Spatial Structures of Tourism Destinations: A trajectory data mining approach leveraging mobile big data

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Abstract

The advancement of mobile technology provides an opportunity to obtain the real-time information of travelers, such as their spatial and temporal behaviors, during their visits to a destination. This study analyzes a large scale mobile phone dataset that captures the cellphone trace of international travelers who visited South Korea. We apply a trajectory data mining approach to understand the spatial structures of tourist activities within three different destinations. Through spatial clustering analysis and sequential pattern mining, the study reveals multiple "hot spots" (or popular areas) in travel destinations and spatial interactions across these places. As a result, this paper provides important tourism implications integrating spatial models with destination planning, which is the foundation of tourism design.

Keywords: Smart tourism; destination planning; big data; mobile sensor data; trajectory pattern mining

Introduction

Introduction

Advanced technologies such as cloud computing, location aware technologies, the Internet of Things, and other applications related to a travel destination have engendered a new concept in the tourism industry, namely smart tourism (Buhalis & Amaranggana, 2014; Xiang, Tussyadiah, & Buhalis, 2015). Smart tourism destinations adopt prevalent information and communication technologies (ICTs), allowing stakeholders to easily access information and obtain knowledge to facilitate the efficient management of destinations. In particular, advancements in mobile sensor technology enable destination marketing organizations (DMOs) to obtain real-time information about travel movements in and around the destination, thus improving the understanding of travel flow patterns (Li, Xu, Tang, Wang, & Li, 2018). Such insights are important for supporting strategic policy-making decisions concerning destination planning, which have become the foundation of smart tourism destinations (Li, Meng, & Uysal, 2008).

A number of scholars have investigated tourism planning with various themes, such as competitive advantages, planning process, strategic planning, and policy-making (Getz, 1986; Mill & Morrison, 1999), as well as community-oriented planning and sustainable development (Harrill & Potts, 2003). However, there is a lack of extant studies that adopt spatial concepts/models into comprehensive development of destination planning (Dredge, 1999; Stienmetz, Kim, Xiang, & Fesenmaier, 2020). Even among the extant studies about spatial characteristics of destination regions, existing approaches have mainly focused on the development of functional models to address what is there rather than developing an approach that delivers what destination planners should do.

Thanks to the evolution of mobile technology, the big data generated from mobile network systems contain rich information about a large representative population of visitors to a destination. Detailed travel mobility data help DMOs understand how attractions and destinations interact spatially through the lens of tourist flow. Travel movement defines a series of center and sub-centers (or travel hot spots) at different levels and directions, which illustrate the typology of the destination structure. This insight derived from spatial configuration of destination regions from travel flow can be a fundamental knowledge to enhance land-use planning and design of travel destinations (Stienmetz et al., 2020). Accordingly, this research explored travel movement patterns by applying mobile big data analytics and integrates the insights of travel mobility into the framework of destination planning to make a destination competitive and sustainable. In order to address this purpose, this study adopted the approaches often applied in urban studies for exploring the spatial structure of cities, an important research topic in urban planning. Recent literature on urban planning suggests that large cities are complex and show polycentric structures where a city includes multiple centers due to vigorous interactions between various components including people, materials, and information (Rodrigue, 2016). Burger and Meijers (2012) suggested various levels and formats of spatial interactions between multiple centers depending on the unique characteristics of each city (or region).

Therefore, the purposes of this research are (1) to identify tourism hot spots (or popular areas) as centers or sub-centers of a city and their spatial distributions within travel destinations, (2) to illustrate spatial interactions between tourism hot spots based on dynamic travel flows, and (3) to suggest an approach to integrating spatial configurations of tourist activities into destination planning. The findings of this research provide important contributions to tourism planning. Numerous studies have explored travel mobility to identify types of movement patterns and predict places to be visited by travelers (e.g., Mckercher & Lau, 2008; Vu, Li, Law, & Ye, 2015; Vu, Li, Law, & Zhang, 2018). However, this current study attempts to integrate the insights about spatial structures and interactions gained from mobile big data analytics with destination planning. Built on a fundamental study by Beritelli, Reinhold, and Laesser (2020) proposing a flow-based view of destination, this study suggests a tourism big data approach to estimating travel mobility as part of a demand-driven construct to design destination planning. Furthermore, this study applies theories/concepts in urban planning and spatial big data analytics to explore travel mobility and understand the typologies of popular places in travel destinations and engagement of tourists with the attractive areas. These findings can guide tourism planners to design collaborative projects that involve multiple regions containing a variety of attractions, and thus to enhance visitors' experiences, which can serve as the foundation of tourism design (Stienmetz et al., 2020).

Literature Review

Smart city/smart tourism destination

Scholars have discussed the conceptualization of a smart destination, which principally originated from a smart city. Giffinger and Pichler-Milanović (2007) defined a smart city as "a city well performing in a forward-looking way in economy, people, governance, mobility, environment, and living, built on the smart combination of endowments and activities of self-decisive, independent, and aware citizens" (p. 11). In general, a smart city refers to the search for and identification of intelligent solutions that enable modern cities to improve the quality of services provided to citizens (i.e., tourists in the tourism context). To successfully make a city "smarter," it has been suggested to consider multiple components of a smart city, including smart economy, smart people, smart governance, smart mobility, smart environment, and smart living (Albino, Berardi, & Dangelico, 2015). Considering the nature of tourism, which involves the movement of people across different places, smart mobility referring to accessibility within and outside a city is one of the key dimensions to be investigated when discussing smart tourism destinations associated to travel flows.

The idea of smart mobility stresses the importance of “everyware” (or ubiquitous computing) in undertaking smart destinations (Greenfield, 2013). Omnipresent computing and digitally instrumented devices embedded into the urban environment (e.g., mobile sensors, transport infrastructure, and camera networks) are used to monitor, manage, and control city flows and processes, and to generate data, such as locations visited by people and activities that people engaged in (Kitchin, 2014). Integrating and analyzing information produced by diverse types of everyware offer a comprehensive and cohesive understanding of a city that ultimately improves efficiency and sustainability in city management (Hancke, Silva, & Hancke Jr, 2013).

Introducing the notion of a smart city (or smart mobility) into tourism destinations requires the dynamic integration of technological platforms that facilitate collecting and analyzing travelers’ behavior at a destination (Buhalis & Amaranggana, 2013). Several tourism researchers have defined smart destinations as a combination of advanced information technology and physical infrastructure, along with sensors, smart devices (e.g., mobile technology), and big data analytics executed within a certain geographical area (Gretzel, Werthner, Koo, & Lamsfus, 2015; Werthner et al., 2015). That is, connecting the physical world to digital space is a fundamental concern in smart tourism development (Gretzel, Sigala, Xiang, & Koo, 2015). Thus, smart tourism can be regarded as places that involve available technological and analytical tools for demand and supply to cocreate values and experiences for visitors and benefits for stakeholders at destinations. Gretzel et al. (2016) suggested a concept of smartness by referring to a complex technological infrastructure embedded into urban areas (i.e., travel destination) to improve economic, social, and environmental prosperity. Smartness involves the interconnectivity and interoperability of connected technologies, which engender a massive amount of varying data to identify the insights of visitors into a destination and accomplish value maximization for stakeholders (Buhalis, 2019). Importantly, the integrated technology can track travelers' movement accurately and comprehensively, and the insights into dynamic travel flow can facilitates achieving smart tourism in general and smart mobility in particular.

Understanding travel patterns and geospatial Analysis

Travel patterns denote people's movement or travel flow from one place (or tourism attraction) to another. One well-known approach to analyzing travel patterns is to show flows on the basis of an origin–destination matrix (Hwang & Fesenmaier, 2003). Research on tourist movement is a complex process associated with travelers' behavioral decisions, such as where and when to visit and move to other places (Xia, Zeephongsekul, & Packer, 2011). As one of fundamental papers, Lew and McKercher (2006) suggested four types of territorial models explaining tourist behaviors and three types of linear path models in local destinations. Considering urban transportation modeling and tourist behavior, the study of Lew and McKercher (2006) proposed factors that influence travelers' movement patterns at the destination.

A review of the literature on travel movement shows that travel diaries have been largely used to collect information on tourists' movement behavior at destinations (Mckercher & Lau, 2008). Tourists are required to annotate their routes, stopping places, and activities, on the map in a daily dairy. However, the accuracy of the information and details of movement, including specific routes and the time taken to arrive at and stay in a certain place, is restricted due to high reliance on tourists' recall of details (Shoval, Isaacson, & Chhetri, 2014; Thimm & Seepold, 2016).

