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Exploring the Highway Travel Patterns Affected by COVID-19 through Outbreak to Recovery Stages – A Case Study in Guizhou Province

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ABSTRACT

The examination of highway travel behaviour during the COVID-19 pandemic can provide valuable insights into the impacts of the pandemic and associated policies on human mobility patterns. This paper proposes a comprehensive examination, measurement and characterisation approach in the perspective of network and community structure. To capture the changes in travel behaviour, four stages were defined based on four consecutive Augusts from 2019 to 2022, during which varying levels of restrictions were implemented. The findings reveal interesting trends in travel patterns. In 2020, after the clearance of pandemic cases, there was a remarkable increase of over 10% in highway trips. However, in 2021, with the emergence of COVID-19 variants, there was a significant decline of over 30% in highway trips. By employing complex network analysis, key metrics of the primary network, including link weight, node flux and network connectivity, exhibited a notable decrease during the pandemic. These changes in network properties also reflect the spatial heterogeneity of highway travel demand. Moreover, the outcomes of community detection shed light on the evolution of the highway community structure, highlighting the efficacy of a community-collaboration strategy for highway management during public emergency events, as it fosters strong local interaction within the community.

KEYWORDS

COVID-19 pandemic; highway transaction dataset; travel behaviour; complex network analysis; community detection.

1. INTRODUCTION

Playing an important role in supporting intercity travel, the highway is one of the essential parts in the transportation system. Nevertheless, the travel pattern is susceptible to external factors, including weather conditions, critical events and transportation restriction policies [1]. The COVID-19 pandemic has had a significant impact on travel behaviour and society as a whole, affecting more than 200 countries and approximately 700 million people [2, 3]. To mitigate the transmission of the virus, various transportation restrictions were implemented during the pandemic and post-pandemic stages, including stay-at-home orders, remote education, limitations on non-essential activities within cities or provinces, and, in some cases, unrestricted movement. Consequently, understanding the effects of the pandemic on travel behaviour and how individuals respond to different restriction policies has become crucial.

In particular, Guizhou province, situated in the southwestern region of China, poses unique challenges due to its mountainous and hilly terrain, with over 90% of its area characterised by such topography. Consequently, highways have emerged as the primary transportation corridors within Guizhou, given the lack of alternative routes. The diffusion of the COVID-19 pandemic in China has exhibited the characteristic pattern of "case clustering and mobile diffusion" [4, 5]. As a result, the Chinese government has implemented diverse restriction policies, constantly adjusting them across different cities and stages of the pandemic transmission [6, 7]. Strict measures, including blocking highway entrances and exits, limiting public transport and implementing community closures, have gradually been eased and lifted. However, as the COVID-19 pandemic has persisted for the past three years, it has significantly affected travellers' perceptions and behaviours [8]. Therefore, conducting an investigation into highway travel patterns in this western mountainous province remains meaningful, as it can provide valuable insights to support traffic management and operations during emergency events.

Additionally, extensive of research studies have been conducted to investigate the interaction between the COVID-19 pandemic and travel behaviour of highway system. In order to quantify the impacts, various measurements and statistics, such as province-wide traffic variation [9], weekly average daily traffic (WADT) and traffic accidents [10], state-wide highway volume [11] and national logistic level [12], are introduced. However, existing research studies mainly examined the spatial-temporal pattern of highway travel in statistical methods, and few studies attempted to deeply understand the travel behaviour from network perspective.

Simultaneously, development of information technology, such as electronic payment systems and electronic toll collection (ETC) technology, provide detailed highway travel information and support the further analysis of travel characteristics during the pandemic. Compared to the existing research on highway travel patterns during the COVID-19 in terms of the traditional detectors [13], the electrical transaction technology made the travel information to be fixed to "unique vehicle and unique ID". According to the statistics from the Ministry of Transport of China, the market penetration of ETC for freight and passenger car exceed 50% and 70%, respectively [14]. Nevertheless, rare research studies have been conducted to examine the highway travel behaviour with detailed transaction data.

In light of the aforementioned context, this paper aims to enhance the understanding of the correlation between COVID-19 and highway travel patterns through providing a comprehensive examination, measurement and characterisation approach, during the outbreak and recovery stages of the pandemic. Spatial-temporal analysis and the concept of complex networks are employed to furtherly examine the community structure of the highway network in Guizhou province. Thus, valuable insights can be gained regarding the impact of the pandemic on highway travel behaviour and the subsequent recovery process. This research seeks to contribute to the existing body of knowledge in the field and provide useful implications for transportation planning and management in times of crisis. The remainder of this paper is organised as follows. Section 2 provides a comprehensive review of the relevant literature. Section 3 presents the methodology employed for the analysis, while Section 4 showcases the results of the analysis and provides discussions. Finally, the conclusions and implications derived from the study are presented in the concluding section.

2. LITERATURE REVIEW

Analysing highway travel patterns has always been a significant area of interest for researchers and traffic practitioners. A wealth of literature has been dedicated to investigating, understanding and predicting these travel patterns, utilising various data sources [15]. Generally, stationary data and probe data have been extensively used as the two major types of data source. Among them, the sensor data is the most widely-utilised stationary data, which collects various traffic parameters, including traffic volume, speed and density, etc. Cao et al. utilised the speed and density to construct the traffic state index (TSI), on the basis of fuzzy logic [16]. Regarding spatial-temporal analysis, a short-term convolutional neural network (CNN) model was developed by Wen et al. to forecast significant traffic attributes [17]. A number of researchers also explored multiple source dataset in the analysis. For instance, the data derived from local detectors and probe sensor in vehicles were fused to measure the traffic congestion level [18]. However, the sensor data is anonymous data without the origin and destination.

