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Review Article

Landscape metrics in assessing how the configuration of urban green spaces affects their cooling effect: A systematic review of empirical studies

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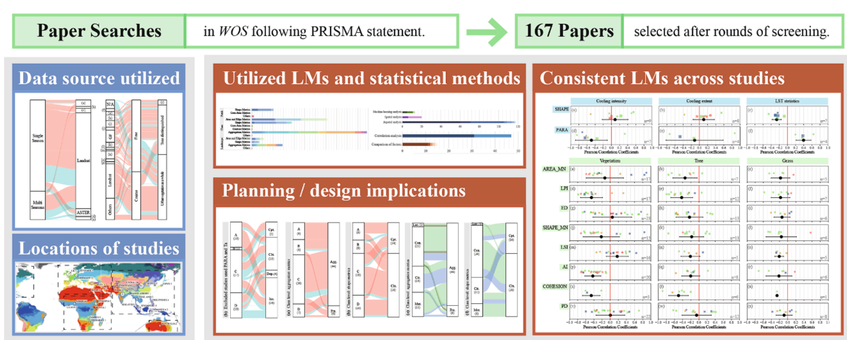
HIGHLIGHTS

- 167 studies on UGS configuration and cooling effect using LMs were reviewed.
- Diverging suggestions on UGS configuration at patch and class level exist.
- Contextual and methodological factors cannot help interpret the diverging suggestions.
- Few specific planning and design implications on UGS configuration were given.
- Future directions for better implications to UGS planning and design are discussed.

GRAPHICAL ABSTRACT



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ABSTRACT

Urban green spaces (UGS) are effective mitigations to excessive urban heat. Landscape metrics (LMs) have been widely used to assess how UGS configuration, i.e., edge and area, shape complexity, and aggregation, may facilitate better cooling. However, application of configurational LMs has produced diverging suggestions for planning and design practice, which cannot provide urban and landscape designers with holistic insights for future sustainable development. Thus, we conducted a systematic review to (1) summarize the contextual and methodological factors in pertinent studies, and (2) synthesize extractable results and implications, and see if the contextual and methodological factors may help to interpret the diversity in planning and design implications. A total of 167 studies were identified, covering 90 cities in 27 countries belonging to 16 Köppen climate zones. Evolving statistical methods have been applied, including spatial, non-spatial, and non-parametric machine-learning analyses. Synthesis of correlation coefficients reveals that patch-level metric SHAPE, and class-level metrics LPI, AI and COHESION yielded generally consistent trends across studies. No consensus was obtained based on patch-level metrics, while class-level analyses suggest aggregated, patchy, larger, and complex-shaped

Abbreviations: LMs, landscape metrics; UGS, urban green spaces; LU, land use; LC, land cover; LPI, largest patch index; TE, total edge; ED, edge density; AREA, patch area; GYRATE, radius of gyration; PARA, perimeter-area ratio; SHAPE, shape index; FRAC, fractal index; CIRCLE, related circumscribing circle; CONTIG, contiguity index; PAFRAC, perimeter-area fractal dimension; CORE, core area; CAI, core area index; ENN, Euclidean nearest neighbor distance; PROX, proximity index; IJI, interspersion and juxtaposition index; PLADJ, percentage of like adjacencies; AI, aggregation index; CLUMPY, clumpiness index; COHESION, patch cohesion index; LSI, landscape shape index; nLSI, normalized landscape shape index; NP, number of patches; PD, patch density; DIVISION, landscape division index; SPLIT, splitting index; MESH, effective mesh size; SIMI, similarity index; CONNECT, connectance; CONTAG, contagion.

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UGS facilitate better cooling. Contextual and methodological factors cannot help interpret the diverging suggestions. Few specific planning and design implications on UGS configuration were given. Future studies are suggested to specify either a land-use or land-cover perspective to align with practical scales in planning and design practice, and to formulate specific implications beyond binary suggestions by echoing the heterogeneity of thermal environment and UGS pattern under precise planning and design contexts with practical illustration.

1. Introduction

The increased intensity of heat waves and continuously exacerbated urban heat island effect pose great threats on citizens' health and quality of life (Jiang et al., 2019; Sun et al., 2019). The regulation effect of urban green spaces (UGS) on urban climate has been widely evaluated and recognized (Gunawardena et al., 2017; Wong et al., 2021), with researchers and practitioners advocating the optimization of UGS to deal with the excessive urban heat (Klemm et al., 2018).

Landscape ecology provides a theoretical foundation for understanding the relationship between UGS spatial patterns and urban heat mitigation, as it focuses on the relationship between ecological pattern and processes (Turner et al., 2001). Based on the patch-matrix model in landscape ecology, landscape metrics (LMs) have been widely used as quantification of land use/land cover (LU/LC) patterns at patch, class, and landscape levels (Uuemaa et al., 2013). Since the development of LMs (O'Neill et al., 1988), hundreds of metrics describing morphological aspects including edge and shape complexity, fragmentation, and connectivity have been developed, which has also been identified as a conceptual common ground between ecological and visual landscape character (Fry et al., 2009).

The UGS pattern has been quantified by compositional and configurational LMs, which have been intensively evaluated in relation to UGS's cooling (e.g. Chang and Li, 2014; Li et al., 2012; Zhou et al., 2011; Kong et al., 2014). Compositional studies, which focused on the coverage abundance of UGS, have reached the consensus that enhancing UGS coverage may provide better cooling (e.g. Bowler et al., 2010; Yu et al., 2020b). However, considering that enhancing UGS coverage in a city unlimitedly is unrealistic, configurational studies have endeavored to link UGS configuration with more effective cooling, focusing on the UGS spatial arrangement against other urban elements (Zhou et al., 2011). Configurational LMs effectively quantify UGS morphology, although inherent characteristics such as inter-correlation among LMs exist (Chen et al., 2014a; Peng et al., 2010). Closely linked with landscape planning and design, using configurational LMs to assess UGS are expected to provide reference to support evidence-based planning and design (Brown & Corry, 2011).

However, the application of configurational LMs as morphological indicators to link UGS with their cooling effects have produced diverging results in studies worldwide. For instance, by using shape index as a quantitative parameter, compact UGS shape (e.g., Ekwe et al., 2020; Yu et al., 2017) and complex UGS shape (e.g., Peng et al., 2021, Du et al., 2017) have both been linked with better cooling, with opposing conclusions even existing in past literature reviews (Fu et al., 2022; Zhu et al., 2022). Such a situation cannot provide urban and landscape designers with consistent references in practice. A closer inspection is needed on whether contextual variables, e.g., background climate zone (Wu et al., 2022b) and urban context, and methodological factors, e.g., data source and resolution (Li et al., 2013), metrics selection and calculation method (Chen et al., 2014a), pose impacts on the association between UGS configuration and UGS cooling. This understanding can provide guidance to both planning and design practice and future scientific studies.

Previous reviews in pertinent fields are still missing an overall evaluation on accumulative knowledge of configurational LMs and UGS cooling. On the one hand, reviews on LMs in general have summarized their evolving history (Frazier & Kedron, 2017), theoretical and methodological improvement (Lausch et al., 2015; Šímová & Gdulová, 2012), and different ecological processes that have been evaluated (Uuemaa et al., 2013). A special focus on UGS configuration and urban heat mitigation is missing among these reviews. On the other hand, studies reviewing the climate mitigation effects of UGS have focused on aspects such as effects of various UGS types (Bartesaghi Koc et al., 2018; Bowler et al., 2010; Gunawardena et al., 2017; Hami et al., 2019; Jamei et al., 2016; Liu et al., 2021; Motazedian & Leardini, 2012; Saaroni et al., 2018; Wong et al., 2021; Yu et al., 2020b), urban vegetation's cooling effects (Ellison et al., 2017; Rahman et al., 2020), and research methodology progress (Aslam & Rana, 2022; Derdouri et al., 2021; Liu et al., 2021; Toparlar et al., 2017). A review concerning UGS configuration for heat mitigation has covered a broad range of research scales, methods and results (Fu et al., 2022), while lacking an exclusive focus on the quantification of UGS morphology. Zhu et al. (2022) evaluated the complex issue of how UGS morphology impacts their cooling and energy-saving effects, however, they did not comprehensively cover all morphological issues quantified by LMs.

Therefore, we conducted a systematic review to holistically examine how UGS quantified by configurational LMs may impact the cooling effect analysis and findings. Our review synthesized related studies based on their data source, research method, location, and climate zones. We further adopted descriptive and *meta*-analysis to assess which and what types of LMs have been most widely used and found effective in analyzing UGS cooling. The proposed suggestions on UGS planning and design were also synthesized, followed by a discussion on how these results can be linked with urban and landscape planning and design practice. Several recent global and nationwide studies covering study sites located in different climate zones have endeavored to answer these questions (Wang et al., 2022; Wu et al., 2022b; Yue et al., 2019). We focused on reviewing studies with one to several study sites for cross-comparison with these global empirical studies to provide a holistic picture of the latest research in this field.