The emergence of social media websites (e.g., photo-sharing systems, such as Flickr, and TripAdvisor) and mobile technology helps tourism researchers obtain a large amount of geographical (or geotagged, georeferenced) information of travelers (Salas-Olmedo, Moya-Gómez, García-Palomares, & Gutiérrez, 2018; Zheng, Zha, & Chua, 2012). Travelers tend to upload their photos to online community platforms to share their travel experiences. Researchers have analyzed the geotagged information on photos to understand travel trajectory patterns at destinations. Despite the widespread usage of such data, geo-tagged information has several limitations: (1) the data sparsity issue (i.e., extremely few records for individuals); (2) potential bias of the population associated with selective travelers who post on social media during their trips, which does not represent the underlying population; and (3) few online sources to access geotagged data (Wong, Law, & Li, 2017). As an alternative, GPS and tracking technologies have been recently linked to mobile phones to enable researchers to resolve challenges using (1) improved spatial and temporal accuracy, (2) extended tracking periods, and (3) easy and timely digital data collection (Raun, Ahas, & Tiru, 2016).

Along with diverse types of data that reflect travel movement behavior, a variety of analytical methods for delineating travel movement have been presented (Orellana, Bregt, Ligtenberg, & Wachowicz, 2012; Raun et al., 2016; Zheng et al., 2012). For example, Leung, Vu, Rong, and Miao (2016) proposed a method for estimating travel statistics by analyzing geotagged photos uploaded by travelers to Flickr. The researchers used a density-based clustering algorithm to identify the popularity of temples in Hong Kong and visit behavior across nationality and time. The results identified the specific activities that travelers engaged in and different preferences between local and international visitors. A similar method using Flickr data was applied to assess the spatiotemporal patterns of tourist accommodations in

Vienna and present variations in accommodation demand across different seasons (Sun, Fan, Helbich, & Zipf, 2013).

Salas-Olmedo et al. (2018) presented the spatial behaviors of urban tourists by integrating tracking data from different online sources including Panoramio for sightseeing, Foursquare for travel consumption and Twitter for connected accommodations. They provided inclusive views of travel activities in cities and suggested the feature of multifunction tourism spaces at destinations. Using GPS data, tourism researchers can understand the aggregated movement of visitors in natural recreational areas (Orellana et al., 2012). The application of movement pattern analyses facilitates discovering places of interests to visitors and represent the generalized sequence where travelers largely visited. In addition to tourism studies that focused on a specific city and/or district, geographical data have been used to develop destination marketing from a macro perspective, i.e., country by country. Vu et al. (2018) applied travel diary analysis to examine Twitter data and suggested significantly associated countries based on sequential travel patterns. A review of the extant literature indicated that most studies have analyzed geotagged data collected from social media websites. However, these data exhibit several limitations, such as the data sparsity issue, the potential bias of a sample that is largely associated with social media, and few online sources to access geotagged data (Wong et al., 2017). Another challenge is the difficulty in mapping tourist movements within a destination due to the nearly unlimited number of places that people can visit, the distinctive motivations of tourists, and difficulty in formulating a sequence order between places (Shoval, McKercher, Ng, & Birenboim, 2011). To address the aforementioned challenge, the current study proposes trajectory pattern mining as big data analytics with a large amount of mobile sensor data. Mobile sensor data enable the researchers to track comprehensive (spatial and temporal) movement to elucidate travel flow from the moment that travelers have arrived at a destination to one when they leave it. The advantages of mobile tracking data facilitate formulating spatial interactions/communities between travel destinations with which travelers engage. The information obtained from travel mobility suggests important guideline to develop strategic destination planning.

Destination planning and travel movement

Planning is defined as “the process of establishing a strategic vision for an area which reflects a community's goals and aspirations and implementing this through the identification of preferred patterns of land use and appropriate styles of development” (Dredge, 1999p. 774). Planning is a conceptual system whereby destination planners are required to comprehend the structure of the system and develop system models to assess interrelationships among its components (Getz, 1986). Strategic planning has been regarded as an essential tool to make tourism destination successful and sustainable (Liu, Siguaw, & Enz, 2008). In view of that, a number of tourism researchers have investigated various topics of tourism planning such as competitive strategy, strategic planning, corporate strategy, structure, and governance in order to develop an integrated system model for destination planning (Phillips & Moutinho, 2014).

Of the various models proposed, this study highlights an approach that integrates spatial models into destination planning. Spatial models particularly involving trajectory data mining can help planners achieve efficient land use and manage the evolution of a destination over time (Dredge & Jamal, 2015). For example, Dowling (1993) proposed the envoronmentally based tourism development planning model by cosidering spatial patterns of landscape that comprises the interactions of environmental attributes and tourism resources. Reviewing extant literature on spatial models of destination regions and their planning, however, most of the structural models are built on limited empirical evidence. Relevant studies have attempted to understand specific phenomena based on the defined structure of a destination, which is an inductive process that explains a historical process at the place (Dredge, 1999; Orbaslı & Woodward, 2009). That is, existing spatial models of destination regions have focused on the development of functional models to address what is there (i.e., functional models), and not what should be (i.e., normative models). As a way to develop strategic tourism planning, Chancellor (2012) applied behavioral data obtained from a survey of travelers to a destination development. The study employed an intra-destination 'base camp' model built on multi-destination trips (Lue, Crompton, & Fesenmaier, 1993) to understand movement patterns and suggest destination development and marketing opportunities for promotional themes.

The idea of integrating travel movement analysis into the development of destination planning is supported by two key tourism theories/concepts—the concept of cumulative attraction and gravity theory. The concept of cumulative attraction is built on multi-destination trips. Lue et al. (1993) argue that travelers tend to visit a number of attractions in and around a destination in order to maximize value (money, time, and effort) and reduce risk of disappointment (Tideswell & Faulkner, 1999; Wu & Carson, 2008). The concept of cumulative attraction focuses on the importance of linkages between attractions and/or destinations. Places in which attractions are clustered in multi-destination patterns attract more customers who stay longer. In addition, the attractions that are clustered (or linked to other attractions) draw visitors from a more extensive geographical area which enhances market penetration.

From the planning perspective, the logical sequence of travel movement considers spatial dimensions to be essential knowledge to develop attractions and formulate linkages. This argument is supported by Gunn and Var (2002) who stated that individual attractions require a substantial amount of time, effort, and resources to develop a marketing plan when clustered (or linked) attractions could accelerate the competitive advantage of a destination. Mill and Morrison (1999) suggested the idea that the destination itself can be a system comprising a combination of attractions and services. Interdependence of the multiple parts can be the key to success when encouraging travelers to visit and providing a satisfying experience.

Gravity theory presents that a single primary attraction (or destination) has a larger gravitational pull than secondary attraction (or destination) and is another foundation to the importance of understanding travel movement in tourism planning. A primary attraction (or destination) is likely to attract more visitors than secondary attraction (or destination). Clustered attractions (or destinations) that combine primary and secondary attractions (or destinations) can enhance the attraction of the whole region (Harrill, 2005). Even if, clusters that contain several less popular attractions can become a collective entity to reveal a larger destination presence and create a larger gravitational effect.

Lew (2007) argued that tourism planning is a subset of urban planning because similar skills and tools are required as well as consideration of similar community values. As a result, urban planning theory can be employed in the tourism planning process. The idea of clustered attractions can be applied as clustered spaces containing primary and secondary places of 'interest' within a travel destination. Along with the evolution of society, economics, and technology, cities have become more complex and polycentric. Studies that reveal the structure of cities, identify apparent typologies, and illustrate the distributions and interactions of city centers and sub-centers have been emphasized (Kloosterman & Musterd, 2001). Indeed, the spatial arrangement of city centers and how people interact within these centers provide fundamental insights to their management and planning (Roth, Kang, Batty, & Barthélemy, 2011).

There are essentially two dimensions to city centers based on central place theory (Berry & Parr, 1988) that correlates the centrality of settlement and the diversity of products/services provided: nodality and centrality. The *nodality* of a center refers to the cumulative travel flows (e.g., commuting or shopping) relative to the specific center (Sun, Fan, Li, & Zipf, 2016) and the *centrality* of a center refers to the surplus of importance of a center based on incoming flows from other places (or the relative importance of a center) (Burger & Meijers, 2012). Based on these measurements, recent studies in urban planning have explored methods to identify centers by analyzing digital footprint data collected from social media and mobile devices. For example, the study by Sun et al. (2016) proposed three different types of methods—DBSCAN, local Getis-Ord G, and Grivan-Newman—to detect clusters using geo-tag information and delineate the city center with a precise boundary. Zhong, Arisona, Huang, Batty, and Schmitt (2014) reveled the spatial structure of a city network in Singapore based on the analysis of automatic smart card data. Applying the notion of graph theory (Nystuen & Dacey, 1961), the study assessed regional travel demand, identified graph centralities to detect urban centers and uncovered graph community structures in Singapore. These studies in urban planning have not only suggested methods to detect city centers, but also demonstrated the presence of polycentricity—a city with multiple centers as opposed to monocentricity with a single center to the city (Kloosterman & Musterd, 2001; Roth et al., 2011). In addition to identification of polycentricity, Burger and Meijers (2012) suggested various levels and formats of spatial interactions between centers (or sub-centers) depending on the unique characteristics of each city (or regions).

