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National-scale 1-km maps of hospital travel time and hospital accessibility in China

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Ensuring equitable access to health services is crucial for public welfare and social equity, and is a key objective of the United Nations' Sustainable Development Goals (SDGs). However, existing datasets often define hospital accessibility using travel time to hospitals in geographic dimension only, without considering the supply (hospital capacity) and demand (population distribution) dynamics. To overcome this limitation, we developed and validated a national-scale 1 km map of both hospital travel time and hospital accessibility in China. We used the Gaussian two-step floating catchment area (Ga2SFCA) model to calculate hospital accessibility, incorporating hospital capacity and service population. Various file types and statistical indicators are provided, making the dataset highly accessible for non-specialists. The dataset fills the gap in publicly available nationwide hospital accessibility data for China and can serve as a critical tool in optimizing resource allocation and developing targeted strategies to improve healthcare equity.

Background & Summary

Health is a fundamental requirement for human survival. Healthy individuals form the cornerstone of prosperous economies and stable societies. Access to healthcare is recognized as an important facilitator of human health and well-being[1]. Enhancing access to health services and healthcare, bridging the gap between prosperous and vulnerable population groups and achieving universal health coverage have been designated as key objectives under the United Nations' Sustainable Development Goals (SDGs) for 2030[2].

Healthcare accessibility pertains to the eas Ensuring equitable access to health e with which health services can be obtained. This is intrinsically linked to the local population (demand), the distribution, number, and capacity of hospitals (supply), and the development of transportation infrastructure[3,4]. Extensive research has demonstrated that poor hospital accessibility, such as longer travel time to hospitals, is correlated with adverse health outcomes, including higher morbidity and mortality rates[5–8]. There is a significant disparity in the ease of accessing healthcare services between developed and underdeveloped regions. Areas with lower levels of economic development often face a scarcity of medical resources. This unequal distribution of healthcare resources results in inequitable access to health services, imposing substantial costs on both individuals and society[9,10]. Therefore, it is crucial to comprehensively understand the situation of health service access within a country.

Existing datasets often define healthcare accessibility using travel time to hospitals, as it is straightforward to interpret and easy to compute on a large scale. In 2020, Weiss *et al.* published a global dataset of travel time to hospitals at a resolution of 1 kilometer (km)[11]. Similar datasets have been developed for Australia[12] and Nigeria[13], mapping hospital travel times. However, defining healthcare accessibility with travel time does not consider the supply and demand dynamics in hospital allocations, such as the hospital capacity and serviced population. This can result in an assessment of accessibility limited to the geographic dimension, rather than reflecting the actual availability of medical resources for each individual.

Targeting on the limitation of travel time measurement, various accessibility methods like the gravity model, the kernel density method, and the two-step floating catchment area (2SFCA) method were developed. Among

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these, the 2SFCA method is one of the most commonly used in the measurement of healthcare accessibility[10,14–18]. However, due to the diversity of required data (e.g., population, hospital locations and capacities, road networks) and the complexity of large-scale computations, previous studies have been limited to small-scale accessibility case analyses focused on specific cities or regions[19–21].

Moreover, previous applications of the 2SFCA method have not adequately addressed the differentiation of catchment area sizes for hospitals at different levels[22]. Healthcare services are stratified by medical technology, quality, and service capacity. Therefore, hospitals at different levels should exhibit distinct service ranges and patient attraction capabilities. For instance, tertiary hospitals, which provide specialized and advanced medical services, typically draw patients from larger catchment areas than primary hospitals, which mainly manage common illnesses. Treating all hospital levels as having the same catchment area size may result in inaccurate assessments of actual healthcare accessibility[23].

In this study, we present a 1-kilometer resolution map of hospital accessibility in China. We retain the calculation of travel time to nearest hospitals, as it is a simple, intuitive, and readily interpretable accessibility indicator. More importantly, we employ the Gaussian 2SFCA (Ga2SFCA) method to construct a hospital accessibility dataset that accounts for the actual supply and demand dynamics of medical resources. Compared to previous hospital accessibility datasets[11–13,24,25], our dataset exhibits several distinctive features: it covers all regions of China with unprecedented 1 km resolution, constructs supply-demand relationships based on actual hospital capacity and population data, accounts for variations in service ranges across different hospital levels, and calculates travel times to the nearest hospitals using real road networks. Additionally, all input data for this dataset are open-access, and the code is openly available.

