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Identifying urban spatial structure and urban vibrancy in highly dense cities using georeferenced social media data

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A B S T R A C T

Tracking human activities with social media (online social networks) and point of interest data to understand human dynamic distribution, behavior, and high-density urban environments is gaining importance in the domain of urban studies. Recently, social media data have proven to be a rich source of information, providing a novel way to derive urban spatial structures and their impact on the quality of life. Yet, integration of this wisdom in urban planning and policymaking has not been comprehensively investigated in high-density cities such as Hong Kong as it relates to spatial configurations. This study aims to investigate spatial structures and analyze social media data to apprise urban planning with knowledge of human activities. This study also seeks to introduce an exploratory analysis to develop a greater understanding of the interaction between social activities and urban space. The results show that function layout defines urban spatial structure and determines human social activities. The research provides insights regarding a better interpretation of the knowledge of social activities, underlying how well social activities reflect the corresponding urban spatial structure and gaining a detailed understanding of their respective variation in activities.

Keywords:
Compact city
Spatial structure
Social media data
Activity and vibrancy
Urban function
Hong Kong

1. Introduction

Livability refers to those spatial, social, and environmental characteristics and qualities that particularly contribute to human sense of individual and collective well-being and to their sense of satisfaction in being the residents of their unique neighborhood (UN-Habitat, 2017). Most populous cities in developing countries are subjected to the planning and developing of a compact city, as declared by the United Nations Conference on Human Settlements III (UN Habitat, 2017), which can be a way out for sustainable urbanization coping with limited land resources, a deprived urban environment, and intrusion to the natural ecology (Chen, Hui, Lang, & Tao, 2016; Hui, Liang, & Yip, 2018; Jacobs, 1992; Lang, Chen, & Li, 2016). A compact city is usually regarded as a sustainable development mode for high-density cities, as it provides convenient services within neighborhoods, reduces vehicle travel, and counters urban sprawl (Chen, Jia, & Lau, 2008; Lang, Radke, Chen, & Chan, 2016). With such a high concentration of residents, services, and goods, better planning for compact cities can lead to reduced land use, greenhouse gas emissions, and carbon footprint; deliver a higher exchange of information and innovation; and motivate the cities′ vibrancy.

Urban spatial structure is described as an abstract or generalized definition of geographic space distribution (Foley, 1964). Understanding urban spatial structure has compelling significance in the development of planning strategies and policymaking supports for building livable, vibrant, high-density cities, which can be measured in the context of functions and activities (Krehl, Siedentop, Taubenböck, & Wurm, 2016). Planners and decision-makers should understand the formation of urban spatial structures in shaping cities. On the one hand, urban spatial structure symbolizes physical urban space, while on the other hand, human activity space characterizes social dynamics and urban vibrancy. Clearly, urban spatial structure exerts powerful influence on individual daily life, social equity, economic growth, and sustainable development (Anas, Arnott, & Small, 1998; Zhong et al., 2017). A critical facet of exploring human activity patterns is to define the individual's spatiotemporal interaction. Thus, analyzing the spatiotemporal features of human activities is significant when addressing various location choices associated with the physical place, but data from traditional sources are usually expensive and laborious.

Early studies estimated the quantitative characterization of cities based on census data, transportation surveys, or remote sensing data (Jendryke, Balz, McClure, & Liao, 2017). These studies investigated the urban spatial structures and urban functions (such as Lynch, 1960, 1992) as well as people's perceptions of their surrounding neighborhoods (Jacobs, 1992) and the importance of social interactions in the community (Liu et al., 2018). However, given their temporal resolution and the lack of adequate data, these studies could not dynamically investigate urban spatial structure (Roth, Kang, Batty, & Barthélemy, 2011; Lee, You, Eom, Song, & Min, 2018). Some research questions are still hard to answer: How much does urban spatial structure change over a day? Where are human activities centered at different hours of the day? How are these hotspots spatially organized over time? Whether the formation of functional areas of social activities are consistent with the morphological changes of urban spatial structure? This unfolding relationship between online social networks and urban structure needs to be examined using empirical analyses of large-scale datasets.

The emerging source of social media data, such as Facebook data, equips us with a new lens to identify urban spatial structures and different spatial distributions of population, urban economy, land use and human activities (e.g., Jendryke et al., 2017; Laube & Purves, 2006), as well as to understand the vibrancy of a city (Huang & Wong, 2016a,b). In addition, social media data are accessible and convenient for gathering crucial information in a short time, and the distribution includes human activities such as where we live, work, and shop; how we spend our leisure time; and how we travel. Location-based social networking (LBSN) services allow people to share locative information via GPSenabled mobile phones in that they provide information about spatial distribution and its evolvement during the day or over the week. The rationale for the focus on human activity distribution is that facilities and places such as points of interest (POIs) and Facebook check-ins act as the locus of urban functions to describe human activities pattern (Huang & Wong, 2016a,b; Lang, Chen, Chan, Yung, & Lee, 2019). Geolocated information from social media data have been used as the reference to examine the association between cities′ spatial structures and social activities (Steiger, Westerholt, Resch, & Zipf, 2015; Sun, Fan, Li, & Zipf, 2016), and most have reported a statistically significant association between them (Huang & Wong, 2015), but few studies have empirically explored those mechanisms under compact city context.

Taking Hong Kong, a commonly acknowledged compact city, as a case, this study aims to 1) examine the spatial structure of a highdensity city, 2) portray a picture of the correlation between the functional regions and different activities at different times, and 3) put forward a planning approach for improvement strategies in developing the vibrancy and efficiency of compact cities. This research revisited the concept of spatial structure, identified the urban spatial structure of Hong Kong, examined the social activities, and recommended how to improve the public realm of Hong Kong's existing living environment, concentrating on the results of the data analysis with respect to providing information that can be used in planning compact city. In this study, the social media data sources provide insights into understanding urban functions and human activity patterns.

In this article, we focus on the compact city's urban structures and the spatiotemporal human activity patterns within the city. This paper is organized as follows: The introduction section gives the background of this study. Section 2 presents a descriptive literature review that comprises a summary of the reviewed articles and examines the concept of urban spatial structure, urban vibrancy, and related studies in social media data. Section 3 explains the research methods, including the data and analytical methods used. Section 4 elaborates the analysis results. Section 5 discusses the findings from the viewpoint of urban planning practices. Section 6 concludes the paper.

