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Machine learning-based characterisation of urban morphology with the street pattern

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ABSTRACT

Streets are a crucial part of the built environment, and their layouts, the street patterns, are widely researched and contribute to a quantitative understanding of urban morphology. However, traditional street pattern analysis only considers a few broadly defined characteristics. It uses administrative boundaries and grids as units of analysis that fail to encompass the *diversity* and *complexity* of street networks. To address these challenges, this research proposes a machine learning-based approach to automatically recognise street patterns that employs an adaptive analysis unit based on street-based local areas (SLAs). SLAs use a network partitioning technique that can adapt to distinct street networks, making it particularly suitable for different urban contexts. By calculating several streets' network metrics and performing a hierarchical clustering method, streets with similar characters are grouped under the same street pattern. A case study is carried out in six cities worldwide. The results show that street pattern types are rather diverse and hierarchical, and categorising them into clearly demarcated taxonomy is challenging. The study derives a set of new morphometrics-based street patterns with four major types that resemble conventional street patterns and eleven sub-types to significantly increase their diversity for broader coverage of urban morphology. The new patterns capture urban structural differences across cities, such as the urban-suburban division and the number of urban centres present. In conclusion, the proposed machine learning-based morphometric street pattern to characterise urban morphology has an enhanced ability to encompass more information from the built environment while maintaining the intuitiveness of using patterns.

1. Introduction

In the rapidly urbanising world, creating inclusive, safe, resilient, and sustainable cities, as outlined in the United Nations Sustainable Development Goals (SDGs) 9 and 11, is more critical than ever. A key aspect of achieving these goals lies in understanding the urban built environment, which is a reflection of the inherent urban socioeconomic activities of a city (Jacobs, 1961; Li, Li, Zhu, Song, & Wu, 2013; Lynch, 1960; Venerandi, Zanella, Romice, Dibble, & Porta, 2017; Wu, Smith, & Wang, 2021). Many scholars and practitioners believe in a mutual influence between tangible urban space and intangible human activities. Therefore, a better understanding of the urban built environment could inform potential interventions for enhanced urban activities and living (Batty et al., 2013; Çalişkan & Marshall, 2011; Cheng & Shaw, 2018). The morphological study of the physical urban environment involves analysing the forms of basic urban elements, such as streets, buildings, and plots (Moudon, 1997). This study chooses the street as the focus to tap into the morphological study of urban forms, as streets are one fundamental element of a city where human activities are concentrated (Wang & Vermeulen, 2021).

In the study of street forms, street patterns are introduced to ease understanding of the complex street network in the urban built environment. Street patterns refer to the types of planar street layouts in an urban area (Southworth, 1997). Each street pattern stimulates unique urban activities while suppressing others (Alexander, 1977; Jacobs, 1961). Hence, urban planners use them to create urban spaces for different functions. These patterns are defined mainly by conventions and are easily distinguishable with a few unique characters. For example, their visual identity based on the planar imprint, such as grid, radial, and organic appearance, primarily distinguishes these street patterns. This study refers to these street patterns as conventional street patterns. However, using predefined conventional patterns in urban morphology also comes with demerits, as the high degree of abstraction may lead to overgeneralisation and rigidity in depicting reality.

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Analysing street patterns also comes with the challenge of arbitrarily choosing units of analysis, such as administrative boundaries or grids that are not optimised for streets with their network structure (Law, 2017). Thus, its universal application and transferability are not guaranteed.

With technological advancement, the study of urban morphology has entered an ethos with new data and methods (Fleischmann, Feliciotti, & Kerr, 2022). Given the large amount of data available nowadays, the quantitative depiction of streets with a graph structure, together with machine learning-based analysis, allows for the extraction of more intelligence to derive insights into many aspects of cities. Instead of predefining urban types in terms of street forms/patterns, the methods allow a somewhat automated data-driven exploration of urban types given enough data representing the diverse built environment (Wang et al., 2023). They greatly enhanced the ability to carry out large-scale studies, and their reproducibility and transferability.

Nevertheless, there are still limited attempts to use these new metrics and methods for a more comprehensive depiction of the urban street form while maintaining the simplicity of using conventional street patterns. Drawing merits from the simplicity of street patterns and the comprehensiveness of street metrics, this study proposes a new method for the morphometric-based street pattern: clustering based on quantitative characters. The method allows a data-driven manner for exploring potential street patterns instead of conventional ones. The core of the method is measuring and clustering street network characters. For the unit of analysis, this study also adopted a network-based technique to divide the study area to suit the network character of the street and ensure a consistently derived unit of analysis across different study areas. Hence, this method's resulting morphometric-based street patterns could be flexible to accommodate the different urban contexts for large-scale studies while maintaining comparability.

2. Background

Streets have long been recognised as an essential urban element to understanding different urban phenomena. Street network, which refers to streets' topological configuration and connectivity (Jiang & Claramunt, 2004), is a vital aspect of the built environment that influences how people interact with their surroundings, move around, and engage in various activities (Gehl, 2011). Since urban design and planning began, people have intuitively used street patterns to describe and understand street morphology. However, these conventional street patterns have their limits.

Over the years, scholars have proposed many different street patterns to categorise the characters in street networks. These diverse categorisations were introduced for different purposes like transportation studies, urban design and planning, and urban vitality studies (Barthelemy, 2017; Chen, Wu, & Biljecki, 2021; Rifaat, Tay, & De Barros, 2011; Wheeler, 2015). Some also use quantitative metrics, like network metrics, to distinguish different street patterns and explore their implications for urban form and function. For example, Marshall (2004) has summarised the classified street networks based on their configurations. He also suggests different classifications based on street metrics, such as connectivity and complexity. These classifications of street patterns have been focused on the street characters for their specific applications. Some common terminology appears constantly across these different street pattern categories. Patterns such as grid, organic, deformed, and cul-de-sacs, shown in Fig. 1, were widely adopted across different studies (Asami & Istek, 2001; Chen et al., 2021; Dill, 2004; Marshall, 2004). These commonalities show that conventional patterns are based mainly on selected metrics that are visually distinguishable: the streets' curvature, direction, the number of dead-end streets, and the number of streets connected by junctions. Another observation is that most of these street patterns were predefined before the actual study. These street patterns are highly specialised for specific studies. Many more street characters were not covered due to the nature of predefined and highly simplified conventional street patterns. As a result, they only capture limited aspects of streets, which may not reflect diverse street morphology in different parts of the world. Hence, a more holistic representation of street morphology requires a street pattern based on more than just a few visually identifiable metrics.

With the introduction of network science and computing tools, quantitative research on street networks has become increasingly popular (Boeing, 2021; Law et al., 2019; Zhou et al., 2022). One of the influential quantitative methods for analysing street networks is space syntax, proposed by Hillier, Leaman, Stansall, and Bedford (1976). Space syntax developed axial maps to represent street networks and calculate the accessibility and centrality of streets. Similar to Space syntax, other quantitative methods analyse street networks by representing them as a graph, also called network analysis in GIS. Network analysis uses edges and nodes, which are the street segment and street junction (Marshall, Gil, Kropf, Tomko, & Figueiredo, 2018; Porta, Crucitti, & Latora, 2006; Wang, Chen, Mu, & Zhang, 2020), respectively, to represent street networks and examine their network metrics. The application of network analysis in GIS includes the evaluation of urban road network connectivity and its impact on travel demand, safety, and efficiency (Cervero & Kockelman, 1997a; Cooper & Chiaradia, 2020; Jenelius, Petersen, & Mattsson, 2006; Steenberghen, Aerts, & Thomas, 2010). Another application is to explore street networks' relation to land use, socioeconomic activity, and urban form. This can help explain the spatial distribution of urban activities and functions in different parts of the city and how they interact. The network metrics play a vital role in these studies with much software developed. For example, the City Form Lab (Sevtsuk & Mekonnen, 2012) developed a toolbox for urban network analysis that can compute centrality. Boeing (2017a, 2017b) developed OSMnx, a Python package that allows you to download, analyse, and visualise street networks from OpenStreetMap (OSM). Users can use OSMnx to create network graphs and calculate metrics such as orientation entropy and centrality. These new metrics provide more information on street networks and greatly enhance scholars' ability to explore various aspects of urban morphology at a large scale. However, these diverse quantitative methods also raised the bar to comprehend and utilise streets in urban studies and planning.

