A REVIEW OF COMPACTNESS INDEXES OF FORM IN COMPUTATIONAL URBAN DESIGN

CHENGYU SUN[1], XINRU WANG[2] and YU MENG[3]
[1,2,3]*Tongji University; Shanghai Key Laboratory of Urban Renewal and Spatial Optimization Technology*
[1]*ibund@126.com, 0000-0002-5686-5957*
[2]*wangx_ru@126.com, 0009-0004-1316-5581*
[3]*mengyu@tongji.edu.cn, 0009-0007-0905-2885*

Abstract. This study investigates the application and challenges of compactness indexes in computational urban design. It begins with a conceptual review and application analysis of six urban form compactness indexes, classified into four categories. The study then identifies several issues in their current application, including imprecise referencing conditions, interpretational discrepancies, and opacity in computational parameters. Using actual blocks in Shanghai as case studies, it further verifies that parameter settings significantly influence calculation outcomes. This work emphasizes the importance of rigorous analysis of index application conditions in block-scale morphological measurements to prevent biases in computational design results.

Keywords. Computable Indexes, Compactness Indexes, Spatial Autocorrelation Indexes, Nearest Neighbor Distance Indexes, Shape Indexes, Gravity Indexes, Literature Review.

1. Introduction

As computational design expands from individual buildings to the block scale, computational urban design emerges as a pivotal trend. Computable urban indexes, crucial for design evaluation and generation, face challenges when applied across different scales, especially from urban to block scale.

This study examines compactness indexes which are crucial for evaluating urban form and fostering sustainable urban development. The existing compactness indexes vary significantly in terms of definitions and applicability. Drawing from 34 publications (1950-2023), the study identifies six representative compactness indexes across four categories. It introduces their development, definitions, and logic, and emphasizes the application issues and risks. aiming to clarify measurement methods and contribute to computable index development at the block scale.

2. Background

Compactness indexes are primarily used to measure the aggregation or dispersion of urban spatial structures and play a key role in morphological and correlation studies at

ACCELERATED DESIGN, Proceedings of the 29th International Conference of the Association for Computer-Aided Architectural Design Research in Asia (CAADRIA) 2024, Volume 2, 325-334.

both urban and block scales. At the urban scale, these indexes quantify the layout of urban land, public green spaces, and facilities, and explore their distribution characteristics in relation to environmental and economic factors (Y. Liu et al., 2014; Mansour, 2016). At the block scale, compactness indexes are applied to assess the layout of buildings and small green spaces, analyzing their relationships with energy efficiency and environmental sustainability (Zhuang & Zhou, 2019; X. Li et al., 2016; Akrofi & Okitasari, 2023; Ji et al., 2023).

Compactness is fundamental to urban form analysis, and its accurate measurement is crucial. While urban-scale development is well-established, recent attention has shifted towards the block scale. Given the diverse methods of measuring compactness and the challenge of selecting appropriate indexes, further research is needed to clarify the specific meanings and practical utility of these indexes.

3. Four Typical Categories of Urban Compactness Indexes

This study categorizes the current main indexes into four types based on computational logic: Spatial Autocorrelation, Nearest Neighbor Distance, Shape Indexes, and Gravitation Indexes.

Categories	Indexes	Author and Time	Objects	Types	Level	Interpretations
Spatial Autocorrelation	Moran's I	(H. Liu et al., 2021)	CI(1)	Px	US	Cen
		(Sikder et al., 2019)	CI(2)			Cmp
		(Yan et al., 2013)				
		(Rahman et al., 2022)			BS	Cnc & Cont
		(Zhuang & Zhou, 2019)		P		SDP
	......					
Nearest Neighbor Distance	ENN	(Falahatkar & Rezaei, 2020)	CA	A	US	Cen
		(F. Li et al., 2021)				Cmp
		(Zhou et al., 2011)				SDP
	ANN	(Thompson et al., 2022)	CP	P	US	Cmp
		(Naqshbandi et al., 2016)				SDP
		(Almohamad et al., 2018)	UF			
		(Mansour, 2016)				
		(Akrofi & Okitasari, 2023)	CP		BS	Cmp
	......					
Shape Indexes	COLE	(Zhang et al., 2022)	CA	A	US	Cmp
		(Y. Liu et al., 2014)				
		(Dai et al., 2022)	OL			
	......					
Gravitation Indexes	T	(Thinh et al., 2002)	CI	Px	US	Cmp
		(L. Liu et al., 2023)				
	NCI	(Zhao et al., 2011)	CI	Px	US	Cmp
		(Ji et al., 2023)			BS	Conn
		(Wang et al., 2021)				Cmp
		(X. Li et al., 2016)	OL			
	......					

