Simulating the urban spatial structure with spatial interaction: A case study of urban polycentricity under different scenarios

Cai Wu [a,b], Duncan Smith [b], Mingshu Wang [c,a,*]

[a] Faculty of Geo-Information Science and Earth Observation (ITC), University of Twente, Hengelosestraat 99, 7514AE Enschede, the Netherlands
[b] Center for Advanced Spatial Analysis, University College London, 90 Tottenham Court Road, London WC1E 6BT, United Kingdom
[c] School of Geographical & Earth Sciences, University of Glasgow. Glasgow, G12 8QQ, United Kingdom

ARTICLE INFO	ABSTRACT
	Polycentric urban development is gaining momentum in both scholarly research and real-life practice. This brings new demand for planning support systems to simulate and analyse the urban spatial structure in terms of polycentricity under various urban policy scenarios. With the help of emerging urban data, urban simulation techniques, and network science, this study proposes a workflow to simulate the urban spatial structure with spatial interaction as a part of the planning support system. Using Singapore as a case study, this study has explored the resulting urban spatial structure with four employment distribution strategies. The results suggest that planning practices impact urban spatial structure and its spatial interaction by redistributing urban morphological elements, such as employment in this study. Also, our results show that the physical urban spatial structure and spatial interaction are closely related. These results reinforce the role of urban planning practice to achieve a more sustainable and coherent urban built environment. Through this empirical evidence, our workflow exemplifies the potential of the planning support system to help urban planners and governments understand their urban policy regarding urban polycentricity.

1. Introduction

With the rapid urbanisation process and the emergence of megacities worldwide, the cities' management and planning authorities face increasing challenges from a wide variety of urban issues. The provision of necessary urban infrastructure and functions such as housing and transportation network to the new urban dwellers is only one part of the question. Experience showed that the distribution of various urban infrastructure and functions could impact people's behaviour, contributing to the city's overall economic performance, social coherence, and environmental sustainability (Arribas-Bel & Sanz-Gracia, 2014; Liu, Wang, Qiang, Wu, & Wang, 2020; Masip-Tresserra, 2016; Meijers, 2008; Wang, Derudder, & Liu, 2019). As such, the scientific approach to urban management and planning has been increasingly emphasised. As a result, the urban spatial structure study has become an essential part of the scientific process to understand and plan the urban built environment, gaining popularity in academic research (Bertaud, 2004; Meijers, 2008; Münter & Volgmann, 2020; van Meeteren, Poorthuis, Derudder, & Witlox, 2015).

Urban polycentricity, one specific type of urban spatial structure, has been highlighted by academia and urban practitioners, especially during the past decade. Polycentricity refers to the plurality of centres (Meijers, 2008), and the degree of polycentricity is often used to reflect non-trivial urban spatial patterns. Numerous academic researchers have focused on measuring polycentricity and relating it to various urban performances (Adolphson, 2009; Liu & Wang, 2016; Wang et al., 2019; Wang & Debbage, 2021). With the focus of urban studies shifting towards the network of interactions between the different parts of cities, urban flow data are used to describe these interactions (Batty & Cheshire, 2011). In many cases, scholars use spatial interaction, such as the flow of cash or human capital, to represent the spatial interactions between the different part of the city as the dynamics of urban spatial structure (Chen, Arribas-Bel, & Singleton, 2019; Gao, 2015; Rey et al., 2011). Following this research strand, we propose a new workflow to simulate urban spatial structure with spatial interaction data. Furthermore, using polycentricity as the indicator for urban spatial structure, we demonstrate this workflow by simulating spatial interaction and the resulting urban spatial structure under different urban scenarios.

* Corresponding author at: School of Geographical and Earth Sciences, East Quadrangle, University of Glasgow, Glasgow, G12 8QQ, United Kingdom; University of Twente, Faculty of Geo-Information Science and Earth Observation (ITC), P.O. Box 217, 7500 AE Enschede, the Netherlands

E-mail addresses: c.wu@utwente.nl (C. Wu), duncan.a.smith@ucl.ac.uk (D. Smith), mingshu.wang@glasgow.ac.uk, mingshu.wang@utwente.nl (M. Wang).

As cities increasingly face emerging challenges, urban simulation and other information technology were adopted as part of the planning support system (PSS) (Harris & Batty, 1993) for the city manager and urban planner to tackle these urban challenges. Simulation methods such as agent-based modelling and system dynamic model are applied to predict the possible outcomes for different urban policies (Hasegawa, Sekimoto, Seto, Fukushima, & Maeda, 2019; Mueller, Klein, & Hof, 2018). This study will experiment with the proposed workflow with a current urban planning policy: "Bring jobs closer to home" (Yuen, 1998). While industries benefit from economies of scale and concentration in traditional urban monocentric models, the city also suffers from increasing communing time and deteriorating living environment as it expands. One particular example is the spatial mismatch of jobs and housing, where employment is concentrated in specific regions and working households reside in locations that lack job opportunities. This creates greater demand for travelling and presents challenges for social justice and job accessibility (Horner & Mefford, 2007; Wang, Zeng, & Cao, 2021; Zhou, Chen, & Zhang, 2016).

Thus, it is believed that with a proper land use policy (Tomasiello, Giannotti, & Feitosa, 2020), a polycentric urban spatial structure could bring better city performance and a more sustainable model of urban development (Walsh, 2012). The concept of "Bring jobs closer to home" is in line with the polycentricity urban model with the formation of employment outside the traditional central building district (CBD) (De Souza et al., 2016). It is widely adopted as a part of urban policy in compact megacities like Singapore (Urban Redevelopment Authority, 1991) and Hong Kong (Development Department (HKSAR), 2016). This study tests the urban spatial structure via the proposed workflow under different approaches to employment distribution. We believe this will provide new insights for the city manager and urban planner to better understand and plan the urban built environment.

This paper's reminder begins with a literature review that introduces the essential concept and related work. Using Singapore's spatial mismatch as a case study, a spatial interaction model is applied to generate the jobs-housing flow using public transport data and four scenarios with different commercial space allocation strategies. Network Community detection is then applied to the jobs-housing flow to determine the urban centres and their community boundary. At the final stage of the workflow, we measure and contrast the different morphological and functional polycentricity under the different urban scenarios. The more detailed procedure and the case study are introduced in the methodology section. Next, we present the results with discussions on how the different commercial space allocation changes urban centres and the city's overall urban spatial structure. Lastly, we conclude with an evaluation of the new workflow and provided possible applications and future improvements.

2. Literature review

This study involves concepts and methodologies from multiple disciplines to simulate the urban spatial structure under different urban policies. The three most crucial aspects are the concepts of urban spatial structure and its dynamic, spatial interactions to detect urban communities and their boundary, and the measurement of polycentricity. These three concepts and methodologies and interconnected and were applied individually or collectively in many past pieces of research. We will also look into how different urban development models have been proposed to build the foundation for this study's scenario analysis. This section will explore relevant past research that built the theoretical and methodological foundations for the newly proposed workflow.

2.1. Urban spatial structure and its dynamics

As cities continue to grow and expand, people start to look at how the urban space is arranged and the underlying driven force. The study of urban spatial structure is the study of the distribution of urban space and activity in urban settings (Anas, Arnott, & Small, 1998; Krehl, 2015; Wang, Zhou, Long, & Chen, 2016; Zhong, Arisona, Huang, Batty, & Schmitt, 2014). The urban spatial structures are often described using morphological properties such as the concentration and density of population, employment, and built-up area (Bertaud, 2004), which is relatively static. In this study, we refer to it as the *static urban spatial structure*. On the dynamic aspect, the urban spatial structure also includes human activities and interactions, which are more temporal and dynamic. We refer to it as the *dynamic urban spatial structure*.

With a city's expansion, the urban spatial structure can be increasingly decentralised and complex (Zhong et al., 2014). Urban functions, population, employment, and the built-up area have overflowed from the urban centre. Other than traditional central business districts (CBD), urban hubs have formed around the traditional urban core with urban economic and technology as the driving force. Thus, the description of urban spatial structure is associated with the notion of decentralisation and polycentricity from the beginning of its scholarly research (Anas et al., 1998) with works analysed these morphological properties' allocation to reveal the urban spatial structure. For example, some examined how the urban spatial structure changes with the decentralisation of employment in the USA (Arribas-Bel & Sanz-Gracia, 2014). These studies greatly aided the government and urban planners in monitoring the physical development of the city. However, they are only one specific dimension of the cities' urban spatial structure.

The urban spatial structure is the distribution of the city's morphological element and the underlying relations and interactions between the different urban hubs. Among which spatial interactions represented by different kinds of urban flows such as travel flows and commuting patterns within the city are being used to describe the dynamics of the urban spatial structure (Bertaud, 2004; Burger, van der Knaap, & Wall, 2014; Hu, Yang, Yang, Tu, & Zhu, 2020; Sohn, 2005; Zhong et al., 2014). In his paper, Sohn (2005) examined the inherent relationship between an urban spatial structure with the commuting pattern. He suggests that commuting patterns represent the physical allocations of urban spatial interaction in general. Hu et al. (2020) suggested that other than using centralised-decentralised and monocentric-polycentric concepts to describe the urban spatial structure, spatial interactions such as the jobs-housing flow could add crucial information to complete the whole picture. This study will refer to the urban spatial structure measure from the spatial interaction as the *dynamic* one, in contrast to the *static* one measured from the concentration of the morphological element. This study has established the essential concept of static and dynamic spatial structure; we now move on to the simulation and analysis of spatial interactions in the existing literature.

