Predicting Network Integration Based on Satellite Imagery Around High-Density Public Housing Estates Through Machine Learning

Jiahua Dong[1], Shuiyang Lin[1], Jeroen van Ameijde[1]

[1] The Chinese University of Hong Kong, Hong Kong
jiahuadong@link.cuhk.edu.hk; lynnsylin@link.cuhk.edu.hk;
jeroen.vanameijde@cuhk.edu.hk

Abstract. In studies focusing on environmental and health aspects of urban planning, the integration of road networks within the built environment emerges as an important metric for assessing the livability and healthiness of neighborhoods. The complexity and diversity of the road networks are significant for shaping vibrant streets. In Hong Kong's ongoing construction program of large-scale public housing estates, the design prioritizes the connectivity of pedestrian circulation to foster social interaction among residents and encourage the utilization of recreational facilities. In this study, an analytical framework is developed to interpret public housing estate spatial layout based on satellite imagery. It extracts road networks using neural networks and vectorizes results to analyze network integration around estates to predict social interactions. The aim of this process is to employ a machine learning workflow to analyze options for newly planned estates, where the design configuration can be further optimized based on its potential to stimulate social engagement and community interaction. Due to the scalability and universality of the method, the research can contribute to improved road networks and sociable housing complexes in Hong Kong, or in other international cities of similar density and vibrancy.

Keywords: Network Integration, Spatial Structure, Satellite Imagery, Machine Learning, Hong Kong Public Housing

1 Introduction

The impact of the built environment on health and well-being has been well documented and is increasingly researched to assess quality of urban life and build more livable and healthy cities (De Certeau, 1984; Peters et al., 2020; Renald et al., 2010). One aspect of this is the impact of road networks on neighborhoods, communities, and the quality of well-being (Evans, 2003; Gao et al. 2016; Wu et al., 2015, Yen et al., 2009). Road networks are the backbone of cities, providing the foundational structure that shapes their form and guides their growth and evolution (Marshall, 2004). Understanding the relationship between circulation networks, spatial structures, and social behaviors stands as a significant focal point in urban planning studies. For example, Kevin Lynch's (1960) foundational research explored how people memorize paths, edges, areas, nodes, and landmarks. His findings emphasized that people's perception is intricately linked to the spatial arrangement of urban elements and to people’s circulation patterns within cities (Golledge & Gärling, 2004). This highlights the interconnectedness of road networks, spatial layouts, and human experiences in the urban environment.

As Hong Kong’s available land for constructing residential areas is highly constrained, multi-block compact layouts are usually adopted in estate planning (Tang et al., 2019). With the increasing density of public housing, public spaces between tower blocks are gradually compressed. The design ideals of road networks within communities, originally conceived to promote social interaction among residents and facilitate access to recreational facilities, are reportedly diminishing (Hong Kong Housing Authority, 2022). Schittich (2004) emphasized that high-density housing estates can contribute to mental health problems due to a lack of social interaction, when fragmented circulation areas provide inadequate connections to public spaces. Researchers support that the networks in residential areas are important not just for circulation but also as a social hub in neighborhoods (Abu-Ghazzeh, 1999; Sauter & Huettenmose, 2018). The complexity and diversity of pedestrian networks can play a significant role in shaping vibrant urban spaces, which are important stimulants for casual neighboring and socializing.

In recent years, emerging digital tools play an increasingly important role as an analytical assistant in urban design and urban planning. Remote sensing techniques such as satellite imagery can provide accurate and dynamically updated information, to support large-scale urban analysis. Recent advancements in machine learning enable the analysis of urban morphology through graphic interpretation utilizing satellite or aerial imagery of urban neighborhoods. This involves the use of neural networks, including benchmark models such as Unet and GANs (Goodfellow et al., 2014; Ronneberger et al., 2015). The evolution of data-driven urban research, particularly through machine learning, demonstrates the powerful potential of computer vision in classifying or analyzing urban morphology.

