# Urban Spatial Structure From a Street Network Perspective: Mapping Street Patterns With Random Forest Classification

Cai Wu[1[0000-0002-5578-5525]], Jon Wang[1] and Kraak, M. J. [1]

[1] University of Twente, Faculty of Geo-Information Science and Earth Observation (ITC), Hallenweg 8, 7522NH Enschede, The Netherlands

**Abstract.** Street patterns are planar street layouts in a given urban area, which serve as tools for researchers and urban planners to comprehend the structure of urban environments. Nonetheless, the task of mapping street patterns for extensive inter-city studies remains daunting due to the lack of consistency in manual identification methods. With recent technological advancements and data accessibility, new avenues have opened for data-driven techniques in mapping street patterns. This study proposes an innovative framework that employs open data platforms and data processing methods, including network science and supervised machine learning, to map street patterns in cities across the globe effortlessly. Case studies were applied to six cities worldwide and made two key observations from the resulting maps. Firstly, the spatial distribution of street patterns mirrors the urban spatial structure within a city. Secondly, the innate differences between cities become apparent. This study is confident that the novel methodology not only unveils the urban spatial structure across diverse cities but can also be employed to investigate the connection between urban built form and urban activities.

**Keywords:** Street Pattern, Urban Spatial Structure, Urban Morphology, Machine Learning.

## 1 Introduction

The study of urban morphology is crucial to understanding the built environment [1], [2] in increasingly complex cities, and the street is a critical element of morphological inspection. Streets are also a very complex subject to study as countless factors are involved in how a street performs and is perceived by people [3], [4]. To ease the studying process, streets are simplified as a network layout with street junctions as nodes and streets as edges. Street patterns summarising the types of street network layouts were also introduced to further help scholars and planners understand and design streets. Lately, new opportunities have arisen for identifying and mapping street patterns with the introduction of new data and quantitative methods. The new method has great potential to enhance the ability for large-scale urban studies with street patterns.

This research exemplifies the street pattern as an instrument to reveal the urban spatial structure in multiple cities with quantitative methods.

The motivation for this study comes from two aspects: the extensive application of street pattern urban studies while lacking scalability and transferability; the quantitative representation of street network provides new tools for potential solutions for the constraints mentioned above that have not been explored. Existing literature has suggested that, in general, the spatial distribution of street patterns could reflect the different urban functions of the cities and the different stages of urban development due to changes in urban mobility and planning ethos[5], [6]. Street patterns were first introduced to study the morphological differences between the cities based on their visual distinctions. Stephen Marshall[4] introduced the ABCD types of street patterns, which associated the morphological properties with functionality and visual appearances. These are the more general street patterns which are widely applicable to different types of studies [7], [8]. However, the large-scale study is complex because it is difficult to identify these street patterns in a consistent manner. More recently, scholars also identified more categorisations of street patterns for specific purposes of study, like street patterns based on connectivity for transportation studies [9]–[12]. These specialised street patterns are more easily identifiable in large-scale studies but are also subject to limited fields of study. Hence, the existing methods to map street patterns are constantly constrained by the problem of transferability and consistency. Street patterns are either constrained by the limited case study scale or limited applicability in different study fields. With technological advancement, access and calculation of street network data and metrics becomes increasingly available, such as OSMnx and NetworkX making analysing street networks intuitive. Chen [8] used the lasted deep leaning to map the street morphology by their visual identity. Such a method allows for the mass identification of street patterns across large and different study areas. However, the more conventional supervised machine learning method was left unexplored with the advantage of using the abundance metrics to explore the different characteristics of street networks.

To allow for a generalised global morphological study with expandability, this study explores a supervised machine learning approach, namely random forest, to identify the street pattern based on various metrics. The potential use case will be exemplified by mapping the street patterns to show the urban spatial structure. The case study is conducted in six major cities in Asia, Europe, and North America. Each case study city has gone through urbanisation, transferring from a vernacular to a cosmopolitan megacity.