So far, this paper has reviewed the quantitative studies of street networks and the use of street patterns. Current work combining both fields concentrates on recognising existing conventional patterns or

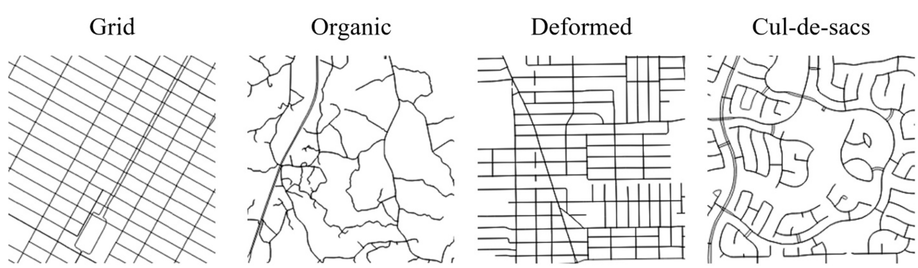


Fig. 1. Some common conventional predefined patterns in existing studies. (Produced by the author with Open Street Map).

global scale studies with the selected metrics and city as the smallest study unit. The former still uses the conventional street pattern, which urban designers and planners widely adopt. However, their classification is largely based on visual identities and leaves out valuable information, as mentioned earlier. This work is exemplified by Chen et al. (2021) deep-leaning approach to mapping street patterns and studying their relationship with urban vitality. For the global-scale study with the city as the unit of analysis, although it generates street network typology with various quantitative methods, it has a granularity that is too large. Hence, it is not the notion of street patterns that urban planners and designers adopted and is not ideal to reveal the city's internal structure. These works are exemplified by Louf and Barthelemy (2014) classification of the city's street network typology using street blocks and Boeing's work Boeing (2018), where he conducted street network analysis on American cities at multiple scales. On the one hand, finding the right balance between using too little or too much of the street metrics is not easy. Although many quantitative street metrics were introduced to depict the street network, a handful of metrics are insufficient to capture the street morphology holistically. At the same time, too many could be elusive and not intuitive to understand and analyse. On the other hand, conventional street patterns are intuitive, but their predefined classification limits their ability to reflect the diversity of street morphology. Consequently, it has confined the application of street patterns to large-scale multidisciplinary research.

This article also acknowledges a common challenge of choosing a unit of analysis when investigating street networks. Some use the city as the unit of analysis, which is too coarse for analysing urban morphology. Currently, most studies adopt a grid-based partition or administrative as the unit of analysis. There is no consensus on defining and delimiting a unit of analysis consistently and meaningfully (Zhang & Kukadia, 2005). Moreover, the effectiveness of these units in capturing the intricate structure of street networks has been a subject of debate. While the grid-based approach generates a universal unit of analysis for multi-city studies, it can be rather rigid for the arbitrary division of the network. On the other hand, using administrative boundaries in urban planning and study is undoubtedly a well-established practice, as they provide a clear framework for governance, policymaking, and project implementation. However, the effectiveness of administrative boundaries depends on how well they align with the actual urban dynamics and characteristics on the ground, in this case, the morphological patterns of streets, which have little rationale to follow administrative limits strictly. Additionally, the administrative boundary lacks universality when studying cities adopting different division systems with different spatial scales. In light of this, Law (2017) explored using a street network to generate adaptive units of analysis to study housing prices that have not been tested for street morphology.

Given the constraints, the existing studies presented an opportunity to amalgamate the abundance of street metrics and patterns for a data-driven morphometric-based street pattern in a cross-city urban morphological study. We apply an unsupervised machine learning method to generate street patterns: the morphometric-based street pattern. It does not require a labelled training dataset and generates network typology automatically. With the new quantitative method, our method aims to explore street patterns' potential to character urban morphology from diverse urban contexts. The resulting morphometric-based patterns could potentially, first, resemble conventional predefined street patterns and maintain the simplicity of using patterns to characterise urban morphology; second, utilise morphometrics, which shows the morphological character intuitively compared to conventional patterns; third, cover the diverse urban environments and captures morphological distinctions in different cities compared to conventional street pattern; Fourth, adopts a suitable scale and unit of analysis which is more suitable for urban scholars, planners, and designers to work with for both inter- and intra-city comparison. The new street pattern depends on the features input with minimum parameter adjustment. This study mapped the new street patterns and performed some initial analysis to determine how they characterise the urban morphology across cities.

3. Methodology

This study proposes an approach for characterising urban morphology based on street patterns using unsupervised machine learning. As illustrated in Fig. 2, the proposed approach consists of three major steps: First, this study represents streets as networks to generate the adaptive unit of analysis; second, it quantifies the street morphology through street metrics; third, it generates morphometric-based patterns through unsupervised hierarchical clustering on top of the measured metrics. The three steps are further elaborated in Sections 3.1, 3.2, and 3.3. The result is the morphometric-based pattern and their mapping in the case study. Mapping the street pattern provides an initial exploration or validity test to see whether it can reveal the internal urban structure of the city and further show the difference across cities.

To test the validity of the proposed method, case study cities are selected based on two principles: the diversity of street networks presented in the cities and the potential for future research. This research has deliberately selected distinct cosmopolitan cities with different historical, economic, cultural, and political backgrounds worldwide, namely Amsterdam, Chengdu, London, Seoul, Houston, and New York City. They are metropolitan cities where changing transportation modes and urban development stages have led to distinct street morphology. The case study selected also has a relatively good amount of research using different data and better open data access with quality, which provides opportunities for future research. As the investigation covers a range of scales, from a broader intercity/urban structure to a more refined district/neighbourhood scale, each study area is set as a 25 km × 25 km square for better comparability between cities. Our proposed method utilised open data and open-source tools to ensure transferability and reproducibility. Street network data is extracted from OpenStreetMap using the open-source Python package OSMnx. Additionally, Python libraries of NetworkX and scikit-learn, along with the open-source GIS tool QGIS, were applied.

3.1. Street-based local area (SLA) as the unit of analysis

In urban studies, the common units of analysis are often based on a grid or an administrative boundary. However, as mentioned earlier, they may not be optimised for studying street morphology. Additionally, the variability in administrative boundary definitions across different regions challenges consistent data organisation and comparative analysis. The Street-based local areas (SLAs), with their standardised process for defining local areas based on actual street networks, offer a universal framework that facilitates comparison and extrapolation of insights across various urban settings. SLAs are defined by four key characteristics (Law, 2017) and optimised for studying street patterns across different cities: 1) *street-based*, which means they are generated from the street network. Hence, all cities have a single unified input; 2) *topological/configurational*, which means the generation of SLA takes into consideration network and layout properties; 3) *discrete* means each SLA is independent of each other and the original street network so that the metrics can be calculated independently; 4) *suitable size* as it is large enough to capture the street networks characteristics but small enough to distinguish the morphological and socioeconomic differences within a city.

