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Anticipating Spatial–Temporal Distribution of Regional Highway Traffic with Online Navigation Route Recommendation

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Abstract: Detailed anticipation of potential highway congestion is becoming more necessary, as increasing regional road traffic puts pressure on both highways and towns its passes through; tidal traffic during vacations and unsatisfactory town planning make the situation even worse. Remote sensing and on-site sensors can dynamically detect upcoming congestion, but they lack global and long-term perspectives. This paper proposes a demand-network approach that is based on online route recommendations to exploit its accuracy, coverage and timeliness. Specifically, a presumed optimal route is acquired for each prefecture pair by accessing an online navigation platform with its Application Programming Interface; time attributes are given to down-sampled route points to allocate traffic volume on that route to different hours; then different routes are weighted with the origin–destination traveler amount data from location-based services providers, resulting in fine-level prediction of the spatial–temporal distribution of traffic volume on highway network. Experiments with data in January 2020 show good consistency with empirical predictions of highway administrations, and they further reveal the importance of dealing with congestion hotspots outside big cities, for which we conclude that dynamic bypassing is a potential solution to be explored in further studies.

Keywords: regional transportation; traffic congestion; online navigation; travel route; origin–destination

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1. Introduction

1.1. Regional Congestion and Its Local Impacts

Congestion goes back nearly as far back as road traffic itself. Though gaining a major share of research attention in this field [1], urban road network is not the only place where congestion takes place. Since the late 1980s, congestions on the interstate system of the United States have raised widespread concerns for the public and the authorities [2,3]; in the 1990s and 2000s, various types of research from academia and state authorities looked into the influence of interstate congestion and looked for possible solutions, mostly about real-time traffic prediction by connected ground sensors or O–D investigations [4–6], increasing and optimizing highway infrastructure [7–9], dynamic optimization based on adaptive navigation during emergencies [10], etc.

Since the 2000s, rapid infrastructure construction and increase in vehicular transportation drew the attention of Chinese researchers to this issue [11–13]. Expressways crossing high population density areas such as Shanghai–Nanjing Express were of particular concern, as they go through and intersect with numerous cities and towns, resulting in vulnerability to and high cost of congestions, even raising complaints from local enterprises that rely highly on smooth circulation [14].

With vehicular transportation further expanding, the problem spread to Northern and Central China, especially in the Lunar New Year and other public vacations when there is enormous tidal traffic nationwide [15]. These regions are not as densely populated as Eastern China but are major sources of interprovincial migrations and are at the central position of the national highway network. Moreover, many towns here are built directly alongside national or provincial highways without an elevated intersection. This can cause severe disruption between the traffic on the highway and the activities of the town, as demonstrated in Figure 1.

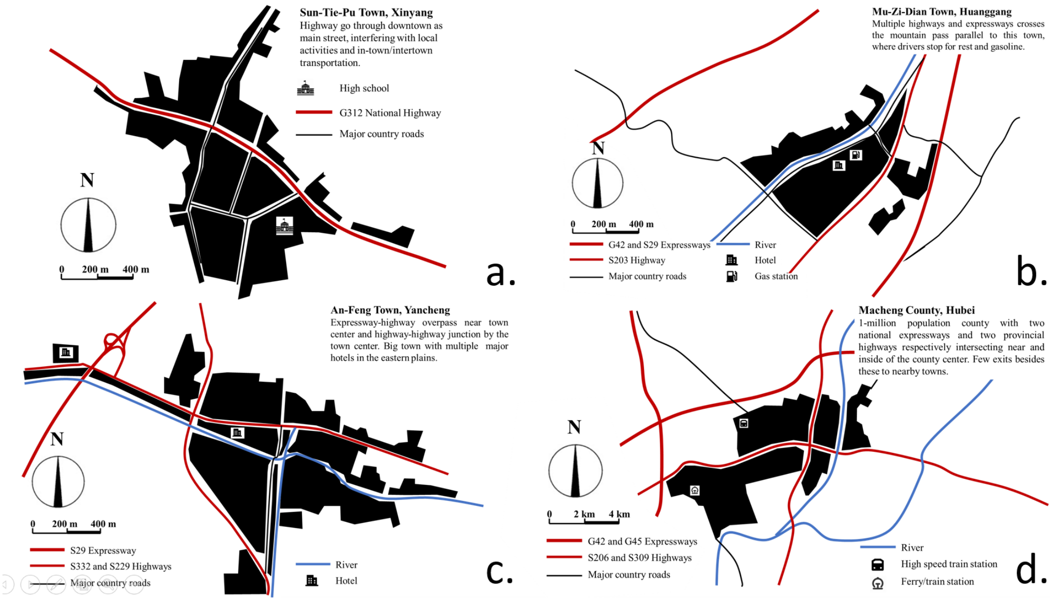


Figure 1. Typical spatial relationship between highway/expressways and towns. (**a**) Pass through, interfere local activities. (**b**) Parallel, town serves as rest stop. (**c**) Intersection within or near towns. (**d**) Intersection within or near small cities, interfere with local inter-town traffic.

On the whole, various factors determine that regional congestions on highways are an inevitable phenomenon that can lead to severe consequences on regional and local economy, transportation safety and travelers' well-being; hence, it is our aim to seek better cognition and response to such congestions with tools newly available in the present days.

1.2. Congestion Monitoring, Analysis and Prediction

When congestion happens, most of the relatively feasible measures involve dispatching local forces to properly guide the traffic both on the highway and on local road network connected to it. To effectively achieve this end, early knowledge of the coming congestion is required. In a static network, experienced local officials would know when and where a congestion could happen to their town based on what happened in previous years. The tricky part is that one change of demand or network can dramatically alter the risk or extent of congestion somewhere hundreds of kilometers away; hence, it is necessary to build a model that can (1) cover entire highway networks and (2) allow manual changes of certain nodes and parameters. Such characteristics, obviously, are also vital if one wishes to evaluate the influence of such scenarios as an expected increase of demand or a segment of road in repairs.

In previous efforts, high-resolution remote sensing images were proven effective in detecting previous congestions or even monitoring presenting ones, but they cannot predict future ones [16]; by accessing the DBMS (Data Base Management System) of the highway toll system or planting sensors along the highway, congestions can be foreseen but only on short notice and in small regions [17,18]. Online map service providers themselves monitor and anticipate congestion by present vehicle speed of their users and historical congestions recorded. All of the methods rely on a known road network and traffic that is already on it, making it difficult to anticipate scenarios with some alterations to either the network or the traffic. Therefore, we propose a novel approach based on both demands and route projection.

1.3. Online Route Planning and Recommendation Services

Online route planning and recommendation services provided by digital map platforms, together with their commercial or open-access API (Application Programming Interface), bring a new possibility for projecting possible routes in practical traffic analysis [19]. Compared with traditional network analysis approaches, there are several obvious advantages: (1) It is based on numerous data collected from authorities and on site, including that of the actual route choices which it collected from users of navigation services, far beyond what a researcher could manage. (2) The algorithms are likely to be more sophisticated and accurate due to long-time improvement and peer pressure as a commercial application. (3) The results are easily acquirable with various alterable parameters, saving much energy for the user, which is particularly important if a method is to be put to practical use. (4) It allows for the compulsory avoidance of certain points, making it possible to generate results for alternative networks.

Previous studies have deemed such sources as useful in service-area delimitation, accessibility evaluation on regional and urban scale, etc.; in this study, we used it to project the possible routes of road travelers from one city to another.

1.4. This Study

This study aimed to propose an approach to anticipate congestions happening on highways and expressways that would help the response of local authorities and regional transportation planning efforts. Four key goals are to be achieved in this effort: (1) potential of full coverage of the national highway and expressway network, so that influence from distant demands can be taken into account; (2) results with proper resolution given based on meaningful spatial units, so that it can be put into practical application; (3) sufficiently prospective, so that congestions can be foreseen in advance; and (4) ability to work in assumed scenarios, so that it can be used for evaluating policies or plans.

