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Supply-demand measurement and spatial allocation of Sponge facilities for Sponge city construction

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A R T I C L E I N F O

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A B S T R A C T

Sponge City Construction (SCC) has been extensively explored for controlling frequent urban waterlogging and non-point source pollution. Assessing the "supply" and "demand" of SCC as a city-wide approach may aid in appropriate areal coverage to achieve optimal performance on flood control based on local priorities and sustainable urban development plans. However, to date, very few studies have examined the potential spatial mismatches in the "supply" and "demand" of SCC. This study presented the development of a framework to explore the supply–demand relationship based on a spatial multi-criteria evaluation of the existing SCC facilities, risk exposure, and socio-economic vulnerability. The feasibility and application of such a framework were successfully demonstrated in a field application in Guangzhou, China. The results indicated that most of the high-density areas in the city centres of Guangzhou were exposed to high risk with strong SCC demands. Furthermore, Liwan and Yuexiu districts exhibited SCC supply deficits, while SCC supply surpluses were observed in other central districts in Guangzhou. The findings of this study provided insight into the development of a generalised and replicable method that could be used to achieve a balance between the "supply" and "demand" of SCC for more participatory, strategic and multifunctional planning of SCC in various urban contexts.

1. Introduction

With the acceleration of urbanisation and climate change, the frequency of urban flooding and waterlog issues are becoming a global concern. The consequential deterioration of urban water quality typically has led to substantial economic losses and threatened human health (Su et al., 2018). To alleviate urban flooding, a series of adaptive initiatives leveraging natural-based solutions have been explored, and they include Low Impact Development, Best Management Practices, Sustainable Drainage Systems, and Water Sensitive Urban Design (Nguyen et al., 2020; Wang et al., 2023; Zhou et al., 2021). These theories and techniques suggest that water management issues can be partially resolved by returning the land uses to the natural state and harvesting rainwater (Xu et al., 2019). Furthermore, the natural hydrological cycle is not merely the circulation of water through the ocean, land, surface and subsurface water bodies but also a process of water purification through natural processes (Oral et al., 2020). Thus, both the quantity and quality of renewable water resources could be attained (Liu and Xia, 2011; Pokorný and Rejšková, 2008).

Among those initiatives, Sponge City Construction (SCC), proposed by the Chinese Government in 2015, is an innovative urban hydrology management program. SCC is defined as "the construction of a low impact development rainwater system for city to adapt to water environment changes like a sponge, and realise the free migration of rainwater" (Guan et al., 2021). With the aim of balancing the urban water resource on a massive scale, SCC integrates the conventional process of controlling surface runoff and other social infrastructure functions, providing multiple ecological benefits (e.g., mitigating air pollution and urban overheating) (He et al., 2019; Li and Zhang, 2022). To date, more than 30 cities in China, such as Beijing, Shanghai, and Shenzhen, have

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been involved in the pilot SCC programs. Some of these cities (e.g., Guangzhou) have been identified as demonstration cities due to their outstanding performance in urban hydrology management (GMPNRB, 2021). Although the implementation of SCC may provide cities with a wide range of benefits, several challenges and risks remain in the development of SCC, just like any other nature-based solutions worldwide. The reasons behind this phenomenon might be the undermined deliverables of SCC, including the inherently limited capabilities for stormwater retention and infiltration (Qiao et al., 2020), poor maintenance (Chen et al., 2021b), a lack of public participation (Xiang et al., 2019), substantial variation in performance due to weather, unrealistic expectations of the long-term performance of low impact development (Zeng et al., 2019), and inadequate planning of the fundamental SCC facilities (Meerow, 2019). Among these reasons, inappropriate spatial allocation of structural practices has been identified as one of the predominant factors that could result in mismatched expectations (Hou et al., 2020; Jiang et al., 2018b; Zhang et al., 2021).

Assessing the balance of SCC facilities' supply and demand supports the appropriate SCC allocation because it is a vital sign of the rationality of the spatial arrangement of the facilities (Wang et al., 2022) and can be used to achieve optimal performance and deliverables, including flood control (Cettner et al., 2013). The definition of SCC balance, however, is yet to be universally accepted since the definitions of facilities' supply and demand vary across different contexts. For example, the supply is defined as "the capacity of the facility system to provide services" by Burkhard and Maes (2017) and "the total amount of demand that can be sustained on average without causing undesirable impacts" by Van Schmidt et al. (2022). The definition of demand can be "the sum of all services currently used in a particular area over a given time period" (Burkhard et al., 2012), "expression of individual agent's preferences for specific attributes of the service" (Schröter et al., 2014), or "the amount of a service required or desired by society" (Villamagna et al., 2013). In this sense, the balance of SCC facilities' supply and demand was defined as "the equilibrium between the benefits obtained under the current SCC supply and the amount of SCC facilities required by a city", while the imbalance refers to the "benefits of SCC supply significantly over or less the amount of SCC facilities required by a city at a given time period" (Villamagna et al., 2013; Wolff et al., 2015).

Many hydrologic and hydraulic models for stormwater management have been explored for assessing urban inundation conditions associated with the supply of SCC facilities (Jiang et al., 2022). Hydraulic models based on one-dimensional and two-dimensional shallow water equations have been widely used to accurately simulate flood inundation area and depth in urban catchments (Bellos et al., 2020). However, hydraulic model applications for large regions may not be practical because they are time-consuming, data demanding, and vulnerable to errors (Chen et al., 2012; Kourtis and Tsihrintzis, 2021). Meerow and Newell (2017) proposed a large-scale model for developing the distribution relationships among SCC facilities as nodes in urban areas. This approach has been widely accepted and used to assess the supply level of water facilities. Most models are constrained by data availability, typically requiring a hydrologic dataset in sub-catchment at a sufficiently fine scale. In some cases, the datasets may be obtained from a wide range of sources, and it may be challenging to validate the accuracy. Furthermore, model development may also be burdened by computational overhead costs (Lyu et al., 2019), particularly in large-scale urban areas (Chen et al., 2021a).

Some studies have also assessed the supply and demand of ecosystem services using social survey techniques to gauge the amount of service provision and demand (Dai et al., 2021). For instance, Xiao et al. (2016) assembled a multidisciplinary team to collect supply and demand data via surveys and created a spatial flow simulation of ecosystem services. Since a questionnaire survey often requires a large number of human resources and the authenticity of data is easily affected by questionnaire design, some model-based methods have been developed to assess the mismatches. Bagstad et al. (2016) used the Artificial Intelligence for Ecosystem Services tool to map perceived ecosystem service hotspots. Based on the Invest model and the expert scale, González-García et al. (2020) evaluated the annual surplus and deficit of the ecosystem in the Madrid region of Spain from 1990 to 2012 in three services: water supply, carbon sequestration and culture. Burkhard et al. (2012) developed a supply and demand assessment framework by first quantifying the supply and demand of ecological services on different land use types using expert assessment methods and then using the difference between supply and demand indicators as a representative of the deviation between the services provided and their demand. This technique has been frequently used to evaluate the supply and demand for ecosystem services because of its high efficiency and simplicity, particularly in places with limited fundamental data (Cai et al., 2017; Herreros-Cantis and McPhearson, 2021). These studies provide insights into understanding the qualitative and quantitative assessment of supply and demand balance in ecosystem service. However, few studies have explored the "supply-demand" relationship and balance performance of SCC due to the difficulties in evaluating synergies among ecological and socio-economic outcomes of the SCC (Meerow, 2019), and the uncertainty in the knowledge of the SCC "demand" (de Manuel et al., 2021).