The effectiveness of SLAs compared to administrative boundaries is evident when considering urban sprawl and areas with dense street networks that do not conform to administrative demarcations. Taking London as an example, in Law's work (2017), the proponents of the SLA approach have demonstrated that it offers a more innovative and precise framework for capturing the unique attributes of areas such as Isle of Dogs in Fig. 3a, which may not align neatly with administrative boundaries indicated in red. Our research has reproduced similar

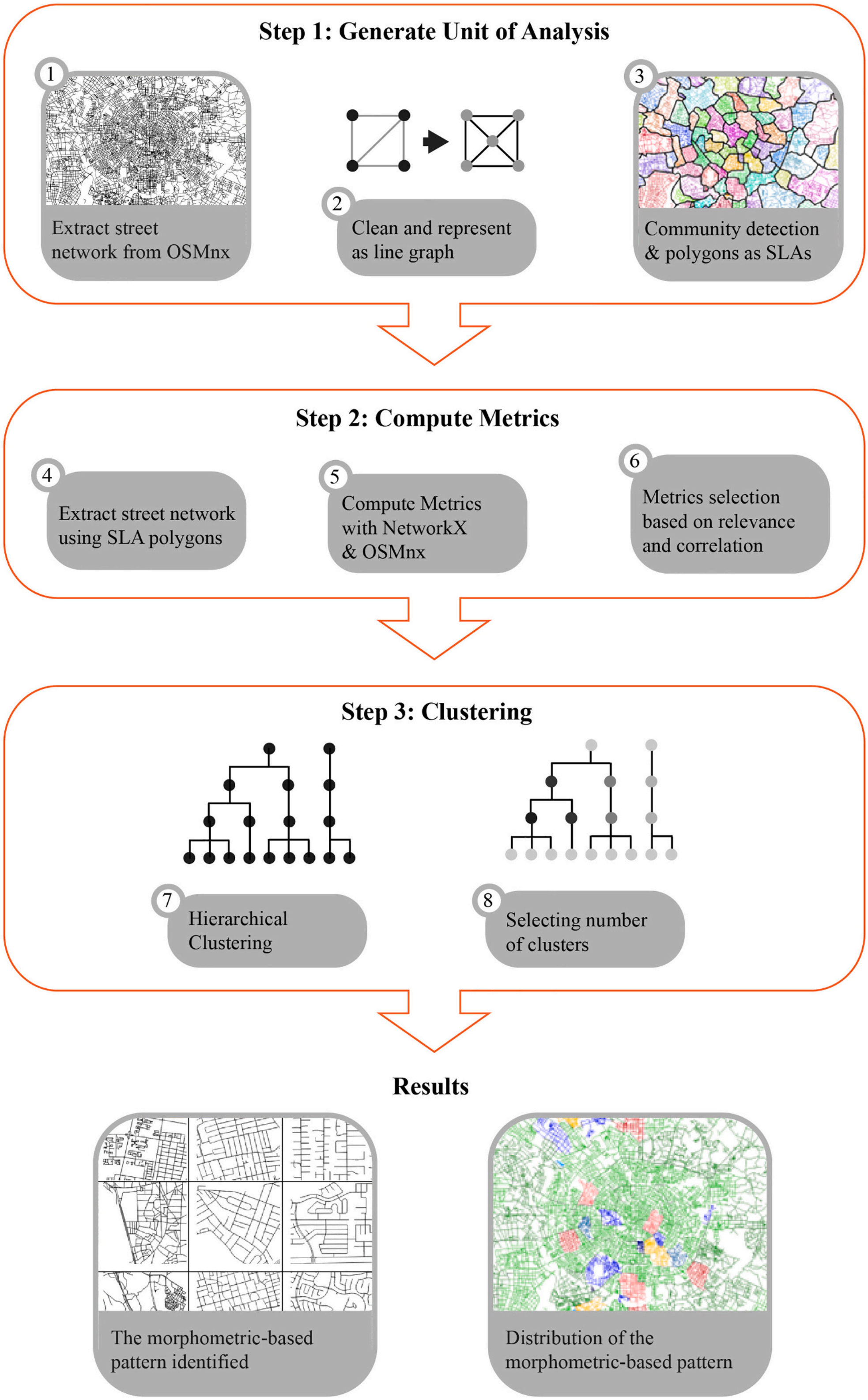


Fig. 2. Three major steps of the proposed method. A more detailed explanation of each specific step will be provided in detail in this section.

findings, indicating that SLAs can provide a more accurate representation of urban areas for planning purposes. This is particularly relevant in metropolises like our case study cities, where urban sprawl has extended beyond traditional administrative boundaries. In such scenarios, a holistic approach to planning that transcends these boundaries is essential. For instance, in cities like Amsterdam (Fig. 3b), the urban fabric is so interwoven with neighbouring areas that they appear continuous. Relying solely on administrative boundaries for planning in these contexts could obscure the broader urban landscape, which the SLA more effectively captures in Fig. 4.

We use OSMnx to extract the street network for all six case study cities from the Open Street Map. The resulting network is a weighted

Fig. 3. 3a The ward division in London did not capture the Isle of Dogs. The streets coloured by SLA show clearly how SLA better defines the Isle.
3b Amsterdam's urban sprawl extends beyond the administrative boundary (indicated in red). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

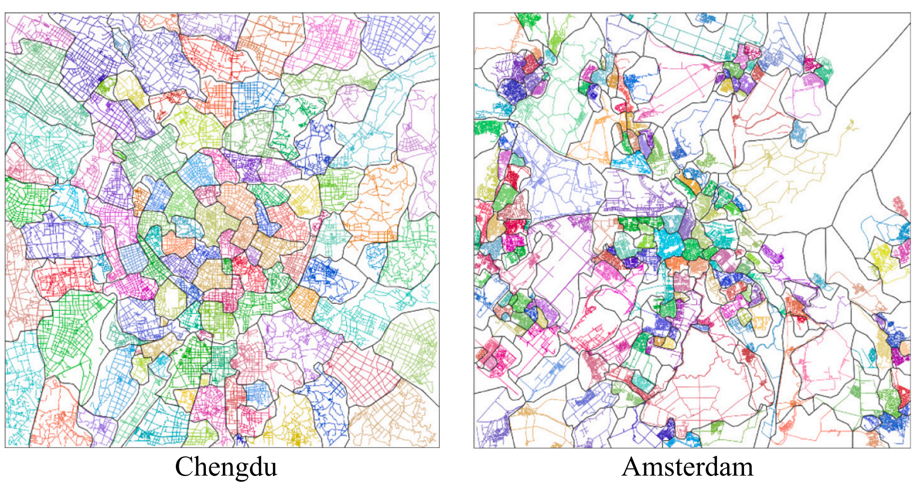


Fig. 4. The coloured networks show the street network extracted from OSMnx and divided by community detection. The thickened boundary shows the polygons generated as SLAs.

directed graph with street length as the weight. Streets and street junctions become edges and nodes, respectively. These graphs preserved the most information and can be transformed into other kinds of graphs (directed/undirected, weighted/unweighted) for later research needs.

To divide the street network into SLAs, the study first transforms the street network into an unweighted and undirected line graph, where the streets become nodes and street junctions become edges. We then perform a community detection technique, specifically modularity maximisation clustering, so streets as nodes can be assigned to different communities to generate the SLAs as subgraphs. The modularity maximisation technique begins with each node in its own community and repeatedly joins the pair of communities that lead to the largest modularity until no further increase in modularity is possible. More details regarding the modularity maximisation technique can be referred to in the work by Clauset, Newman, and Moore (2004). After the SLA subgraphs are generated, QGIS and ArcMap are applied to create and clean the polygons covering the SLA. These polygons are used as the inputs for the OSMnx to recapture the street networks for the metric calculation in the next step. A total of 1054 SLAs are generated across six cities in this research. Fig. 4 shows the street network partitioning and SLA generated in Chengdu and Amsterdam. The different colours distinguish the neighbouring SLAs. As shown, the SLAs can adapt to the street network in different cities and produce comparable units of analysis with similar scales.