2.2. Spatial interaction model and network community detection

Spatial interaction is the network of flow between different spatial locations (Guo, 2009). Travel flow is adopted widely as the proxy for spatial interaction in many studies as people are the "physical carriers, motivate the transfer of materials, money, people, and information between areas in urban space" (Zhong et al., 2014, pp.2179). Today, different forms of flow data are becoming increasingly available and comprehensive to describe the urban spatial interaction thanks to advancements in information technology and open data initiatives: mobile phone records, smart card public transport data, records for taxi and private hail, etc. (Liu, Derudder, & Wu, 2016). Scholars have used these data for spatial analysis, like identifying the urban spatial structure (Zhong et al., 2014) and functional zones (Yuan, 2014), discovering hidden patterns (Yin, 2002), or verifying theories and concepts. While access to these data is still limited and can only describe the past and current situations, the spatial interaction model, also known as the gravity model, could help researchers simulate and predict spatial interactions.

$$T_{ij} \propto \frac{O_i D_j}{C_{ij}^{\beta}}$$

Inspired by the traditional gravity model in newton's physics (Batty & Mackie, 1972), the spatial interaction model can be described where the flow is a function of three variables: the origin repulsiveness, destination attractiveness, and travel cost between the origin and destination. The flow (*T*) is believed to be proportional to the mass of the origin (*O*) and destination (*D*) and inverse proportional to the distance (*C*) between them. It is further developed to the non-constrained model, production/origin constrained model, attraction/destination constrained model, and double constrained model(Fotheringham, 1983). Each model has a unique use case. The production/origin constrained model, in particular, is also known as the retail model; it is adopted to predict the change in the system flow with variation in the attractiveness of the destination. The attractiveness is usually represented in the form of morphological terms like retail floor space. Its application includes but is not limited to optimise location selection for facilities (Guy, 1991). In recent decades, as the scientific approach to study urban built environment is increasingly valued, the application of the spatial interaction model has also been extended to urban spatial analysis, including the simulating urban spatial structure with predict spatial interactions (Chen, Hui, Wu, Lang, & Li, 2019; Gao, Liu, Wang, & Ma, 2013; Sarkar, Wu, & Levinson, 2020; Sohn, 2005).

With the spatial interactions between different parts of the city forming a complex network, network science application as a form of spatial analysis to study the urban spatial structure is also observed. Other than using physical transport network for urban topology studies, the spatial interaction or urban flowas a weighted directional network and was used to detect the urban spatial structure (Liu, Gong, Gong, & Liu, 2015; Zhong et al., 2014). The network approach uses the community detection method to identify urban centres and its boundary to reveal the dynamic urban spatial structure via spatial interaction. Zhong and her colleagues (Zhong et al., 2014, p p. 2181) have attempted to develop a "quantitative method for detecting urban hubs, centre, and borders well as changes in the overall spatial structure of urban movement using daily transportation data" and, more importantly, "identifying communities based on mobility." Here they use the Infomap equation approach developed by Rosvall and Bergstrom (2008) for community detection due to its good performance (Lancichinetti & Fortunato, 2009) and the very nature that the network constructed by urban flow data been weighed and directed. It also showed the potentials of the dynamic urban structure to complete the full urban structure image in addition to the traditional morphological structure. Hence, it could be concluded that the dynamic urban spatial structure detected from spatial interaction could be an asset to evaluating urban development progress.

2.3. Measurement of urban polycentricity

Urban polycentricity is a crucial facet of urban spatial structure. As polycentric urban development becomes increasingly emphasised in urban studies, the definition of polycentricity is also becoming stretched among different studies (van Meeteren et al., 2015). However, its empirical meaning in urban studies is simple and straightforward: the plurality of centres (Meijers, 2005). The study of polycentricity can thus be summarised as identifying urban centres and studying the balance between them. This breaks down the measurement of urban polycentricity into three steps: First, identify the attribute or indicator required by the study to study urban polycentricity; second, identify the urban centres; and lastly, select the suitable technique for measurement.

The early study of polycentricity is regarded as an urban morphological study. Hence, the size balance between these centres has become essential to measure the polycentricity of the urban structure. Common indicators for urban polycentricity include population size (Liu & Wang, 2016), road network density (Liu et al., 2016) and employment (Huang,

Liu, & Zhao, 2015), etc. The morphological size could also be extended to broader concepts such as the buildings' floor space and density. This is because the buildings are regarded as a good proxy for urban density and activities (Adolphson, 2009). Green (2007), Burger and Meijers (2012) have taken a step further and summarised two types of polycentricity. One has been the *morphological polycentricity* mentioned above, which focuses on the scale and size balance of the urban centres; The other one is the functional polycentricity, which extends the idea to the pattern of spatial interaction between the urban centres. The *functional polycentricity* focuses on the balance of the interaction distribution rather than the scale of it. To put in simple words, the more evenly the urban centre's size is distributed, the more morphologically polycentric the urban structure; similarly, the more even the interaction between these centres, the more functionally polycentric the urban structure. Generally speaking, studies find that there is a positive correlation between the morphological polycentricity and functional polycentricity (Burger & Meijers, 2012; Wei et al., 2020): Higher concentration of urban morphological elements such as population and buildings will attract more urban flow; the more balance the distribution, the more balance the flow. Again, these spatial interactions between the urban centre are represented by urban flow data mentioned earlier. Thus, the spatial interactions could be potentially applied to measure the functional polycentricity through a network approach.

The identification of urban centres depends on the purpose, research field, and scale of the polycentric study. Urban polycentricity can largely be considered at two scales: inter-city polycentricity and intra-city polycentricity (Wang et al., 2019). The different scales provide very different contexts regarding what constitutes centres in polycentric urban studies (Wei et al., 2020). Besides the scales, this study also acknowledges the different approaches that scholars deployed to identify the urban centres by the attribute value involved in the study. Common approaches include setting a threshold value (Liu & Wang, 2016), selecting a fixed number of urban centres (Burger & Meijers, 2012), or specifying the centre according to the study needs (Krehl, 2015). We could conclude that the method to identify centres is often discussed case by case, and these diverse techniques enriched the scholar's arsenal for future urban polycentric studies.

Scholars have also proposed different ways to measure polycentricity. A rank-size distribution is commonly deployed to measure polycentricity: top-ranked urban centres are plotted with their rank and size. The closer the value of the gradient of the best fit line is to zero, the more polycentric the urban structure, vice versa (Meijers, 2008; Wang et al., 2019). These studies also acknowledge other means of measurement of morphological polycentricity, such as calculating the standard deviation of the size of the urban centres (Green, 2007; Liu et al., 2016) and using the different index of various aspects (Pereira, Nadalin, Monasterio, & Albuquerque, 2013). While the measurement polycentricity is relatively comprehensive in scholarly research, identifying urban centres and their boundary of the urban spatial structure is still based mainly on the "static structure" of the physical distribution of urban morphological elements mentioned in the previous section. Hence, the study of polycentricity of the dynamic urban spatial structure is left untouched and presents opportunities for further research.

3. Case study area and data

This study selects Singapore as a case study area to demonstrate the proposed framework for the following reasons. First, Singapore is a cosmopolitan island city-state with approximately five million residents. It is well-known for its economic success and sophisticated urban planning and management. After decades of systematic planning and development, Singapore has become a model of efficient urban planning, development, and management. Second, Singapore has gone through suburbanisation and polycentric urban development processes, where settlements and satellite towns have formed outside the traditional urban core. The urban spatial structure of Singapore has become a

polycentric model (Zhong et al., 2014). Third, with its smart nation initiative (Chang & Das, 2020), Singapore provides various open data and encourages their application in research.

The subzone is used as the unit of analysis in this study. Singapore has deployed a hierarchical planning division system: The Singapore city was divided into five planning regions and was further divided into subzones. A subzone is a basic sub-division of Singapore's planning unit. There are a total number of 323 subzones of various sizes. Fig. 1A and B show the subzone with its population and commercial floor space, respectively. A significant number of smaller area subzones are concentrated on the traditional urban centre. The subzone is the smallest planning unit where census data is available for public access, making it ideal for analysis. There are two types of data involved in this study: the census data, including the number of residents, and the aggregated commercial floor space. The second type of data is spatial interaction data. This study uses the morning public transport commuting data to calibrate the spatial interaction model for jobs-housing spatial interaction. The data processing method and a description of data are introduced below.

3.1. Census data

As shown in Fig. 1, two census variables at the subzone level are utilised in this study: Population, which accounts for the number of residents in the subzone, and commercial floor space, which accounts for employment size. The census data are open data published by the Singapore government and accessed through the open data platform (data.gov.sg). It is a data portal launched in 2011 as an initiative by the Singapore government to provide a one-stop portal for open data from public agencies.

The population census data provides the number of residents in June 2017 in different subzones of Singapore. There are a total of 3,966,030 residents recorded, excluding foreign workers and travellers. The distribution of the residents in Singapore varies between different subzones. Subzones in the traditional building districts and satellite towns have a high concentration of residents; subzones with a lower number or no residents mostly undeveloped reserve land or dedicated to a specific use such as nature reserve, port, and industrial zones. The population census data in this study will be used as the housing choice for Singapore's residents.

Commercial floor space (by square metre) is estimated for the different subzones in Singapore. The Singapore master plan 2014 provides information about land use, Gross Plot Ratio (GPR), and land area for the land parcels dedicated to urban use. The GPR is the index deployed by the Singapore urban planning authority to control the development intensity and GPR = Gross Floor Area/Land Area. The floor area can thus be calculated using the GPR times land area. This study considers urban floor space that could be used for employment and work to be commercial and could be used as a proxy for employment. To determine the commercial floor space, we consider retail, office, business park, and some civic land listed in the master plan to be commercial. Since the master plan does not represent the current urban development state with many land parcels undeveloped, we overlayed the land parcels with the existing buildings to identify and remove the undeveloped land parcels from the calculation of the current commercial floor space. The existing buildings were extracted from the open street map in June 2019. With the commercial floor space for each land parcel been estimated, it is aggregated according to their allocated subzone. The resulting distribution of commercial floor space (Fig. 1B) showed that the employment opportunities are prominent in the south and the east coast region.