Note:
Objects (The following classifications are based on specific content and expressions in the literature):
CI: Construction Intensity, which includes the area of urban construction land per unit area, building footprint area, total building area, number of buildings, and green space area.
Conceptualization of Spatial Relationships: **(1)** Contiguity edges **(2)** Distance threshold
CA: Construction Areas, which encompass urban and rural construction lands, and urban patches.
CP: Core Points, including urban central points, residential cluster centers, and ground floor centroids of buildings.
OL: Outlines, which cover town outlines and ground floor outlines of buildings.
UF: Urban Facilities, including urban green spaces and health facility points.
Types: **P**: Point Data **A**: Areal Data **Px**: Pixel
Level:
US: Urban Scale, in this paper, includes research at regional, national, city, county town, and other larger scales.
BS: Block Scale, in this paper, includes research at the scale of blocks, communities, and other smaller scale scales.
Interpretations :
Cmp: Compactness, describes the degree of compactness or dispersion.
SDP: Spatial Distribution Patterns, assesses whether the spatial elements are clustered, random, or dispersed (uniform).
Cen: Centrality **Cnc:** Concentrated **Cont:** Continuous **Conn:** Connectivity

Figure 1. Table of compactness indexes application

Six representative indexes are selected, which are widely applied and effectively embody the characteristics of each category. In the following sections, the paper first summarizes and compares the specific research applications of these six representative indexes based on 22 articles from the Web of Science database (Figure 1), and then provides a detailed introduction to each category of indexes.

3.1. SPATIAL AUTOCORRELATION

Spatial Autocorrelation Indexes assess urban spatial layout compactness by assessing the correlation of adjacent variables, with compactness indicated by adjacent high or low values. Key indexes include Global Moran's Index (MORAN, 1950) and Geary's C (Geary, 1954), with the former often preferred for its better statistical distribution and effectiveness in differentiating urban forms (Tsai, 2005; Wang & He, 2007).

The Global Moran's Index (Moran's I), proposed by Patrick Alfred Pierce Moran in 1950 (MORAN, 1950), is applicable to spatial data such as points, areas, and pixels. Its formula, illustrated for pixel data, is as follows:

$$Moran's\ I = \frac{N \sum_{i=1}^{N} \sum_{j=1}^{N} W_{ij}(X_i - X)(X_j - X)}{\left(\sum_{i=1}^{N} \sum_{j=1}^{N} W_{ij}\right)(X_i - X)^2} \quad (1)$$

In the formula: N is the number of grids, X_i and X_j are the construction intensities of the i-th and j-th grids respectively, X is their average value, and W_{ij} is the spatial weight between grids i and j (Figure 2a). Moran's I values range from -1 to 1, with higher values indicating more compact distributions.

Moran's I is a key tool in urban analysis, effectively used for spatial autocorrelation studies at different scales (Griffith & Chun, 2014; Rahman et al., 2022). At the urban scale, it evaluates urban compactness, distinguishing various urban forms (Tsai, 2005), and assessing spatial distribution patterns in relation to urban elements (Sikder et al., 2019; Liu et al., 2021). At the block scale, it measures the compactness of buildings and community development (Zhuang & Zhou, 2019; Rahman et al., 2022).