2 Related Works

2.1 Urban Morphology, Circulation and Placemaking

The history of urban morphology is discussed around “order” and “perception” (Khachatryan et al., 2020). Talen (2018) argued that “built landscapes have the potential to affect choice, access, opportunity, interaction, movement, identity, connection, mix, security, and stability” (p. 205). As a derived property of urban morphology, pedestrian network design is widely discussed in placemaking theory, in which different spatial layouts are linked to promoting different social activities. The analysis of urban morphology is done through combining graphic representations of urban space with systematic analysis of road networks. The notion of urban space can be traced back to Giambattista Nolli's large map drawing of Rome, which represented the publicly accessible voids of the city as a series of interconnected urban spaces. This representation of spatial structure can be further connected to detailed analysis of circulation potential in street patterns, which is often conducted through network integration analysis. These methods are developed as part of the space syntax theories (Hillier & Hanson, 1984), which address the interactions between spatial networks, movement, co-presence, and social interactions.

There is a growing number of studies discussing how spatial structure influences human perception of space in cities. Lim et al. (2015) discussed the street network integration with different urban blocks sizes and spatial layouts to map the evolution of urban form across different scales. Sun et al. (2021) measured the relationship between the high-density three-dimensional built environment and the distribution of human activities in Hong Kong, investigating the relationship between aspects of the design of pathways and urban spatial vitality. Specifically, in network integration research, Pafka et al. (2020) discussed the limitations of the representation of roads in space syntax theory, comparing different capacities for to-movement and through-movement - the distinction between ‘closeness centrality’ and ‘betweenness centrality’. They examined different network integration values and maps to drive the research on the production of space through social aspects. All these studies revealed the importance of researching road networks comprehensively.

2.2 Machine Learning

In relation to road network analysis, most studies use traditional planning maps to obtain road network data from the real world to conduct analysis. However, map-based road network data lacks certain levels of detail and might not always be up to date with changes implemented on the ground. Hence, using machine learning to extract road networks from satellite imagery has attracted more and more attention. Early machine learning models have focused on the extraction of road surfaces, for example, using the intersection-over-union (IoU) method to improve accuracy. Máttyus et al. (2017) developed DeepRoadMapper, which used deep learning to segment satellite imagery and analyse road topology and connectivity using shortest path algorithms. RoadTracer (Bastani et al., 2018) used an iterative search process to produce road data directly through convolutional neural networks (CNN). RoadNet (Liu et al., 2018) developed multiple data formats as training data such as road boundary and road centerlines using CNNs that enlarged the predicted results and can be used in various analyses. The Connectivity Attention Network tool for satellite imagery road extraction (CoANet) (Mei et al., 2021) specifically focused on the connectivity in the generative results and proved useful in generating highly accurate results. Meanwhile, SpaceNet Road Detection and Routing Challenge, an effective method to automatically extract road networks from satellite imagery developed by Van Etten et al. (2018), has facilitated many studies in the remote sensing field.

After reviewing the existing literature relating to urban morphology analysis and its application towards Hong Kong's high-density urbanism, we found three research gaps. First, due to the high-density context, pedestrian networks in Hong Kong are mainly designed around circulation efficiency. There is a lack of research in analyzing the design of these road networks as public spaces, and how they promote social interactions and casual neighboring, which can support the creation of healthy and livable communities. Second, the research of road networks, for example using space syntax, is often done using axial line-segment mapping to represent street connections (Stavroulaki et al., 2017; Pafka et al., 2020), an abstraction which removes the ability to analyze varied urban elements such as courtyards, plazas, and playgrounds alongside the circulations. Thirdly, we found that most of the machine learning-assisted urban morphology research is conducted for large urban blocks and does not cover the neighborhood scale. Also, there is a lack of research to predict road networks using machine learning - which requires a different interpretation of spatial structures in urban morphology research, compared to urban blocks.