Different from stationary data, the probe data are mainly collected by GPS, floating vehicles and even cellular devices [19]. Taxis constitute the primary source of the GPS dataset, which encompasses vehicle identity, precise coordinates and timestamps ranging from 5 seconds to 1 minute, depending on the GPS device's performance. [20–22]. The trajectory analysis has been commonly utilised to explore the GPS dataset. Other probe dataset has also been introduced to investigate the traffic characteristics. Huang et al. proposed a long short-term memory (LSTM) to predict the peak hour congestion through bus driving time derived from GPS device [23]. In recent years, the cellular data, revealing the spatial-temporal mobility patterns of travellers, was also introduced to measure the traffic flux on roads [24, 25]. Specifically, Jia et al. measured the human movements from Wuhan to the rest of China based on the cellular data, and predicted the spread rate of COVID-19 throughout the country [26]. Nevertheless, the probe dataset would be restricted by the sampling size due to the limited usage of GPS or cellular devices.

On the other hand, the human travel behaviour is significantly affected by the global spread of COVID-19 pandemic, which has not been explored in earlier research [27]. Researchers made huge effort to examine the changes in travel behaviour due to the outbreak of pandemic. Beck et al. attempted to illustrate the changes of travel behaviour during the COVID-19 outbreak based on a household survey [28]. The results indicated the public transit faced the largest hurdle to recover. Based on the traffic survey through smartphones, Parker et al. found that the transit riders were significantly affected by the pandemic, while over 70% of transit riders reported less trips [29]. Similarly, questionnaire survey, paper-based panel survey and web-based survey were also employed as a fundamental means to analyse the travel behaviour. As the contrast, some researchers collected the real-world traffic volume for analysis. Parr et al. compared the spatial-temporal patterns of traffic volume across Florida for 2019 and 2020 [30]. The pandemic impacts on freeway appeared earlier than on arterial. Through cellular network-based data, Gu et al. reconstructed the trip trajectory on highway between two cities [13]. The computed highway flows indicated the fluctuation trend during and after the pandemic. Considering the structural changes in intercity travel, Zhang et al. proposed a weighted stochastic block model (WSBM) to examine the network structure before, during and after the pandemic break in China [12].

Another consideration of existing research is the interaction between governmental policies and travel patterns. He et al. found that the traffic lockdown and "activity restrictions" limited both the spread of COVID-19 and the festival-related travel in China [31]. Similarly, Parr et al. investigated the impacts of travel bans on traffic volume in 10 U.S. states [30]. The results indicated the heterogeneous distribution of decreased traffic volume across time and space. Patra et al. employed two Wi-Fi MAC Scanners to understand the short-term changes of road traffic patterns [29]. Interestingly, Wang et al. found that the number of cars increased to 142%, while the number of trips by driving and transit dropped to 76% and 88%, respectively, during the reopening strategies in New York [32]. However, due to the data accuracy and size, the analysis from the network perspective has been rarely performed.

To the best of our knowledge, although extensive research studies have conducted the analysis on highway travel behaviour, few studies attempted to examine the mobility patterns through the outbreak and recovery stages of COVID-19 pandemic from the perspective of network and community structure. It is still meaningful to explore the highway mobility patterns and emergency response of highway travellers. Despite the traditional network indicators, such as node degree, weight and clustering coefficient, network efficiency, Gini coefficient and spatial autocorrelation were introduced with the consideration of spatial and temporal interaction between highway tollbooths. On the basis of highway transaction data, this paper aims to propose a systematic approach that measures the impacts of the COVID-19 pandemic on highway mobility patterns from a network perspective. By adopting this approach, a comprehensive understanding of the changes in highway travel behaviour during the pandemic and its subsequent recovery can be achieved.

3. METHODOLOGY

3.1 Network properties analysis

Complex network theory has been widely applied in various domains for network analysis, encompassing social relationship networks, supply chain networks and multiple-mode transportation systems [33–34]. In this study, the highway travel behaviour in Guizhou in four consecutive Augusts from 2019 to 2022 were examined by the complex network properties. Specifically, the highway travel pattern experienced a recurrent outbreak process during the COVID-19 pandemic. In order to represent the highway system, tollbooths are considered as nodes, while the connection between pairs of tollbooths is regarded as links. Additionally, the unique number (e.g. i), is assigned to each tollbooth. The connectivity between nodes is presented by the adjacent matrix A. A link between nodes i and j is established and assigned a value of 1 if there are more than one highway trips recorded between them. Otherwise, the link is not built. Furthermore, the link weight $\omega_{i,j}$ represents the trip counts between node i and j. To further investigate the network properties, the specific network properties are addressed as follows.