2. Method

Following the PRISMA statement (Moher et al., 2009), peer-reviewed research papers published in indexed journals in English were searched for in *Web of Science*. Two sets of searches were conducted using the keywords in Table 1 on Feb. 6, 2023. These keywords were intended to identify studies that have evaluated UGS cooling using configurational LMs, either conventional LMs such as those defined by McGarigal et al. (2012) and calculated by using software such as FRAGSTATS or self-defined metrics which quantitatively describe UGS spatial pattern. Keywords for search B evolved from search A by including more descriptions of the UGS spatial pattern, e.g., "shape", "fragmentation", "aggregation", "connectivity". We did not limit the publication date range to conduct an overall evaluation on the reviewed topic. A single database was utilized for the search as it generated a large enough paper pool.

The search and screening process is shown in Fig. 1. The initial screening of paper titles and abstracts included studies with the following criteria, that the study (1) evaluated cooling effects or thermal performance of UGS in an urban area, no matter how UGS or urban area is defined; (2) applied configurational LMs to quantify UGS; (3) was a case study of specific study site(s) based solely on observation data and didn't utilize simulation method. Compositional LMs as defined by Leitão (2006) and McGarigal et al. (2012) were excluded from consideration, while their interaction with configurational LMs was included

Table 1
Two sets of search keywords in *Web of Science*.

Search	Criteria	Search Terms
A	Restrict to built and urban area	ALL = (urban)
	Restrict to cooling and urban thermal environment studies	AND ALL = (temperature OR cooling OR thermal OR “heat mitigation”)
	Restrict to landscape metrics	AND ALL = (“landscape metric*” OR “landscape index” OR “landscape indices”)
B	Restrict to built and urban area	ALL = (urban)
	Restrict to cooling and urban thermal environment studies	AND ALL = (temperature OR cooling OR thermal OR “heat mitigation”)
	Restrict to green spaces	AND TS = (green space* OR greenspace* OR green infrastructure OR “urban forestry” OR park OR tree OR vegetation OR “plant species”)
	Restrict to green spaces configuration studies	AND TS = (configuration OR arrangement OR spatial pattern OR landscape pattern OR “landscape metric*” OR “landscape index” OR “landscape indices” OR shape OR fragment* OR aggrega* OR connect*)
	Exclude simulation studies	NOT TS = (simulation OR ENVI-met)

within the review scope. Additionally, our review solely focused on empirical evidence based on observations, and all simulation studies were therefore beyond the scope of our review. The contributions of simulation studies to the scientific evidence and application in this field deserves further investigation.

Deep screening of full text was conducted, and data addressing the following questions were extracted, namely, (Q1) which city and Köppen climate zone was the study site located in, and at what scale was UGS cooling evaluated; (Q2) what data was used for temperature indicator(s) and UGS identification; (Q3) what configurational LMs have been used in different analytical levels; (Q4) what statistical methods have been applied to examine the relationship with UGS cooling; and (Q5) what suggestions on UGS planning and design have been given based on these evolving statistical methods. During this deep review process, a snowball strategy was used to incorporate relevant studies that appeared in the reference lists of reviewed papers but were not successfully identified in the search strategy (Greenhalgh & Peacock, 2005). Eventually, 167 papers were reviewed. Detailed information of reviewed studies is given in Appendix A.

3. Geographical range, temporal range, and data sources

In response to (Q1) and (Q2), reviewed papers were summarized based on the locations and climate zones of studies, and the data sources of temperature indicators and UGS identification and classification.

3.1. Geographical and temporal range

Fig. 2 demonstrates the distribution of reviewed studies by cities and world’s current Köppen climate classification (Beck et al., 2018). The study sites identified in our review covered 90 cities in 27 countries belonging to 16 Köppen climate zones. Cities with a temperate climate (Köppen climate Zone C, 111 studies in 46 cities) and continental climate (Köppen climate Zone D, 51 studies in 14 cities) were the most evaluated. Specifically, humid subtropical climate (Cfa) had received the most attention (59 studies of 18 cities), followed by hot-summer continental climate (Dwa, 43 studies of 6 cities) and dry-winter humid subtropical climate (Cwa, 30 studies of 13 cities). Cities located in the southern hemisphere, especially South America, were rarely evaluated.

3.2. Data sources

3.2.1. Data source of temperature indicator

As shown in Fig. 3(A), compared to air temperature (13 studies), most studies used surface temperature as the source of temperature indicators (157 studies), largely due to the accessibility of a wide spatial coverage (Derdouri et al., 2021). Though featuring a coarse resolution, freely accessible surface temperature data, e.g., Landsat, MODIS, has enabled multi-year analysis of UGS cooling (50 studies), ranging from several years (e.g. Sun et al., 2020; Tan et al., 2021) to decades (e.g. Das et al., 2020; Masoudi & Tan, 2019). High-resolution surface temperature obtained by airborne flights (Bartesaghi-Koc et al., 2020; Li et al., 2017; Liu et al., 2022a; Weber et al., 2014; Yan et al., 2019) and downscaled data (Zawadzka et al., 2020; Zawadzka et al., 2021) have also been utilized, which has enabled fine-scale analysis on the spatial heterogeneity of urban thermal environments and UGS patterns (Zawadzka et al., 2020). Comparatively, assessments of air temperature have been restricted to field measurements of local neighborhoods (e.g. Du et al., 2021; Jaganmohan et al., 2016; Li et al., 2020b; Li et al., 2021b; Lu et al., 2012; Qian et al., 2018; Vaz Monteiro et al., 2016) or around meteorology stations (Feng et al., 2020; Shaker et al., 2019; Wen et al., 2011), with the rare study evaluating vertical temperature structure (Yang et al., 2021a).

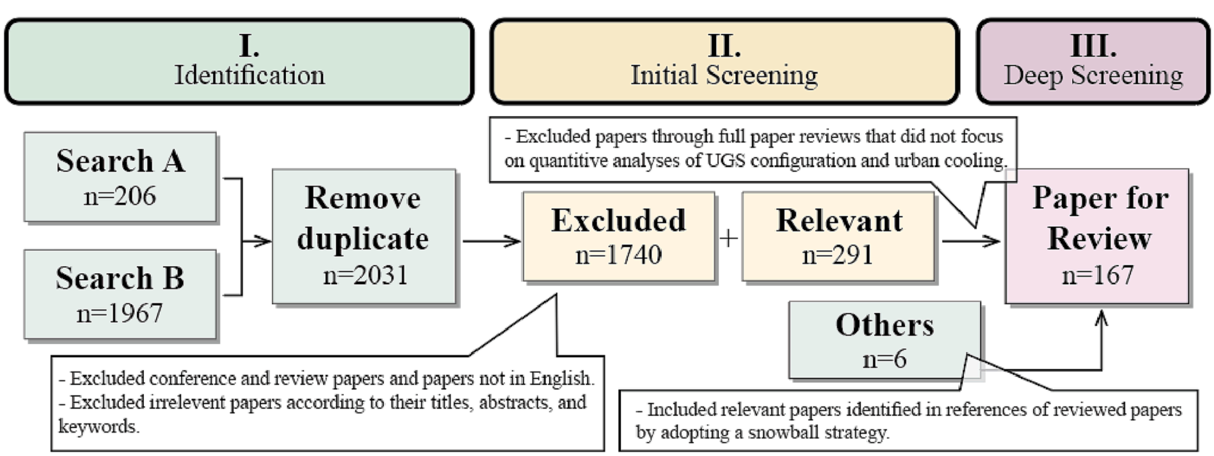

Fig. 1. Review workflow.