This research explored state-of-the-art machine learning techniques to extract road network distributions of Hong Kong's high-density urban neighborhoods. Its aims were to study the distribution of road networks more effectively in high density-built environments, to understand the relationship between spatial structures and their socializing capacity. Based on a large training dataset containing paired satellite imageries to road network drawings, we tested which models can be applied as effective and timely urban analytics tools to help designers to take better consideration of the relationship between spatial layout and road network qualities. The project used a machine learning workflow to extract road network data to analyze local road network distributions, aiming to highlight where design configurations could be improved to stimulate social engagement and community interaction. By adopting a newly developed machine learning road extraction model, our study demonstrates how new computational methods can be used to quantitatively analyze spatial properties, and critically assess the spatial structure of the city. If implemented, improved circulation design based on network integration analysis could support social mixing, casual neighboring and placemaking processes that help shape inclusive and vibrant communities.

3 Methodology

Our methodology consisted of three stages. First, we collected a set of satellite images of three case study housing estates. In parallel, a recently developed connectivity attention network for road extraction from satellite imagery (Mei et al., 2021) was adapted and tested. We used the dataset from SpaceNet, an open-source provider of pre-labelled, high resolution satellite imagery. Second, we tested the ability of the workflow to predict road network distribution outcomes on new layouts unknown to the algorithm. After the road networks were extracted, we used the Rhino3D vectorization tool to simplify them. Finally, network integration analysis was conducted in Grasshopper to predict human flows and to explore whether the workflow can predict residents' decisions and social interactions across networked public spaces with various sizes and connectivity characteristics.

3.1 Road Network Extraction Using Satellite Imagery

In the road network extraction process, we used the training data provided by SpaceNet. The SpaceNet collection includes 30 cm high-resolution satellite images together with approximately 8,000 km of manually labelled and verified road centerlines (Van Etten et al., 2018). The main cities that have been collected by SpaceNet are Shanghai, Paris, Las Vegas, and Khartoum.

The architecture of CoANet includes an encoder-decoder network, a strip convolution module (SCM) and a connectivity attention module (CoA). A strip convolution module is used to align with the form of the road and extract its linear features in CoANet and a connectivity attention module is used to forecast the road connectedness between adjacent pixels.

The SCM layer is designed to capture long-range contextual information in an image by dividing it into strips and performing convolution operations across the strips, which is suitable for road networks. Specifically, the layer applies 1D convolutions across the rows and columns of the image strips separately, followed by a global average pooling operation. The resulting feature maps are concatenated and fed to the next layer in the network. The connectivity module uses binary representations for every pixel in the satellite imagery based on ground truth masks, where every 8 pixels that surround the center pixel are being calculated individually.

3.2 Centerline Extraction and Network Integration Analysis

The process of extracting the road centerlines was carried out through the Arcscan toolbar in ArcGIS. ArcScan is an extension module in ArcGIS, which is used to convert scanned images into vector element layers. The ArcScan extension module supports capturing raster pixels which helps ensure the elements are created accurately. Hence, we could easily capture raster centerlines, intersections, corners, endpoints, and entities. Specifically, the first step in this process was to use a "vectorized trace" tool that tracks raster pixels to generate lines or polygons. Then, the reclassification tool was used to unify the grid values and generate the centerlines.

In the network integration analysis, we connected the road network data to open-source Grasshopper algorithms which visualize the network integration value using gradient color. Integration is seen as a central concept in space syntax (Hiller & Hanson, 1984; Hillier, 1996). It measures how many turns and changes a person must make to get from one space in the system to another, and reveals the relationship between the part and the whole in terms of connectedness or isolation. Integration of a node is expressed by a value that indicates the degree to which a node is integrated or segregated from a system, or from a partial system consisting of nodes a few steps away. It can be measured with either Relative Asymmetry (RA_i) or Real Relative Asymmetry (RRA_i):

$$RA_i = \frac{2(MD_i - 1)}{n-2} \quad \text{and} \quad RRA_i = \frac{RA_i}{D_n}$$

where n is the number of axial lines of an urban system, and this D-value gives the standardized value for the integration value from mean depth (MD) (Kruger, 1989).