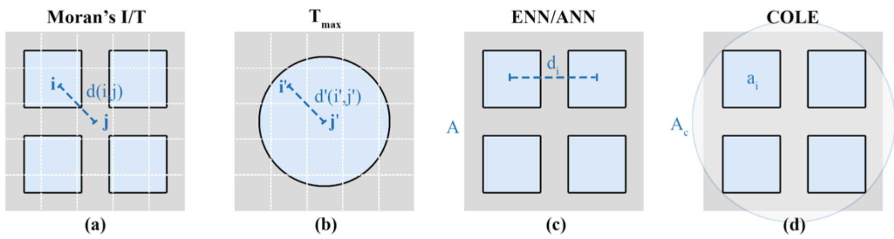

Figure 2. Indicator calculation process diagram

3.2. NEAREST NEIGHBOR DISTANCE

Nearest Neighbor Distance indexes evaluate spatial distribution by measuring the distance between a point and its nearest neighbor. Common indexes include Euclidean Mean Nearest Neighbor Distance (ENN), Average Nearest Neighbor Ratio (ANN), G function, and F function (Wang & He, 2007), with ENN and ANN being particularly popular for their intuitiveness. The formula for calculating ENN is:

$$ENN = \frac{\sum_{i=1}^{n} d_i}{n} \quad (2)$$

In the formula: d_i is the distance between a element and its nearest neighboring element, and n is the number of elements (Figure 2c). A lower ENN value indicates a higher degree of compactness.

In urban studies, ENN is a foundational index, extensively used in research on urban patterns (Li et al., 2021; Zhou et al., 2011). Notably, in landscape pattern analysis, the elements are predominantly areal rather than point data, thus the focus is on calculating the nearest edges of areal data, emphasizing 'continuity'.

In 1954, Clark and Evans developed ANN based on ENN (Wang & He, 2007). This index first calculates the ENN for all elements within a region, then determines the expected ENN under a Complete Spatial Randomness (CSR) model. By comparing these two distances, ANN quantifies the spatial compactness and identifies distribution patterns. The formula for ANN is:

$$ANN = \frac{ENN}{E(ENN)} = \frac{2\sqrt{n/A}\sum_{i=1}^{n} d_i}{n} \quad (3)$$

In the formula: E(ENN) is the expected distance under CSR, and A is the area (Figure 2c). Higher ANN values indicate more dispersion, with values below 1 indicating clustering, 1 indicating randomness, and above 1 indicating uniformity.

Compared to ENN, ANN provides a standardized result, enabling comparisons across different studies and spatial scales, mitigating the impact of raw distance variations. It helps determine whether spatial distribution is clustered, random, or dispersed. At the urban scale, ANN measures the distribution of facilities (Mansour, 2016), green spaces (Almohamad et al., 2018), and explores urban (Naqshbandi et al., 2016) and settlement patterns (Thompson et al., 2022). At the block scale, it assesses communities and buildings compactness (Akrofi & Okitasari, 2023).

3.3. SHAPE INDEXES

The Shape Indexes measure urban compactness by contrasting irregular urban forms with regular geometric shapes, particularly circles as the most compact benchmark. Included are Richardson's perimeter compactness, Gibbs' longest axis compactness, Cole's minimum circumscribing circle compactness (COLE index) (Chen, 2011; Lin, 1998), perimeter-based CI index (Huang et al., 2007; Li & Yeh, 2004), and the convex hull-based CHAD index (Colaninno et al., 2011). Among these, COLE, introduced in 1964 (Cole, 1964), is widely used for its simplicity and effectiveness (Lin, 1998). The formula for COLE is:

$$COLE = \frac{A_o}{A_c} = \frac{\sum_{i=1}^{n} a_i}{A_c} \quad (4)$$

In the formula: A_o is the measured area of the region, A_c is the area of the region's minimum circumscribing circle, a_i is the area of the i-th element, and n is the number of elements (Figure 2d). The values range from 0 to 1, with higher values indicating more compact distributions.

