Investigating spatial relationship between physical built-environmental vitality and social vitality in London

Programme: MRes Spatial Data Science and Visualisation

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1 Introduction

Urban growth is an aggregation process (Bergsman et al., 1972), in which the built environment and social elements are continually enriched and flourished. Along with the urbanization process, the concentration of urban land and human activities within cities has become a persistent and increasing tendency (Liu et al., 2012; Montgomery, 2008). However, a rising literature documents that urban land expands faster than social vitality grows, which results in declining urban densities and inefficient use of urban land (Liu, 2018; Long et al., 2012; Xu et al., 2019). The mismatch of physical urban expansion and social vitality brings challenges to sustainable development (e.g., optimal land resources use) (Chi et al., 2015; Dempsey et al., 2011; Jin et al., 2017). In terms of land consumption, low densities and sprawling development have the characteristics of inefficient land resources use and have negative environmental impacts (Camagni et al., 2002). Identifying the spatial aggregation patterns of physical urban expansion and social growth is vital to understand the urban system and helps provide a basis for land resources use and policy implications.

With the latest research progress, it is now widely accepted that urban vitality is affected by urban morphology (physical built environment) and urban society (social vitality) (Burger and Meijers, 2012; Jin et al., 2017; Yue et al., 2019). Urban vitality is defined as the urban morphology that supports urban function and social activities (Lynch, 1984). Jacobs (Jacobs, 1961) argued that the combination of human activities and living places is composed of urban vitality. Previous studies quantified urban vitality's characteristics mainly from the two dimensions: the physical built-environmental vitality and social vitality, which are two important indicators of urban vitality. The physical built-environment is classified as the element of the physical environment that is built or modified by human activity (Saelens and Handy, 2008), which includes urban areas, buildings, public areas, structures, and transportation systems, etc. (Brownson et al., 2009). Moreover, Social vitality refers to the immaterial environment involving urban life, including economic development, culture, social rights, and social management etc. (Banerjee, 2001).

Quantifying the spatial aggregation of both physical built-environmental vitality and social vitality will contribute to our knowledge of dual urban vitality and perhaps in developing countries or rapidly urbanizing regions. Understanding the spatial aggregation of physical built-environment and social vitality in cities is beneficial for sustainable development and urban planning.(Zeng et al., 2018).

2 Research question

Although previous studies have found that social vitality in most regions lags behind physical urban growth, there is limited research on quantifying the spatial patterns and aggregation levels and on comparing the spatial differences between the two urban vitalities. The understanding of the mismatch between the physical urban expansion and the social development in cities is rather limited due to the lack of a quantitative measurement criterion. In this study, we seek to explore the spatial distribution patterns of physical and social vitality in London and the extent to which they match spatially. We propose a framework combining the physical aspect of built-environment and social vitality to understand urban elements' spatial aggregation.

3 Literature review

As part of the urban environment that is easily observed and described, the physical built-environment has attracted considerable attention from scholars (Gospodini, 2001; Sauer, 2008). The studies of urban spatial structure can be traced back to the concentric structure of Burgess (Burgess, 1925), the single-center structure with sector distribution proposed by Hoyt (Hoyt, 1939), and the multi-center structure proposed by Harris and Ullman (Harris and Ullman, 1945). Researches on the physical built-environment have developed rapidly from the mid-twentieth century (Burger and Meijers, 2012; Kloosterman and Musterd, 2001; McPherson, 1981). Until now, the measurement of the morphology, pattern, and spatial structure of cities still mainly focuses on the physical built-environmental terms (Broadbent, 2003; Gospodini, 2001; Li et al., 2016).

With urbanization, many diverse populations are concentrated in cities, which has led to an increase in attractiveness to social and economic activities (Madlener and Sunak, 2011; Törnqvist, 1968). The social and economic attributes of urban space are getting more and more attention from researchers (Castells, 1989; Gerecke et al., 2019; Lefebvre and Nicholson-Smith, 1991; Louail et al., 2015; Tonkiss, 2005; Yeh et al., 1995). Green (2007) used social network analysis to define morphological and functional polycentricity. Dempsey et al. (2011) explored and defined the concept of social development in detail in the urban context and explored the relationship between urban form and social development. Eisazadeh and Vahdani (2017) collected data through the field method to explore the role of urban spaces and structures in increasing social vitality. Zarin et al. (2015) evaluated the physical and social aspects of street vitality in Tehran. Zumelzu and Barrientos-Trinanes (2019) used quantitative and qualitative methods to explore urban morphology's effects on urban vitality. Tu et al. (2020) investigated the spatial patterns of urban vitality indicated by multisource urban sensing data (points-of-interest, social media check-ins, and mobile phone records).