$$D_n = \frac{2\{n[log_2((n+2)/3)-1]+1\}}{(n-1)(n-2)}$$

4 Results

Figure 1 shows the visualization of the ground truth results and the generated results. Our results reveal that the overall accuracy of road network extraction using CoANet is very high. However, a few situations have influenced accuracy, for instance shadows, trees, distortion of the buildings in the satellite imagery. The connectivity attention module ensured the accuracy of the road networks connections, which shows that this method is generally better than using traditional machine learning architecture Unet and GANs. The experiment highlights several avenues for further improvement. We used the SpaceNet satellite imagery dataset, which does not specifically include Hong Kong. Although the satellite image segmentations are not varied city by city, building an additional training dataset by adding Hong Kong satellite images to the training process might help to embed local characteristics in the training dataset and increase the reliability of the outcomes. Second, the amount of data in our experiments was limited. Future experiments should use a larger and more diverse training dataset to help the network to learn more varied characteristics of the data and produce more realistic outputs.

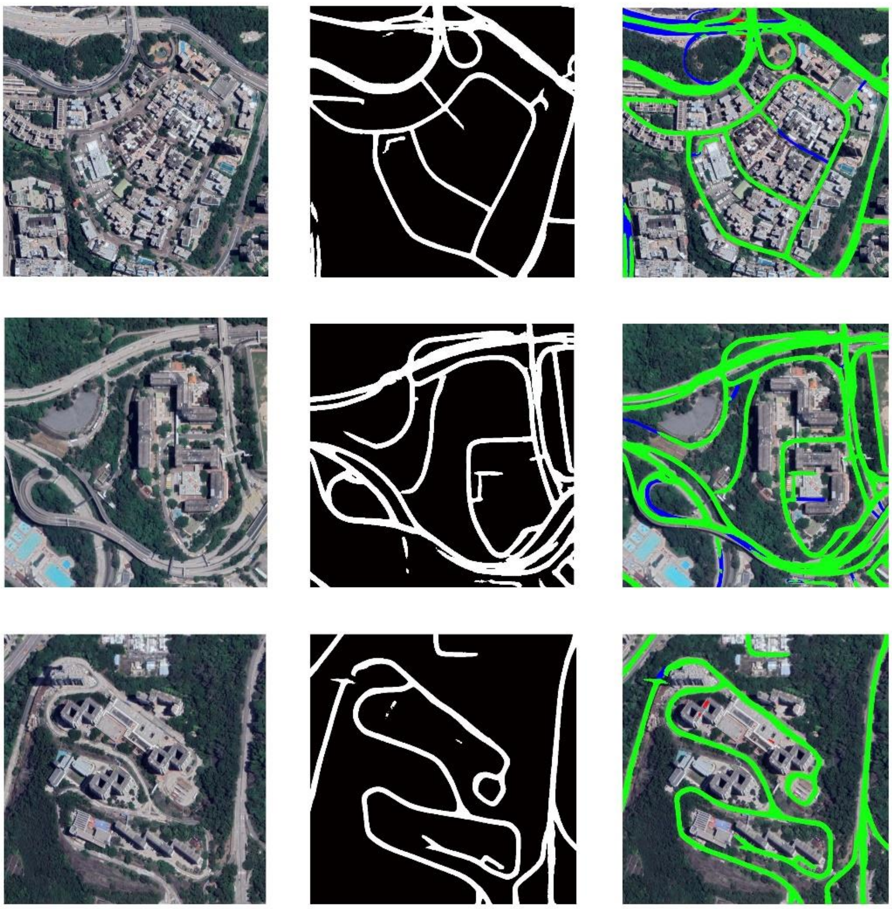

Figure 1. Extracted road networks: Green (true positive); Blue (false negative); Red (false positive) (From top to down: Estates 1, 2 and 3)