2. Literature review

2.1. Urban spatial structure

Urban spatial structure refers to the spatial distribution of internal elements and the interaction of various urban factors in the urban system, including both the physical and perceived environments, i.e., the socio-economic environment (Anas, Amott, & Small, 1998)(Li et al., 2018). There have been a few typical modes of urban spatial structure defined by Burgess (2008), Hoyt (1939), Harris and Ullman (1945), and Knox (1982). The extent of urban spatial structure can be recognized as centralized versus decentralized (Krehl, 2015), monocentric versus polycentric (Roth et al., 2011), or clustered versus dispersed (Lee, 2007), where density is considered as a core concept in describing urban spatial structure (Vasanen, 2012). Density measures how concentrated human activities are in a given area unit (Cervero and Kockelman, 1997). A large number of researches have presented evidence that urban built-up area density and human activity density are closely associated (Levy, 1999). On the one hand, physical densities are a static nature of spatial structures and are linking with the ratio of built-up area in an urban environment; on the other hand, social activity density expresses the intensity of human interactions in an urban environment (Krehlet al., 2016). The interrelationship between urban elements and their integration in a functional entity is the essence of urban spatial structure.

In urban research, the urban spatial structure is highly interrelated with urban function that refers to the interaction of people and activities. Urban spatial structure can be measured by the degree of spatial concentration of human activity. Huang and Wong (2015) argued that studies of urban structure focus on activity analysis for evaluating livability. Some studies show by field observations that empty buildings are found in certain parts of high-density areas (Hui, Dong, Jia, & Lam, 2017). On the contrary, human activity density is subject to continual change in socioeconomic processes (Krehl et al., 2016). In particular, the distribution of human activities results in the process of urban spatial structure transformation. Recent studies on quantitative measurements of urban spatial structure (Wachowicz, Arteaga, Cha, & Bourgeois, 2016) have shown that they can be considered as the sets of human interactions among different functional regions in an urban area, referring to daily behavior for entertainment (Chen et al., 2011). 2.2. Urban vibrancy and social activities

Vibrancy refers to the number of people in and around active or lively places at various times of the day and night (Muñiz & GarciaLópez, 2010) and the presence of an active street life (Jalaladdini & Oktay, 2012). Vibrancy is a critical indicator of livability in high-density cities, and it has positive impacts on the economy and people's social and economic lives. Vibrancy, vitality, viability, and livability interchangeably describe the quality of life, which concerns urban space as a socially satisfying environment with three principal features: sustenance, safety, and consonance (Lynch, 1992). Vibrant cities provide viable places for sociability, connections, and involvement in multiple activities (Findlay & Sparks, 2009).

Individual activities are determined by a broad range of elements, of which the most essential ones consist of urban spatial structure (Huang & Wong, 2016a,b). The well-structured urban space accommodates function and enables human social activity when a livable and vibrant place defines the essential characteristics of an urban environment for a high quality of urban life (Jacobs & Appleyard, 1982). A comprehensive literature review on social interaction is found in Ratti, Frenchman, Pulselli, and Williams (2006), in which the studies payed attention on urban spatial structure and its corresponding land use functions (Tian, Wu, & Yang, 2010; Lang, Long, & Chen, 2018; Lang, Long, Chen, & Li, 2019), illustrating that the characterization of urban spatial structure can be examined more closely using urban socioeconomic and land use data (Shaw & Yu, 2009). A few works contribute to a better understanding on the relationship between social activities and the corresponding urban spatial structure (Lansley & Longley, 2016) and indicate that quantitative analysis of social activity is a reliable measurement for exploring urban spatial structure (Stuart Chapin, 1968; Longley, Adnan, & Lansley, 2015).

2.3. Social media data for measuring urban structure and human activities

An emerging research agenda leads to a new paradigm of collecting, analyzing, and modeling urban structures through social media crowdsourcing and location-based service tracking (Stanilov & Batty, 2011) to provide a new lens for understanding the bottom-up mechanisms that physically and socially drive urban structure (Jin & Batty, 2013). The growth of social media communication on mobile devices provides solid opportunities for understanding the interaction between cities and human being. Social media covers a wide range of concept, and it is often considered from many different perspectives, there being a large amount and variety of social media applications and platforms. With the advances made in GPS-installed accessories such as smart phones and tablets, and the prevalence usage of internet social media network tools or applications, e.g. Facebook, hundreds of millions of location-based social media data are achieved from location-based check-ins from LBSN services. The excessive possibilities of interactive social media tools/applications/platforms such as Facebook has been progressively considered by a large number of research disciplines during the last few years. Users' geo-tagged check-ins on social networking tools not only documents the geographical locations where the users have been but also indicates the users' general behavioral habits and preferences. The geo-tagged data from online checked-in social media tools can be regarded as a bridge reflecting both users' online and offline activities (Hu et al., 2015).

Social media data, as a kind of crowdsourced open data regarding human activity choices, provide a unique and advanced angle to portray people's spatio-temporal preferences and to model human mobility patterns. Location-based social media data with detailed information about POIs and check-in data observed at the individual level contain rich and dynamic information over space and time for spatiotemporal analysis (Gonzalez, Hidalgo, & Barabasi, 2008), aiming to better understand collective human activities, functionalities, and characteristics of a city. Studies have applied individual-based check-in data (including cell phone cellular signaling data and data collected from GPS-embedded tracking devices) to identify mobility pattern (Kim & Kim, 2013; Lee et al., 2018; Shen et al., 2013), to deduce daily activity cluster and land-use cluster (Farber, Páez, & Morency, 2012; Jones & Pebley, 2014; Wong & Shaw, 2011) and to analyze urban spatial structure (Long & Thill, 2015; Zhong et al., 2017). Yet, empirical research toward exploring urban spatial structure and human social activity using crowdsourcing data is still generally unrevealed (Fan, Yu, & He, 2017). In addition to the bias of various population crowds using social media tools is undeniable, representing only a part of the whole population group. For example, with place category and time, people may log into social media applications more frequently to commercial locations than to residential locations, and people tend to report past or future venues rather than an on-going event place. There may also be an age crowd deviation (such as young people would like to use location-based service applications more often) (Steiger et al., 2015). Regardless, all the studies confirm promising results that taking advantage of social media data reflect valuable information based on a huge number of users (Hu et al., 2015; Shelton, Poorthuis, & Zook, 2015; Sun et al., 2016). It is imperative for multidisciplinary cooperation among computing scientists, urban geographers, policymakers, and urban planners to better integrate together in urban planning processes.