COLE, integrating both location and area information, is frequently used for measuring urban spatial compactness at the urban scale (Dai et al., 2022; Liu et al., 2014), with a particular focus on axial expansion attributes (Zhang et al., 2022). As the circumscribing circle's diameter increases, the COLE index decreases, hitting the lowest in linear urban forms. This indicates that COLE not only reflects the compactness but also the tendency towards circular or band-like structures.

3.4. GRAVITATION INDEXES

Newton's law of universal gravitation, adapted in various disciplines including urban studies, offers a new perspective for measuring urban compactness. This approach uses the average gravitational pull of urban spaces to define compactness, which is directly proportional to construction intensities and inversely proportional to the square of distance. Common Gravitation Indexes include T (Thinh et al., 2002), NCI (Zhao et al., 2011), NVCI (Wang et al., 2021), and PROX (Colaninno et al., 2011), with T and NCI being particularly widely discussed and applied.

In 2002, Thinh et al. introduced the Average Gravitation Index (T) to address the lack of distance measurement in compactness assessments (Thinh et al., 2002). The formula for T is:

$$T = \frac{\sum \frac{1}{c} \frac{X_i X_j}{d^2(i,j)}}{N\,(N-1)/2} \tag{5}$$

In the formula: N, X_i, and X_j are the same as in formula (1), $d(i,j)$is the geometric distance between the i-th and j-th grids, and c is a constant for dimensionless results (Figure 2a). T values are greater than 0, with higher values indicating more compact distributions.

The T index's 'gravity' between any two elements is inversely proportional to the square of their distance. Consequently, as a city expands, increasing average distances between elements lead to reduced gravitational pull, potentially lowering the T value. This suggests a bias in measuring compactness across cities of different sizes: underestimating larger cities and overestimating smaller ones. To address this bias, Zhao et al. (2011) introduced the Normalized Compact Index (NCI) in 2011, standardizing the T index using an equivalent circle. The formula for NCI is:

$$NCI = \frac{T}{T_{max}} = \frac{M(M-1)}{N(N-1)} \times \frac{\sum_{i=1}^{N} \sum_{j=1}^{N} \frac{X_i X_j}{d^2(i,j)}}{\sum_{i'=1}^{N} \sum_{j'=1}^{N} \frac{X_i{}' X_j{}'}{d'^2(i',j')}} \tag{6}$$

In the formula: N, X_i, X_j, and $d(i,j)$are the same as in formula (6), M is the number of grids in the equivalent circle, $X_i{}'$and $X_j{}'$ are the construction intensities of grids i' and j' within the equivalent circle, and $d'(i',j')$ is their geometric distance (Figure 2b). NCI values range from 0 to 1, with higher values indicating more compact distributions.

NCI, recognized as a mature compactness index (Jia et al., 2018), is used at the urban scale for measuring urban forms (Zhao et al., 2011), and at the block scale for assessing building layout compactness and green space connectivity (Li et al., 2016; Wang et al., 2021; Ji et al., 2023).

4. Common Issues in the Application of Indexes

Upon reviewing current applications of compactness indexes, this study identifies three main issues: imprecise referencing conditions, interpretational discrepancies, and opaque computational parameters, which may mislead research outcomes.

4.1. LACK OF VERIFICATION FOR APPLICABILITY

Some studies, when selecting indexes, do not fully consider their applicability across disciplines, subjects, and scales. For instance, in assessing the compactness of buildings at the block scale, literatures have adopted indexes like ANN (from biological distribution studies) (Akrofi & Okitasari, 2023), CHAD (from architectural form studies) (Colaninno et al., 2011), and Moran's I (from urban scale studies) (Zhuang & Zhou, 2019). However, the suitability of these indexes for the specific research context and content remains questionable due to the lack of a rigorous verification process.