Additionally, assessing supply–demand mismatches only is not enough for the decision support of SCC development as the decision also requires knowledge exchange and popularisation of successful experiences for future planned upgrades (Jiang et al., 2018a). While several studies have studied the rationality of SCC resource spatial distribution, few of them focused on SCC development or improvement, particularly in terms of resource allocation and construction planning. Applying the proximity network can be a potential approach for decision support of SCC since it realises rapid exploration of complex systems by simplifying nodes and associated edges of components and interactions between components (in the form of nonlinear interaction) (Barabási, 2009; Vespignani, 2012). The proximity network has widely been used in decision support of complex urban systems (Ellinas et al., 2015; McGill et al., 2021). Vitoriano et al. (2011) created a multi-criteria optimisation model for post-disaster emergency response based on the proximity network, taking into account performance measures such as response time, distribution fairness, or reliability and safety of routes of action in order to plan resource allocation during post-disaster evacuation or rebuild key transportation routes and material distribution nodes in the transportation network. Hidalgo et al. (2020) used a proximity network approach to parameterise American amenities, simulated the ideal community amenities combination mode, and provided optimisation direction for community unit amenities combination. Due to the high application potential in guiding the optimisation of urban SCC facilities layout, especially in megacities with high heterogeneity, the network is employed for the decision support of SCC in this study.

To address the research gap in "supply-demand" measurement and decision support of SCC, a methodological assessment approach was explored to prioritise allocating SCC facilities. The main objectives are to (1) propose a methodological approach based on the index of mismatches between the "supply" and "demand" of SCC; (2) identify the priority areas where SCC facilities can be strategically placed to achieve a balance of the "supply" and "demand"; and (3) evaluate the application and development of SCC in Guangzhou, China. This method will facilitate urban planners to develop an appropriate spatial distribution plan for SCC facilities at a city-wide scale for flooding control and water resource management. The method could be generalised and applied to other cities and communities.

2. Method and materials

A framework for allocating SCC facilities has been developed, see Fig. 1. The framework begins with mapping the "supply" and "demand" of SCC. Then, a spatial multi-criteria evaluation is performed to assess the "demand" for SCC facilities by considering spatial exposure and socio-economic vulnerability. The "demand" proximity network is used

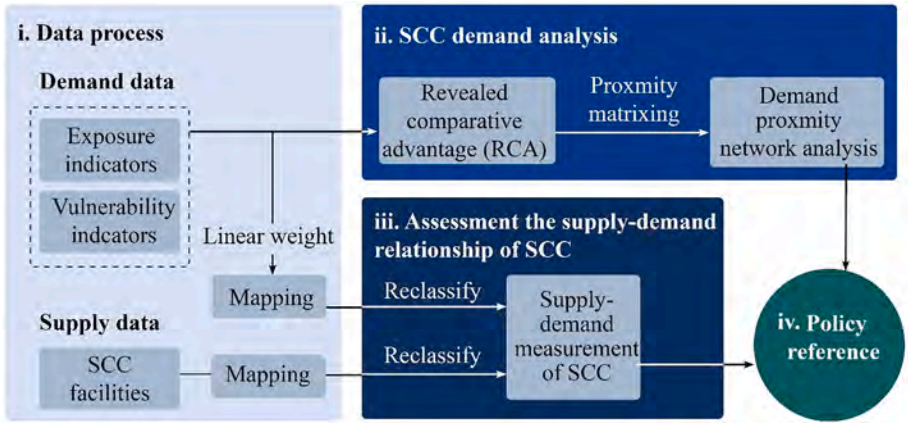

Fig. 1. The proposed framework for allocation of "supply" and "demand" in an urban region.

to establish the similarity in demand among various townships. Then by comparing the "supply" and "demand" of the facilities, an analysis is carried out to match the distributions and levels of the "supply" and "demand" scenarios. Finally, a spatial plan for SCC facilities is recommended to support the allocation of the SCC facilities using proximity network analysis and the degree of matching between the "supply" and "demand".

2.1. Study site

Guangzhou is one of the largest cities in South China, with a subtropical monsoon climate. The city was selected as the study area for two reasons: First, Guangzhou had been selected as a demonstration city of the SCC in June 2021 (GMPNRB, 2021); and second, the city is covered by highly impermeable surfaces and experiences uneven distribution of precipitation, an ideal candidate with a high risk of urban flooding (Hallegatte et al., 2013). Guangzhou has 179 townships distributed in 11 districts (Fig. 2), including six central districts (i.e., Yuexiu, Liwan, Tianhe, Haizhu, Huangpu, and Baiyun) and five suburban districts (i.e., Conghua, Huadu, Zengcheng, Panyu, and Nansha). A total of 476 facilities (i.e., green park space, construction zone, water project and road engineering) have been implemented or planned in parks, roadways, and waterways according to the Sponge City Plan of Guangzhou for 2016–2025.

