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Editorial

Measuring human-scale urban form and its performance

1. Introduction

This special section of Landscape & Urban Planning (LAND) “Measuring human-scale urban form and its performance” represents a collection of approaches to analyzing, describing and understanding the physical fabric of human-scale urban form and its corresponding socioeconomic and environmental performance. The rapid development of information and communication technology (ICT) is gradually becoming integrated with the built environment, which leads to the rise of new urban science manifesting as a new infrastructure of sensing, data collection, and analysis of urbanism (Townsend, 2015).

Throughout the history of architecture, urban planning and landscape architecture, most existing theories about human-scale urban form that can be directly seen by the eyes or touched by the hands have been generated using social science approaches, such as surveys, or even through subjective intuition and practical experience. Herein, the “human-scale” means a fine scale characterized by the human body and its surroundings, i.e., a scale that is directly visible, touchable, and appreciable in a person’s daily life (Long & Ye, 2016). Recently, technological advances made possible the objective study of how people interact with their surrounding environment. By integrating multi-source urban data and geospatial analyses with machine learning algorithms, it is now possible to gain insights into how people use urban spaces, how they feel about them, and how spaces perform in various kinds of situations (Zhang, Ye, Zeng, & Chiaradia, 2019).

Examples of such data include Street View Images (SVIs) provided by Internet companies such as Google and Baidu, 3-D models of buildings and streets generated by laser scanning (LiDAR), geotagged photos uploaded by users to websites such as Flickr, digital footprints of human being tracked by sensors such as mobile phones, wearable devices and social media records. These data depict the physical and nonphysical dimensions of urban form and its environmental, energetic, and thermal performances, in addition to describing people’s mobility, activity, and emotional states as they live within urban areas, at fine temporal and spatial scales. Meanwhile, newly developed analytical techniques, including geospatial analyses, machine learning, data mining and virtual reality, also supplement an objective and direct understanding of human-scale urban form by making use of the new emerging data. Scholars are now able to objectively measure human-scale urban form with these tools.

This special section provides an exploration of a novel lens through which to understand small-scale urban form and its social performance, thus facilitating planning and design at such a scale. We aim to address theoretical, methodological, and empirical issues in human-scale urban form and its performance using new emerging data and cutting-edge techniques.

2. Background

The study of human-scale urban form, i.e., the shapes, plans, and structures of the built fabric, and its associated performance has been ongoing since the 1960s. As a rethinking of modernist planning and design, a series of pioneering urbanists, such as Jacobs (1961) and Lefebvre (1962), initially described the characteristics of human-scale urban form and how it contributes to positive social and cultural performance. Following this movement, subjective descriptions of human-scale urban form and how its benefits centers of activity were then given by Gehl (1971), Lynch (1981), Whyte (1980), Montgomery (1998), and others. Quantitative studies have been made as a further exploration on human-scale, physical form and perceived quality (Smith, Nelischer, & Perkins, 1997; Oh, 1998; Jackson, 2003; Fan & Khattak, 2009). In response, Ewing and Clemente (2013) noted that it is possible to measure elusive qualities that were previously unmeasured in the book *Measuring Urban Design: Metrics for Livable Places*. Since the publication of that book, scholars have gradually extended this field of research (Marcus, Berghauser Pont, & Barthel, 2015; Mueller, Lu, Chirkin, Klein, & Schmitt, 2018; Lu, Sarkar, & Xiao, 2018; Long & Huang, 2019; Ye, Xie, Fang, Jiang, & Wang, 2019; Middel, Lukasczyk, Zakrzewski, Arnold, & Maciejewski, 2019).

New research potential has emerged due to the widespread use of new data theories and analytical methods. First, open data and big data with detailed geo-references provide an opportunity to quantitatively reflect on both urban form and its performance (Zhou & Long, 2016; Ye & Liu, 2018). On the one hand, an explosion of big data and open data with the development of improved computing capacity have opened up a human-centered perspective by enabling the measurement of how people experience urban form in a new, accurate and consistent way. Numerous types of data, including cell phone data, social media data, and geotagged photographs, provide a human-centered approach that can deepen urbanists’ understandings of urban form’s various performances in the spatial and temporal dimensions (Ferreira, Poco, Vo, Freire, & Silva, 2013; Dunkel, 2015; Glaeser, Kominers, Luca, & Naik, 2015; Song, Long, Wu, & Wang, 2018; Vanderhaegen & Canters, 2017). On the other hand, the new data environment also helps provide a detailed and quantified illustration of urban form. In addition to the commonly used Open Street Map (OSM), which provides a basic physical framework, there are many other data generated on the human scale that have been used in recent years. For instance, Google Street View has been used to inform aspects of 3-D city model construction (Torii, Havlena, & Pajdla, 2009), to quantify street greenery (Li et al., 2015; Long & Liu, 2017), and to layer interpretation with respect to the ground, pedestrians, vehicles, buildings and sky (Yin & Wang, 2016).

