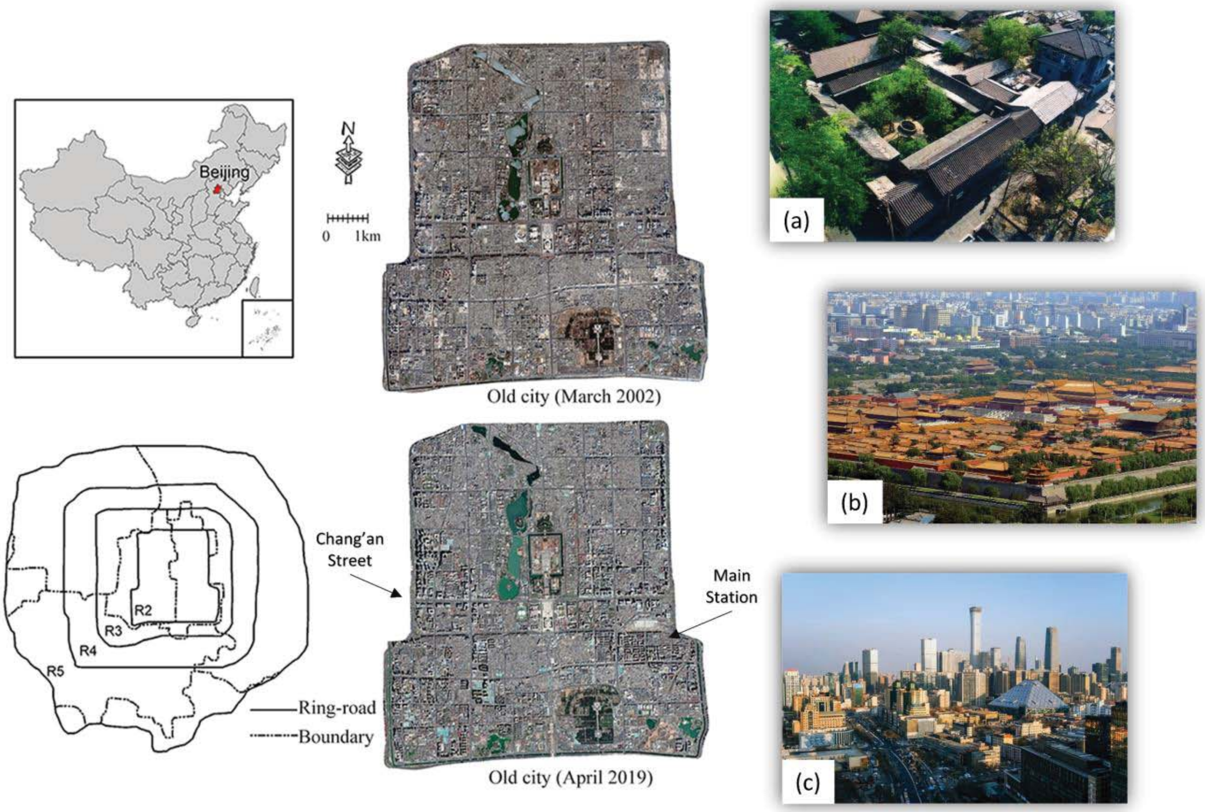

Figure 1. Location of study region. a) a sample of courtyard house; b) a sample of royal buildings; c) a sample of modern buildings in Beijing' old city.

2.2 Data

For this study, 12 Landsat 8 images across 12 months are downloaded from USGS (https://earthexplorer.usgs.gov/) to retrieve LST. The retrieved LST product using atmosphere correction methods has a spatial resolution of 30 m with the accuracy around 1K by consulting literature (Jiménez-Muñoz et al., 2014; Berger et al., 2017). The climate in Beijing city has seasonality, however, it's hard to distinguish the specific data. For a better understanding of seasonal influence of urban morphology across scales, hot season (June, July, Aug, and September), moderate season (March, April, May, October, November), and cold season (December, January and February) were defined based on mean value of extracted LSTs across months (Appendix A1). 3D building data comes from the Resource and Environment Science and Data Center, Chinese Academy of Science. Tree height data downloaded from Google Earth Engine comes from Global Forest Cover Change dataset with a spatial resolution of 30 m and good accuracy (RMSE = 6.6 m, MAE =4.45 m) (Sexton et al., 2013; Wu et al., 2022). All the data were geometrically corrected to WGS84/UTM Zone 50 N, and detailed information are shown in Table 1.

Table 1. Data Source

Data sources	Data	Local time	Component-derived	Spatial resolution
Landsat 8 OLI/ TIRS	21 Jan 2019	10:53	land surface temperature	30 Meter
	03 Feb 2018	10:52		
	26 Mar 2019	10:52		
	08 Apr 2018	10:53		
	13 May 2019	10:53		
	14 Jun 2019	10:53		
	27 Jun 2018	10:52		
	17 Aug 2019	10:53		
	02 Sep 2019	10:53		
	20 Oct 2019	10:53		
	05 Nov 2019	10:53		
	04 Dec 2018	10:53		
Building data	2016		Building height and footprint	3 Meter
Tree data	2015		Tree height and footprint	30 Meter

3. Methods

Detailed data processing consists of three steps (Fig. 2): 1) Urban building metrics were calculated across 15 scales using building footprint and height information; 2) The LST over 12 months were retrieved from Landsat 8 OLI/ TIRS remote sensing images; 3) Pearson correlation coefficient was applied to calculate the associations between metrics and LSTs across scales and months; 4) Random forest algorithm was applied to evaluate the relative importance of morphological metrics and tree height on affecting the LSTs across scales and months; 5) Multiscale relationships among seasons are obtained using temporal average. In step 3 and 4, only those windows with the spatial proportion of vegetation plus water below 0.3 were selected to create the building-LST data pairs. This is conducive to avoid the influence of large-body water and vegetation. In addition, for different scales, we only change the window size, but not change the original resolution of building data (3 m) within a window. Considering the spatial heterogeneity of urban landscape, the metrics at each scale were recalculated, not simple spatial aggregation. This kind of design is conducive to avoiding some modifiable area unit problems (MAUP) arising due to data resampling, to improve the fit to the real situation, and to strengthen the reliability of the multiscale relationship between urban morphology and LST.