Node degree. Generally, the node degree is the most direct and understandable characteristic to measure the node centrality. The number of nodes connecting to a given node can be represented by node degree and can be calculated using the adjacent matrix. Consequently, higher node degree means the higher activity and importance for the network. In this study, both the in-degree and out-degree are considered, as the highway network is constructed as a directed graph. The in-degree represents the number of incoming links or connections to the node, while the out-degree represents the number of outgoing links or connections from the node. Then, the node degree can be defined as follows:

$$D_i = \sum_{j \in V} (a_{ij} + a_{ji}) \tag{1}$$

where V presents the adjacent set of nodes for node i, and a_{ij} and a_{ji} represents the connectivity between i and j in both directions, which can be derived from the adjacent matrix.

Network connectivity. Saberi et al. stated the network connectivity could illustrates the systematic view of link and node, which is another commonly used network property analysis [33]. In this study, it can be expressed as follows:

$$NC = \frac{2 \cdot L}{n^2} \tag{2}$$

where the count of nodes is represented by n, while the number of links by L.

Node flux. Similar to the link weight, the count of trips can be presented by the node flux. However, node flux introduces the trips either begin or end for one selected highway tollbooth. Therefore, it can be expressed as *Equation 3*.

$$NF_i = \sum_j \omega_{ij} \tag{3}$$

where ω_{ij} is the link weight.

Clustering coefficient. Fishman et al. and Chen et al. employed the clustering coefficient in previous study to measure the performance a specific network, which also reveals the degree to which two adjacent nodes are likely to connect themselves [34, 35]. Thus, the clustering coefficient can be introduced as *Equation 4* for node i.

$$CC_i = \frac{2}{D_i(D_i - 1) - 2D_i(R)} T_i \tag{4}$$

where CC_i represents the clustering coefficient for node i. The directed triangle numbers are presented by T_i, while D_i is the node degree.

Network efficiency. In the network perspective, the traffic information transmission between nodes can be measured by the network efficiency, as expressed in *Equation 5*.

$$E = \frac{1}{N(N-1)} \sum_{i \neq j} \frac{1}{d_{ij}} \tag{5}$$

where the shortest distance between nodes can be presented by d_{ij}. The d_{ij} will be set to $+\infty$, if there is no highway trip between nodes. Therefore, the value of E ranges from 0 to 1, while a large value means the high efficiency of the network.

Gini coefficient. The Gini coefficient is well known for measuring the income distribution and was introduced to deal with the heterogeneous distribution of travel demand within traffic system [36, 37]. In this study, the general Gini coefficient format is as follows:

$$G = 1 + \frac{1}{n} - \frac{1}{n^2 \bar{x}} \sum_{i=1}^{n} (n - i + 1) x_i \tag{6}$$

where the Gini coefficient is ranged from 0 to 1. The high value of the Gini coefficient means the high inequality. x_i is the service rate for highway tollbooth.

Spatial autocorrelation. Generally, the spatial autocorrelation analysis should calculate the Moran's Index within the regional network structure. The definition of Moran's I is as follows:

$$I = \frac{n}{\sum_{i=1}^{n} \sum_{j=1}^{n} w_{i,j}} \cdot \frac{\sum_{i=1}^{n} \sum_{j=1}^{n} W_{i,j} (y_i - \bar{y})(y_j - \bar{y})}{\sum_{i=1}^{n} (y_i - \bar{y})^2} \tag{7}$$

where n is the number of highway tollbooth. y_i is the observed point for node i, while $W_{i,j}$ is the spatial weight.

3.2 Detection of community structure

On the other hand, the community detection is regarded as one of the most effective methods for visualising and understanding the underlying structure of a network or graph [38]. Indeed, the techniques for inferring communities in networks have found extensive applications in various fields such as sociology, biology and computer science. In the context of this study, inferring communities in the highway network involves dividing tollbooth sites into disjoint clusters, where tollbooths within the same cluster exhibit stronger connections in terms of highway travel behaviour. This approach allows for a closer examination of the relationship and patterns among tollbooths within the network. In total, communities in the network must demonstrate similarities in mobility patterns.

Over the past decades, an extensive number of literature has conducted the community detection. Specifically, the most popular modularity mass function, proposed by Newman and Girvan, attempts to discover the likely existence of clusters by comparing the true edge density with the expected density in a subgraph [39]. In relation to the number of links and node degree, the expected number of edges between pairs of nodes can be estimated. Therefore, the difference between actual and estimated number of edges for all node pairs within the same community can be computed. Thus, the modularity function is expressed as follows:

$$Q = \frac{1}{2l} \sum_{i,j} \left(A_{ij} - \frac{D_i D_j}{2l} \right) \delta(C_i, C_j) \tag{8}$$

where A_{ij} is the adjacent matrix. D_i is the node degree for i. If node i and j are in the same community, the value of δ function is 1, otherwise zero. l is the number of links in the highway network.

4. RESULTS AND DISCUSSION

4.1 Study area and data source

The study area, Guizhou province, China, is majorly composed of mountainous and hilly plateaus, which is presented in *Figure 1*. Thus, highway plays an important role in transportation corridor, which is easily affected by the COVID-19 pandemic. Specifically, Guizhou is famous worldwide for the mountain tourism and over 70 national and provincial scenic districts attract a large amount of tourists. The tourism period is also the highest traffic volume period for the highway. Additionally, the pandemic experienced the process of recurrent outbreak and clearing, while traffic restrictions adjusted simultaneously. Therefore, this paper selects four consecutive Augusts as the study period, which can be divided to four distinct stages as follows:

Stage 1 (August 2019): Normal condition without the COVID-19 pandemic. In August 2019, there was no restriction on travel in Guizhou.

