Quantifying natural hazards' perturbation on human mobility for returners and explorers: A case study of Typhoon Mangkhut

Ruoxi Wang, Yan Wang, Nan Li, Jing Li

Abstract

The mobility patterns of urban population, which are known to bear significant regularity, could be largely affected by extreme weather events, reflecting the perturbation of such events to people's daily life. In this study, we investigated the influence of the 2018 Typhoon Mangkhut on the mobility pattern of urban population in the City of Guangzhou, by analyzing the trajectories of over 75 thousand anonymous individuals in the city before and during the typhoon. We found that information extracted from these individuals' most visited locations during normal days was not sufficient to support accurate prediction of their mobility pattern during the two-day typhoon event. We further classified all individuals as returners or explorers, based on the strength of correlation between their recurrent mobility and overall mobility. The trajectories of the two groups showed that returners' mobility pattern was more severely affected by the typhoon than explorers, and the difference between the two groups became less distinctive under the impact of the typhoon. The findings of this study contribute to the existing literature by advancing the knowledge on human mobility patterns under the impact of natural hazards, which would be valuable for predicting mobility pattern of urban population under similar extreme events and enabling informed emergency management decisions and resilient urban planning.

N. Li (Corresponding author) • R. Wang Dept. of Construction Management, Tsinghua University, Beijing 100084, China Email: nanli@tsinghua.edu.cn

R. Wang Email: 41507452@xs.ustb.edu.cn

Y. Wang Dept. of Urban and Regional Planning, University of Florida, Gainesville, FL 32611, U.S.A. Email: yanw@ufl.edu

J. Li

Zhejiang Merit Interactive Network Technology Co., Ltd., Hangzhou, 310012, China Email: lij@getui.com

1.Introduction

The continuous global urbanization trend in recent decades has underpinned the need to understand and predict human mobility patterns in urban settings, for which the increased accessibility to various geospatial data made available by the latest technological advancements has provided great opportunities (Lu and Yu 2012; Forghani and Karimipour 2018). Prior research on human mobility has been mainly focusing on characterizing the statistical spatiotemporal properties of human trajectories, by studying population's displacements (Brockmann et al. 2006), time intervals between displacements (Wang et al. 2014) and radius of gyration of trajectories (Gonzalez et al. 2008). These studies have largely advanced existing knowledge about human mobility. However, most of these studies have focused on human mobility under normal circumstances, whereas there is obvious gap and exceptional need to investigate how human mobility patterns would be perturbed in times of extreme natural events (Bagrow et al. 2011). Several studies, by analyzing the trajectories of mobile phone users, found that major disasters such as earthquakes could cause regional population migration (Bagrow et al. 2011), and extreme weather events such as heavy rainfalls or strong winds could diversify population activities (Horanont et al. 2013). More recently, voluntarily-reported Twitter data were analyzed to uncover patterns of human mobility in the New York City during Hurricane Sandy (Wang and Taylor 2014), which revealed that human mobility displacements during the disasters followed a truncated power-law distribution, and that the perturbed human mobility was resilient, as the radius of gyration of human trajectories during the hurricane were strongly correlated with that of human trajectories during normal days. A more recent study of Wang and Taylor (2016) suggested, however, that human mobility might be much less resilience when impacted by more powerful natural perturbations. Notwithstanding its importance, there has been limited research on human mobility under extreme natural event-caused perturbations.

In prior research, most visited locations (MVLs) have been widely used to charaterize human mobility. For instance, González et al. (2008) posited that people have the tendency to return to primary locations. Song et al. (2010) used mobility networks to represent trajectories of mobile phone users, and found that people tended to spend most of their time at a few MVLs, which suggested a recurrent nature of human mobility. Radius of gyration r_g , which characterizes an individual's tendency to deviate from the center

of his or her own movements, has been widely used to quantify the spatial range of the individual's trajectories (Gonzalez et al. 2008; Wang and Taylor