4.2. CONFUSION IN INTERPRETATION

We also found interpretational discrepancies and ambiguities in index results (see Figure 1, 'Interpretation'). For instance, Moran's I is typically viewed as indicating spatial patterns or compactness, but some interpret it as urban centrality (H. Liu et al., 2021) or continuity (Rahman et al., 2022). Moreover, the concepts of compactness and density are frequently confused, exhibiting significant 'collinearity' in real urban environments. This poses a question: if compactness and density are interchangeable, why not simplify compactness calculations with density measurements? Thus, clarifying these concepts is crucial to prevent data misinterpretation.

4.3. NEGLECT OF PARAMETER SETTING

4.3.1. Parameter Settings in Existing Studies

In the computation of indexes, parameter setting clarity and transparency are often neglected. For example, in Moran's I, Tsai suggested that distance thresholds are more effective than mere adjacency at the urban scale (Tsai, 2005). These thresholds can be based on city size (Yan et al., 2013) or incremental spatial autocorrelation (Rahman et al., 2022). However, the lack of detailed parameter settings in some studies (Sikder et al., 2019; Zhuang & Zhou, 2019) may impact research accuracy and sustainability.

Moreover, the sensitivity of indexes to grid sizes is a commonly ignored issue, which has been discussed by original proposers and validators. Thinh et al. calculated the T values for cities at ten grid sizes and found a significant correlation of the value at the 500×500m scale with the average, thus choosing it as the study size (Thinh et al., 2002). Zhao et al. observed non-monotonic variations in NCI values across grid sizes (Zhao et al., 2011), and Yan et al. found that Moran's I values maintain good consistency across grid sizes in Nanjing and Suzhou studies (Yan et al., 2013). Yet, scale sensitivity is frequently neglected in practical applications.

It is noted that indexes within the aforementioned two categories, calculated using pixel data, are prone to issues with parameter settings. To further explore the impact of parameter settings on computational results, this study employs actual blocks in Shanghai for calculations.

4.3.2. Method

This study selected two typical spatial configurations in Shanghai as calculation samples: one is residential buildings (s1) with small individual areas and numerous units, and the other is office buildings (s2) with large individual areas but fewer units. Four commonly used grid sizes of 20m, 30m, 40m, and 50m were employed. Consequently, a square region measuring 600 meters in length, divisible by each of these sizes, was selected as the calculation area. Based on the original building layout (Least Compact), each building unit was moved towards the center of the calculation range to form two comparison groups - More compact and Most compact - to observe the differences in the indexes responses to various parameter settings. The sample setup is detailed in Figure 3.

The calculations were performed in ArcGISPro3.0.2 software, using Python scripts to invoke geographical processing tools and index calculation formulas. The study calculated three indexes, among which Moran's I used two different spatial weights: 'Contiguity edges only' and 'Inverse distance=200m' (one-third of the calculation range side length).

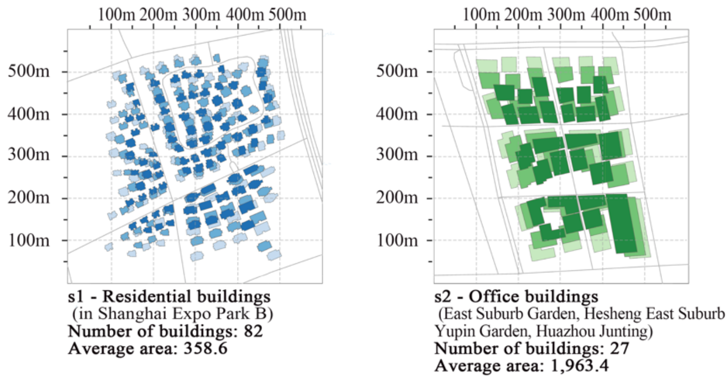

Figure 3. Diagram of block sample layouts

4.3.3. Results

The computation results are depicted in Figure 4, where the horizontal axis represents grid size, and the vertical axis denotes the indicator values. Clearly, different grid sizes and spatial weight settings of indexes indeed affect the compactness calculation outcomes, and this impact varies across different types of blocks, exhibiting diverse range intervals and trends.