3.2. *Metrics for street network*

This study proposes to use various metrics to capture different characters of the street network in SLA. Different metrics require different graph inputs; hence, this study transforms the original graph into the graph needed. The SLA only provides the boundary for the calculation. These metrics are generated using the Python network package OSMnx and NetworkX. Since many of these metrics are highly correlated and may require extensive computing power, catering to the needs of this study, 13 metrics were preserved after reviewing.

As shown in Table 1, these thirteen metrics can be generalised into three categories: one measures the basic spatial attribute/appearance of the network, including *Street Length, Diameter, Circuity, and Orientation Entropy;* these are Composition metrics. The second category associates the street network's fundamental properties, including *k_avg, Self-loop, L-junction, T-junction, and X-junction*, referred to as the configuration metrics. Lastly, this study proposes explanatory metrics, which inform the more sophisticated network properties, including *Degree Pearson, Transitivity, Global reaching Centrality, and Global Efficiency*.

Table 1
List of metrics.

	Metric	Definition	Value remark
Composition	Street Length[1]	Calculate the graph's average edge length.	In meters
	Diameter[1]	It is the shortest distance between the two most distant nodes in the network.	In meters higher value implies slower movement through the network.
	Circuity[1]	Circuity is the sum of edge lengths divided by the sum of straight-line distances between edge endpoints.	1 to ½π higher value implies the street is more circular
	Orientation Entropy[1]	Orientation entropy is the entropy of its edges' bidirectional bearings across evenly spaced bins.	1.386 to 3.584 higher value implies the streets are more ordered.
Configuration	k_avg[1]	graph's average node degree (in-degree and out-degree)	higher value implies better connectivity with more route choices.
	Self-loop[11]	Calculate the percentage of edges that are self-loops in a graph.	0 to 1
	L-junction[1]	The proportion of nodes with two streets connected	0 to 1
	T-junction[1]	The proportion of nodes with three streets connected	0 to 1
	X-junction[1]	The proportion of nodes with four streets connected	0 to 1
Explanatory	Degree Pearson[2]	Compute the degree assortativity, which is the similarity of connections in the graph concerning the node degree, which means the number of streets connected to a street junction.	−1 to 1 higher value implies the streets are more ordered.
	Transitivity[2]	The ratio between the observed number of triangles and the number of closed triplets in the graph	0 to 1 Higher value implies the network contains internal communities.
	Global Reaching Centrality[2]	The global reaching centrality of a weighted directed graph is the average over all nodes of the difference between the local reaching centrality of the node and the greatest local reaching centrality of any node in the graph.	0 to 1 A higher value means the network shows a more hierarchical structure.
	Global Efficiency[2]	The average efficiency of all pairs of nodes in a graph is the average multiplicative inverse of the shortest path distance between the nodes.	0 to 1 A higher value means the network shows better accessibility.

In General, the three dimensions of these metrics are adapted from Marshall's work (2004), where he originally proposed composition and configuration to denote the geometry and topology properties. By employing this tripartite framework, we aim to offer a more comprehensive analysis that can inform urban design and policymaking. The composition metrics collectively describe the street network's physical appearance and foundational layout. Configuration metrics help us understand the network's potential for connectivity and movement within the urban fabric. Lastly, Explanatory metrics are designed to interpret more sophisticated properties of the network that explain its broader implications for urban dynamics. These metrics provide insights into the network's efficiency, hierarchy, and the potential for community formation within the urban environment. The conceptual underpinnings of this framework are rooted in the need to understand urban streets beyond their physical form, considering their role in urban dynamics and their impact on urban planning and social interactions by considering different facets of the street properties.

The metrics are adapted from the foundational work on network analysis provided by OSMnx[1] (Boeing, 2017b, 2019) and NetworkX[2] (Hagberg, Swart, & Chult, 2008), with specific references marked in Table 1. Readers are directed to the cited literature for a more detailed explanation of the metrics and their computational equations, accessible via the provided links.

3.3. Clustering

The final step is to use the machine learning method to derive the morphometric-based street patterns from the metrics generated from the previous step. This study adopted the hierarchical clustering method. Hierarchical clustering is an unsupervised classification algorithm with a wide range of applications in various fields (Xu & Wunsch, 2005). It hierarchically groups similar data points to form larger clusters. Similar to other common clustering algorithms, such as K-means, the basic formula for hierarchical clustering is based on a distance measure between the data points in feature space. The algorithm is flexible enough to be adapted to handle different research granularity and different clustering objectives, making it a versatile tool for generating morphometric-based street patterns in this study (Sarle, Jain, & Dubes, 1990). In this study, the data points are the SLAs, and the input features for each data point are calculated in the previous step.

The malleability in choosing the number of clusters enhances the flexibility of the proposed method. Researchers can decide on this number based on the needs of their study. By choosing different cluster quantities, the algorithm can reveal varying granularity of street patterns. Hierarchical clustering enables the exploration of the relationships between these different street patterns. The ideal number of clusters in this study will be determined using traditional methods such as the silhouette score, which measures how similar an object is to its own cluster compared to other clusters. It should be noted, though, that silhouette scores often serve only as weak references, given their underlying assumptions and the inherent complexity of the data. Nevertheless, they can help gauge the amount of city-specific information that can be gleaned. Fig. 5 demonstrates a higher silhouette score when the number of clusters is between 3 and 11. As depicted in Fig. 6, fewer

[1] Internals Reference - OSMnx 1.6.0 documentation: https://osmnx.readthedocs.io/en/stable/internals-reference.html#osmnx-stats-module.

[2] Algorithms — NetworkX 3.1 documentation: https://networkx.org/documentation/stable/reference/algorithms/index.html.

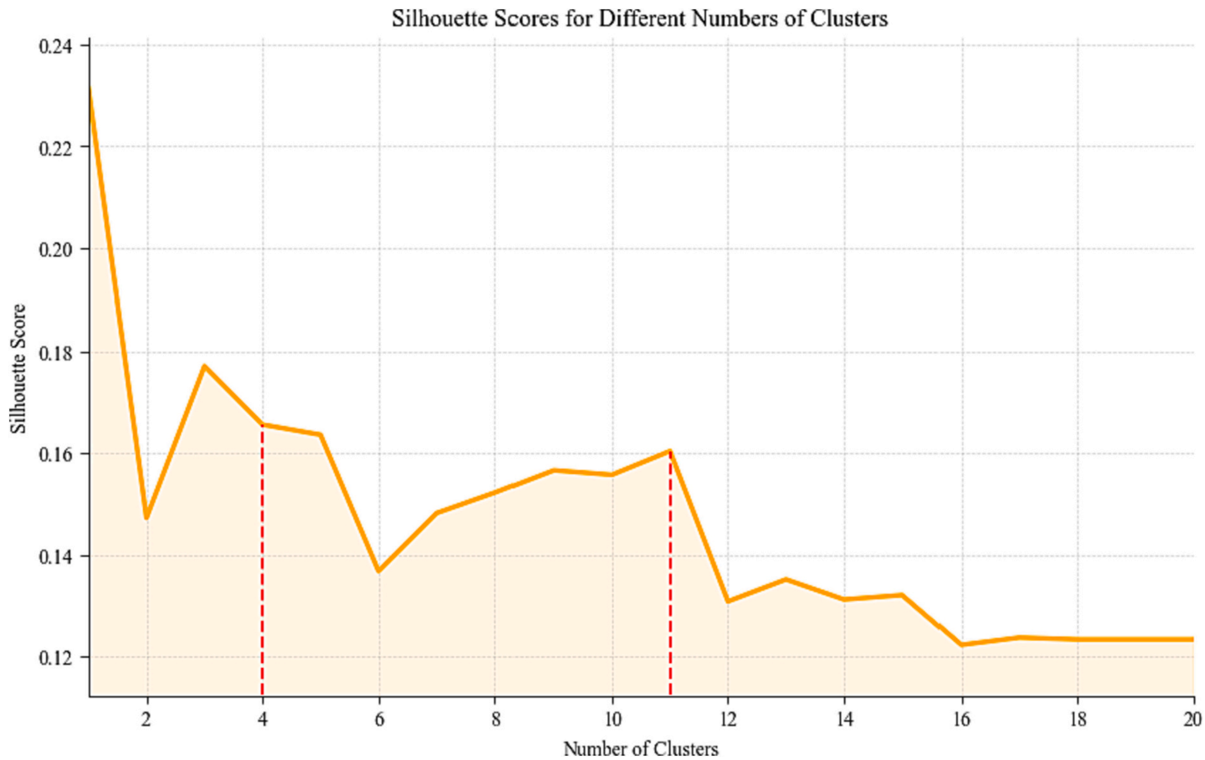


Fig. 5. Silhouette score for clustering.