The employment represented by the commercial floor space and the population could be used to study the relationship between jobs and housing, an established research topic in transportation studies (Cervero & Duncan, 2006; Hu et al., 2020; Zhou et al., 2016). A spatial mismatch is apparent in Singapore. While the population is generally distributed

widely across Singapore, employment opportunities are clustered in certain areas. This has resulted from the specific geography and history of Singapore (Yuen, 1998). The change in job-housing balance is believed to lead to a change in commuting trips (Cervero & Duncan, 2006); hence spatial interaction is the focus of this paper.

3.2. Public transport commuting data

The public transport commuting data are also obtained from the open data portal provided by the Land Transport Authority (LTA) of Singapore. The LTA is a public agency responsible for planning, developing, and maintaining the land transport infrastructure and systems. Two sets of data are used: bus and rail transit data between different stations on an hourly basis for weekends and weekdays in May 2019. Based on the research scope, only weekdays data is kept. The public transport volume over time is presented in Fig. 2 below:

There are 6,634,544 bus trip records and 803,592 train trip records. It can be observed that the morning peak lasts four hours, from 6 am to 9 am. Following Zhong et al. (2016), this study selected the morning peak data on weekdays to simulate the jobs-housing spatial interaction as it is a better representation and shows more regularity (Zhong et al., 2016). This study aggregates the flow between the bus stops and train stations based on their subzone located. The bus flow and train flow can thus be merged into one public transport commuting network. Note that the bus stop and train station are absent in some subzones. Hence there is no flow connection, and they are absent from the network. The result is a matrix that contains the travel between all the subzones in Singapore.

4. Proposed workflow and methods
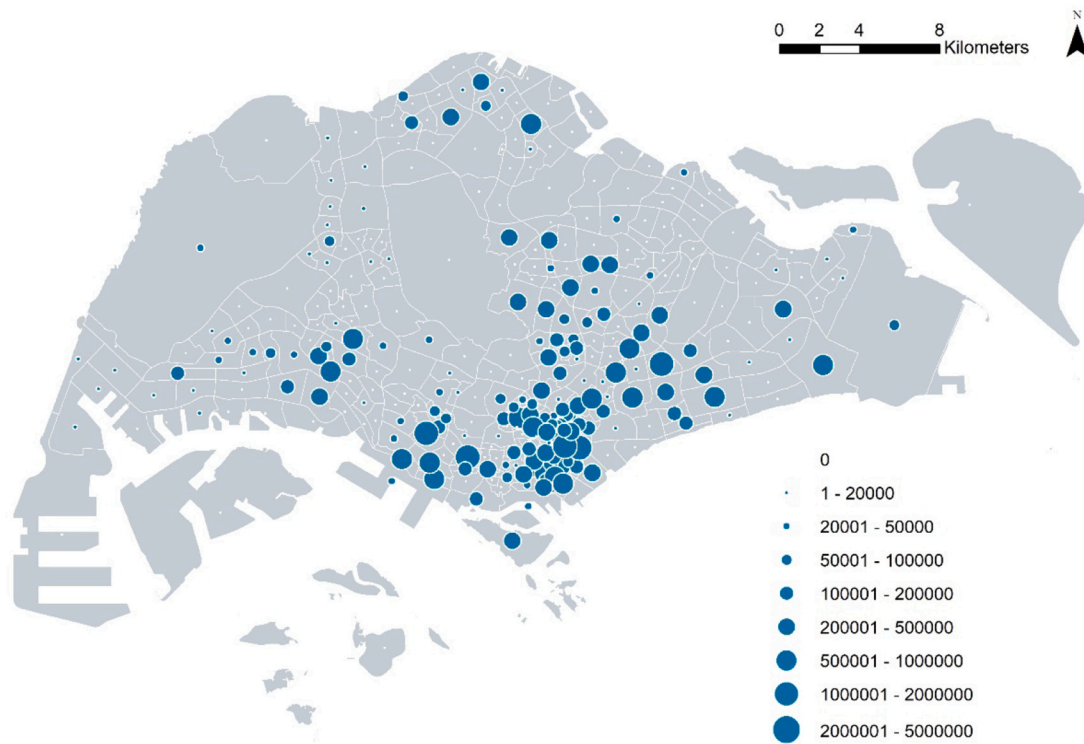
4.1. Proposed workflow

This paper aims to study the dynamic urban spatial structure in terms of polycentricity for four different employment distribution scenarios and proposed a workflow (Fig. 3) using network community detection and spatial interaction models. Spatial interaction network, particularly the jobs-housing spatial interaction, is used to detect the urban centres and the resulting functional polycentricity. This study calibrated a production-constrained spatial interaction model (Clarke, Langley, & Cardwell, 1998) via the morning peak traffic flow to simulate the jobs-housing spatial interaction network under the four different urban employment distribution scenarios. The detailed workflow is illustrated below, and this section will go through details about the different methodologies applied in this study. The unit of analysis is the subzone which is the smallest planning unit of Singapore and also where the census data is available at the most refined scale.

4.2. Employment distribution scenarios

Employment is represented by the commercial floor space in this study, and we proposed four different employment distribution scenarios. We are interested in how people's jobs-housing interaction and the resulting dynamic urban spatial structure will change with the relocation of employment opportunities. Many modern urban planning theories and practices promote bringing jobs closer to home and mixed land use for smart urban growth to address the increasing challenge of urban expansion and spatial mismatch, such as increasing commuting time (Cervero & Duncan, 2006). Numerous studies have also explored the relationship between employment distribution and cities' performance (Arribas-Bel & Sanz-Gracia, 2014; Hu et al., 2020; Tomasiello et al., 2020). Under this circumstance, Singapore has already listed "Bringing jobs closer to home" as an essential agenda in its urban development policy. This means the government is planning to improve the jobs-housing balance by bringing more job opportunities to where the working population is located. This could potentially improve the spatial mismatch. The commercial floor space estimated in this research
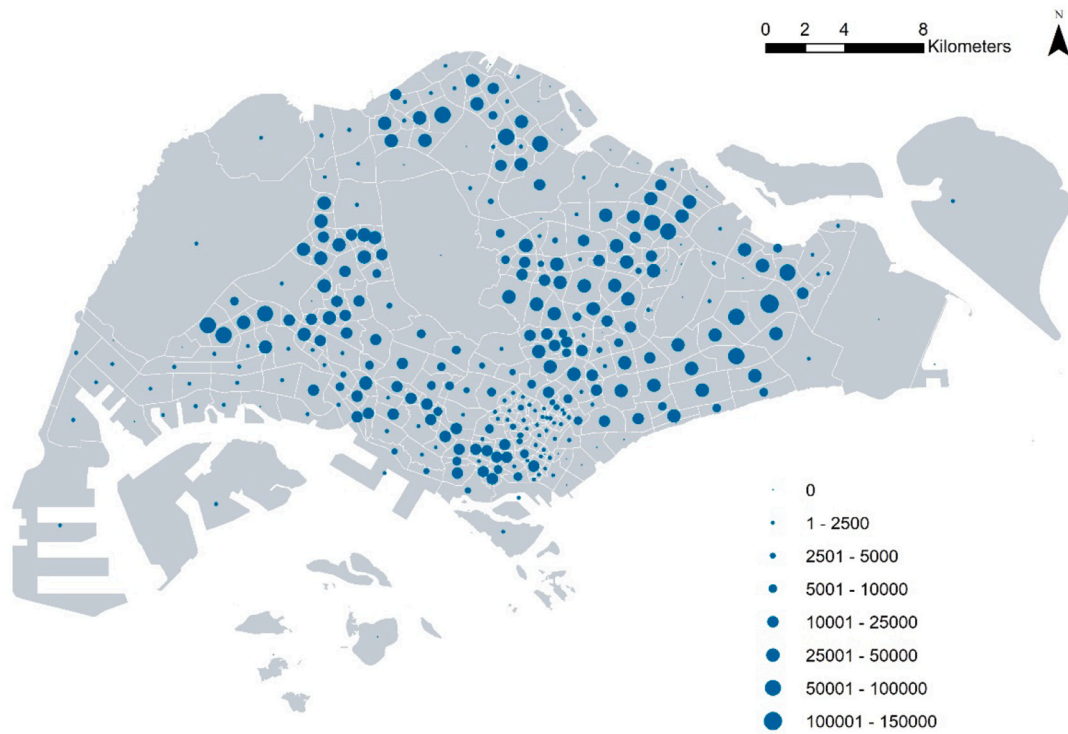
A) Distribution of the population in subzones

B) Distribution of commercial floor space (by square metre) in subzones
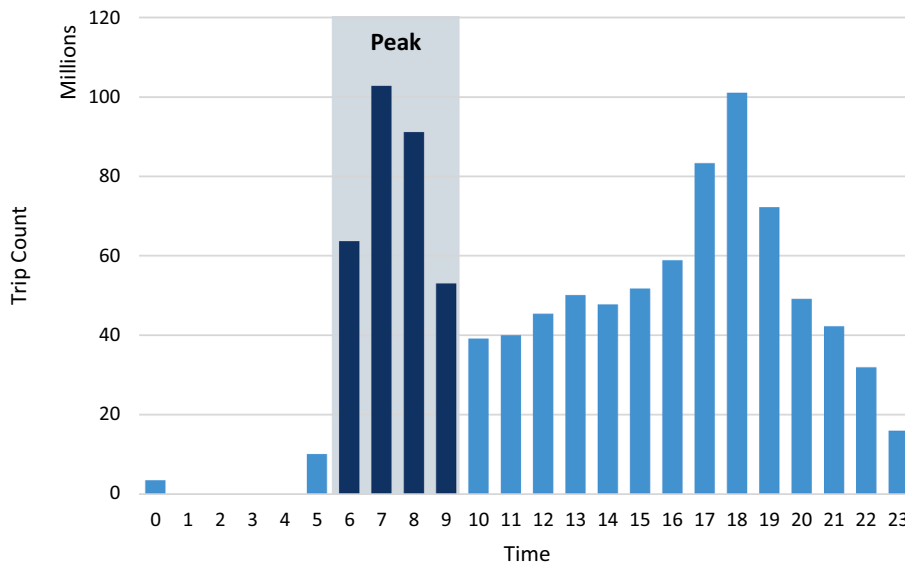
Fig. 1. Subzones in Singapore.