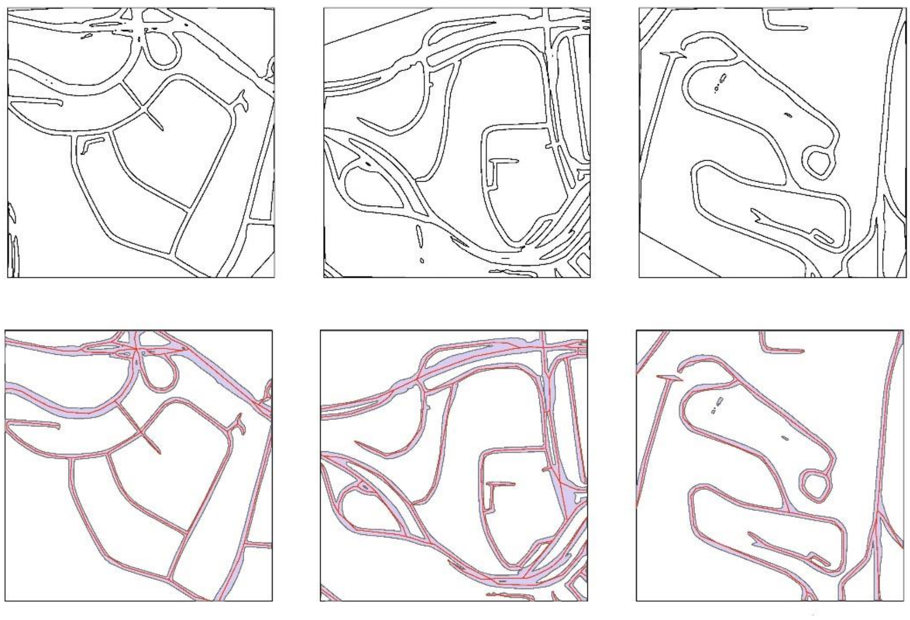

Figure 2. Centerline extraction (From left to right: Estates 1, 2 and 3)

Figure 3. Network integration analysis using gradient representation (From left to right: Estates 1, 2 and 3)

Figure 3 shows the network integration visualizations, after the automatic extraction of road centerlines (Figure 2). From Figure 3 we can see that Estate 1 has a higher degree of local integration in the northern area, which represents better local accessibility. The separate conditions in the south result in a significant decrease in integration when considering overall network integration around the whole estate. Therefore, designers could potentially take action to strengthen the links between the north and south. Estate 2 shows that there is a slight difference in the degree of integration between points, but the overall accessibility is relatively even. Estate 3 shows a better local integration in the middle, but less overall integration, demonstrating the need to strengthen the links between the central areas and the boundaries. In overall comparison, Estate 2, with the best apparent integration across the estate, features the most fine-grained network without dead-end roads. This highlights the importance of small urban plots and short and frequent connections across urban neighborhoods.

The connectivity of road networks is the foundation of network analysis. After using Grasshopper to successfully generate network integration results, the workflow we explored proved to be easy to use, reproduce and scale up. Further studies will be planned to conduct more detailed analysis and comparison of quantitative network integration values.

5 Discussion

The study presented here exhibits several limitations that can be addressed in future developments of the methods and the scopes. The satellite imagery can only represent the 2D environment of the built environments, which does not fully represent the complex visual qualities of Hong Kong's multi-layered public space networks. Improved three-dimensional spatial structure analysis methods such as 3D pedestrian network analysis using betweenness centrality (Sun et al., 2021) have recently emerged and could potentially be incorporated in our workflow. Meanwhile, the satellite imagery road network extraction can be enhanced through previously mentioned methods to incorporate customized training data. Future directions can utilize 3D tools to produce road network analysis visualizations, integrating Human-Computer Interaction (HCI) interfaces to provide accessible and relevant information to designers, residents, and other non-expert stakeholders.

