Exploring Urban Mobility from Taxi Trajectories: A Case Study of Nanjing, China

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Abstract: Identifying urban mobility patterns is a crucial research topic in geographic information science, transportation planning, and behavior modeling. Understanding the dynamics of daily mobility patterns is essential for the management and planning of urban facilities and services. Previous studies have utilized taxi trajectories collected from the Global Positioning System (GPS) to model various types of urban patterns, such as identifying urban functional regions and hot spots. However, there is limited research on how the results of these studies can be used to inform real-world problems in urban planning. This research examines the development of sub-centers in Nanjing, China based on Taxi GPS trajectories. The results indicate a clear separation between the urban center and the sub-centers. In addition, we also clustered the time series of taxi pick-up locations to model dynamic urban movement and identify outlier patterns. The results demonstrate the importance of considering human mobility patterns in identifying urban functional regions, which provides valuable input for urban planners and policy makers.

1 INTRODUCTION

In recent decades, modeling human mobility patterns has become an important research topic in various fields such as computational physics, urban planning, Intelligent Transport Systems (ITS), and Geographic Information Science (GIS). The growing availability of location-aware devices, such as the Global Positioning System (GPS) receivers and smart phones has provided new challenges and opportunities for planners and policy makers to analyze, model, and predict human mobility patterns (Chen et al., 2015). Commonly used datasets include (but are not limited to) georeferenced mobile phone data (Ahas, 2005; Calabrese et al., 2013), location-based social media check-ins (Cao et al., 2015; Lee et al., 2016), Bluetooth tracking data (Delafontaine et al., 2012), and floating car GPS locations (Ge et al., 2017, Jiang et al., 2009). Among these datasets, GPS-enabled floating cars are particularly effective at capturing intra-urban mobility patterns across street networks due to their high spatial precision and sampling resolution (Jiang and Zhang, 2018; Yang et al., 2018; Hu et al., 2018; Ge et al., 2017). In practice, floating cars are often observed as taxis or shared rides in many cities, where each floating car periodically records its coordinates via a GPS receiver and stores the information in a central server (Liu et al., 2012).

Previous studies have used taxi GPS data to analyze human mobility patterns from both the individual and urban perspectives (Atmaji and Sig, 2016; Castro et al., 2013; Chen et al., 2017; Cui et al., 2016; Fanhas and Saptawati, 2016). On the one hand, many individual-oriented studies focused on the morphology and internal characteristics of taxi trajectories and its implication for refining traditional mobility models, such as modifying the power law distribution under a given spatio-temporal context (Jiang et al., 2009). These studies provided quantitative support to better understand urban dynamics and to help maintain sustainable mobility in urban systems. For example, Santi et al., (2014) quantified the benefit of ridesharing by translating spatio-temporal sharing problems into a graph-theoretic framework.

On the other hand, studies also investigated how taxi trajectories revealed the characteristics of urban functional regions and the interactions between urban areas (Mazimpaka and Timpf, 2015; Tang et al., 2015; Hu et al., 2014). For example, Liu et al., (2016) used taxi GPS data to analyze the spatial interaction patterns between parcels, as well as the real-time land use patterns reflected by the interaction.

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Although recent studies have provided valuable input to advance the theories and methods in modeling urban mobility patterns from taxi trajectories, few studies have directly connected their empirical results to real-world planning problems and challenges that cities face, nor have they used the results to validate a planning policy that has actually been implemented. As such, this study is conducted from a problem-driven instead of a data-driven perspective. It is motivated by the 1991-2010 development and planning agenda published by the local government of Nanjing, China (Nanjing City Council, 1995), where the city reviewed challenges of over-crowded central business areas (CBD) and the associated imbalance in urban resources. The city proposed to rapidly grow several suburbs of Nanjing as functional sub-centers for local residents. This research utilizes one-week taxi GPS data from 2010 to address the following research questions:

- Spatially, are there established functional sub-centers in Nanjing as proposed in the development plan? If so, how does this multi-center urban structure affect the distance and direction distribution of taxi trips in Nanjing?
- Temporally, how should the mobility dynamics of urban functional regions be modeled? Are there any regions with outlier time series?