2014). Adapted from the definition of r_g , Pappalardo et al. (2015) defined the k-th radius gyration $r_g^{(k)}$ to measure an individual's recurrent mobility range dominated by his or her top k MVLs. Furthermore, they conducted correlation analysis between r_g and $r_g^{(k)}$ to examine the similarity between the recurrent mobility and the overall mobility. One gap in the existing literature is that, while many studies, based on the recurrent nature of human mobility, have demonstrated the feasibility of approximating an individual's r_g using $r_g^{(k)}$, and in other words an individual's mobility range can be approximated based on his or her top k MVLs (Pappalardo et al. 2015; Wang et al. 2017), little research has been done to investigate whether it would be possible to predict an individual' future r_g based on their current MVLs, and how would the accuracy of this prediction be impacted by extreme natural events such as typhoons. To address this gap, we proposed Hypothesis 1 as follows:

Hypothesis 1: The prediction accuracy of individuals' r_g based on their MVLs will decrease under the influence of natural hazards.

In addition, Pappalardo et al. (2015) classified population into two categories, including returners and explorers, based on the strength of correlation between their recurrent mobility and overall mobility. The mobility range of returners is dominated by the recurrent mobility between a few MVLs, while explorers have strong tendency to explore new locations and their recurrent movement have little contribution to their overall mobility. To assess the differences between how returners and explorers are influenced by extreme natural events-caused perturbation, we posed the following two hypotheses:

Hypothesis 2: Both returners and explorers are affected by extreme natural events, however, the magnitudes of impact on returners and explorers, reflected by changes in the similarity between their recurrent mobility and overall mobility, are different.

Hypothesis 3: The magnitude of difference between mobility patterns of returners and explorers changes under extreme natural event-caused per-turbations.

To examined the above three hypotheses, we specifically studied the mobility of population in the City of Guangzhou, China during the Typhoon Mangkhut in the mid September of 2018. Typhoon Mangkhut was the world's most powerful tropical cyclone in 2018, which caused considerable damages throughout Southern China, the Philippines, Guam and the Northern Mariana Islands. It was one of the strongest storms to affect Southern China in more than six decades (James et al. 2018). In Guangzhou, heavy rain and severe wind lashed buildings, resulting in city-wide inundation and a large number of fallen trees along streets, which seriously affected the population's mobility in the city (Xinhua 2018b).

2. Data and Methods

2.1 Data preprocessing

This study used anonymized geolocation data collected from mobile devices used by the population in Guangzhou. Our dataset covered daily trajectories of around 0.75% of the entire population in Guangzhou, from August 16 to September 17, which included two days when Typhoon Mangkhut affected Guangzhou, and four weeks immediately before the event. Typhoon Mangkhut began to affect Guangzhou around 5pm on Sunday, September 16, 2018 and lasted until 8am Monday, September 17, 2018.

Trajectories associated with individuals who were not in Guangzhou during the typhoon or had less than five geolocation data entries per day on average were excluded, in order to ensure high quality of the trajectories data used in the analysis. A total of 75,665 individuals were included in the final dataset. On average, each individual had about 90 geolocations per day.

Then, the DBSCAN algorithm (Wang et al. 2018) was applied to remove abnormal data, and extract each individual's MVLs based on their trajectories before the typhoon. Two key input parameters in the DBSCAN algorithm were set as follows: the maximum search radii was set as 100 meters, which was consistent with the accuracy of the trajectories data; and the minimum number of points to form a cluster was set as three. The MVLs were determined as the centroids of extracted location clusters. The MVLs of each individual were then ranked according to how often they were visited.

2.2 Data analysis

2.2.1 Extraction of MVLs

Previous studies showed that between weekdays and weekends people may have different mobility patterns, characterized by their displacements, trip durations and time intervals (Oliveira et al. 2016; Feng et al. 2018). To account for the fact that human mobility patterns may differ between weekdays and weekends, we studied the individuals' mobility on Sundays (Group 1) and Mondays (Group 2) separately. For Group 1, we studied mobility pattern during the typhoon event based on trajectories data of September 16 (Sunday), and compared it with human mobility pattern on previous Sunday (i.e. September 9) which was considered as a baseline period. In this study, individuals' MVLs, which were extracted from their trajectories before typhoon and represented their mobility patterns under normal status, were used to predict their mobility range during the typhoon event. To ensure sufficient representativeness, the MVLs were extracted from trajectories of three immediately preceding Sundays (i.e. August 19, August 26 and September 2). The MVLs for Group 2 were extracted in the same way.

