Uncovering Spatiotemporal Patterns of Travel Flows Under Extreme Weather Events by Tensor Decomposition

Zhicheng Deng
School of Urban Planning and Design, Peking University Shenzhen Graduate School, Shenzhen, Guangdong, China
Key Laboratory of Earth Surface System and Human-Earth Relations of Ministry of Natural Resources of China, Peking University Shenzhen Graduate School, Shenzhen, Guangdong, China

Zhaoya Gong[1]
School of Urban Planning and Design, Peking University Shenzhen Graduate School, Shenzhen, Guangdong, China
Key Laboratory of Earth Surface System and Human-Earth Relations of Ministry of Natural Resources of China, Peking University Shenzhen Graduate School, Shenzhen, Guangdong, China

Pengjun Zhao
School of Urban Planning and Design, Peking University Shenzhen Graduate School, Shenzhen, Guangdong, China
Key Laboratory of Earth Surface System and Human-Earth Relations of Ministry of Natural Resources of China, Peking University Shenzhen Graduate School, Shenzhen, Guangdong, China
College of Urban and Environmental Sciences, Peking University, Beijing, China

Abstract

Extreme weather events have caused dramatic damage to human society. Human mobility is one of the important aspects that are impacted significantly by extreme weather. Currently, focus on human mobility research during extreme weather is often limited to the transport infrastructure and emergency management perspectives, lacking a systematic understanding of the spatiotemporal patterns of human travel behavior. In this research, we examine the structural changes in human mobility under the severe rainstorm that occurred on July 20th, 2021 in Zhengzhou, Henan Province, China. Innovatively applying a tensor decomposition approach to analyzing spatiotemporal flows of human movements represented by the mobile phone big data, we extract the characteristic components of human travel behaviors from the spatial and temporal dimensions, which help discover and understand the latent spatiotemporal patterns hidden in human mobility data. This study provides a new methodological perspective and demonstrates that it can be useful for uncovering latent patterns of human mobility and identifying its structural changes during extreme weather events. This is of great importance to a better understanding of the behavioral side of human mobility and its response to external shocks and has significant implications for human-focused policies in urban risk mitigation and emergency response.

2012 ACM Subject Classification Information systems → Geographic information systems

Keywords and phrases Urban travel behavior, Origin-Destination flows, Non-negative CP decomposition, Spatiotemporal analysis

Digital Object Identifier 10.4230/LIPIcs.GIScience.2023.27

Category Short Paper

Funding *Zhaoya Gong*: Shenzhen Science and Technology Program JCYJ20220818100810024.
Pengjun Zhao: Shenzhen Science and Technology Program JCYJ20220818100810024.

[1] Corresponding author

12th International Conference on Geographic Information Science (GIScience 2023).
Editors: Roger Beecham, Jed A. Long, Dianna Smith, Qunshan Zhao, and Sarah Wise; Article No. 27; pp. 27:1–27:6
Leibniz International Proceedings in Informatics
Schloss Dagstuhl – Leibniz-Zentrum für Informatik, Dagstuhl Publishing, Germany

1 Introduction

Cities are not simply spaces with idealized morphologies; rather, we should understand them as complex systems composed of networks and flows [1]. Within cities, residents travel by various transportation modes, which is reflected in the spatiotemporal patterns of urban travel behavior, forming different urban rhythms and spatial structures. Understanding these travel behavior patterns is crucial for helping to better understand the complex urban system, thereby bringing implications to people-oriented policies and promoting urban management capabilities.

According to the 2023 IPCC Report on Climate Change [4], human-caused climate change has recently affected the weather and extreme climate in all regions of the world, causing widespread damage and destruction to nature and humanity. Existing research has shown that when faced with extreme weather, the patterns of human mobility can exhibit spatiotemporal characteristics different from those in normal times [10, 3]. However, in the field of GIScience, most studies still adopt the transport infrastructure and emergency management perspectives, utilizing GIS methods to investigate human behavior during disasters or to simulate the evacuation patterns of individuals [9, 5]. These studies lack a systematic understanding of the spatiotemporal patterns of human mobility under external impacts.