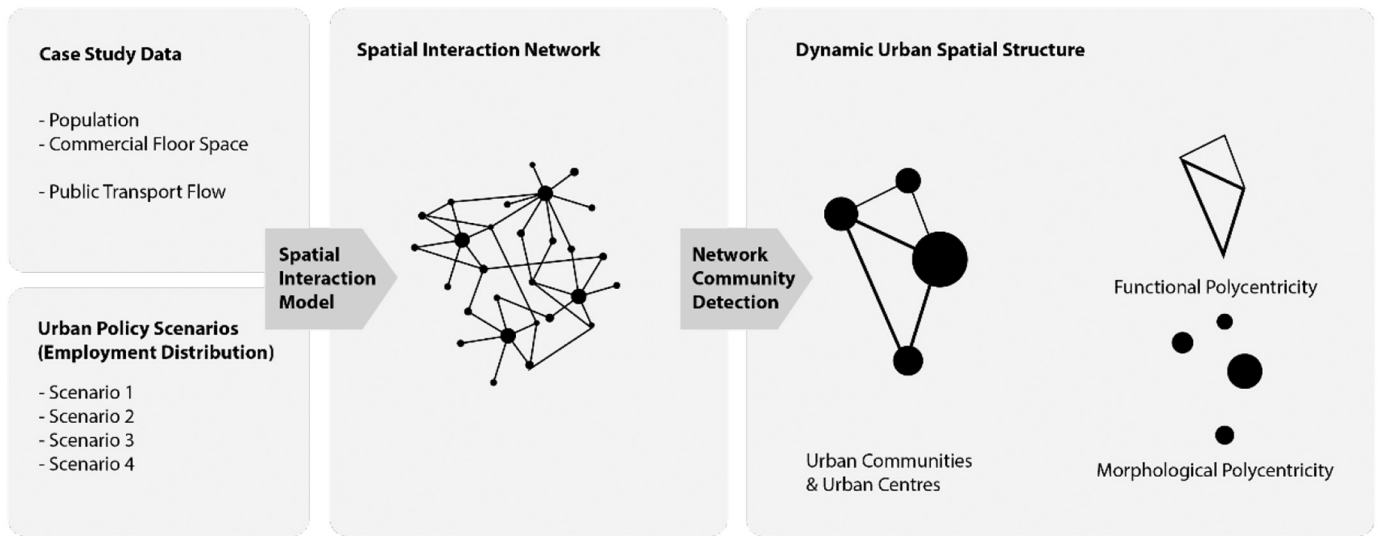**Fig. 2.** Public transport trip count by hour.

Fig. 3. Proposed workflow.

includes office floor space and retail floor space, which associate with service industries, which account for approximately 75% of Singapore employment, according to the Singapore Ministry of Manpower. Using Singapore as an example, we redistribute the employment via the redistribution of commercial floor space into the subzones. Each scenario is proposed to make the employment less centralised to reduce the spatial mismatch. The details of the four different scenarios we proposed in addition to the current situation are listed below with descriptive data (Table 1 and Fig. 4).

The above scenarios showed four different urban policies to distribute the commercial floor space in the principle of "Bringing jobs

closer to home". The commercial floor space is redistributed through our unit of analysis: the subzones. Some focus more on balance between the subzones like Scenario 1 and Scenario 2; some focus on balance in terms of spatial distribution like Scenario 3; Last but not least, some focus on the balances between residents like Scenario 4, which the jobs-housing balance is best achieved. Although they are purely theoretical, all four scenarios are a potential solution to the current spatial mismatch. Due to the division of subzones and the population distribution, the commercial distribution also shows different patterns.

4.3. Simulate urban spatial interaction: spatial interaction model

To simulate the spatial interaction between the commercial floor space and the residents, namely the jobs-housing interaction, we proposed a simple production constrained spatial interaction model (Fotheringham, 1983). The subzone's resident population is used as the origin attribute, which generated the outflow of trips. The commercial floor space is used as the destination attribute that attracts the trips. Since this study is a preliminary attempt of the workflow to study the different employment distribution scenarios, the changes in population

Table 1
Descriptive data for commercial floorspace (by m^2).

	Scenario 1	Scenario 2	Scenario 3	Scenario 4
Mean	114,340	114,340	114,340	114,340
Median	114,340	214,720	57,809	39,576
Standard Deviation	0	107,254	349,359	9241
Sum	36,932,007	36,932,007	36,932,007	36,932,007

Scenario 1: by mean commercial floor space in all subzones

Scenario 2: by mean commercial floor space in subzones with residents

Scenario 3: by proportional of land area in subzones with residents

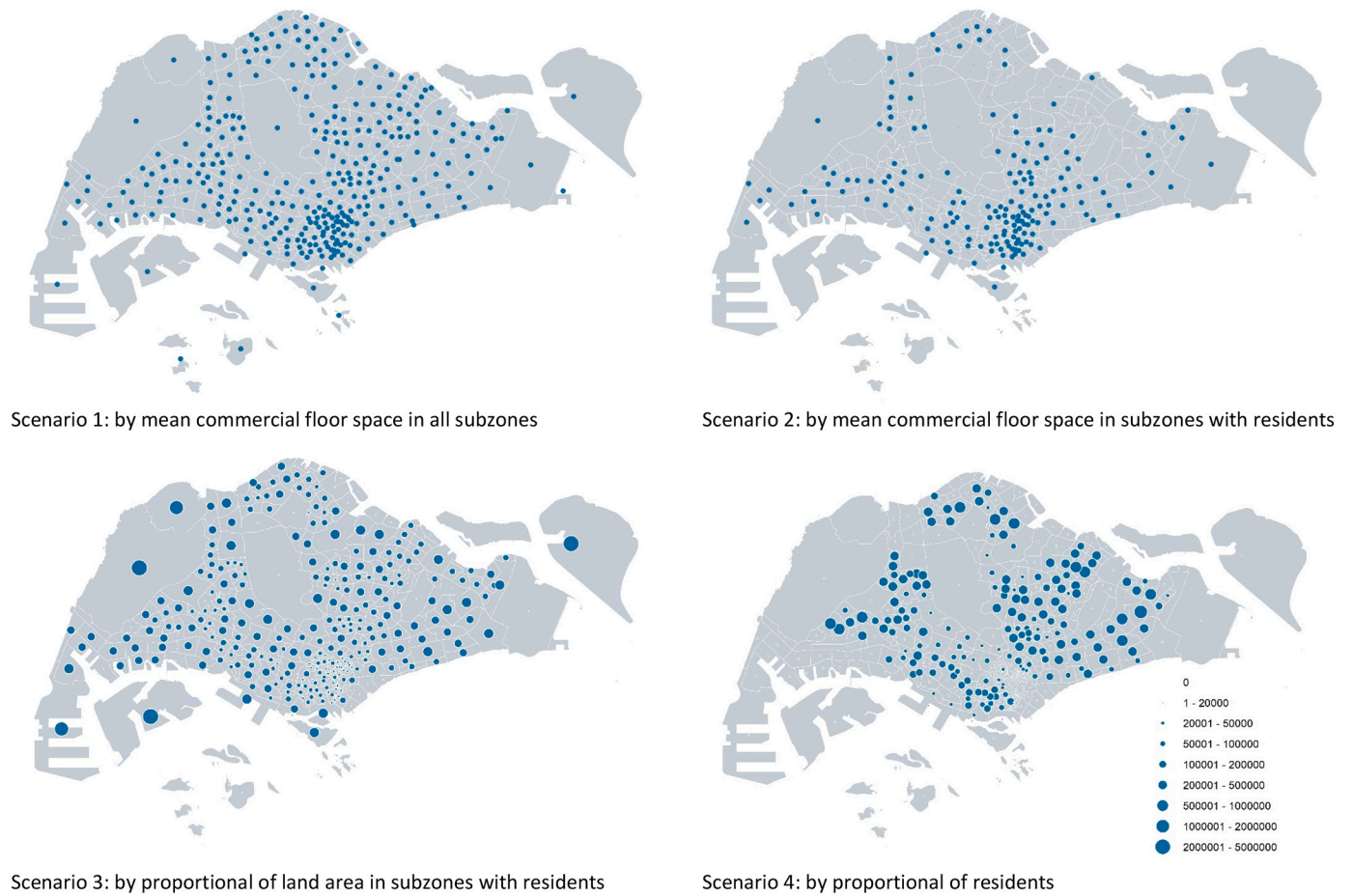Scenario 4: by proportional of residents

Fig. 4. Proposed distribution of commercial floor space in subzones (by m^2).

and travel distance between subzones were not considered. Using the existing traffic flow data, current population, and commercial floor space distribution, we can calibrate the formula and simulate future traffic flow with changes in the commercial floor space. The formula is given as follows:

$$T_{ij} = A_i O_i D_j{}^{\alpha} c_{ij}{}^{-\beta}$$

where T_{ij} denotes the number of jobs-housing interactions between origin subzone i and destination subzone j (i.e., the flow between origin i and destination j). O_i is the number of residents that need to travel for work. A_i is the total outflow of the origin. D_j is the commercial floor space, representing the employment opportunity that attracts flows into j. c_{ij} is the friction or the cost of travelling between i and j, which is proxied by distance in this study. α and β are parameters for the respective attributes, which need to be estimated with known attributes: T_{ij}, O_i, D_j and c_{ij}.