2 RESEARCH RESIGN

2.1 Data

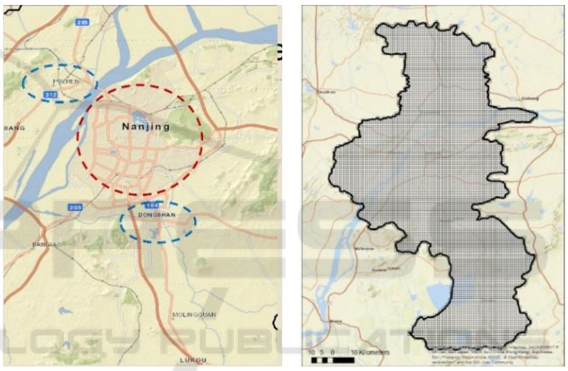
The dataset utilized in this research is obtained from Nanjing City, China. Nanjing is the capital of Jiangsu province, situated in the Yangtze River Delta Region in China. With an administrative area of 6,600 km^2 and a total population of over 8 million, Nanjing is the second largest city in eastern China and is well known for being a major cultural, economic, tourist, and transit center.

The dataset used in this research contains approximately 135 million GPS locations of 7,194 taxis between June 4, 2010 and June 10, 2010. In addition to GPS coordinates, the dataset also includes a unique identifier (ID) for each taxi, a unique ID for each record, the timestamp for when the location was logged, driving speed, driving direction, and the current status of the taxi, where 0 indicates that the taxi is free to pick up passengers and 1 indicates that the taxi is currently occupied. The sampling resolution is between 15 to 30 seconds. On average, there are 4,666 records per day per taxi. Table 1 provides a sample record of our dataset.

Table 1: A sample taxi record.

Record ID	10000000
Taxi ID	13451852779
Longitude	118.779696
Latitude	32.025413
Speed (km/h)	25
Direction (degree)	50
Status	1

Figure 1a shows the administrative boundary of our study area. To facilitate the analysis, we divided the study area into 1km*1km grid cells. Figure 1b shows the approximate main urban center in Nanjing (in red) and two close-by sub-centers (in blue): Pukou district in the northwest and Dongshan district in the south.



(a) (b)

Figure 1: Study area. (a) 1km*1km grid cells; (b) Urban center and sub-centers.

2.2 Methodology

2.2.1 Preprocessing Data and Calculating Spatial Indicators

Previous studies have used the number of taxi trips to represent the activeness of an urban area (Ferreira et al., 2013). In this study, we identify the pick-up and drop-off points of each trip based on the “occupied” status field in the original data. Over 1.3 million trips were extracted. For each trip, we calculate the travel distance between the pick-up and the drop-off points, as well the travel direction as defined in Figure 2. Note that in this study we are interested in how the origination of taxi trips helps explain the delineation of sub-centers in Nanjing, so we only consider the pick-up points in each grid cell.

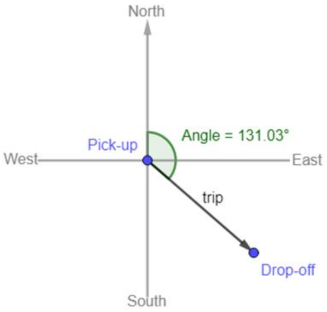


Figure 2: Calculate travel direction.

The number of pick-ups and the median travel distance represent the magnitude and the scale of mobility originated from different urban areas. In addition, we are also interested in how travel direction provides informative input for the urban structure in Nanjing. A direction entropy indicator is defined to present the randomness of travel directions. The formula is derived as follows:

$$E = -\sum_{i=1}^{N} p_i \log_2 p_i \qquad (1)$$

Where p_i refers to the percentage of trips going to a given direction, and N stands for the total number of directions (Table 2). For simplicity, we divided the space into eight directions. The direction entropy is considered an indicator for the consistency of travel directions.