To this end, we utilized methods very similar to those of a typical urban-level traffic analysis: determine the origin and the demand, find possible routes, quantitate the traffic flow, allocate traffic to spatial objects and analyze the traffic pressure. Different data sources are involved in this process, including AMAP route recommendation, which provides probable routes for each origin–destination pair; Baidu Migration, which provides the total volume of daily travelers between such pairs; and Tencent Location Big Data, which elaborate the proportion of road traffic in these flows. The applicability of these data sources is limited, as the characteristics they have as commercial products are not completely supportive of our analytical needs in this study; hence, methods are explored and developed to cope with data sizes, null values, lack of detailed temporal information, etc. Compared to existing approaches which rely on off-line investigation and geo-data, the utilization of online navigation and migration data has ensured very close connection to actual travel behaviors: (a) the former is the direct basis for planning travel routes for most people in current days, with comprehensive consideration regarding fuel and toll costs, time consumption, driving experience, etc.; and (b) the latter is an empirical reflection of origin and destination of numerous actual trips, with little adverse influence from sampling deviation or delay. Our study developed a systemic approach that realizes the integration of these two data sources in the anticipation of highway congestion by creating demand-weighted travel routes, providing a potential new path for more accurate and dynamic traffic management with regional-scale coordination.

The complete framework of this approach is shown in Figure 2. A case study was conducted based on the data from a typical weekend shortly before Spring Festival, when major inter-regional tidal migrations tend to take place in China for traditional family reunions. The results of hourly congestion anticipation were looked into regarding townships and major junctions, showing consistency with known congestions.

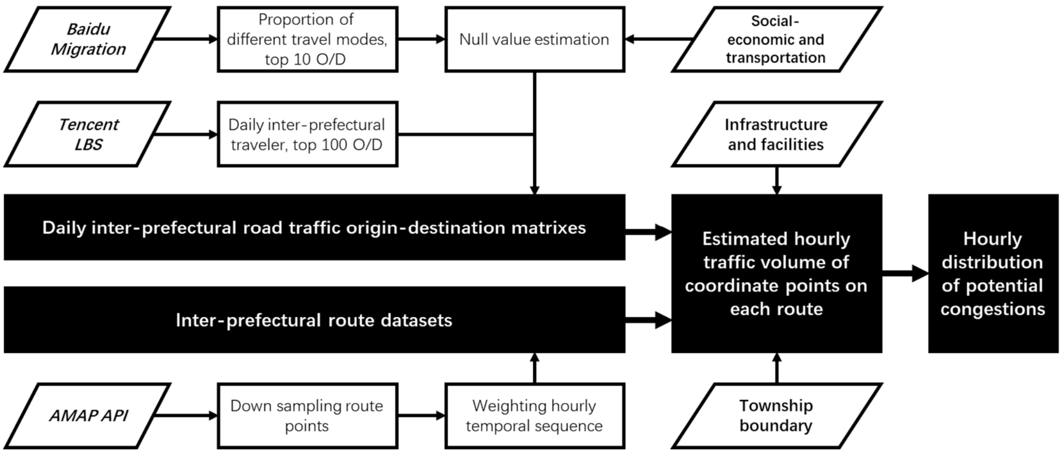


Figure 2. Framework of this study.

2. Materials and Methods

2.1. Research Scope

Route dataset generation and traffic-demand analysis are conducted between any two prefecture-level administrative areas or equivalents (abbreviated to prefectures hereafter) in China, except for Sansha in Hainan and those in Taiwan Province, which are on islands neither connected to the mainland by road network nor by routine ferry transportation; thus, they are unlikely to cause congestion elsewhere. Prefectures are administrative spatial units in China between provinces and counties; typically, there is a main urban center with major transportation facilities and commercial services, several satellite towns, and a population of several millions in a prefecture. As the transportation hub of the entire prefecture, it is appropriate to assume that long-distance traffic mostly happens between urban centers of prefectures. The traffic demand data were acquired in January 2019, while the route recommendation data were acquired in January 2020.

Congestion anticipation is conducted on both national and local scales. On the national scale, estimated congestion is given to each township, the smallest administrative unit with a local government in China. It is also often the smallest unit with highway connection and a police force; hence, it is a good object for considering the local impact of regional congestion and its response. On the local scale, a finer anticipation with highway joints, etc., also considered as objects is conducted in Wuhan Metropolis, but with more reference data at hand. The study area and the spatial scale of prefectures and townships is demonstrated in Figure 3.

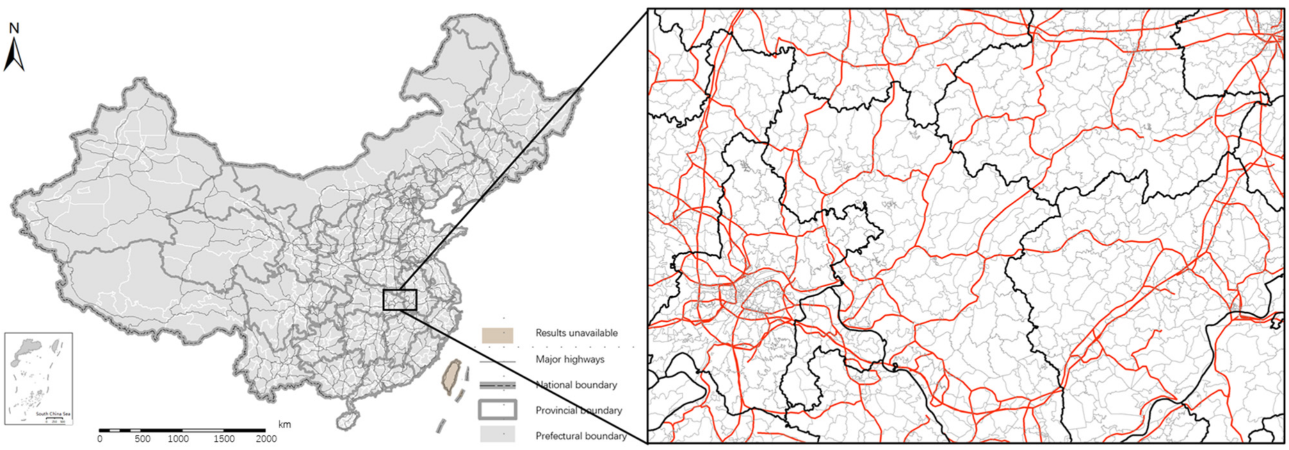


Figure 3. Study area and prefecture/township spatial units.

2.2. Materials and Their Acquirement

The method is mostly based on two data sources: route recommendation acquired from online map and navigation platforms, which provides the estimation of travel time between any two prefectures and depicts the probable routes from one to the other; and daily prefectural origin–destination data from telecommunication/internet services providers, which characterizes the actual traffic demand and the proportion of road traffic among them. These data and their acquirement are elaborated as follows.

Furthermore, three kinds of reference data are used to allocate route nodes to meaningful spatial units: administrative boundaries of townships and highway and expressway shapefiles. The administrative boundaries are a verified map data, map number GS(2017)1579; and highway and expressway data were purchased from www.udparty.com on 1 February 2020, a geospatial data provider [19].

2.2.1. Route Recommendation Data

The AMAP API was used with Python 3.6 and Requests library for acquiring route recommendation data. AMAP is a major digital map and navigation services provider that was established in 2002, with a substantial market share in individual map services, taxi and delivery navigation, social network applications, etc. Any other providers of online navigation services are also applicable as the source of route-recommendation data, such as Google Maps, and those with open-source APIs are more convenient in use. As is demonstrated in Figure 4, given a destination, an origin, time of departure and route preference, it generates a route recommendation and the corresponding travel time and travel distance by exploiting basic geoinformation, crowdsourced incident reports, historic user data, etc. To acquire the information needed from the recommendation, the following steps are taken:

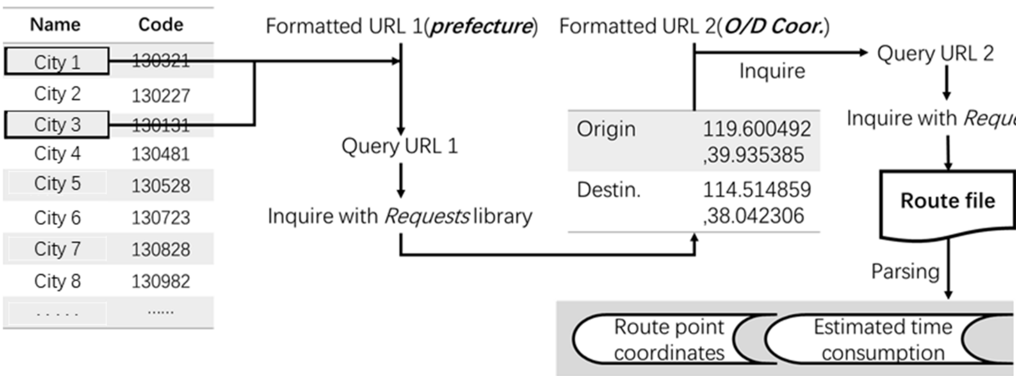


Figure 4. The process of acquiring route-recommendation data.