Recent studies have found that there is spatial interdependency between physical built-environment and social activities (Burger and Meijers, 2012; Gerecke et al., 2019; Yue et al., 2019). While there is a mismatch between built-environment and social activities, social activities' advancement generally lags behind built-environment development (Yue et al., 2019). A large area was constructed into a built environment, but it attracted few residents, social and economic activities, which led to the phenomenon of "ghost cities" (Batty, 2016; Jin et al., 2017). This phenomenon is mainly due to overemphasizing physical built-environment expansion while neglecting the promotion of social vitality.

4 Methodology

4.1 Study area and data sources

London was selected as our study area, the capital and largest city of England and the United Kingdom. It should be noted that the selection of an appropriate geographical scale is important for urban analytics, as fine-scale data are often considered highly sensitive from census outputs, and lots of information will be lost with lower precision data. We use the mesoscale data provided by the Office for National Statistics (ONS) grouping in the Lower Layer Super Output Area (LSOA). The LSOA contains between 1000 and 3000 inhabitants living in between 400 and 1200 households: At this scale, it is possible to show slight variations in the area's composition, while the sample size in each area is statistically reliable.

The past measurement of physical built-environmental vitality is based on various data sets, such as building height data, land use maps, remote sensing images, and road networks (Cai et al., 2017; Jin et al., 2017; Liu et al., 2019; Yue et al., 2010). In this study, we use the building height data. Buildings are the most important feature of physical built-environment structure, and we collect the building height data in London from https://buildingheights.emu-analytics.net/.

In measuring social vitality, the most predominant data includes trajectory data of human activities and location-based points-of-interest (POIs) data (Li et al., 2018; Ma et al., 2017; Pelletier et al., 2011; Yao et al., 2017). Past research has shown that small catering businesses, while not reflecting all aspects of social vitality, can serve as indicators of urban places' attractiveness (Ye et al., 2018; Xia, Yeh and Zhang, 2020). A vitality area tends to have a thriving small catering business. On the one hand, this is because the survival of small catering businesses depends on footfall and intensive social activity. On the other hand, the areas where small catering businesses develop are usually suitable and promote walking and resting activities. Therefore, where small catering businesses develop, places tend to be densely populated, and we use POIs of small catering businesses to estimate social vitality. We collect POIs data from Digimap (https://digimap.edina.ac.uk/), and select six preliminary categories of POIs:

Cafes, snack bars and tea rooms; Fast food and takeaway outlets; Fast food delivery services; Fish and chip shops; Pubs, bars and inns; Restaurants.

4.2 Measurements of physical built-environmental vitality and social vitality

Two indicators are used: physical building vitality (BV) and social vitality (SV). BV can be obtained from the data collected on building height, which contains information on the spatial coordinates, basic contours and floor area of the building. BV is the ratio of the total floor area to the area of LSOA.

$$BV_i = \frac{V_i}{A_i}$$

where BV_i is the physical built-environment vitality of LSOA i, V_i is the total floor area of LSOA i, A_i is the area of s LSOA i. V_i can be calculated by sum the f

SV can be obtained from the POI data collected. This data contains the spatial coordinates of the POI, together with information on the type of POI, and the SV reflects the density of small catering business poi in the LSOA.

$$SV_i = \frac{N_{poi}}{A_i}$$

where SV_i is the social vitality of LSOA i, N_{poi} is the number of small catering business in LSOA i, A_i is the area of LSOA i.