2.2.2 Metrics

To test our hypotheses, we conducted quantitative analysis based on the trajectories dataset. Radius of gyration r_g , has been widely used as the characteristic distance covered by an individual's daily trajectories (Song et al. 2010). . Specifically, r_g can be calculated based on the following equation (González et al. 2008):

$$r_g = \sqrt{\frac{1}{n} \sum_{t=1}^{n} \left[2r \times \sin^{-1} \left(\sqrt{\sin^2 \left(\frac{\phi_t - \phi_c}{2}\right) + \cos \phi \cos \phi_c \sin^2 \left(\frac{\phi_t - \phi_c}{2}\right)} \right) \right]^2}$$
(2.1)

where n is the number of the individual's visited distinct locations, r is the radius of the earth, ϕ is the latitude, ϕ is the longitude, t is the number of times each location is visited by the individual, and c is the center of mass of the individual's movements.

Moreover, Pappalardo et al. (2015) introduced the concept of the k-radius of gyration $r_g^{(k)}$, which is used to describe the recurrent mobility range of an individual, dominated by the individual's top k MVLs. The k-radius of gyration $r_g^{(k)}$ can be calculated based on the following equation (Pappalardo et al. 2015):

$$r_{g}^{(k)} = \sqrt{\frac{1}{k} \sum_{t=1}^{k} \left[2r \times \sin^{-1} \left(\sqrt{\sin^{2} \left(\frac{\phi_{t} - \phi_{c}^{(k)}}{2} \right) + \cos \phi \cos \phi_{c}^{(k)} \sin^{2} \left(\frac{\varphi_{t} - \varphi_{c}^{(k)}}{2} \right) \right) \right]^{2}} \quad (2.2)$$

2.2.3 Correlation analysis

Correlation analysis between radius of gyration r_g and the k-radius of gyration $r_g^{(k)}$ has been widely used in prior research to quantify the similarity between an individual's overall mobility and recurrent mobility (Pappalardo et al. 2015; Wang et al. 2017). In this study, we define the prediction accuracy of individuals' r_g using their MVLs as the Pearson correlation coefficient between $r_g^{(k)}$ and r_g at the population level. Specifically, for each individual, his or her r_g^t (radius of gyration under typhoon status) and r_g^n (radius of gyration under normal status) were calculated based on his or her trajectories during the typhoon and during the baseline period, respectively. The individual's $r_g^{(k)}$ (the k-radius of gyration) was also calculated, based on the geolocations of his or her top k MVLs extracted from trajectories under normal status. Then, the correlation analysis was conducted at the population level. For a given value of k, the Pearson correlation coefficient (*PCC_t*) (Wang et al. 2017) between $r_g^{(k)}$ and r_g^t and was calculated based on the following equation (Zaiontz 2018):

$$PCC_{t} = \frac{\operatorname{cov}(\mathbf{r}_{g}^{(k)}, \mathbf{r}_{g}^{t})}{\sigma_{\mathbf{r}_{g}^{(k)}}\sigma_{\mathbf{r}_{g}^{t}}}$$
(2.3)

where cov is the covariance, and σ is the standard deviation. The Pearson correlation coefficient (*PCC_n*) between $r_g^{(k)}$ and r_g^n was calculated in the same way.