Stage 2 (August 2020): From the COVID-19 pandemic outbreak in Wuhan, the patient cases were clearing in March 2020 and the traffic restriction was eased in the second half of the year. In August 2020, the intercity travel within and outside the province was allowed.

Stage 3 (August 2021): The Delta variants of COVID-19 was spread to China in April 2021. The recurrence of the pandemic resulted in a strict traffic control policy on non-essential trips. In August 2021, the intercity and interprovincial travel was strictly limited in Guizhou.

Stage 4 (August 2022): As the infection of COVID-19 was sporadic, the prevention of the pandemic was adjusted to “Normal prevention policy” in August 2022. The nucleic acid detection was essential for travellers outside the city, and the isolation time was up to 14 days if a traveller was from the medium-high risk area.

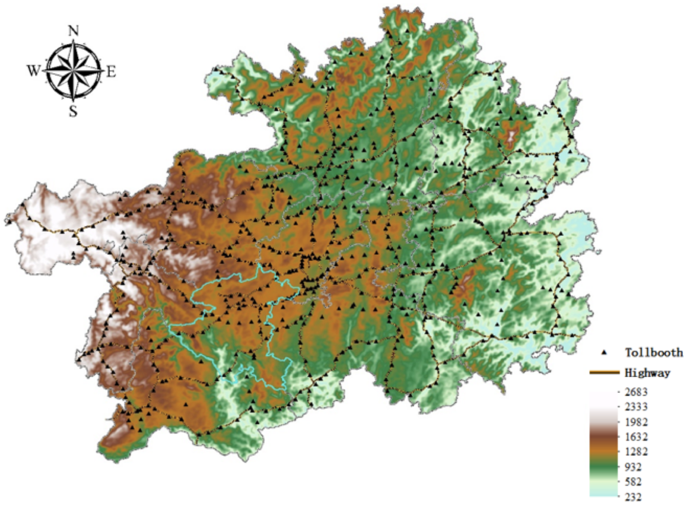

Figure 1 – The terrain of the study area Guizhou province

The utilised highway transaction dataset took four months, including four consecutive Augusts from 2019 to 2022. Highway transaction dataset provides detailed travel information. The entrance and exit station illustrate the origin and destination for a highway trip, which also indicates the spatial distribution of traffic. Other available attributes, such as ID, vehicle plate, time and payment, are shown in *Table 1*.

Table 1 – Highway transaction data format

Field	Data type	Description
Transaction ID	Int	The Transaction ID of records
Vehicle plate	Var	Vehicle plate number, unique
Entry station ID	Var	The station ID where vehicle enters highway
Entry time	Date	The date and time when vehicle enters highway
Exit station ID	Var	The station ID when vehicle enters highway
Exit time	Date	The date and time when vehicle enters highway
Transaction fee	Float	Fee for highway toll
Other fields		

Moreover, transaction records may contain the missing value or incorrect information, which should be modified or removed. After the cleansing process, over 6 million records are involved. In this paper, the vehicles are divided into passenger cars and freight vehicles, which play different roles in the highway transportation system.

4.2 Spatial-temporal analysis

The highway transaction dataset was also cleansed with removing the erroneous records. Those extremely long or short highway trips within the Guizhou province are considered as invalid trips, which should be discarded to avoid the bias results.

Subsequently, the temporal analysis for passenger and freight cars from 2019 to 2022, respectively, as *Figure 2* shows. Interestingly, in 2020, i.e. stage 2, there was a significant increase up to 15% in total traffic volume when compared to the stage 1 in 2019, which demonstrates the recovery of highway trips to normal levels. The clearing of COVID-19 cases and easing travel policy resulted in the increase in traffic. However, the traffic volume of passenger cars was fluctuated, while the traffic volume of freight cars was relatively stable, which is mainly caused by the flexibility of travellers, especially for the tourists. For stage 3 in 2021, there was a dramatic decrease up to 30% in traffic volume, as the COVID-19 Delta variant exploded in China. The strict traffic control policy constrained a large amount of intercity and inter provincial highway travel. Similarly to the stage 3, the stage 4 was also under the strict traffic control policy, as the COVID-19 cases were not clearing. Additionally, people's perception of the pandemic also improved the self-control of long-range trips. As a result, the traffic volume during stage 4 is basically equal to that in stage 3. Moreover, the comparison of hourly traffic volume is presented in *Figure 3*. Specifically, the highway travel volume in Guizhou province illustrates the similar single-peak trend from 2019 to 2022. Nevertheless, the traffic volume in stage 3 and 4 has not been recovered to the amount in stage 1 and 2, due to the strict traffic control policy. These fluctuations highlight the dynamic nature of travel behaviour during the recovery stage and the influence of the evolving pandemic situations.