To accommodate different application scenarios and facilitate use by non-specialists, we offer datasets and visual maps at grid, county, city and province levels. Furthermore, to better understand the disparities in hospital accessibility across regions, we calculated and released healthcare equity metrics measured by the Gini index. We believe that the datasets can serve as critical tools for government health departments in optimizing resource allocation, identifying underserved areas and developing targeted strategies. Our datasets and accompanying case study demonstrate the potential for data-driven approaches to support precise healthcare planning and policy development, ultimately contributing to improved public health outcomes and reduced healthcare disparities in China.

Methods

In this study, we calculated the travel time between settlements (grids) and the nearest hospitals across the country using OpenStreetMap data and the Contraction Hierarchies pathfinding algorithm. Based on the travel time calculations, WorldPop data, and medical facility capacity, the Ga2SFCA model was employed to assess the accessibility of hospitals nationwide. Additionally, the Gini index was utilized to evaluate the equity and balance of the spatial distribution of accessibility at different scales.

Travel time to hospitals. Before calculating the accessibility of hospitals based on supply and demand, it is essential to comprehensively understand the travel time for Chinese residents to reach hospitals. In China, residents may travel to hospitals by walking, public transportation, or driving. According to the design of China's healthcare system, primary healthcare institutions serve the local population with basic health services within walking distance, while hospitals are planned with a service scope and capacity based on vehicular traffic. Given the difficulty of obtaining nationwide public transportation data, including transit routes and schedules, we chose driving travel time as a standard measure of accessibility, consistent with most large-scale studies both in China[25] and internationally[11–13].

Classic algorithms such as Floyd[26] and Dijkstra[27] can address pathfinding problems in small areas and simple road networks. However, directly applying these algorithms to China's vast territory and dense road network is impractical. Therefore, we employed the Contraction Hierarchies[28] (CH) algorithm to optimize and accelerate distance calculations within the road network. This algorithm preprocesses the network by adding shortcuts through contracting nodes in a sophisticated order, allowing these shortcuts to bypass "less important" nodes during shortest path queries, thus reducing both spatial overhead and time complexity. The CH algorithm has been widely applied in the processing of large-scale road networks[29,30].

We used the Contraction Hierarchies (CH) algorithm and OpenStreetMap (OSM, www.openstreetmap.org) road network data to calculate the travel times from each settlement to the nearest hospital. Considering the hierarchical diagnosis and treatment system in China, we provided four datasets: travel times to the nearest hospitals (all levels), as well as travel times to the nearest primary, secondary, and tertiary hospitals. Given that the population data was get from the WorldPop project (https://www.worldpop.org) at a resolution of 30 arc (approximately 1 km at the equator), the center point of each grid was considered a settlement. The relevant information of medical institutions, such as the number of beds and addresses, was collected from a medical big data platform "YAOZH" (https://db.yaozh.com/). It is noteworthy that YAOZH, a leading open medical database in China, integrates comprehensive medical information from both authoritative domestic and international institutions and has been cited in numerous prestigious medical journals[31–33]. Geographic coordinates of hospitals were converted from hospital addresses using the geocoding API provided by Baidu Maps (https://lbsyun.baidu.com/). A total number of 13776 hospitals with capacity information were obtained, including 3034 tertiary hospitals, 6876 secondary hospitals, 1728 primary hospitals, and 2138 unclassified hospitals. Driving speeds on the road network were determined based on the 'maxspeed' tags from OSM.

Hospital accessibility. Among the various methods for measuring spatial accessibility, the 2SFCA method is one of the most commonly used[1,10]. To address the limitations of the original 2SFCA method, which employs a binary classification in its distance-decay function, several studies have proposed modifications, resulting in various model variants such as the Enhanced 2SFCA (E2SFCA)[14], the Kernel Density 2SFCA (KD2SFCA)[34], and the Gaussian 2SFCA (Ga2SFCA)[15]. Although these approaches differ in their handling of distance-decay functions, they can all be synthesized within the generalized 2SFCA (G2SFCA) framework proposed by Wang[10].

The Gaussian function exhibits a gentler decline near the threshold starting point, which better aligns with patients' preference for accessing healthcare services close to their residence[10,35]. As a result, the Ga2SFCA method has been widely applied in practical studies of healthcare accessibility[15,35–37]. Additionally, in a large-scale nationwide accessibility modeling, we aimed to minimize manual parameter settings to enhance the model's generalization and adaptability. The Ga2SFCA method requires only one parameter (the maximum search radius), which helps reduce subjectivity and uncertainty associated with parameter settings[15,23]. Therefore, the study adopted the Ga2SFCA method to calculate hospital accessibility.