1. Generate coordinates list.

First, the name of each prefecture is traversed as the *prfct* parameter in the following URL (Uniform Resource Locator):

'https://restapi.amap.com/v3/geocode/geo?address=' + *prfct* + '&output=' + *format* + '&key=' + *userkey*

where *userkey* is a set of code applied beforehand, and *format* is the page format of the URL, which, in our case, is 'json'.

Then all URLs are linked to by the *requests.get* method, and the WGS-84 coordinates of the prefectural government of the prefecture are returned in property *geocodes.location* and saved in a text file. Given that an overwhelming majority of prefectural governments lie in their downtown areas, we consider them acceptable as the central point of the prefecture when analyzing at the regional scale.

2. Request route recommendation file.

A coordinates pair is generated between any two aforementioned prefectural central points, which are traversed as the *olo* parameter and *dlo* parameter in the following URL:

'https://restapi.amap.com/v3/direction/driving?origin=' + *olo* + '&destination='
+ *dlo* + '&strategy=' +*strategy* + '&output=' + *format* + '&key=' + *userkey*

where *strategy* is a route preference code referring to minimum time, minimum distance, avoid expressways, etc. In this case, the default strategy (code 10) is used. Particularly, all URLs in this step are accessed between 00:00 to 04:00 a.m., so that urban traffic has minimum influence on the estimation of time consumption.

Like in step 1, the URL returns a json webpage with all details of the recommended route. The information on the page is then saved to a text file for each coordinates pair.

3. Acquire coordinate points and time consumption.

The property *route.paths.steps* is first extracted from the route file with the *json.loads* method in Python 3.6. A step list is returned in which each step contains tens to hundreds of coordinate points and an *instruction* property indicating the distance and duration of this step and what to do next after passing points in this step. The coordinate points are first saved as a 4-column list, representing the longitude, latitude, sequence number of the step it lies in and the projected time consumption of this step, respectively. A fifth column is given by allocating the time consumption of each step equally to every point in that step and accumulating all of the previous steps, representing the total time consumption from the starting point to the given point.

2.2.2. Origin–Destination Data

The origin–destination data were acquired from http://qianxi.baidu.com/ from 21 January 2020 to 8 March 2020, a site run by Baidu recording prefecture-level traveler volume on a daily basis [20]. Baidu is the leading search engine provider in China and also a major digital map and navigation services provider, with many mobile applications depending on its location-based services. Other mobile communication providers are also potential sources for such OD data, given that they cover a wide range of users and aggregate their data into desensitized matrixes with at least 1-day temporal resolution and prefectural or municipal spatial resolution. In China, China Telecom provides similar desensitized data for commercial analysis or government think tanks. With location data from Baidu Map users and dependent applications, it estimates the amount of traveler movement from one prefecture to another and gives a linear index to characterize such movement. These indexes can be acquired through the following steps:

1. Acquire overall daily move in/out amount index for each prefecture.

A list of names and administrative codes of all prefectures is traversed as the *adcode* parameter when generating URLs as follows:

'http://huiyan.baidu.com/migration/historycurve.jsonp?dt=province&id='
+ *adcode* + '&type=' + *direction* + '&startDate=' + *date1* + '&endDate=' + *date2*

where *date1* and *date2* are the first and the last day on which you would like to acquire data, respectively, formatted as YYYYMMDD; and *direction* determines whether the data acquired are about travelers that went into or out of the prefecture, expressed as *move_in* and *move_out*, respectively. The returned json page is saved to a .csv file indexed by administrative codes and date.

2. Acquire spatial distribution of origin/destination of move in/out travelers.

Visit the following URLs with the same parameters as are used in the previous steps:

'http://huiyan.baidu.com/migration/cityrank.jsonp?dt=province&id='
+ *adcode* + '&type=' + *direction* + '&date=' + *date*

The traveler destination/origin distribution from/to a given city on a given day is saved on a .csv table. It covers the top 100 origins and destinations for each prefecture. The blank points are neglected and are considered as zero values because of the following (as shown in Figure 5): (1) For each origin, the percentage of the travelers left out will be insignificant. The number of travelers from an origin to different destinations obey power-law distribution, in which the top 100 destinations typically receive 90 percent of the travelers. (2) For the whole network, the absolute number of the travelers left out will be insignificant. Though the left-out destinations can still mean a large absolute number when the origin is a densely populated prefecture, the top 100 origin data of small destinations will fill in that blank. What really is left out are just the minor destination/origins of small origin/destinations.

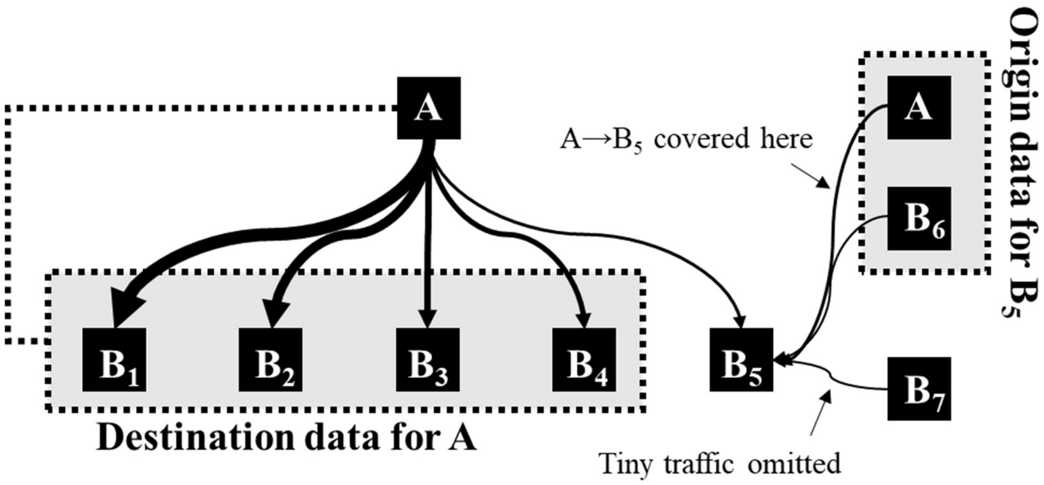


Figure 5. Explanation of how top 100 origin–destination data sufficiently represent traffic demands. 'A' represents a major city with large traffic volumes, and 'B_1' to 'B_7' represents other prefectures. The direction of the arrow indicates the direction of traffic flow and the width of the arrow indicates the volume of the traffic flow.

2.2.3. Road-Traffic-Proportion Data

The Baidu origin–destination data are easily acquirable on a daily basis, but they do not elaborate how many of the travelers travel on the road. On the other hand, Tencent, another corporation mainly as an SNS (Social Network Service) provider, provide a proportion of road, train and flight travelers between any two prefectures on any given day, since 2016, with similar techniques to Baidu [20]. Assuming that this proportion does not change dramatically over time, we purchased the nationwide data on January 2019 to use as a multiplication factor in determining road-traffic demand.

Unlike the Baidu data, however, only the top 10 origins and destinations are covered by Tencent data. Hence, an approach to infer the road-traffic proportions of the left-out OD pairs needed to be developed, and it is introduced in Section 2.3.2.