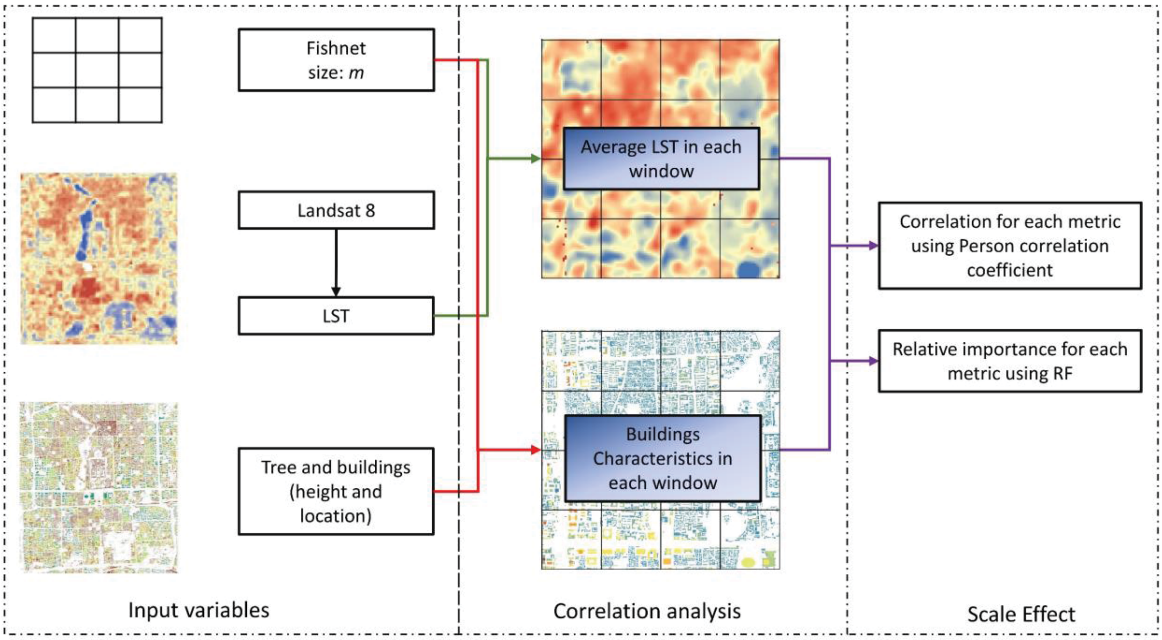

Figure 2. Work flow chart.

3.1. Building metrics

Targeted analysis of building characteristics is vital to compare its influence on the urban heat environment within cities. The 3D landscape metrics applied in this study for measuring urban morphology, are designed based on patch mosaic model and gradient model (Guo et al., 2021). Using four levels of heterogeneity defined by McGarigal et al. (2012), 'cells' refer to the building pixels, 'patches' refer to the enclosed building region according to various height thresholds, and 'classes' refer to the mixture of different building patches with similar building height. In this study, the height thresholds for building classes were: low buildings (below 10 m), sublow-rise buildings (10 m – 20 m), middle-rise buildings (20 m – 30 m), subhigh-rise buildings (30 m – 100 m) and high-rise buildings (over 100 m). The selected metrics consist of composition metrics and configuration metrics, aiming to characterize the surface fluctuation, building diversity and spatial structure characteristics (e.g., compactness and spatial arrangement regularity) in a built-up landscape (Table 2). The composition metrics are further divided into 2D and 3D metrics depending on whether 3D vertical landscape elements were taken as main variable for calculation or not.

Table 2. Selected building metrics for measuring urban morphology.

Metrics	Abb.	Type	Measure of the …
Building coverage ratio	BCR	Composition-2D	building coverage degree in a window.
Edge density	ED	Composition-2D	building segmented by the boundary.
Euclidean nearest-neighbor Mean Distance	ENN	Composition-2D	isolation degree of each buildings class, and can be taken as indicator for measuring the road width.
Patch density	PD	Composition-2D	evenness and building number of urban building pattern.
Mean building height	BH	Composition-3D	mean height of urban buildings.
Surface area	SA	Composition-3D	surface fluctuation compared with plane area
Mean Volume index	VOL	Composition-3D	mean volume of urban buildings.
Building surface slope	SSL	Composition-3D	integral slope of building surface, which is the sum of surface fluctuation at adjacent building pixels.
Surface developed ratio	SDR	Composition-3D	deviation of building surface to projected plane
Standard deviation of height	SQ	Composition-3D	undulation of the urban buildings surface.
Percentage of patch type	PLAND	Composition-3D	proportion of each buildings class in the urban building pattern, including low-rise (LB), sublow-rise (SLB), middle-rise (MB), subhigh-rise (SHB) and high-rise buildings (HB).
Landscape shape index	LSI	Configuration	deviation between patch shape and regular circle or square with same area.
Building Shade metrics	CNI	Configuration	effect of buildings forming ventilation paths, defined by the ratio between building height and building spacing (ENN).
Largest patch index	LPI	Configuration	largest space occupation of single building.
Landscape division index	LDI	Configuration	aggregation degree of buildings. LDI = 0 when the landscape consists of single patch
Landscape fractal dimension index	LFI	Configuration	irregularity and complexity of urban buildings landscape shape.
Shannon’s diversity index	SHDI	Configuration	diversity of urban buildings landscape.

Cohesion index	COI	Configuration	connectivity and aggregation of the urban building pattern.
Proximity index	PROX	Configuration	proximity, defined by the ratio between building height and square of building spacing (ENN).

3.2. Random Forest

The random forest is a nonlinear ensemble model based on decision trees for classification or regression (Hutengs and Vohland, 2016). For regression, the decision tree partitions the data based on the thresholds for the covariates, and it can grow continuously by recursively dividing data (Logan et al., 2020). Compared with single decision tree, random forest have better generalization preformation and ~~well~~ reduce the variance of the model. During the process of forest generation, it generates an internal unbiased estimate of generation error, with better accuracy among current algorithms. In addition, Random Forest is advantageous of reducing the risk of over-fitting by averaging a large number of de-correlated individual trees, and can deal with the multi-collinearity issue in the linear models, even a large proportion of data is missing. After training samples, the variables can be reclassified based on their contribution to the final regression value. In this study, LST is selected as the predictor, while the building features and tree height consist of a new variables group for regression (regression tree set-up: number of regression trees = 600, minimum number of observations per tree leaf = 5). Then, the relative importance (IM) of metric f can be obtained using following equation.

$$IM_f = \sum_{S \in N\{m\}} \frac{|S|!\,(M-|S|-1)!}{M!}\left[LST_x(S \cup \{f\}) - LST_x(S)\right]$$

where N is the set of all features for the training dataset with dimension M, S is the permutation subset of N with dimension $|S|$, $LST_x(S \cup \{f\}) - LST_x(S)$ is the difference of predicted value with and without feature f using feature set S. Through temporal average, we can get relative importance $IM_{f,sc,se}$ of feature f on LSTs over different experimental setups (various scales sc

and seasons se). Based on the descending order of relative importance among variables, 5 importance levels are defined: IM1 (variables ranked 1 – 5), IM2 (variables ranked 6 – 10), IM3 (variables ranked 11 – 15), IM4 (variables ranked 16 – 20), IM5 (variables ranked 21 – 24). This is conducive to further illustrate how dominant factors change with scales.