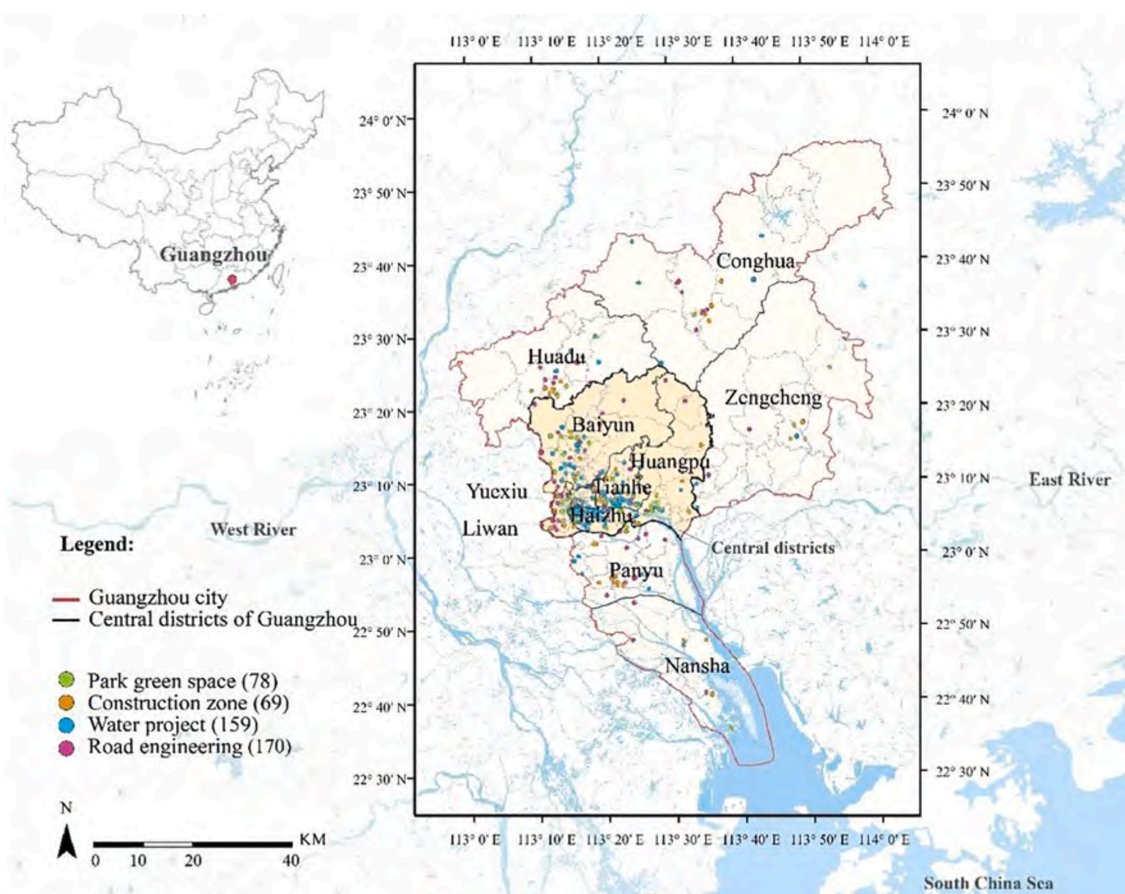

Fig. 2. The study area and major SCC facilities in Guangzhou.

This study collected information on land cover and land use, Digital Elevation Model (DEM), road network, building configuration, night-time light, and climatic data to assess the exposure and the associated risks. The census data, rental price, and Gross Domestic Product (GDP) of the townships were also collected for vulnerability assessment. Details of the data collected are shown in Table S1.

2.2. Mapping the supply–demand of SCC

2.2.1. Mapping the SCC supply

The existing SCC facilities were extracted using a geographic information system (GIS) to represent the current "supply". According to Special Planning of Guangzhou Sponge City (2016–2025) and the 2021–2025 construction tasks of Sponge City Construction in Guangzhou, 476 facilities distributed to 174 townships were regarded as spatial points for "supply" assessment. The supply level in each township depended on the number of SCC facilities in that township.

2.2.2. Mapping the SCC demand

According to several studies, the need for SCC facilities may be reflected as a risk-reduction imperative (Wolff et al., 2015). The assessment indicators based on risk comments of physical asset exposure and socio-economic vulnerability were identified following the work of Amadio et al. (2019). The indicators were subsequently combined to establish an index for mapping SCC demands using the normalisation and linear combination method.

(1) Identifying spatial exposure indicators

The objectives of SCC are primarily concerned with reducing spatial exposure to hazards, including runoff discharge, runoff quality, air pollution, and urban heat island effects, according to the evaluation standard for sponge city construction (GB51345-2018). As a result, runoff coefficient (RC), total suspended substance (TSS), Fine particulate matter (PM 2.5, aerodynamic diameter < 2.5μm), and physiological equivalent temperature (PET) were chosen to evaluate the spatial exposure.

RC was selected as an exposure indicator since it has been widely used to estimate urban runoff flow (Herreros-Cantis and McPhearson, 2021). This study employed the rational method developed by O'Loughlin et al. (1996) to calculate the RC. First, the land use data with a grid size of 30x30 m were segmented for each township. Then, the number of land use types and the corresponding areas covered in each township were identified to calculate the RC at the township level using Eq. (1).

$$RC_j = \frac{\sum_{m=1}^{|M|}(LUA_j^m \times RC_j^m)}{Area_j} \tag{1}$$

where RC_j represents the runoff coefficient of township j, LUA_j^m denotes the area of each land use type m in township j; RC_j^m represents the runoff coefficient of land type m in township j, M represents the number of land type m, and $Area_j$ represents the total area of the street in township j.

TSS is a representative non-source pollutant closely linked to land use (Wang et al., 2018), and is utilised to assess the surface runoff water quality in this study. To measure the severity of pollution, the largest accumulation of TSS simulated is commonly adopted to determine the runoff quality (Haiping and Yamada, 1996). In this paper, the functional domain area of the townships was calculated using the point of interest tool (POI) (Zhai et al., 2019). The functional domain area, street area and the maximum TSS were used as input to Eq. (2) for TSS calculation.

$$MPB_j = \frac{\sum_{1}^{|A|}(FD_j^a \times MPB_j^a)}{Area_j} \tag{2}$$

where MPB_j is the largest possible accumulation of TSS of town j;FD_j^a is the area of each functional domain a of township j, MPB_j^a represents the maximum possible accumulation of TSS of functional domain a, and $Area_j$ represents the total area of the street in township j.

Several air pollution indicators are in use, including the air quality index (AQI), ozone, and particulate matter. This study used PM 2.5 to characterise the status of air pollution based on its annual average concentration due to its negative impacts on high mortality risk (WHO, 2013) and data availability. The PM 2.5 of each gird (30x30m) in 2020 was calculated using Eq. (3) (Eeftens et al., 2012). The PM 2.5 of a township was defined as the mean PM 2.5 of all grids within the township. Fig. 3d shows the PM2.5 of the townships in Guangzhou.

$$APM2.5 = 26.101 + 4.743 \times IL_{-500} + 9.808 \times ADS \tag{3}$$

where $APM_{2.5}$ presents the annual average PM 2.5 in the year 2020; IL_{-500} is the impervious surface area of a 500-meter radius buffer zone; and $ADSu$ is the annual average wind speed of 10 m in u direction. IL_{-500} of each grid is collected by sliding through Python's array tool.

The outdoor thermal comfort indices were used as an exposure indicator because it directly assesses the impacts of urban overheating on physiological reactions and human well-being compared with other thermal indicators, such as ambient temperature and land surface temperature (Li and Liu, 2020; Qi et al., 2023). PET is one of the earliest thermal comfort indices and has been widely used to assess the outdoor thermal environment (Binarti et al., 2020). PET was also adopted in this study to assess the thermal environment of each township based on the urban climatic analysis map. The specific calculation process and method can be found in Ng et al. (2008). The input parameters of the model include land use, DEM, building data (e.g., area and height) and climatic data (e.g., wind speed). All the data were downsampled to 30x30m grids for calculating PET. PET values of all grids within a township were averaged and used to represent the PET value for the said township.

(2) Constructing socio-economic vulnerability index

Social and economic vulnerability indicators include the aged, youth, female population, GDP, and the level of education and income. A township with a large vulnerable population and poor financial conditions tends to be less resilient to risks (Rigolon et al., 2018). Specifically, the data on the population and corresponding proportions include those over 60 years old, under 14 years old, females, and people with an education level below high school. According to the method developed by Chen et al. (2016), the cost of rent was used to determine the poverty level of the low-income group. The GDP in each township was reallocated according to the observed distribution of light intensity during the night (Mirza et al., 2021).