Therefore, travel movement defines a series of subcenters at different levels and directions, which illustrate the typology of the destination structure. This study proposes an approach that integrates insights from travel movement patterns by applying theories in urban planning to understand the structure of travel destinations consisting of multiple popular areas with tourist activities obtained using mobile big data analytics. Beritelli et al. (2020) argue that travel flow is featured by visitors' intentional directions. Indeed, the travel flow is a dynamic structure involving constant movement and changes, which thus can be said that "tourism develops along flow" (Reinhold, Laesser, & Beritelli, 2015, p. 138). Therefore, understanding travel mobility at the destination is essential not only to identify areas for improvement and local strengths but also to develop strategic destination planning.

Methodology

Data collection

The researchers were able to access privileged mobile roaming datasets of international travelers who visited South Korea during the last 12 months (August 1st, 2017 – July 31st, 2018). One of largest telecom companies in South Korea that includes approximately 40% of market share for services collects the mobile sensor data, and that one of researchers in this study collaborates this current research project with the telecom company. Three cities such as Jeonju, Gangneung and Chuncheon – three of the most popular tourism cities in South Korea containing a number of heritage and food attractions – have been chosen as case studies (see Figure 1).

[Please insert Figure 1 about here]

The dataset includes the mobile phone trajectories of international travelers who visited any of the three following cities in South Korea — Jeonju, Gangneung and Chuncheon — during the study period. Each mobile phone user's trajectory consists of records that track the locations he/she stayed as well as the starting and ending time that defines each stay period. The time periods between consecutive stays indicates a user's movements between locations. The locations are tracked at the level of cellphone towers, of which their densities in space affect the spatial granularity of the dataset. The dataset documents the cellphone trajectories of 116,807 international travelers. In particular, 18,625 of them visited Jeonju during the study period, compared to 33,219 for Gangneung, and 66,646 for Chuncheon. The cellphone trajectories of these travelers in each city are used as input for subsequent analysis. Please also note that this research has retained the anonymity of the subjects in accordance with research ethics. Namely, no information was collected that could potentially enable researchers to identify individuals, such as gender, names, phone numbers, etc.

Data analysis

This study has employed a series of spatial big data analytics (Zheng, 2015), which comprises three steps such as the identification of stay points, spatial clustering based on density, and trajectory pattern mining approach to discover the spatial interactions between clusters (see Figure 2).

[Please insert Figure 2 about here]

Initially, a series of spatial descriptive analyses was used to understand profiles of travelers and initial distribution of their movement. A set of point-density analysis was applied to assess stay points of mobile roaming data. Then, density-based spatial clustering of applications with noise (DBSCAN) was employed to group stay points that are close in the space (Khan, Rehman, Aziz, Fong, & Sarasvady, 2014). Widely used in data mining and machine learning, the clustering algorithm requires two parameters for implementation, which are distance measurement (usually Euclidean distance) and the minimum size of a cluster. Outliers will also be marked in low-density regions. In order to find popular areas of interest, only the stay points visited with a high frequency were used as the input of DBSCAN. Note that we adopt DBSCAN over other exploratory spatial analysis methods (e.g., hotspot analysis, or mapping the visitation frequency of each cellphone tower) for two reasons. First, given that each cellphone tower (or its service area) covers a limited geographic area, especially in densely populated areas, individual cellphone towers might not be the ideal spatial unit to represent activity locations that are meaningful to tourists. Thus, performing the DBSCAN would allow us to group adjacent cellphone tower with an adequate number of tourist visits into a cluster. These clusters, which usually consist of one or more cellphone towers, are more effective in revealing the areas and regions in the city that are attractive to tourists. Second, performing the DBSCAN would effectively reduce the number of locations we used for the analysis of sequential pattern mining. Instead of finding significant travel sequences at the cellphone tower level, the sequential pattern mining algorithm is able to produce meaningful results at the level of clusters generated from DBSCAN, which suggest popular travel routes across the attractive areas in a city. In this research, stay point was captured at the level of cellphone tower. The visiting frequency of a cellphone tower is accumulated once a tourist stayed there for more than 30 minutes based on a guideline of tourism big data analysis suggested by Bifulco, Carten ì and Papola (2010) and Jongno City office (2019). Note that in the clustering process, we filter those cellphone tower that were seldom visited by the mobile users. In particular, by sorting the cellphone towers by frequency in descending order, we select the most active cellphone towers that account for 80% of the total visits for the clustering analysis. The cut-off value would be different for each city, which depends on the respective total visit count. For example, in Jeonju, the frequency threshold is 123, meaning that cellphone tower with a total visiting frequency below 123 (throughout the year) is not included in the clustering process. The improved DBSCAN starts from the most popular cellphone towers and search for its neighbors within a defined radius, which was chosen as 300 meters for Jeonju and 350 meters for Gangneung and Chuncheon in this study. Note that the choice of the radius is affected by the spatial granularity of the data in three cities. To understand the spatial density of cellphone towers in each city, we measure, for each cellphone tower, its distance to the nearest peer. We find that the median nearest distance values are 181 meters for Jeonju, 344 meters for Gangneung, and 282 meters for Chuncheon. This gives us a general picture of the spatial resolution of cellphone observations in the three cities. Thus, we choose the radii such that their values are higher than the spacing gaps between cellphone towers in the corresponding city. Since cellphone towers in Jeonju are more densely distributed, we adopt a smaller radius. The algorithm would group density-connected stations for each cluster. In this project, the minimum size was set to be 1 (i.e., one single cellphone tower can also form a cluster). Given a destination city, the DBSCAN algorithm groups cellphone towers into a series of clusters, with each cluster including one or more cellphone towers in close proximity. These clusters and their visitation frequencies can effectively reveal the popularities of different areas in the city. Besides showing the spatial patterns of these clusters, in this paper we perform a sequential pattern analysis to extract frequent travel patterns of tourists at the level of these clusters. First, given an individual travler's mobile phone trace, by merging consecutive data points that fall within the same cluster, we transform the trajectory to a cluster-level sequence $T = \{\alpha_1, \alpha_2, \dots \alpha_n\}$, with α_i denoting the i^{th} cluster that the individual traversed through. We name α_i as an event.

In order to extract frequent travel patterns from user trajectories, we adopt an efficient algorithm, the Sequential PAttern Discovery using Equivalence classes (SPADE). The SPADE algorithm utilizes a lattice-theoretic approach that can decompose the original search space to improve the efficiency of sequential pattern mining (Zaki, 2001). The algorithms takes a collection of sequence as input, and output a series of frequent sequences with a user-specified length and a threshold of minimum support.

In our analysis, a user's trajectory $T = \{\alpha_1, \alpha_2, \dots \alpha_n\}$ is considered as a sequence. By specifying the length of the frequent patterns (denoted as k) and minimum support (denoted as $minsup$), the SPADE algorithm aims to find all the length-k sequences $\alpha_1 \rightarrow \alpha_2 \rightarrow \cdots \rightarrow \alpha_k$ such that all these sequences occurred more than $minsup$ times. For instance, given $k = 2$ and $minsup = 10$, the SPADE algorithm will identify all length-2 sequences from user trajectories, such that for each 2-length sequence $\alpha_a \rightarrow \alpha_b$, there are at least 10 tourists that were observed with travel pattern $\alpha_a \rightarrow \alpha_b$. Note that → simply denotes a "happen-after", meaning that there could be intermieate stops (i.e., clusters) in a tourist's travel sequence between α_a and α_b. For each city in this analysis, we perform the SPADE algorithm for $k = 2$ and $k = 3$. This algorithm also requires setting minimum support as the parameter (Peng & Liao, 2009). This study set the minumum support as 1 so that the results show all sequential paths available in the data set.

Results

Number of daily users over the year

The daily number of tourists in the three cities from 1 August, 2017 to 31 July, 2018 has been estimated at first. The visitor count was added once the tourist had record within the city. The average daily visitors to cityis 128 for Jeonju, 275 for Gangnueng, and 222 for Chuncheon. It is noteworthy that there was a surge of foreign tourists in Gangneung during February 2018, which might be associated with the Pyeongchang 2018 Winter Olympics.