## 2 Methodology

The primary research objective of this research is to reveal the urban spatial structure in multiple cities by mapping the street pattern with a random forest classifier. To achieve this, this study has proposed a new quantitative method to ensure transferability across different cities and consistency in identifying street patterns. There are three main components. First, street networks are extracted from a single source of OpenStreetMap; second, all metrics were calculated quantitatively via NetworkX and OSMnx. Lastly, a random forest classifier was eventually applied to identify the street

patterns. To ensure the consistency and optimisation of the study unit, this study adopted the Street-based Local Area (SLA) as the primary study unit [13]. Four types of street patterns were adopted from existing studies for mapping: Gridiron, organic, hybrid and cul-de-sacs. The mapping of the four street patterns across the six cities is eventually analysed and compared to show the urban spatial structure.

### 2.1 Case study area and quantitative metrics

Six cities are selected as the case study. Since they have different sizes and administrative divisions, this study unifies the case study area in a square with a 25km side length. SLA is the primary study unit compared to a grid or administrative boundary in past research. This is because SLAs are more optimised for studying streets [13] and ensures universal applicability between different cities. Street network data are extracted from Open Street Map, an open data platform. These ensure a universal data source. By representing streets as networks, several street morphological metrics are computed to capture the physical characteristics of the streets. The computation is implemented using network analysis tools such as Network and OSMnx [14]. This study eliminated metrics with high correlations to ensure a better classification result. The result is 1054 SLAs across six cities with 13 metrics. The explanation of the metrics is shown below in Table 1.

Table 1. List of Metrics.

| | |
|---|---|
| Street Length | Calculate the graph's average edge length. |
| Diameter | It is the shortest distance between the two most distant nodes in the network |
| Circuity | Circuity is the sum of edge lengths divided by the sum of straight-line distances between edge endpoints. |
| Orientation Entropy | Orientation entropy is the entropy of its edges' bidirectional bearings across evenly spaced bins. |
| k_avg | graph's average node degree (in-degree and out-degree) |
| Self-loop | Calculate the percentage of edges that are self-loops in a graph. |
| L-junction | The proportion of nodes with two streets connected |
| T-junction | The proportion of nodes with three streets connected |
| X-junction | The proportion of nodes with four streets connected |
| Degree Pearson | Compute the degree assortativity of a graph. Assortativity measures the similarity of connections in the graph with respect to the node degree. |
| Transitivity | The transitivity or clustering coefficient of a network is a measure of the tendency of the nodes to cluster together. |
| Average clustering | The clustering coefficient (Watts-Strogatz) is a measure of how complete the neighbourhood of a node is. Here, it is the average clustering coefficient over all of the nodes in the network. |
| Global reaching centrality | the proportion of the graph is reachable from the node's neighbours. |
| Global Efficiency | the average multiplicative inverse of the shortest path distance of all pairs of nodes |

### 2.2 Types of Street Patterns and Random Forest Classification

Existing studies have proposed various street patterns based on the different purposes of the study. This study adopted the most common street patterns: Gridiron, Organic, Hybrid and Cul-de-sacs [10], [15]. Gridiron is a typical street pattern with uniform directions, straight streets, and right-angled X-shaped crossroads. The organic street pattern is contrary to the gridiron, the street is curly with various directions, and the street junction also has a diverse appearance. Hybrid street patterns fall between the gridiron and organic. Lastly, cul-de-sacs are most recognisable for their dead-ends and circular streets. 300 SLAs are randomly picked and manually identified for their street pattern. They are used for training and testing the random forest model. A standard random forest classification procedure is carried out, and the resulting classifier has the highest accuracy of 64% when using six features. As a preliminary exploration of using supervised learning to identify street patterns, this research deems it adequate for the current study.