Another critical issue is determining the catchment area sizes (maximum search radius) in the Ga2SFCA method. Given the nationwide scope of our dataset, setting these parameters based on survey data of residents' healthcare travel preferences[38,39] or calculating patients' actual travel times using map navigation Application Programming Interfaces (APIs)[22,23] would be impractical and highly time-consuming. Therefore, we adopted a more standardized and widely accepted approach—establishing search radius thresholds based on hospital service ranges[38,40,41]. This method is highly applicable to our research, as hospital service ranges tend to be relatively consistent across different regions in China. Referencing the "Golden Hour" rule[42] and numerous studies[18,20,23,40,41,43] for healthcare accessibility, we ultimately set the maximum search radius for primary, secondary, and tertiary hospitals at 30, 45, and 60 minutes, respectively. It is important to note that the primary hospitals in our database do not include primary healthcare institutions such as community health service centers or village clinics. If these institutions were included, we believe a 15-minute search radius would be appropriate for this category.

The Ga2SFCA method calculates hospital accessibility in two steps. In the first step, for each medical facility j, the capacity-to-population ratio R_j within a search radius T_0 is calculated as follows:

$$R_j = \frac{S_j}{\sum_{k \in \{t_{jk} \leq T_0\}} D_k g(t_{jk})} \tag{1}$$

where S_j represents the supply capacity of facility j, quantified by the number of hospital beds in this study; D_k is the demand represented by the population in grid k within the catchment area of j; $g(t_{jk})$ is the distance decay function based on the Gaussian function, expressed as:

$$g(t_{ij}) = \frac{e^{-1/2 * (t_{ij}/t_0)^2} - e^{-1/2}}{1 - e^{-1/2}},\ t_{ij} \leq T_0 \tag{2}$$

where t_{ij} is the travel time between settlement i and facility j, as addressed in the previous section; T_0 is the travel time threshold, representing the maximum service radius for primary (30 minutes), secondary (45 minutes), and tertiary (60 minutes) hospitals. Exceeding T_0 will be considered inaccessible ($A_i = 0$).

The second step is to obtain the hospital accessibility A_i for each settlement (grid) i:

$$A_i = \sum_{j \in \{t_{ij} \leq T_0\}} R_j g(t_{ij}) = \sum_{j \in \{t_{ij} \leq T_0\}} \frac{S_j g(t_{ij})}{\sum_{k \in \{t_{jk} \in T_0\}} D_k g(t_{jk})} \tag{3}$$

a larger value of A_i indicates better hospital accessibility at a settlement.

Inequality measurement. The Gini index was employed to measure hospital accessibility inequality based on our dataset(details in Usage Notes). The Gini index was initially designed to measure income or wealth inequality among populations, but it is now extensively utilized to assess the equity of healthcare resource distribution[20,44,45]. It ranges from 0 to 1, with 0 indicating perfect equality and 1 indicating perfect inequality. We calculated the Gini index (G) based on the accessibility rank of both individuals (assigning the same accessibility value to all individuals within a grid) and grids as follows:

$$G = 1 - \sum (y_i + y_{i-1})(x_i + x_{i-1}) \tag{4}$$

where y is the cumulative proportion of accessibility, x is cumulative proportion of population, and i represent individual or grid. When i represents an individual, G is the Population-based Gini index. When i represents a grid, G is the Grid-level Gini index. The Gini index helps to understand the disparity in accessibility distribution, with higher values indicating greater inequality.

Multiscale spatial analysis. The travel time to hospitals and hospital accessibility were calculated at a 1 km resolution. Considering the scale effect in geospatial analysis, using different spatial unit sizes may yield varying information or characteristics. Furthermore, for non-GIS or non-computer science professionals, offering datasets at multiple scales allows them to select the most relevant data for their research themes or project needs. Therefore, the two data products we provided were at four spatial scales: 1 km grid, county/district, city, and province. Additionally, we computed the Gini index and statistical metrics for both datasets across multiscale for easy reference.

File	Format	Spatial scale	File size [MB]
Travel time to nearest hospitals			
time_to_nearest_hospitals	GeoTIFF, SHP, CSV	Grid, County/district, City, Province	374 MB
time_to_nearest_primary_hospitals	GeoTIFF, SHP, CSV	Grid, County/district, City, Province	375 MB
time_to_nearest_secondary_hospitals	GeoTIFF, SHP, CSV	Grid, County/district, City, Province	375 MB
time_to_nearest_tertiary_hospitals	GeoTIFF, SHP, CSV	Grid, County/district, City, Province	375 MB
Hospital accessibility by Ga2SFCA			
accessibility_grid	GeoTIFF	Grid	263 MB
accessibility_county	SHP, CSV	County/district	73.6 MB
accessibility_city	SHP, CSV	City	27.7 MB
accessibility_province	SHP, CSV	Province	10.5 MB
Hospital accessibility Gini index			
accessibility_Gini	SHP, CSV	County/district, city, province	111 MB
Technical validation			
technical_validation	CSV	Province, city	18.5 MB

Table 1. Format, spatial scale and size of data records.