2.3. Procedures and Methods

Our method generally includes three steps: (1) Generate a route dataset by preprocessing route recommendations from AMAP and join it with meaningful spatial units or objects. (2) Formulate an origin–destination matrix from Baidu and Tencent traveler data. (3) Anticipate possible congestion spot and time by allocating traffic load on a route to the spatial units it consists of.

2.3.1. Generate Route Dataset

Generating the route dataset is a vital step to the whole process. The original route recommendation file describes the recommended routes as a series of coordinates points approximately 100 m apart. These coordinate points are not suitable objects for locating potential congestions for two reasons: (1) The volume of the data would be numerous, with most routes consisting of several thousands to tens of thousands of coordinate points, piling up to an approximate 10-million-point dataset, which would be very stressful to our hardware. (2) It is unlikely that we can realize accurate anticipation on 100 m resolution; hence, results on this scale are not practical references for local authorities. (3) Traveling prefectures can take hours, so the route cannot be regarded as a point on the temporal scale.

In correspondence, two measures are taken: (1) The coordinate points from the route files are down-sampled to a proper scale, at which the route is still sufficiently continuous, while the data volume would suffice hardware conditions. The ratio of down-sampling is determined by considering the potential spatial units that they are to be joined with. (2) The traffic load on each route is temporally allocated to its node, assuming that the hour at which the travelers depart obeys known distributions and satisfies basic preference for the time of arrival.

This process is elaborated as shown in Figure 6.

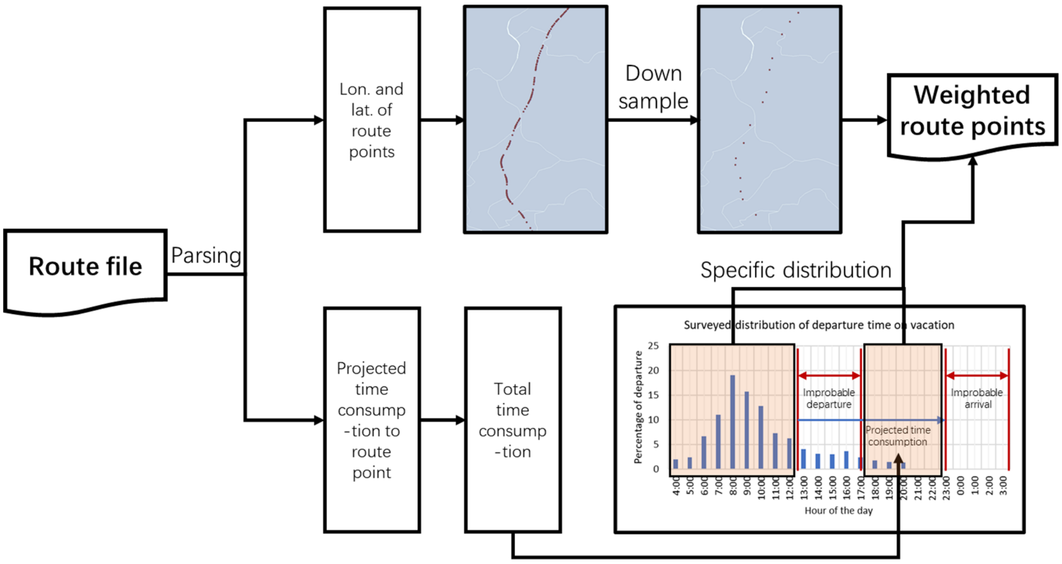


Figure 6. The process of generating route datasets.

1. Down-sample route points.

To determine a proper ratio of down-sampling route points, it is vital to avoid omitting the town centers and townships it goes through. To this end, three geometrical and statistical aspects must be considered: (1) how the navigation points are distributed on the route, (2) how far apart are consecutive navigation points and (3) how the down-sampling process would affect the successful detection of route–township intersection. Figure 7a,b provide the geometrical conceptualization of the intersection problem: high down-sample rate could cause undetected intersection of near-straight routes (Scenario 1), or false detection on sharp turns (Scenario 2). This section determines the most acceptable down-sample rate that sufficiently reduces computational pressure while causing minimal false detections or undetected intersections.

Consider the following facts to determine basic parameters: (1) The mean land area of townships in China is around 234 km^2, determining that the center of each pair of neighboring towns are approximately 15.3 km apart. The distance would be longer for towns in underpopulated areas in Western China and shorter for townships near city centers, of course, but generally applicable in areas most connected to regional congestion, as discussed in the Introduction. (2) The general minimum radius on highways with a speed limit of 80~120 km/h (a range most commonly seen for national/provincial highways and expressways) is 2500~5500 m for transition curves, 900~2100 m for compound curves and 400~1000 m for circular curves. Transition curves make up the majority of a highway line.

(3) The average population of a township is about 34 thousand. According to Chinese urbanization rate and planning regulations, that would mean approximately 2 km^2 of built-up land in each town center.

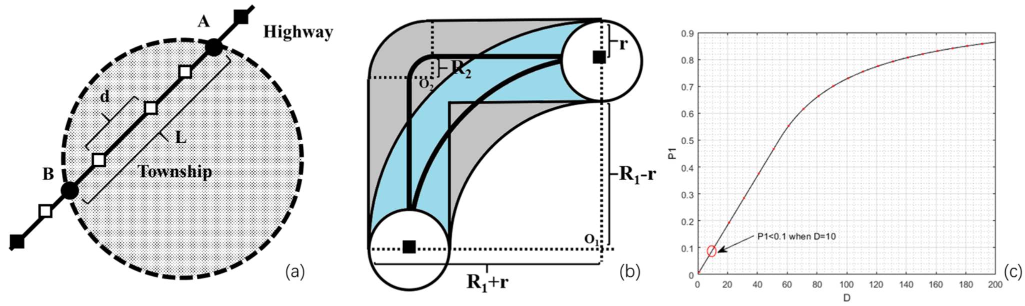
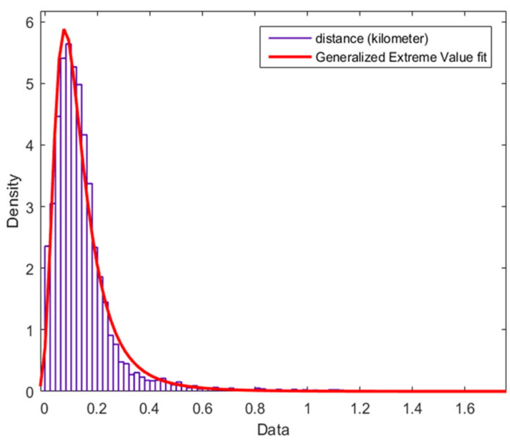


Figure 7. (**a**) Conceptual representation of undetected intersection of a route and a township caused by down-sampling. (**b**) Conceptual representation of undeterminable relationship between a route and a township caused by down-sampling. (**c**) $P_1 - D$ relationship.

An unsampled route from Wuhan to Beijing, which contains 7529 coordinate points through Central and Northern China, was picked for discovering the distribution of neighboring coordinate point distance. The Generalized Extreme Value (GEV) distribution was presumed. The GEV represents the distribution of maximum or minimum values from independent distribution. This is close to the nature of distance values between consecutive navigation points: the distance between two checkpoints, such as turns, intersections, landmarks, etc., abides various distributions restricted by road engineering specifications or planning regulations; navigation points from digital maps are mostly set on these checkpoints, and the distances between consecutive navigation points is thus largely decided by the longest allowed distances of such checkpoints. Moreover, the GEV displays a better performance than other commonly used distribution functions (Figure 8). The fitted distribution is calculated as follows [21]:

$$\begin{cases} F_1(d) = 1 - \exp\left(\frac{k}{\sigma}(d-\mu)^{\frac{1}{k}} - 1\right) \\ k = 0.2229,\ \sigma = 0.0639,\ \mu = 0.0877 \end{cases}, \tag{1}$$

where d is the distance between two neighboring coordinate points.