To calibrate the model, this study used the morning peak public transport travel as the number of residents and current estimation of commercial floor space in the subzones as T_{ij}, O_i, D_j, respectively. The calibrated best fit value for α and β is 0.06744 and 1.73152, respectively with coefficient of determination at 0.47. These parameters show that subzones with more commercial floor space will attract more urban flow; the longer the travel distance, the less attractive a subzone is. Assuming the population (O_i) in each subzone and the travel distance c_{ij} is unchanged, the calibrated model can simulate the jobs-housing interaction for the four different scenarios with the new employment (D_j) value.

The result of this step is the four spatial interaction networks under the four different scenarios we proposed. The nodes are the different

subzones, and the edges are the spatial interaction between them. This paper uses the calibrated formula to recalculate spatial interaction under the current scenario. It will be used as the baseline for comparison of the change in urban spatial structure and polycentricity. The calibrated spatial interaction is preferred over the public transport data to serve as the baseline, the current situation, as it can better reflect the changes between different scenarios and is a better representation of the jobs-housing interaction. Hence, five spatial interaction networks are produced in this step, including the four proposed employment scenarios and the current one that serve as the baseline. The baseline (current scenario) has a mean travel distance of 3718 meters. The proposed scenarios 1,2,3, and 4 have a mean travel distance of 3502, 3700, 3485 and 3459 meters, respectively. These networks could be used further to determine urban clusters via network community detection and measure the functional polycentricity.

4.4. Network community detection

This study's spatial interaction network is a directed network weighted by the volume of the interaction. Thus, the Infomap methodology (Rosvall, Axelsson, & Bergstrom, 2009) is applied here for its best performance, as stated in the literature review. The community detection decomposes complex networks into different modules based on their internal interactions for ease of analysis. The Infomap method uses the map equation instead of modularity as the parameter to determine community detection results. The map equation "specifies the theoretical limit of how concisely we can describe the trajectory of a random walker on the network "(Rosvall et al., 2009, p. 1) and can better be used for focuses on the flows of the network for partition. The lower the map equation, the better the community detection results. A more detailed

description of the map equation and algorithm could be found in Rosvall, Axelsson, and Bergstrom's paper(Rosvall et al., 2009).

The Infomap community detection method can be implemented in R using the igraph package (https://igraph.org/r/). The four spatial interaction networks simulated with the spatial interaction model and the baseline scenario were analysed using the Infomap community detection method using igraph in R. The network was divided into different sub-networks with each subzone in the network assigned membership an urban community. Subzones belonging to the same urban community are considered to have close relationships. The changes in the urban community border and indicate changes in spatial interaction. These urban communities describe the urban spatial structure and could be regarded as different urban centres to measure polycentricity.

4.5. Measuring the polycentricity

There are two types of polycentricity involved in this study: morphological and functional polycentricity. The polycentricity is measured using urban centres as the unit of analysis. Instead of using traditional administrative boundaries, we use the community detected as the unit of analysis to measure polycentricity. Commercial floor space and Centrality are the indicators selected to measure the morphological and functional polycentricity, respectively. The details of these indicators could be found in Table 2.

The commercial floor space is a straightforward measurement. The commercial floor space (C) in each urban community will be calculated by aggregating the commercial floor space of the commercial buildings (c_i) in their constituted subzones. The commercial floor space is calculated earlier, and details could be found in the data section. For Centrality, this study adopted the definition in Burger and Meijers' (2012) research with some simplification to suit the study's urban scale. Here this study uses the total number of flows directed to the urban community as the measurement for functional polycentricity, which excludes the internal flow. As the indicator for functional polycentricity, which focuses on the balance between the interaction of the urban communities, the Centrality is the inter-community trips. The higher the numberer of trips from the external community, the higher the Centrality. It could also be regarded as the In-degree centrality, which is the total number of trips going into the urban community excluding the loop. The spatial interaction network is simplified into the urban communities' spatial interaction network to calculate the urban communities' Centrality. We apply this to all five scenarios, including the current and proposed commercial floor space distribution situation.

A rank-size method is used to measure the polycentricity with a log transformation to ensure better results (Gabaix & Ibragimov, 2011). In line with previous literature (Burger & Meijers, 2012; Wang et al.,

2019), a fixed number of urban centres/communities are selected to measure the polycentricity: the top 4 in terms of commercial floor space and in-degree centrality, respectively. This paper selects four urban centres due to Singapore's geographic character. With a natural reservoir in the middle, four urban centres could be identified in the South, North, East, and West of Singapore. The slope of the regression line of the rank-size distribution is used to measure the degree of polycentricity, with commercial floor space assessing the morphological polycentricity and the Centrality assessing the functional polycentricity.

5. Results and discussion

5.1. Urban communities and urban centres

The first result regarding the dynamic urban spatial structure is the urban communities detected from the spatial interaction. The proposed method also suggested that the urban centres could be identified from these urban communities to act as the analysis unit to measure polycentricity. The five sets of spatial interaction networks generated different results for urban communities. The detection results are displayed as follows, the dashed white line in the four proposed scenarios indicates the original border in the current scenario for easy contrasting. The order of the urban community is ranked by employment and Centrality (Fig. 5).

The overall structure and distribution of the urban communities are largely consistent with the distribution of the employment changes. Major urban communities could be identified with ease: the central community located at the traditional CBD in the southern tip of Singapore island, the East Coast and Changi community along the east coastline, the Jurong and West Coast community in the west coastline, the North and Punggol community on the north of the island. The Tuas community is an industrial cluster. The urban community detection's consistency may reflect the strong influence of current physical infrastructure in the urban spatial structure dynamics. However, changes could still be observed, like the shifting boundary of the urban community and the emerging of smaller urban communities like Woodlands and Paya Lebar. Since urban communities' distribution mostly follows the Singapore land's geographic character, with urban development around the central reservoir in four directions, this study deems four urban centres sufficient to measure the polycentricity.

To measure the polycentricity, this study ranks the urban communities according to their commercial floor space and Centrality. In terms of ranking, the employment ranking and Centrality ranking display different trends across scenarios. In general, the urban communities' employment ranking varies tremendously, and the centrality ranking appears to be very consistent with the different employment distribution strategies. The top four urban communities by Centrality are consistently Central, East Coast, North East, and West Coast community, which coincide with Singapore's geographic character. These discrepancies between the ranking in employment distribution and centrality ranking show that the sheer size of commercial floor space may not attract proportional urban flow. Other than the commercial floor space, other factors also impact the spatial interaction not included in the model. With the top four urban communities, this study proceeds to measure the polycentricity of the overall urban spatial structure.

5.2. Polycentricity

Building on the current situation, four commercial floor space allocation scenarios are tested, as stated in the methods. Each of the morphological and functional polycentricity was compared against those in the current scenario. The results are illustrated in Fig. 6 and indicated how spatial planning practices might impact the dynamic urban spatial structure.

In Scenario 1, we simply distributed the commercial place evenly across the subzones in Singapore. Regardless of their population, size,

Table 2
Indicators for urban polycentricity calculation.

Indicator	Polycentricity	Formula	Description
Commercial Floor Space	Morphological	$C = \sum c_i$ (by m^2)	The commercial floor space (C) is equal to all the sum of all the floor space of the buildings (c_i) that is related to commercial activities in the urban community.
Centrality	Functional	$Centrality = T_j - t_j$	The Centrality is a measurement of the attractiveness of the urban community. It is the number of trips originate from the outside of the community j which is equal to the number of total trips destinates to community j (T_j) minus the internal trips of community j (t_j).
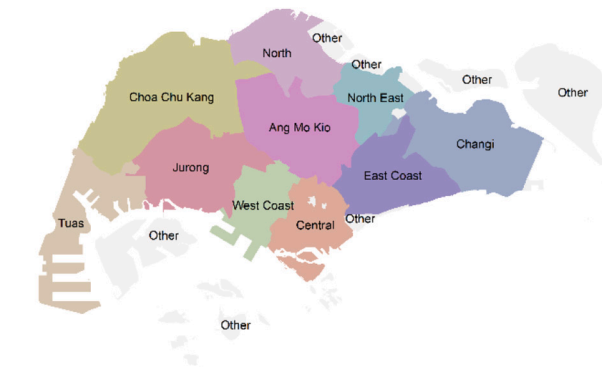
Current Scenario

By Employment	By Centrality
Central	**Central**
Jurong	**East Coast**
East Coast	**North East**
West Coast	**West Coast**
North	Ang Mo Kio
Changi	Jurong
North East	Changi
Choa Chu Kang	Choa Chu Kang
Ang Mo Kio	Toa Payoh
Tuas	North
Toa Payoh	Tuas
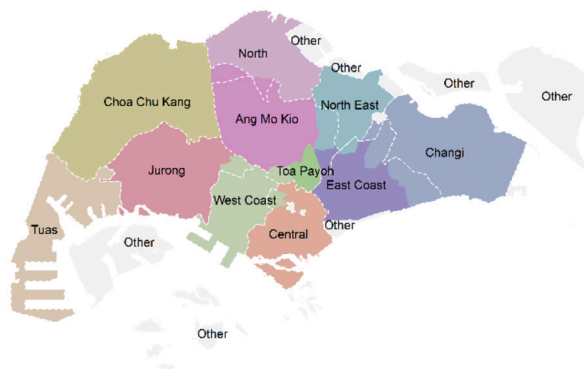
Scenario 1: by mean commercial floor space in all subzones

By Employment	By Centrality
Central	**Central**
Jurong	**East Coast**
East Coast	**North East**
West Coast	**West Coast**
North	Ang Mo Kio
Changi	Jurong
North East	Changi
Choa Chu Kang	Choa Chu Kang
Ang Mo Kio	Toa Payoh
Tuas	North
Toa Payoh	Tuas

Fig. 5. Community detection results.

and location, each subzone will have a fixed commercial floor space of approximately 114,040 square meters. The result is an increase in morphological polycentricity and a slight increase in functional polycentricity. This is expected as the evenly distributed commercial floor space across the subzones contributed to the increasing polycentricity of commercial floor space. This also results in a more balanced spatial interaction between the different urban communities as people have a more balanced choice for work or shop. Thus, increased the functional polycentricity of the urban system.