4.3 Local Moran's I statistics

Local indicators of spatial association (LISA) have been used to evaluate the local interaction between the physical built-environment and social vitality. Past research has shown that LISA can detect significant areas that may indicate spatial patterns (Chen, Liu, & Li, 2017; Xia, Yeh and Zhang, 2020). We use bivariate LISA to identify the significant LSOAs with high physical vitality and low social vitality, or with high social vitality and low physical vitality. The pattern of LISA can indicate a mismatch between physical built-environment and social vitality. We calculate the bivariate variable LISA, as

$$I_i^{k,l} = Z_{i,k} \sum_{j=1}^{n} W_{ij} \times z_{j,l}$$

$$\mathrm{z_{i,k}} = \frac{(\mathrm{X_{i,k}} - \overline{\mathrm{X_k}})}{\sigma_\mathrm{k}}, \ \mathrm{z_{i,l}} = \frac{\mathrm{X_{i,l}} - \overline{\mathrm{X_l}}}{\sigma_\mathrm{l}}$$

where $X_{i,k}$ and $X_{i,l}$ are the values of BV and SV for LSOA i; $\overline{X_k}$ and $\overline{X_l}$ are the means of BV and SV; and σ_k and σ_l are the standard deviations of variable BV and SV. According to LISA statistics, four categories can be clustered, including low BV LSOAs with low SV (LL), high BV LSOAs with high SV (HH), high BV LSOAs with low SV (HL), low BV LSOAs with high SV (LH). LISA statistics were calculated in R (version 4.0) in this study.

5 Results

5.1 Spatial patterns of physical built-environmental vitality and social vitality

We calculated the physical built environment vitality and social vitality for each LSOA, and the histograms are shown in Fig. 1., from which we can see that the maximum frequency of social vitality is much higher than physical built-environmental vitality, which indicates that social vitality has a higher degree of agglomeration than physical built-environmental vitality, and also implies that the difference in social vitality between LSOAs is much greater than physical built-environmental vitality. We show the spatial patterns of physical built-environmental vitality and social vitality using the Jenks natural breaks method into four levels, as shown in Fig. 2. From the spatial distribution, we can see that although both social vitality and physical built-environmental vitality reflect an agglomeration pattern in the city centre, social vitality is much more clustered than physical built-environmental vitality.

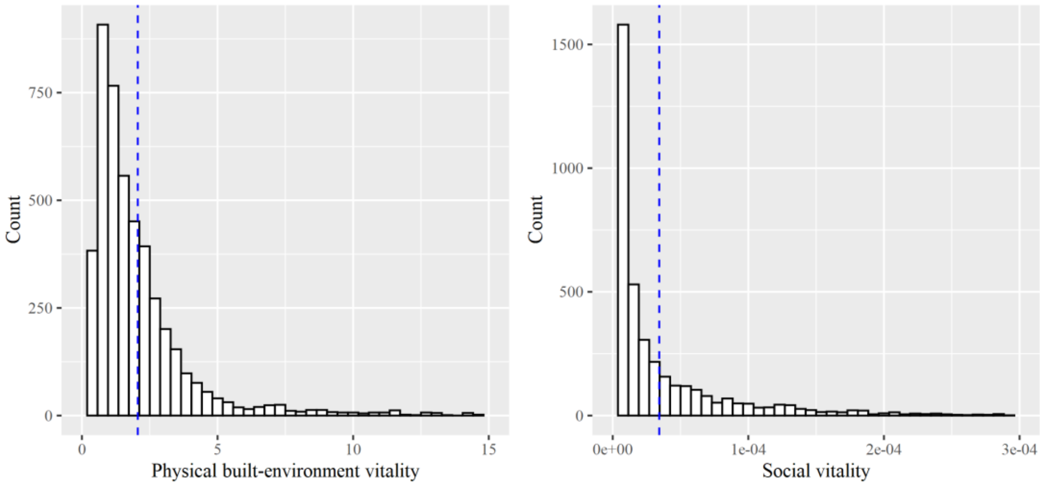

Fig. 1. Histogram plot of physical built-environmental vitality and social vitality in London.

From the diagram, we can see that the cities exhibit polycentric characteristics in both physical built-environment and social vitality, but it shows a mismatch of these two aspects. In terms of spatial agglomeration pattern, the physical built-environment vitality mainly presents the two-level aggregated pattern of "main center and sub-centers." High-density elements are concentrated in the city's main center, and some moderate-aggregated sub-centers are formed around it. The elements of social vitality are highly concentrated in urban central areas, with several low-density clusters near the main center.