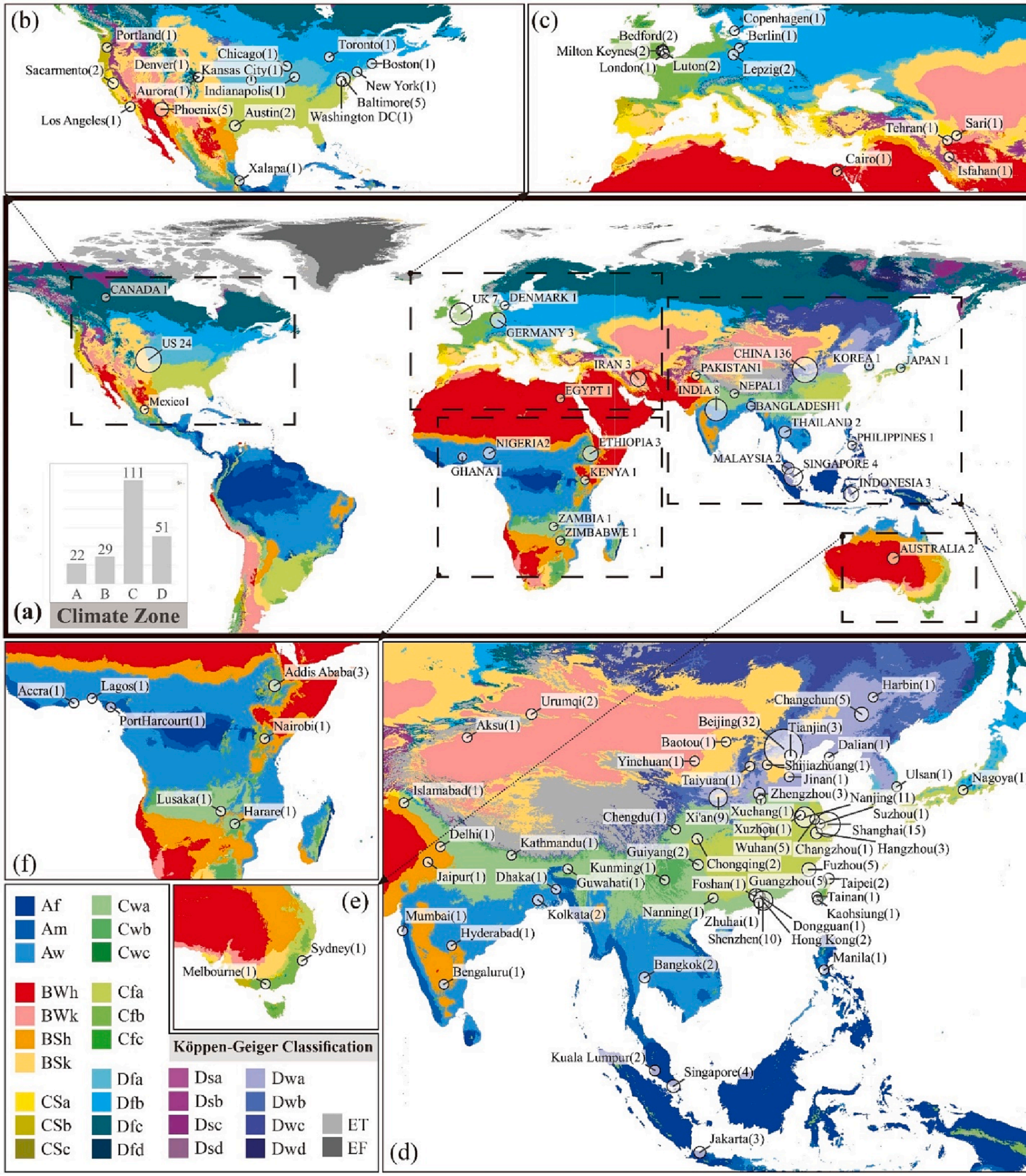

Fig. 2. Distribution of reviewed studies categorized by (a) countries and (b-f) cities following world's current Köppen climate classification (Beck et al., 2018).

3.2.2. *Data source of UGS identification*

As UGS is a concept which has been diversely defined by past studies of different disciplines (Taylor & Hochuli, 2017), we identified two types of UGS definition in the reviewed papers, i.e., UGS as types of land cover (129 studies), and UGS as types of land use (38 studies). The former considers UGS as all types of urban vegetation coverage, while the latter as particular types of ecological land uses featuring a combination of various types of land cover but dominated by urban vegetation, e.g., parks.

Multiple data sources have been utilized to identify UGS, as shown in Fig. 3(B), including various types of remote sensing data, e.g., satellite images, and LiDAR data, whose resolution ranges from submeter to hectometer. The resolution of data significantly affects the detection of UGS, as well as the values of LMs (Li et al., 2013). Although mapping of

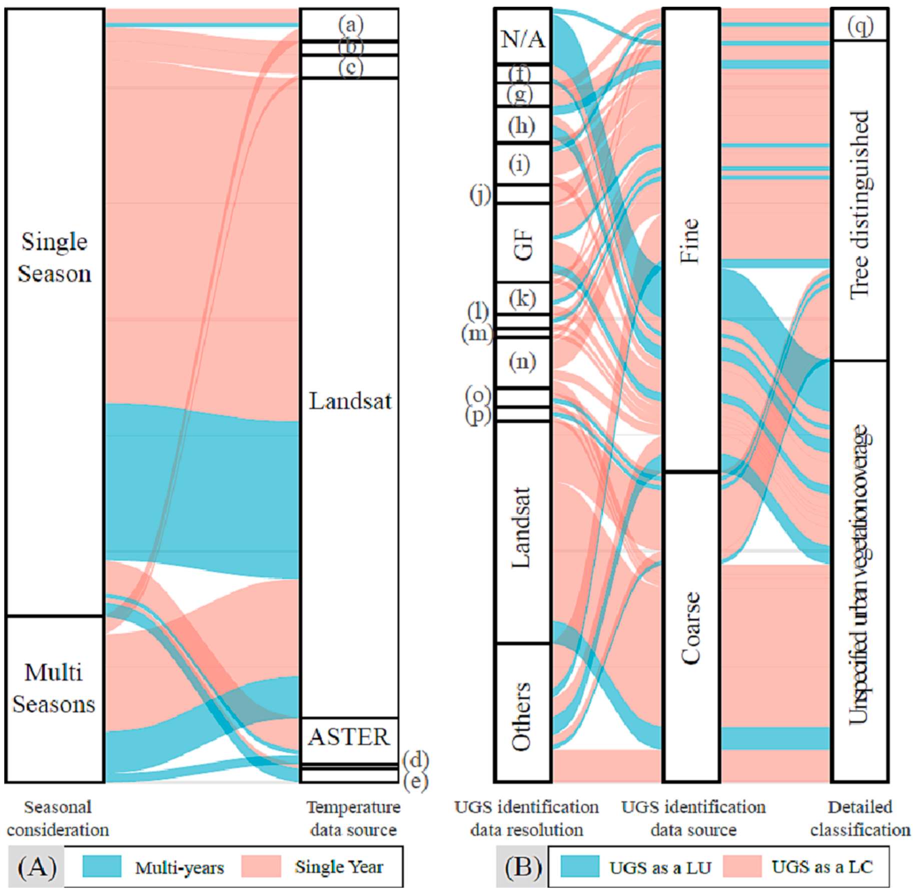

Fig. 3. Data source of (A) temperature indicator and temporal consideration, and (B) UGS identification and classification (Note: (a) Field measured, (b) Meteorology data, (c) Aerial scanner, (d) HJ-1B, (e) MODIS, (f) Aerial image, (g) LiDAR, (h) Google Earth, (i) IKONOS, (j) NAIP, (k) QuickBird, (l) WorldView, (m) ZY, (n) SPOT, (o) Sentenial, (p) ASTER, (q) More detailed classification.).

UGS does not necessarily require very-high resolution data, as it could be represented by large and detectable vegetation clusters (Neyns & Canters, 2022), detection of small or single-canopy vegetation clusters can only be achieved by using fine resolution data.

Hence, we divided the data sources into two categories, i.e., fine and coarse resolution, based on whether the data can support the identification of single-tree canopy (Fig. 3(B)). The former included high and very high-resolution data, e.g., LiDAR data, IKONOS, Gaofen, etc., and the latter included medium resolution data, e.g., Sentinel, Landsat, etc. Both resolutions were used for detailed classification of UGS, with 69 distinguishing tree canopies. More detailed classifications of vegetation types have also been conducted in some studies, such as distinguishing shrubs (An et al., 2022; Cao et al., 2010; Chen et al., 2014b; Zhang et al., 2009), categorization based on vegetation heights (Bartesaghi-Koc et al., 2020; Rakoto et al., 2021), between evergreen and deciduous trees (Yin et al., 2019), and different functional UGS types (Yang et al., 2017a).

4. UGS configurational metrics in assessing their cooling effects

In response to (Q3) – (Q5), the UGS configurational LMs assessed in the reviewed papers were categorized into 2D and 3D metrics, and their frequency in the reviewed papers were synthesized. The statistical methods used for evaluating the relationship between UGS configuration and urban thermal environment were summarized quantitatively and qualitatively. Proposed suggestions on UGS planning and design in these papers were further identified and analyzed against the extracted contextual and methodological factors.

4.1. 2D metrics describing the horizontal UGS pattern

Different aspects of UGS configuration are quantified by LMs under 3 levels, i.e., patch, class, and landscape level, and 4 categories, i.e., area and edge, shape, core area, and aggregation metrics, as classified by McGarigal et al. (2012). The frequency of 2D configurational metrics used in reviewed papers are demonstrated in Fig. 4. Among the three analytical levels, class level metrics have been most widely applied. Detailed usage of 2D metrics in the reviewed papers are listed in Appendix B.

4.1.1. Patch level metrics assessing individual UGS

Focusing on UGS patches, 51 studies have evaluated the relationship between UGS cooling and 2 aspects of UGS configuration, i.e., UGS patch morphology, and configuration of landscape elements in and around UGS patches. The former is quantified by patch level shape metrics, which describes UGS shape complexity as “compact” and “complex”, and the latter by class and landscape level LMs. Among these studies, 18 have assessed UGS as LC of urban vegetation, while the other 32 as a particular type of LU dominated by urban vegetation, such as different types of urban parks.