4. Results

4.1. Changes of urban morphology features at locations and scales

This study selected 15 window sizes from 30 m to 300 m. The spatial distribution of selected morphological metrics at 90 m is shown in Fig. A2, which illustrated a significant location-dependent pattern. For the courtyard houses region and royal buildings, the building density, building coverage ratio, spatial proportion of low-rise and sublow-rise buildings, landscape fragmentation, shape index, edge density, fractal dimension index exceeds that significantly than the modern building region, while the latter displayed a built-up pattern with higher building height, surface area, volume, building spacing, diversity and building surface fluctuation (indicated by SQ, SSL and SDR). In addition, higher trees are more distributed at the urban parks and royal garden. The trees along the modern buildings also showed a relatively higher tendency than that in the courtyard houses region.

The frequency distribution density (Fig. 3, applying kernel smoothing at spans of 60, 120, 180, 240, 300 m) of selected metrics indicates the discrete level of data distribution. The higher the peak value, the denser the data here. Focusing on the horizontal axis, the position corresponding to peak value tended to increase with the increase of scales, particularly for the absolute indicators (e.g., ENN, BH, SA and VOL). Larger window size means more buildings included and the open space among buildings can be better displayed. However, the changing tendency of peak values differ from metrics type. The peak values of 3D composition metrics tended to decrease with size increasing (except metrics for measuring spatial proportion of building types because most of them were distributed around zero), while those of 2D metrics and most configuration metrics tended to increase. Increasing peak values with sizes means more data aggregation. When studying coupled influences on LST with other metrics, if the peak value of one metric had an increasing tendency with sizes, the ability of this metric in explaining LST might get improvement, conversely verse. In this case, 3D characteristics and corresponding surface fluctuation might be dominant for describing urban morphology at small sizes, but with the increase of window size, the role of 3D metrics ~~turned to be~~ weaker and that of 2D and configuration characteristics ~~got~~ strengthened. This replacement is likely to ~~causing~~ different influence on urban heat environment across scales.

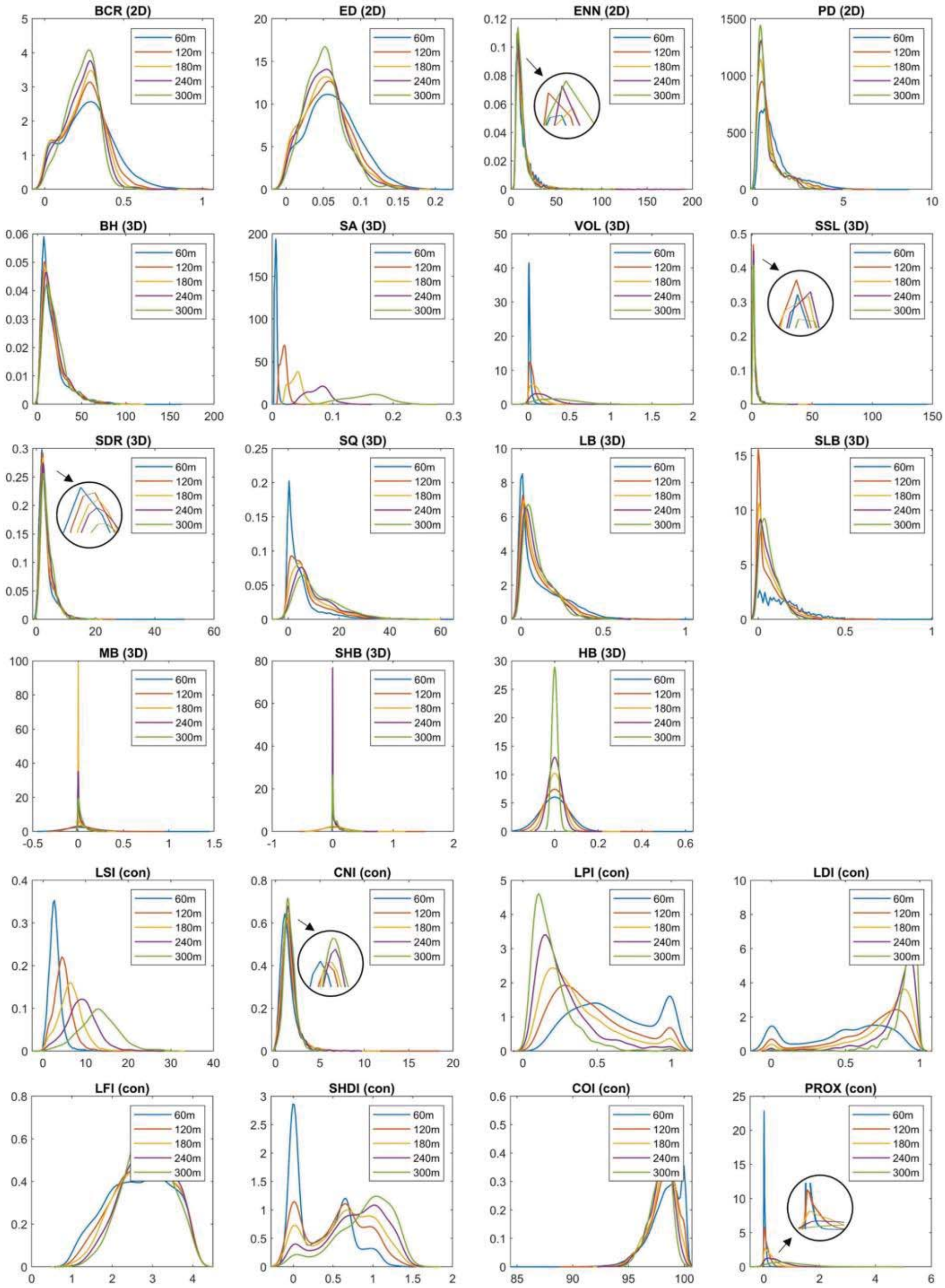

Figure 3. Variations of Kernel distribution density over selected scales (x-axis means the value range, while y-axis means the density value). The estimate is based on the normal kernel function, using the window parameter (bandwidth=2). '2D' represents 2D composition metrics, '3D' represents 3D composition metrics, and 'con' represents configuration metrics.