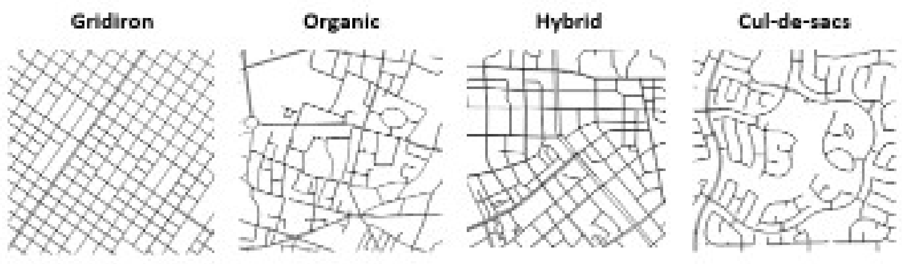


Fig. 1. The four street patterns

## 3 Results and Discussion

The random forest classifier indicates that the five most crucial attributes are: Circuity (14.4%), X-junction (12.2%), Street length (10.1%), Degree Pearson (9.8%), and orientation entropy (8%), collectively accounting for 55% of the classification outcome's explanation. Table 2 presents the average values of these metrics for each street pattern. The majority of these values correspond to the general descriptions of the patterns, with gridiron and organic types at opposite ends of the spectrum and the hybrid situated in between. The cul-de-sac style stands out with the highest circuity, street length, and the lowest X-junction and Degree Pearson values. Most of these characteristics can be easily discerned through visual observation, which is likely due to the original training dataset being manually identified based on the patterns' visual distinctions.

Table 2. The average value for TOP 5 features.

| | Gridiron | Organic | Hybrid | Cul-de-sacs |
|---|---|---|---|---|
| Circuity | 1.023 | 1.071 | 1.063 | 1.098 |
| X-junction (%) | 38.4 | 13.5 | 18.8 | 12.0 |
| Street Length (m) | 119.3 | 82.8 | 115.5 | 131.7 |
| Degree Pearson | 0.343 | 0.104 | 0.160 | 0.047 |
| Orientation Entropy | 2.803 | 3.349 | 3.132 | 3.265 |

Several observations can be made with respect to urban spatial structure after mapping the street patterns. Generally, most cities show a ring structure with two to three layers of street patterns. A core is present in the centre of the case study area, which can be considered the historical urban area. Depending on the city, the core is mainly occupied by either gridiron or organic types of street patterns. Surrounding the urban core is the second layer; it results from urban expansion and is considered the extension of the urban core. Street network in this layer generally forms at a different time period compared to the urban core, which breaks away from the conventional pattern and appears to be hybrid. Lastly, the outermost layer at the city's periphery mostly shows a Cul-de-sacs pattern. They are considered suburban areas. Hence, the urban spatial structure revealed by the street pattern not only shows urban functions through the urban-suburban division but also reflects the different stages of urban development.

The mapping of street patterns also shows the urban structural differences between cities. First, as mentioned earlier, some cities show three layers of ring structure while others only have two. Houston and London are typical cities with three layers of urban spatial structure where an urban core, urban extension and suburban division are clearly identifiable. The gridiron inner core in Houston and the organic inner core in London reflect the difference in the planning and urban development in North American and traditional European cities. On the contrary, Chengdu and Amsterdam show a two-layer urban spatial structure where the urban core is not recognisable from the street pattern. In addition, the street pattern mapping also, to some degree, reflects the polycentricity [16], [17] of the cities. For example, the study area in the Amsterdam region clearly shows a polycentric urban spatial structure with multiple urban core present. This is probably due to the fact the study area has covered surrounding cities like Haleem and Zaandam, which the street pattern is able to capture. While cities like Chengdu and Houston appear to be more monocentric.

The proposed method and the street patterns mapping show promising results and prove their potential in the urban morphological study. A further application in more cities can help to study the spatial distribution of street patterns and urban spatial structure at a larger scale. The proposed study unit, SLA, also performs well in capturing the street networks' character. Still, some limitations need to be addressed. First, due to time constraints, the street pattern categorisation adopted in this study is still too general and vague for a more refined study. The manual identification in the training set also lacks cross-referencing. Second, among the fourteen metrics, only six were significant in the classifier, meaning some information was lost. This either means these metrics are less relevant in the definition of street pattern or the street pattern categorisation is ineffective in capturing the character of the street network. Lastly, we would like to point out the inherent limitation of using streets pattern in urban morphology. Streets are one of the many urban elements present in the built environment. Hence, streets alone are insufficient for a holistic urban study and present an opportunity for a study involving multiple urban elements such as buildings.