With the widespread adoption of smartphones and the development of positioning technology, a vast amount of population activity data has been generated, which is now widely used in urban research [6, 2, 11]. This kind of data contains information about human travel behavior, interactions between different areas of the city, and the spatial structure of the city. The availability of these data and corresponding analysis methods provide possibilities for quantifying and measuring human travel under normal conditions and during natural disasters, as well as analyzing the spatiotemporal patterns of travel flows.

This study utilizes travel flows recorded by mobile phones to construct a tensor of human mobility, and decomposes it using tensor factorization methods to extract the spatiotemporal characteristics. As a case study, this paper focuses on a torrential rain event that occurred on July 20th, 2021 in Zhengzhou, Henan Province, China, which resulted in 380 deaths and affected more than a million people [8]. This paper explores the differences in urban travel behavior under normal conditions and external impacts of the rainstorm, reveals the spatiotemporal patterns hidden in travel behavior, and analyzes the underlying spatiotemporal mechanisms causing changes in human mobility patterns after the rainstorm.

2 Methods and Data

2.1 Methods

Multidimensional travel flows can be organized in a “space-time” format to construct a spatiotemporal tensor. In this study, for the analysis of travel flows, we use Origin-Destination (OD) pairs as the spatial dimension and time as the temporal dimension to store and express the travel flow values between the origins and the destinations.

Tensor decomposition is a low-rank approximation method for tensors. Through tensor decomposition, we can extract the main characteristics and relationships in the travel flows. In this study, the CANDECOMP/PARAFAC (CP) tensor decomposition is chosen, which is a representative and easy-to-understand analysis method, to decompose a high-order tensor into a sum of rank-1 tensors. The principle of decomposition is shown in Figure 1, with the tensor constructed from the original data denoted by $\mathcal{X} \in \mathbb{R}^{I \times J}$. I is the number of OD pairs, J is the length of the time unit, and R is a positive integer, representing the rank in the tensor decomposition, which is the number of features in each dimension. R modes are obtained by the decomposition. $OD_r, T_r(r = 1, ..., R)$ are the characteristics of the spatial and temporal dimensions, and λ_r is the corresponding weight. Considering the non-negativity of the travel flows, this study uses the Non-negative CP (NNCP) decomposition proposed by Shashua and Hazan [7] to implement.

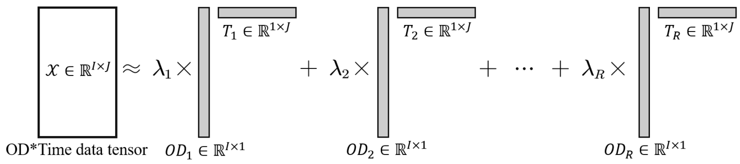

Figure 1 The CP decomposition for travel flows.

2.2 Data

Zhengzhou is located in the central-northern part of China, and is the capital city of Henan Province. It is also the economic and population center of Henan Province and an important transportation hub for the entire country with an enormous amount of floating population. From July 19th to 23rd, 2021, a torrential rain disaster occurred in Zhengzhou, which broke the historical record of extreme meteorological observation in mainland China, causing heavy casualties and property losses. In this study, we select Zhengzhou as the research area, and divide it into basic spatial units of 1 km * 1 km grids, as shown in Figure 2.

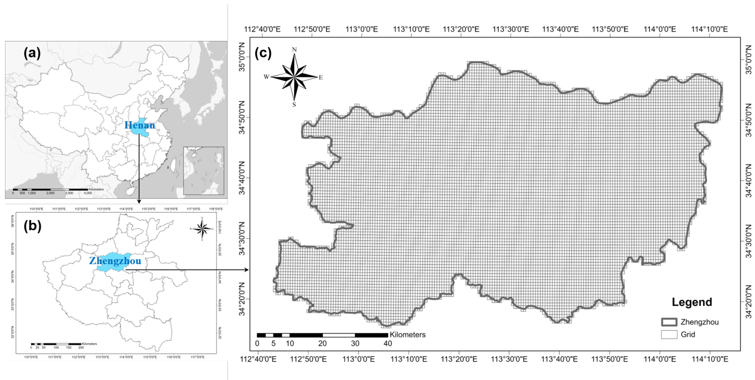

Figure 2 The geographical location of our research area. (a) the research area in China; (b) the research area in Henan Province; (c) the spatial distribution of grids in Zhengzhou.