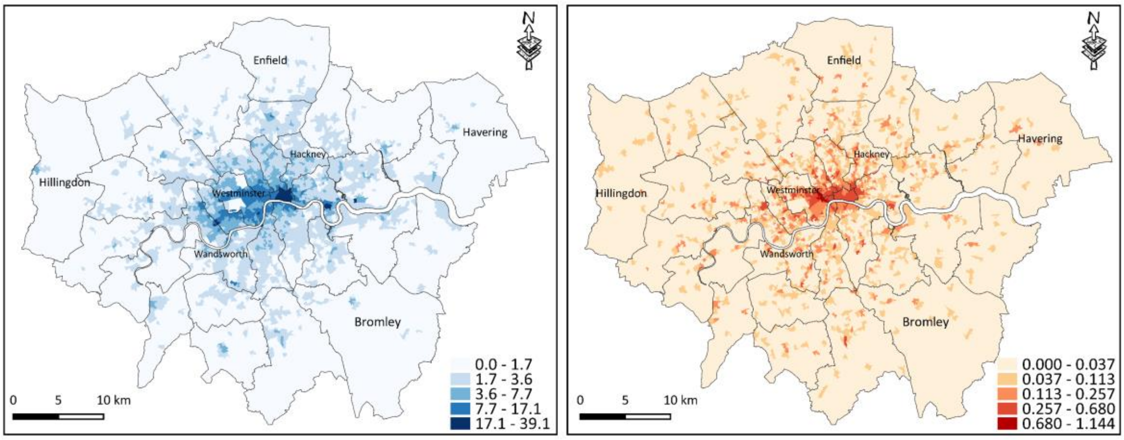

Fig. 2. Spatial pattern of physical built-environmental vitality and social vitality in London.

5.2 Spatial relationship between physical built-environmental vitality and social vitality

The results of the global Moran's I is 0.47 and that is highly significant (p-value < 0.01), which indicates a significant spatial autocorrelation between physical built-environmental vitality and social vitality. This result means both physical built-environmental vitality and social vitality are relatively high in urban centres and relatively low on the urban fringe, suggesting that the local patterns of urban physical built-environmental vitality and social vitality are similar.

Based on the LISA statistics, LSOAs were clustered into HH, HL, LH, and LL. The hot spot (HH) zones are concentrated near and around the city centre, the cold spot clusters (LL zones) are mainly scattered in the periphery of the city; the insignificant (NS) zones occupy a large area in and around the city centre; the six LSOA zones show LH clustering, this clustering indicates that there is a high social vitality and a low physical built-environmental vitality in this LSOA zone, the two largest of which are in the Westminster district which may be due to the influence of inner-city parks. It is worth noting that six other LSOA areas are identified as HL agglomerations. They are mainly located in the periphery of the city, which suggests that in these areas, the urban building is developing faster than social dynamics in comparison and may become urban. No contiguous HL agglomerations were identified in the results, suggesting that the development of urban buildings in London has largely kept pace with the development of social dynamism. Some HH areas are concentrated near the city centre, reflecting the monocentric urban character of London, and the presence of rivers does not affect the concentration of HH hotspots.