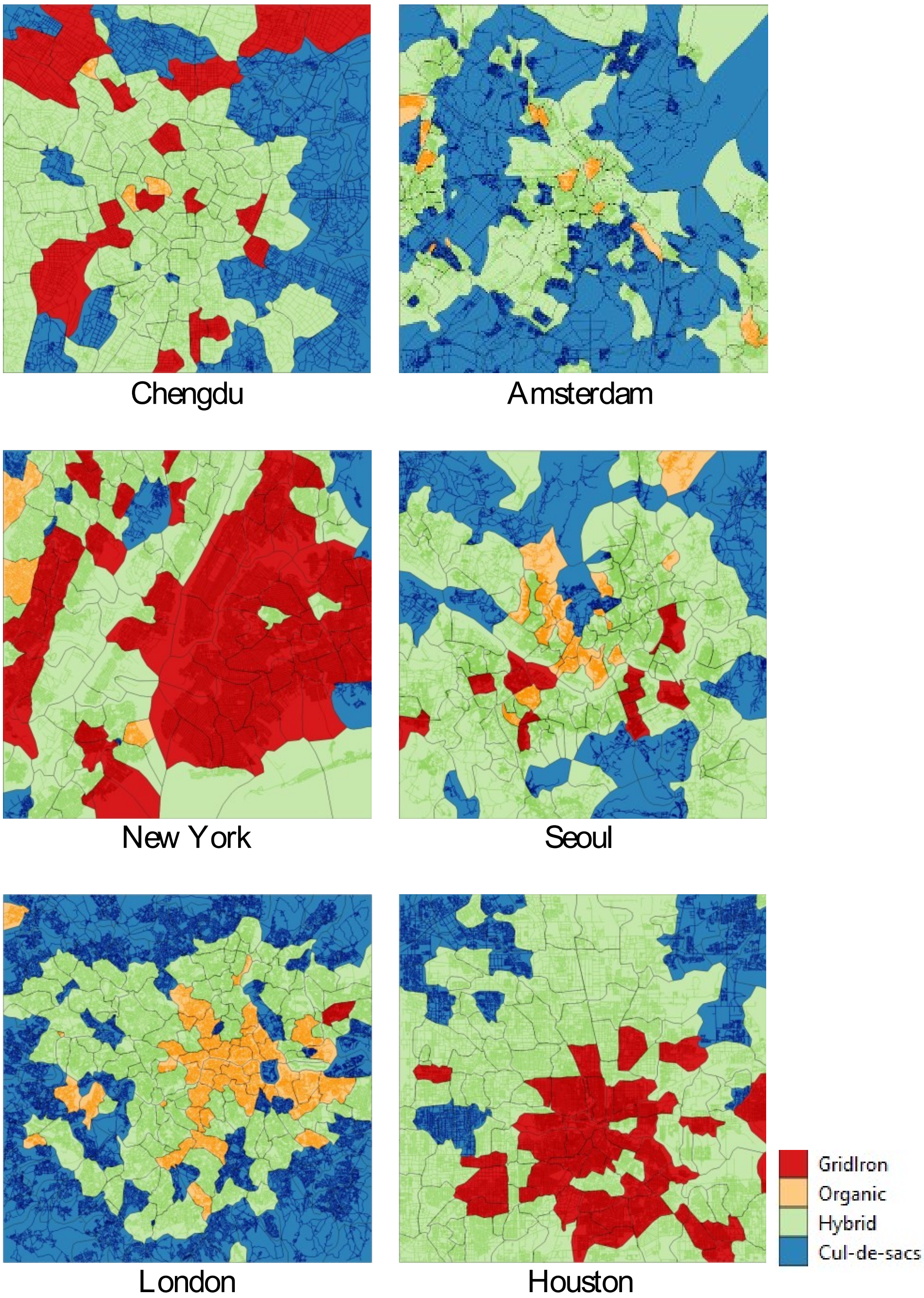


Fig. 2. The mapping of street patterns in six case study cities.

# 4 Conclusion

Through the proposed framework, this paper has exemplified how the quantitative approach could identify street patterns, and in turn, it reveals the urban spatial structure for cross-comparison between different cities. In short, this article first proposed that network and machine learning methods have shown promising results in studying street patterns. Second, this research provides a new perspective for viewing urban spatial structure and presents opportunities for further research. Their distribution roughly shows a ring structure which reflects the historical core, new urban extension, and suburban/rural division of urban spatial structure. In addition, the different street patterns presented in different cities with different percentages and their spatial distribution indicate the inherent differences and characters in cities. This research provides a new perspective for viewing urban spatial structure and presents opportunities for further research. However, the limitation of a single urban morphological element, such as the street network, to reflect the urban spatial structure needs to be further addressed to generate more fruitful results.