In Scenario 2, commercial floor space is evenly distributed across subzones with residents. Subzones with no residents are not assigned to any commercial floor space. The decreasing morphological polycentricity may have resulted from the smaller division subzones clustered at the traditional central business district resulting in a strong urban centre. While other communities typically consisted of fewer subzones, the larger area was further split into smaller communities according to the dynamic urban structure's detection results. As commercial floor space distribution becomes monocentric, people's desire to travel for work and entertainment also increased, leading to a more polarised travel pattern and decreasing functional polycentricity.
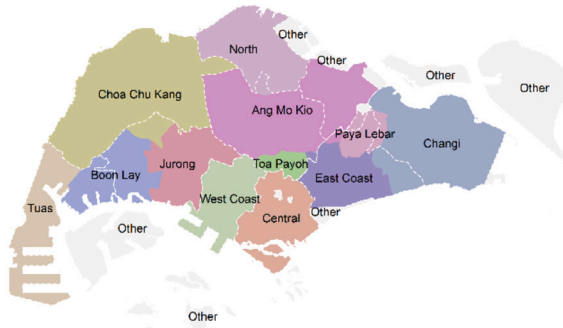
In Scenario 3, the commercial floor space is equally assigned to the

residents of Singapore. Depending on the number of residents, each subzone will be assigned the commercial floor space that is proportional to the residents while the total commercial floor space area is conserved. By doing so, Singapore has become increasingly morphologically polycentric in a significant way. Since the commercial floor space is directly proportional to the resident population, Singapore's increasing morphological polycentricity indicated that the population is roughly even between the top four communities detected. In terms of functional polycentricity, the spatial interaction between the communities has also become more balanced. This is expected as the more balance the distribution of commercial floor space, the more balanced the people's motivation to travel to different communities.

In Scenario 4, the distribution of commercial floor space focuses on geographic balance. Each subzone with the residence was assigned the commercial floor space proportional to the land area. The resulting polycentricity is similar to Scenario 1, with the degree of morphological and functional polycentricity both increased.

6. Discussion

First, concerning the "Bring jobs closer to home" urban planning

Scenario 2: by mean commercial floor space in subzones with residents

By Employment	By Centrality
Central	**Central**
East Coast	**East Coast**
Ang Mo Kio	**Ang Mo Kio**
West Coast	**West Coast**
Choa Chu Kang	Jurong
Jurong	Choa Chu Kang
Boon Lay	Toa Payoh
Changi	Changi
North	Boon Lay
Toa Payoh	Paya Lebar
Tuas	North
Paya Lebar	Tuas
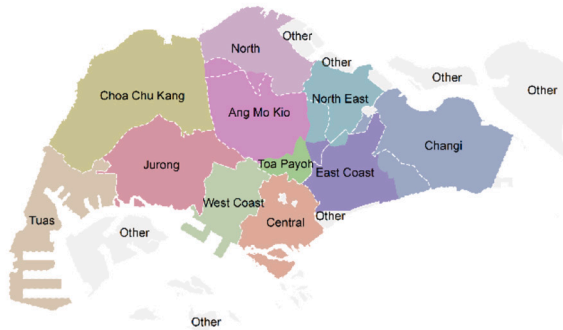
Scenario 3: by proportional of land area in subzones with residents

By Employment	By Centrality
Choa Chu Kang	**Central**
Jurong	**East Coast**
Changi	**North East**
Tuas	**West Coast**
North	Ang Mo Kio
East Coast	Jurong
Central	Choa Chu Kang
North East	Toa Payoh
West Coast	Changi
Ang Mo Kio	North
Toa Payoh	Tuas
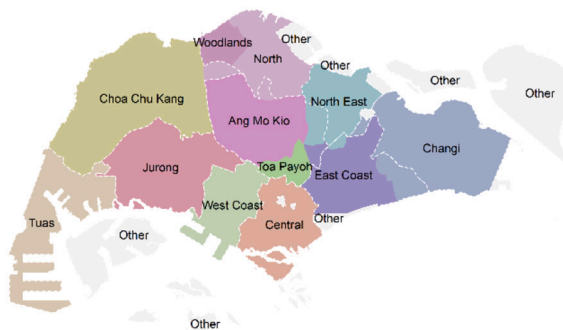
Scenario 4: by proportional of residents

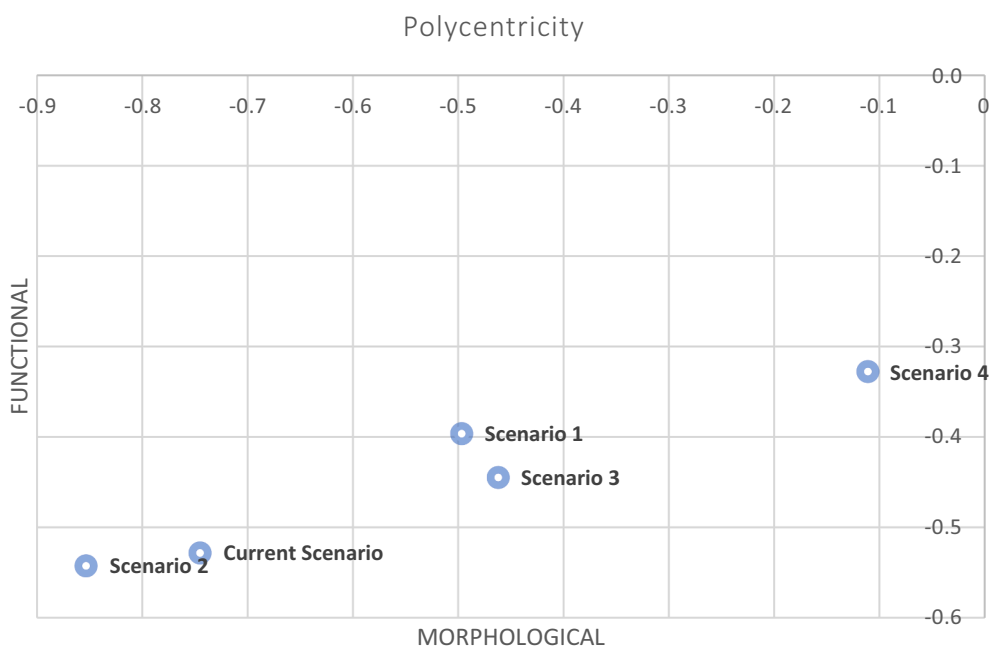| By Employment	By Centrality
North East	**Central**
Jurong	**East Coast**
Changi	**North East**
East Coast	**West Coast**
Choa Chu Kang	Jurong
North	Ang Mo Kio
Central	Toa Payoh
Woodlands	Choa Chu Kang
Ang Mo Kio	Changi
Toa Payoh	North
West Coast	Woodlands
Tuas	Tuas

Fig. 5. (*continued*).

Fig. 6. Morphological and functional polycentricity.

policy, the proposed workflow has simulated dynamic urban spatial structure and measured respective polycentricity using a different distribution of commercial floor space. This workflow provides opportunities to evaluate the specific urban policy's impact from both spatial and dynamic perspectives. With different scenarios as a different degree of policy implementation, i.e., jobs-housing balance, the urban policy's effect also varies. In general, the "Bring jobs closer to home" policy has resulted in a more decentralised urban spatial structure by the number of urban communities detected. Although the centrality ranking for the top four urban communities largely remains unchanged, it still results in a more balanced urban spatial structure in terms of morphological and functional polycentricity. In the extreme case scenario three, the "Bring jobs closer to home" concept is most thoroughly implemented and achieved the optimum polycentricity. This coincides with the policy's intention, which is to achieve a more balanced jobs-housing interaction. It could be further concluded that the different distribution of the commercial floor space, or the employment opportunities it represents, will impact both the dynamic urban spatial structure and the polycentricity. Although assessing a specific urban policy or planning strategy requires an evaluation from multiple perspectives, our proposed workflow provides potential justification from an urban spatial structure aspect.

Second, in terms of polycentricity, this study could generalise that redistribution of employment closer to the residents could lead to a more polycentric dynamic urban spatial structure, both morphologically and functionally, from the simulation result. It could also be observed that the increasing morphological polycentricity was always accompanied by increasing functional polycentricity. This indicates the correlation between the two polycentricity, as stated in the existing literature (Burger & Meijers, 2012). From this evidence, we could suggest that the degree of polycentricity could be altered through urban policies and planning. Nevertheless, one caveat is that the urban polycentricity measure adopted in this study is only one specific attempt of measurement. As (Derudder, Liu, Wang, Zhang, Wu & Caset, 2021) point out, various conceptual and empirical concerns may lead to different polycentric urban development measures. While the modification of static urban spatial structure with urban planning policy is obvious and has been practised for a long time, our finding suggests the underlying interactions between the static and dynamic urban spatial structure also gone through changes. The means

the effect of planning on the dynamic urban spatial structure is also profound. Hence, the alteration of spatial interaction also needs to be included in the decision-support mechanism for a better and holistic urban policymaking and planning process.

Third, such a result brings us to the notion that simulation is part of a planning support system. As stated earlier in this paper, with information technology and data, simulation has deeply embedded in the current planning support system (Dong, Ma, Cheng, & Xin, 2017). This study's proposed workflow has combined the popular spatial interaction model with the emerging polycentricity measurement to simulate the urban spatial structure. This added new perspectives and dimensions to the planning support system with existing tools and technology. As polycentric development is increasingly emphasised in literature and practices (Taubenböck, Standfuß, Wurm, Krehl, & Siedentop, 2017; Wang, 2021), this workflow will help urban planners and policymakers predict the effect of specific urban policies on the urban spatial structure in terms of both morphological and functional polycentricity.