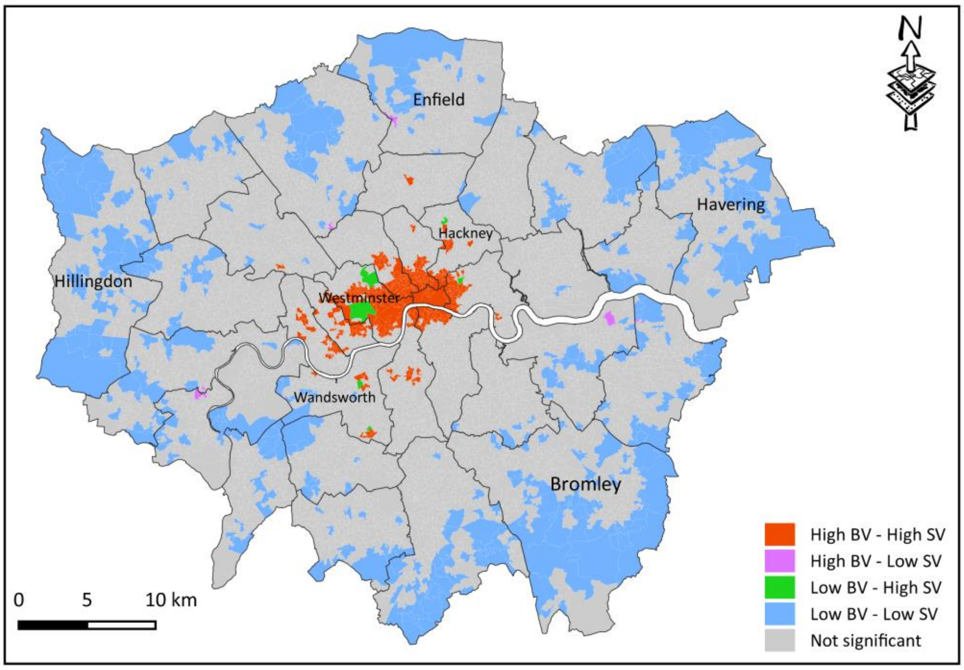

Fig. 3. Local spatial correlation between physical built-environmental vitality and social vitality in London.

6 Discussion

The present study estimated spatial aggregation patterns of urban vitality in London. Then we quantify and compare the aggregation degree of social vitality and physical built-environmental vitality. The similarities and disparities are revealed between the physical built-environmental vitality and social vitality. Physical built-environment vitality and social vitality both show polycentricity, but the spatial aggregated patterns of dual urban vitality have a huge difference. Physical built-environment vitality show a highly apparent polycentricity spatial distribution structure with dispersed high-density clusters throughout the city. In contrast, low-density clusters can be observed around the main center of social vitality. Both the densities of physical built-environment vitality elements and social vitality elements show an obvious distance decay from the center of the city, but the densities of physical vitality decrease slower, indicating a low aggregation degree. A spatial correlation analysis is presented to characterize spatial aggregation patterns between physical built-environment vitality and social vitality.

With unprecedented urban growth and urban expansion, the recreation and enhancement of urban vitality are necessarily emphasized to sustainable urban development. This research's main contribution lies in the quantitative analysis of the spatial aggregation degrees of physical and social properties of urban vitality. Urban sustainable development not only relates to physical construction but also to social and economic activities. With the wide application of big and open data, assessing urban vitality from multiple dimensions provides the basis for recreating and enhancing urban vitality. Built environments are direct reflections of the degree of urban physical construction. The density of small catering businesses demonstrates the prosperity and vitality of urban socio-economic activities. The quantitative estimation of the aggregation degree of multiple dimensions of urban vitality provides a theoretical reference for improving the city's comprehensive vitality.

Although the study has demonstrated the spatial aggregated patterns and correlation of physical built-environment vitality and social vitality, it has certain limitations in terms of the spatial scale.

Considering human activities and social networks, the results of urban vitality estimation on a fine spatial scale may be more comprehensive, which is a key reflection of urban vitality. The spatial aggregation mechanism of urban vitality elements is a crucial issue in understanding the development of polycentric aggregation in cities. It also requires extensive fine-scale statistics collection and big data capture, and we will focus on in future work.

7 Conclusion

This study carried out a spatial aggregation assessment of urban vitality and compared London's physical built-environment vitality and social vitality. The results suggest a spatial mismatch between the physical built-environment and social vitality: the physical built-environment vitality has multiple centers with dispersive distribution, whereas social vitality primarily lies in the urban central area. The development of social vitality generally consistent with that of the physical built environment in London. Both physical built-environment vitality and social vitality show a clear trend of decreasing as the distance from the city center increases. The global Moran results show a significant spatial autocorrelation between physical built-environmental vitality and social vitality.

These findings enhance our understanding of spatial patterns of urban elements and the evolution of urban multiple elements. In future research, the quantitative assessment of spatial aggregation with finer spatial scales will be explored (e.g., blocks and grids). Furthermore, the dynamic changes of urban vitality will be taken into account.

References

Anas, A., Arnott, R., Small, K.A., 1998. Urban spatial structure. Journal of economic literature 36, 1426–1464.