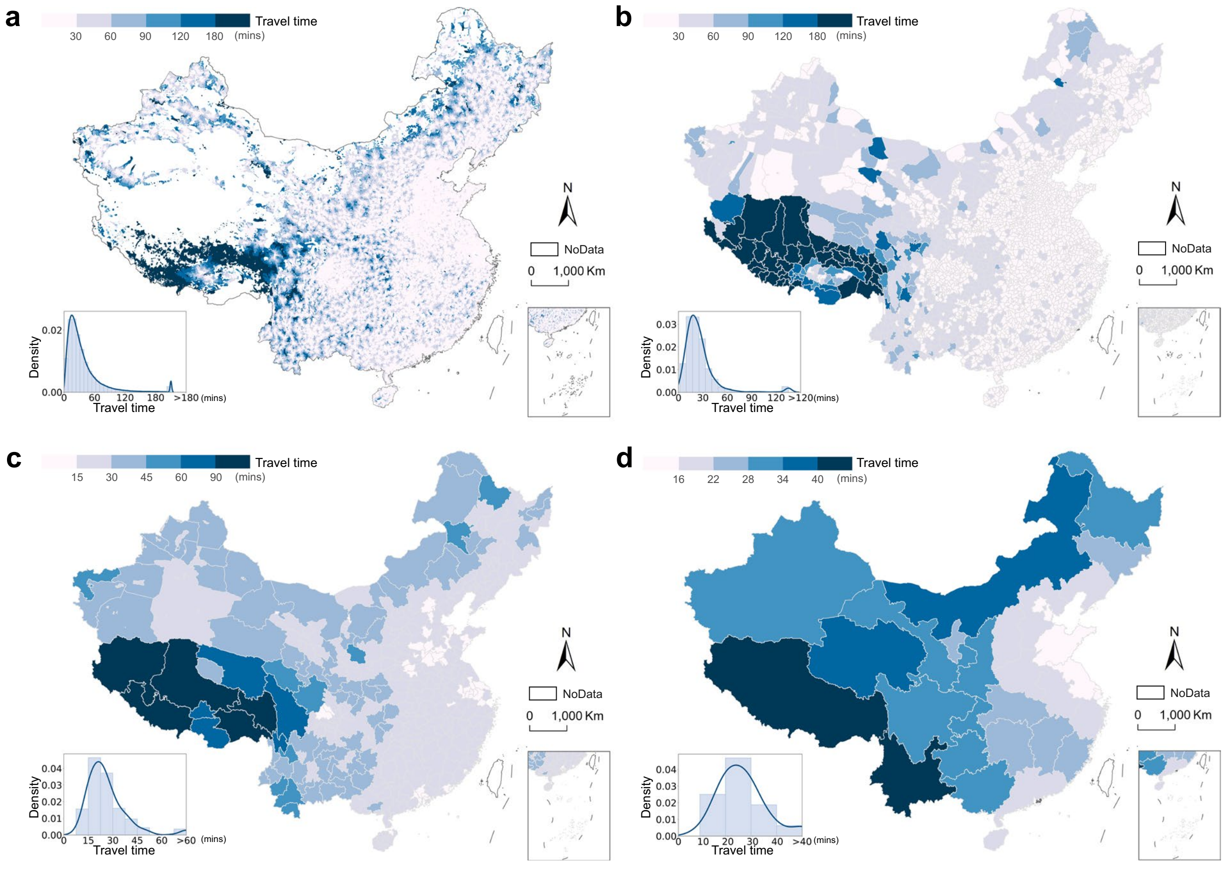

Fig. 1 The travel time to the nearest hospitals at multiple spatial scales: (**a**) grid; (**b**) county; (**c**) city; (**d**) province. In each figure, the small plot in the lower-left corner illustrates the data distribution using a histogram and Kernel Density Estimate (KDE) plot. The X-axis represents travel time (mins) and the Y-axis represents the probability density.

Data Records

The datasets are available in the figshare repository[46] and are organized into four folders: *Travel time to nearest hospitals*, *Hospital accessibility by Ga2SFCA*, *Hospital accessibility Gini index* and *Technical validation*. Details regarding file format, spatial scale and size are provided in Table 1.