4.2. Association between morphological metrics and LST over scales and seasons

Among the 2D composition metrics, the building coverage ratio (BCR) is positively related the LST, similar phenomena are also seen in edge density (ED) and patch density (PD; see Fig. 4). Building spacing (ENN) is negatively related to LST. Higher building coverage, complex edge condition and compact building layout lead to more hat accumulation and less heat loss. More solar radiation is transferred into sensible heat fluxes and more heat storage is stored into the buildings, which together cause a higher LST. In addition, with the increase of window size, the Pearson coefficients tended to increase and reached a stable state. The changing tendency of 3D metrics with scales are similar with 2D scales. Most of metrics displayed a negative relationship with LST except low-rise building proportion. Negative values mean that significant building surface fluctuation might cool neighborhood environment. The reason is that selected 2D metrics are related to more sensible heat fluxes, but 3D metrics directly affect the spatial distribution of incoming solar radiation. This also explained the differences for 2D and 3D metrics over seasons. 3D metrics showed higher association with LST during cold seasons, different with 2D metrics that showed higher association during hot season. During hot season with strong radiation, heat accumulation caused by 2D features might be significant on the influence of LST than the building shade. When it turned into cold season, spatial distribution of incoming solar radiation would be the main reason for LST changes.

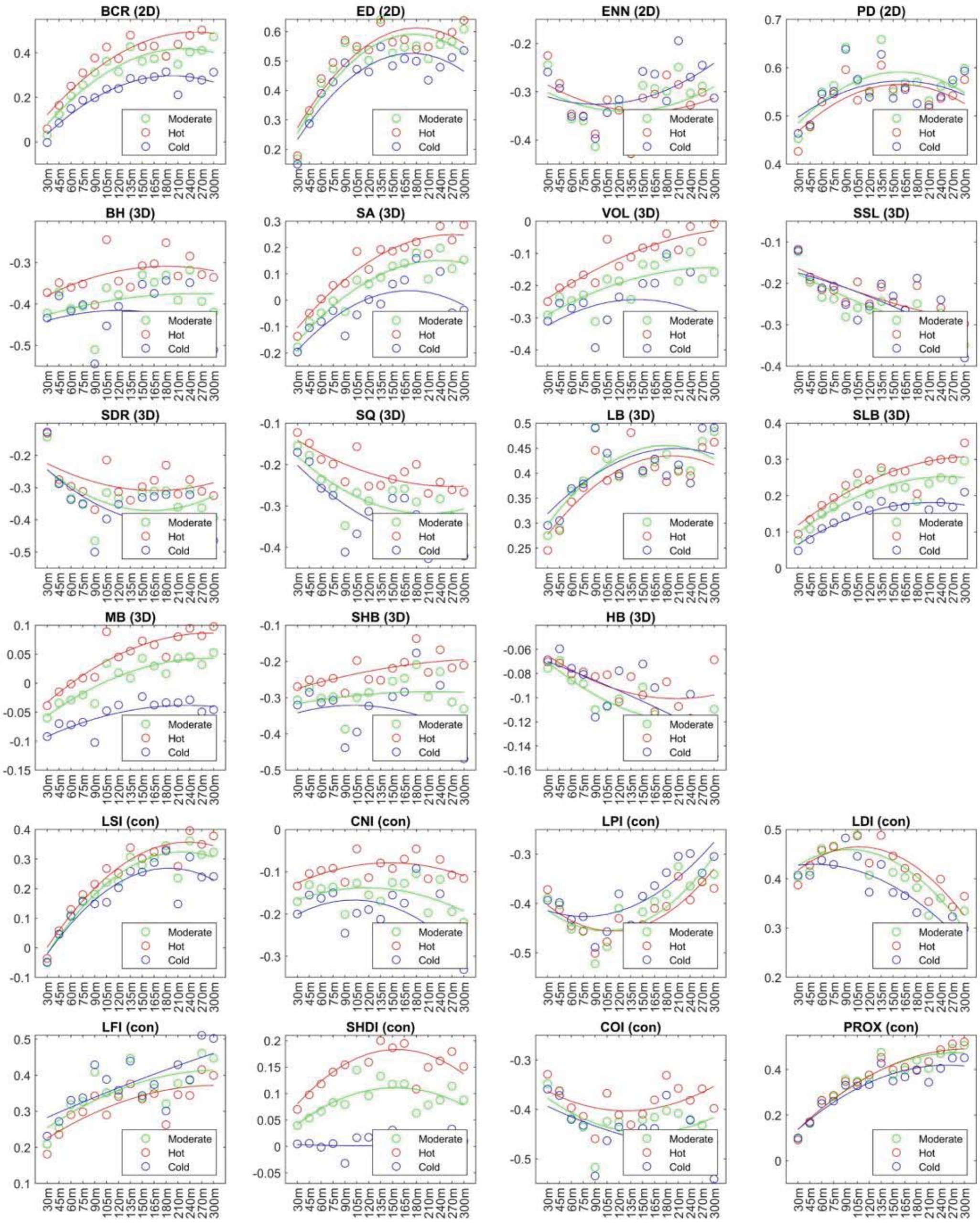

Figure 4. Variations of Pearson correlation coefficients (y-axis) for different metrics group over different scales (x-axis). '2D' represents 2D composition metrics, '3D' represents 3D composition metrics, and 'con' represents configuration metrics; the season is indicated by Hot, Moderate, and Cold (sect. 2.2).

The association between LST and configuration metrics among scales were similar with composition metrics. The lower coefficients are expected at small sizes. Under these sizes, the single window only involves limited buildings, therefore, the spatial configuration of building layouts is not obvious. With the increase of window size, the Pearson coefficients tended to increase because more and more buildings are included and building styles tended to be multiple. LDI, LFI, PROX and LSI were positively related to LST, while COI and LPI negatively related to LST. Complex building shape indicated by LFI and LSI, larger surface area to building spacing ratio (PROX), and complex edge condition (LDI) would lead to increase of LST. Larger largest patch index (LPI) means more building shade, while better patch cohesion condition (COI) is conducive to urban ventilation, which lead to lower LST. In addition, most of configuration metrics showed a higher value during hot season. The reason is similar to 2D composition metrics, which affect LST mainly through heat accumulation through complex buildings layout.

4.3. Relative importance of morphological metrics in influencing LST across scales and seasons

With the increase of window size, mean values of R^2 tended to increase from 0.51 to 0.82, while that of RMSE tended to decrease from 1.2 to 0.7, as expected (Fig. 5a and 5b). Three scale groups were further defined: small scales (30 m – 90 m) with an obvious increase of R^2, medium scales (105 m – 165 m) with a slow increase of R^2, and large scales (180 m – 300 m) with relatively stable variations of R^2. Fig. 5c displays the monthly variations of RMSE for regressed LST, which indicates a lower accuracy at hot seasons than moderate and cold seasons. This seems to correspond with the changes of solar radiation, sun duration and intensity. For the relative importance of selected metrics, tree height displayed the highest contribution to the variations of LST at most scales (Fig. 5d). Another point is the season-dependent impacts, particularly at large scales. Significant influence of tree height was revealed during hot season. This is due to coupling function of building shade and latent heat fluxes. During the cold season, the solar radiation is very low and the tree leaves fall, reducing evapotranspiration and the influence on LST.