Notably, at the block scale, Moran's I values do not monotonically change with grid size, inconsistent with Yan et al.'s findings. Moreover, the distinction of setting adjacency only or distance thresholds on compactness measurements is not substantial, contradicting Tsai's observations. Instead, the type of samples has a more pronounced effect. These discrepancies underline that index calculations and their applicability differ between block and urban scales.

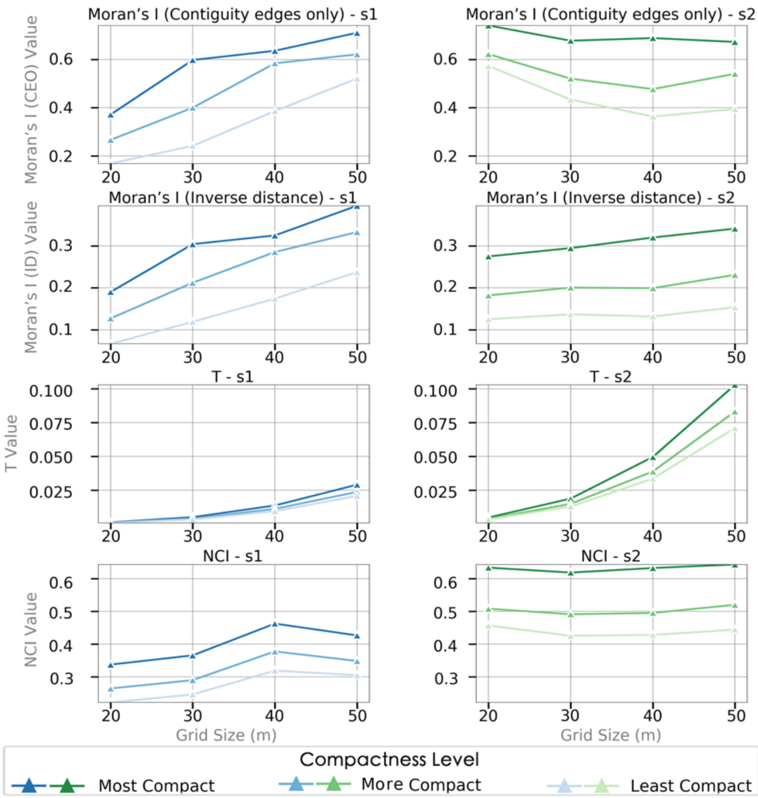

Figure 4. Calculation results of the indexes

5. Conclusion and Future Work

This study conducted a conceptual review and application analysis of six compactness indexes, categorized into four types. The research identified issues in the application of these indexes, including imprecise reference conditions, interpretation disparities, and opaque computational parameters.

Using actual blocks in Shanghai, the study further examined the impact of parameter settings on calculation results. The results confirm the influence of parameter settings and their variability across different calculation scales and building types, highlighting the risks of blindly adopting parameters from different research contexts. It is suggested that researchers conduct pre-calculations to determine the optimal grid size and other parameter settings that best suit specific objects and research objectives.

At present, research on urban compactness at the block scale is limited (Rahman et al., 2022). However, as computable urban design evolves, refining indexes for this scale becomes a key direction in the field of urban form measurement. This study's insights aim to provide valuable guidance and inspiration for subsequent research.

References

Akrofi, M. M., & Okitasari, M. (2023). Beyond costs: How urban form could limit the uptake of residential solar PV systems in low-income neighborhoods in Ghana. *Energy for Sustainable Development,* 74, 20–33. https://doi.org/10.1016/j.esd.2023.03.004

Almohamad, H., Knaack, A. L., & Habib, B. M. (2018). Assessing spatial equity and accessibility of public green spaces in Aleppo City, S*yria. Forests*, 9(11). https://doi.org/10.3390/f9110706

Chen, Y. (2011). Derivation of the functional relations between fractal dimension of and shape indices of urban form. Computers, Environment and Urban Systems, 35(6), 442–451. https://doi.org/10.1016/J.COMPENVURBSYS.2011.05.008

Colaninno, N., Roca, J., & Pfeffer, K. (2011). Urban form and compactness of morphological homogeneous districts in Barcelona: Towards an automatic classification of similar built-up structures in the city. In Proceedings of the 51st European Regional Science Association (ERSA) Congress (pp. 769). European Regional Science Association (ERSA).