Angel, S., Parent, J., Civco, D.L., Blei, A.M., 2016. Atlas of Urban Expansion—2016 Edition, Volume 1: Areas and Densities, New York: New York University, Nairobi: UN-Habitat, and Cambridge, MA: Lincoln Institute of Land Policy.

Banerjee, T., 2001. The Future of Public Space: Beyond Invented Streets and Reinvented Places. Journal of the American Planning Association 67, 9–24. https://doi.org/10.1080/01944360108976352

Batty, M., 2016. Empty buildings, shrinking cities and ghost towns. SAGE Publications Sage UK: London, England.

Bergsman, J., Greenston, P., Healy, R., 1972. The agglomeration process in urban growth. Urban Studies 9, 263–288.

Botev, Z.I., Grotowski, J.F., Kroese, D.P., 2010. Kernel density estimation via diffusion. The annals of Statistics 38, 2916–2957.

Bren, D.C., Reitsma, F., Baiocchi, G., Barthel, S., Guneralp, B., Erb, K.H., Haberl, H., Creutzig, F., Seto, K.C., 2017. Future urban land expansion and implications for global croplands. Proceedings of the National Academy of Sciences 114, 8939–8944. https://doi.org/10.1073/pnas.1606036114

Broadbent, G., 2003. Emerging concepts in urban space design. Taylor & Francis.

Brownson, R.C., Hoehner, C.M., Day, K., Forsyth, A., Sallis, J.F., 2009. Measuring the Built Environment for Physical Activity: State of the Science. American Journal of Preventive Medicine, Measurement of the Food and Physical Activity Environments 36, S99-S123.e12. https://doi.org/10.1016/j.amepre.2009.01.005

Burger, M., Meijers, E., 2012. Form follows function? Linking morphological and functional polycentricity. Urban studies 49, 1127–1149.

Burgess, E.W., 1925. The growth of the city: An introduction to a research project. The City 47–62.

Cai, J., Huang, B., Song, Y., 2017. Using multi-source geospatial big data to identify the structure of polycentric cities. Remote Sensing of Environment 202, 210–221.

Castells, M., 1989. The informational city: Information technology, economic restructuring, and the urban-regional process. Basil Blackwell Oxford.

Chen, Z., Yu, B., Song, W., Liu, H., Wu, Q., Shi, K., Wu, J., 2017. A New Approach for Detecting Urban Centers and Their Spatial Structure With Nighttime Light Remote Sensing. IEEE Transactions on Geoscience and Remote Sensing 55, 6305–6319. https://doi.org/10.1109/TGRS.2017.2725917

Cushman, S.A., McGarigal, K., Neel, M.C., 2008. Parsimony in landscape metrics: Strength, universality, and consistency. Ecological Indicators 8, 691–703. https://doi.org/10.1016/j.ecolind.2007.12.002

Dong, T., Jiao, L., Xu, G., Yang, L., Liu, J., 2019. Towards sustainability? Analyzing changing urban form patterns in the United States, Europe, and China. Science of The Total Environment 671, 632–643. https://doi.org/10.1016/j.scitotenv.2019.03.269

Gerecke, M., Hagen, O., Bolliger, J., Hersperger, A.M., Kienast, F., Price, B., Pellissier, L., 2019. Assessing potential landscape service trade-offs driven by urbanization in Switzerland. Palgrave Commun 5, 1–13. https://doi.org/10.1057/s41599-019-0316-8

Giuliano, G., Small, K.A., 1991. Subcenters in the Los Angeles region. Regional science and urban economics 21, 163–182.

Gong, P., Li, X., Zhang, W., 2019. 40-Year (1978–2017) human settlement changes in China reflected by impervious surfaces from satellite remote sensing. Science Bulletin 64, 756–763. https://doi.org/10.1016/j.scib.2019.04.024

Gospodini, A., 2001. Urban design, urban space morphology, urban tourism: an emerging new paradigm concerning their relationship. European Planning Studies 9, 925–934.

Harris, C.D., Ullman, E.L., 1945. The nature of cities. The Annals of the American Academy of Political and Social Science 242, 7–17.