4.1.1.1. Calculated temperature indicators. Concerning the utilized temperature indicators, 46 studies were based on LST, with the rare usage of field-measured Ta (5 studies). Six types of temperature indicators were used: UGS cooling intensity (CI, 40 studies), cooling distance (CD, 22 studies), cooling area (CA, 6 studies), cooling gradient (CG, 8 studies), cooling efficiency (CE, 8 studies), and descriptive statistics of temperatures within UGS (15 studies). However, differences

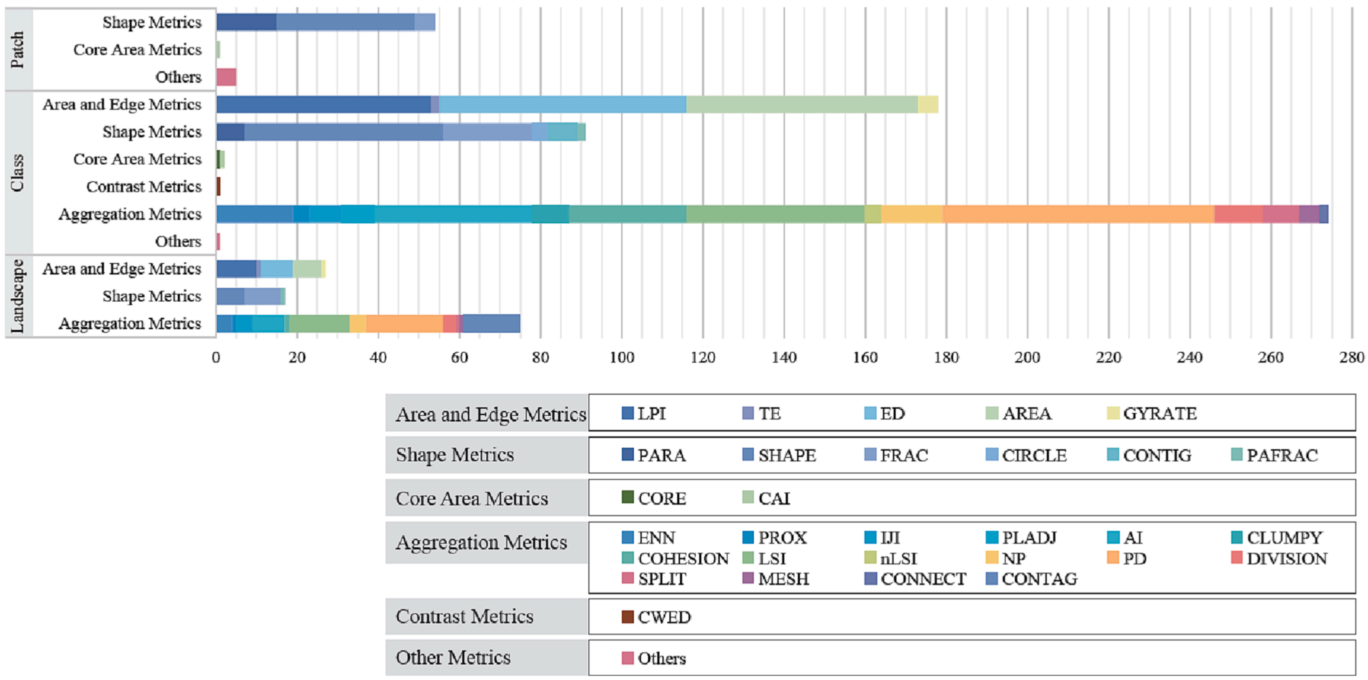

Fig. 4. The frequency of 2D metrics used in reviewed papers (Note: Refer to Appendix B for LMs abbreviations.).

existed in how each indicator was calculated. For example, in the calculation of CI, different temperature references were used, such as mean of the whole study area (Zhou et al., 2019), or local reference of certain buffer zones. When buffer zones were used, different calculation methods were used such as the fixed buffer zone size (Ekwe et al., 2020; Lu et al., 2012), transects across UGS (Tan & Li, 2013), and detection of first turning point (Yu et al., 2017). And a spatial accumulative perspective differentiates them from the maximum cooling perspective (Du et al., 2022; Peng et al., 2021). Such nuanced differences in temperature indicator calculation adds complexity when comparing across studies.

4.1.1.2. Utilized statistical methods. The relationship between these temperature indicators and configurational LMs has been evaluated through multiple statistical methods (Fig. 5). The most frequently used bivariate analyses were correlation (31 times) and OLS regression (16 times). We synthesized the extractable Pearson correlation coefficients according to the combination of independent and dependent variables, as shown in Fig. 6. Results indicate consistent negative correlations between SHAPE and LST statistics (Fig. 6(c)), and PARA and CI (Fig. 6 (d)), and a consistent positive correlation between PARA and LST statistics (Fig. 6(f)). To examine if consistent trends existed in certain climate zones, we applied *meta*-analyses to the data extracted from studies with similar study characteristics (The result summary is demonstrated in Appendix C). Significant pooled Pearson correlation coefficients were obtained for SHAPE in Köppen climate zone C and D, however, due to significant heterogeneity and limited sample size of these studies, conclusions could not be drawn. In addition, considering that both PARA and SHAPE increase as patch shape becomes irregular, opposing suggestions on the UGS shape therefore emerge (Fig. 6 (c), (f)). This may be explained by the fact that although the frequently used three shape metrics (PRAR, SHAPE, and FRAC) provide similar information, their effectiveness is not identical. PARA is sensitive to patch size, and with a constant shape, its value decreases as patch gets larger, while SHAPE and FRAC mathematically overcome this issue (McGarigal et al., 2012). For this reason, PARA is also described as a problematic metric (Chen et al., 2014b).

Multivariate (12 times) and machine learning analysis (3 times) were used to compare the relative contribution of UGS configurational factors and other factors to UGS cooling. Factors describing UGS morphology at patch level did not always play significant roles, compared to patch size (Chen et al., 2014b; Jaganmohan et al., 2016; Lu et al., 2012; Shih, 2017) or biophysiological factors NDVI (Yan et al., 2021). When looking into different area groups, effects of UGS shape may vary (Yan et al., 2021; Yang et al., 2020). Apart from patch size, the influences of vegetation types (Chen et al., 2014b) and different times of the day (Lu et al., 2012) were also found. Additionally, the impact of landscape element configuration within and surrounding the UGS is also non-negligible (Cheng et al., 2015; Li et al., 2021b; Sun et al., 2021; Tan et al., 2021; Wu et al., 2021; Qiu & Jia, 2020), and such impacts may also vary when applying different temperature indicators (Yan et al., 2021).

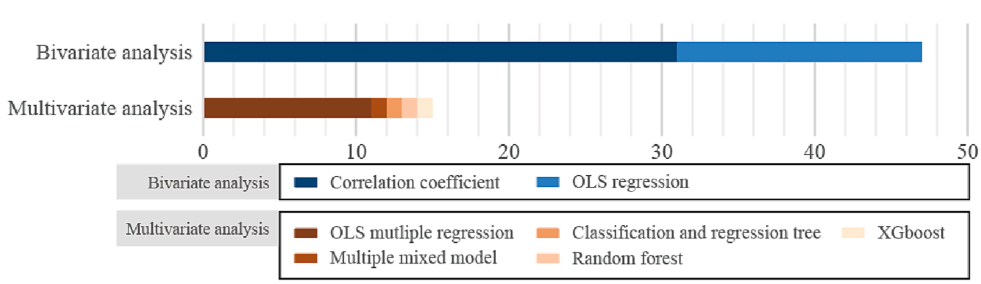

Fig. 5. Frequency of utilized statistical methods in UGS patch-oriented studies.

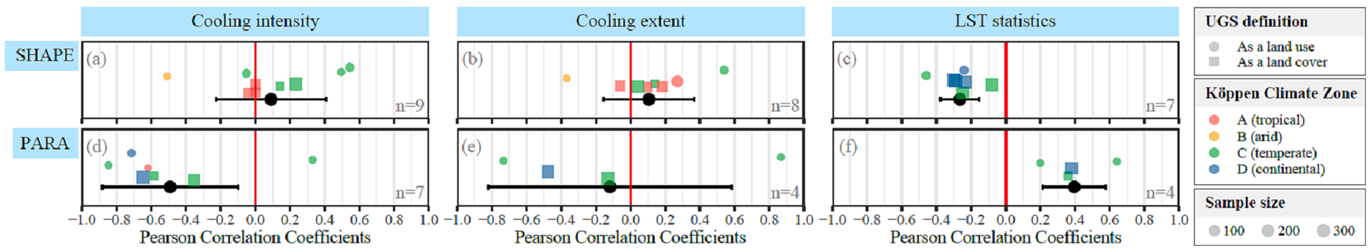

Fig. 6. Mean and standard deviation of Pearson correlation coefficients in reviewed papers between patch-level configurational LMs and different temperature indicators. (Note: all plotted studies used daytime LST. Methods for temperature indicators calculation were similar in each group. See Appendix D for origins of the extracted data.).

A global analysis evaluated 30 cities in different climate zones using a consistent method and the FRAC metric to describe the shape of UGS patch (Wang et al., 2022). Although the study suggested that complex UGS shape was associated with stronger cooling intensity, more than half of the sampled cities demonstrated insignificant bivariate relationships. Without a further multivariate analysis, the significance of UGS patch shape compared to the other above-mentioned factors is therefore missing.