7. Conclusion

This research has proposed a new workflow using urban spatial interactions to simulate and measure the dynamic urban spatial structure with polycentricity. Using Singapore as a case study, this study detected and measured Singapore's dynamic urban spatial structure using the urban centres identified through spatial interaction networks. We have also explored how these spatial interactions could change with different commercial floor space allocation scenarios across Singapore; thus, it predicted how commercial floor space allocation would affect the dynamic urban structure. Two types of polycentricity are involved in this research to describe the urban spatial structure. Our simulation results suggest that urban planning practice could alter the static and dynamic urban spatial structure; the increasing morphological polycentricity is always accompanied by functional polycentricity, suggesting its positive correlation.

This study concluded that the proposed work could add value to the existing PSS by providing a new perspective on assessing urban policies that focus on the urban spatial structure and polycentric development. Although the preliminary case study has shown the workflow's potential to help urban planners and policymakers, some inherent limitations still

need to be considered. First, this study only experiments with the workflow and model at a theoretical level; its practical use is still uncertain. The scenarios proposed in the case study are hypothetical compared to policy implementation in reality; the redistribution of commercial floor space is unlikely to happen at such a dramatic scale due to various social-economic constraints. Hence, the scenario we explored is limited at the theoretical level and may not be directly transferrable to aid decision-making in practice. Second, the implementation of urban policy is much more complicated than the simplified model in this study. It is essential to acknowledge that there are many more factors in play when considering the jobs-housing interaction other than commercial floor space distribution. To name a few, factors such as the transport infrastructure (Erlander & Stewart, 1990; Tsekeris & Stathopoulos, 2006), people's choice for housing and labour markets (Hincks & Wong, 2010), and provision of municipal service (Lundberg, 2006). They all have a profound impact on the resulting spatial interaction and dynamic spatial structure. A holistic urban policy is likely to also look into these factors. Thirdly, the jobs-housing imbalance and spatial mismatch mentioned in this paper are examples of potential topics studied through the urban spatial structure using the proposed workflow. The discussion and exploration of these topics remain at an early stage. For example, more potential issues like social segregation, inequality, and unemployment are associated with a spatial mismatch, which requires more sophisticated research and discussion. Hence, the research scope and effort constraints reframe us from drawing a further conclusion on the topics. Lastly, this workflow only simulated the dynamic urban spatial structure in terms of polycentricity; it still requires other models to simulate the urban policy's overall performance from other aspects. After all, the urban spatial structure and polycentricity are only part of the story for a better and more sustainable built environment.

Nevertheless, these limitations suggest future works that could help the workflow achieve its full potential as part of a PSS. This workflow could be applied to actual planning practices where the implementation of urban planning policy is way more realistic. By doing so, we could evaluate the sensibility of this workflow and determine its usefulness to actual planning practice. Another potential direction of future work is to refine further the spatial interaction model applied in the workflow with actual planning practice. For example, the allocations of residence, commercial floor space, and transportation infrastructure improvements can be accounted for concurrently for more nuanced simulations.

Acknowledgements

References

Adolphson, M. (2009). Estimating a polycentric urban structure. Case study: Urban changes in the Stockholm region 1991–2004. *Journal of Urban Planning and Development, 135*(1), 19–30. https://doi.org/10.1061/(ASCE)0733-9488(2009)135: 1(19).

Anas, A., Arnott, R., & Small, K. A. (1998). Urban spatial structure. *Journal of Economic Literature, 36*(3), 1426–1464. https://doi.org/10.1007/978-1-349-04537-2_6.

Arribas-Bel, D., & Sanz-Gracia, F. (2014). The validity of the monocentric city model in a polycentric age: US metropolitan areas in 1990, 2000 and 2010. *Urban Geography, 35* (7), 980–997. https://doi.org/10.1080/02723638.2014.940693.

Batty, M., & Mackie, S. (1972). The calibration of gravity, entropy, and related models of spatial interaction. *Environment and Planning A: Economy and Space, 4*(2), 205–233. https://doi.org/10.1068/a040205.

Batty, M., & Cheshire, J. (2011). Cities as flows, cities of flows. *Environment and Planning. B, Planning & Design, 38*(2), 195–196. https://doi.org/10.1068/b3802ed.

Bertaud, A. (2004). *The spatial organization of cities: deliberate outcome or unforeseen consequence?*.

Burger, M., & Meijers, E. (2012). Form follows function? Linking morphological and functional Polycentricity. *Urban Studies, 49*(5), 1127–1149. https://doi.org/10.1177/0042098011407095.

Burger, M. J., van der Knaap, B., & Wall, R. S. (2014). Polycentricity and the Multiplexity of urban networks. *European Planning Studies, 22*(4), 816–840. https://doi.org/10.1080/09654313.2013.771619.

Cervero, R., & Duncan, M. (2006). Which reduces vehicle travel more: Jobs-housing balance of retail-housing mixing? *Journal of the American Planning Association, 72*(4), 475–490. https://doi.org/10.1080/01944360608976767.

Chang, F., & Das, D. (2020). Smart nation Singapore: Developing policies for a citizen-oriented Smart City initiative. In *Developing National Urban Policies* (pp. 425–440). Singapore: Springer. https://doi.org/10.1007/978-981-15-3738-7_18.

Chen, M., Arribas-Bel, D., & Singleton, A. (2019). Understanding the dynamics of urban areas of interest through volunteered geographic information. *Journal of Geographical Systems, 21*(1), 89–109. https://doi.org/10.1007/s10109-018-0284-3.

Chen, T., Hui, E. C. M., Wu, J., Lang, W., & Li, X. (2019). Identifying urban spatial structure and urban vibrancy in highly dense cities using georeferenced social media data. *Habitat International, 89*, 102005. https://doi.org/10.1016/j.habitatint.2019.102005.

Clarke, G., Langley, R., & Cardwell, W. (1998). Empirical applications of dynamic spatial interaction models. *Computers, Environment and Urban Systems, 22*(2), 157–184. https://doi.org/10.1016/S0198-9715(98)00021-0.

De Souza, R., Lau, H. C., Goh, M., Lindawati, N., W. S, & Tan, P. S. (2016). Retail precinct management: A case of commercial decentralization in Singapore. In , 12. *Transportation research procedia* (pp. 765–776). BV: Elsevier. https://doi.org/10.1016/j.trpro.2016.02.030.

Derudder, B., Liu, X., Wang, M., Zhang, W., Wu, K., & Caset, F. (2021). Measuring polycentric urban development: the importance of accurately determining the "balance" between "urban centers". *Cities, 111*, Article 103009. j.cities.2020.103009.

Development Department (HKSAR). (2016). *Hong Kong 2030+: Towards a Planning Vision and Strategy Transcending 2030*.

Dong, J., Ma, C., Cheng, W., & Xin, L. (2017). Data augmented design: Urban planning and design in the new data environment. In *2017 IEEE 2nd International Conference on Big Data Analysis, ICBDA 2017* (pp. 508–511). Institute of Electrical and Electronics Engineers Inc.. https://doi.org/10.1109/ICBDA.2017.8078685

Erlander, S., & Stewart, N. F. (1990). *The Gravity Model in Transportation Analysis: Theory and Extensions (p. 226)* (p. 226). Zeist VSP Publishers 1990 [publisher not identified]. Retrieved from http://books.google.com/books?hl=en&lr=&id=t Id3PU1leR8C&pgis=1.

Fotheringham, A. S. (1983). A new set of spatial-interaction models: The theory of competing destinations. *Environment and Planning A: Economy and Space, 15*(1), 15–36. https://doi.org/10.1177/0308518x8301500103.

Gabaix, X., & Ibragimov, R. (2011). Rank- 1/2: A simple way to improve the ols estimation of tail exponents. *Journal of Business and Economic Statistics, 29*(1), 24–39. https://doi.org/10.1198/jbes.2009.06157.

Gao, S. (2015). Spatio-temporal analytics for exploring human mobility patterns and urban dynamics in the Mobile age. *Spatial Cognition and Computation, 15*(2), 86–114. https://doi.org/10.1080/13875868.2014.984300.

Gao, S., Liu, Y., Wang, Y., & Ma, X. (2013). Discovering spatial interaction communities from mobile phone data. *Transactions in GIS, 17*(3), 463–481. https://doi.org/10.1111/tgis.12042.

Green, N. (2007). Functional polycentricity: A formal definition in terms of social network analysis. *Urban Studies, 44*(11), 2077–2103. https://doi.org/10.1080/00420980701518941.

Guo, D. (2009). Flow mapping and multivariate visualization of large spatial interaction data. *IEEE Transactions on Visualization and Computer Graphics, 15*(6), 1041–1048. https://doi.org/10.1109/TVCG.2009.143.

Guy, C. M. (1991). Spatial interaction modelling in retail planning practice: The need for robust statistical methods. *Environment and Planning. B, Planning & Design, 18*(2), 191–203. https://doi.org/10.1068/b180191.

Harris, B., & Batty, M. (1993). Locational models, geographic information and planning support systems. *Journal of Planning Education and Research, 12*(3), 184–198. https://doi.org/10.1177/0739456X9301200302.

Hasegawa, Y., Sekimoto, Y., Seto, T., Fukushima, Y., & Maeda, M. (2019). My City forecast: Urban planning communication tool for citizen with national open data. *Computers, Environment and Urban Systems, 77*, 101255. https://doi.org/10.1016/j.compenvurbsys.2018.06.001.