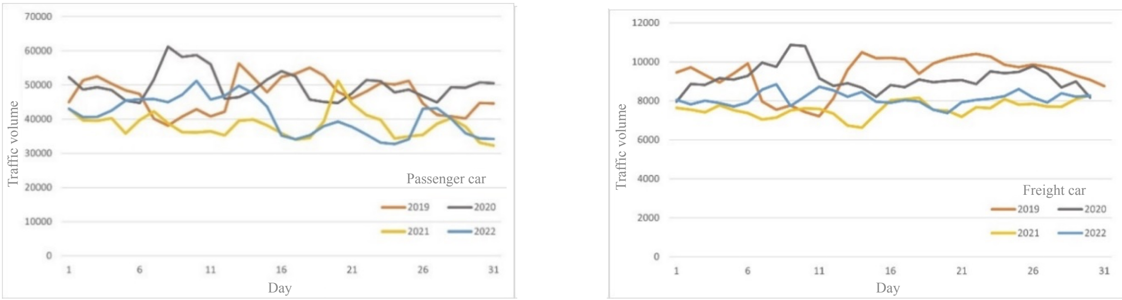

Figure 2 – The daily traffic volume for passenger and freight cars

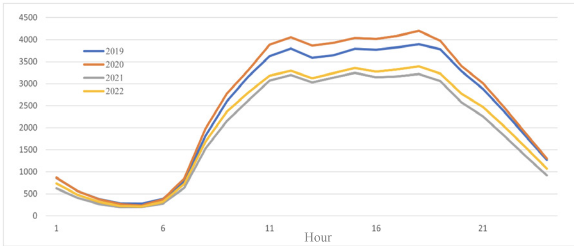

Figure 3 – The comparison of hourly traffic volumes from 2019 to 2022

Moreover, the highway travel duration and toll amount were examined and compared in terms of cumulative density and shown in *Figure 4*, which illustrates the significant difference between various stages. Notably, the average highway trip duration in August 2021 and August 2022 is the lowest within the study period. The observed changes can be primarily attributed to the outbreak of the COVID-19 pandemic and the subsequent implementation of travel restrictions, which decreases the long-range trip between cities. Specifically, there is no significant difference for average toll amount in four stages, which is believed to be affected by the adjustment of highway toll policy. For instance, the highway trips for the patients or anti-pandemic materials are toll free.

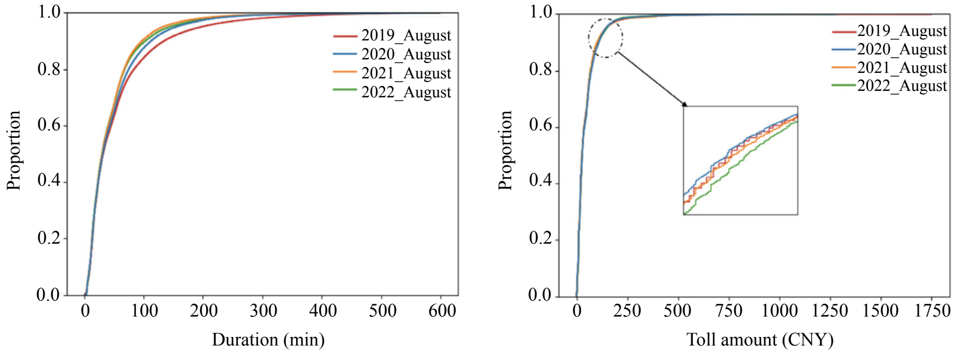

Figure 4 – Cumulative density for travel duration and toll amount

Furtherly, the spatial distribution of highway travel behaviour in each tollbooth for various stages was presented in *Figure 5*. The study found that there is a relatively homogeneous distribution of highway travel demand in Guizhou from 2019 to 2022. The central district and north-eastern district demonstrate the high travel demand in the study period, mainly due to the mountainous terrain and concentrated population. Even though the total number of highway trips decreased significantly in stage 3 and 4, the central district surrounding the provincial capital keeps the high travel demand.

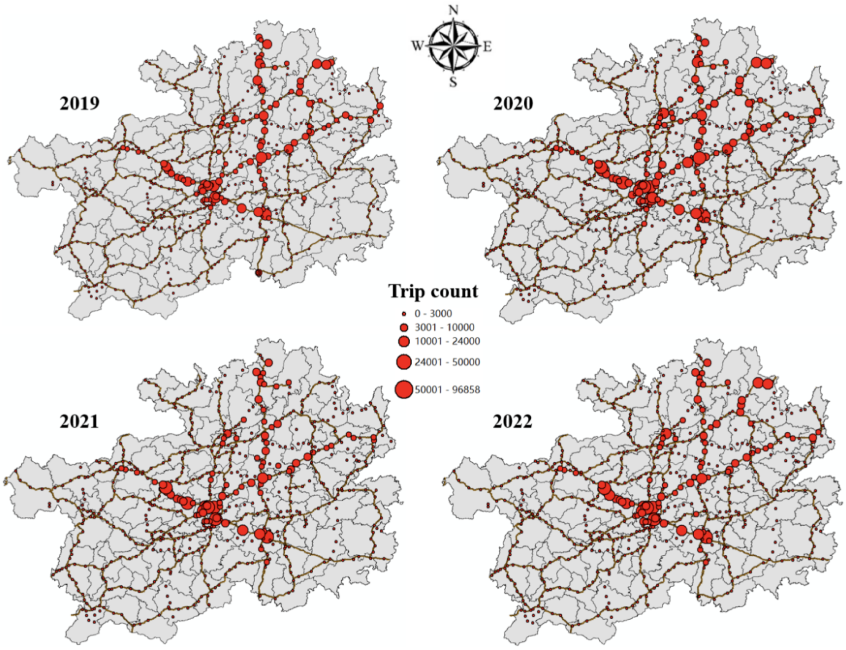

Figure 5 – Spatial characteristics of monthly average highway trips from 2019 to 2022