Fit	Log likelihood	Variance
Exponential	7089.27	0.021
Extreme Value	18.6383	0.121
Generalized Extreme Value	7876.65	0.015
Gamma Distribution	5222.30	0.022
Logistics	6236.41	0.010
Normal	4545.92	0.018
t Location-Scale	7120.72	0.030

Parameter	Estimation	Std. error
k	0.2229	0.0091
σ	0.0639	0.0007
μ	0.0877	0.0008

Figure 8. Distribution of the distance between two neighboring route coordinate points.

Assuming that a route line is plotted with a coordinate point sequence abiding only the minimum radius requirements and the above distribution, and that the coordinate points are to be down-sampled by a rate, D, consider the following consequences:

$$Scenario\ 1: P_1 = 1 - \frac{L}{D \times E(d)},\ E(d) = 0.14\ \text{km},\ L < E(r) \tag{2}$$

and

$$Scenario\ 2: \begin{cases} P_2 = \dfrac{S_2}{S_1} \\ S_1 = \dfrac{4-\pi}{4} \times R_1^2 + \dfrac{4-\pi}{4} \times R_2^2 + (2-\pi) \times r^2 + \dfrac{4+\pi}{4} \times R_1 r + \dfrac{4-\pi}{4} \times R_2 r \\ S_2 = \dfrac{\pi-4}{4} \times R_1^2 - \dfrac{3\pi+4}{4} \times r^2 + \dfrac{\pi+4}{2} \times R_1 r \\ R_1 = D \times E(d), E(d) = 0.14\ \text{km}, R_2 = 0.4\ \text{km},\ r = 0.7981\ \text{km} \end{cases}, \tag{3}$$

where in Scenario 1, P_1 is the possibility that the route goes into and out of a township from respective random points at minimum curvature, but no coordinate point falls in it; L is the length of the highway that lies within the township (as is explained by Betrand's Paradox, the probability distribution of the chord lengths in a circle is not a well-defined problem and leads to various different conclusions. Hence, in this study, we employed the simple version that it is linearly distributed); $E(r)$ is the expected half distance between the centers of two neighboring townships; and $E(d)$ is the expected half distance between two neighboring coordinate points. In this case, the township is much larger than the curvature radius, so curvature is neglected. In Scenario 2, P_2 is the possibility that it cannot be determined whether a given quarter turn goes through a nearby town center; R_1 is the maximum curvature radius of the turn; and R_2 is its minimum curvature radius, which we already know is 0.4 km. These two scenarios are typical negative consequences of the down-sampling process that we intend to avoid if possible.

To make sure that the down-sampling process does not significantly influence the result, P_1 in Scenario 1 must be sufficiently, low and the occurrence of Scenario 2 must be avoided, if possible, so that the majority of the route–township intersection can be detected. From Figure 7b, we can see that only when $R1 - r > r$, and equivalently $D \geq 12$, is Scenario 2 possible; and Figure 7c tells us that P_1 climbs rapidly with the increase of D but remains slightly under 0.1 when $D \leq 10$. It is then safe to say that 1:10 would be an appropriate down-sampling rate for coordinate points in the route file.

2. Endow time attributes.

With the data we obtain, it is difficult to know when exactly the travelers leave their origin city. Studies and common sense deem that people prefer departing and arriving after dawn and before midnight. Some recent studies discovered in their surveys that intercity travelers in China tend to depart from home between 8:00 a.m. and 10:00 a.m., or from 12:00 p.m. to 16:00 p.m. With these, we compromise an approximation by (1) creating the following probability distribution per data and model from [22]:

$$\begin{cases} P(h) = 1 - \exp\left(\frac{k}{\sigma}(h-\mu)^{\frac{1}{k}} - 1\right) \\ k = 0.0828,\ \sigma = 2.2822,\ \mu = 8.4472 \end{cases}, \tag{4}$$

where h is the hour at which a hypothetical traveler departs. (2) For each route, extract its projected time consumption by obtaining the *route.paths.duration* property of the route file, using the *json.loads* method in Python 3.6. If departure during hours (h_1, h_2) result in arrival between 22:00 p.m. and 6:00 a.m., these hours will be removed from the domain of definition of the $P(h)$ correspondent to this route, which will then be normalized to the new domain of definition.

After this, each down-sampled coordinate point, p, will be given a weight sequence, t_p, for each hour of the day, in which

$$t_p(h) = \int_h^{h+1} P(h), h\epsilon[0:23] \cap \mathbf{N} \quad (5)$$

This sequence is then saved as the time attribute of this route.

2.3.2. Create Road-Traffic-Demand Matrix

The road-traffic0demand matrix provides the traffic-demand information that essentially determines the traffic volume allocated to each route. It is generated by combining the total-traffic-demand and road-traffic-proportion data through the following steps:

1 Transform the origin–destination data and the road-traffic-proportion data into matrixes, respectively.

First, all prefectures are sequenced by their administrative codes. A 362×362 empty matrix is then created for each day; the data files for that day are traversed, and the data value for traveling from prefecture O to prefecture D is placed at $(O,\ D)$.

2 Infer blank values in road-traffic-proportion matrix.

The road-traffic-proportion data only cover an average of about 2.5% in all city pairs for each single day; this is far from enough for the eventual prediction but adequate for modeling this proportion. In previous research [23], the transportation-mode choice of regional travelers was found to depend on various factors, including the purpose of the trip, the economic condition of the traveler, the time consumption of different modes, the departure and arrival hour, etc. Therefore, a property set is created for each city pair by (1) using methods in [24] to generate time consumptions and trip opportunities' matrixes for all city pairs regarding feasible road, plane and rail routes; and (2) referring to statistical yearbooks to include the GDP per capita of the departure prefecture and the industry structure of the arrival prefecture, respectively, as a rough characterization of the economic capability and the purpose of travelers from the departure prefecture. Each of these properties is represented by a 362×362 numeric matrix and reshaped to single columns to form the input dataset. Regression methods perform badly in regard to directly correlating the input and output variables, and scatter figures between these variables indicate a complex, possibly segmental relationship. Hence, a single-layer backpropagation network with 10 hidden neurons is trained by using the Levenberg–Marquardt algorithm. Moreover, prefecture pairs with no railway or flight connections are directly given the value 1. A result of the transformation is shown in Figure 9a,b; the variables used by and performance of the network are presented, respectively, in Figure 9c,d.

3 Generate a road-traffic-demand matrix: Matrixes containing total OD travel demands and road-traffic proportion on the same day are dot-multiplied to generate the estimated road-traffic-demand values, stored in a new 362×362 matrix, V.

2.3.3. Generating Traffic Volume Distribution

In Section 2.3.1, we estimated the spatial and temporal distribution of the traffic volume from one prefecture to another; in Section 2.3.2, we estimated the total traffic volume to be distributed. In this section, the traffic volumes of each prefecture pair are allocated spatially/temporally according to their distribution and overlaid with other prefecture pairs to evaluate the total traffic stress sometime and somewhere; potential hotspots are then spatially joined with meaningful POIs or administrative regions to provide policy implications. This process is elaborated as follows (Figure 10).

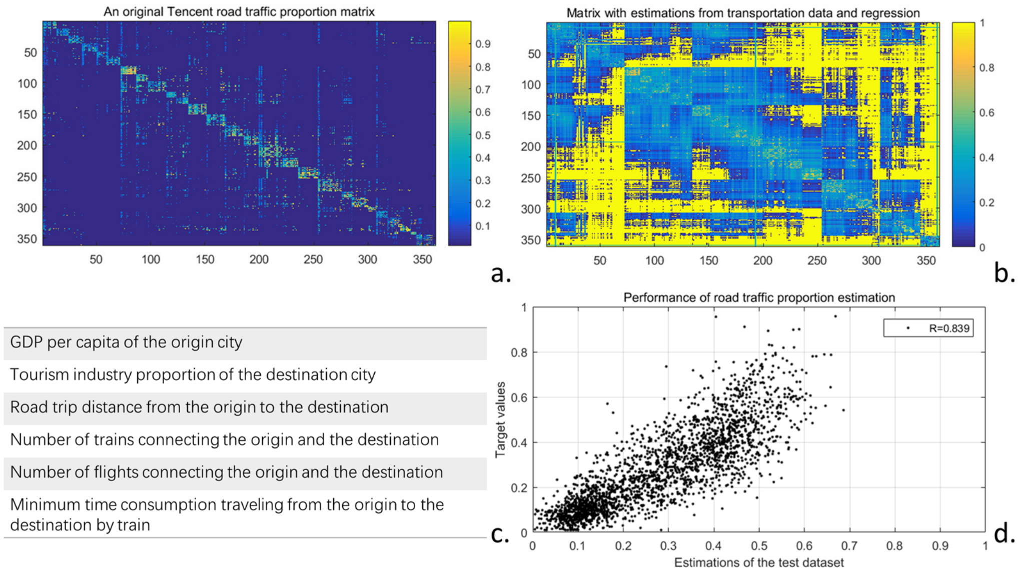


Figure 9. Estimating null values of Tencent road-traffic-proportion data. (**a**) A scaled map of road-traffic-proportion matrix generated directly from Tencent data. (**b**) Road-traffic-proportion data with estimated values. (**c**) Variables used in the estimation. (**d**) Fitting performance of the estimation.