# References

1. V. Oliveira and V. Medeiros, "Morpho: Combining morphological measures," Environ. Plan. B Plan. Des., vol. 43, no. 5, pp. 805–825, Sep. 2016, doi: 10.1177/0265813515596529.
2. S. M. Wheeler, "Built Landscapes of Metropolitan Regions: An International Typology," J. Am. Plan. Assoc., vol. 81, no. 3, pp. 167–190, Jul. 2015, doi: 10.1080/01944363.2015.1081567.
3. A. Turner, "From Axial to Road-Centre Lines: A New Representation for Space Syntax and a New Model of Route Choice for Transport Network Analysis," https://doi.org/10.1068/b32067, vol. 34, no. 3, pp. 539–555, Jun. 2007, doi: 10.1068/B32067.
4. S. Marshall, Streets and Patterns. 2004.
5. J. Huang et al., "A city is not a tree: a multi-city study on street network and urban life," Landsc. Urban Plan., vol. 226, p. 104469, Oct. 2022, doi: 10.1016/J.LANDURBPLAN.2022.104469.
6. G. Boeing, "Off the Grid…and Back Again?: The Recent Evolution of American Street Network Planning and Design," J. Am. Plan. Assoc., vol. 87, no. 1, pp. 123–137, 2021, doi: 10.1080/01944363.2020.1819382/SUPPL_FILE/RJPA_A_1819382_SM4089.PDF.
7. B. Jiang, Y. Duan, F. Lu, T. Yang, and J. Zhao, "Topological Structure of Urban Street Networks from the Perspective of Degree Correlations," Aug. 2013, doi: 10.1068/b39110.
8. W. Chen, A. N. Wu, and F. Biljecki, "Classification of urban morphology with deep learning: Application on urban vitality," Comput. Environ. Urban Syst., vol. 90, p. 101706, Nov. 2021, doi: 10.1016/J.COMPENVURBSYS.2021.101706.
9. R. Louf and M. Barthelemy, "A typology of street patterns," J. R. Soc. Interface, vol. 11, no. 101, p. 20140924, Dec. 2014, doi: 10.1098/rsif.2014.0924.
10. S. Marshall, "From streets to patterns," pp. 235–258, Aug. 2004, doi: 10.4324/9780203589397-13.

11. S. M. Rifaat, R. Tay, and A. De Barros, "Effect of street pattern on the severity of crashes involving vulnerable road users," Accid. Anal. Prev., vol. 43, no. 1, pp. 276–283, Jan. 2011, doi: 10.1016/J.AAP.2010.08.024.
12. "Urban Vitality in Dutch and Chinese New Towns: A Comparative Study Between ... - Jing Zhou - Google Books." [Online]. Available: https://books.google.nl/books?hl=en&lr=&id=0IdDA0EpWKUC&oi=fnd&pg=PA16&dq=street+pattern+urban+vitality&ots=VXRhXd8EEU&sig=PK6mB0bYvRcCLXi6HpJXQWHNzgs&redir_esc=y#v=onepage&q=street pattern urban vitality&f=false. [Accessed: 30-Mar-2020].
13. S. Law, "Defining Street-based Local Area and measuring its effect on house price using a hedonic price approach: The case study of Metropolitan London," Cities, vol. 60, pp. 166–179, 2017, doi: 10.1016/j.cities.2016.08.008.
14. G. Boeing, "Methods and Measures for Analysing Complex Street Networks and Urban Form," SSRN Electron. J., Aug. 2017.
15. R. Cervero and K. Kockelman, "TRAVEL DEMAND AND THE 3Ds: DENSITY, DIVERSITY, AND DESIGN," 1997.
16. C. Wu, D. Smith, and M. Wang, "Simulating the urban spatial structure with spatial interaction: A case study of urban polycentricity under different scenarios," Comput. Environ. Urban Syst., vol. 89, p. 101677, 2021, doi: 10.1016/j.compenvurbsys.2021.101677.
17. M. J. Burger, B. De Goei, L. Van Der Laan, and F. J. M. Huisman, "Heterogeneous development of metropolitan spatial structure: Evidence from commuting patterns in English and Welsh city-regions, 1981-2001," 2010, doi: 10.1016/j.cities.2010.11.006.