4.3 Discussions of complex network analysis

As described in data source section, four consecutive Augusts from 2019 to 2022, namely stage 1 to 4, were selected as the study period. Specifically, the COVID-19 pandemic experienced the outbreak, clearing and variant process, which resulted in various traffic restriction policies for the highway. Therefore, the highway transaction dataset was extracted to construct the complex network. *Table 2* summarises the network performance of the highway network from 2019 to 2022 in the study.

Table 2 – Network properties in each stage

Property	2019 Stage 1	2020 Stage 2	2021 Stage 3	2022 Stage 4
Node	461	521	554	583
Link	10670	12530	11277	13936
Connectivity	0.10	0.11	0.07	0.08
Mean degree	46.29	48.10	40.71	42.81
Max degree	422	464	496	511
Mean weight	146.27	149.76	129.11	110.44
Max weight	40212	56059	34587	37519
Mean flux	3684.78	3745.35	2760.49	2766.31
Max flux	191580	250256	217452	203468
Network efficiency	0.54	0.55	0.53	0.53
Clustering coefficient	0.22	0.23	0.17	0.18
Gini coefficient	0.939	0.942	0.940	0.941
Moran's I	0.26	0.33	0.19	0.24

The results show the increasing number of nodes by year while the links number is oscillating. It is mainly caused by the construction of a new tollbooth and decreased trips between tollbooths. Interestingly, the clearing of pandemic patients and loosing traffic restrictions may induce the recovery and even increase of highway travel. Thus, the network connectivity value increased approximately by 10% from 2019 to 2020. However, the COVID-19 variant and strict traffic restrictions in 2021 resulted in the significant decrease of intercity travel, which is proved by the lowest network connectivity 0.07. For stage 4 in 2022, the connectivity recovered slowly as the recurrence of the pandemic.

The node degree demonstrates the number of tollbooths connected to the selected tollbooth. As expected, the mean node degree increased in 2020 and decreased in 2021 and 2022, which indicates the interaction changes between highway tollbooths. For instance, under the strict traffic policy, some highway tollbooths were closed and highway trips were forbidden. Nevertheless, the tollbooths with the highest node degree always provided the important service from 2019 to 2022. These tollbooths, providing excellent highway service for essential trips even under the COVID-19 pandemic, must be considered in the traffic policy against emergency.

Furthermore, the link weight represents the number of trips between tollbooths, while the node flux indicates the total number of trips that either originate from or terminate at a selected highway tollbooth. These metrics provide insights into the intensity of traffic flow and the importance of specific tollbooths in the highway network. Similar trend was found in both link weight and node flux. For instance, the fast clearing of COVID-19 cases induced a significant increase of link weight and node flux in 2020. However, the maximum link weight decreased approximately 40% in 2021 due to the COVID-19 variant and strict traffic restrictions. The highway travel has not been recovered to the normal condition in 2022.

The average clustering coefficient measures the level of node interaction in the network. The low value in 2021 indicates the worse local connection in highway network due to the COVID-19 variant and traffic restrictions. Additionally, the measurement of network efficiency demonstrates the overall performance of the highway system in stage 1 and 2. Specifically, the Gini coefficient is over 0.9 from 2019 to 2022, which indicates the extremely uneven distribution of highway travel demand. This can be attributed to the concentration of highway travel demand in the central capital district.

Furthermore, the Moran's Index indicates the spatial correlation for the highway trips. The highest value of Moran's Index in 2020 is over 0.3, which indicates the potential community structure of the highway network. In addition, the local Moran's Index was employed to analyse the spatial clustering characteristics of highway travel patterns, as presented in *Figure 6*. The results presented the concentration of highway trips in the central capital district in Guizhou province, where the population is concentrated and transportation facilities are well built. On the contrary, the marginal area in Guizhou is composed of highway tollbooths with low travel demand. There exist similar spatial clustering characteristics from 2019 to 2022.

To further understand the network structure, the community detection approach was utilised to examine the highway community structure in four consecutive Augusts from 2019 to 2022. *Figure 7* illustrates the detected communities in each period, in terms of the modularity-based approach. Generally, the major structure of the highway network is consistent in four stages. Community 2, 3 and 4 are found from 2019 to 2022. Community 2, as identified within the highway network, is situated in a mountainous area with a moderate altitude, while community 3 is located in the mountainous area with medium altitude. Community 4 is composed of hilly area. It is mainly determined by the terrain in Guizhou. Community 1 experienced significant changes that were influenced by the outbreak of the COVID-19 pandemic and the subsequent implementation of traffic restrictions. These changes likely impacted the connectivity and travel patterns within this community, leading to notable shifts in its composition and characteristics. In 2019 and 2020, community 1 covered a large area, which indicates the connection of long-range highway trips. In 2021, intercity travel is strictly limited, and community 1 was split into community 1 and 5 with small size. With the adaption to the traffic policy, people actively reduce the long-range highway trips, which mainly results in the disappearance of community 1 in 2022. The community structure addresses the gradual adjustment of highway travel behaviour.