The *Travel time to nearest hospitals* and *Hospital accessibility by Ga2SFCA* folders contain travel time and accessibility data at four spatial scales. The *Travel time to nearest hospitals* folder provides travel times to the

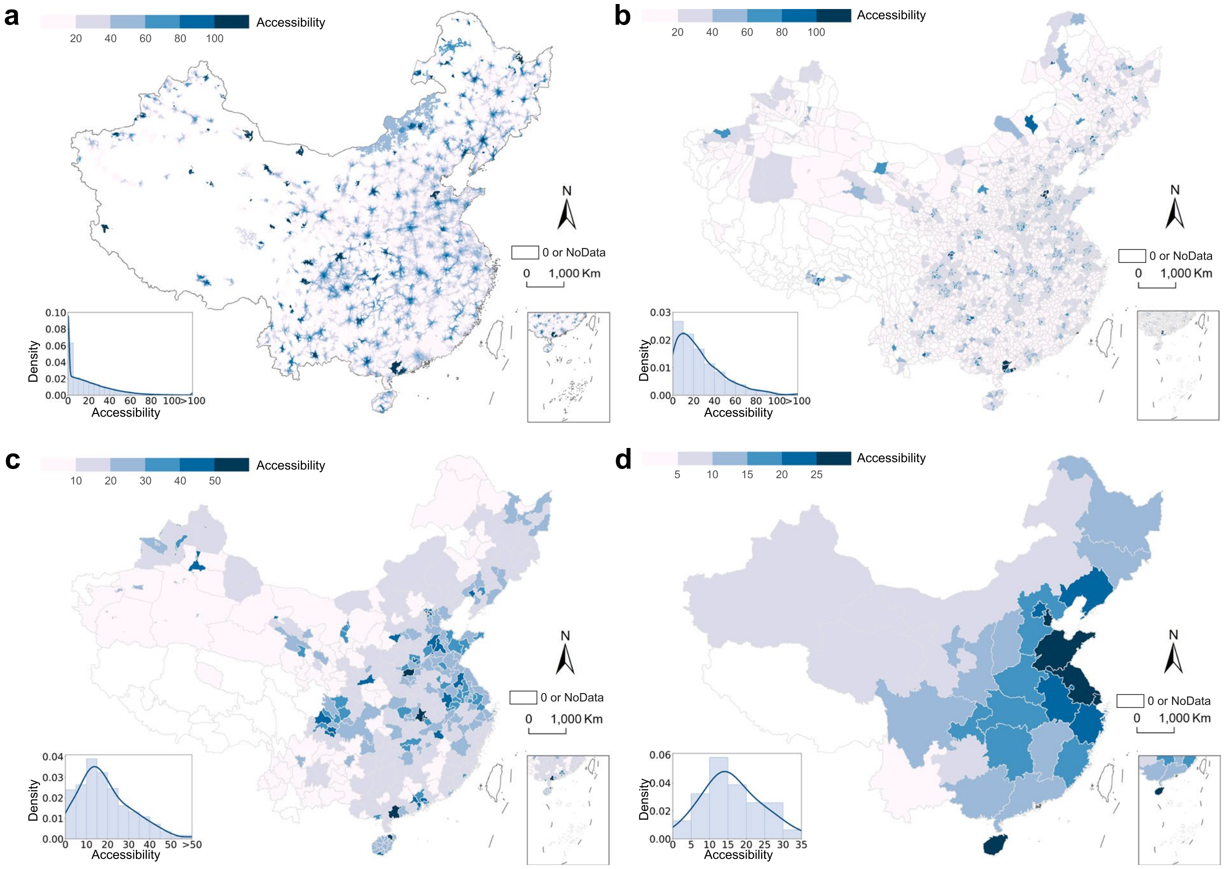

Fig. 2 Hospital accessibility at multiple spatial scales: (**a**) grid; (**b**) county; (**c**) city; (**d**) province. In each figure, the small plot in the lower-left corner illustrates the data distribution using a histogram and Kernel Density Estimate (KDE) plot. The X-axis represents hospital accessibility and the Y-axis represents the probability density.

nearest hospitals (all levels), as well as to primary, secondary, and tertiary hospitals. These datasets feature a maximum resolution of 30 arc seconds (approximately 1 km at the equator) and are available for download in GeoTIFF format. The pixel values in the grids represent travel time (minutes) or accessibility. Aggregated results at county/district, city and province levels, including statistical characteristics (e.g., minimum, maximum, mean, quartiles, and standard deviation), are provided in both shapefile (SHP) and comma-separated values (CSV) formats. Shapefile (SHP) is a widely-used digital vector storage format for geographic information system (GIS) software, which stores location, shape, and attributes of geographic features. It can be read and manipulated using GIS software such as QGIS and ArcMap, as well as programming languages like R and Python. The statistical indicators provided in the CSV file will be particularly useful for non-professionals or those without mapping requirements.