Table 2: Define eight travel directions.

Direction	Angle
North-Northeast	[0,45)
Northeast-East	[45,90)
East-Southeast	[90;135)
Southeast-South	[135;183)
South-Southwest	[180;225)
Southwest-West	[225;270)
West-Northwest	[270;315)
Northwest-North	[315;360)

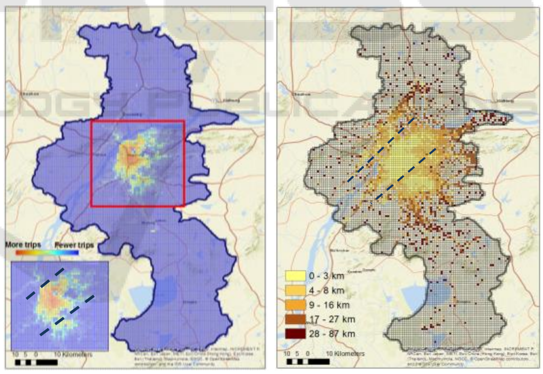
2.2.2 Modeling Temporal Patterns

In addition to the spatial heterogeneity of human mobility, previous studies also explored urban functional regions based on temporal variations of activities. The second analysis of this study explores how the number of pick-ups varies at different times of the day. We aggregate the number of trips for each grid cell by hour and use a dynamic time warping (DTW) algorithm to measure the similarity of hourly mobility patterns between grid cells. DTW has proven to be robust to distortion in time series (Yuan and Raubal, 2012, Zhang et al., 2008), so it allows us to group similar patterns and identify outlier patterns.

3 PRELIMINARY RESULTS

3.1 Exploring Urban Sub-Centers

Figure 3a shows the density distribution of taxi pick-ups. As expected, most trips originate from the urban center; however, the Dongshan sub-center also demonstrates a cluster of pick-up points. The other sub-center, Pukou, has substantially lower densities of pick-up points. Figure 3b shows the distribution of median trip length by grid cell. As can be seen, the results map shows three delineated areas, and there is a clear division between sub-centers and the city center, where taxi trips get longer for places farther away from the city center or a sub-center. This demonstrates an evident separation of urban functional regions, where residents can take a short trip (i.e., 0-3km) for their daily needs inside each center or sub-center.



(a) (b)

Figure 3: Spatial distribution of taxi trips (the dashed lines delineate the urban center and the sub-centers). (a) Density of pick-ups; (b) Median travel distance.

To verify this finding, we also calculated the direction entropy for each grid cell. As discussed in Section 2.2.1, direction entropy represents the randomness of movement direction. A lower entropy for a given cell indicates that trips from this cell follow a more unified moving direction. Similar to Figure 3b, Figure 4 also demonstrates a clear division between the urban center and sub-centers, where trips originate from the central area are likely to go to different directions (i.e., with a high direction entropy), but trips that start from the border of urban centers follow a more unified direction, as they are mostly going into the urban center/sub-center.

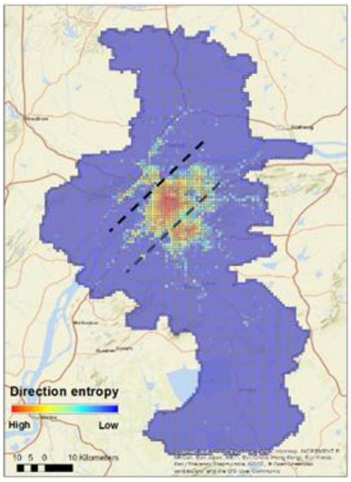


Figure 4: The distribution of direction entropy.