3 Results and Discussions

3.1 Overall impact of typhoon on human mobility pattern

Prior research has pointed out that, when the value of k is large enough, the overall mobility range could be estimated by the top k MVLs (Pappalardo et al. 2015; Wang et al. 2017). This suggested that the correlation between the overall and recurrent mobility would become stronger when the value of k increases, which was obvious because more MVLs would lead to better approximation of the overall mobility. When MVLs were used to predict future mobility, however, this was no longer the case. As Figure 1 shows, in

our study, the values of PCC_t and PCC_n were always below 0.5, suggesting limited correlation between current recurrent mobility range and future overall mobility range, and that neither PCC_t or PCC_n had stable trend to increase as the value of k increased. These results had two important implications. First of all, the prediction accuracy of the overall mobility range in a future day was limited, regardless of whether there was any extreme natural event, hence a better approach for this prediction was needed. Secondly, simply including more MVLs in the prediction would not necessarily lead to better prediction results, probably because the list of MVLs and their rankings would significantly differ when population's movement was impacted by the natural extreme events.

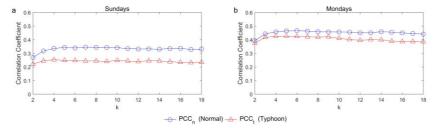


Fig. 1. Correlation coefficient between current recurrent mobility and future overall mobility for entire population

By comparing the value of PCC_t and PCC_n , it showed that the prediction accuracy of individuals' r_g^t based on their MVLs decreased during the typhoon, as evidenced by the fact that PCC_t was consistently smaller than PCC_n under different k values on both Sundays and Mondays. We accepted Hypothesis 1 of this study based on this finding that the MVLs, which were often visited under normal status and represented individuals' mobility behaviors, had much less influence in determining their mobility under the influence of natural hazards.

In addition, it was observed that values of PCC_t and PCC_n were generally higher on Mondays than Sundays, indicating that MVLs extracted on Mondays were relatively more predictive of individuals' mobility patterns on Mondays in the future. Moreover, we further examined the difference between the correlation coefficients under normal status and typhoon status. For each of the two groups and each given value of k, we calculated the difference between PCC_t and PCC_n , and the mean and variance of the difference over all values of k. The mean and variance was 0.045 and 0.013 respectively for Mondays, and 0.090 and 0.013 respectively for Sundays. The higher mean value in Group 2 suggested that the typhoon caused more significant impact on human mobility pattern on Sundays. This may be due to the fact that the direct impact of Typhoons Mangkhut and heavy rainfall began to fade away in the early morning of Monday September 17, 2018. Despite that many roads were inundated, people were begining to return to work (Han 2018).

3.2 Different impacts of typhoon on returners and explorers

We further investigated the similarity between recurrent and perturbed mobility among returner and explorers. Returners and explorers have distinct mobility patterns: returners are individuals whose mobility range is dominated by a few most frequently visited locations, while explorers have a strong tendency to explore a larger number of different locations. Following the study by (Pappalardo et al. 2015), we classified the individuals into returners and explorers using a bisector method, namely individuals whose

mobility pattern satisfies $r_g^{(k)} > \frac{r_g}{2}$ are coded as k-returners, while otherwise individuals are coded as k-explorers. As aforementioned, the calculation of $r_g^{(k)}$ and r_g were both based on geolocation data collected in three Sundays

or Mondays before the typhoon. The values of PCC_t and PCC_n for returners and explorers were calculated, respectively. In all cases, the values of PCC_t and PCC_n were positive and the p-values were less than 0.01, showing significant positive correlations both between recurrent and normal mobility and between recurrent and perturbed mobility.

As Figure 2 shows, under normal conditions, returners had larger PCC_n values than explorers, which was consistent with findings reported in prior research (Pappalardo et al. 2015; Wang et al. 2017). Likewise, when affected by typhoon, returners had larger PCC_t values than explorers, which indicated that returners and explorers tended to maintain their distinct degrees of similarity between recurrent mobility and overall mobility during the typhoon event. In addition, it is noteworthy that, as the value of k increased, the values of PCC_t and PCC_n for k-explorers fluctuated significantly. This was probably because the number of explorers decreased

quickly as the value of k increased, hence the results were more sensitive to and affected by the randomness in the trajectories of each individual.