He, H.S., DeZonia, B.E., Mladenoff, D.J., 2000. An aggregation index (AI) to quantify spatial patterns of landscapes. Landscape Ecology 15, 591–601. https://doi.org/10.1023/A:1008102521322

Hoyt, H., 1939. The structure and growth of residential neighborhoods in American cities. US Government Printing Office.

Jacobs, J., 1961. The Death and Life of Great American Cities. Randow House, New York.

Jiao, L., 2015. Urban land density function: A new method to characterize urban expansion. Landscape and Urban Planning 139, 26–39. https://doi.org/10.1016/j.landurbplan.2015.02.017

Jin, X., Long, Y., Sun, W., Lu, Y., Yang, X., Tang, J., 2017. Evaluating cities' vitality and identifying ghost cities in China with emerging geographical data. Cities 63, 98–109.

Kane, K., Connors, J.P., Galletti, C.S., 2014. Beyond fragmentation at the fringe: A path-dependent, high-resolution analysis of urban land cover in Phoenix, Arizona. Applied Geography 52, 123–134. https://doi.org/10.1016/j.apgeog.2014.05.002

Kloosterman, R.C., Musterd, S., 2001. The polycentric urban region: towards a research agenda. Urban studies 38, 623–633.

Lefebvre, H., Nicholson-Smith, D., 1991. The production of space. Oxford Blackwell.

Li, M., Kwan, M.-P., Wang, F., Wang, J., 2018. Using points-of-interest data to estimate commuting patterns in central Shanghai, China. Journal of Transport Geography 72, 201–210. https://doi.org/10.1016/j.jtrangeo.2018.09.004

Li, M., Shen, Z., Hao, X., 2016. Revealing the relationship between spatio-temporal distribution of population and urban function with social media data. GeoJournal 81, 919–935.

Liu, G., Yao, X., Luo, Z., Kang, S., Long, W., Fan, Q., Gao, P., 2019. Agglomeration centrality to examine spatial scaling law in cities. Computers, Environment and Urban Systems 77, 101357. https://doi.org/10.1016/j.compenvurbsys.2019.101357

Liu, Y., 2018. Introduction to land use and rural sustainability in China. Land Use Policy 74, 1–4.

Liu, Z., He, C., Zhang, Q., Huang, Q., Yang, Y., 2012. Extracting the dynamics of urban expansion in China using DMSP-OLS nighttime light data from 1992 to 2008. Landscape and Urban Planning 106, 62–72.

Louail, T., Lenormand, M., Cantu Ros, O.G., Picornell, M., Herranz, R., Frias-Martinez, E., Ramasco, J.J., Barthelemy, M., 2015. From mobile phone data to the spatial structure of cities. Sci Rep 4, 5276. https://doi.org/10.1038/srep05276

Lynch, K., 1984. Good city form. MIT press.

Ma, X., Liu, C., Wen, H., Wang, Y., Wu, Y.-J., 2017. Understanding commuting patterns using transit smart card data. Journal of Transport Geography 58, 135–145. https://doi.org/10.1016/j.jtrangeo.2016.12.001

Madlener, R., Sunak, Y., 2011. Impacts of urbanization on urban structures and energy demand: What can we learn for urban energy planning and urbanization management? Sustainable Cities and Society 1, 45–53. https://doi.org/10.1016/j.scs.2010.08.006

McGarigal, K., Marks, B.J., 1995. FRAGSTATS: spatial pattern analysis program for quantifying landscape structure. Gen. Tech. Rep. PNW-GTR-351. Portland, OR: U.S. Department of Agriculture, Forest Service, Pacific Northwest Research Station. 122 p 351. https://doi.org/10.2737/PNW-GTR-351

McPherson, J.C., 1981. The implications of central place theory for urban structure in a declining region: the North American experience. Papers in Regional Science 47, 35–43.

Montgomery, M.R., 2008. The urban transformation of the developing world. science 319, 761–764.

Nelson, A.C., 1986. Using land markets to evaluate urban containment programs. Journal of the American Planning Association 52, 156–171.