4.1.2. *Class level metrics assessing UGS configuration against other urban components*

Found in 97 studies, class level aggregation metrics, area and edge metrics, and shape metrics were most evaluated (Fig. 4). Among these studies, 92 have assessed UGS as LC of urban vegetation, while only 5 have assessed UGS as a type of LU. The following two aspects bring complexity to the analysis.

4.1.2.1. Calculation of metrics. In the calculation of class level LMs, two types of analytical units have been utilized, i.e., (1) moving window or calculation grids of particular sizes, and (2) land units of certain administration or classification schemes. The usage of different sizes of moving window or calculation grids has triggered the evaluation on LMs' scale effects by adopting multiple grid sizes ranging from <100 m to 18.5 km. Although several methods have been applied to find the optimal analytical scale, including observing the changes of LMs (Masoudi & Tan, 2019), and comparing statistical results with temperature indicators using correlation (Terfa et al., 2020) and regression models (Hu et al., 2021), a consistent optimal analytical scale does not exist (Liu et al., 2018a; Yan et al., 2019; Yang et al., 2021b; Zhou & Cao, 2020). Instead, the analytical scale varies across cities and seasons (Guo et al., 2019), and is influenced by the statistical models (Zhou et al., 2017) and resolution of temperature data (Liu et al., 2022a; Yan et al., 2019). Nevertheless, such difference in LMs' performance under different analytical scales has yielded implications to focus on different configurational aspects at local, city, and regional scales in practice (Liu et al., 2018a; Song et al., 2020; Wu et al., 2022c).

The usage of land administration or classification schemes has enabled analyses to be more closely linked to urban structure and function. Application of administration units such as urban block and census tract echo the urban fabric (Chen et al., 2022d; Li et al., 2016; Li et al., 2013; Li et al., 2012; Peng et al., 2018; Pramanik & Punia, 2019; Yao et al., 2020; Zhang et al., 2022b). And when urban functions are overlaid (An et al., 2022; Li et al., 2017; Zhou et al., 2011), or certain land classification schemes are applied, such as urban functional zones (Huang & Wang, 2019; Ke et al., 2021; Li et al., 2020a; Li et al., 2021a; Tang et al., 2023; Yang et al., 2021a), such analyses provide more specific information on the UGS configuration in different land types. However, rarely have studies applied schemes based on domestic land use classification as an analytical unit (Masoudi et al., 2021), although this may provide the most direct implications on UGS planning and design practice.

4.1.2.2. Evolving statistical methods. Bivariate and multivariate analyses assess the relationship between configurational LMs and temperature indicators. Compared to the variety of temperature indicators used at patch level analysis, the calculated temperature indicators at class level are less diverse. Evolving statistical models have been used to analyze the relationship between UGS configuration and their cooling effects, as shown in Fig. 7. While strengthening the understanding of configurational LMs' contributions by overcoming the inapplicability of certain methods due to variable and model assumptions, such transformations from non-spatial analysis to spatial analysis and non-parametric machine learning methods complicates cross-study comparisons and the implications for planning and design practice.

Correlation analysis has been most widely applied among the class level analyses. The extractable Pearson correlation coefficients between class-level configurational LMs and mean LST are displayed in Fig. 8, demonstrating consistent results in several LMs. For studies that have analyzed unspecified vegetation coverage, generally consistent negative correlations exist for LPI and AI. While for studies that have specified tree canopy, AREA_MN, LPI, LSI, AI, and COHESION show a generally negative correlation. Inconsistent results were reported when using PD and ED. We also conducted *meta*-analysis with climatic zone as subgroups to detect consistent metrics across climate zones (Result

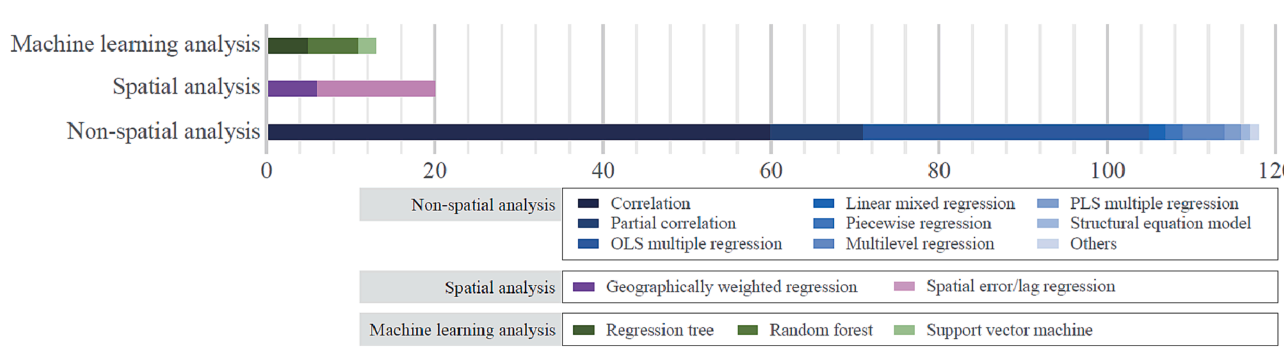

Fig. 7. Frequency of utilized statistical methods in evaluating the relationship between configurational LMs and temperature indicators.

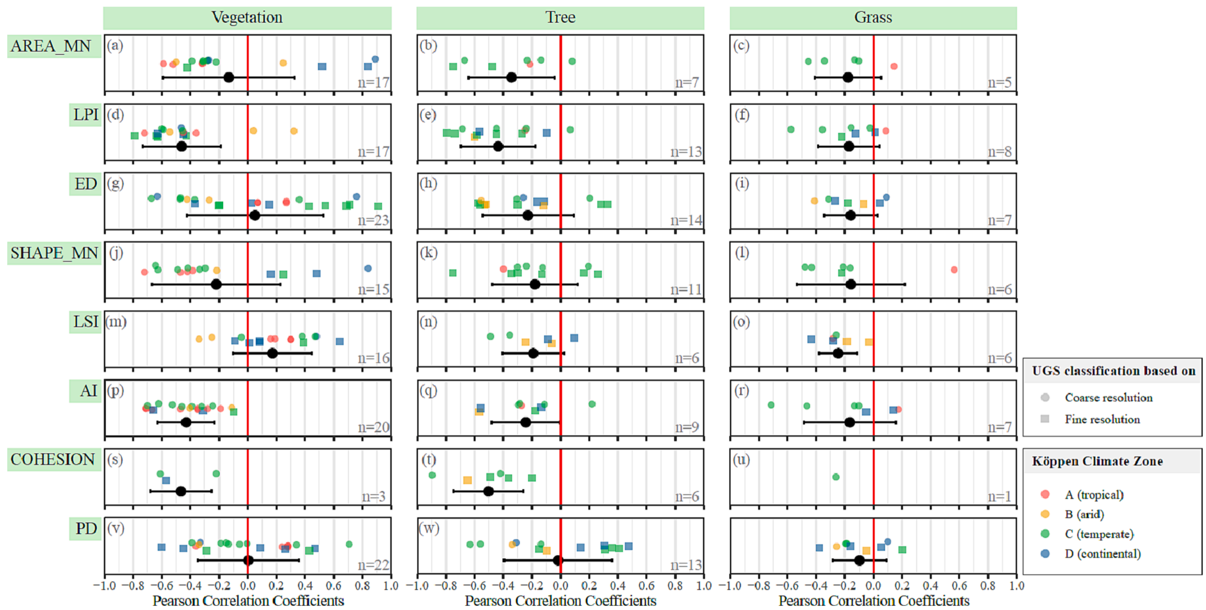

Fig. 8. Mean and standard deviation of Pearson correlation coefficients in reviewed papers between class-level configurational LMs and mean LST. (Note: All plotted studies have used mean daytime LST as dependent variables, and have considered UGS as a type of land cover extracted from remote sensing images. n at the bottom right refers to the number of city cases included. See Appendix D for origins of the extracted data.).

summary shown in Appendix C). Although AI of urban vegetation coverage demonstrated a significant negative pooled coefficient, for the same reasons as the patch-level analysis, no conclusion on this is drawn. The resolution of data used for UGS detection was found to have an influence on the bivariate relationship (Li et al., 2013). However, such influence seems strong only for PD of tree canopy (Fig. 8(w)), with UGS classification based on fine resolution data more inclined to demonstrate positive correlations.

Compared to compositional factor, i.e., proportion of UGS coverage, configurational factors were widely found to demonstrate weaker effects. Measures have been taken to eliminate the influence of UGS composition. Some studies have applied partial correlation to control for the compositional effect, detecting weaker or even opposite correlations, e.g., area and edge metrics LPI and AREA_MN/AM (He et al., 2021; Li et al., 2013; Masoudi & Tan, 2019; Masoudi et al., 2019; Zhou et al., 2017), shape metrics SHAPE_MN/AM and FRAC_AM (Li et al., 2013; Masoudi et al., 2019; Zhou et al., 2017), and aggregation metrics ENN_MN/AM (Masoudi & Tan, 2019; Masoudi et al., 2019). Another way to restrict the influence was through grouped analyses based on classification of UGS proportion levels (Wesley and Brunsell, 2019; Yao et al., 2020; Zhang et al., 2022c; Zhou et al., 2019). These studies found that the relative contribution of different configurational factors varied across different levels of UGS coverage (Yao et al., 2020; Zhou et al., 2019).