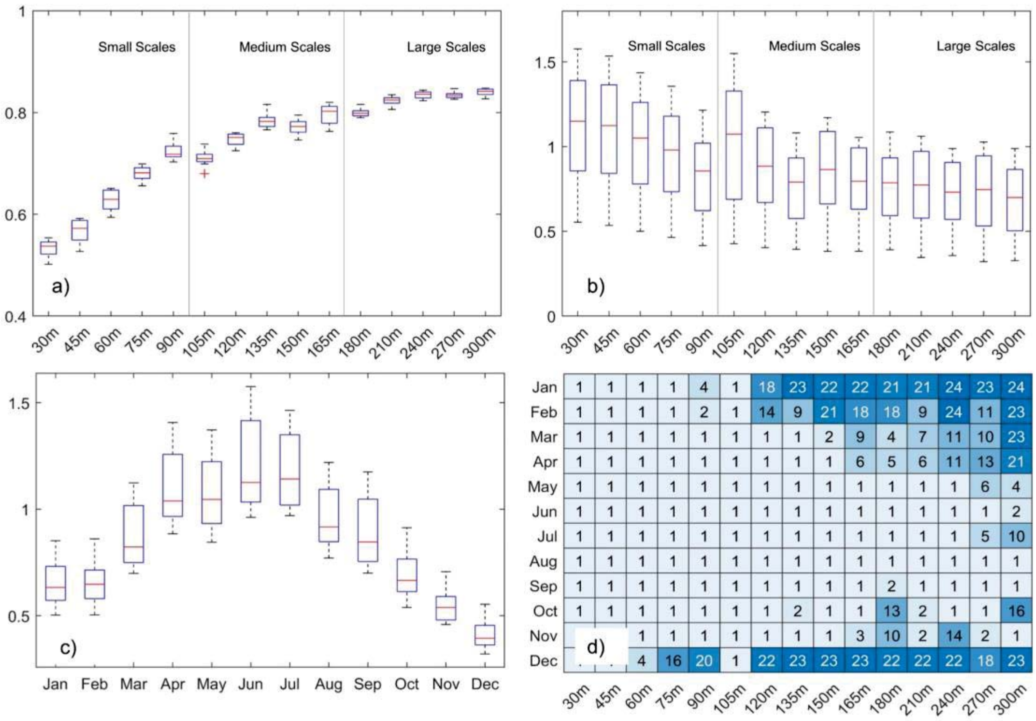

Figure 5. a) Variations of R^2 for predicting LST over scales using random forest; b) Variations of RMSE over scales; c) Variations of RMSE over months; d) Relative importance of tree height in predicting LST over scales and months. '1' means the top-1 importance, and so on. Red line in each box indicates the median value.

For the relative importance of building metrics, there were no significant differences along seasons (Appendix A3), but significant across scales (Fig. 6). Fig. 6a displayed the detailed changes of relative importance of each metric at small, medium and large scales. 2D composition metrics (PA, ED, ENN and PD) all showed much higher importance to the variations of LST than 3D and configuration metrics at large scales. The results turned to be opposite at small scales that 3D metrics, particularly BH, SA, VOL and surface fluctuation parameters (SQ, SSL and SDR). Fig. 6b displayed the changes of relative importance of various metrics groups over scales. It's significant that 3D metrics tended to decrease, while 2D metrics tended to increase with size increasing. The crossing point existed ~~in the~~ medium scales (105 m – 165 m), ~~that~~ the 2D and 3D metrics both showed higher contribution to the LST. ~~Another point is that~~ the relative importance of configuration metrics is below I3 across all scales, much lower than composition metrics (2D and 3D metrics), which might indicate a relative weak influence of configuration metrics. In addition, according to the results of

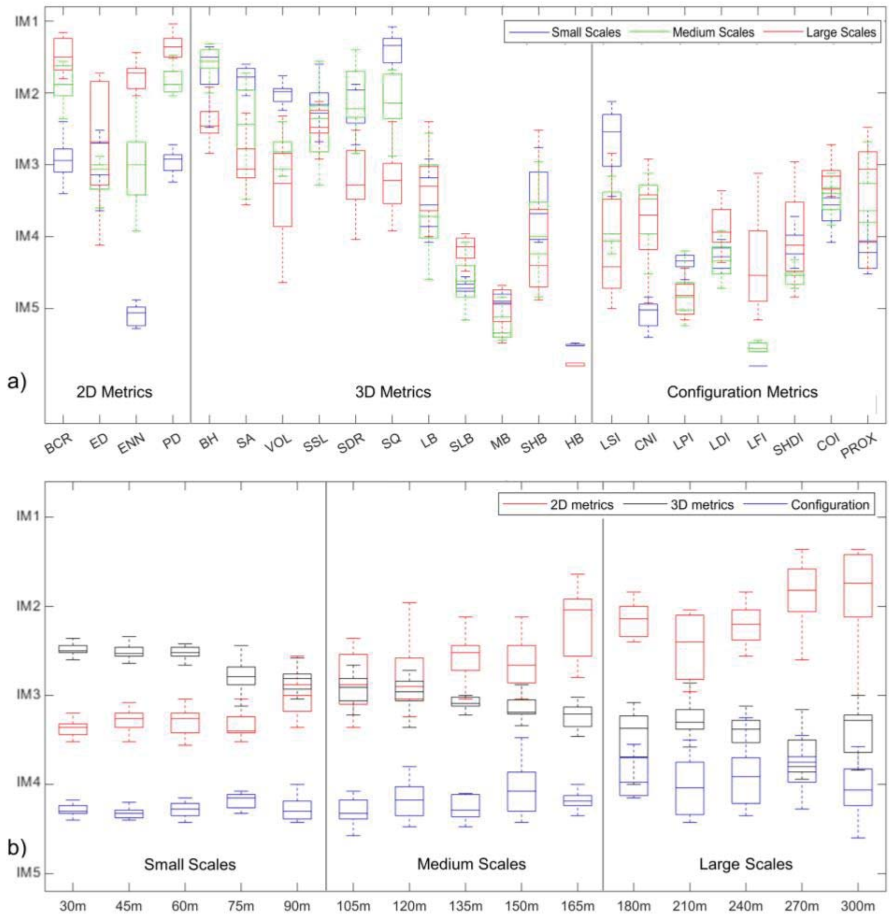

Figure 6. a) Changes of relative importance of each metric at a specific scale group (small, medium or large) for all seasons; b) Changes of relative importance of various metrics belonging to the same building metric type (2D composition, 3D composition or configuration metrics) for all seasons. Red line in each box means the median value.