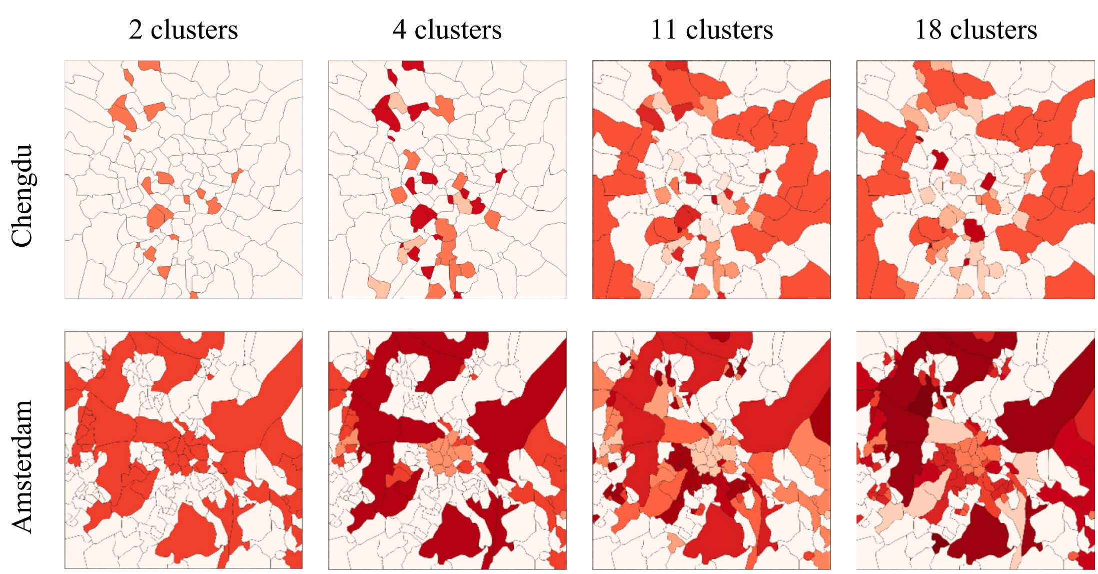


Fig. 6. Different mapping of morphometric-based street patterns when selecting different numbers of clusters. The mapping shows a spectrum from simplicity to complexity.

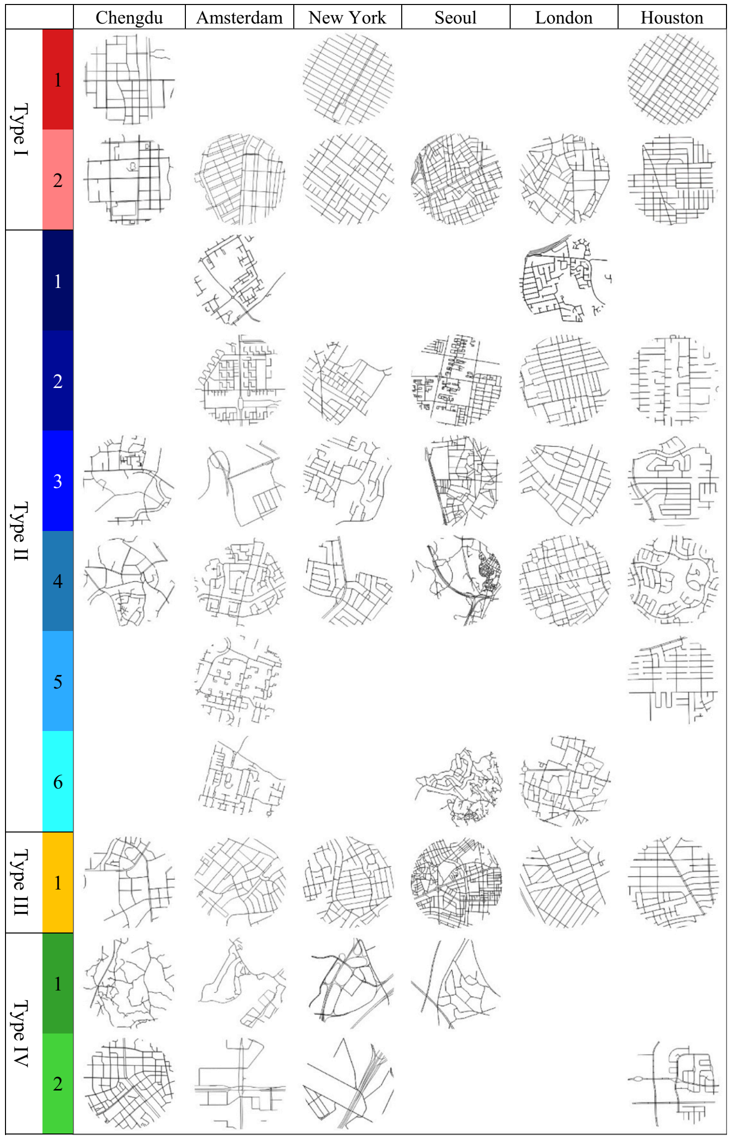
clusters can successfully capture more general differences between the street patterns in Chengdu and Amsterdam for straightforward interpretation. Conversely, a larger cluster number can reveal more subtle differences. If the number is too small, like 2 clusters, major differences are bypassed; when the number is excessively large, like 18 clusters, mapping changes become negligible. As such, an overabundance of clusters tends to increase complexity without offering extra information. By referring to the data from Figs. 5 and 6, this study has determined to set the number of clusters at four major types and eleven subtypes.

4. Results

4.1. Major morphometrics-based patterns

Four major types of street patterns are identified at a broader scale which resembles the conventional patterns, and a further eleven subtypes are introduced for more subtle analysis. The street patterns identified are shown in Table 2, and their average metrics values are shown in Table 3. By visually examining Table 2, Type I has a clear identity as the gridiron typology; Type II and Type II appear more organic or hybrid. Type IV is distinguishable primarily with street networks that

Table 2
Identified patterns in case study cities. (Empty cell means the street pattern is not present or not prominent in the city).



are affiliated with an artillery road. Within the types, there are diverse appearances of street patterns that are not directly separatable from a visual aspect. Hence, it cannot directly respond to any earlier predefined street patterns. From a metric perspective, the four types have very distinctive mean values for almost all metrics.

Type I can be visually identified as the 'Grid' type, reflected in the streets' low curvature of 1.03 in circularity and uniformed direction with a low orientation entropy of 2.74 and the highest proportion of X-Junction of 0.37. It also has the largest degree Pearson value of 0.32, meaning most street junctions have very similar four streets connected throughout the network. The lowest value in the transitivity of 0.03 means the network is uniform and does not contain smaller communities.