(3) Aggregating the exposure and vulnerability indicators

A comprehensive indicator for each township was constructed by integrating the exposure and vulnerability indicators. First, all exposure and vulnerability indicators were normalised using the max–min method (Eq. (4)). Then, the normalised indicators were combined to establish a comprehensive indicator (Eq. (5)) using the linear combination method (Speak et al., 2018).

$$X' = \frac{X - X_{min}}{X_{max} - X_{min}} \tag{4}$$

$$CI = \frac{\sum_{i=1}^{n} X_i}{N} \tag{5}$$

where X' is the normalised value; X represnts the original value; X_{min} and X_{max} are the minimum and maximum value, respectively; CI is the comprehensive indicator; Xi is the normalised value of the ith indicator; and N is the total number of indicators.

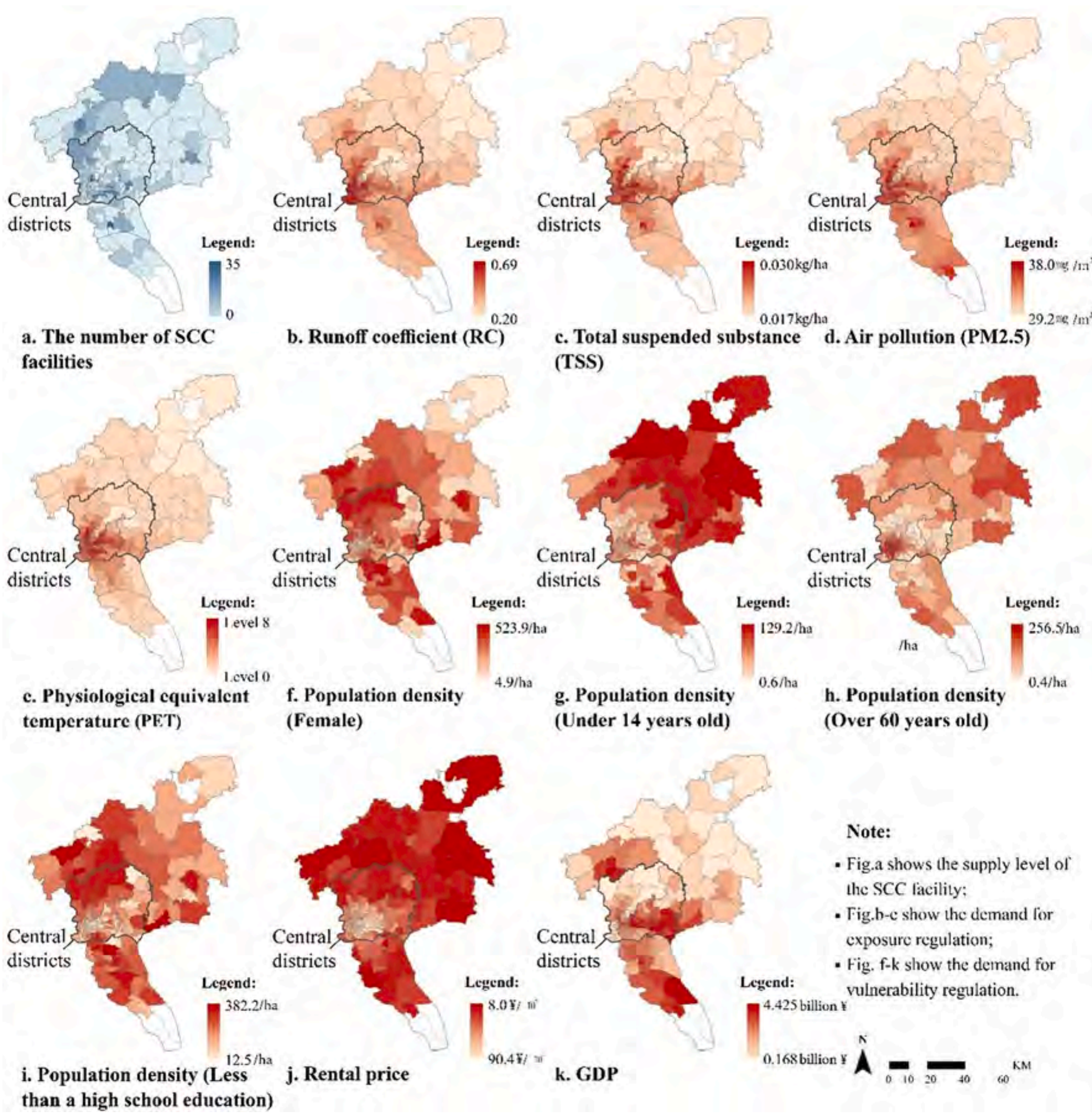

Fig. 3. The spatial distribution of the "supply" and "demand" indicators. Note: Huanglongdai township, Liuxihe township, Dalingshan township in Zhengcheng district, and Wanqingsha township, Longxue township in Nansha district were not included in the figure as the relevant data were not available.

2.3. Assessment of the supply–demand of SCC

2.3.1. Proximity matrix analysis of demand proximity network

To analyse the supply–demand of SCC, it is critical to identify the proximity, i.e., the group combination similarity of demand types faced between two nodes (or townships). The proximity matrix-based complex network proposed by Hidalgo et al. (2007) was used to extract the group combinations formed by similarity within a network structure. Specifically, the risk characteristics faced by each township were firstly established by calculating the revealed comparative advantage (RCA). Then, the proximity is characterised based on the minimum conditional probability for two nodes with the same RCA (Eq. (6)). After that, a proximity matrix was generated using a confusion matrix (Eqs. (7) and 8). Finally, a complex network was realised by using a maximum spanning tree algorithm. The sample size was defined as 176, which is consistent with the total number of townships used in this study.

$$\varnothing_{cd} = \min\{P(RCA_{ic}= 1|RCA_{id} = 1), P(RCA_{id}= 1|RCA_{ic} = 1)\} \tag{6}$$

$$RCA_{ic} = \begin{cases} 1, & x_{ic} > M_i \\ 0, & x_{ic} \le M_i \end{cases} \tag{7}$$

$$M_i = \frac{\sum_{a=1}^{a} x_i}{A} \tag{8}$$

where $\varnothing_{cd}$ is the proximity between township c and township d, RCA_{ic} is the RCA of the i indicator in township c; $P(RCA_{ic}= 1|RCA_{id} = 1)$ denotes the Conditional Probability when township c also has the same indicators same as township d; x_{ic} is the value of the demand indicator i in township c; M_i represents the average value of the demand indicator i of all townships; A indicates the number of townships.

The Fast-Newman algorithm (Eq. (9)) was used to detect the group relationship in the network (Newman, 2006). In this algorithm, the nodes in the network were divided by maximising the modularity of each cluster. The gravity in the

$$Q = \frac{1}{2m}\sum_{c,d}\left[B_{cd} - \frac{k_c k_d}{2m}\right]\delta(h_c, h_d) \tag{9}$$

where Q represents the modularity of a cluster; B_{cd} denotes the weighting of the edge between townships c and township d; kc is the sum of the weightings of edges attached to township c; h_c denotes the cluster to which township c is assigned; the value of $\delta(u, v)$ is 1 if $u = v$ and 0, otherwise, and $m = \frac{1}{2}\sum_{cd} B_{cd}$.