Figures 1 and 2 illustrate travel time to hospitals and hospital accessibility at grid, county/district, city, and province levels. Median values are used for visualization at the aggregated scales. "NoData" indicates areas with no population data or a population of zero, primarily found in sparsely populated regions such as the Qinghai-Tibet Plateau and the Taklamakan Desert.

The *Hospital accessibility Gini index* folder contains Gini index calculations at county/district, city and province levels. The *Technical validation* folder includes randomly generated origin-destination (OD) coordinate pairs and corresponding travel time estimates using the CH model and APIs, as discussed in the Technical Validation section.

Technical Validation

We used professional map service platforms as external data sources to validate travel time estimates, which is widely adopted in various studies[12,47,48]. Specifically, we compared our travel time estimates with Route Planning API from Baidu Map (https://lbsyun.baidu.com/), Gaode Map (https://lbs.amap.com/) and Tencent Map (https://lbs.qq.com/), the three largest and most authoritative map navigation service providers in China.

We generated 62,000 OD coordinate pairs by randomly selecting 10 hospitals as destinations (D) and 200 coordinates as origins (O) in each province. After cleaning invalid and outlier values, a final validation dataset of 53,022 pairs of OD coordinates and corresponding travel time estimates were obtained. A sample record of the validation dataset is shown in Table 2. We then compared our travel time estimates, based on the CH model and OSM road networks, with the estimates from the three APIs.

Province (City)	O_lon	O_lat	D_lon	D_lat	CH model	Baidu*	Baidu	Tencent	Gaode
Guangdong	112.6063	22.0485	113.0884	23.0397	92.3	88.8	116.8	121.7	117.4
Guangdong	112.5986	22.8672	113.0884	23.0397	49.8	38.8	54.2	52.8	54.2
Guangdong	114.9498	23.7988	113.0884	23.0397	150	156.8	195.6	202.5	187.3
…	…	…	…	…	…	…	…	…	…

Table 2. A sample record of the validation datasets.

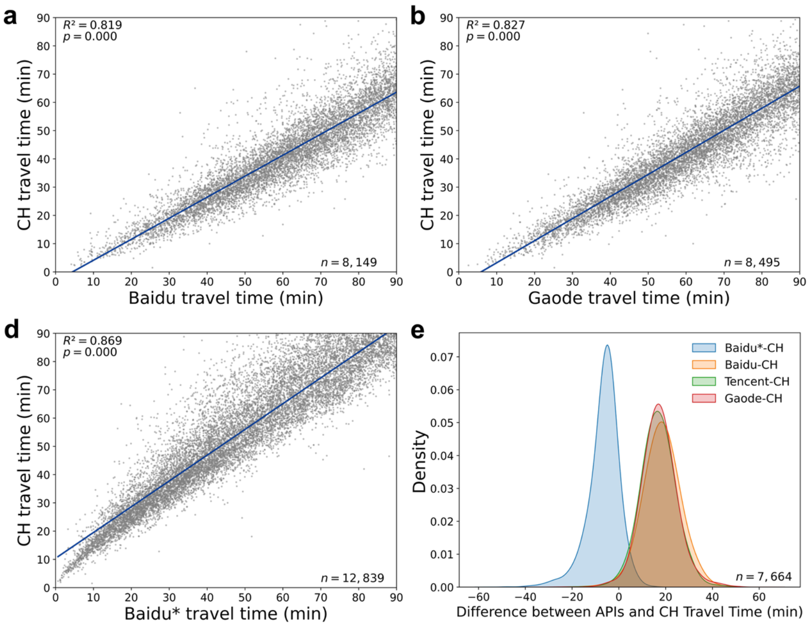

Fig. 3 Comparison of travel time estimates from APIs and the CH model, using random OD samples selected from province levels. (**a–c**) Comparison between the travel time derived from Baidu, Gaode, and Tencent Maps APIs under real-time traffic conditions and estimated by CH model. (**d**) Comparison between the optimal travel time derived under ideal traffic conditions from Baidu Maps and estimated by CH model. (**e**) The differences between APIs results and CH model estimates.

Given that the maximum search radius (T_0) was set to 60 minutes in the accessibility calculations, and to facilitate comparison, we allowed a tolerance of 30 minutes, setting the threshold for both data sources at 90 minutes. The Baidu Map API provides values for both real-time traffic and ideal conditions, while the Gaode Map API and Tencent Map API only offer real-time traffic values. Hypothesis tests and confidence intervals(CIs) were conducted using bootstrapping with 10,000 resamples[49].