Multivariate analysis examines the relative contribution among configurational LMs. A selection of LMs is often conducted prior to analysis based on the frequency of usage in previous studies, typicality of each LM category, and statistical methods such as correlation (Zawadzka et al., 2020) and principal component analysis (Masoudi & Tan, 2019; Masoudi et al., 2019). In some cases, new factors were constructed by using principal component analysis (Chen et al., 2014a; Liu et al., 2022b), which may, however, lead to indirect implications for practice (Liu et al., 2018a). Besides the most frequently used ordinary least squares (OLS) multiple regression (35 times), other statistical methods were used to select optimal models (Chen et al., 2020; Guo et al., 2021; Peng et al., 2018), detect potential thresholds (Liu et al., 2018b), and compare independent contributions of LMs through redundancy analysis (Feng et al., 2020; Song et al., 2020) and partitioning (Guo et al., 2019; Peng et al., 2018).

More studies have begun paying attention to the data characteristics that might violate the prerequisites of certain statistical methods, including non-normal distribution, multicollinearity (Liu et al., 2018a), and spatial autocorrelation (Li et al., 2012). Some studies overcome such deficits through sampling (Athukorala & Murayama, 2020; Estoque et al., 2017; Wu & Zhang, 2018; Yao et al., 2020). Yet other studies responded to these questions by employing more suitable statistical methods, including partial least squares multiple regression (Liu et al., 2022a; Liu et al., 2018a; Zhang et al., 2022a), mixed-effect modelling (Chen et al., 2022b; Greene & Kedron, 2018; Kamarianakis et al., 2017; Li et al., 2017), spatial regression, and geographically weighted regression.

Among these methods, spatial analyses (25 studies) are often adopted, including spatial regression (i.e., spatial lag/error model), geographically weighted regression, and application of Geodetector (Yin et al., 2019), and have found contrasting results with bivariate and multivariate analyses. In studies applying both spatial and non-spatial analysis, or their combinations (Guo et al., 2020b), spatial analyses demonstrate enhancement in model performances (e.g. Chakraborti et al., 2019; Li et al., 2021a; Li et al., 2012; Masoudi et al., 2021; Shaker et al., 2019), especially at finer analytical scales (Zhou et al., 2017). Such spatial analyses imply that the influences of configurational LMs on UGS cooling are spatially heterogenous. It is also found that spatial analyses identify dominant configurational LMs in different areas of a city (Guo et al., 2021).

Non-parametric machine learning methods provide alternative solutions by making no assumptions of variables, which are effective in dealing with non-linear responses and distinguishes it from the former two categories. Classification and regression tree (Rakoto et al., 2021), gradient boosted regression (Yu et al., 2020a; Zhou et al., 2022), random forest regression (Wu et al., 2022a), and support vector machine (Chen et al., 2022a) have been applied. Different machine learning methods have been compared, with random forest regression demonstrating better performance in predicting LST than boosted regression and support vector machine (Chen et al., 2022a). Thresholds of configurational LMs for effective cooling were identified by machine learning (Lyu et al., 2023). However, although not limited by intrinsic data characteristics and model assumptions, rarely do machine learning studies provide explicit spatial-related implications.

The results based on spatial analysis and non-parametric machine-learning demonstrated enhanced performance but diversified dominant configurational LMs to UGS cooling compared with non-spatial analysis studies. As a result, we could not generalize any specific recommendations based on these results. Based on these evolving statistical methods, the only consensus we managed to find is that compositional factor, i.e., the proportion of UGS, demonstrates a greater effect than configurational factors, with only few exceptions (Du et al., 2016; Li et al., 2016; Shaker et al., 2019). Contribution of UGS configuration is even stated as weak in some cases (Liu et al., 2022a; Peng et al., 2018).

4.1.3. Landscape level metrics assessing overall configuration under different contexts

Landscape level metrics describing the heterogeneity of urban landscape regardless of patch or class types have also been widely assessed (e.g. Bera et al., 2022; Das et al., 2020; Du et al., 2016; Galletti et al., 2019; Guo et al., 2020a; Liu & Weng, 2009). However, the usage of landscape level metrics has been criticized as inappropriate (Liu et al., 2018a; Liu et al., 2018b), as they cannot describe UGS specific configuration but can only describe the overall configuration of all urban elements. Nevertheless, we identified one particular case in which landscape level metrics were used to assist the detection of key UGS coverage threshold above which correlations between landscape level metrics and LST became significant, indicating the significance of UGS coverage as a prerequisite for producing effective cooling effects (Xie et al., 2013).

Additionally, we identified some applications of landscape level metrics that successfully quantified UGS specific configuration by using different analytical units. Examples are studies by Yang et al. (2017a), Rakoto et al. (2021), Wang et al. (2021b), and Wang et al. (2021a), in which landscape level metrics were used to quantify the overall configuration of different UGS types, casting light on the configuration of different types of UGS. Such application could be extended in future studies by adopting suitable UGS classification schemes under particular scales and contexts, which can provide references to planning or design tasks.

4.2. 3D metrics studies describing vertical UGS pattern

To tackle the shortcoming of LMs that focus on 2D spatial pattern descriptions, 3D metrics were used in 14 reviewed papers (Chen et al., 2022b; Chen et al., 2020; Chen et al., 2022c; Chen et al., 2021; Chen et al., 2022d; Gage & Cooper, 2017; Huang & Wang, 2019; Lyu et al., 2023; Wu et al., 2022a; Yang et al., 2021a; Yu et al., 2020a; Yuan et al., 2021; Zeng et al., 2022; Zhang et al., 2022a) and 1 global study (Wu et al., 2022b) (Table B4). Compared to the vertical characteristics of UGS (10 papers), those of buildings have been paid more attention to (14 papers). This section reviews the contribution of these 3D metrics to the urban thermal environment, as they are frequently compared with the 2D LMs reviewed above.

LST, including the calculated LST difference, was the only temperature indicator analyzed in the reviewed studies using 3D metrics. Height (15 papers) and volume (6 papers) were the most frequently used 3D metrics. Their statistics, including mean, maximum, minimum, variance, skewness, and kurtosis, were applied to describe vertical pattern variances. Additionally, sky view factor (4 papers), and leaf area index (1 paper) were also used. However, although these 3D metrics describe the vertical structure of urban elements, they barely provide information on UGS morphology or configuration. Morphology characteristics, such as the vertical shape (Huang & Wang, 2019) and the application of 2D metrics to quantify vertical spatial pattern (Yu et al., 2020a) have been rarely applied.

Comparisons between 2D and 3D metrics were conducted to assess their significance to urban thermal environment. Besides the recognized contribution of 2D LMs (Chen et al., 2022d; Huang & Wang, 2019; Yang et al., 2021a), the incorporation of 3D metrics greatly enhanced the interpretation of temperature indicators (Chen et al., 2022b; Wu et al., 2022b). Rarely have studies claimed that 3D metrics outweigh 2D metrics in analyzing temperature indicators (Wu et al., 2022a). Such relationship also varies across seasons (Chen et al., 2022d; Huang & Wang, 2019), times of the day (Chen et al., 2020; Chen et al., 2021; Wu et al., 2022b;), land use clusters (Gage & Cooper, 2017), and climate zones (Wu et al., 2022b). Significant interactions between 2D LMs and 3D metrics also exist (Zhang et al., 2022a). The contribution of vegetation to the urban thermal environment was found less prominent than buildings (Yuan et al., 2021), but depended on vegetation coverage (Chen et al., 2022c; Zeng et al., 2022).

However, the UGS planning and design implications based on these analyses are indirect. In these studies, UGS were all defined as LC, i.e., urban vegetation coverage. Based on 3D metrics describing UGS height, studies have recommended different vegetation types to achieve better cooling, generally suggesting the prominent effect of trees (Lyu et al., 2023; Wu et al., 2022b; Yu et al., 2020a). However, such information has also been given in studies that have conducted detailed subclassification of UGS and used 2D LMs, instead of 3D metrics (Bartesaghi-Koc et al., 2020; Rakoto et al., 2021), as classification of different vegetation types can also describe the vertical structure of UGS. It is also reported that 3D metrics can be treated as 2D ones when analyzing vegetation coverage (Yu et al., 2020a). Therefore, studies providing more specific knowledge on UGS vertical structure based on 3D metrics are still needed. Some previous studies that have specified key threshold of tree height (Chen et al., 2022c) or linked with scenarios of urban renewals (Chen et al., 2022d), but such studies are still rare.