6 Conclusions

This research presents an innovative workflow to automatically extract road networks from satellite imagery, extract centerline using ArcGIS and analyze local network distribution properties. The method can quickly be adapted to develop built environment proposals and provide timely responses to any changes in their spatial structure. This could provide efficient insights for urban designers to evaluate ongoing planning projects. In Hong Kong, repetitive spatial layouts resulting from standardized design approaches in estate planning can affect individuals' perceptions of public open spaces (Dong & van Ameijde, 2023). Public spaces which are easily accessible and connected by well-designed circulation networks can help promote socializing, by providing convenient and inviting places for people to meet and interact.

By adopting a machine learning model to extract road networks, our study demonstrates how new computational methods can speedily respond to urban renewal processes. The proposed workflow can be used to evaluate the potential correlation between the vibrancy of public spaces and network integration. If implemented, improved public spaces and walking paths can support social mixing, casual neighboring and placemaking processes that help shape inclusive and vibrant communities. Due to the scalability and universality of the method, the research can contribute to more walkable pedestrian networks and sociable housing complexes in Hong Kong, or other international cities of similar density and vibrancy. The approach has the potential to contribute to enhanced planning strategies focused on augmenting community engagement and interaction with the surrounding urban areas. This can foster the social integration and mobility of public housing residents within the context of creating livable and inclusive cities.

References

Abu-Ghazzeh, T. M. (1999). Housing layout, social interaction, and the place of contact in Abu-Nuseir, Jordan. *Journal of environmental psychology*, *19*(1), 41-73.

Bastani, F., He, S., Abbar, S., Alizadeh, M., Balakrishnan, H., Chawla, S., ... & DeWitt, D. (2018). Roadtracer: Automatic extraction of road networks from aerial images. *In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition* (pp. 4720-4728).

Certeau, M., (1984). *The practice of everyday life.* Vol 1 Arts de faire.

Dong, J., & van Ameijde, J. (2023, July). The Impact of Spatial Layout on Orientation and Wayfinding in Public Housing Estates Using Isovist Polygons and Shape Matching Algorithms. In *International Conference on Computer-Aided Architectural Design Futures* (pp. 655-669). Cham: Springer Nature Switzerland.

Evans, G. W. (2003). The built environment and mental health. *Journal of urban health*, 80, 536-555.

Gao, M., Ahern, J., & Koshland, C. P. (2016). Perceived built environment and health-related quality of life in four types of neighborhoods in Xi'an, China. *Health & place*, 39, 110-115.

Golledge, R. G., & Gärling, T. (2004). Cognitive Maps and Urban Travel. In D. A. Hensher, K. J. Button, K. E. Haynes, & P. R. Stopher (Eds.), *Handbook of Transport Geography and Spatial Systems* (pp. 501–512). Emerald Group Publishing Limited. https://doi.org/10.1108/9781615832538-028

Goodfellow, I. J., Pouget-Abadie, J., Mirza, M., Xu, B., Warde-Farley, D., Ozair, S., ... & Bengio, Y. (2014). Generative adversarial networks. *arXiv 2014. arXiv preprint arXiv:1406.2661.*

Hillier, B. (1996). *Space is the Machine: a configurational theory of architecture*, Cambridge University Press, Cambridge.

Hillier, B. and Hanson, J., (1984). *The Social Logic of Space*, Cambridge University Press.

Hong Kong Housing Authority., (2022), Report on Population and Households in Housing Authority Public Rental Housing.

Khachatryan, H., Rihn, A., Hansen, G., & Clem, T. (2020). Landscape aesthetics and maintenance perceptions: Assessing the relationship between homeowners' visual attention and landscape care knowledge. *Land Use Policy*, 95, 104645.

Krugger, M.J.T. (1989). On node and axial maps: distance measures and related topics. Paper presented at *European Conference on the Representation and Management of Urban Change, Cambridge, 28-29 September 1999*.