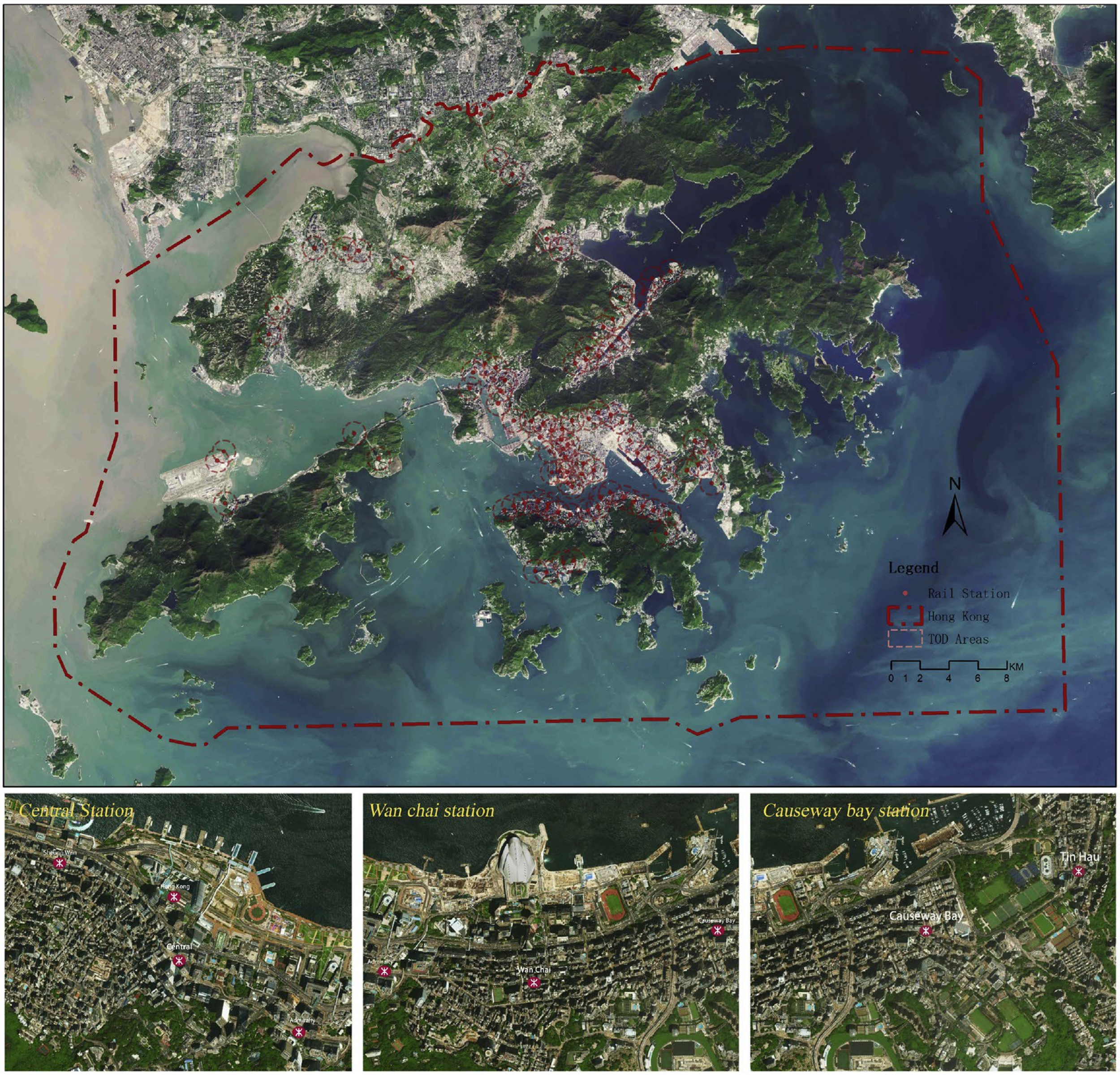
Social media data with spatial data reflect the structure of a city. In recent studies, analytic method using geo-tagged social media data has been largely developed to examine urban structure (e.g. Huang & Wong, 2016a,b; Lee et al., 2018; Liu, Sui, Kang, & Gao, 2014; Shelton et al., 2015). Hu et al. (2015) calculated POIs with a spatiotemporal method of a clustering algorithm over time from geo-tagged images. Paldino, Bojic, Sobolevsky, Ratti, and González (2015) used geo-tagged photographs to extract the attraction of cities by providing information for how and where to increase service development. Steiger et al. (2015) derived human location-based tweets to identify clusters of home to work relations from people's social media activities and their mobility patterns. Shelton et al. (2015) demonstrated that it was feasible to detect people's activities and mobility by analyzing locationbased tweets concerning intra-neighborhood isolation, mobility, and injustice. These studies indicate a trend towards quantifying the real usage and functionality of urban space and comprehending the urban dynamics (Schläpfer et al., 2013). The aforementioned studies have limited the contribution of geo-tagged social media data to uncovering a city's spatial structure and its response for urban planning and designs for compact cities.

In respect of urban planning and its related policymaking, social media data can be regarded both as a synergy tool and as a big data source, e.g., Facebook, Twitter, Flickr, Instagram, and online comment services. Analysis using large amounts of social media data is able to offer meaningful insights for urban planners that are useful to the urban planning and design circumstances (Zheng, Zha, & Chua, 2012). Tasse and Hong (2014) believe that it is possible for city planners to use location-based social media data in their planning practices. It can offer preferred data source that can be applied to improve urban planning and quality of life in cities by mapping mobility and city structures. Bingham-Hall and Tidey (2016) study how social media data analysis and visualization can improve local neighborhoods and help decisionmaking by shed light on indigenous issues. Identification of social activities and spatial functionality is applicable in researching into the characters of cities and neighborhoods (Farber et al., 2012), which is of great value for urban planners in exploring the city structure. Geotagged Facebook posts and POIs identify urban spaces in actual use for business area, housing usage, nightlife activity, leisure behavior, and weekend social activity pattern as well as industrial districts. Thus, this study addressed the emergence of social media data to rediscover the urban spatial structure in high-density cities and its impacts associated with social activities.