2.3.2. Supply-demand measurement of SCC

The construction of large-scale SCC has been carried out in the central districts of Guangzhou since 2016. Whereas the construction in the suburbs is still in progress and with certain uncertainties (GMPNRB, 2021). This study, therefore, mainly focused on the "supply-demand" balance of SCC in the central districts of Guangzhou. The matching measure was utilised to assess the "supply-demand" balance of SCC. First, the townships were classified into three "supply" and "demand" categories (i.e., high, medium, and low with scores of 3, 2, and 1, respectively) according to their "supply" and "demand" values. Specifically, all townships were ranked according to their supply and demand levels. If the rank of a township is higher than one-sixth in supply or demand, it is defined as the high supply or demand category. Townships with ranks less than one-sixth or half are defined as the medium and low supply or demand categories, respectively. The ratio of the high, medium, and low "supply" or "demand" townships was defined as 1:2:3 so that we can identify the almost top 15% high "supply" or "demand" townships to align with Guangzhou's urban development policy to increase the total built-up areas for SCC from 30% in 2022 to 45% in 2025 (PGGM, 2021, 2022). Second, the "demand" scores of townships were subtracted from the corresponding "supply" scores to estimate the overall scores of "supply-demand" balance (ranging from −2 to 2). Positive and negative scores indicate the oversupply and undersupply of SCC facilities, respectively. The high absolute value of overall scores indicates the high "supply-demand" imbalance of SCC in townships, while the low absolute value indicates a relative balance with a slight difference between the supply and demand of SCC.

3. Results

3.1. The spatial distribution of SCC supply and demand indicators

Fig. 3 shows the spatial distribution of SCC supply and demand indicators in Guangzhou. Guangzhou's SCC supply level was unevenly distributed throughout municipalities, with the centre district having more amenities than the suburbs (Fig. 3a). For example, the Tianhe district in the urban area had 58 facilities, significantly higher than the Nansha district (7 facilities) in the suburban areas. All exposure indicators (Fig. 3b-e) showed a similar spatial distribution and are concentrated in the southwest of the central district, which is one of the city's oldest. This finding is consistent with previous research, which has demonstrated that these exposure risks are directly associated with urban form. For instance, high impermeability makes high-density cities more vulnerable to runoff danger than suburbs (Zhang et al., 2018) and runoff running through urban areas carries more sediment (Yazdi et al., 2021). The interplay between the discharge of concentrated pollutants (industrial waste gas, tail gas, etc.) and urban form exacerbates urban air pollution (Yang et al., 2020). At the same time, the heat island effect is common in urban areas due to modified land cover, urban fabric and urban geometry (Qi et al., 2022a). In contrast to exposure indicators, high-vulnerability locations, particularly population density (less than a high school education) and rental price indicators, were primarily found in suburban areas (Fig. 3f-k).

3.2. Demand proximity network analysis

Fig. 4a presents the results of proximity network analysis, clustering the townships with the same spatial characteristics and similar levels of SCC demand. The spatial distribution of clustered townships is shown in Fig. 4(b-c). Four townships (i.e., Xinzao, Guanzhou, Huazhou, and Pazhou) were not included in any cluster, and the rest of the townships were divided into four clusters. The townships in Cluster 1 and Cluster 2 were mainly situated in the urban areas, while those in Cluster 3 and Cluster 4 were predominantly distributed in the suburban areas. To better identify the characteristics and risks of each cluster, low-performance indicators were assigned to the cluster according to the RCA values. If more than 50% of the member townships in the cluster spot low performance in an indicator, that indicator was adopted as the low-performance indicator for this cluster (Table 1).

There were 53 townships in Cluster 1 (green colour in Fig. 4), mainly situated in Guangzhou's old districts (e.g., Yuexiu, Liwan and Haizhu) and industrial areas. More than 90% of the townships in this cluster showed low performance in all exposure indicators (i.e., RC, TSS, PM2.5 and PET), indicating the high-risk exposure of this cluster. 88.7% of the townships in Cluster 1 showed low performance in vulnerable people over 60 years old. Cluster 2 (red colour in Fig. 4) included 32 townships, most of which were Guangzhou's newly developed urban areas. This cluster also showed high-risk exposure because of low performance on PET and TSS. The low-performance vulnerability indicators in Cluster 2

Table 1
Low-performance indicators of four clusters.

Indicators	Cluster 1	Cluster 2	Cluster 3	Cluster 4
Total number	53	32	66	19
RC	98.1%*	93.8%*	7.6%	0%
TSS	94.3%*	96.9%*	7.6%	0%
PM2.5	96.2%*	87.5%*	10.6%	5%
PET	92.5%*	96.9%*	10.6%	0%
Population density (Female)	3.8%	100%*	80.3%*	0%
Population density (Under 14 years old)	32.1%	31.3%	66.7%*	80%*
Population density (Over 60 years old)	88.7%*	34.4%	28.8%	50%*
Population density (Less than high school education)	5.7%	84.4%*	84.8%*	0%
Residential income	9.4%	18.8%	86.4%*	8%
GDP	52.8%*	62.5%*	48.5%	35%

Note:* means low-performance indicators of clusters.

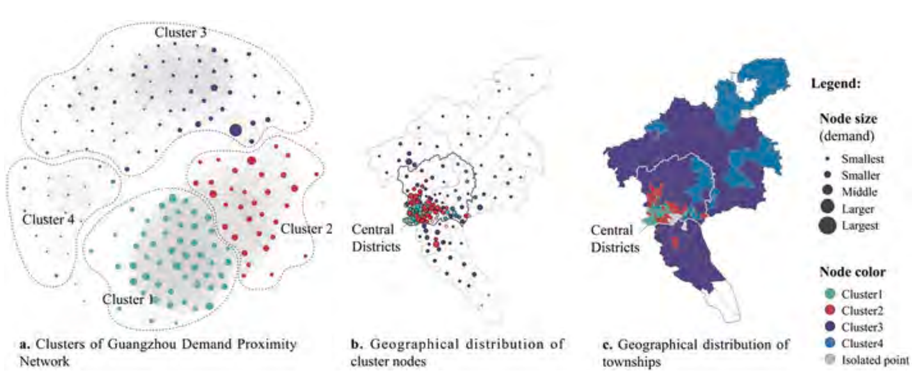

Fig. 4. Proximity matrix analysis of the supply–demand network.

were attributable to population density (Female and below high school level of education), and GDP. Cluster 3 (purple colour in Fig. 4) included 66 townships and was mainly distributed in the newly developed urban or suburban areas. The townships in this cluster were particularly vulnerable due to low performance in education level, income, and vulnerable population (female and under 14 years old). There were 19 townships in Cluster 4 (blue colour in Fig. 4), situated in the mountains and secondary forests in Guangzhou. The over 60- and under 14-year-old populations were the vulnerable groups in this cluster. Overall, the "demands" of the clusters in the urban areas (Clusters 1 and 2) were homogeneous with high-risk exposure, while the "demands" of clusters in suburban areas (Clusters 3 and 4) were similar to low-risk exposure but high vulnerability in the population under 14 years old.