The travel flow data used in this study covers a period of two weeks, from July 10th to July 23rd, 2021, with a time resolution of one hour. In order to remove abnormal values that may affect the experiment, we impose a threshold on the value of OD flows. Only flows with a daily average value greater than 10 are included, resulting in 1,027,568 OD pairs on 336 time units. Moreover, we perform smoothing processing on the experimental data to reduce the effects of anomalies and peaks and obtain results with better reconstruction rates, using a window size of 3, with a convolution kernel set to [0.3, 0.4, 0.3]. The same data quantity are maintained.

Based on the above data, we construct a travel tensor with a size of [1027568, 336]. Each row represents an OD pair, and each column represents an hour. The value in each element represents the flow volume from the origin to the destination within one hour. The first 168 columns represent the first week or normal conditions, and the remaining 168 columns represent the second week or the external impact of Zhengzhou torrential rain disaster.

3 Results

3.1 Original Data Analysis

Firstly, we evaluate and analyze the impact of the torrential rain event on the travel behavior of people based on the original data. The total travel volume during the period from July 10th to 23th is shown in Figure 3. It can be inferred that there exists a daily rhythm in the residents' travel behavior. In addition, due to the impact of the torrential rain in Zhengzhou, the travel volume significantly and relatively decreases after July 19th, which implies a transition from the normal behavior pattern to the abnormal behavior pattern.

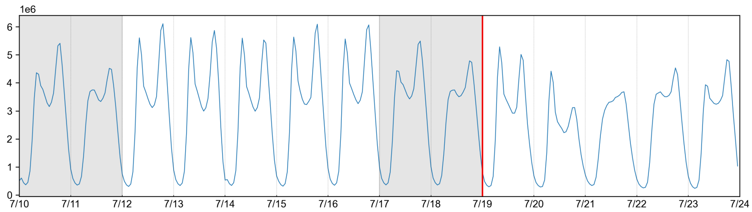

Figure 3 Total travel volume changing with time.

3.2 Decomposition Results

We use NNCP decomposition to extract spatiotemporal modes of travel behavior, obtaining two outputs: temporal patterns and spatial patterns. The rank parameter is selected according to the root mean square error of decomposition results at different ranks. We use the rank 6 at the elbow point as an example for experiment and analysis. Six modes are obtained by decomposition, and their weights are sorted as follows: 87980.86, 73816.80, 61583.89, 59256.50, 57573.24, and 48475.62. The corresponding temporal patterns and spatial patterns are shown in Figure 4. In spatial patterns, values of decomposition results are aggregated according to the origins and destinations.

In the sub-figure of temporal patterns, the gray background represents weekends, and the white background represents weekdays. The red vertical line represents the start day of the torrential rain in Zhengzhou. The most important mode a represents the overall trend of the city's travel behavior. Compared to weekends, weekday travel volumes are lower. On the day before the heavy rain of July 19th, the travel behavior still shows a normal pattern. However, after July 20th, the travel volume decreases greatly and reaches its minimum on July 21st. Mode b can be interpreted as the morning peak mode, which reaches its peak around 7:00–10:00. Compared to mode a, the peak height of mode b is also higher on weekdays than on weekends, and there is a secondary peak in the afternoon (around 14:00). Mode c represents the evening peak mode, and there is a secondary peak at around 12:00, which corresponds to the secondary peak of mode b. Mode d represents the abnormal travel mode caused by external impacts such as torrential rain and other additional information outside the main mode. It increases greatly from July 20th and reaches its peak on July 21st, then drops rapidly. Mode e shows the travel flows after the evening peak during the late night (20:00–23:00), and mode f represents the stronger characteristics of the morning and evening peaks.