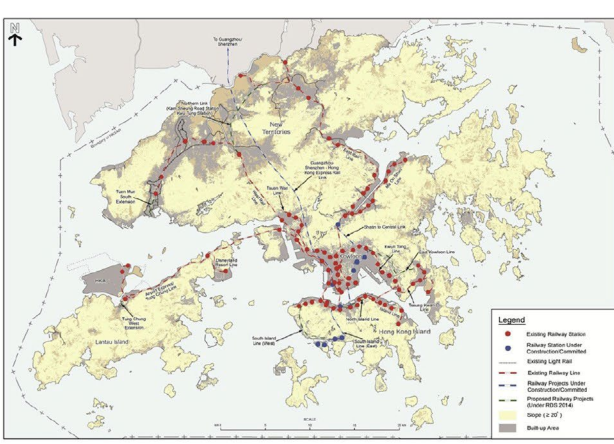
3. Research methodology

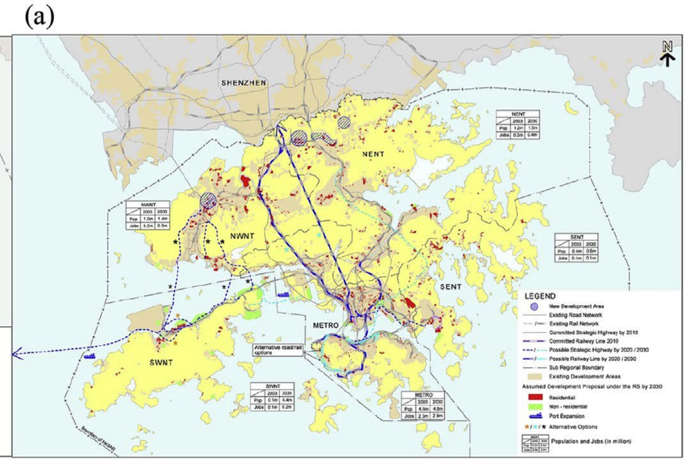
3.1. Study area

In this study, Hong Kong was chosen to be a case study sample, given the vast number of Facebook users in this city and its prototype of building a compact city. Hong Kong, Specialized Administrative Region of China, has a total area of 1100 km^2, with about 24% of its built-up area populated with more than 7 million people. Since the metro system was developed in the 1970s, Hong Kong has adopted a high standard of design and a development strategy for a high-quality urban life with incentives to emphasize walkways connecting to landmarks, malls, parks, office buildings, taxi stands, bus terminals, residential areas, promenades, government buildings, community service centers, facilities, etc. The Hong Kong MTR extends for 187 km, with 93 stations in 2017, and an average distance of 2 km between stations. A map of the locations is shown in Fig. 1a, and the Hong Kong 2030 Planning Vision and Strategy for metro development map is shown in Fig. 1b. As seen in Hong Kong 2030 + : Planning and Urban Design for a Livable High-Density City, envisioned by the Planning Department of Hong Kong (Hong Kong Development Bureau, 2017), the city will continue its compact city development schema (shown in Fig. 1c) to build upon existing urban context, and urban spatial structure has been definitely defined for the future development. This study focuses on the links between urban spatial structure and its impacts on urban vibrancy embedded in human social activities in Hong Kong, which summarizes the basic



(a)





(b) (c)

Fig. 1. The study area of Hong Kong. (a) (b) Railway Development in Hong Kong; (c) Strategic planning for spatial development. Source: Fig. 1(a) authors adopted aerial image from Google Map 2017; Fig. 1(b) achieved from Hong Kong 2030: Planning Vision and Strategy – Strategic Environmental Assessment by Planning Department of Hong Kong SAR on June

2007; Fig. 1(c) achieved from Hong Kong 2030+: Planning and Urban Design for a Liveable High-Density City by Planning Department of Hong Kong SAR on October 2016 (Hong Kong Development Bureau, 2017).

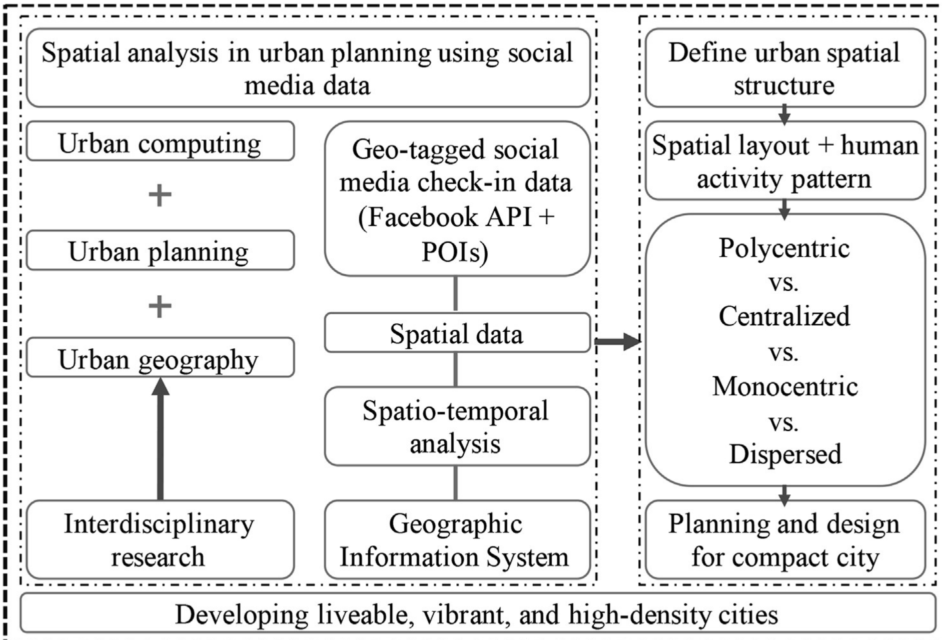


Fig. 2. Theoretical framework of this study.

characteristics of urban spatial structure in high density cities, and this can be applied to other dense cities by incorporating their local characteristics. The theoretical framework of this study is shown in Fig. 2.

3.2. Data and method

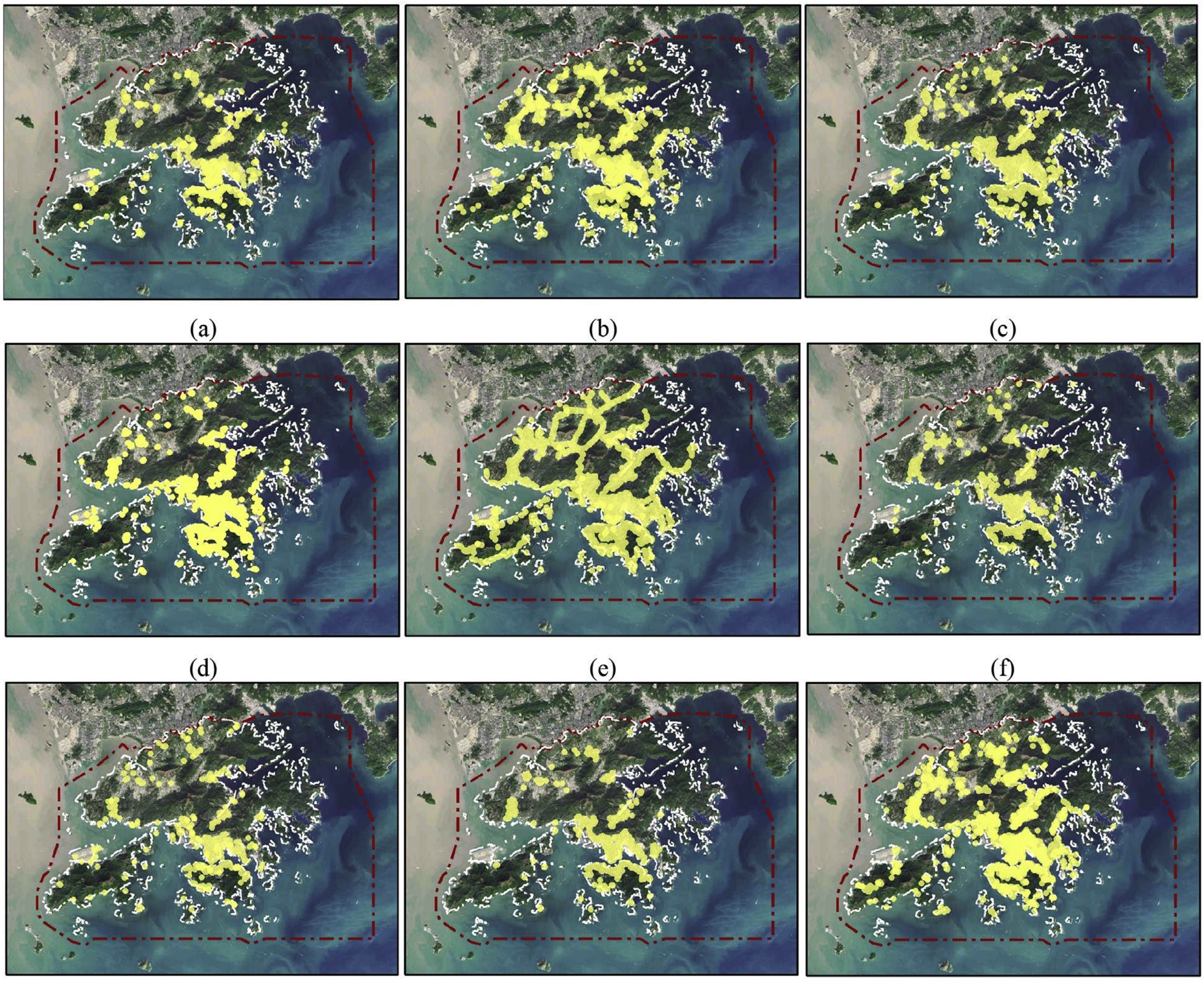
Geographical data and geospatial big data cover the main districts of Hong Kong at both city and building levels, integrating spatial and social media data that include the urban base map, POIs, and social media check-ins. The data adopted in this study was collected from the internet social network Facebook. Facebook check-ins were used as a proxy for tracking human distribution and depicting social activities. This provides high-resolution positioning when users opt to geotag their posts with their current location. Data collection and processing from Facebook in real time using a streaming application program interface (API), i.e., exploited Facebook API, allows us to infer human activity from social media. This enabled an aggregation of individuals by means of mobile devices with a timestamp to capture activity patterns across the city. Data was collected as a sliding window interactive analysis of social networking for one week, which provided a sufficient data sample of periodic identification characteristics, i.e., sampled from weekdays (Monday and Thursday), and one weekend day (Saturday), and recorded hourly from 09 to 10 o'clock, 12–13 o'clock, 15–16 o'clock, 18–19 o'clock, and 21–22 o'clock. Data collection from Facebook API was accessed from a Python filter based on the search function geocode that specifies a geographic location (the latitude/ longitude geographical boundary of Hong Kong). The maps were generated in ArcGIS Desktop 10.5.