Pelletier, M.-P., Trépanier, M., Morency, C., 2011. Smart card data use in public transit: A literature review. Transportation Research Part C: Emerging Technologies 19, 557–568. https://doi.org/10.1016/j.trc.2010.12.003

Peng, J., Zhao, S., Liu, Y., Tian, L., 2016. Identifying the urban-rural fringe using wavelet transform and kernel density estimation: A case study in Beijing City, China. Environmental modelling & software 83, 286–302.

Saelens, B.E., Handy, S.L., 2008. Built environment correlates of walking: a review. Medicine and science in sports and exercise 40, S550.

Sauer, C., 2008. The morphology of landscape, in: The Cultural Geography Reader. Routledge, pp. 108–116.

Schneider, A., Woodcock, C.E., 2008. Compact, dispersed, fragmented, extensive? A comparison of urban growth in twenty-five global cities using remotely sensed data, pattern metrics and census information. Urban Studies 45, 659–692. https://doi.org/10.1177/0042098007087340

Seto, K.C., Golden, J.S., Alberti, M., Turner, B.L., 2017. Sustainability in an urbanizing planet. Proceedings of the National Academy of Sciences 114, 8935–8938. https://doi.org/10.1073/pnas.1606037114

Terrell, G.R., Scott, D.W., 1992. Variable kernel density estimation. The Annals of Statistics 20, 1236–1265.

Tonkiss, F., 2005. Space, the city and social theory: Social relations and urban forms. Polity.

Törnqvist, G., 1968. Flows of Information and the Location of Economic Activities. Geografiska Annaler: Series B, Human Geography 50, 99–107. https://doi.org/10.1080/04353684.1968.11879320

Tsai, Y.H., 2005. Quantifying urban form: Compactness versus "Sprawl." Urban Studies 42, 141–161. https://doi.org/10.1080/004209804200309748

Von Böventer, E., 1976. Transportation costs, accessibility, and agglomeration economies. Papers in Regional Science 37, 167–183.

Wrenn, D.H., Irwin, E.G., 2012. How do land use policies influence fragmentation An econometric model of land development with spatial simulation. Environmental Economics 3, 81–95.

Wu, Q., Liu, H., Wang, S., Yu, B., Beck, R., Hinkel, K., 2015. A localized contour tree method for deriving geometric and topological properties of complex surface depressions based on high-resolution topographical data. International Journal of Geographical Information Science 29, 2041–2060. https://doi.org/10.1080/13658816.2015.1038719

Xia, C., Yeh, A. G.-O. and Zhang, A. (2020) 'Analyzing spatial relationships between urban land use intensity and urban vitality at street block level: A case study of five Chinese megacities', Landscape and Urban Planning, 193, p. 103669. doi: 10.1016/j.landurbplan.2019.103669.

Yao, Y., Li, X., Liu, X., Liu, P., Liang, Z., Zhang, J., Mai, K., 2017. Sensing spatial distribution of urban land use by integrating points-of-interest and Google Word2Vec model. International Journal of Geographical Information Science 31, 825–848.

Yeh, A.G.-O., Xu, X., Hu, H., 1995. The social space of Guangzhou city, China. Urban Geography 16, 595–621.

Yue, W., Liu, Y., Fan, P., 2010. Polycentric urban development: the case of Hangzhou. Environment and planning A 42, 563–577.

Yue, W., Wang, T., Liu, Y., Zhang, Q., Ye, X., 2019. Mismatch of morphological and functional polycentricity in Chinese cities: An evidence from land development and functional linkage. Land Use Policy 88, 104176. https://doi.org/10.1016/j.landusepol.2019.104176

Zeng, C., Song, Y., He, Q., Shen, F., 2018. Spatially explicit assessment on urban vitality: Case studies in Chicago and Wuhan. Sustainable Cities and Society 40, 296–306. https://doi.org/10.1016/j.scs.2018.04.021

Zhou, X., Wang, Y.-C., 2011. Spatial-temporal dynamics of urban green space in response to rapid urbanization and greening policies. Landscape and Urban Planning 100, 268–277. https://doi.org/10.1016/j.landurbplan.2010.12.013

Declaration of Authorship

I, Zhengzi Zhou, confirm that the work presented in this assessment is my own. Where information has been derived from other sources, I confirm that this has been indicated in the work.

Zhengzi Zhou

Date of signature: Monday, 11 January 2021

Assessment due date: 11 January 2021