Travel behaviors at the destination

We have estimated the frequency of moving tourists across hours. As the mobile roaming dataset only speaks for the meaningful stay of users over recorded periods, it is safe to assume that the mobile phone users were moving during the time periods that are not specified in the records. The number of moving users was computed at 10-minute intervals. The percentage of moving users out of total tourists for each interval was averaged over one year, as shown in the figures below. These figures roughly indicate how many tourists were moving and how this number changed during the day. In the three cities, the number of moving users during daytime notably surpassed the counterpart during nighttime. However, there was a drastic fall of moving users in Chuncheon around 1:00 and 2:00 pm (see Figure 5), while the other two cities did not have such a pattern (see Figures 3 and 4). Travelers in Jeonju and Gangneung were most likely to travel to the destinations between 11:00 am and 6:00 pm.

[Please insert Figures 3, 4, and 5 about here]

In terms of length of stay and travel distance, international travelers tend to stay in Jeonju for 2.52 days, Gangneung for 3.02 days, and Chuncheon for 1.22 days. They are likely to travel about 2.92 km in Jeonju, 5.62 km in Gangneung, and 2.76 km in Chuncheon per day.

Spatial density

According to clustering analysis, 222 out of 782 cellphone towers in Jeonju were grouped into 107 clusters through the algorithm, which covers 80.18% of total density. Figure 6 illustrates the spatial patterns of the clusters. Since there are many clusters, to avoid visual clutter, we selected the clusters for which their total visit accounted for more than 1% of the total and annotated them with different colors. Note that the areas labelled A, B, and C refer to the heritage, university, and local markets in Jeonju, respectively. These areas, taking up a considerable proportion of the visiting frequency, suggest that they enjoyed much greater popularity among tourists.

[Please insert Figure 6 about here]

In Gangneung (see Figure 7), the cellphone towers with more than 809 visits can be input into the clustering algorithm. As a result, only 55 out of 704 cellphone towers were grouped into 27 clusters through DBSCAN analysis, which indicates that the other 649 cellphone towers occupied a very small proportion of visiting frequency. The distance threshold in the clustering analysis was set to 350 meters. Marked by differet colors, the clusters with visit counts greater than 1% of the total are very densely distributed near the sea, which suggests that most tourists want to visit localized areas.

[Please insert Figure 7 about here]

As for Chuncheon (see Figure 8), the cut-off value of visiting frequency is 179, and thus 103 out of 861 cellphone towers were selected for clustering analysis. As with Gangneung, by setting the search radius to 350 meters, there were 50 clusters found by the DBSCAN algorithm. Again, clusters with a visiting frequency greater than 1% of the total were annotated by different colors, and most of them were located in central and southwestern Chuncheon.

[Please insert Figure 8 about here]

Sequential pattern mining

The spatial arrangement of these frequent visitation patterns were then visualized. Figure 8 shows the frequency visitation pattern with a length of 2 (i.e., directional interactions between two spatial clusters). The sequences indicate that tourists moved from one cluster to another. The arrowed lines represent the direction of the movement, and the numbers describe how frequent these patterns occur (measured as the total number of times the pattern is detected, normalized by the total number of sequences analyzed). A self loop indicates that some users paid repeated visits to the same area (cluster).

As shown in Figure 9, most of the sequences occurred within a confined geographic area (i.e., areas A, B, and C in Figure 1). The places including C1, C51, C40, C23, C6, and C7 is the heritage area including Jeonju Hanok Village, which is the most popular travel attraction in the city. In particular, C1 has been recognized as a hub where travelers appear in a loop pattern—that is, they start traveling from C1 and return back to the same place in the same line of Lew and McKercher (2006)'s finding. Another hot place consisting of C19, 44, and 4 involves Chonbuk National University and a famous national park named Deokjin Park. It shows the spatial interactions between the Jeonju Hanok Villege and Deokjin Park areas. Interestingly, the area comprising C27, 80, and 38 does not have a significant interaction with other places. It is recognized that many accommodations are in the place, and the data have been mostly observed at night. The length-3 sequences and their relative percentages have been estimated; however, the insights from this analysis are consistent to the results from the length-2 sequences (see Appendix I).

[Please insert Figure 9 about here]

In Gangneung (see Figure 10), there were still considerable self loops within a single cluster, which means that many tourists seek for activities within a confined geographic area or pay repeated visits to that cluster. Unlike Jeonju, the clusters where most sequences occurred are not necessarily connected together in the space. There were also certain people occasionally traveling from one popular cluster to another. More specifically, C1 indicates the center of the city where the museums and national library are located. Travelers show a pattern from C1 to C26 that is a popular region for restaurants. C27 is the area of Gyeongpo Beach, which is the most well-known beach in South Korea. International travelers tend to travel from C27 to C18, where many sports complexes are placed. This pattern has been largely observed during

Pyeongchang 2018 Winter Olympics. For further consideration, Appendix II show the results of length-3 sequences.

[Please insert Figure 10 about here]

In Chuncheon (see Figure 11), the clusters that took up the most sequences were distributed in the central and southwestern areas. For the latter, there were also inter-connections between popular clusters, which suggests that tourists might be willing to visit several different destinations during a day. In more detail, C4 and 19 refer to Nami Island, which is a famous destination for international travelers. The area of Nami Island is closely connected to C20 and 17 (Gyeonggang Station for rail-biking activity) as well as C36 and 37, which includes an integrated resort. This reveals that travelers are likely to visit the area of C11 and 12, where most popular restaurants are located. Investigating times when travelers visited C11 and 12 reveals that people tend to have dinner in that area. The results of length-3 sequences in Chuncheon that show coherent insights with length-2 sequences are presented at Appendix III.

[Please insert Figure 11 about here]

Discussion

The advancement of ICTs accelerates the realization of smart tourism destinations (Gretzel, Sigala, et al., 2015). In particular, the evolution of mobile technology not only facilitates communication between users, but also enables destination marketers to obtain real-time/contextual information about users. Mobile sensor data include details of travelers' activities during their stays at destinations, elucidating movement patterns and travel flow in an inclusive and sophisticated level. This research analyzed mobile big data that represented the spatial behavior of international travelers who visited three cities in South Korea, namely, Jeonju, Gangneung, and Chuncheon, across 12 months. This study initially adopted trajectory mining approaches to identifying “hot spots” (or tourism centers) and travel movement patterns within intra-destinations. It reveals heterogeneous typologies of “hot spots” and varied formats of spatial interactions based on travel flow across different cities. These findings are vital to design sustainable and innovative destination planning and management which can eventually enhance destination competitiveness. Along with the flow-based destination management (Beritelli et al., 2020), this study that applies mobile big data analytics suggests an approach to integrating mobility intelligences with the development of destination planning. As a result, this study provides important academic and practical implications.

When reviewing the tourism literature on travel behavior, the understanding of travel behavior at the during-trip stage is limited compared to the abundant studies focusing on the pre- and post-trip stages. This bias can be attributed to restricted access to relevant data that reflect travel behavior/experience at destinations. Although several studies have analyzed geotagged data from social media websites (e.g., Flickr, Four Square, and Twitter), this type of data has its limitations, such as the data sparsity and the potential bias of a sample that is largely associated with social media with few online sources to access geotagged data (Wong et al., 2017). The current study, which analyzes mobile sensor data, suggests an innovative approach that overcomes the known limitations of social media data and generates major insights that improve a comprehensive understanding of travel flow at destinations.

In particular, the findings suggest that travelers do not tend to visit all parts of a city, but only specific places. For example, among 782 cellphone tower coverages in Jeonju, 222 were used to generate spatial clusters (hot spots), revealing that international travelers primarily visit approximately 30% of the areas in Jeonju City. The two other cities exhibited more dramatic results. For example, international travelers mostly visit only 8% of the regions in Gangneung and 12% of the regions in Chuncheon. This finding is associated with the inequality of tourism demand, which has been extensively discussed at the national level (Li, Chen, Li, & Goh, 2016). That is, travelers are likely to visit limited attractions as opposed to visiting the entire places equally, which suggests the existence of primary and secondary attractions based on gravity theory.

Furthermore, this study demonstrated the presence of multiple attractive regions within a city that reveals its polycentric structure. Unlike a monocentric city (Fujita, Krugman, & Venables, 1999), contemporary cities have more complex structures, often displaying a pattern of polycentricity comprising multiple centers (Roth et al., 2011). Built on the notion of polycentricity, this study revealed the clustering of multiple hot spots (i.e., multiple centers) based on travel flows. In other words, the results not only identified multiple tourism centers in the three destinations, but also described the decomposition of multiple travel flows at various scales.