An overlay on the spatial and temporal dimension revealed the urban spatial structure in respect to changes in human social activities within the city. Exploratory data analysis was applied to detect spatial cluster in 1 km lattices at city level. The analysis included social activities density, inactive spaces and times, interactions in relation to urban structure, and the variety of functions within the POIs. Density here is defined as the number of individual visiting unit area during a pre-determined time unit. Multi-scale visualization of massive graphs on social media content was conducted to map human activity patterns. Input were location-based social networking Facebook posts at the POIs, indexed by both place category and time. Facebook check-ins were also calculated the sum in each building to determine clustering activity patterns and people concentration at building level. Three local neighborhoods were chosen to show the patterns of spatial locations of users' frequent check-ins at various times, namely, Causeway Bay, Wan Chai, and Central, and to present the relationship between activities and urban (neighborhood) morphology. Georeferenced Facebook check-ins corresponded to specific locations and were impacted by every user's personal preference in spatial behavior. Thus, Facebook dataset and particular contextual information may be defined as indicators for how closely the virtual and physical worlds are inter-connected among many others. Facebook users check into social activities at POIs (restaurants, hotels, etc.), which indicates the spatial distribution of activities, thereby referring to an underlying urban structure at the neighborhood level and at city level.

4. Results and findings

4.1. Defining the compact city's urban spatial structure at city level

Over the study period, about 3.4 million to 8.4 million Facebook check-ins were collected on average per day, gathered from over 50,000 unique POIs. Fig. 3 shows the uneven distribution of POIs identified throughout the city in 9 main categories. Catering (12,615 valid geotagged locations) and transportation (7,974) had by far the greatest number of functional places, followed by entertainment (6,775), edifies (4,762), tourist spots and parks (4,270), hotels and banks (4,039), health and service (3,490), government and agencies (1,753), and research and education (1,664). Spatial views of Facebook users (see Fig. 4) revealed clusters of 498,150 new Facebook check-ins, which are colored in dark beige according to the active user density in each grid. The density is aggregated on a grid composed of 1 km^2 cells to Facebook check-in numbers, ranging from about 18,370 newly checked-in users on Thursday morning between 9 and 10 o'clock to 56,550 on Saturday night between 21 and 22 o'clock. To be specific, 21,800 different checkins were recorded on Monday from 09 to 10 o'clock, 26,360 from 12 to 13 o'clock, 30,150 from 15 to 16 o'clock, 30,150 from 18 to 19 o'clock, and 41,780 from 21 to 22 o'clock; on Thursday, there were 18,370 from 09 to 10 o'clock, 27,700 from 12 to 13 o'clock, 37,860 from 15 to 16 o'clock, 26,840 from 18 to 19 o'clock, and 23,310 from 21 to 22 o'clock; and on Saturday, there were 22,820 from 9 to 10 o'clock, 38,430 from 12 to 13 o'clock, 47,320 from 15 to 16 o'clock, 48,710 from 18 to 19



(a) (b) (c) (d) (e) (f) (g) (h) (i)

Fig. 3. POIs. (a) Hotel and bank; (b) Entertainment; (c) Catering; (d) Mansion; (e) Transportation; (f) Research and Education; (g) Government and Agency; (h) Health and Service; (i) Tourist and Park.

o'clock, and 56,550 from 21 to 22 o'clock.

Highlighted cells in Fig. 4 contour the areas of sparse Facebook check-in coverage and the areas of high Facebook check-in density. The spatial organization of the 1 km^2 hotspots in Hong Kong's metropolitan area indicate its spatial structure, with two distinct areas of high-concentrated activities: the north coast of Hong Kong Island and the south coast of Kowloon Peninsula. Aggregating human social activities in grids reveals the different spatial composition as well as the functions. The human social activity pattern shining upon POIs highly corresponds to the polycentric spatial structure of Hong Kong and are coinciding with the geographical locations of important nodes of towns and districts, the spatial distribution of built-up areas and population, and the laying position and direction of infrastructure routes, i.e., highways, metro lines, etc. Given the development of TOD approach, the new downs in Hong Kong, as important centers, not only hold a rising share of population, but also accommodated increasing economic activities, employment, social activities, and educational, cultural and entertainment activities. The results also reveal the polycentric spatial organization of the city that is located at major metro interchanges and the clearly compact and centralized development within each cluster. Furthermore, human activity patterns in a time series exhibit effects of regular variation from low activity in the morning to high activity at night, and from low activity on the weekdays to high activity during the weekends. It is noteworthy that the lowest number of social activities were found on Thursday compared to both other weekdays and weekends.