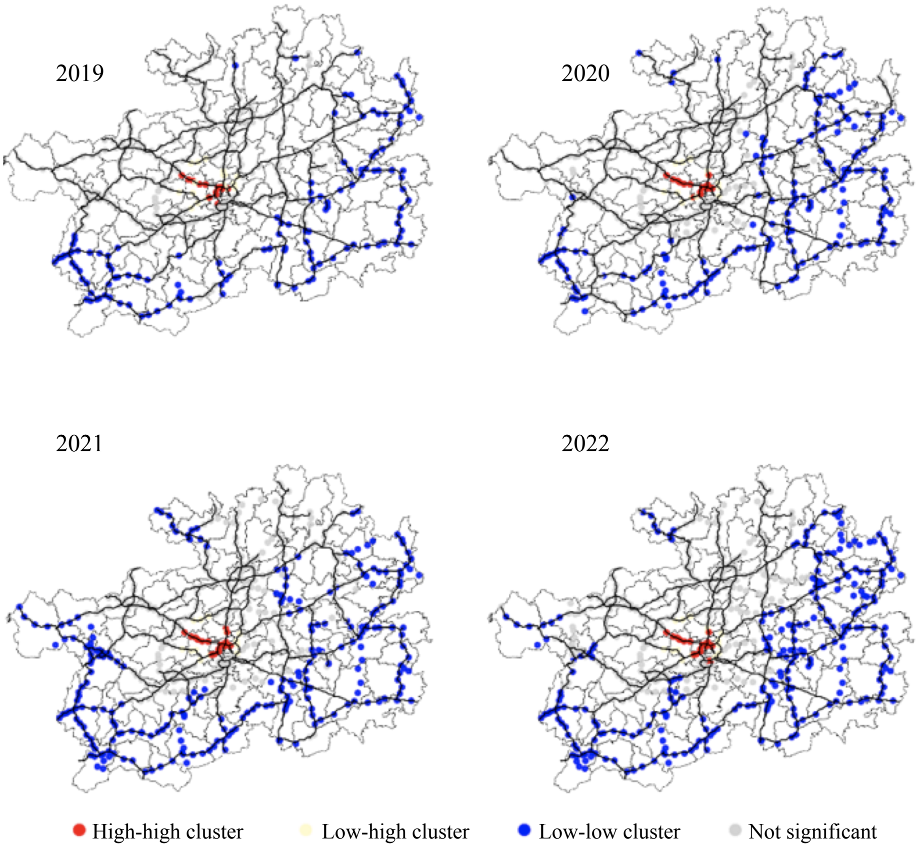

Figure 6 – Spatial clustering characteristics for highway trips

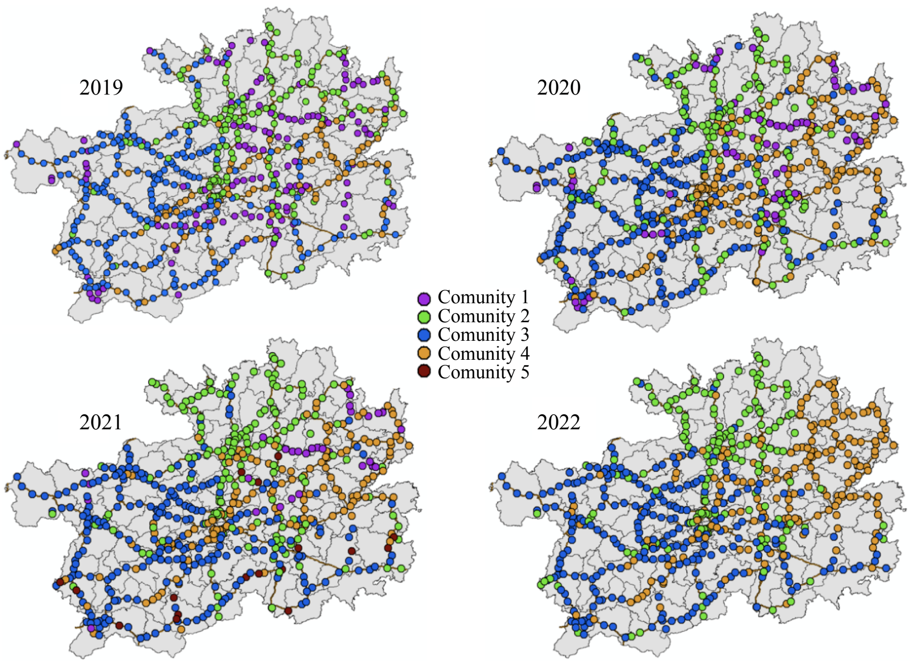

Figure 7 – Community structure for highway system from 2019 to 2022

The findings of this study hold significant implications for the highway management authorities. The study suggests the adoption of a community-collaboration strategy for highway management during public emergency events such as the COVID-19 pandemic. This strategy involves fostering collaboration and communication among different tollbooth communities, allowing for better coordination and response to changing traffic conditions and restrictions. Specifically, the tollbooths with high node degree, which can provide stable connection to other tollbooths, should be considered to be maintained in priority during an emergency.