3.3. Supply-demand balance of SCC

Fig. 5 shows the "supply-demand" balance of SCC in the central districts of Guangzhou. The results show that 37.5% of the townships in the central districts showed a relatively balanced "supply-demand". Of these townships, 37.8% showed high "supply" and "demand" and were situated around the southwest of the central districts (Fig. 5b). It is not surprising the high SCC demand in these districts since they are located in the urban areas and have a high level of exposure. For example, Jinhua township had a high number of SCC facilities (17), and all its exposure values of RC, TSS, PM2.5 and PET were the top ten among all townships. Comparatively, the balanced townships showed low "supply" and "demand" and were predominantly clustered in the northeast. This is because many townships (e.g., Luogang, Changlin, and Yonghe townships) are newly developed and suburban areas with a low number of SCC facilities (less than 1) and a low level of exposure and vulnerability, particularly in GDP. Fig. 5c shows that most townships (62.5%) were not balanced between the "supply" and "demand" of SCC. "Oversupply" was the primary cause in certain townships, indicating adequate SCC facilities and resources. The townships with oversupply were also located in suburban areas with a low level of exposure and vulnerability. Other townships showed insufficient supplies, and they were mainly situated in the southwestern area. This is mainly attributed to the low SCC facilities and extremely high demand for SCC in this area. For instance, the Hualin has no SCC facilities but the highest TSS, RC, PM 2.5 and second-highest PET, implying high priority in the future allocation of SCC facilities.

At the district level, the ratios (Fig. 5d) of "balanced" and "imbalanced" townships in Huangpu, Tianhe, and Baiyun were approximately 1:1, while the number of "imbalanced" townships in other districts was

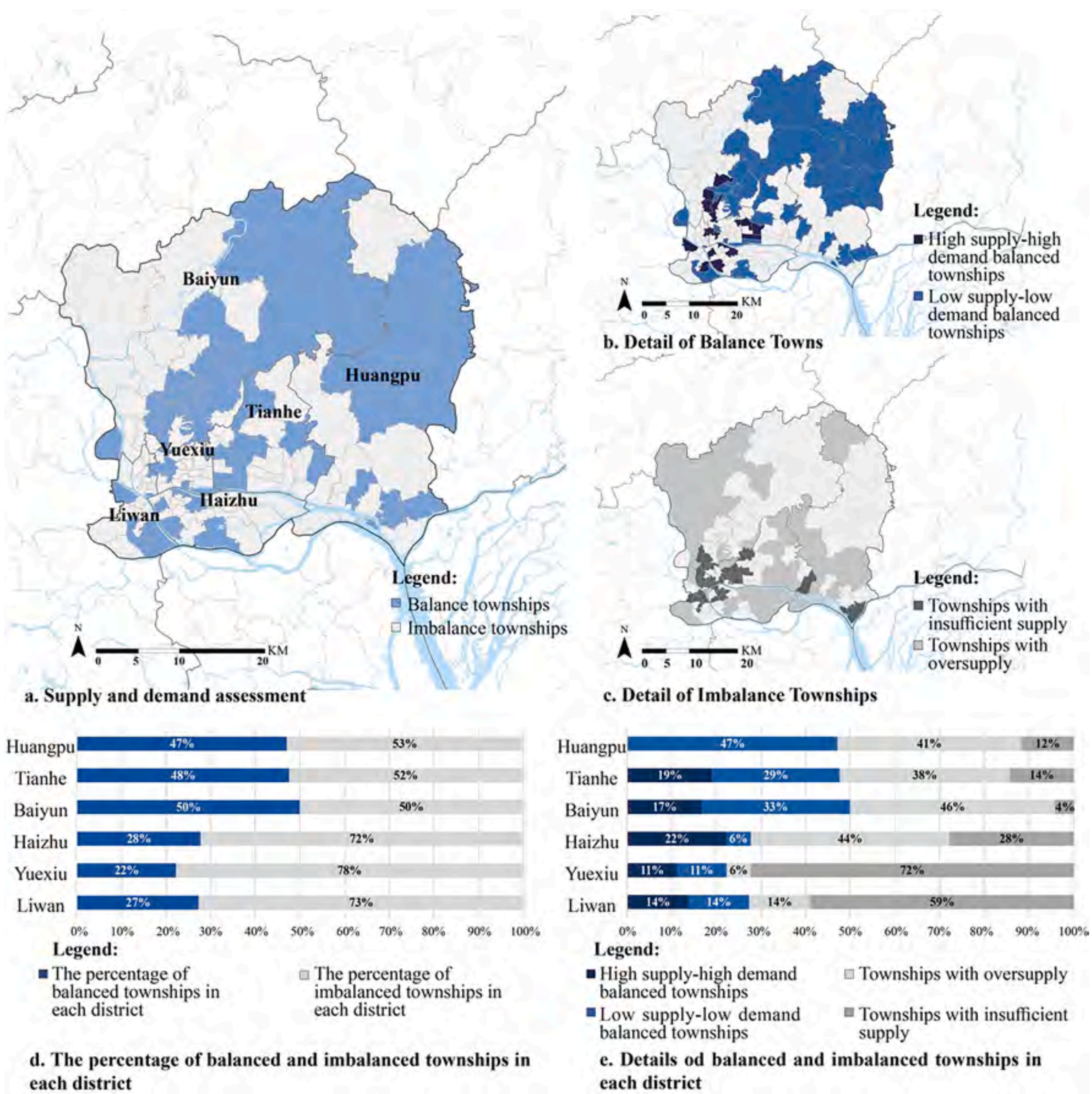

Fig. 5. "Supply-demand" of SCC in the central district of Guangzhou.

almost 2.5 times higher than the number of “balanced” townships. The main reason for the imbalance in most districts was “oversupply” (Fig. 5e). For example, 46% of the townships in Baiyun were “oversupplied”. In comparison, most townships in Yuexiu (72%) and Liwan (59%) showed insufficient “supply”, indicating inadequate SCC in these areas.

4. Discussion

4.1. The assessment of the SCC supply–demand balance

This study has developed a model for assessing spatial mismatches in the “supply” and “demand” of SCC facilities to achieve optimal performance. The model quantified the SCC demands based on the risk concepts of exposure and vulnerability to address uncertainty in the knowledge of the SCC “demand” (de Manuel et al., 2021). The exposure and vulnerability indicators (e.g., RC, PM 2.5, and population density) were identified according to the criteria in the evaluation standard for sponge city construction (GB51345-2018) and association with SCC demands. The reasonableness of our method has been demonstrated by Wolff et al. (2015), who defined risk reduction as one type of demand in ecosystem service.

Also, assessing the supply–demand should fully consider the urban contexts, as the “supply” performance and “demand” requirements vary significantly across cities and locations of facilities (Zhang and Chui, 2018). This study identified the indicators for measuring the supply–demand balance of SCC, considering the environmental and socio-economic demands of cities. Compared with previous studies (Bellos et al., 2020; Chen et al., 2012; Jiang et al., 2022; Kourtis and Tsihrintzis, 2021; Meerow and Newell, 2017), our model focuses on tailoring the relationship between supply and demand to the urban contexts.