The results showed a significant positive correlation between our travel time estimates and the APIs estimates ($R^2 = 0.82–0.87$, $p < 10^{-4}$), as illustrated in Fig. 3. The median travel time estimate was 5.43 minutes higher than Baidu ideal conditions(Baidu*) estimate ($p < 10^{-4}$, 95%CI = 5.32–5.57), but 18.55 minutes lower than Baidu real-time estimate ($p < 10^{-4}$, 95%CI = 18.32–18.75), 17.4 minutes lower than Gaode real-time estimate ($p < 10^{-4}$, 95%CI = 17.23–17.55), and 17.1 minutes lower than Tencent real-time estimate ($p < 10^{-4}$, 95%CI = 16.82–17.23).

Additionally, we considered the reliability of estimations on a smaller scale. Validation was conducted by randomly selecting five hospitals within each city as destinations (D) and 100 coordinates as origins (O), and finally 156,108 records were obtained as the validation dataset (Fig. 4). The R^2 values between the two data sources ranged from 0.77 to 0.83 ($p < 10^{-4}$). The median travel time estimate was 7.53 minutes higher than Baidu ideal conditions(Baidu*) estimate ($p < 10^{-4}$, 95%CI = 7.47–7.58), but 16.97 minutes lower than Baidu real-time estimate ($p < 10^{-4}$, 95%CI = 16.88–17.05), 16.4 minutes lower than Gaode real-time estimate ($p < 10^{-4}$, 95%CI = 16.33–16.47), and 15.5 minutes lower than Tencent real-time estimate ($p < 10^{-4}$, 95%CI = 15.43–15.57).

The results were as expected since our calculations used the maximum speeds from the OSM road network without considering traffic conditions, making them closer to Baidu ideal travel times. According to the validation standards in related studies[12,47,48], this level of error is acceptable and our estimates are reliable. In fact, removing the 90-minute travel time threshold yields better results (province-level $R^2 = 0.96–0.97$, city-level $R^2 = 0.88–0.90$; $p < 10^{-4}$).

Usage Notes

We have produced two datasets covering all of China: travel time to hospitals and hospital accessibility based on capacity-to-population ratios. These datasets are available in GeoTIFF or SHP file formats and can be analyzed and visualized using GIS software, such as QGIS and ArcMap, as well as Python and R packages like Geopandas, SF, etc.

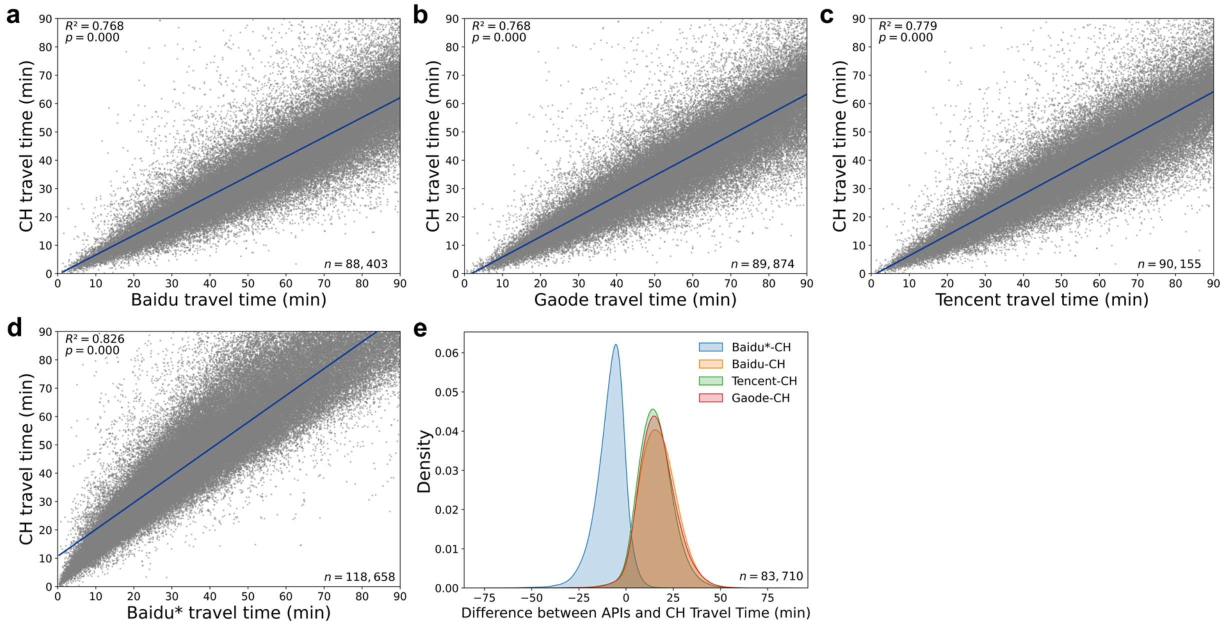

Fig. 4 Comparison of travel time estimates from APIs and the CH model, using random OD samples selected from city levels.