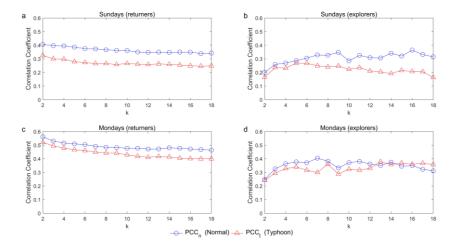


Fig. 2. Correlation coefficient between recurrent mobility and overall mobility for both returners and explorers

Furthermore, for both returners and explorers, we calculated the difference between PCC_t and PCC_n for each k value, and the mean and variance of the difference over all k values. The results are summarized in Table 1. Based on the results, the k-returners' mobility pattern was more affected by the typhoon compared to the k-explorers, as the former had higher mean difference between PCC_{t} and PCC_{n} . This finding suggested that Hypothesis 2 should be accepted. Returners' mobility was strongly dependent on a small number of MVLs such as home, working places, schools and places of important social relationships under normal status (Xuan et al. 2016), however, the above analysis revealed that the prediction accuracy of returners' r_{e}^{t} based on their MVLs notably decreased under the influence of the typhoon. In response to the typhoon landfall, companies and governmental agencies in Guangzhou were ordered to halt work and schools suspended classes to ensure the safety of workers and students (Xinhua 2018a). And some of MVLs were less accessible due to the direct impact of the typhoon or the indirect effects of damage to traffic infrastructure caused by the typhoon. Returners did not visit MVLs such as schools, companies and other nearby locations as frequently as they would normally. For explorers, the impact on them appeared to be not as significant as the impact on returners when some MVLs became inaccessible considering that any individual MVL would have little contribution to the overall mobility of explorers. Therefore, the accuracy of predicting returners' r_g^t based on their MVLs decreased more significantly than explorers.

 Table 1. Comparison of similarities of recurrent mobility and overall mobility between normal status and typhoon status

	Type of indi-		
	viduals	Mean	Variance
Sundays	Returners	0.096	0.007
	Explorers	0.085	0.044
Mondays	Returners	0.052	0.012
	Explorers	0.038	0.023

Additionally, we examined how the difference between mobility patterns of returners and explorers changed during the typhoon. For each of the two groups and each given value of k, we calculated the difference of the values of PCC_t and PCC_n between k-returners and k-explorers, and the mean and variance of the difference over all values of k. The results are shown in Table 2.

Table 2. Comparision of similarities of recurrent mobility and overall mobility between returners and explorers

	Status	Mean	Variance
Sundays	Normal	0.058	0.054
	Typhoon	0.047	0.037
Mondays	Normal	0.139	0.052
	Typhoon	0.107	0.067

As the results show, the perturbation caused by the typhoon weakened the difference between returners and explorers in their mobility patterns. Therefore, Hypothesis 3 was rejected. A possible explanation for this result might be that, for the majority of the returners, they were prevented by the typhoon from visiting the dominant MVLs in their mobility, especially on Monday when they normally needed to go to work or school, hence causing their mobility pattern to appear to be closer to that of the explorers.

4 Conclusions

Descriptive approaches are widely used by prior research to capture the changes in statistical properties of human mobility during extreme natural events. In a case study in Guangzhou, we studied Typhoon Mangkhut's influence on the mobility pattern of people with different mobility behaviors. The results demonstrated (1) that the accuracy of predicting individuals' r_{e} based on their MVLs decreased notably under the influence of the typhoon; (2) that the mobility patterns of explorers and returners were perturbed differently by the typhoon: the accuracy of predicting returners' r_{o}^{t} based on their MVLs have reduced more than explorers; and (3) that the difference between mobility patterns of returners and explorers was reduced by the typhoon-caused perturbation. There are some limitations in this study which we aim to address in future research. These limitations include that the we only measured the human mobility range before and during the typhoon, which could not be used to determine whether specific locations individuals visited had changed during the typhoon. In addition, MVLs needed to be extracted from longer time period of individual's historical trajectories to improve their representativeness. Findings in this research could help policymakers predict urban population's mobility patterns during extreme events and hence inform better emergency management decisions and resilient urban planning.

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