4.2. Understanding crowd activities and vibrancy at street level

The distribution of collected Facebook check-ins between selected neighborhoods at street level are shown in Figs. 5 and 6, which present the time evolution of the total number of Facebook users per hour or per entire day during an average weekday and weekend. The analysis results display the density of Facebook users′ check-ins that were aggregated in each building when they activated their apps in the specific locations. In all cases, the estimation of the neighborhood Facebook check-ins are within or in close proximity to their affiliated buildings. Each colored building represents different units of check-ins among the three neighborhoods, Causeway Bay, Wan Chai, and Central, as shown in Fig. 5. From red color to blue color indicates high value to low value of Facebook check-ins. Generally, large commercial complexes contain a high quantity of social activities, although there are slight variations on different dates. Known as some of the most prosperous areas in the city, the three neighborhoods exhibit a distinct spatial layout and accommodate a different intensity of activities to a large extent, depending on their functions. At street level, compared to the observation at city level, urban function also determines human social activities on top of urban form.

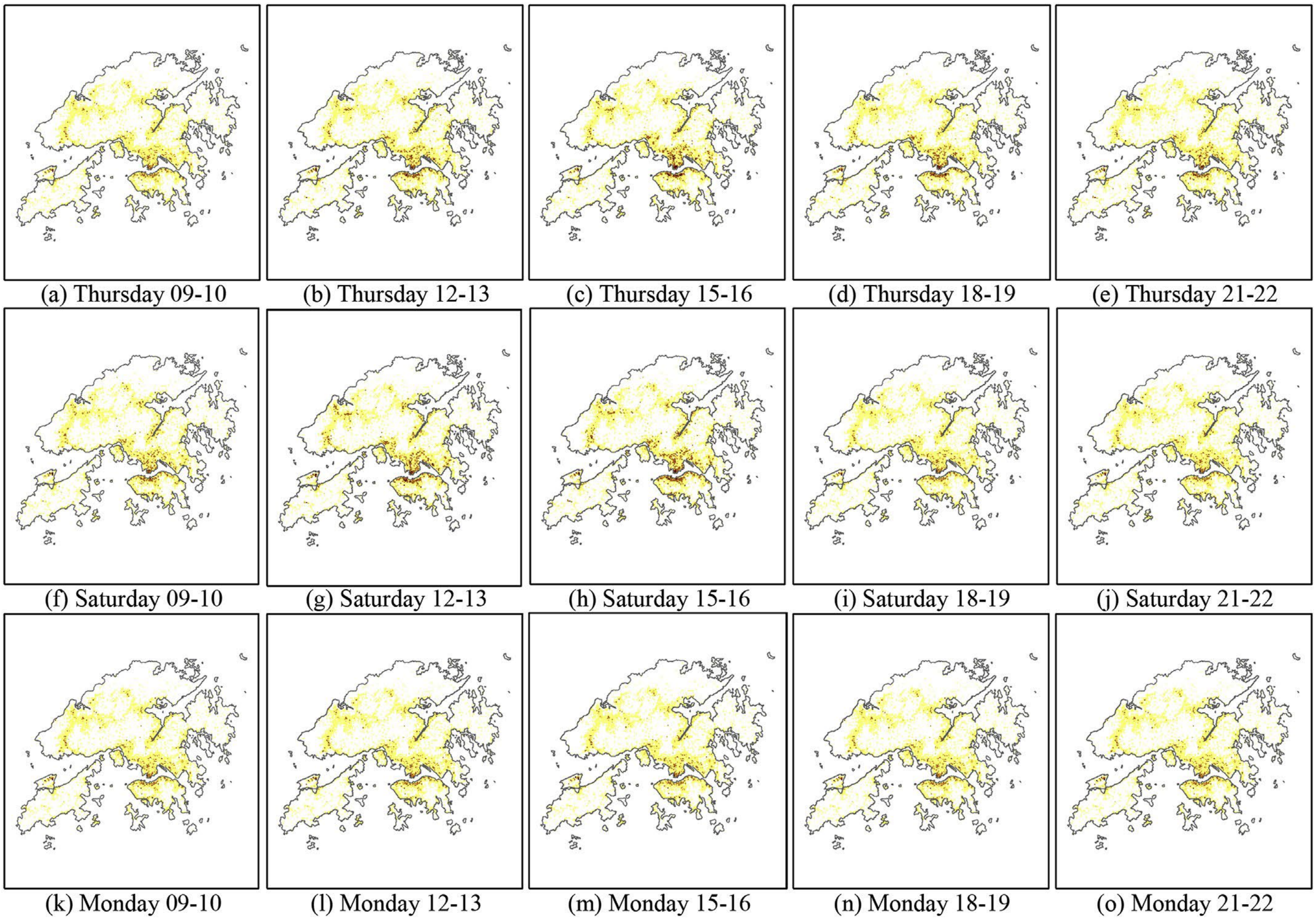


Fig. 4. Facebook check-ins. Monday, Thursday, and Saturday defer to date 20170710, 20170706, and 20170708 respectively. Notes: From dark yellow color to light yellow color indicates high value to low value of Facebook check-ins. (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

To distinguish the dynamic change in human social activity spatiotemporally, we ran analyses on the three neighborhoods. The time slots sampled cover 9–10 o'clock, 12–13 o'clock, 15–16 o'clock, 18–19 o'clock, and 21–22 o'clock from weekdays to weekends (Monday, Thursday, and Saturday), some of which are shown in Fig. 6. Table 1 gives a whole picture of the changing activities from time to time. Central assembles a huge crowd of social activity on Monday during the day and drops to low activity on Monday night. It embodies an average quantity of activities during the day on Saturday compared to a high rise at night on Saturday. It is noteworthy that office and business functions dominate on weekdays, while leisure and nighttime entertainment functions take the lead for weekends, especially for nightlife. Residential and commercial functions together occupy Causeway, where there is a large number of activities during the day on Saturday, the highest number of activities on Saturday evening, and it drops at night, being closer to weekday numbers. On weekday nights, there is a higher value of social activities compared to weekday daytime. In Wan Chai, the residential function is predominant; a mass of social activities take place in the morning and at night, where even more emerge during the night on both weekdays and weekends. We can still see a significant portion of commercial function present in the area, e.g., more people moving around from afternoon to nighttime on Saturday. Overall, business and office activities appear to be the main function in Central, accompanied by nightlife, like bars and pubs. Commercial function is primary in Causeway Bay, concomitantly mixed with certain residential and office areas. Wan Chai shows a large proportion of residential function, generally mixed with commercial.

5. Discussions and implications

In this study, we characterized urban spatial structure using social media data in Hong Kong, to highlight the important activity centers at city level and street level. In particular, we examined Facebook checkins as a valid proxy indicator of people's social networking activities in terms of the urban-built environment and investigated urban spatial structures by characterizing spatio-temporal patterns of people's social activities, reflecting typical collective human behavior. The results indicate that the entire body of those check-ins within the urban built-up area are highly concentrated. The spatial organization of large and densely populated urban areas are characterized by functional clusters that are profiled as high-density and distributed through the city, such as the node-like built urban space in Hong Kong.