We combine the temporal patterns to interpret the spatial patterns. In mode a, the results for the origins and the destinations are relatively similar. The high-value areas mainly include the central city of Zhengzhou, the airport area, and the centers of the county-level

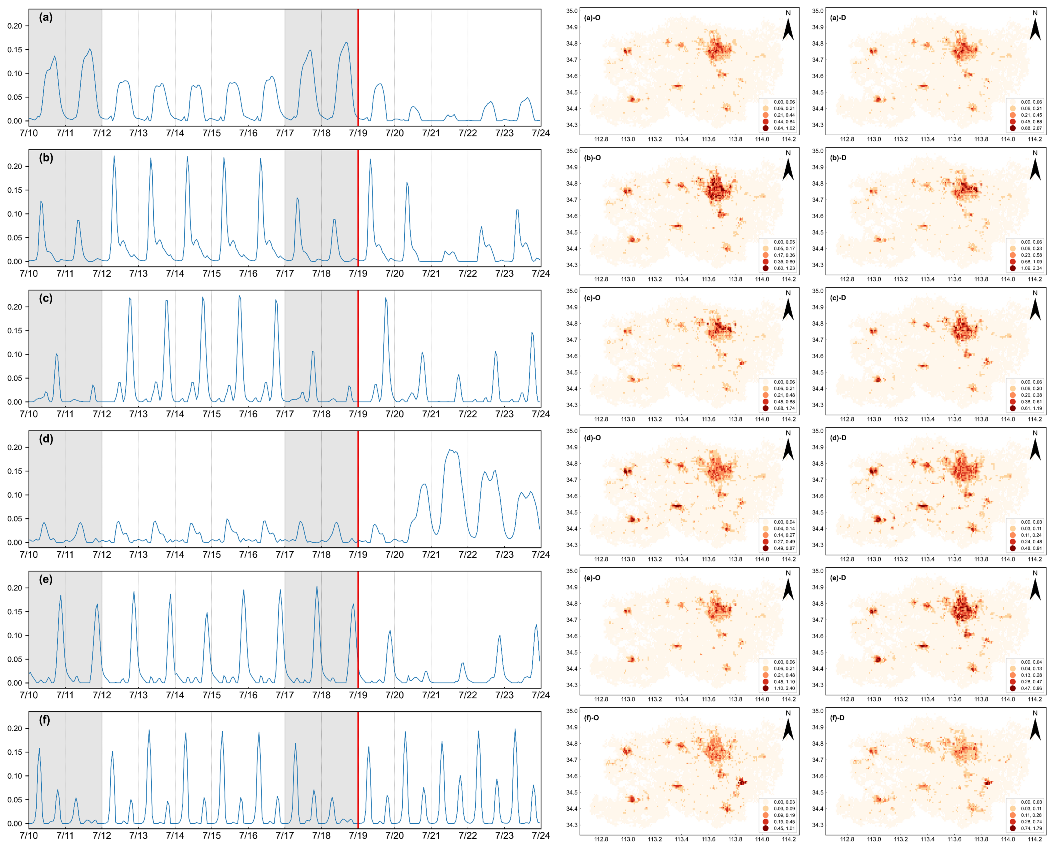

Figure 4 Spatiotemporal patterns of travel flows.

cities. Mode b–O corresponds to modes c–D and e–D. Combined with the temporal patterns, it shows that the origins of the early peak flow are consistent with the destinations of the late peak flow and the late night flow, reflecting the commuting patterns of urban residents for work and life. It can be inferred that the primary residences are Weilai Road Street, Nanyang Road Street, Jingba Road Street, and Tongbai Road Street, etc., while their work locations are Jicheng Road Street (provincial government and other administrative regions), Zhengzhou East Station area, and Zhengzhou Railway Station area. Therefore, it may also contain information about cross-regional travel. Unlike previous modes, mode d reflects the travel patterns during heavy rain periods, with higher values in the areas of county–level city centers, which are more affected by the rainstorm. These areas experience relatively increased travel due to rescue and other activities, while the central city areas have a significant decrease in travel intensity. Mode f is mainly located in the Foxconn Park area. Combined with the time mode, it may reflect the commuting mode of its workers.