Lim, L., Yang, T., Vialard, A., Feng, C., & Peponis, J. (2015). Urban morphology and syntactic structure: A discussion of the relationship of block size to street integration in some settlements in the Provence. *The Journal of Space Syntax*, 6(1), 142-169.

Liu, Y., Yao, J., Lu, X., Xia, M., Wang, X., & Liu, Y. (2018). RoadNet: Learning to comprehensively analyze road networks in complex urban scenes from high-resolution remotely sensed images. *IEEE Transactions on Geoscience and Remote Sensing*, 57(4), 2043-2056.

Lynch, K. (1960). *The image of the city*. Cambridge: MIT Press.

Marshall, S. (2004). *Streets and patterns*. Routledge.

Máttyus, G., Luo, W., & Urtasun, R. (2017). Deeproadmapper: Extracting road topology from aerial images. *In Proceedings of the IEEE international conference on computer vision* (pp. 3438-3446).

Mei, J., Li, R. J., Gao, W., & Cheng, M. M. (2021). CoANet: Connectivity attention network for road extraction from satellite imagery. *IEEE Transactions on Image Processing*, 30, 8540-8552.

Pafka, E., Dovey, K., & Aschwanden, G. D. (2020). Limits of space syntax for urban design: Axiality, scale and sinuosity. *Environment and Planning B: Urban Analytics and City Science*, 47(3), 508-522.

Peters, M., Muellmann, S., Christianson, L., Stalling, I., Bammann, K., Drell, C., & Forberger, S. (2020). Measuring the association of objective and perceived neighbourhood environment with physical activity in older adults: challenges and implications from a systematic review. *International journal of health geographics*, 19, 1-20.

Renald, S.A., Smith, T., Hale, P.A., (2010). Systematic review of built environment and health. Fam. *Community Health* 33 (1), 68–78. https://doi.org/10.1097/FCH.0b013e3181c4e2e5.

Ronneberger, O., Fischer, P., & Brox, T. (2015). U-net: Convolutional networks for biomedical image segmentation. *In Medical Image Computing and Computer-Assisted Intervention–MICCAI 2015: 18th International Conference, Munich, Germany, October 5-9, 2015, Proceedings, Part III* 18 (pp. 234-241). Springer International Publishing.

Sauter, D., Huettenmose, R.M. (2018). Liveable streets and social inclusion. *Urban Des. Int.* 13 (2), 67 –79. https://doi.org/10.1057/udi.2008.15

Schittich, C. (2004). *High-Density Housing: Concepts, Planning, Construction.* München: Birkhäuser. https://doi.org/10.11129/detail.9783034615112

Stavroulaki, I., Marcus, L., Pont, M. B., & Nilsson, L. C. S. (2017). Representations of street networks in space syntax towards flexible maps and multiple graphs. *In 11th International Space Syntax Symposium, SSS 2017, Lisbon, Portugal, 3-7 July 2017* (Vol. 5, pp. 174-1).

Sun, G., Webster, C., & Zhang, X. (2021). Connecting the city: a three-dimensional pedestrian network of Hong Kong. *Environment and Planning B: Urban Analytics and City Science*, 48(1), 60-75.

Talen, E. (2018). Urban morphology in urban design. *Teaching urban morphology*, 205-217.

Tang, W.S., Lee, J.W.Y, Hui, T.W. & Yip, M.K.C. (2019). The "Urban density" question in Hong Kong: From absolute space to social processes. *City, Culture and Society*, 17, 46-53, 48.

Van Etten, A., Lindenbaum, D., & Bacastow, T. M. (2018). Spacenet: A remote sensing dataset and challenge series. *arXiv preprint arXiv:1807.01232.*

Wu, Y. T., Prina, A. M., & Brayne, C. (2015). The association between community environment and cognitive function: a systematic review. *Social psychiatry and psychiatric epidemiology*, 50, 351-362.

Yen, I. H., Michael, Y. L., & Perdue, L. (2009). Neighborhood environment in studies of health of older adults: a systematic review. *American journal of preventive medicine*, 37(5), 455-463.