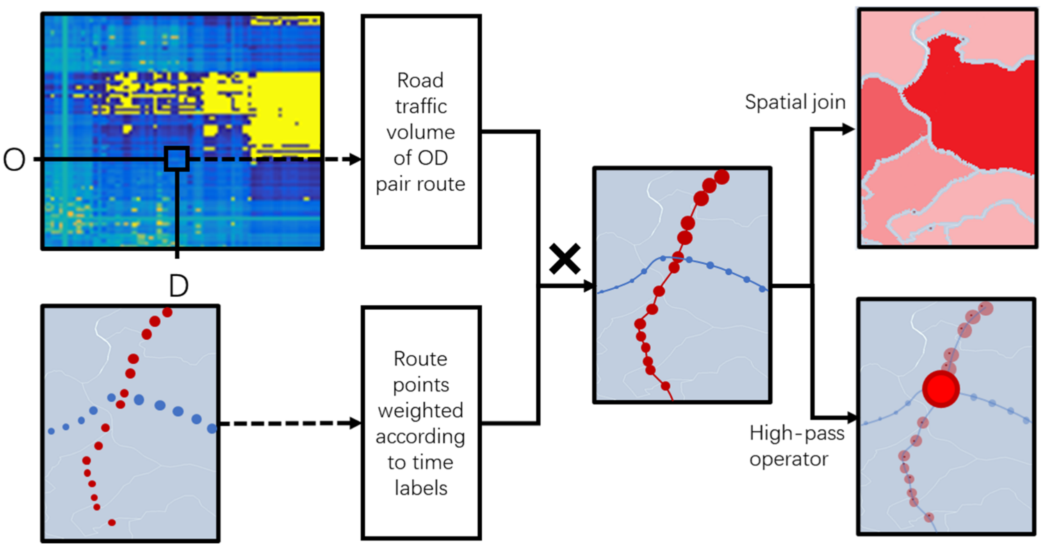


Figure 10. The process of generating traffic volume distribution.

1. Allocate traffic flow to coordinate points

Each route generated in Section 2.3.1 is expanded to a $N \times 26$ table $T_{(O,D)}$, assuming that it is down-sampled to N coordinate points. With the longitude and latitude values saved in the first two columns, each of the other 24 columns represents the traffic volume allocated to this position, on this route, and during a given hour of the day. The value on cell (p, h) in this table is given by the following:

$$T_{(O,D)}(p,h) = V(O,D) \times t_{p(O,D)}(h) \tag{6}$$

where p is the coordinate point in question, h is the hour of the day and $t_{p(O,D)}$ is the aforementioned weight sequence of prefecture pair (O, D).

2. Join with meaningful spatial objects.

First, all spatial objects in question are given 24 properties, each standing for an hour of the day, with the *add_field_management* method in Arcpy, the python library for ArcGIS; then route points on the same route are connected into a polyline feature by using *make_route_events* and *to_shapefile* methods.

Spatial joining is conducted on two scales thereafter. On a national scale, each township is checked for intersection with all existing routes. Then the sum of maximum T of coordinates within or nearby this township on intersecting routes is given to it as the anticipated traffic volume index that would go through the township. On a local scale, a high-pass operator detects possible highway intersections and high-volume segments near town centers, hence recognizing specific hotspots that would require attention.

2.4. Method Implementation and Hardware Requirements

With the carefully deliberated down-sampling process and matrix-based calculations, the proposed approach requires minimum computational resources to implement. In terms of hardware, 16 GB of RAM or more is preferred to realize simultaneous processing of numerous large matrixes. In terms of software, during data-table initialization or when updating navigations data, it requires a computer environment with Python 2.7 interpreter or above, ArcGIS 10.3 or above and any recent MATLAB versions with Statistics Toolbox. After that, Python programs can constantly acquire migration data, and MATLAB or other matrix computation software can update the anticipation results synchronously.

3. Results

The traffic-demand data for 18 January and 19 January were processed as a case study of the above methods. This is the last weekend before the Lunar New Year, when the national highway network carries numerous numbers of travelers returning home from big cities. Distribution anticipation results of 10:00 a.m. and 14:00 p.m. are generated and demonstrated for a cross-hour comparison.

Figures 11 and 12 show the anticipated volume index of all townships in Northern, Eastern, Southern and Central China. Both highway networks and populations are sparse in Western China; therefore, it is omitted from the map. We can see that, during the early hours of the day, the traffic flow would be mostly concentrated near major urban agglomerations and regional/provincial centers, where travelers just departed from big cities not long ago; or major transportation arteries such as the Beijing–Zhengzhou part of Beijing–Hong Kong–Macau expressway, where travelers gather from its sides to travel northward or southward to other provinces. Some less populated and less developed prefectures, such as Xinyu, also gather considerable traffic even in the early hours of the day due to their specific geographical conditions. It is at a major passage through the Luoxiao Mountains, thus making it the intersection of three highways directed to Chengdu, Shanghai and Shenzhen; and it is also less than two hours away from Changsha and Nanchang, two nearby provincial capitals, allowing it to gather traffic in the morning. The eastern vicinities of Laiwu, including Qingdao–Lanzhou Highway, Beijing–Shanghai Highway and Binzhou–Laiwu Highway, also see much traffic due to their proximity to Jinan, the provincial capital of Shandong.

To conclude, towns and small cities where major highway arteries intersect are probably vulnerable to morning surges of vacation traffic especially if they are close to regional centers. Large volumes of travelers come out from big cities and agglomerate at these intersections, where there are not enough alternative routes to disperse them.

In the afternoon, the situation is quite different. As is shown in Figure 12, major urban agglomerations and regional centers are comparatively much relieved, while more pressure is now on regional passages. Mountainous areas parting two plains are more often congested in this scenario due to the lack of alternative routes and their distances to more populated regions.

It is worth noting that, in Central and Northern China, the hinterland of China's mainland highway network, there are many adjacent or closely parallel townships where the traffic volumes are anticipated to change in opposite ways. It indicates that, first, accurate characterization of the exact route is indeed necessary for anticipating potential congestions, especially with developed highway network and various alternatives for travelers going through the region; second, with proper guidance of passing traffic in advance, such a developed highway network can allow for more efficient exploitation of its capacity. A more explicit depiction of this change can be interpreted from Figure 13.

The results also show good consistency with empirical knowledge at the local scale. Before the Spring Festival, Hubei highway management administrations released their prediction of places of probable highway congestion, as is shown in Figure 14 (right); and a maximum value of our prediction on road segments on January 18 is shown in Figure 14 (left). We can see that the two predictions are generally consistent. Moreover, segment 11 in Figure 14 (left), Shiyan–Laohekou segment of Fuzhou–Yinchuan Highway, was closed due to heavy snow; and segment 12, Qianjiang segment of G50 highway, was not on the listed spots, but actual severe congestion was reported later.