Hincks, S., & Wong, C. (2010). The spatial interaction of housing and labour markets: Commuting flow analysis of north West England. *Urban Studies, 47*(3), 620–649. https://doi.org/10.1177/0042098009349777.

Horner, M. W., & Mefford, J. N. (2007). Investigating urban spatial mismatch using job–housing indicators to model home–work separation. *Environment and Planning A: Economy and Space, 39*(6), 1420–1440. https://doi.org/10.1068/a37443.

Hu, L., Yang, J., Yang, T., Tu, Y., & Zhu, J. (2020). Urban spatial structure and travel in China. *Journal of Planning Literature, 35*(1), 6–24. https://doi.org/10.1177/0885412219853259.

Huang, D., Liu, Z., & Zhao, X. (2015). Monocentric or polycentric? The urban spatial structure of employment in Beijing. *Sustainability, 7*(9), 11632–11656. https://doi.org/10.3390/su70911632.

Krehl, A. (2015). Urban spatial structure: An interaction between employment and built-up volumes. *Regional Studies, Regional Science, 2*(1), 290–308. https://doi.org/10.1080/21681376.2015.1034293.

Lancichinetti, A., & Fortunato, S. (2009). Community detection algorithms: A comparative analysis. *Physical Review E - Statistical, Nonlinear, and Soft Matter Physics, 80*(5). https://doi.org/10.1103/PhysRevE.80.056117.

Liu, X., Gong, L., Gong, Y., & Liu, Y. (2015). Revealing travel patterns and city structure with taxi trip data. *Journal of Transport Geography, 43*, 78–90. https://doi.org/10.1016/j.jtrangeo.2015.01.016.

Liu, X., Derudder, B., & Wu, K. (2016). Measuring polycentric urban development in China: An intercity transportation network perspective. *Regional Studies, 50*(8), 1302–1315. https://doi.org/10.1080/00343404.2015.1004535.

Liu, X., & Wang, M. (2016). How polycentric is urban China and why? A case study of 318 cities. *Landscape and Urban Planning, 151*, 10–20. https://doi.org/10.1016/j.landurbplan.2016.03.007.

Liu, X., Wang, M., Qiang, W., Wu, K., & Wang, X. (2020). Urban form, shrinking cities, and residential carbon emissions: Evidence from Chinese city-regions. *Applied Energy, 261*, 114409. https://doi.org/10.1016/j.apenergy.2019.114409.

Lundberg, J. (2006). Spatial interaction model of spillovers from locally provided public services. *Regional Studies, 40*(6), 631–644. https://doi.org/10.1080/00343400600868788.

Masip-Tresserra, J. (2016). *Polycentricity, Performance and Planning Concepts, Evidence and Policy in Barcelona, Catalonia of Architecture and the Built Environment, OTB-Research for the Built Environment TOC.* A+BE | Architecture and the Built Environment. Retrieved from https://repository.tudelft.nl/islandora/object/uuid%3Aad2758a1-733d-4ceb-974e-adcc59dbdb8c.

van Meeteren, M., Poorthuis, A., Derudder, B., & Witlox, F. (2015). Pacifying Babel's tower: A scientometric analysis of polycentricity in urban research. *Urban Studies, 53* (6), 1278–1298. https://doi.org/10.1177/0042098015573455.

Meijers, E. (2005). Polycentric urban regions and the quest for synergy: Is a network of cities more than the sum of the parts? *Urban Studies, 42*(4), 765–781. https://doi.org/10.1080/00420980500060384.

Meijers, E. (2008). Measuring polycentricity and its promises. *European Planning Studies, 16*(9), 1313–1323. https://doi.org/10.1080/09654310802401805.

Mueller, C., Klein, U., & Hof, A. (2018). An easy-to-use spatial simulation for urban planning in smaller municipalities. *Computers, Environment and Urban Systems, 71*, 109–119. https://doi.org/10.1016/j.compenvurbsys.2018.05.002.

Münter, A., & Volgmann, K. (2020). Polycentric regions: Proposals for a new typology and terminology. *Urban Studies.* https://doi.org/10.1177/0042098020931695, 004209802093169.

Pereira, R. H. M., Nadalin, V., Monasterio, L., & Albuquerque, P. H. M. (2013). Urban centrality: A simple index. *Geographical Analysis, 45*(1), 77–89. https://doi.org/10.1111/gean.12002.

Rey, S. J., Anselin, L., Folch, D. C., Arribas-Bel, D., Sastré Gutiérrez, M. L., & Interlante, L. (2011). Measuring spatial dynamics in metropolitan areas. *Economic Development Quarterly, 25*(1), 54–64. https://doi.org/10.1177/0891242410383414.

Rosvall, M., Axelsson, D., & Bergstrom, C. T. (2009). The map equation. In *, 178. European Physical Journal: Special Topics.* https://doi.org/10.1140/epjst/e2010-01179-1.

Rosvall, M., & Bergstrom, C. T. (2008). Maps of random walks on complex networks reveal community structure. *Proceedings of the National Academy of Sciences of the United States of America, 105*(4), 1118–1123. https://doi.org/10.1073/pnas.0706851105.

Sarkar, S., Wu, H., & Levinson, D. M. (2020). Measuring polycentricity via network flows, spatial interaction and percolation. *Urban Studies, 57*(12), 2402–2422. https://doi.org/10.1177/0042098019832517.

Sohn, J. (2005). Are commuting patterns a good indicator of urban spatial structure? *Journal of Transport Geography, 13*(4), 306–317. https://doi.org/10.1016/j.jtrangeo.2004.07.005.

Taubenböck, H., Standfuß, I., Wurm, M., Krehl, A., & Siedentop, S. (2017). *Measuring morphological polycentricity-a comparative analysis of urban mass concentrations using remote sensing data.* https://doi.org/10.1016/j.compenvurbsys.2017.01.005.

Tomasiello, D. B., Giannotti, M., & Feitosa, F. F. (2020). ACCESS: An agent-based model to explore job accessibility inequalities. *Computers, Environment and Urban Systems, 81*, 101462. https://doi.org/10.1016/j.compenvurbsys.2020.101462.

Tsekeris, T., & Stathopoulos, A. (2006). Gravity models for dynamic transport planning: Development and implementation in urban networks. *Journal of Transport Geography, 14*(2), 152–160. https://doi.org/10.1016/j.jtrangeo.2005.06.009.

Urban Redevelopment Authority. (1991). *Towards a Tropical City of excellence.* Singapore: Urban Redevelopment Authority.

Walsh, C. (2012). Territorial agenda of the European union 2020: Towards an inclusive, smart and sustainable Europe of diverse regions. *Planning Theory and Practice, 13*(3), 493–496. https://doi.org/10.1080/14649357.2012.707391.

Wang, H., Zeng, W., & Cao, R. (2021). Simulation of the urban jobs–housing location selection and spatial relationship using a multi-agent approach. *ISPRS International Journal of Geo-Information, 10*(1), 16. https://doi.org/10.3390/ijgi10010016.

Wang, M., Derudder, B., & Liu, X. (2019). Polycentric urban development and economic productivity in China: A multiscalar analysis. *Environment and Planning A, 51*(8), 1622–1643. https://doi.org/10.1177/0308518X19866836.

Wang, M., Zhou, J., Long, Y., & Chen, F. (2016). Outside the ivory tower: Visualizing university students' top transit-trip destinations and popular corridors. *Regional Studies, Regional Science, 3*(1), 202–206. https://doi.org/10.1080/21681376.2016.1154798.

Wang, M. (2021). Polycentric urban development and urban amenities: Evidence from Chinese cities. *Environment and Planning B: Urban Analytics and City Science, 48*(3), 400–416. https://doi.org/10.1177/2399808320951205, 239980832095120.

Wang, M., & Debbage, N. (2021). Urban morphology and traffic congestion: Longitudinal evidence from US cities. *Computers, Environment and Urban Systems,* Article 101676. j.compenvurbsys.2021.101676.

Wei, L., Luo, Y., Wang, M., Cai, Y., Su, S., Li, B., & Ji, H. (2020). Multiscale identification of urban functional polycentricity for planning implications: An integrated approach using geo-big transport data and complex network modeling. *Habitat International, 97*, 102134. https://doi.org/10.1016/j.habitatint.2020.102134.

Yin, H., Wong, S., Xu, J., & Wong, C. K. (2002). Urban traffic flow prediction using a fuzzy-neural approach. *Transportation Research Part C: Emerging Technologies, 10*(2), 85–98.

Yuan, N. J., Zheng, Y., Xie, X., Wang, Y., Zheng, K., & Xiong, H. (2014). Discovering urban functional zones using latent activity trajectories. *IEEE Transactions on Knowledge and Data Engineering, 27*(3), 712–725.

Yuen, B. K. P. (1998). *Planning Singapore : From plan to implementation.* Singapore: Singapore Institute of Planners. Retrieved from https://books.google.co.uk/books?id=txvvIj6qS8QC&pg=PA81&dq=tien+fang+fwa&source=gbs_toc_r&cad=4#v=onepage&q&f=false.

Zhong, C., Arisona, S. M., Huang, X., Batty, M., & Schmitt, G. (2014). Detecting the dynamics of urban structure through spatial network analysis. *International Journal of Geographical Information Science, 28*(11), 2178–2199. https://doi.org/10.1080/13658816.2014.914521.

Zhong, C., Batty, M., Manley, E., Wang, J., Wang, Z., Chen, F., & Schmitt, G. (2016). Variability in regularity: Mining temporal mobility patterns in London, Singapore and Beijing using smart-card data. *PLoS One, 11*(2), Article e0149222. https://doi.org/10.1371/journal.pone.0149222.

Zhou, X., Chen, X., & Zhang, T. (2016). Impact of megacity jobs-housing spatial mismatch on commuting behaviors: A case study on central districts of Shanghai, China. *Sustainability (Switzerland), 8*(2). https://doi.org/10.3390/su8020122.