4.3. Proposed planning and design implications

To evaluate the proposed planning and design implications in reviewed papers, we first categorized them into four types, following the criteria listed in Table 2. The degree of specificity of these four categories increases progressively. Studies that have used landscape-level metrics to assess the configuration of overall landscape components were excluded, as they failed to provide information on UGS configuration as mentioned in the previous section. Among the 158 studies, excluding 4 studies that did not provide implications to practice, 32 insights, 116 recommendations and 6 guidelines were provided. Few studies provided direct guidelines.

Insights and recommendations were given the most. Shown in Figs. 9 and 10, we extracted the suggestions of these two types of implications from patch and class level studies, and illustrated their relation with the above-synthesized contextual variables (i.e., background climate zone, and UGS definition), and methodological factors (i.e., research scale, data source, and statistical method used). For patch level studies, we first tried to categorize these suggestions with the background climate (Fig. 9(a)). We excluded studies that based their suggestions on the controversial metric PARA (Fig. 9(b)) and Ta as temperature indicator (Fig. 9(c)) to reach a relatively uniform research method among the compared studies. However, we found that diversity in UGS morphology

Table 2
Types of UGS planning and design implications based on (Graça et al., 2022).

Types of implication	Description	Quantity
Insights	Relevant information for practitioners emerging from the articles, which requires an additional interpretation from the reader to translate the research results to planning and design practice.	32
Recommendation	Including a specific recommendation for practitioners, more specific than insights.	116
Guideline	Featuring design guidelines, which are more detailed and comprehensive than recommendations.	6
Planning/Design proposal	New planning and design for the study area is proposed, and their performance was assessed.	0

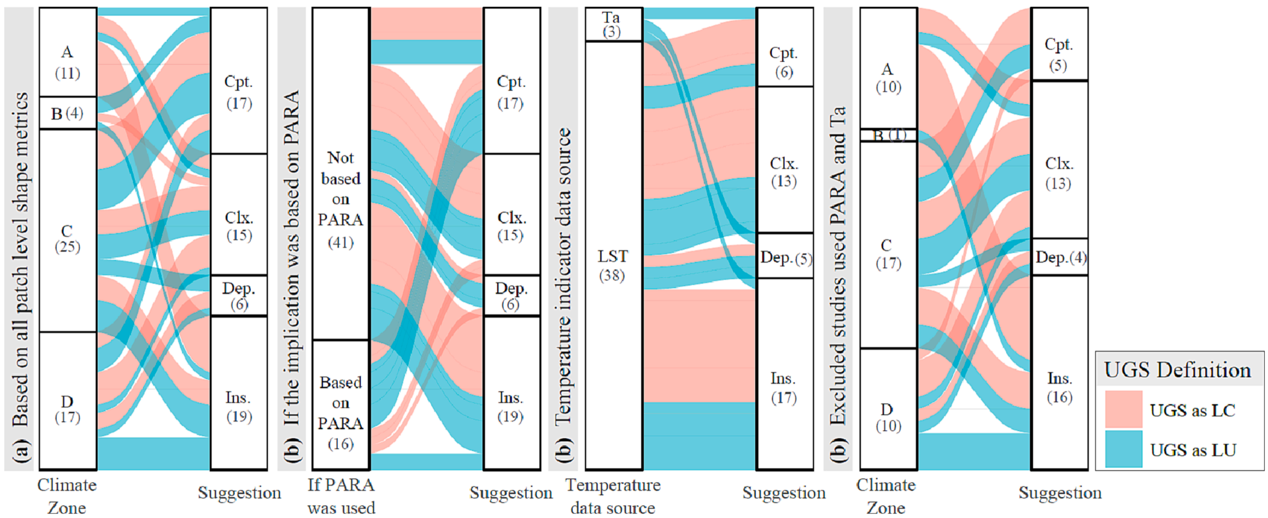

Fig. 9. Diverging suggestions on UGS morphology for urban cooling based on patch level shape metrics. (a-c) illustrate all extracted suggestions based on patch level LMs. (d) illustrates those excluding studies using PARA and Ta. (Note: ***Cpt.*** Compact, ***Clx.*** Complex, ***Dep.*** Depends, ***Ins.*** Insignificant results, ***LC*** UGS as a land cover, ***LU*** UGS as a land use. Number in bracket refers to the quantity of study belonging to that category).

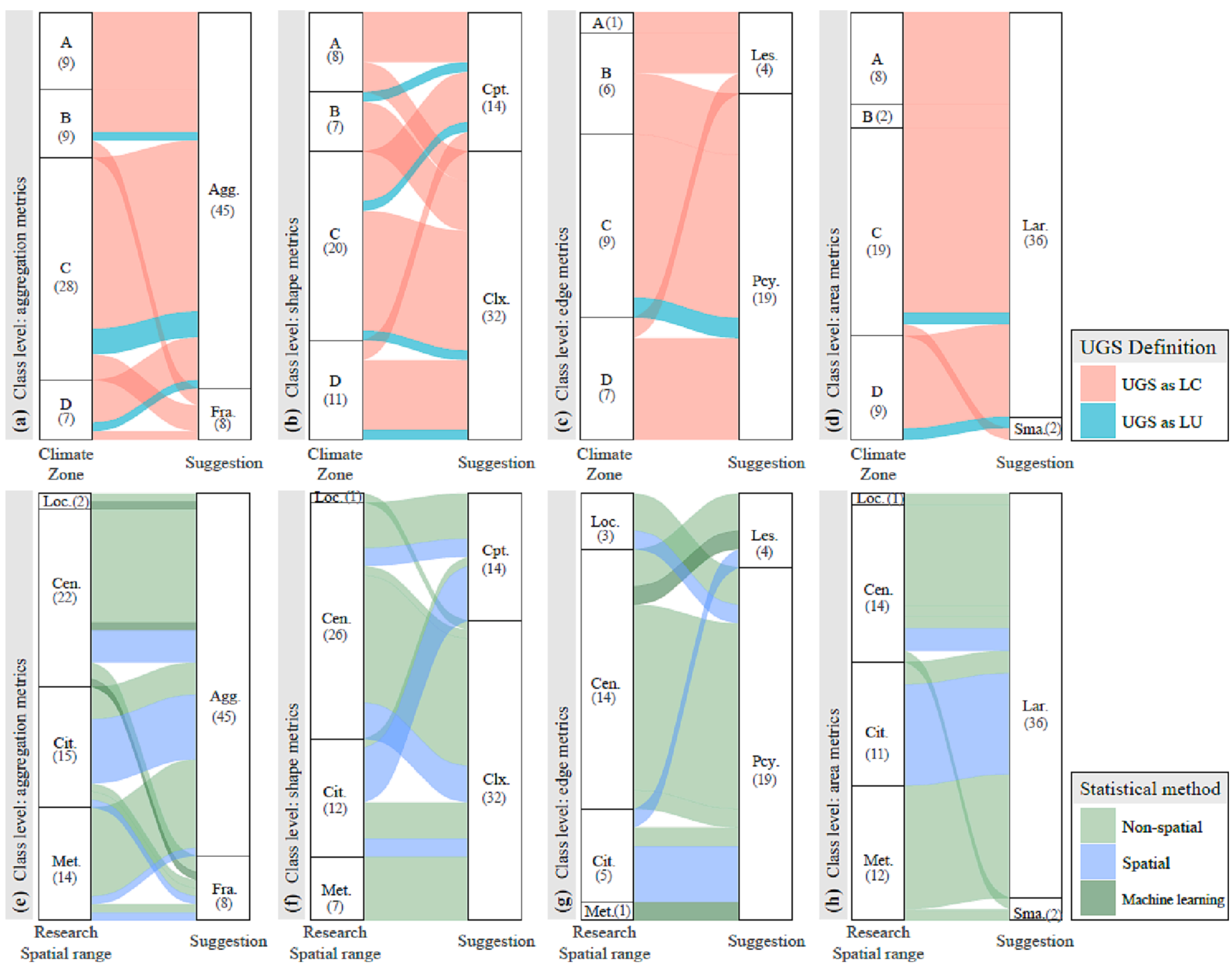

Fig. 10. Diverging suggestions on UGS configuration for better urban cooling based on class level (a, e) aggregation metrics, (b, f) shape metrics, (c, g) edge metrics, (d, h) area metrics. (Note: ***Agg.*** Aggregated, ***Fra.*** Fragmented, ***Les.*** Less patchy, ***Pcy.*** Patchy, ***Lar.*** Larger, ***Sma.*** Smaller, ***Loc.*** Local neighborhood, ***Cen.*** Central built-up area, ***Cit.*** City boundary, ***Met.*** Metropolitan area. Number in bracket refers to the quantity of study belonging to that category).

suggestions still exist (Fig. 9(d)). Nevertheless, such results are similar to Wang et al. (2022)'s global analysis covering cities belonging to different climate zones, which suggested that irregular UGS shapes can promote better cooling, but found more than half of their bivariate analyses were insignificant.