Type II could be considered 'Organic' as it does not have a uniform visual identity. In contrast, it has a diverse appearance across different cities. In terms of configuration, its roads are circular, with the largest circuity of 1.09. The orientation entropy of 3.22 is also significantly higher than type I, which means a more varied street direction. Composition-wise, it has the most prominent global efficiency of 0.12. This means this street pattern makes the travel between the road junctions relatively fast. The low degree Pearson correlation of 0.03 means the node degree distribution in street junctions is more random, leading to a more disordered street form. This is also reflected in the proportion of junctions with the highest self-loop of 0.0076, L-junction of 0.013, and lowest X-junctions of 0.1. Type II is a somewhat chaotic pattern that differentiates itself with diversities in street junction's node degree and visual appearance. The lack of uniformity makes it somewhat organic in a conventional sense.

Type III, the 'Hybrid', is a pattern that falls between Type I and Type II by visual appearance. While it clearly shows a degree of formality and uniformity compared to Type II, it is way less rigid than Type I. This is reflected in the metrics with a high orientation entropy of 3.29 and medium curvature of 1.05. It is also less grid with the highest proportion of T-junctions of 0.68 present and a relatively low Degree Pearson value of 0.22 in the street network. The low global reaching centrality of 0.021 means it has the most miniature hierarchical network structure. It also has the lowest self-loop proportion of 0.0018 but is not directly observable.

Table 3
Average metrics values for major type and sub-type morphometric-based street patterns identified.

Type	I	I-1	I-2	II	II-1	II-2	II-3	II-4	II-5	II-6	III (-1)	IV	IV-1	IV-2
Street length (m)	125.18	123.71	125.87	99.6	67.01	95.094	136.39	101.95	99.26	93.18	93.57	211.35	255	188.72
Diameter (m)	39.26	38.55	39.59	36.47	16.53	27.79	24.9	33.61	17.24	47.99	38.83	32.64	35.36	31.25
Circuity	1.03	1.02	1.03	1.09	1.08	1.09	1.08	1.09	1.25	1.07	1.05	1.06	1.08	1.05
Orientation entropy	2.74	2.56	2.82	3.22	3.07	2.53	3.19	3.26	2.81	3.46	3.29	3.23	3.41	3.14
k_avg	4.93	5.2	4.8	4.63	4.33	4.69	4.57	4.69	5	4.54	5.41	4.48	4.55	4.44
Self-loop	0.0022	0.00064	0.0029	0.0076	0	0.0066	0.0034	0.0081	0.045	0.0053	0.0018	0.0021	0.003	0.0016
L-Junction	0.0061	0.0039	0.0072	0.013	0.013	0.0079	0.0086	0.012	0.017	0.017	0.0039	0.0061	0.0064	0.0059
T-Junction	0.54	0.43	0.59	0.65	0.56	0.6	0.66	0.66	0.7	0.66	0.68	0.59	0.64	0.57
X-Junction	0.37	0.51	0.3	0.1	0.064	0.17	0.17	0.11	0.13	0.053	0.22	0.27	0.17	0.32
Degree Pearson	0.32	0.39	0.28	0.03	-0.21	0.052	0.16	0.048	0.095	-0.014	0.22	0.27	0.13	0.34
Transitivity	0.03	0.025	0.032	0.042	0.029	0.042	0.048	0.045	0.083	0.036	0.044	0.046	0.057	0.041
Global reaching centrality	0.03	0.027	0.032	0.029	0.016	0.015	0.14	0.019	0.035	0.02	0.021	0.056	0.056	0.055
Global efficiency	0.11	0.11	0.10	0.12	0.23	0.14	0.16	0.11	0.23	0.082	0.1	0.12	0.11	0.12

Type IV is the 'Tree', a network pattern with smaller communities affiliated with an artillery road. Besides its visual identity, this character is reflected in the highest global reaching centrality, which shows a hierarchical network structure. It also distinguished itself from the others with a low k_avg of 4.48 and the longest average street length of 211.35 m. Meanwhile, the global efficiency is high at 0.12, and the network's diameter is low at 32.64, meaning relatively good connectivity. The higher transitivity value of 0.046 also means the pattern is more fractured than the other patterns: communities of more densely connected street junctions are present.

To conclude, the morphometric-based street pattern shows a certain degree of similarity but not a direct fit with the conventional patterns. Traditional patterns could be identified relatively quickly based on visual distinction, which is not the case here. Some critical metrics in the classification, such as self-loop proportion and global reaching centrality, are not directly identifiable visually. Nevertheless, the morphometric-based street pattern captured the distinctions of the different pattern types from different perspectives. As exemplified by the mirage and diverse appearance of the different patterns across different cities, neither conventional nor the four major morphometric-based patterns are sufficient to describe the street network. This research further divides the four major types into 11 subtypes for more thorough investigation and mapping. Type I and Type IV were further divided into two subtypes, Type II with six subtypes, while Type III remains a single pattern. Due to time constraints, this paper will skip the general introduction of the specific subtypes and discuss them in relation to their distribution in cities.

4.2. *Detailed morphometric-based pattern across cities*

The distribution of the street patterns in Fig. 7 is analysed from within and between the cities. Within the cities, the urban spatial structure can be identified from the spatial distribution of the different patterns. Between the cities, it is clear that the composition of street patterns is distinctive, and their spatial distribution also shows structural differences. The four colours, red, blue, yellow, and green, represent the four major morphometric-based street patterns identified, while the different tones denote the different subtypes. With the help of the metrics, this study also digs deeper into the different characteristics of the street pattern and what it means for the city.

The difference between cities is identifiable from the distribution of the major types. North American cities show a majority of Type I pattern, which means most of the cities' street networks follow a grid pattern; London and Amsterdam show a majority of Type II pattern, whilst Seoul uniquely has a Type III majority. Their street network thus shows a more organic or hybrid pattern. Chengdu has a Type IV presence predominance, which means the street network follows a more hierarchical structure. Regarding diversity, Seoul, Chengdu, and London are visually unitary, with a single pattern type covering almost the entire study area. In contrast, Amsterdam, New York, and Houston are more diverse, with different street patterns in different city regions. This shows the inherent difference in the nature of the cities. For example, the planning of North American cities has a clear ring structure showing the urban expansion from a single urban core (Clark, 2008). Chengdu and Seoul have similar monocentric structures. In contrast, Amsterdam and London show a more polycentric urban spatial structure.

Looking at a smaller scale, with the help of the finer sub-types, the mapping of the street patterns revealed more stories about the cities. Firstly, New York and Houston show a clear urban and suburban divide from the street pattern. The urban core, the oldest part of the city, is covered by the most rigorous grid pattern, Type I-1. Surrounding the urban core is the street network of Type II, which breaks free from the rigid plan but still retains a grid formation. Further away from the urban core, it is permeated with more 'organic' street patterns such as different variants of Type II and 'hybrid' Type III. Among them, Type III is more often overserved in our study area in New York and Type II – 4 in the fringe of Houston. This coincides with the difference in the scale and the degree of urbanisation between the cities, as New York has a longer history and a larger urbanised area and population compared to Houston. Hence, it is possible to deduct that Type III shows a higher degree of planning than Type II – 4 with a higher degree Pearson's correlation of 0.22 compared to 0.048.