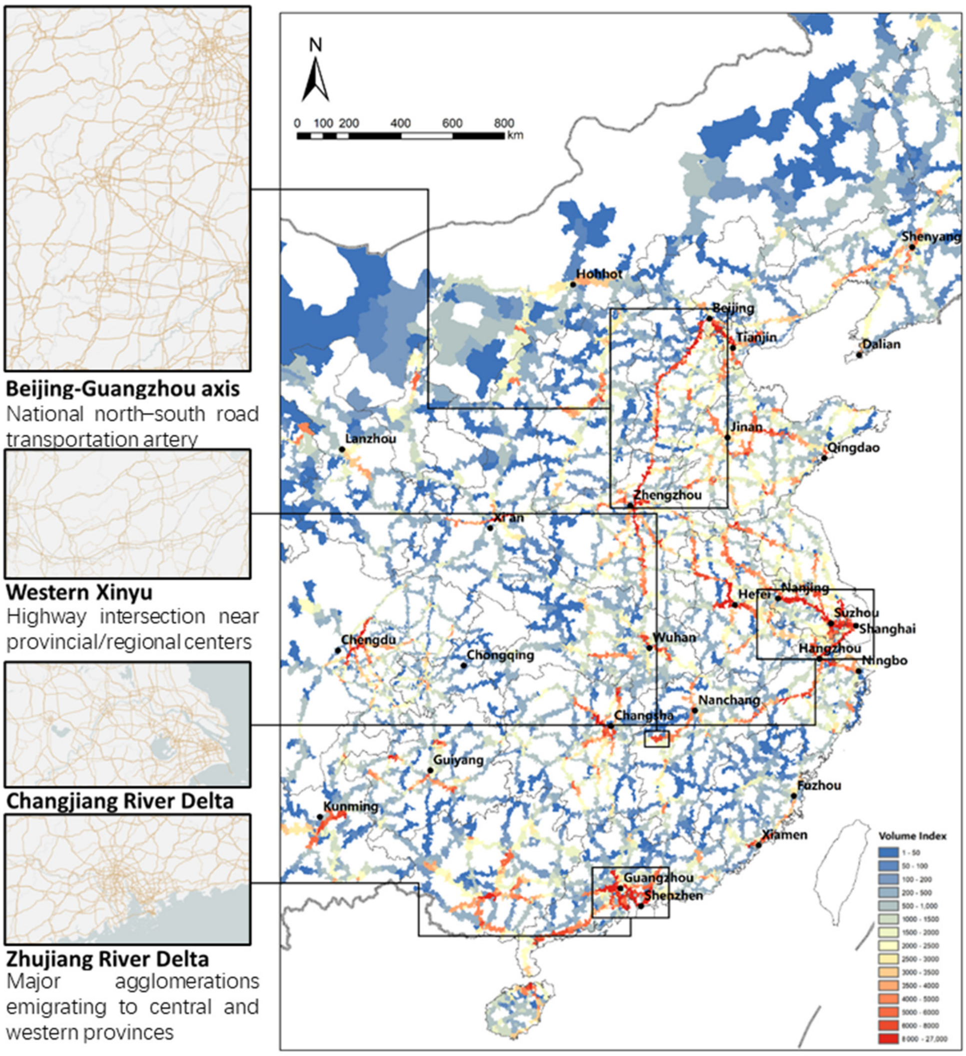


Figure 11. Projected traffic volume distribution at 10:00 a.m.

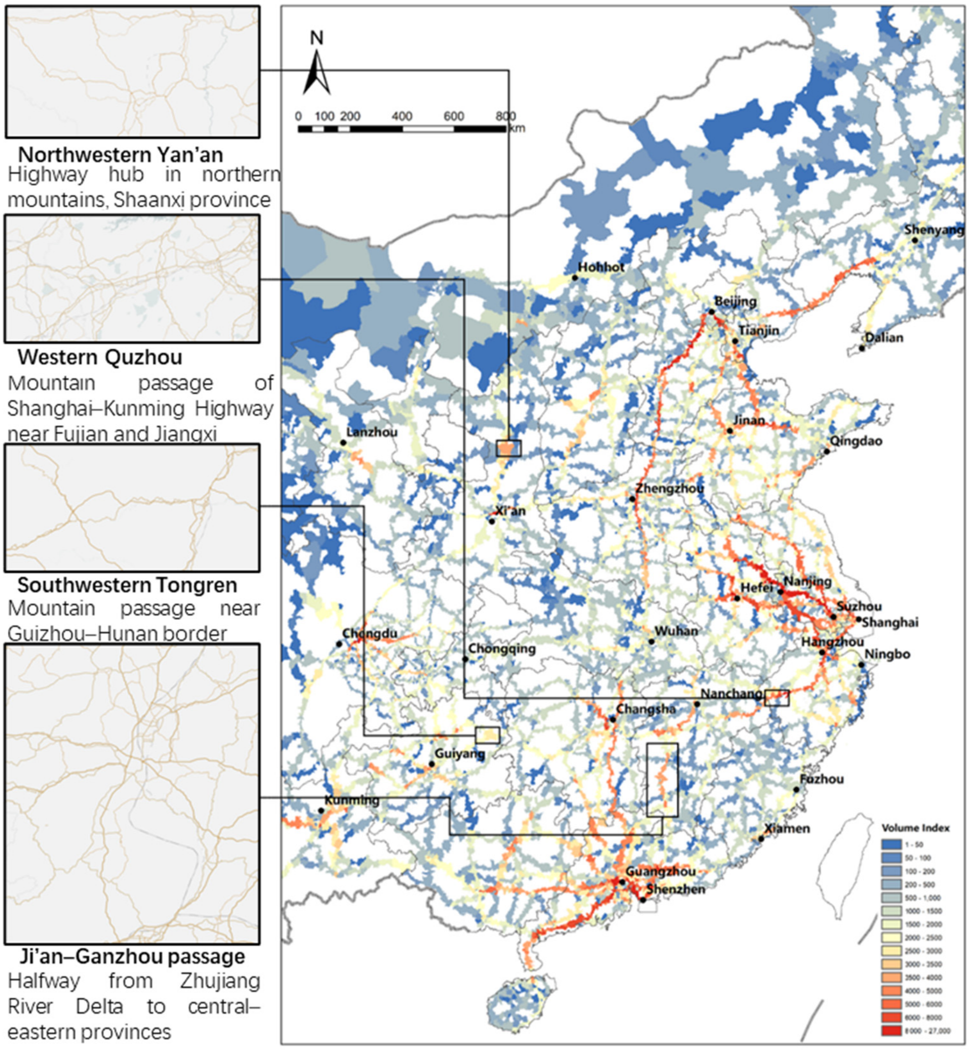


Figure 12. Projected traffic volume distribution at 14:00 p.m.