For class level studies, as shown in Fig. 10, aggregated, complex-shaped, patchy, and larger UGS are more linked with better cooling. Similarly, the contextual variables of climate zone, research scale, and statistical methods did not help to explain the diverging suggestions. Multi-city studies at class-level have parallelly suggested that smaller and dispersed vegetation coverage (Yue et al., 2019) and scattered tree coverage (Wu et al., 2022b) were associated with reduced urban heat island effects. However, it should be taken into consideration that these suggestions were based on the cumulative combined effect of all cities, although the effects of configurational LMs vary across climate zones (Wu et al., 2022b).

A few studies have provided specific design guidelines from the perspective of UGS configuration (Bartesaghi-Koc et al., 2020; Chen et al., 2022c; Shi & Zhao, 2022; Zhang et al., 2022b). Chen et al. (2022c) suggested a tree height threshold of 15 m for effective cooling. Zhang et al. (2022b) focused on a local neighborhood, and gave out design guidelines from a practical point of view. Shi & Zhao (2022) recommended five strategies that could be applied in UGS planning, each covering different aspects of UGS composition and configuration, which could accommodate different needs in UGS planning of highly heterogeneous cities. LMs were used in Bartesaghi-Koc et al. (2020) to classify and evaluate different UGS types based on their cooling effects, and suggestions were given on the cooling capacity. Additionally, two studies demonstrated the potential to provide location-specific guidelines (Guo et al., 2020b; Guo et al., 2021), which can point out specific locations in a city to enhance thermal environment through UGS configuration. However, no planning or design proposal was produced among all reviewed studies.

5. Discussion

This review provided a holistic evaluation on studies assessing UGS cooling and UGS configuration quantified by LMs, in terms of their contextual background, methodology, results, and implications for practice. We aimed to discover possible explanations for the diverging planning and design implications in reviewed studies, which was not successful. Although more detailed methodological factors, such as the precise overpass time of satellites, could possibly have impacted study results, these factors would unlikely help to explain the diverging suggestions, considering the similar results found in several global studies.

In addition, we evaluated the planning and design implications of reviewed studies, and discovered relatively low transferability to practice, featuring unspecific suggestions on planning and design practice that cannot sufficiently support evidence-based design (Brown & Corry, 2011). The following sections provide suggestions on future studies to better link research and practice and further understand UGS configuration and its cooling effect.

5.1. Specifying the UGS definition at either the planning or design scale

With a scale ranging from regional to city scale planning of ecological spaces, UGS planning deals with the LU balance and plays a governing role in framing UGS design, which focuses more on site-scale design of elements and objects (von Haaren et al., 2014). Among reviewed studies, although most have focused on city to metropolitan scale, a rarity of studies have assessed UGS as LUs at these scales (Fig. 10), which cannot guide the planning of ecological lands at a city level. Such an analysis is a prerequisite for providing design implications on the configuration of vegetation coverage, which is a design consideration. Such design consideration additionally varies across different urban contexts, as demonstrated in climate adaptation guidelines by Klemm et al. (2018). Comparatively, less studies have been conducted at the typical design scale of local neighborhood, let alone having carefully evaluated the configuration of different types of urban vegetation at a finer scale (Hu et al., 2021; Li et al., 2020b; Rhee et al., 2014; Yan et al., 2019). Besides, whether UGS is considered as a LU or LC determines the implications of configurational LMs, as the practical meaning of morphology aspects such as edge or shape complexity of a park boundary or shape of vegetation coverage are totally different.

Therefore, a clearer target in future studies to address either UGS planning or design is suggested to incorporate the hierarchical consideration of planning and design. Distinguishing the hierarchy in UGS planning and design also corresponds to the cross-scale concepts of green infrastructure and nature-based solutions (Nesshover et al., 2017). Such concepts integrate UGS as both LUs (e.g., parks and ecological lands) and LCs (e.g., street trees), and calls for strategies according to the scale of application (IUCN, 2020). Besides separated evaluation, incorporating both LU and LC perspectives can provide LU-specific UGS design guidelines, which has been addressed in some reviewed studies. One method of doing so was by using different types of analytical grids for the calculation of LMs, e.g., urban functional zones (Huang & Wang, 2019; Ke et al., 2021; Li et al., 2020a; Yang et al., 2021a), and self-defined LU categories (An et al., 2022; Galletti et al., 2019; Zhang et al., 2009; Zhou et al., 2011). Another application is the direct intersection of LU and LC (Masoudi et al., 2021). However, a land classification scheme identical to that used in domestic urban planning practice is seldom applied (Dugord et al., 2014; Masoudi et al., 2021; Weber et al., 2014), let alone the sub-classification of UGS as different land-uses categories (Yang et al., 2017a), which may best accommodate the local UGS planning and design practice. Future work may also link with precise planning and design contexts to provide more direct guidance, such as linking UGS configurational LMs changes and thermal environments (Shaker et al., 2019; Zhang et al., 2022b) with the process of urban renewal. Such analyses can evaluate the contribution of past urban renewal projects to alleviate excessive urban heat, or propose where to carry out urban renewal and adjust the UGS configuration to achieve such goals.

5.2. Formulating specific implications beyond binary recommendations

Although the evolving statistical methods from non-spatial to spatial to non-parametric machine learning analysis addresses the intrinsic and spatial characteristics of urban thermal environment and UGS pattern, proposed planning and design implications are mostly non-spatial and binary. These binary recommendations are usually opposite extremes of a same aspect of UGS configuration, e.g., complex or compact (based on shape metrics), aggregated or fragmented (based on aggregation metrics), and patchy or less patchy (based on edge metrics). The suggestions derive directly from the positive or negative result of the statistical methods used. However, despite the consistent trends that seem exist in data synthesis of Pearson correlation (Figs. 6 and 8) and cross climate zone *meta*-analysis (Appendix C), variances in LMs' performance also exist in multi-city study of the same background climate (Fan et al., 2019), and single-city study across different development stages (Ye et al., 2021). In such circumstances, pursuing universal suggestions on UGS configuration may be inappropriate, as they cannot respond to the spatial and temporal heterogeneity of thermal environments and UGS patterns in different cases.

Therefore, future studies should aim to delineate the spatial and temporal heterogeneity of UGS configuration's impact on cooling, which may concretize specific implications beyond current binary suggestions. Several reviewed studies have produced location-specific guidelines (Guo et al., 2020b; Guo et al., 2021; Xie et al., 2020), which can be further extended by applying detailed subclassification of vegetation types, and may address questions such as "where to improve tree/grass/vegetation coverage configuration to achieve better cooling". Such analysis can be elaborated with more accurate depictions of urban thermal heterogeneity (Zawadzka et al., 2020). In addition, temporal considerations are still lacking, i.e., whether ideal UGS configuration varies spatially across developmental stages, and how to balance the trade-offs to reach an optimized UGS configuration.

In addition, the internal relationship between configurational metrics and their practical meaning is awaiting clarification, so as to provide better link with practice. Due to the intrinsic inter-correlation between configurational LMs, evaluation on LMs' interaction is still rare (Wang et al., 2023; Wang et al., 2021a; Yin et al., 2019), however this may help to understand the practical meaning of configurational LMs. Unlike compositional factors, which are included in current guidelines as a particular size or coverage proportion (Ouyang et al., 2020; Yu et al., 2020b), UGS configuration quantified by LMs are less explicit for planners and designers to be aware of their implications. Considering patch level SHAPE as an example, the reported upper values range from 2.11 to 14.08 (Asgarian et al., 2014; Du et al., 2017; Du et al., 2021; Jaganmohan et al., 2016; Lu et al., 2012; Park & Cho, 2016; Shih, 2017; Sun et al., 2020; Yang et al., 2017b; Yu, et al., 2017), however very few studies have illustrated the corresponding shapes of these UGS. Similarly at class-level, the identified key UGS configurational thresholds (Liu et al., 2018b; Lyu et al., 2023) can only become transferable knowledge with a clear demonstration of their morphological meaning. In this context, practitioners need explicit demonstration and illustration of these values, so as to link with actual planning and design practice.

6. Conclusion

In this paper, the complexity of how better urban cooling is linked with the configuration of UGS quantified by LMs is described qualitatively and quantitatively. Besides the synthesis of contextual and methodological factors in the reviewed studies, special attention was paid to summarize and evaluate accumulative morphological implications on UGS planning and design practice. We summarized that patch-level metric SHAPE and class-level metrics LPI, AI, and COHESION yield generally consistent trends across studies. Concerning morphological aspects of edge and area, aggregation, and shape quantified by class-level LMs, more patchy, larger, aggregated, and complex shapes are more recommended to facilitate better cooling. However, contextual and methodological factors could not be consolidated to help interpret the diverging planning and design suggestions proposed. We also found low transferability in the planning and design suggestions of reviewed studies, which hampers the application of scientific results in practice. Future studies are suggested to provide more specific implications through specifying either a land-use or land-cover perspective to align with practical scales in planning and design practice, and to formulate specific implications beyond binary suggestions by echoing the temporal and spatial heterogeneity of thermal environment and UGS pattern under precise planning and design contexts with practical demonstration and illustration.

Declaration of Competing Interest

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

Data availability

Data will be made available on request.

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Appendix A. Supplementary data

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