3.2 Temporal Variations of Urban Trips

As discussed in Section 2.2.2, we aggregate the number of pick-ups by hour for each grid cell, so each cell is associated with a 24-hour time series showing the temporal pattern of taxi pick-ups. To ensure data quality, here we only consider cells that average more than ten pick-ups per hour. For each cell, the hourly pick-ups values are divided by the maximum of the 24 hourly values. This standardizes the magnitude of data and helps with investigating the internal structure of each time series (Yuan and Raubal, 2012). Based on the DTW algorithm described in Section 2.2.2, we construct the distance matrix for the relative time series associated with each grid cell. The output is a distance matrix *D*, in which D_{ij} represents the DTW distance between cell *i* and *j*. Based on the DTW matrix, we conducted a hierarchical clustering analysis to identify outlier time series. There are several methods to set the number of clusters in hierarchical clustering. As an example analysis, here we adopt the criteria discussed in Mardia et al., (1979), where numCluster = max(2; sqrt(n/2)), *n* is the number of cells. Here outliers are defined as clusters with fewer than 3 cells.

Figure 5 shows the clustering results, where red indicates outliers and blue are regular cells with more than 10 pick-ups per hour. Figure 6a shows the time series of pick-ups from an example outlier cell (highlighted in the inset map of Figure 5). As can be seen, the number of taxi pick-ups increases during night hours. The background imagery in Figure 6b shows that this cell covers a residental neiborghood, and the increasing night hour pick-ups are not consistent with common sense, where more residents should arrive instead of depart home during night hours. The result demonstrates that more detailed activity patterns need to be investigated in follow-up studies. For example, it is possible that many residents in this area work during night hours, or there may be recereational events that attract people to go out at night. This example demonstrates the effectiveness of our methods in capturing fine-scale activity patterns that may not be reflected by basic land use satelite imagery.

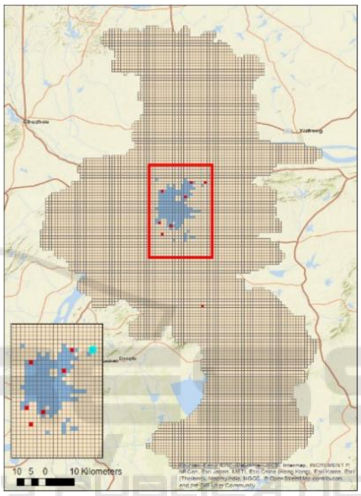
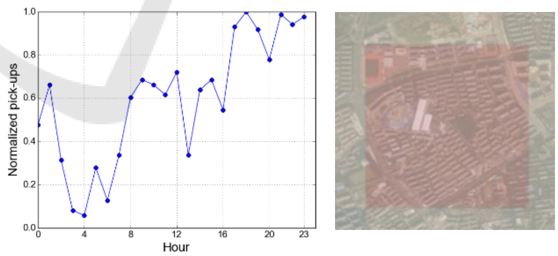


Figure 5: Outlier cells.



(a) (b)

Figure 6: An example outlier cell. (a) 24-hour time series of pick-ups; (b) Satellite imagery.

4 CONCLUSIONS

This study examined the urban mobility patterns in Nanjing, China based on taxi GPS trajectories. We analyzed the distribution of pick-up locations, travel distance, and travel direction. All three indicators demonstrate a clear division between the city center of Nanjing and the sub-centers. The result can be used to support and examine the development agenda of Nanjing City Council, where city officials proposed to further grow sub-centers to release the pressure from the central business area. In addition, we also explored the temporal dynamics of different urban regions based on a DTW algorithm. The extracted outliers demonstrated the importance of incorporating human mobility and activity data to refine small-area land use classification. Further research can focus on incorporating more indicators from the taxi trajectories to improve the accuracy of the analysis. It is also important to cross-validate the results with other public data, such as census and urban demographic data. Also, further research may involve extending the study period to analyze seasonal time series patterns when the data becomes available. The methodology discussed in this paper can be applied to other cities to identify urban functional regions and provide useful input for policy makers.

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