This study also reveals the difference between the destination structures of the three cities studied. The cities of Jeonju and Chuncheon clearly display a polycentric structure with hot spots identified within the margins of attraction. However, Gangneung presents a morphologically monocentric structure in which the distribution of tourist activities mainly locate around the city center (Burger & Meijers, 2012). The levels of spatial interactions between hot spots also varied between the three cities. While Jeonju and Chuncheon showed ample interactions between the clustering of hot spots (i.e., functional polycentricity), Gangneung presents limited linkages between hot spots labeling morphological polycentricity (Burger & Meijers, 2012). This can be explained by the functions of cities. Jeonju and Chuncheon are capitals of Jeollabuk-do and Gangwon-do provinces, respectively, that include provincial government buildings. The polycentric urban development alleviating the urban diseases (e.g., traffic congestion, air pollution, shortage of affordable housing, and crowdedness) fulfil the wide distributions of infrastructure in general and travel attractions in particular (Sweet, Bullivant, & Kanaroglou, 2017). Dispersed travel attractions in polycentric metropolitan areas (e.g., Jeonju and Chuncheon) encourage for travelers to stimulate dynamic travel flows visiting multiple hot spots and spatial interactions. In contrary, Gangneung located at the coastal area is relatively less developed comparing to two other cities, and shows most of travel visits are concentrated on the central business district.

Linking to tourism theories, the results of spatial interactions by sequential pattern mining analytics present loop patterns. Lew and McKercher (2006) proposed a number of movement path models and suggested the circular loop. Consistently, the current study suggests the existence of a loop movement pattern wherein travelers mostly leave a core place (or base) and return to it after visiting multiple attractions, which falls in line with the base camp model proposed by Lue, Crompton, and Fesenmaier (1993). More specifically, the circular loop pattern is particularly apparent in Jeonju where a couple of popular travel areas exist (e.g., attractions of national park and traditional-style village). Travelers are likely to show circular patterns within the travel zones and present spatial interactions between those two areas. Travelers visiting other two cities display different movement patterns comparing to ones traveling in Jeonju. Those who visit Gangneung tend to show a chaining model that signifies linear point-to-point patterns. That is, international travelers are likely to visit a beach area initially, and move to city center by stopping over several popular places within the center. Tourists visiting Chuncheon seem to form radiating hubs that link to other attractions suggested by Lew and McKercher (2006). That is, an integrated resort serves as a hub that generates point-to-point patterns as well as circular loop. As show in the results, Chuncheon is a type of day-trip destination where travelers have motivations to diversely explore attractions in a single day.

From the methodological perspective, this study suggests an innovative method for tourism big data analytics. Sequential pattern mining using the SPADE algorithm enables researchers to analyze a massive amount of mobile sensor data and produce statistical inferences on comprehensive trajectory mining results. Most tourism studies that used GPS data have applied descriptive methods (e.g., Shoval et al., 2011; Shoval, Schvimer, & Tamir, 2018). This study, however, suggests the usefulness of trajectory data mining as a tool for generating mobility insights and provide important implications to develop destination planning and management. Corresponding details of managerial implications are discussed in the following.

With regard to practical implications, the findings of this research provide a foundation for destination design and planning. For example, DMOs can use the result to develop travel packages. When selecting places to recommend to visitors, understanding the places where travelers visit the most and developing spatial connectivity between them is important. This study sheds lights onto specific guidance for destination planning and development. Saarinen, Rogerson, and Hall (2017) asserted that the contextual dimension should be considered in tourism planning. The spatial interactions of tourism destinations derived from trajectory mining analytics, which considers points of interests and local travel attractions, can suggest an innovative approach to recognizing tourist flows at intra-destinations and develop sustainable tourism planning. This finding enables DMOs to construct collaborative management associating hot places where travelers are likely to visit in their daily trajectory. The collaborative management would help destination planners to reduce their costs and travelers to enhance their travel experiences. More specifically, the structure of spatial interactions facilitates for DMOs developing dynamic travel packages. Indeed, the sequence of places where travelers are likely to visit at the destinations reflects the structure of the experiences based on the idea of ‘staging” that highlights storytelling in tourism design (Pine & Gilmore, 1998). Directed travel mobility this research identified should suggest a guidance for DMOs on how to design travel itinerary (or packages) considering certain hot places and their arrangements so as to provide staging experiences with visitors.

This study also suggests different information such as numbers of hot spots and the directions of travel routes suggested according to different characteristics of cities. The information about structure and interactions of hot spots can enhance the transportation infrastructure so as to facilitate travel mobility during their visits to the destinations. From the perspective of infrastructure planning, establishing efficient transportation system is of importance to facilitate travel mobility that largely associates with tourists' experiences. The insights of spatial interactions guide for policy-makers to improve transportation systems. For example, it is suggested for policy-makers in Jeonju to develop bus routes that can connect tourism hot spots within the destination. However, in case of Gangneung, transportation services that facilitate travelers to move from coastal area into city center are recommended. For Chuncheon, the location of an integrated resort should contain sufficient transportation facilities so that travelers can easily move to other hot places. This implies that policy-makers in Chuncheon are necessary to review the existing transportation infrastructure connecting between coastal areas and city center.

In addition, this information can be utilized as an underpinning in developing destination recommendation systems, suggesting information and/or services for consumers to facilitate their decision-making processes (Fesenmaier, Wöber, & Werthner, 2006). In terms of smart mobility, such insight will be useful in assessing the transportation system of a place. Transportation departments and DMOs should evaluate the current accessibility of transportation systems to verify whether a destination provides sufficient number and types of transportation for travelers moving across different hot places.

In conclusion, understanding travelers' behavior during destination visits is an essential step in developing strategic destination planning to make a destination smart. This study applied big data analytics to analyze mobile sensor data and identified tourism hot spots based on dynamic travel flows and spatial interactions across the hot spots. It is recognized that tourism studies in this field have mostly utilized survey methods (Wu & Carson, 2008) or analyzed geotagged data from social media websites (Wong et al., 2017). This work investigates mobile network-based positioning data, overcoming the limitations of previous methods, and proposes the integrative approach of spatial big data models with destination planning. In contrast with extant studies focusing on understanding travel pattern behaviors, this study attempts to explore the application of travel mobility into designing destination planning and development. This study primarily performs the trajectory pattern mining analysis over the full dataset. The tourism literature has suggested variations of travel behaviors over time with regard to seasonality. Thus, an idea that understands the behavioral characteristics of tourists across different seasons is highly suggested for future study.