Spatial accumulating in the vicinity of highly regularly visited POIs and social activities underlies the complex spatial structure through social networks and characterize urban structures through human social activity patterns with LBSN services. From the perspective of spatial and functional layout, the satellite cities or new towns in Hong Kong are not only built with residential function but are mixed with commercial, business, office, and industrial functions, which is quite different from many other high-density cities in the world, making the satellite city into a “sleep city.” And the spatial distribution of social activities is consistent with the morphological changes of urban spatial structure as well. These achievements are shaped by the characteristics and success of Hong Kong's urban planning strategies and development efforts. People's work, study, entertainment, and leisure are retained within the

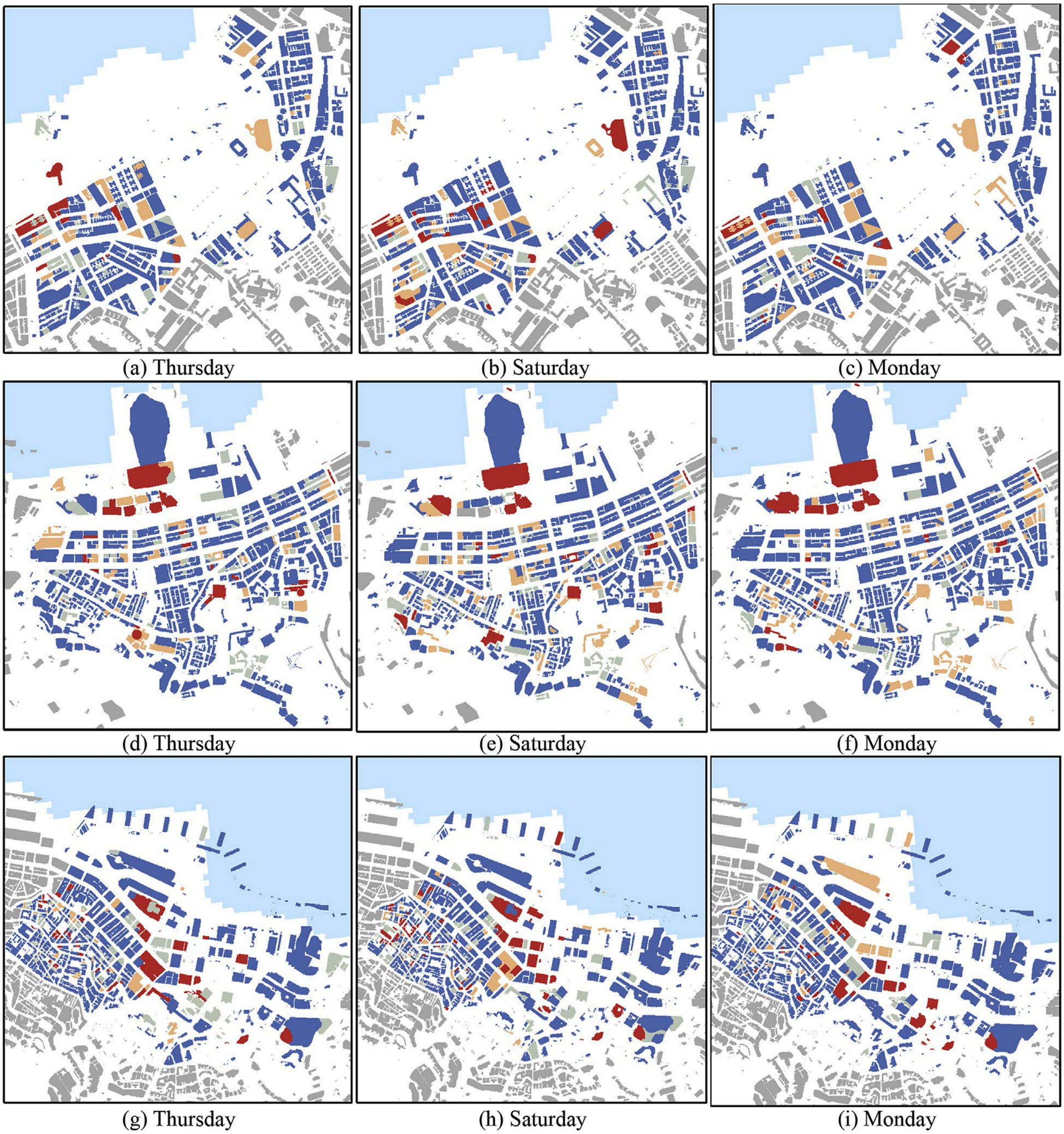


Fig. 5. Facebook check-ins in one day. (a–c) Causeway Bay; (d–f) Wan Chai; (g–i) Central. Monday, Thursday, and Saturday defer to date 20170710, 20170706, and 20170708 respectively. Notes: From red color to blue color indicates high value to low value of Facebook check-ins. (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

local community (Hui & Yu, 2009; Hui et al., 2012a; b), which not only reduces the pressure on the central districts of Hong Kong but also, in a wider range, relieves traffic congestion and other urban overcrowding issues. Networked multi-centers or decentralized clustered cities provide the possibility to move easily along rail transit or structured main roadways from one urban neighborhood to another, which seems to be consistent with the theory of a compact city (Chen et al., 2008). Such development concepts and strategies also make the city and neighborhood vibrant, and ensure the quality of life in high-density cities. From the view at the street level, improving the efficiency, coverage, and quality of public transportation networks to the various neighborhoods is the first priority; within the clustered communities, each neighborhood stays vibrant and maintains many social activities, helping reduce social inequalities. That is the mode of a compact city deserves.

The given method could also be generalized to investigate people's dynamic behaviors not only at a city scale or street level but also at a regional level. Determining the spatial distribution of social activities is a quantitative manpower input and often leads to finite sample cases. Therefore, the study of huge spatio-temporal people's social activity agglomerations achieved from crowdsourcing information can facilitate us to understand urban structure. Facebook farther improves current social networking systems by supplementing the spatial information with an LBSN service and enables users to share details of their individual places as the key point of social interactions, which is in line with similar research of Shen & Karimi (2016) and Steiger et al. (2015) for analyzing people's whereabouts and social activities. Social network