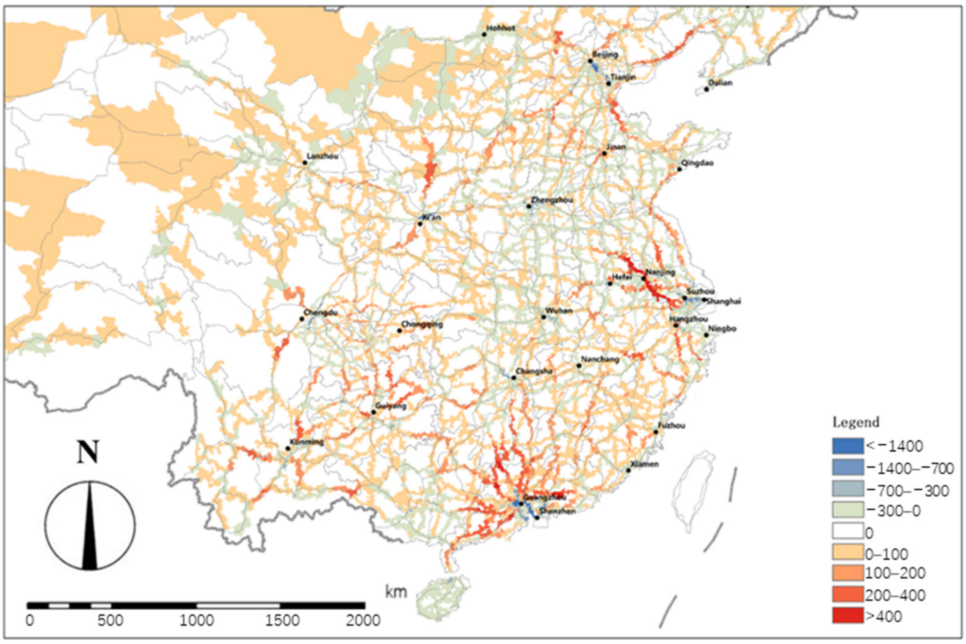
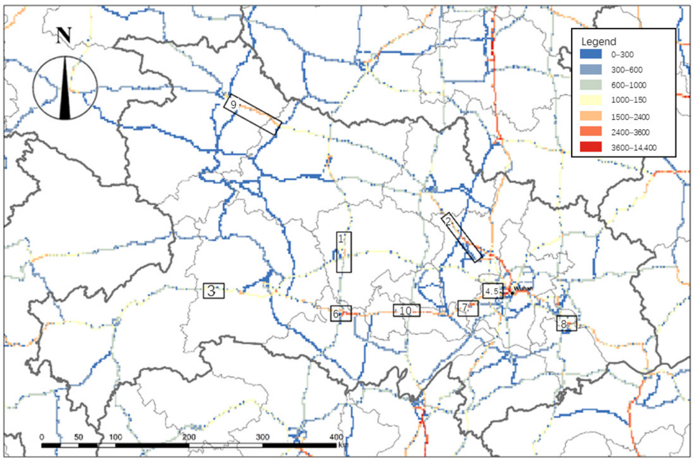


Figure 13. Change of projected traffic volume from 10:00 a.m. to 14:00 p.m.



No.	Highway	Position
1.	G55	Chen'an to North Jingmen
2.	G70	Xiaonan Interchange to North Xiaogan
3.	G50	Entry of Jinlong Tunnel, E-W direction
4.	G42	Hanchuan–Dongxihu Interchange
5.	S15	Hongmiao Interchange
6.	G55	Jingzhou Changjiang Bridge
7.	G50	Huyu–Hancai Expressway Interchange
8.	G50	Hualian Interchange
9.	G70	Shiyan–Laohekou Segment
10.	G50	Qianjiang Segment

Figure 14. Prediction of traffic volume or congestion spots of Hubei. Left: our results. Right: empirical prediction by provincial authorities.

4. Discussion

4.1. Implications on Highway Congestion Response

The results displayed in Section 3 reflect on actual highway management and congestion response in two major ways. First, the potential spot of a congestion is dependent on various dynamic factors and is indeed difficult to judge only from its surrounding space. The change of traffic demand or route choice of travelers somewhere eventually results in the increase or decrease of traffic load in some faraway place. Hence, a global and dynamic perspective of the big picture is important in building a reliable model to predict congestion on regional highway networks. Second, closely parallel highways can have very different traffic loads, resulting in an inefficient use of the highway network and causing unnecessary congestion. This could provide possible directions of highway congestion response that cause minimum long-term impacts.

4.2. Defects and Possible Improvements of This Study

4.2.1. Spatial Resolution of Traffic Demand

Commercial purchase and internet downloads can only get us prefectural-level origin–destination data of regional travelers. Experiments in this paper are based on the assumption that the scalar difference between the size of a prefecture and the length of a regional route is big enough to consider prefectures as origin/destination points. As most road transportation hubs are the urban centers of prefectures, this should suffice when a certain amount of error is tolerable. However, in densely developed regions, the influence of the distribution of departing/arriving travelers within the prefecture is no longer negligible; moreover, in many specific occasions, traffic between neighboring or nearby prefectures can be a large part of highway/expressway traffic, in which case even the township the origin/destination lies within can significantly influence the route the traveler will take. This could be largely improved with further government/business cooperation and the development of data services, as commercial representatives of LBS service providers such as Baidu and China Unicom claim that county-level data are technologically acquirable, and township-level data can be extracted but are not reliable enough.

4.2.2. Consideration of Highway/Expressway Capacity

Apparently, the actual capacity of a highway/expressway segment is nearly as important as the traffic volume itself when anticipating a potential congestion, besides other less predictable factors, such as traffic accidents and road maintenance. According to national technological standard JTG B01-2014, the designed maximum speed of highways and expressways in China can vary from 80 km/h to 120 km/h, and the minimum number of lanes is two in both directions. Moreover, specific conditions such as tolls, tunnels, bridges, etc., can influence the capacity of a highway segment in a way that easily leads to congestion. In further studies, it should be feasible to acquire highway/expressway grade attributes from national geographical information and surveying agencies.

4.2.3. Dynamic Interaction of Nearby Regional Traffic

If a congestion lasts for longer than several hours on a certain road segment, the time consumption prediction given by the API will be far off from reality. Consequently, the basis for time distribution prediction of this study will no longer hold. In fact, in severe congestion on highway/expressway networks, the congestion can often last until late midnight, extending the impact on prediction accuracy from cross-hours to cross-days. A possible solution to this is extending the route dataset acquirement to a wider spectrum by accessing the AMAP API under various different scenarios and thus acquiring sufficient time consumption data in different situations.

4.2.4. Result Verification

The results of our method should be further tested and verified on a large scale and with actual real-time congestion data. There are no sources of national-scale historic congestion data that are known to us, and acquiring real-time congestion evaluation from navigation platforms is difficult and time-consuming. However, it can be improvised by exploiting the fact that navigation platforms take real-time congestion into account when anticipating time consumption. An origin–destination matrix can be constructed by randomly selecting the centers of neighboring counties or prefectures, and routes can be generated by using methods that are the same as in Sections 2.2.1 and 2.3.1. We can compare the real-time time consumption anticipation by navigation platforms on peak hours and at other times and tell whether these platforms detect congestion on the route in between. It could have been down during recent public vacations, but the temporary decrease of regional traveling this year unfortunately denies this possibility.

4.3. Potential Further Directions

Further studies should aim toward practical policy solutions of regional congestion problems. The local impacts of regional-scale highway/expressway congestion and the retroaction from local activities to congestion itself should be studied. Data including land use and road network of townships and small cities, key services and attractions for road travelers in towns near highway routes, and local activities potentially intervening highway traffic should be collected. On such a basis, spatial planning for towns and small cities can hopefully be improved for better interactions with nearby highways.

Furthermore, the potential of dynamically bypassing highway traffic to parallel routes according to prior simulations should be looked into [25]. Besides traditional ways such as on-site road signs, cooperation with online map providers to dynamically influence route recommendations sent to users could be a promising and convenient path.

5. Conclusions

This paper proposed a novel way of predicting road-traffic volume and potential congestions on regional highway network by facilitating mature, accurate route recommendation data from online map and navigation services providers and dynamic regional traveler origin–destination data from LBS services providers. Nationwide coverage, constant update and relatively good accuracy make them a good source of data.

To construct a feasible model, the paper explored methods to reduce calculations and fill in blank values of the original data. Parameters were tested and determined for down-sampling route points downloaded from AMAP API, fit null values in road-traffic-proportion datasets, etc. Moreover, a method was developed to weight different route points on the same routs according to the presumed time of departure and anticipated time consumption. Some of the work would have been unnecessary if commercial and open-source data allowed for better data coverage, but it was necessary in this study to test the proposed method under the given conditions.

The prediction results at the township level of two separate hours on January 18, 2020, are displayed and discussed under a more general context, leading to characteristics of potential congestion hotspots; such characteristics, however, do not promise good prediction from a model using static data, as road segments that are closely parallel are found to be widely different in terms of their predicted traffic loads. It also suggests that dynamically bypassing traffic according to prior prediction and simulation would be a good way to reduce congestion in regions with a dense highway network.

The more spatially detailed results of Hubei province were selected for a comparison with empirical prediction from local highway administrations. The two results show good consistency, especially outside big cities, where there is little response force, and the precise prediction of incoming congestion may be particularly useful.

Finally, we would like to focus our further studies on improving and verifying the proposed model and try to construct cross-scale models to introduce local impacts and retroactions from local activities, thus better preparing it for supporting the decision-making process.

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