5. Discussions and Conclusions

5.1. Influencing mechanisms of urban morphology on LST over scales

Multiscale studies for the relationship between urban morphology and LST is increasingly found in the literature, and aim to find the turning point over scales. We found some ~~excited~~ conclusions. In this study, we applied a suite of building metrics for measuring urban morphology and the results indicated that with increase of window size, 2D composition and configuration gradually replace the dominant role of 3D composition metrics for describing urban morphology, which coincided with Li and Hu (2022) for the same region. This change is important and conducive to further reveal in-depth influencing mechanisms between urban morphology and urban heat environment.

Combining the results of correlation and relative importance of building metrics, the composition metrics showed higher influence on the variations of LST than configuration metrics across scales. Similar findings were also indicated by Liu et al. (2018) and Guo et al. (2021). Composition metrics focus on the measurement of building number, density, building spacing and surface roughness, which directly affect the incoming solar radiation and corresponding sensible heat fluxes. The configuration metrics focus on the spatial structure of buildings layout in projected plane, rather than the vertical information. This may affect LST through heat accumulation and urban ventilation condition, which explained the correlation with LST, but the weakness in reflecting building shade might lead to less importance than composition metrics.

Among the composition, 2D metrics and 3D metrics differ with scales. At large scales, the relative importance of 2D metrics totally exceed that of 3D metrics. This conclusion is similar ~~with~~ Lu et al. (2021), Huang and Wang (2019), and Li and Hu (2022). In their studies, when the window size ~~over~~ 120 m, building coverage ratio ~~turned to be~~ the most important ~~among all the~~ metrics. At small scales, the influence of 3D metrics on LST are much more significant than 2D metrics. Our finding ~~is coincided~~ with Li and Hu (2022), who found a higher importance of building height at 60 m. The difference over scales indicated the changes of influencing mechanisms. Larger scale means more buildings included in one window, and more incoming solar radiation are transferred into sensible and soil heat fluxes. In addition, for a dense and irregular built-up landscape, these heats are hard to release, and may lead to more heat storage and heat accumulation, then leading to higher LST. At small scales, the building height, surface area, volume and SQ are the dominant building characteristics over windows. Higher values generate more building shade, reflect more solar radiation, and lead to weaker energy transformation. The results indicated that this influence may exceed the influence of heat accumulation on LST, and causing a higher importance of 3D than 2D composition metrics.

In this study, the selected metrics can explain over 80% variations of LST across seasons at large scales. Even at small scales, our results performed much better than ~~the same-type researches~~. In additiona~~l~~ to more building features considered, another reason is the tree height. Tree height was the most important factor for the variations of LST in most ~~of~~ months and scales. Comparing with other vegetation index (e.g., NDVI), tree height is much more sensitive to the reflected solar radiation. Higher trees and wider leaves might cause stronger evapotranspiration and larger shade, which is conducive to cool the neighborhood environment. In contrast, we made additional experiments to compared the accuracy with tree height and without tree height (Fig. 7). The results indicated that tree height data can improve the model accuracy well, particularly at small scales. Considering the significant cooling effect, tree height should be involved for the studies of relationship between urban morphology and LST.

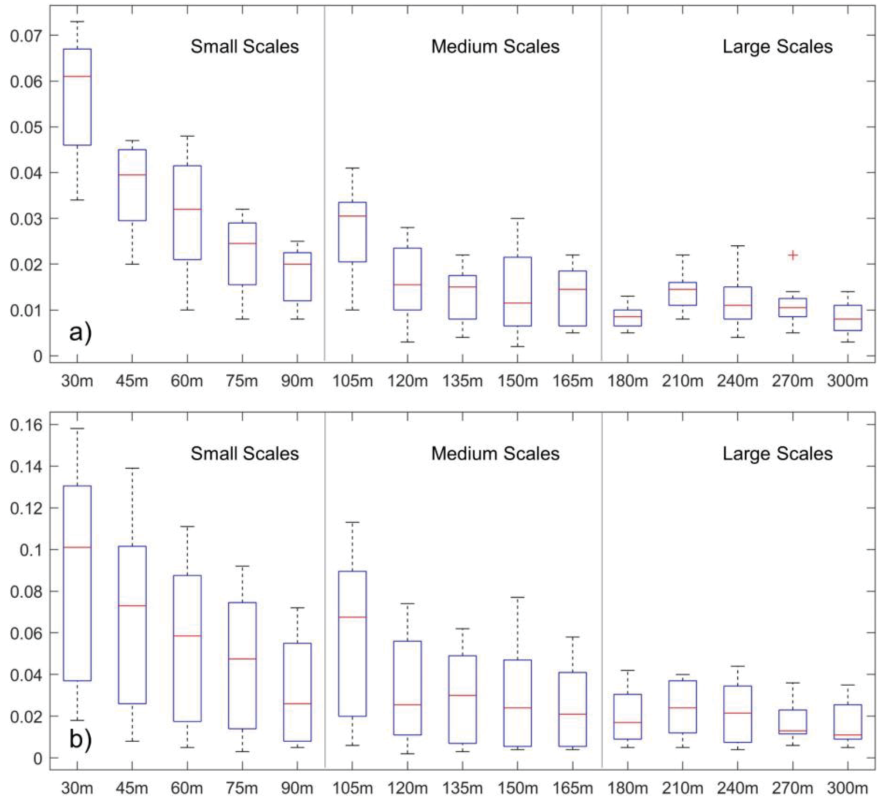

Figure 7. Differences of R^2 (a) and RMSE (b) in predicting LST using tree height and without. Red line in each box means the median value.

5.2. Influencing mechanisms of urban morphology on LST over seasons

The changes of influencing mechanism also ~~get demonstration~~ across seasons. Pearson correlation coefficients showed a stronger influence of 2D composition metrics than 3D metrics during hot season, but a weaker influence during cold season. This conclusion is the same with Guo et al. (2021) and Huang and Wang (2019). For Beijing's old city, the solar radiation is quite strong from June to September. In spite of lots of building shade from high-rise buildings and efficient evapotranspiration from vegetation and water, strong convection between air and building surface together with dense building layouts lead to high temperature. The metrics which are sensitive to this influence, such as building coverage ratio, patch density and building spacing, all displayed higher correlations at these months. During the cold season in Beijing, the human comfort is significantly different with the sun rise and without, because of weak solar radiation and short sun duration. And lower solar elevation angle lead to larger building shade area, particularly around the high-rise buildings. Li et al. (2021) supported this point that they found a higher contribution of building shade index on winter temperature.