Cole, J. P. (1964). Study of major and minor civil divisions in political geography. In The 20th International Geographical Congress.

Dai, X., Jin, J., Chen, Q., & Fang, X. (2022). On Physical Urban Boundaries, Urban Sprawl, and Compactness Measurement: A Case Study of the Wen-Tai Region, China. Land, 11(10). https://doi.org/10.3390/land11101637

Falahatkar, S., & Rezaei, F. (2020). Towards low carbon cities: Spatio-temporal dynamics of urban form and carbon dioxide emissions. Remote Sensing Applications: Society and Environment, 18, 100317. https://doi.org/https://doi.org/10.1016/j.rsase.2020.100317

Geary, R. (1954). The Contiguity Ratio and Statistical Mapping. The Incorporated Statistician, 5, 115–145. https://doi.org/10.2307/2986645

Griffith, D., & Chun, Y. (2014). Spatial autocorrelation and eigenvector spatial filtering. Handbook of Regional Science, 1477–1507.

Huang, J., Lu, X. X., & Sellers, J. M. (2007). A global comparative analysis of urban form: Applying spatial metrics and remote sensing. Landscape and Urban Planning, 82(4), 184–197. https://doi.org/https://doi.org/10.1016/j.landurbplan.2007.02.010

Ji, R., Wang, K., Zhou, M., Zhang, Y., Bai, Y., Wu, X., Yan, H., Zhao, Z., & Ye, H. (2023). Green Space Compactness and Configuration to Reduce Carbon Emissions from Energy Use in Buildings. Remote Sensing, 15(6). https://doi.org/10.3390/rs15061502

Jia, Y., Tang, L., & Gui, L. (2018). Study on the formulation and application of the urban spatial form dispersion index (NDIS). Acta Ecologica Sinica, 38(20), 7269-7275.

Li, F., Zhou, T., & Lan, F. (2021). Relationships between urban form and air quality at different spatial scales: A case study from northern China. Ecological Indicators, 121, 107029. https://doi.org/https://doi.org/10.1016/j.ecolind.2020.107029

Li, X., Lv, Z., Hijazi, I. H., Jiao, H., Li, L., & Li, K. (2016). Assessment of Urban Fabric for Smart Cities. IEEE Access, 4, 373–382. https://doi.org/10.1109/ACCESS.2016.2517072

Li, X., & Yeh, A. G.-O. (2004). Analyzing spatial restructuring of land use patterns in a fast growing region using remote sensing and GIS. Landscape and Urban Planning, 69(4), 335–354. https://doi.org/https://doi.org/10.1016/j.landurbplan.2003.10.033

Lin, B. (1998). Measurement methods and evaluation of urban spatial form. Urban Planning Forum, (03), 42-45+65

Liu, H., Huang, B., Zhan, Q., Gao, S., Li, R., & Fan, Z. (2021). The influence of urban form on surface urban heat island and its planning implications: Evidence from 1288 urban clusters in China. Sustainable Cities and Society, 71. https://doi.org/10.1016/j.scs.2021.102987

Liu, L., Xun, L., Wang, Z., Liu, H., Huang, Y., & Bedra, K. B. (2023). Peak Carbon Dioxide Emissions Strategy Based on the Gray Model between Carbon Emissions and Urban Spatial Expansion for a Built-Up Area. Applied Sciences, 13(1). https://doi.org/10.3390/app13010187

Liu, Y., Song, Y., & Song, X. (2014). An empirical study on the relationship between urban compactness and CO2 efficiency in China. Habitat International, 41, 92–98. https://doi.org/10.1016/j.habitatint.2013.07.005