Second, many new analytical methods also contribute to the human-scale understanding of urban form and its performance. Machine

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learning algorithms, especially convolutional neural networks, provide an approach that is capable of distilling information on the social performance of urban form from a large amount of street view image data or geotagged photos (Rundle, Bader, Richards, Neckerman, & Teitler, 2011; Zamir, Darino, & Shah, 2011; Naik, Philipoom, Raskar, & Hidalgo, 2014). Meanwhile, these machine learning algorithms, such as Support Vector Machine and Random Forest, address the complex, interactive relationships among built environment features. In addition, morphological tools, such as Spacematrix (Berghauser-Pont & Haupt, 2010), Urban Network Analysis (Sevtsuk & Mekonnen, 2012), and Form Syntax (Ye, Yeh, Zhuang, Van Nes, & Liu, 2017), provide opportunities to quantitatively analyze urban form and measure these previously unmeasurable detailed morphological features.

The combination of a new data environment and new analytical methods facilitates a sophisticated approach to the human-centered urban form research program. Several studies are gradually emerging that are measuring the intangibles that were hard to measure in the past. For instance, the combined application of wide-coverage street view images and machine learning algorithms has been used to measure the construction and maintenance quality of building façades and the continuity of street walls (Liu, Silva, Wu, & Wang, 2017), walkability (Lu et al., 2018), visual quality (Tang & Long, 2018), and human sensing of place (Zhang et al., 2018; Middel et al., 2019). With the help of multisource urban data and analytical tools, the economic benefits of high-quality human-scale urban form have also been explored (Ye et al., 2019).

With these tools and approaches, scholars are able to objectively measure both human-scale urban form and its performance, although four decades have passed since Rapoport (1977) set the goal of developing a man-environment approach to urban form and design. In short, we are witnessing the transition into a new science of cities with a focus on human-centered issues.

While there is an increasing literature in this field, to solidify the direction of research towards measuring the human-scale urban form and its performance, further systematic exploration is still needed. We need a clear conceptual framework and sophisticated empirical studies to illustrate the emerging research potential of the new data environment and new analytical methods. Not only do we need a thorough and scientific understanding of the urban form and its performance, but this knowledge must also serve as a foundation for the exploration of alternative futures. In this special session, we seek to develop a systematic discussion of the potential of the new technologies and data approaches in this field.

3. This special section

This special section contains six related papers. Xu (2018) combines several geospatial datasets with transportation survey data to evaluate the relationship between the street-scale urban form and walking activities from the perspective of the elderly population, while Shach-Pinsly (2018) combines GIS datasets with crime records from different sources to measure the urban elements that influence the sense of security in the built environment. Apart from the ever-improving GIS datasets, increasing the availability of SVIs and their nature with regard to reflecting human-scale urban form has enabled researchers to effectively measure the street elements and conditions from the users' perspective. Ye et al. (2018) demonstrate how to integrate high-resolution measurements on both eye-level street greenery and accessibility through street view image extraction and spatial design network analysis (sDNA), taking Singapore as an example. Lu (2018) provides an approach to evaluating both the quantity and quality of street greenery and the association of those characteristics with recreational physical activity in outdoor environments using SVIs and survey data collected from 1390 participants in 24 real estate projects in Hong Kong. Moreover, researchers can further their research in both the spatial and temporal dimensions. Li and Ratti (2018) use Google Street View panoramas and building height models to generate hemispherical images to better estimate the spatiotemporal distribution of solar radiation within street canyons from a human-scale perspective. Tang and Long (2018) use Tencent SVIs taken in 2012 and 2016 to explore the visual quality of street space and its temporal variation in the Hutong area in Beijing. The six included papers can be regarded as an early exploration of human-scale urban form measurements and evaluation of the performance of human-scale urban form, indicating promising opportunities in both academic research and practical applications. We expect more extensive and in-depth studies in this avenue in the near future, given the ubiquitous Internet of things and the popularity of wearable devices, which are promising data sources for human-scale urban form research.

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