Amsterdam also shows a clear urban structure from street pattern mapping. Unlike other case study cities, the scale of Amsterdam is much smaller; hence, the study area also covered surrounding cities like Almere and Haarlem and captured the urban and rural divisions. Type I

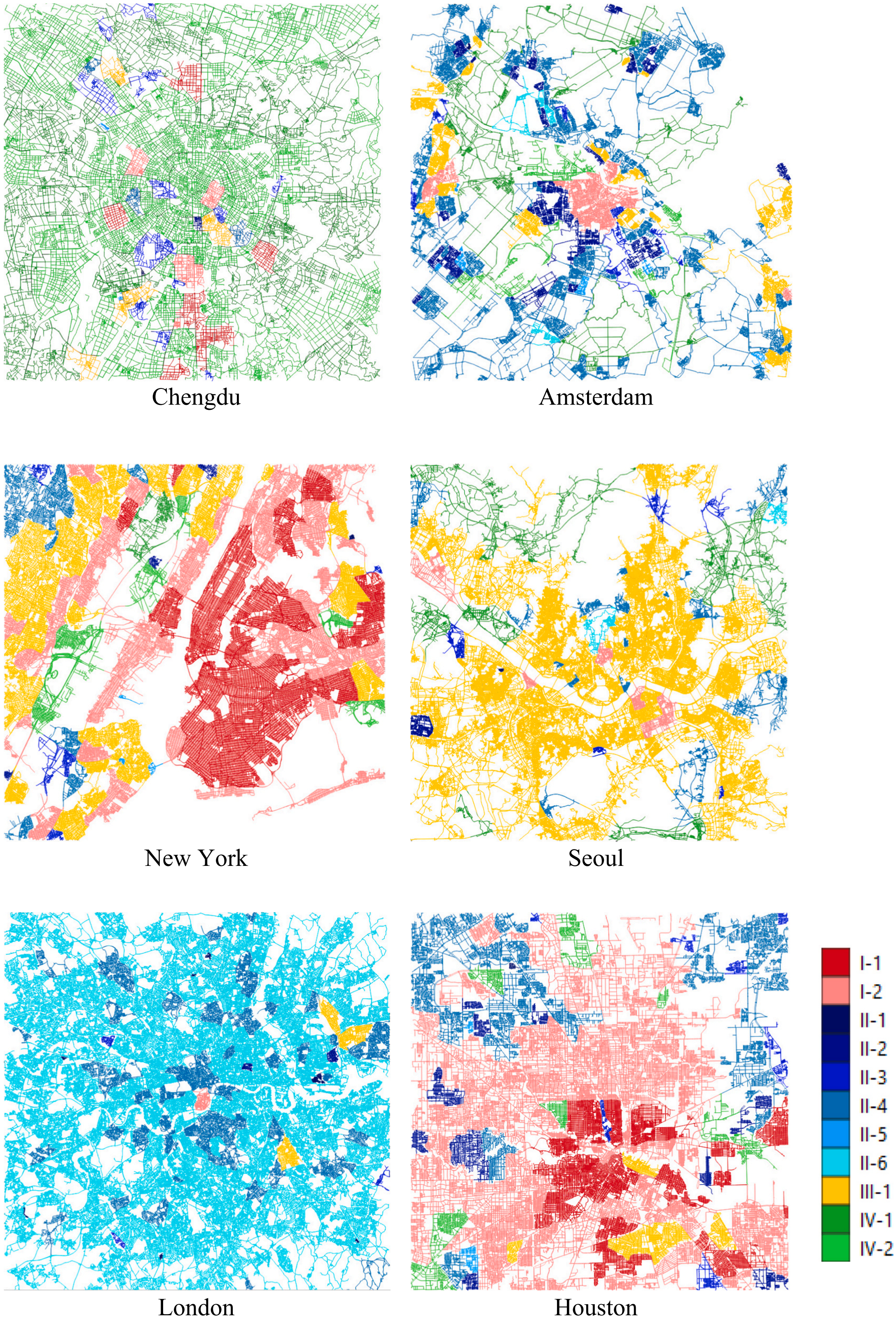


Fig. 7. The mapping of morphometric-based pattern with the eleven subtypes.

-2 pattern is noticeably present in the centre of Amsterdam as the urban core. It is also in the centre of Haarlem, a neighbouring satellite city in the North-west. Type II-2 and Type III are common street patterns in Amsterdam's denser urbanised areas. Type II-2 is similar to Type I with uniform street directions, except it has a lower X-node proportion of 0.17. While the smaller built-up areas and settlements scattered between the cities mostly show Type II-4 and Type IV street patterns. Hence, this study could conclude that in Amsterdam, the street pattern follows a grid pattern in the city centre and grows more organic into the fringe. It is worth noticing that Amsterdam shows a different urban structure than

American cities, and the same patterns appear in very different locations.

As mentioned earlier, London appeared to be unitary. It shows no clear singular urban core in the study area. Rather than a single urban core with Type II -4 street patterns, some SLAs scattered in the study area also have the same street pattern, given London a less monocentric urban spatial structure. Type II - 6 is another dominant street pattern in the city, with occasional Type I and Type III. Type II – 6 shows the 'organic' character with a high orientation entropy of 3.46 and a low degree Pearson correlation of −0.014. It also has the lowest global efficiency of 0.082 and the longest diameter of 47.99 in all the subtypes, meaning that commuting in streets of such a pattern requires more effort than in other patterns. Seoul has a unique Type III dominant street network, with some Type IVs appearing in the mountainous region. These two cities are more organic and show less structural identity than American cities and Amsterdam.

Finally, as the only Chinese city in the case study, Chengdu shows a unique street pattern composition. It has a type IV dominant street pattern across the city. Type IV is a street pattern showing a hierarchical structure like a tree where the major road branches out into more minor roads. In the case of Chengdu, the centre and peripheral of the case study area are occupied by Type IV-2 and Type IV–1, respectively. The significant difference between them is that Type IV -1 is more organic with higher orientation entropy and lower degree Pearson. It also has a longer average street length. This means Chengdu has more rigorous planning at the centre. Some Type I and Type II patterns are also present along the vertical central axis, especially in the south, where new development is carried out. These patterns together told the unique urban settings of Chengdu.

These variations in street forms from one city reflect each city's unique historical, cultural, economic, and environmental contexts. Furthermore, they influence how residents and visitors experience and interact with the urban environment. By studying these differences, we can derive insights into the successes and challenges of different urban designs and apply these lessons to create more liveable, sustainable, and vibrant cities.

5. Discussion

This research demonstrated the possibility of reaching a comprehensive, systematic and consistent description of street form for better urban morphological study. Street patterns play a vital role in shaping the urban experience, acting as the blueprint upon which cities function and evolve. At its core, the layout of streets shapes not just movement, but also the very fabric of socioeconomic interactions. For example, Busy intersections often burgeon into commercial hubs, while tranquil cul-de-sacs might become coveted residential spaces (Cervero & Kockelman, 1997b). Using street patterns to predict these economic trajectories can guide zoning and infrastructure decisions, optimising urban growth. Street patterns also influence cognitive behaviours. Predictable grid-like structures can ease navigation, reducing mental strain, whereas intricate patterns might stimulate curiosity and exploration (Jacobs, 1961). Such nuances are critical for urban planners aiming to nurture specific urban activities. Furthermore, the street pattern often encapsulates historical and cultural narratives, reflecting ancient trade dynamics, colonial impositions, or indigenous planning philosophies (Andrews, 1942). These patterns serve as silent storytellers, offering glimpses into a city's past and cultural ethos. Our morphometric-based street pattern offers new opportunities for more large-scale explainable applications in similar fields. Here, we would like to further elaborate on the potential and challenges raised using quantitative identification of street patterns in large-scale urban studies.