The model can identify the balanced and imbalanced townships based on the relative relationship between the supply and demand of SCC facilities. The results can not only inform the priority (or imbalanced) townships that urgently need the SCC facilities and the predominant reasons for the imbalance but also identify the balanced townships that can be the references for SCC development or improvement. Since the demand of SCC facilities keeps changing (Wolff et al., 2015), the results serve to inform the state of relative “balance” or “imbalance” of townships in SSC at a given period. For example, the overall score of “0″ in this study means a small range of difference between ”supply“ and ”demand“ rather than an absolute ”supply-demand“ balance. This means that the current SCC supplies may not really satisfy the SCC demands in the balanced townships.

4.2. “supply” and “demand” of SCC in Guangzhou

The cluster analysis of proximity networks reveals that the townships situated within the urban areas (Cluster 1 and Cluster 2) showed higher risk exposure compared to those situated in the newly developed and suburban areas (Cluster 3 and Cluster 4). The results show that more than 90% of the townships in Cluster 1 and Cluster 2, and less than 10% of the townships in Cluster 3 and Cluster 4, showed high-risk exposure, possibly because the former in the central areas has been developed during the earlier period and has caused more severe environmental impacts in their development (Cai et al., 2020). For example, urban sprawl has changed the natural land into impermeable surfaces, leading to a higher risk of runoff volume and water pollution in urban areas

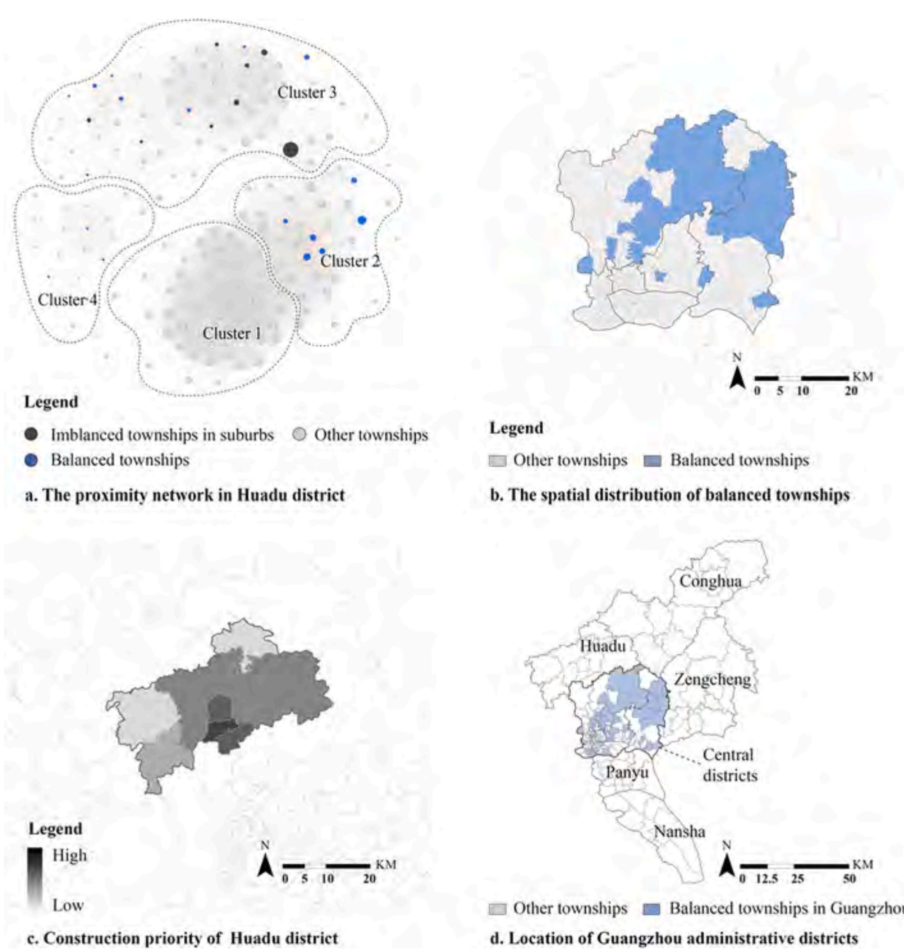

Fig. 6. The reference network for the construction of SCC at the Huadu district.

(Yazdi et al., 2021). Also, poor thermal comfort in urban areas can result from urban heat island effects (Qi et al., 2021) and poor wind flow and urban ventilation (He et al., 2020).

It is also noted that most townships in Yuexiu and Liwan showed insufficient “supplies” (Fig. 6e), due to the high SCC demand and the low number of SCC facilities in these districts. On the one hand, the high “demand” is mainly attributed to the high-risk exposure and vulnerability, as demonstrated by Pan et al. (2010), who assessed Guangzhou’s environmental flood risk (e.g., flood frequency, annual rainstorm day, and annual precipitation) and human-related vulnerability (e.g., flood control factors, population density, and GDP). The results of the present study show that Yuexiu and Liwan districts have a higher flood risk and vulnerability to the subject area and population compared to other districts in the central areas. On the other hand, the area of low coverage of SCC facilities was situated in densely populated and built-up townships, plausibly due to space availability in the built-up townships and high costs of retrofitting (Hou et al., 2021).

4.3. Implications

This study assessed the “supply” and “demand” of SCC and clustered townships with “balanced” and “imbalanced” “supply-demand” using proximity network analysis. The results provide insight and guidance to SCC development and the extent of implementation. At the district level, the “balanced” and “imbalanced” townships in the central districts have been identified (Fig. 5). In one interpretation, decision-makers would get to understand the situations of the “imbalanced” townships under their care so that they could consider appropriate priority and strategies to implement SSC at the township and district level. To further support SCC planning for the “imbalanced” districts, “reference networks” at the district level could be mapped out by integrating the results of “supply-demand” balance and “demand” proximity network analysis. The reference networks allow decision-makers to examine the “balanced” townships with similar attributes and use the townships as a reference to guide the construction of SCC in districts under their charge. As an example, Fig. 6 provides the reference network for the Huadu district. It can be seen that the“ imbalanced” township were all situated within Clusters 1 and 2 (Fig. 6a). Fig. 6 (b-c) shows the “balanced” township with similar attributes, and they could then be used as a reference to SCC planning in Huadu district. The reference networks of other districts are included in Fig. S1-5. In addition, the low-performance indicators, as described in Table 1, allow decision-makers to identify the main reasons for being “imbalanced” in a certain district. For example, Yuexiu and Liwan depicted a high percentage of “imbalanced” townships (70%), and the predominant reason for the “imbalance” was the inadequate level of SCC “supply”.