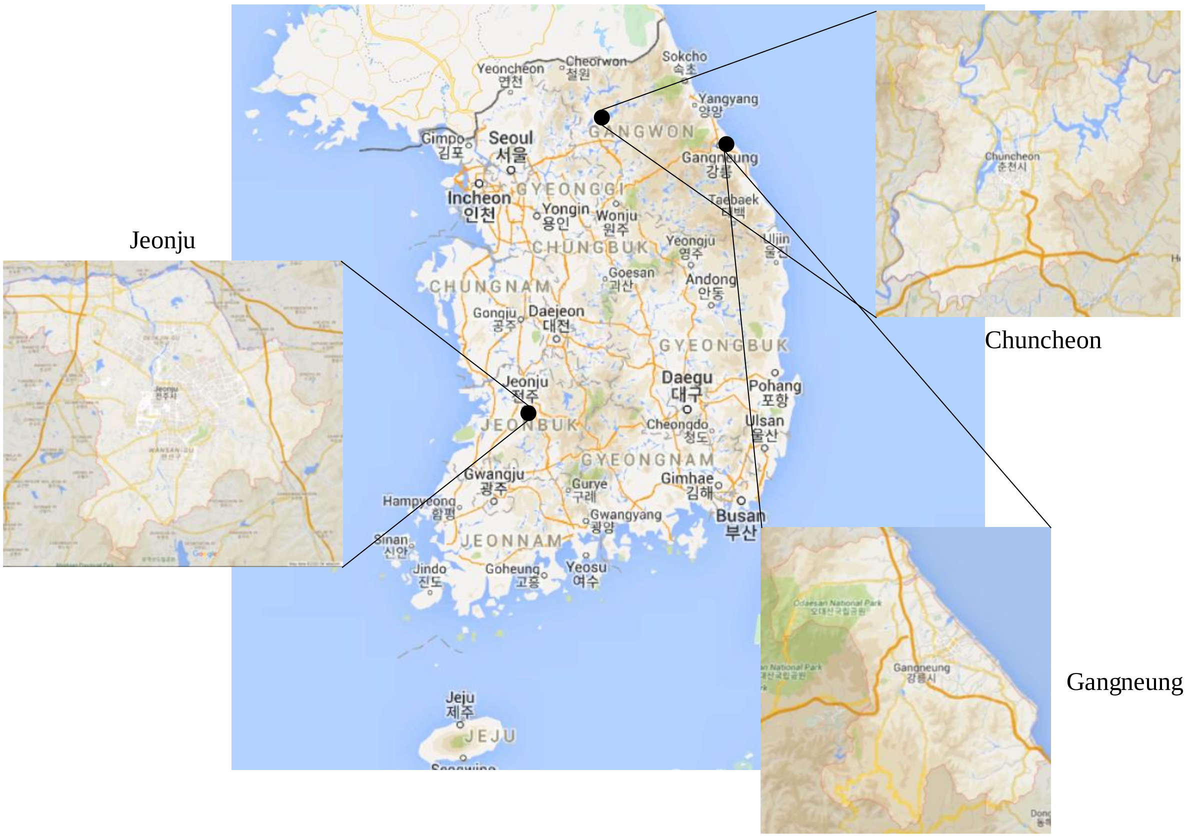

Figure 1. Selected cities of case study

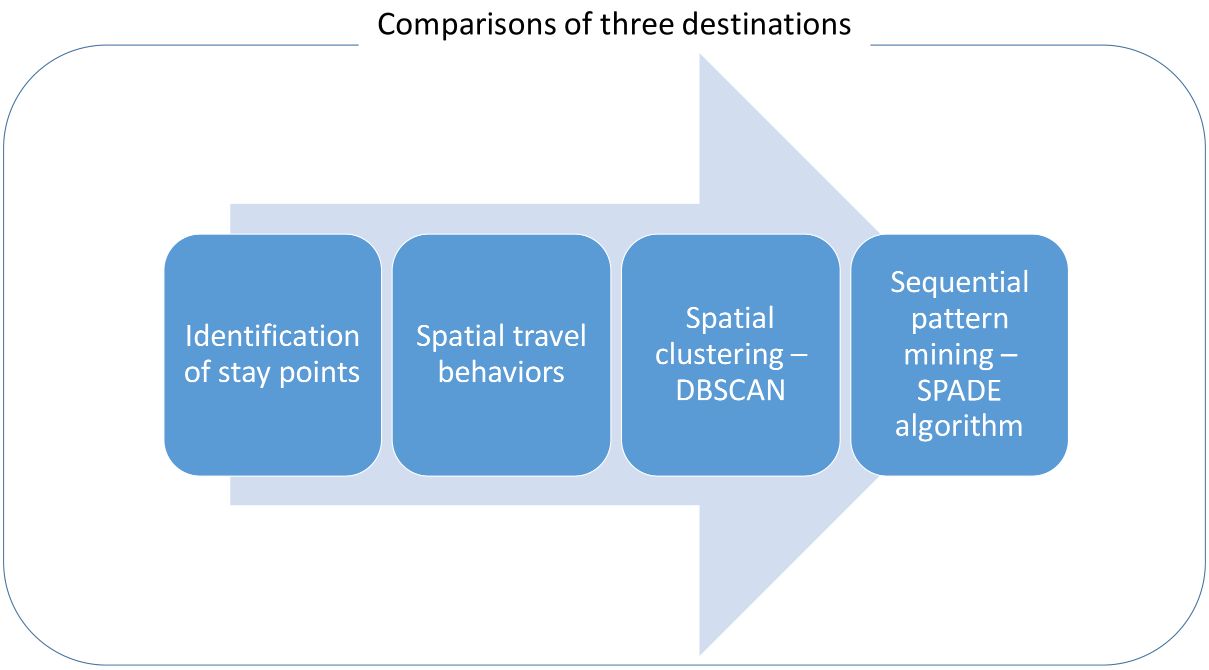

Figure 2. A process of data analysis

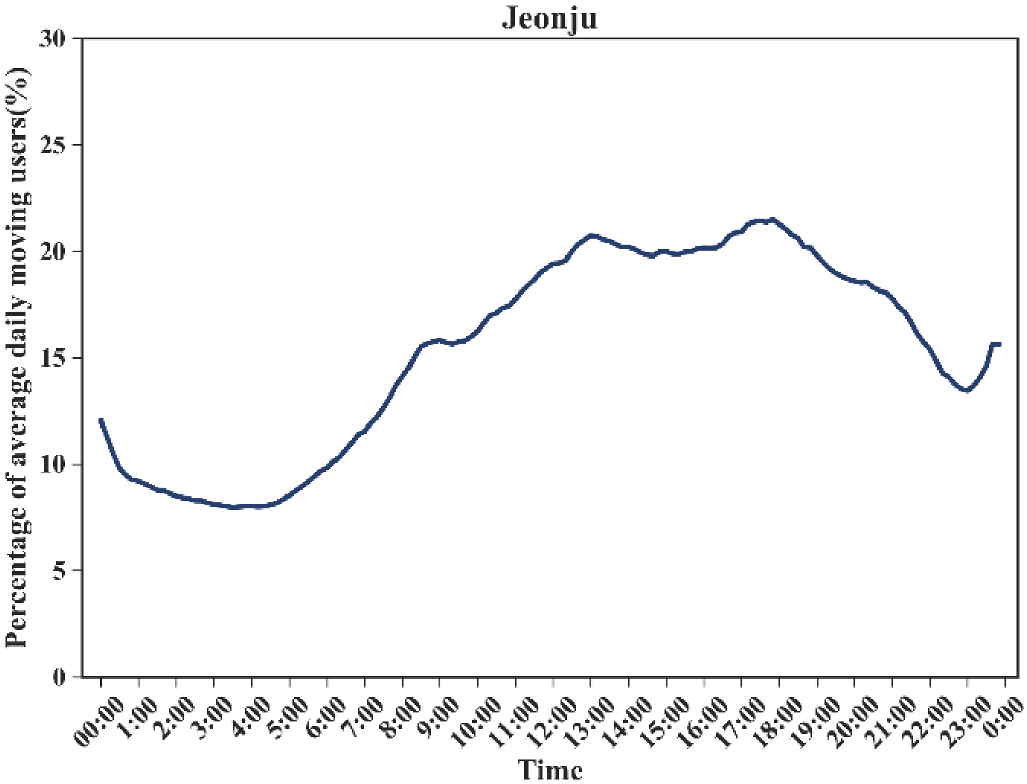

Figure 3. Frequency of average daily moving users at Jeonju

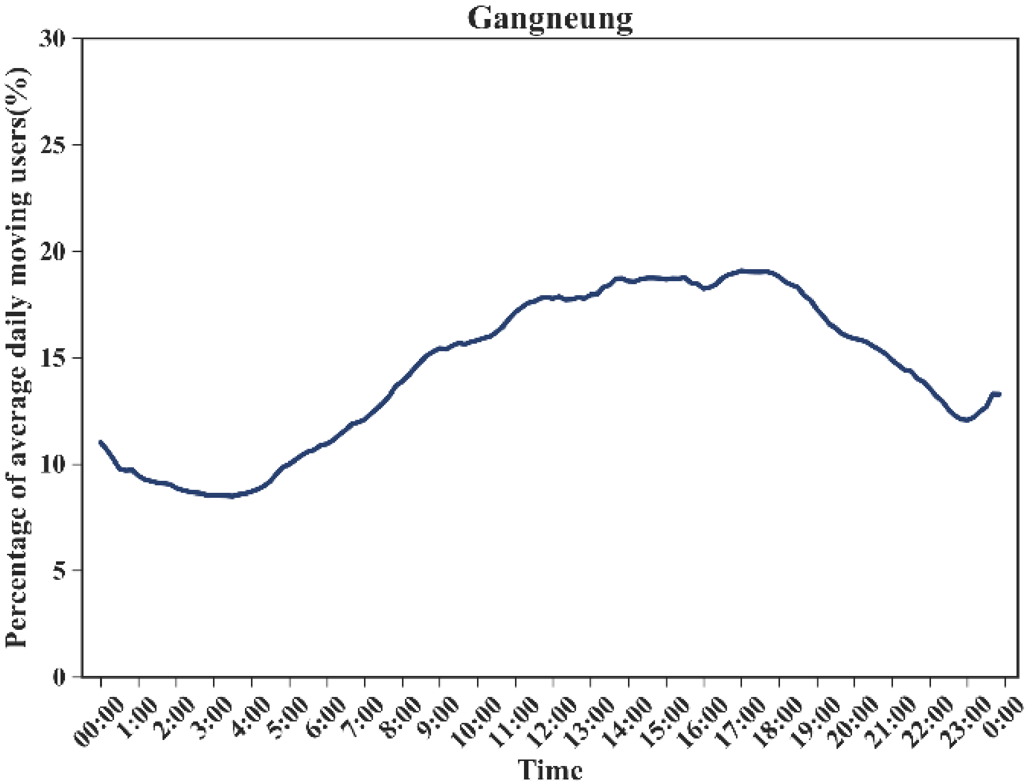

Figure 4. Frequency of average daily moving users at Gangneung

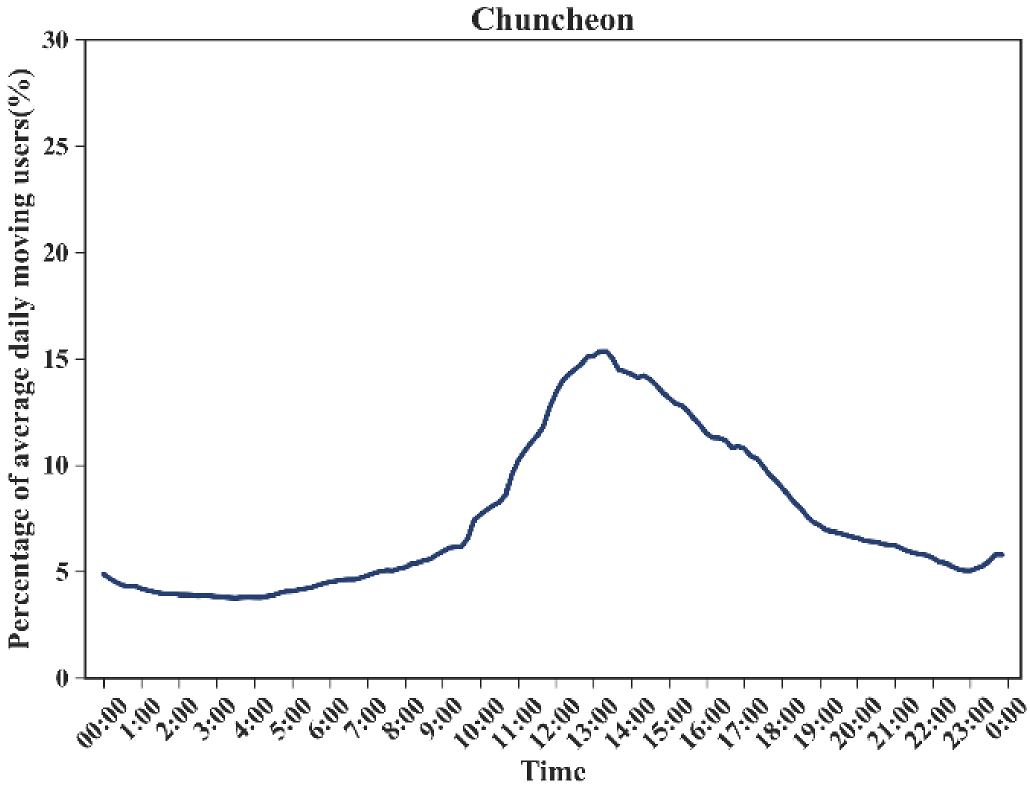