In spite of no seasonal significance of relative importance of building metrics, a larger RMSE was displayed during the hot months, and then moderate, cold seasons, which coincide with the changes of Pearson coefficients. Lower regression accuracy indicates a much more complex relationship between LST and urban morphology. During hot season, latent heat fluxes are stronger than that at cold season. In this study, although we make a filter of windows (spatial proportion of water plus vegetation less 0.3), some vegetation (green roof materials and vegetation along vertical walls) or water regions are included in the window for calculation. The mixed pixels in LST map is 30 m resolution, which is controlled by various land use and land cover types. More important, the metrics that we selected in this study are sensible to sensible heat fluxes, hardly to reflect latent fluxes. Although we consider tree height, the parameters directly related to evapotranspiration (e.g., volume and surface area) is neglected. However, at cold season, the latent heat flux is very weak because of weak solar radiation, bare~~d~~ trees and frozen water. ~~Most of net radiation from sun are~~ transferred into sensible heat flux~~es~~ and heat storage, which lead to a higher accuracy of regressed LST.

5.3. Recommendations for urban planning

The scale in this study refers to the window size, which represents different aspects to understand urban morphology. Our results demonstrate a scale-dependent influence of urban morphology on LST, and may supply some useful scientific suggestions for urban planning from the aspect of heat management. Large scales represent the large-scale relationships, while small scales represent the local conditions and planners may follow the order: first the whole, then the parts. At large scales, people need to consider the coverage of buildings, building spacing, and the configuration with other land use or land cover types firstly. This might have an important influence on the urban heat environment for the whole city. Later, in local regions, 3D surface roughness might be considered in addition to 2D plane features. This is the scale that 2D and 3D composition together affect LST, suggested by our study. For more details, the building height, surface fluctuation, and building spacing should be considered, which might be conducive to create better ventilation paths and more efficient heat release.

5.4. Potential application and limitations of this study

One potential application of urban morphological indicators is for LST downscaling. Remote sensing hardly extracts the high resolution LST product because the thermal infrared bands only detect a range of low-energy wavelength (Hutengs and Vohland, 2016; Pu, 2021). One useful solution is to develop downscaling models. The morphological indicators can be taken as influencing factors for predicting high-resolution LST in urban regions. ~~One thing needs to mind is that~~ ~~m~~ost of literature assume the relationship as scale-independent (Pu, 2021). Our study has ~~proofed~~ scale effect for the relationship between urban morphology and LST, but this relationship is relatively stable within a certain scale range. We suggest~~ed~~ the ratio from native resolution for LST downscaling to target resolution should not be too large, and it's best to control under 3 times. Another application is ~~large-~~comparison of urban morphology across the world. With the development of high-resolution remote sensing sensors (e.g., Sentinel series), building footprint and building height products at nation, continent and global scale have been released (Frantz et al., 2021; Esch et al., 2022; Yang et al., 2022). Together with the temporal analysis, we can understand spatiotemporal changes of urban morphology across the world, and discuss the influence of urbanization on urban development as well as their potential influence on urban ecosystems.

Impacts of urban morphology on LST may depend on seasons, day/night, regions and scales. This study considered the seasons and scales during the daytime, but omitted nocturnal influence and regions. The nocturnal urban temperature is highly related to human comfort, and may cause more power consumption for cooling or heating, which in turn, lead to serious air pollution and greenhouse gas emissions (Salamanca et al., 2014; Guo et al., 2021). The urban morphology, particularly the physical form varies ~~from~~ cities (Guo et al., 2022), may lead to various influence on LST. In addition, regardless of the use of the linear Pearson coefficient or the nonlinear relative importance of the metrics on LST, they are not directly related to the cooling or heating efficiency of building features. Partial dependence plots might supply the solution. For further studies, we would integrate these factors to see whether there is similarity of the influence among cities from scale and season.

Appendix A

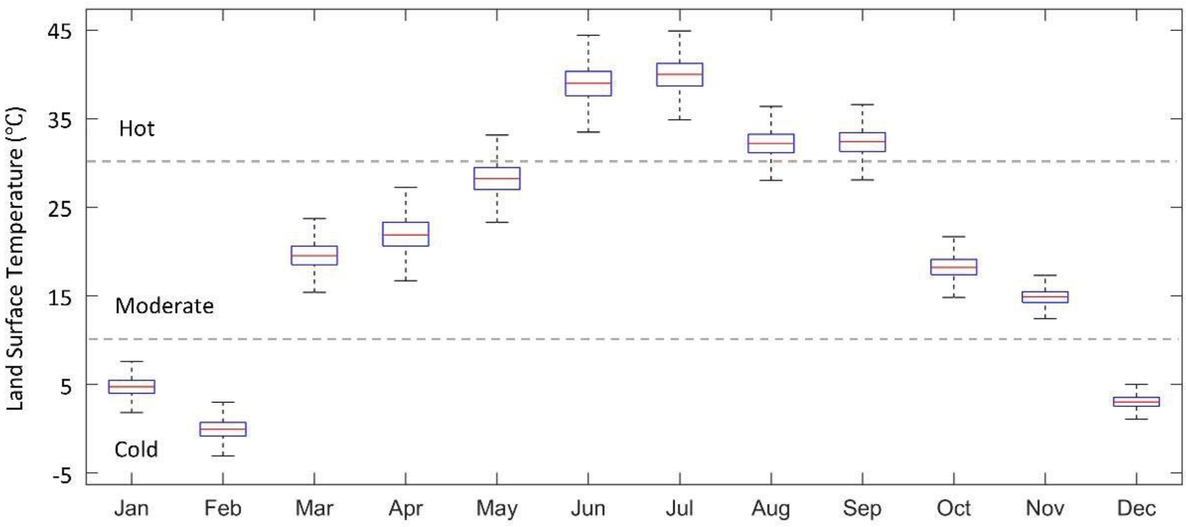

Figure A1. Monthly variations of extracted LSTs and defined three seasons in Beijing's old city. Red line in each box means the median value.