4 Conclusions and Discussions

In this study, we use NNCP decomposition to extract and analyze different urban travel patterns before and during the 720 torrential rain event in Zhengzhou, Henan Province, China. We find that there are multiple spatial and temporal patterns. The temporal patterns include morning peak, evening peak, daytime flow, late night flow, and early morning flow. The spatial patterns correspond to the interaction between residence and workplace, and the interaction between residence and other functional places, and so on. In particular, under the external impact of the torrential rain disaster, people may shift their travel modes to avoid potential risks. Temporally, the travel pattern shows an intense increase from July 20th after the torrential rain, reaching a peak on July 21st, followed by a rapid decline. Spatially, the internal travels within counties are relatively strengthened, and different travel patterns are also observed in the urban area.

This paper innovatively applies a tensor decomposition approach to analyzing spatiotemporal flows of human movements under extreme weather events, effectively extracting different urban travel behavior characteristics under different circumstances, and exploring the response of urban travel behavior patterns to extreme weather. However, there is still room for improvement in this study. Currently, the interpretation of the obtained travel pattern results is based on exploratory analysis and limited to speculative discussions. In the future, more confirmative analysis can be conducted to validate the multi-scale characteristics of travel patterns. For temporal patterns, time series analysis can be used to extract time-frequency domain characteristics, providing descriptions and predictions. For spatial patterns, methods such as network community detection can be used to divide urban areas.

References

1 Michael Batty. *The new science of cities.* MIT press, 2013.

2 Francesco Calabrese, Mi Diao, Giusy Di Lorenzo, Joseph Ferreira Jr, and Carlo Ratti. Understanding individual mobility patterns from urban sensing data: A mobile phone trace example. *Transportation research part C: emerging technologies*, 26:301–313, 2013.

3 Boyeong Hong, Bartosz J Bonczak, Arpit Gupta, and Constantine E Kontokosta. Measuring inequality in community resilience to natural disasters using large-scale mobility data. *Nature communications*, 12(1):1870, 2021.

4 IPCC. *Climate Change 2023: Synthesis Report. A Report of the Intergovernmental Panel on Climate Change.* IPCC, Geneva, Switzerland, (in press), 2023.

5 Marianna Loli, George Kefalas, Stavros Dafis, Stergios A Mitoulis, and Franziska Schmidt. Bridge-specific flood risk assessment of transport networks using gis and remotely sensed data. *Science of the Total Environment*, 850:157976, 2022.

6 Tao Pei, Stanislav Sobolevsky, Carlo Ratti, Shih-Lung Shaw, Ting Li, and Chenghu Zhou. A new insight into land use classification based on aggregated mobile phone data. *International Journal of Geographical Information Science*, 28(9):1988–2007, 2014.

7 Amnon Shashua and Tamir Hazan. Non-negative tensor factorization with applications to statistics and computer vision. In *Proceedings of the 22nd international conference on Machine learning*, pages 792–799, 2005.

8 The State Council Disaster Investigation Team. Investigation report on '720' heavy rainfall disaster in zhengzhou,henan. Technical report, The State Council of People's Republic of China, 2022.

9 Brian Tomaszewski. *Geographic information systems (GIS) for disaster management.* Routledge, 2020.

10 Qi Wang and John E Taylor. Patterns and limitations of urban human mobility resilience under the influence of multiple types of natural disaster. *PLoS one*, 11(1):e0147299, 2016.

11 Yang Xu, Jiaying Xue, Sangwon Park, and Yang Yue. Towards a multidimensional view of tourist mobility patterns in cities: A mobile phone data perspective. *Computers, Environment and urban systems*, 86:101593, 2021.