Figure 5. Frequency of average daily moving users at Chuncheon

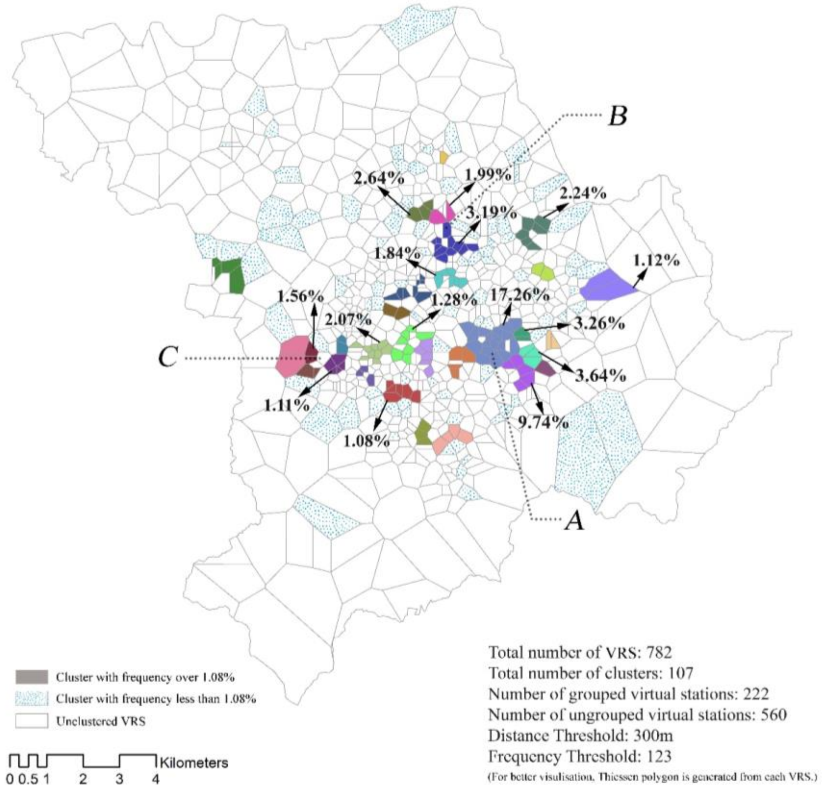

Figure 6. Results of DBSCAN Analysis in Jeonju

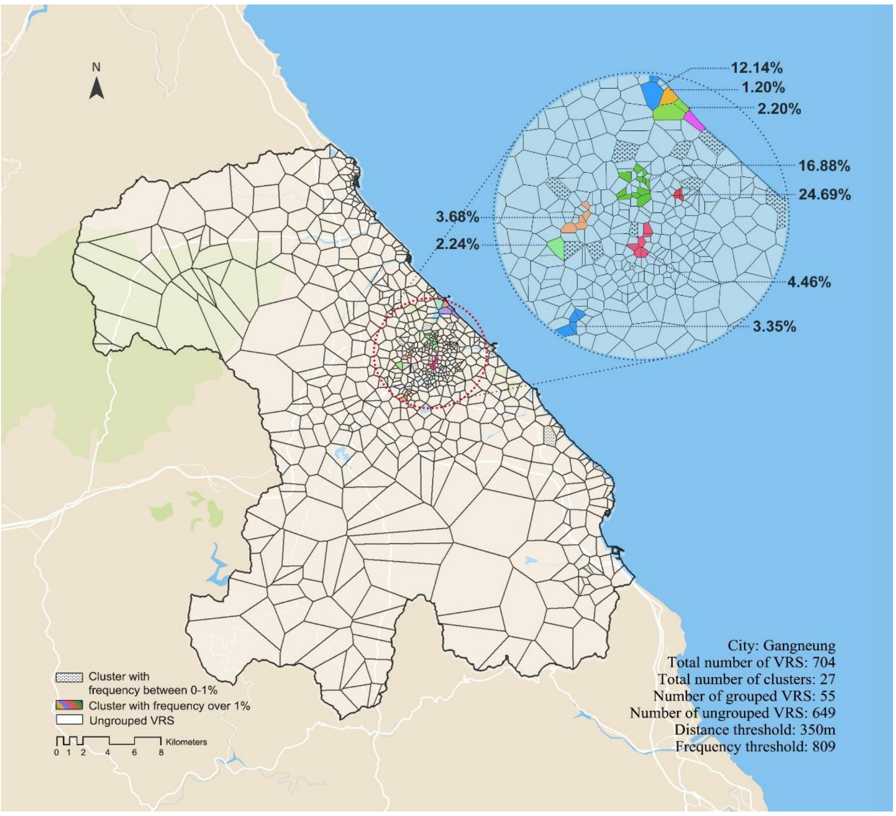

Figure 7. Results of DBSCAN Analysis in Gangneung

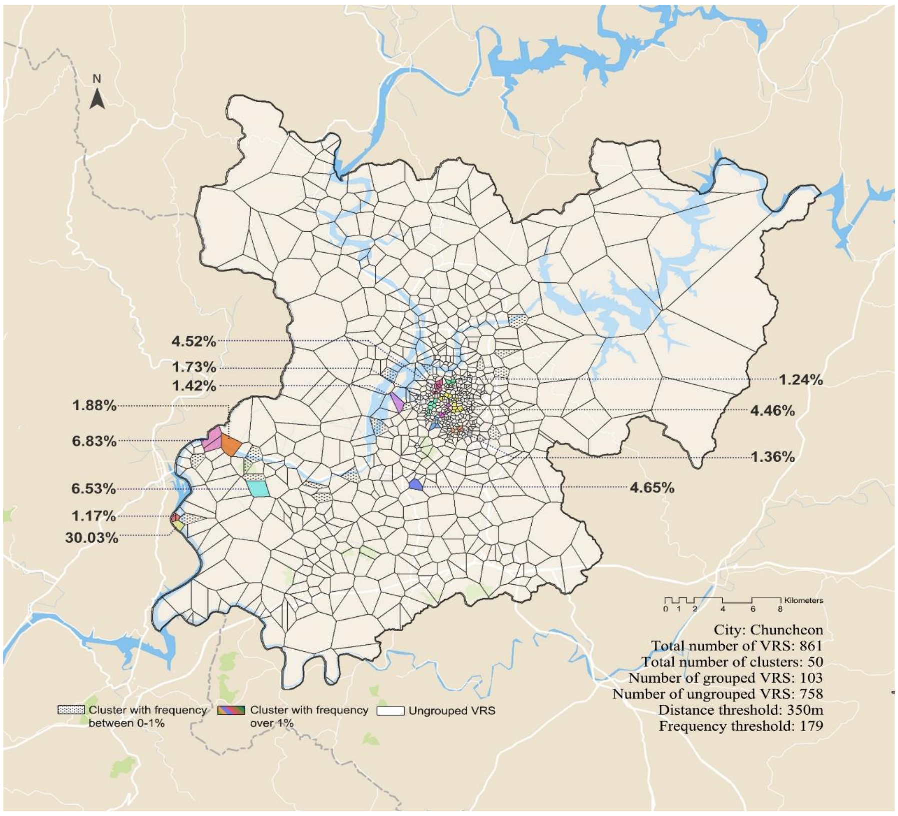

Figure 8. Results of DBSCAN Analysis in Chuncheon

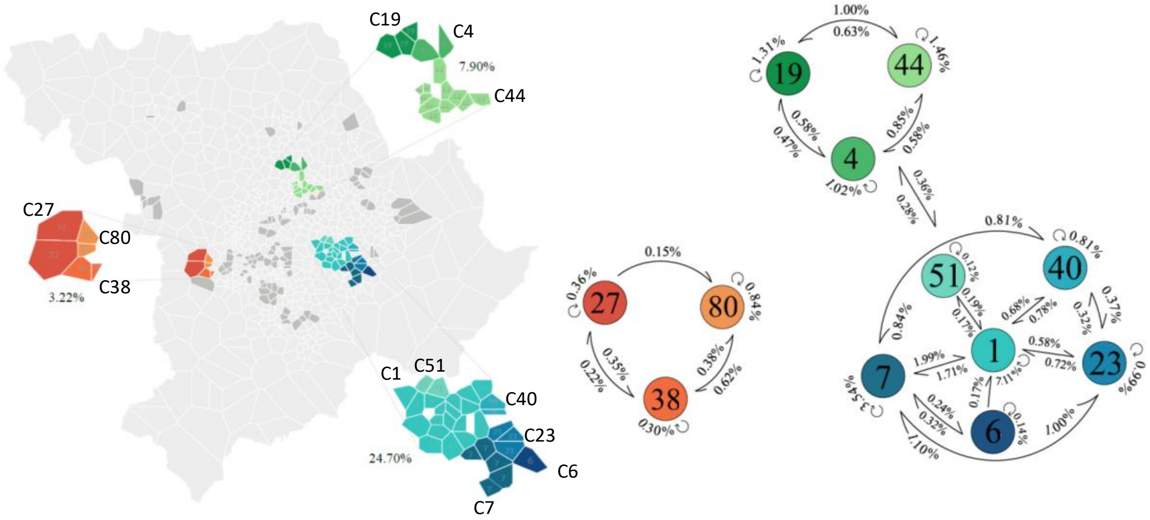