At the township level, since the “supply” and “demand” of various townships vary significantly, a context-based approach is required for the management and construction of sponge cities. Maps of context-based reference networks for the construction of SCC at the township level are included in Fig. 7. Taking the Xinhua township in the Huadu district as an example (black points in Fig. 6a), decision-makers may first extract the townships in the same cluster as these townships showed similar SCC “demand” and urban contexts. Then, the extracted townships with the “supply-demand” balance may be identified using the map of reference networks (Fig. 7). This example shows that there are 6 “Balanced” townships (the inner circle in Fig. 7), such as Shijing and Shipai. Both townships have similar “demand” and urban contexts as

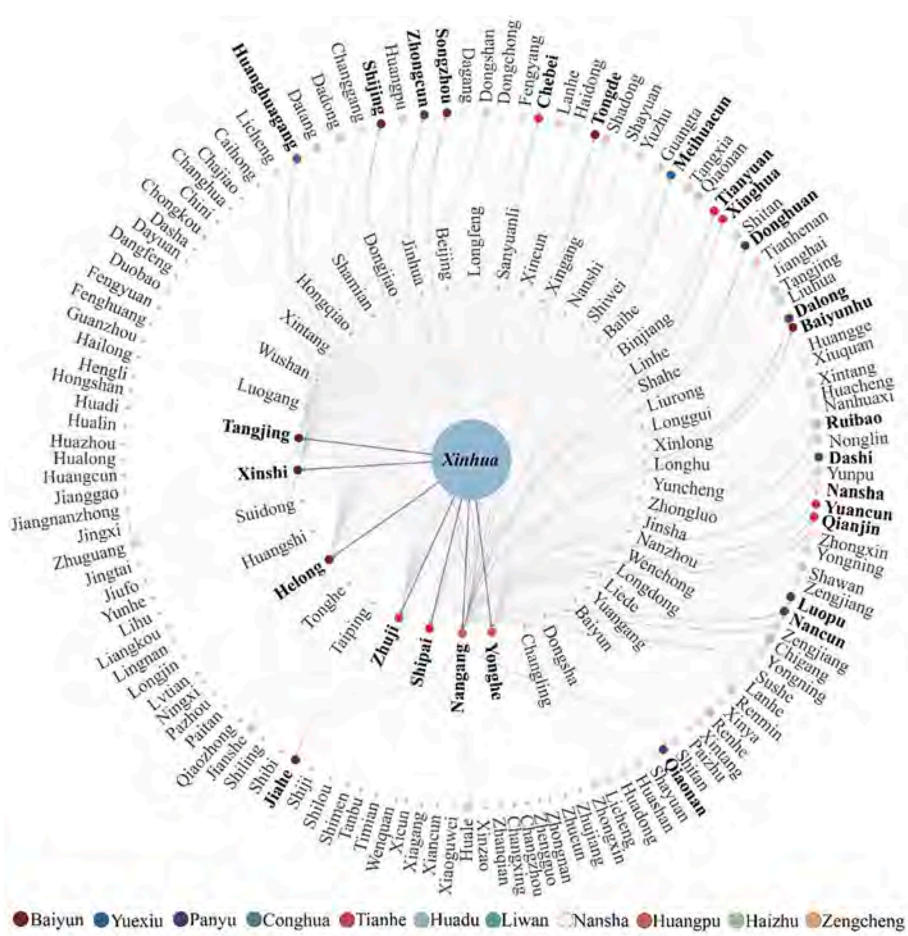

Fig. 7. The reference network for the construction of SCC at the township level.

that of Xinhua and can therefore be used as a reference for SCC "supply" allocation in Xinhua. The outer circle of the network (Fig. 7) exhibits a different perspective, implying a group of "imperfect" townships which could benefit from joint management or experience sharing among the townships.

It is also noted that the reference network maps could be used jointly with other management methods in the SCC practices. For instance, the reference network shown in this paper is well-suited to management information systems (MISs), which may serve as the communication channel among various components of the sponge city (Sorensen et al., 2021; Zhang et al., 2019). Integrating the reference network and MISs allows decision-makers to identify appropriate strategies for SCC development in a certain target area. Consider highly built-up and "imbalanced" townships. The development of SCC in such townships may have many challenges, such as insufficient space and the high cost of retrofitting (Hou et al., 2021). Decision-makers may then adopt certain strategies (e.g., green roofs and bioretention systems) based on the experience of "balanced" townships (spotting the same urban contexts using reference networks and identifying appropriate ones using MISs).

4.4. Limitations

This study assessed the state of balance in the "supply-demand" of SCC in Guangzhou based on matching and mapping methodologies. It focuses on the "supply-demand" of SCC at the district and township level rather than the local or community level. It is well-noted that guidance at a local level is crucial in the actual planning of SCC and design variables. Therefore, a planning approach based on the local or community level should be developed. Also, RCA was employed to analyse the uncertainty of exposure and vulnerability indicators, and subsequent identification of low-performance indicators for each township, and clustering of townships with similar attributes. This method is qualitative in nature and could only serve to provide a "high" and "low" performance assessment based on the clustering techniques rather than a systemical uncertainty analysis. Finally, there are several types of SCC facilities, such as green parks, water projects and grey infrastructures. This study mainly considers the quantity of SCC facilities in the supply assessment and does not discuss the quality of different facilities. However, the supply quality varies across the facility types, for example, the green parks and water projects have varying performances in flood control and human health promotion (Qi et al., 2022b). Thus, the quality of SCC facilities should be fully considered to support a more comprehensive assessment in the future.

5. Conclusions

This study described the development of a method to evaluate the state of the "supply-demand" balance of SCC facilities, which can be used as a rationale for allocating resources and facilities for a certain objective. The following conclusions can be drawn. First, the proposed methodology integrates the state of "demand" and "supply" in the process of allocation of SCC facilities. In this way, the writers successfully explored the supply–demand relationships and identified the priority regions for allocating and distributing SCC resources and facilities in Guangzhou. Second, the clustering results of the "demand" proximity network mapping indicate that townships with similar "demand" shared strong spatial attributes. Townships in densely built-up urban areas exhibited high-risk exposure and strong SCC demand. Suburban urbanising townships exhibited a certain degree of high vulnerability. Third, more than 50% of townships in Guangzhou's central districts showed "supply-demand" imbalances. The lead reason for imbalanced townships in Yuexiu and Liwan districts was the insufficient supply of SCC resources and facilities, while the imbalanced townships in the remaining districts showed oversupply.

The successful SCC implementations were evaluated and used to transfer the successful experience to similar areas through mapped reference networks at district and township levels. The reference network maps can be used to support the rational allocation of SCC facilities and reduce the mismatch between the "demand" and "supply". The method proposed in the present study may be used as an assessment tool and aid decision-making in SCC development. This method may also be integrated with other management methods to improve the overall efficiency of SCC development.

CRediT authorship contribution statement

Mo Wang: Conceptualization, Methodology, Writing – original draft, Supervision. **Haojun Yuan:** Methodology, Investigation, Software, Visualization, Data curation. **Dongqing Zhang:** Methodology, Validation, Supervision. **Jinda Qi:** Conceptualization, Validation, Formal analysis, Methodology, Writing – review & editing. **Qiuyi Rao:** Validation, Formal analysis, Data curation. **Jianjun Li:** Methodology, Validation, Supervision. **Soon Keat Tan:** Methodology, Validation, Supervision.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.ecolind.2023.110141.

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