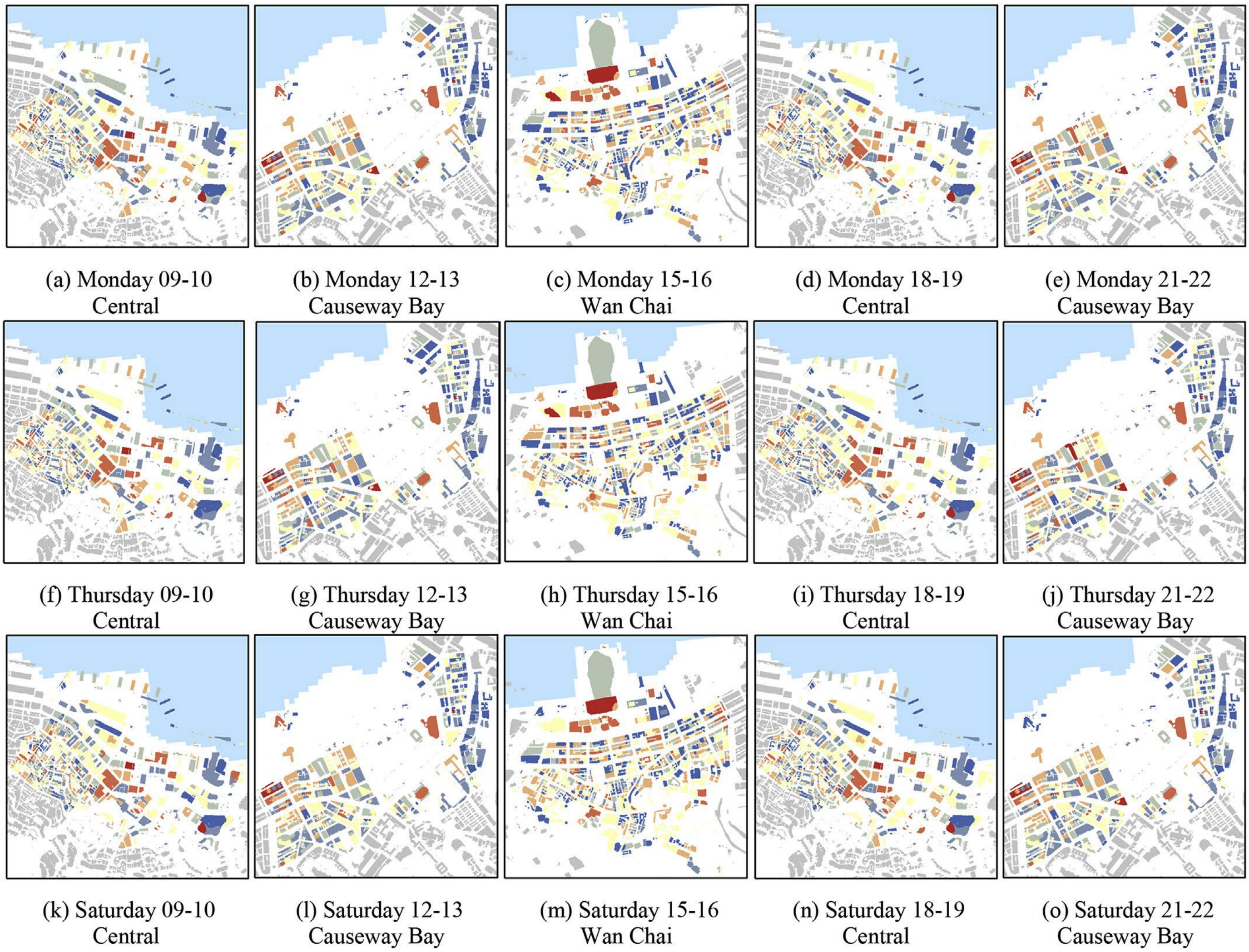


Fig. 6. Hourly and daily Facebook check-ins in Central, Causeway Bay, and Wan Chai. Monday, Thursday, and Saturday defer to date 20170710, 20170706, and 20170708 respectively. Notes: From red color to blue color indicates high value to low value of Facebook check-ins. (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

Table 1
Hourly and daily Facebook check-ins changes in the neighborhoods of Central, Causeway Bay, and Wan Chai.

Central	09–10	12–13	15–16	18–19	21–22
Monday	9750	8451	9452	9452	3951
Thursday	5094	2089	3981	2613	4956
Saturday	3034	5168	2348	6543	13,380
Causeway Bay	09–10	12–13	15–16	18–19	21–22
Monday	4870	2741	7944	7944	9623
Thursday	4617	6415	8540	2016	8888
Saturday	5518	8409	7980	10,200	10,650
Wan Chai	09–10	12–13	15–16	18–19	21–22
Monday	8547	8550	4804	5804	8028
Thursday	8078	7544	5306	2390	6241
Saturday	9586	2366	8862	9710	13,028

users posting on Facebook indicate a spatio-temporal virtual footprint in the real word (geolocation and timestamp). Each Facebook check-in includes a corresponding geographical location extracted from the GPSembedded devices, i.e. the mobile phones. In this context, emerging location-based services for discovering urban spatial structures and human dynamic activities, in particular, geo-tagged Facebook datasets, is a promising way to comprehend the geographical progresses within online social networking tools/applications.

6. Conclusion

Cities are changing in shape and spatial nature. Delineating the urban spatial structure to perceive the civic functions and spatial characters of urban built up areas is of great importance for improving the efficiency and quality of life and for supporting urban planning applications. Yet, few quantitative research studies have dynamically investigated urban spatial structure. In the context of exploring human scale activity in the built environment, there have been few studies in the case of high-density cities from city level to street level due to the limited resources. Taking Hong Kong as a case, this study explored the spatial distribution of human activities with quantitative measurements of urban spatial structure using social media data in a dense urban environment. The findings retrieve Hong Kong urban spatial structure with more accurate spatial information and more samples in contrast to existing studies by showing a one-week result using periodic information and the spatial distribution of a 1-h result. The research showcases how a variety of GPS-tracked social media at various levels in a city are applied to characterize urban structures and identify central places, which helps to improve our understanding of the city and provides useful information for urban planning in the new agenda of urban studies.

The key findings are as follows: One, the spatial structure of Hong Kong is compact and is characterized by a considerable agglomeration of people and their activities. The compact city's physical aspect is related to the spatial configuration, while the functional aspect is associated with the various daily activities. Likewise, urban vibrancy and people's perceptional reactions to urban space are influenced by the dense urban structure, diverse urban function, and well-planned street configuration. Two, this study presented a way to discover the urban structure that builds upon functions using both traditional and crowdsourced data and reflected its reaction on human activities driven by a variety of usages and users. We demonstrated how social media data can spatially profile human activities by using Facebook check-ins to temporally and spatially analyze these activities in respect to their geographical settings.

Knowledge that is linked with human activities and urban spatial structure is applicable in trying to plan and build a compact city. Additionally, the data-driven knowledge will lead to better perceptions on the unrevealed possibilities for methods and urban planning theories. LBSN service data using Facebook API and urban GIS layers can provide sound results in the observation of crowd behavior such as human mobility and social activities. In future work, more efforts should be made to investigate the relationship between people and space to improve the quality of life. We will focus on in-depth analysis of urban spatial structure using mobile phone data among these functional origin-destinations for urban planning. We may also explore detailed individual activities by types, covering a wide range of time series and territorial areas to explore the relationship between behavioral choice and the quality of urban built environments and to enlighten its planning and policy response.

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