Figure 9. Results of Sequential Pattern Mining with Length-2 sequences in Jeonju

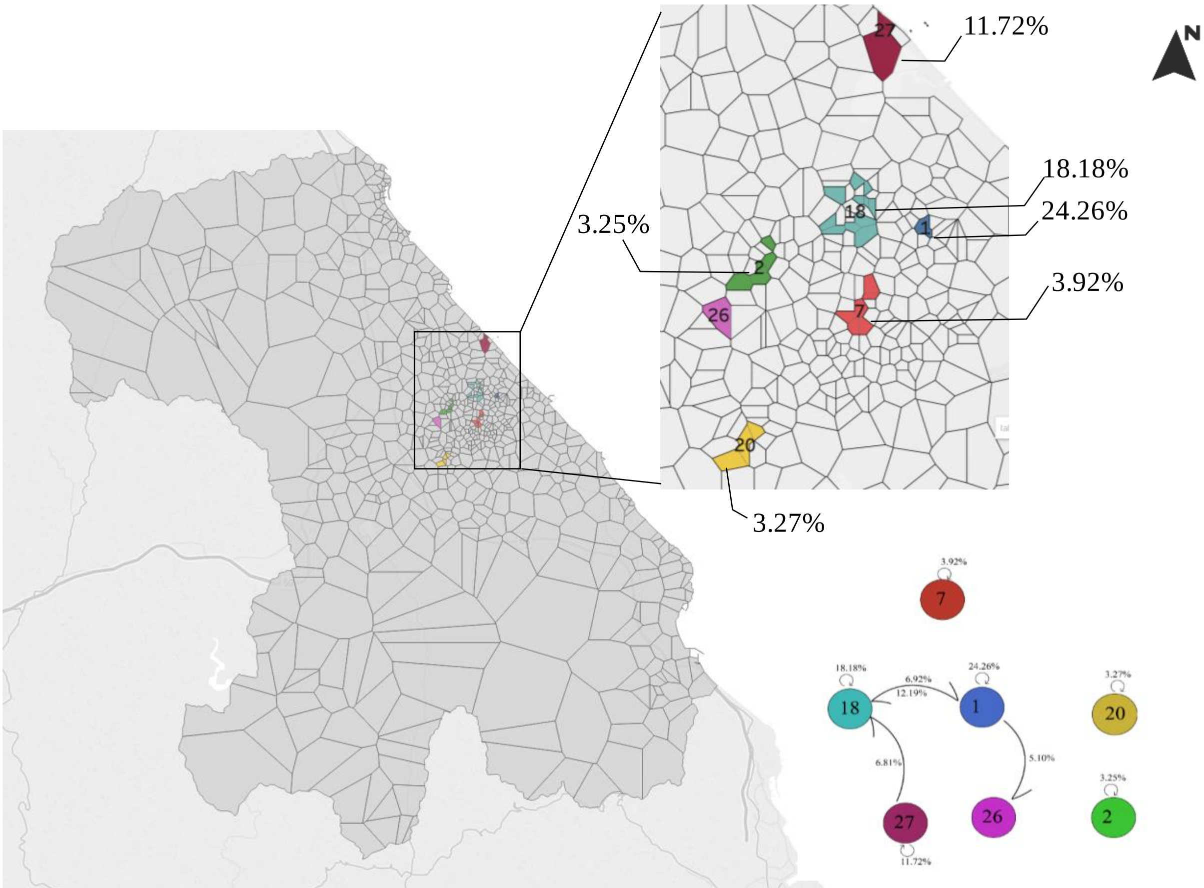

Figure 10. Results of Sequential Pattern Mining with Length-2 sequences in Gangneung

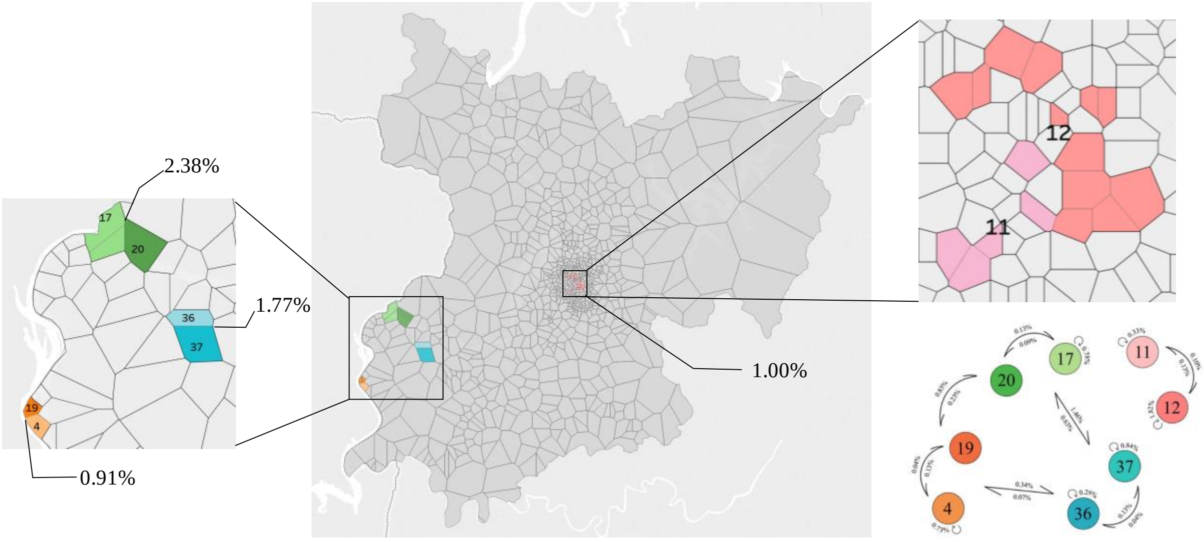

Figure 11. Results of Sequential Pattern Mining with Length-2 sequences in Chuncheon

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