On the other hand, the proposed methodology for measuring the impacts of the COVID-19 pandemic on highway mobility patterns from a network perspective has the potential for broader application beyond the specific context of this study. For instance, the methodology can be scaled up to analyse highway transaction data from different regions, or even countries. As long as the necessary data is collected, the approach can be applied to understand the impacts of the pandemic on highway mobility patterns in various geographical contexts. Additionally, the methodology can be used to evaluate the effectiveness of transportation policies and interventions implemented during the pandemic. By examining the network-level impacts of specific measures, such as travel restrictions or infrastructure changes, policymakers can assess their effectiveness and make informed decisions for future crisis management.

5. CONCLUSION

In contrast to the existing research on highway travel behaviour, this paper proposes a systematic approach to deeply understand the spatial-temporal characteristics in the network perspective on the basis of highway transaction data. Specifically, stages with various factors, such as the clearance of COVID-19 cases, the emergence of COVID-19 variants and traffic restrictions, are investigated. By considering these stages, the study provides a more holistic understanding of how the highway travel behaviour evolves in response to changing circumstances during the ongoing pandemic. The utilisation of the highway transaction dataset allows for a detailed spatial-temporal analysis of mobility patterns, enabling the identification of trends and changes in travel behaviour over time and across different locations. Moreover, the construction of a highway complex network based on the dataset helps uncover the underlying community structure and connectivity of the highway system. To further understand the network structure, community detection was used for the highway community structure in the study period:

- Although the COVID-19 pandemic seriously influenced the transportation system, the highway trips increased over 10% in 2020 due to the clearing of pandemic cases and easing traffic policy. In contrast, the outbreak of COVID-19 Delta variants resulted in a dramatic decrease of highway trips in 2021.
- From a network perspective, major metrics such as link weight, node flux, network connectivity and clustering coefficient experienced a noticeable decrease during the pandemic. This indicates a change in the network properties of the highway system, reflecting the impact of the COVID-19 pandemic on travel demand.
- Despite the influence of the mountainous terrain on the basic community structure in Guizhou, the community detection approach utilised in this study reveals the evolution of the highway community structure. This evolution indicates the impact of changing traffic restrictions on the organisation of tollbooth communities within the highway network. The identification of evolving community structures provides insights into the dynamic nature of highway travel behaviour and the adaptation of tollbooths to changing conditions.

From a policy perspective, this paper offers a valuable and in-depth understanding of the impact of the COVID-19 pandemic and traffic restrictions on highway travel patterns. The findings highlight the importance of managing tollbooths collaboratively during emergency events. Given the strong local connections within communities, it is crucial to establish a collaborative approach to tollbooth management. In particular, tollbooths with high node degrees, indicating stable and significant connections to other tollbooths, should be prioritised and maintained to support essential highway trips during emergencies. These tollbooths play a crucial role in maintaining connectivity and ensuring the smooth operation of the highway network, especially during critical times. By focusing resources and attention on these key tollbooths, policy-makers can effectively manage and support essential transportation needs during emergency events. From the local government perspective, a community-collaboration strategy is recommended, which requires active participation and engagement from highway management authorities, tollbooth operators and relevant stakeholders. It involves establishing communication protocols, sharing real-time information and coordinating responses to dynamic traffic conditions and restrictions. By adopting this strategy, highway management authorities can enhance their capabilities to manage emergencies, mitigate disruptions and ensure the safety and well-being of highway users.

Indeed, the proposed approach has great potential to be utilised in other regions or areas with highway and for the understanding of mobility behaviour in response to the pandemic and other public events. Further research can be conducted to delve deeper into individual mobility patterns during unexpected disruptions, such as public emergency events. One approach could involve implementing a demographic survey to examine the behaviour and preferences of travellers in adjusting their planned highway trips during emergency situations. This would provide valuable insights into how individuals react and adapt to disruptions, allowing for a better understanding of their decision-making processes and potential mitigation strategies. In addition, the detected community in the highway network can also be considered in the planning and construction of the highway.

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探索COVID-19疫情影响下的高速公路出行模式：以贵州省为例

摘要：

通过对COVID-19大流行期间高速公路出行行为的研究，可以为了解疫情及相关政策对人类流动模式的影响提供有价值的见解。本文提出了一种以网络和社区结构视角的综合研究方法，对高速公路出行行为进行研究、评估和描述。为了捕捉出行行为的变化，研究将时间划分为四个阶段，基于2019年到2022年连续四个8月份的数据，这期间实施了不同程度的限制措施。研究结果揭示了出行模式的有趣趋势。在2020年，疫情病例清零后，高速公路出行量显著增加了10%以上。然而，在2021年，随着COVID-19变异株的出现，高速公路出行量显著下降了30%以上。通过采用复杂网络分析，主要网络的关键指标，包括链路权重、节点流量和网络连通性，在疫情期间表现出明显的下降。这些网络属性的变化也反映了高速公路出行需求的空间异质性。此外，社区检测的结果揭示了高速公路社区结构的演化，突出了在公共紧急事件期间采用社区协作策略进行高速公路管理的有效性，因为这有助于促进社区内的本地互动。

关键词：

COVID-19疫情；高速公路交通数据集；出行行为；复杂网络分析；社区发现