Mansour, S. (2016). Spatial analysis of public health facilities in Riyadh Governorate, Saudi Arabia: a GIS-based study to assess geographic variations of service provision and accessibility. Geo-Spatial Information Science, 19(1), 26–38. https://doi.org/10.1080/10095020.2016.1151205

MORAN, P. A. P. (1950). NOTES ON CONTINUOUS STOCHASTIC PHENOMENA. Biometrika, 37(1–2), 17–23. https://doi.org/10.1093/biomet/37.1-2.17

Naqshbandi, Z., Fayaz, S., & Bhat, M. (2016). A quantitative analysis of spatial organization of the urban centers in Kashmir Valley: A geographic information systems-based study using primacy index, rank-size rule, and nearest neighbor index. Journal of Experimental Sciences, 7, 11–19.

Rahman, M. H., Islam, M. H., & Neema, M. N. (2022). GIS-based compactness measurement of urban form at neighborhood scale: The case of Dhaka, Bangladesh. Journal of Urban Management, 11(1), 6–22. https://doi.org/10.1016/j.jum.2021.08.005

Sikder, S. K., Behnisch, M., Herold, H., & Koetter, T. (2019). Geospatial Analysis of Building Structures in Megacity Dhaka: the Use of Spatial Statistics for Promoting Data-driven Decision-making. Journal of Geovisualization and Spatial Analysis, 3(1). https://doi.org/10.1007/s41651-019-0029-y

Thinh, N. X., Arlt, G., Heber, B., Hennersdorf, J., & Lehmann, I. (2002). Evaluation of urban land-use structures with a view to sustainable development. Environmental Impact Assessment Review, 22(5), 475–492.

Thompson, A. E., Walden, J. P., Chase, A. S. Z., Hutson, S. R., Marken, D. B., Cap, B., Fries, E. C., Piedrasanta, M. R. G., Hare, T. S., Horn, S. W., Micheletti, G. J., Montgomery, S. M., Munson, J., Richards-Rissetto, H., Shaw-Müller, K., Ardren, T., Awe, J. J., Brown, M. K., Callaghan, M., … Chase, D. Z. (2022). Ancient Lowland Maya neighborhoods: Average Nearest Neighbor analysis and kernel density models, environments, and urban scale. PLoS ONE, 17(11 November). https://doi.org/10.1371/journal.pone.0275916

Tsai, Y. H. (2005). Quantifying urban form: Compactness versus "sprawl." Urban Studies, 42(1), 141–161. https://doi.org/10.1080/0042098042000309748

Wang, D., Zhang, G., Lin, T., Hu, X., Zhao, Z., & Shi, L. (2021). Exploring the connection between urban 3d form and building energy performance and the influencing mechanism. ISPRS International Journal of Geo-Information, 10(10). https://doi.org/10.3390/ijgi10100709

Wang, Y., & He, H. (2007). Spatial data analysis method. Science Press.

Yan, Y., Chen, S., Li, G., et al. (2013). Urban compactness index and its application: Compactness of built-up areas in Nanjing and Suzhou. Progress in Geography, 32(5), 733-742.

Zhang, L., Zhang, L., & Liu, X. (2022). Evaluation of Urban Spatial Growth Performance from the Perspective of a Polycentric City: A Case Study of Hangzhou. Land, 11(8). https://doi.org/10.3390/land11081173

Zhao, J., Song, Y., Shi, L., et al. (2011). Study on the compactness assessment model of urban spatial form. Acta Ecologica Sinica, 31(21), 6338-6343.

Zhou, W., Huang, G., & Cadenasso, M. (2011). Does spatial configuration matter? Understanding the effects of land cover pattern on land surface temperature in urban landscapes. Landscape and Urban Planning, 102, 54–63. https://doi.org/10.1016/j.landurbplan.2011.03.009

Zhuang, Y., & Zhou, L. (2019). Quantitative research of urban form and density index of central city block in Shanghai. Journal of Tongji University (Natural Science), 47(08), 1090-1099.