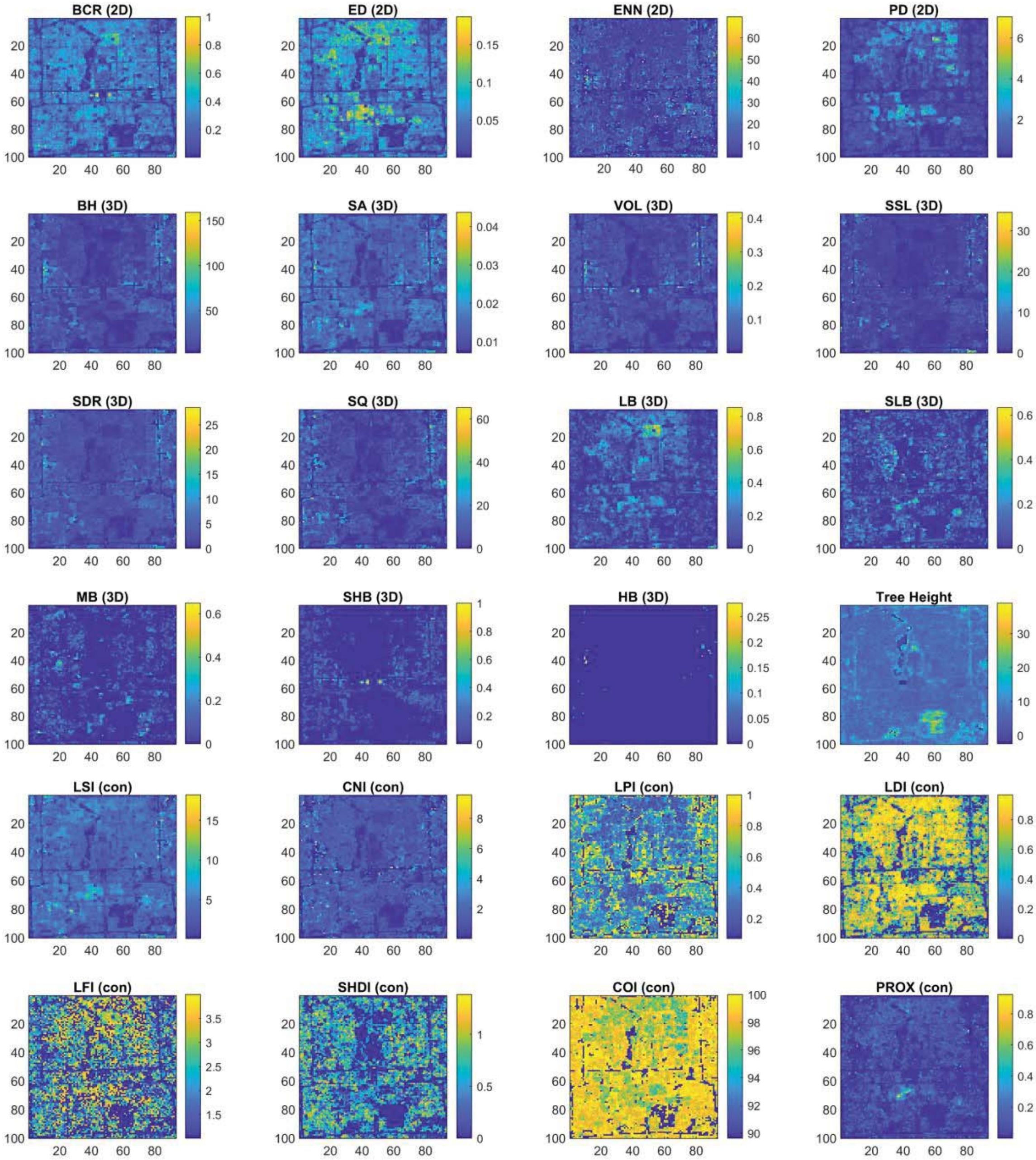

Figure A2. Spatial distribution of selected building metrics and tree height at 90 m scale. '2D' represents 2D composition metrics, '3D' represents 3D composition metrics, and 'con' represents configuration metrics.

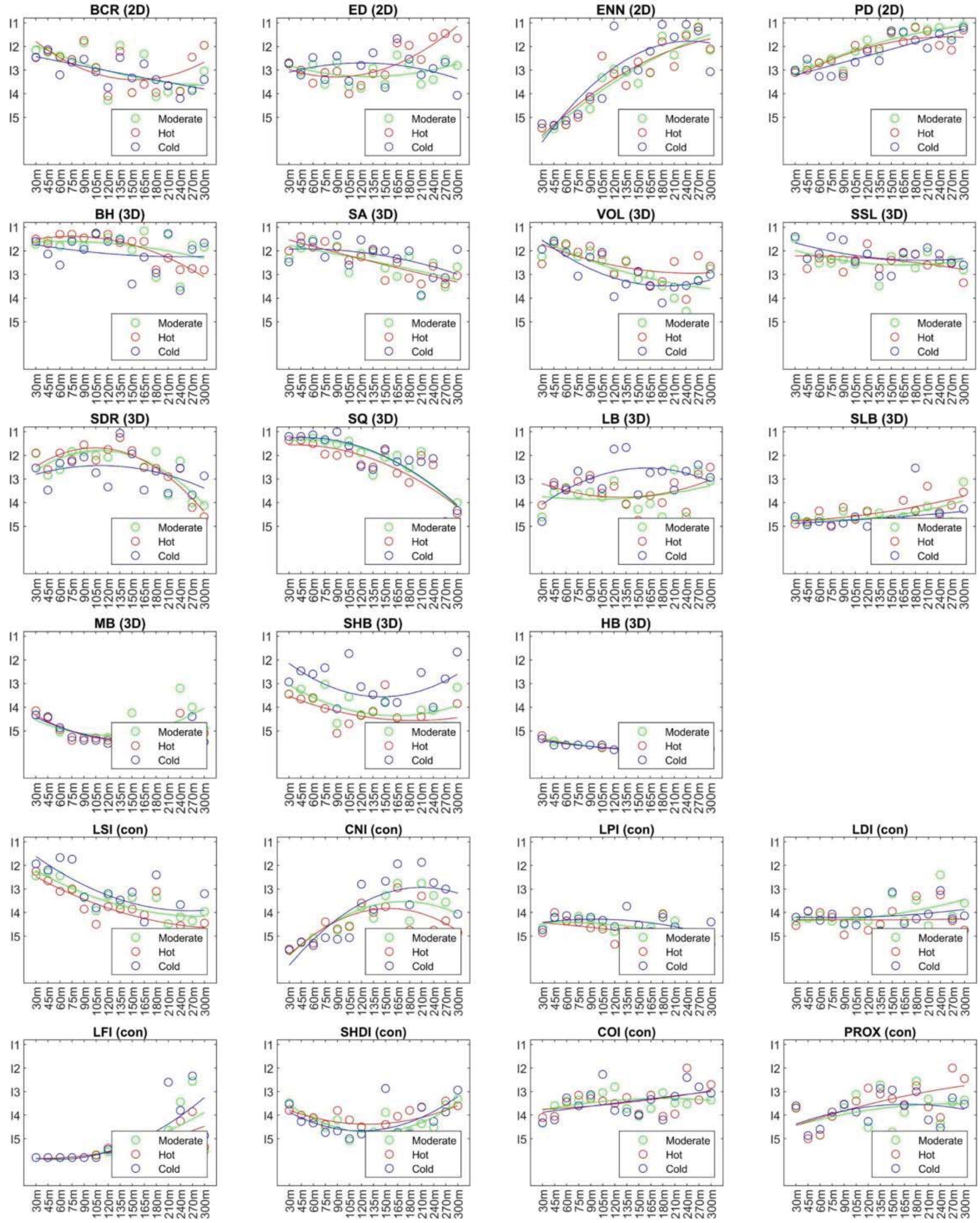

Figure A3. Relative importance of each building metric over seasons. '2D' represents 2D composition metrics, '3D' represents 3D composition metrics, and 'con' represents configuration metrics.

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