First, conventional predefined street patterns rely on visual distinctions that need to be further investigated before application in general quantitative large-scale urban studies. The four major morphometric-based street patterns indeed resembled conventional street patterns. This consistency suggests that the traditional street pattern captures a portion of the essence of the street network. However, Table 2 shows diverse visual appearances within each pattern considering different cities. Another relevant observation is that some visually similar SLAs, which may belong to the same conventional patterns, are grouped under different morphometric-based patterns, like Type I and Type III in Seoul, which comes from the same city, others like Type II-2 from London and Type I-2 from Houston which are visually similar SLAs from different cities. This suggests that morphometric-based patterns, unlike their conventional counterpart, may capture street network properties that are not apparent visually. The difference in the dominant types across the cities suggests that conventional predefined street patterns may falsely assume that street networks in different cities could be categorised under the same set of street patterns. Recently, computer vision (CV) techniques based on visual characters have been more frequently observed in urban studies. Some sought to use CV methods to map street patterns from a visual perspective (Chen et al., 2021), and some use street view images to assess the built environment (Kang, Zhang, Gao, Lin, & Liu, 2020; Wang & Vermeulen, 2021; Zhang, Chapple, Cao, Dennett, & Smith, 2020). Similar to conventional street patterns, the missing information resulting from neglected non-visual metrics in computer vision methods may lead to inclusive results depending on the research scope. Hence, the proposed morphometric-based street patterns provide an alternative for preliminary explorations of using street patterns in urban studies and data-driven urban planning. This is because of its adaptivity to accommodate diverse street properties and urban contexts, leading to the second point of discussion: the double-edged sword of flexibility.

Second, the quantitative method proposed in this research has two merits, flexibility and reproducibility, but it is also subject to limitations (Yap, Janssen, & Biljecki, 2022). For flexibility, this research employs SLA as the unit of analysis and hierarchical clustering to produce morphometric-based street patterns at different granularities. For the unit of analysis, SLA presents a more standardised and adaptable framework that can capture the continuity and characteristics of the urban environments, facilitating cross-study comparisons and potentially leading to more universally applicable insights in urban planning. In hierarchical clustering, when fewer clusters are selected, the most common types, such as the grid and organic types, can be identified. When more clusters are selected, the morphometric-based street pattern can provide a range of patterns to represent the complex urban environment worldwide. This allows researchers to modify the number of clusters to suit their research needs. To handle the complexity of the built environment, this study also proposes additional street metrics to provide more information for clustering algorithms. While these methods are convenient and powerful and increase flexibility, it is essential to note that the resulting morphometric-based patterns may be susceptible to input features and settings. Different features, clustering methods, and numbers of clusters may result in different categorisations of street patterns. Therefore, increasing the number of metrics does not necessarily lead to better results, and their effects require further investigation (Ron-Ferguson, Chin, & Kwon, 2021; Zhang & Kukadia, 2005). Another advantage of using a quantitative method to identify such patterns is its enhanced reproducibility. Given the same input, the user can always count on consistent results. The process and the result of the morphometric-based street pattern are relatively straightforward and objective. However, it always depends on the people to interpret the results based on the research interest and background information. For instance, Type I-2 represents Amsterdam's city centres, which is not the case in Chengdu. Scholars need to interpret the mapped patterns with prior knowledge about the city. Hence, as Batty has pointed out, in cross-disciplinary urban studies, the results cannot be interpreted lightly (Batty, 2001, 2020a, 2020b). A profound understanding of the local context and knowledge of urban phenomena is required. It is where potential subjectivity and uncertainty are introduced. Nevertheless, these two merits allow cross-comparison of street morphology through multiple dimensions.

Lastly, this paper would like to discuss streets' ability as an urban morphological element to reveal information for urban studies. Mapping morphometric-based patterns primarily reflects the urban spatial structure and patterns at a higher level. Differences in street morphology between cities were noticeable first, followed by the urban spatial structure within a city, where basic functional patterns such as urban-rural division were revealed. The study concludes that the proposed method of morphometric-based street patterns offers advantages for urban studies across multiple cities compared to conventional street patterns. It can reflect different street patterns between cities and reveal a city's spatial structure. However, street patterns cannot reflect subtle urban phenomena and short-term changes. For example, the change in land use and urban gentrification (Jacobs, 1961; Venerandi et al., 2017; Zhang et al., 2020) may not change the street network. Although the street network can reflect some long-term and broader-scale trends in the city, such as the urban expansion history (Huang et al., 2022; Zhao et al., 2017), its longevity also limits it from being a good indicator of recent, fast-paced development in the city (Kandt & Batty, 2021). Another criticism of the street network's ability to depict urban morphology is that it is planar and does not consider the vertical dimension of the urban space (Boeing, 2020; Bruyns, Higgins, & Nel, 2021; Harris, 2015). The building block is another important urban element that is intensely researched (Biljecki, Chow, & Lee, 2023; Labetski, Vitalis, Biljecki, Arroyo Ohori, & Stoter, 2023). Therefore, a more holistic description of the physical environment requires other complementary urban elements. Hence, the proposed method of morphometric-based street patterns may be more suitable for a universal study of street morphology at a broader level.

6. Conclusion

This study introduces a new approach to urban morphology studies by proposing morphometric-based street patterns by utilising unsupervised clustering machine-learning methods and designating the SLA as the adaptive unit of analysis. The motivation behind this research is the urgent need to improve urban planning practices by providing a more comprehensive, flexible, and metric-based method to analyse street morphologies. As urban areas worldwide face unprecedented challenges related to rapid urbanisation, population growth, and climate change, there is a pressing need for innovative tools that can help urban planners and policymakers make informed decisions. This research is crucial as it addresses this gap by offering a novel method that not only accurately depicts urban environments but also holds the potential to reveal intricate morphological distinctions between cities, which can ultimately contribute to creating more sustainable and liveable urban spaces. This aligns with Sustainable Development Goals 9 and 11, which call for building resilient infrastructure, promoting inclusive and sustainable industrialisation, and making cities and human settlements inclusive, safe, resilient, and sustainable.

In urban studies and urban planning, there is an increasing trend toward using quantitative methods to describe the physical urban environment and study the relationship between form and function (Arribas-Bel & Fleischmann, 2022). This research contributes to such a trend four-fold. First, the SLA and hierarchy clustering method deployed in the method ensured an adaptive application for large-scale quantitative studies. Second, this research also exemplified the effectiveness of this method by identifying hierarchical patterns in terms of major and subtypes of street patterns and showing their capability to depict the diverse urban environment. Third, this study compared and discussed the different characteristics of urban morphology with street patterns between the case study cities by suggesting there may be more differences than similarities. Fourth, this study also completed the exploration by discussing potential challenges for such a quantitative method. It is crucial to choose models and metrics depending on the research scope, especially for studies that span multiple cities with distinct characteristics or smaller-scale studies. In such cases, subtle details may be overlooked, leading to vague descriptions of smaller-scale physical forms of cities.

Despite the challenges, this research represents a pioneering effort to apply unsupervised machine-learning techniques to map urban morphology with street patterns. The real-world significance of this work lies in its potential to enhance the credibility and applicability of quantitative approaches in urban studies, ultimately contributing to sustainable urban development. Future work will focus on improving street data quality, broadening the application of morphometric-based street patterns in diverse urban studies, and examining their correlation with various urban phenomena, such as socioeconomic activities. This will provide deeper insights into the complex dynamics of urban built environments, ultimately fostering the creation of more sustainable and liveable urban spaces.

Author statement

The authors have NO affiliations with or involvement in any organization or entity with any financial interest (such as honoraria; educational grants; participation in speakers' bureaus; membership, employment, consultancies, stock ownership, or other equity interest; and expert testimony or patent-licensing arrangements), or non-financial interest (such as personal or professional relationships, affiliations, knowledge or beliefs) in the subject matter or materials discussed in this manuscript.

During the preparation of this work, the author(s) used ChatGPT in order to correct spelling/grammar mistakes and improve readability. After using this tool/service, the author(s) reviewed and edited the content as needed and take(s) full responsibility for the content of the publication.

CRediT authorship contribution statement

Cai Wu: Conceptualization, Data curation, Formal analysis, Methodology, Visualization, Writing – original draft, Writing – review & editing. **Jiong Wang:** Conceptualization, Methodology, Supervision, Writing – review & editing. **Mingshu Wang:** Supervision, Writing – review & editing. **Menno-Jan Kraak:** Supervision, Writing – review & editing.

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