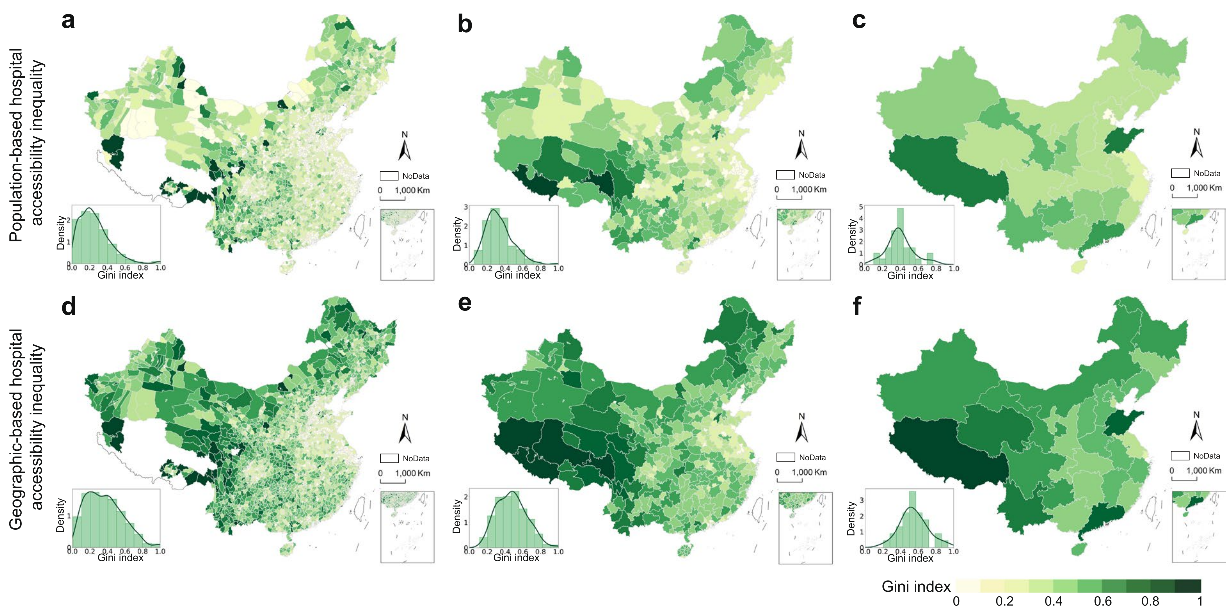

Fig. 5 Spatial distribution of hospital accessibility inequality at county, city, and province levels using the Gini index. (**a–c**) Population-based Gini index. (**d–f**) Grid-level Gini index. In each figure, the small plot in the lower-left corner illustrates the data distribution using a histogram and Kernel Density Estimate (KDE) plot. The X-axis represents the Gini index and the Y-axis represents the probability density.

The availability of our codes and datasets allows users to adjust the search radius according to different research themes and situation (e.g., hospital types, patient types). This is facilitated by our high-resolution travel time modeling based on OSM road networks, which requires substantial computational resources and memory requirement.

The datasets provide insights into the current status of healthcare resource allocation in China across multiple spatial scales, including travel time and per capita accessible resources. They can directly support analyses of equity and balance in hospital resource distribution, a critical concern for governments and public health sectors worldwide. For example, Fig. 5 illustrates an application of our dataset, demonstrating the use of the Population-based Gini index and Grid-level Gini index to assess inequality in hospital accessibility. Researchers and policymakers can efficiently evaluate healthcare accessibility and equity at specific spatial scales or within particular regions, integrating factors such as topography, economic development, and transportation infrastructure for a more comprehensive analysis. Consequently, our nationwide high-resolution hospital accessibility dataset provides comprehensive data support for government health departments, aiding in the development of more informed and reasonable healthcare policies and resource allocation strategies.

Despite our efforts to ensure the reliability of our hospital accessibility datasets, several limitations should be acknowledged. Firstly, due to data limitations, we focused primarily on spatial factors and simplified the definition of demand to population size. In reality, non-spatial factors—such as gender, age, race/ethnicity, education, and income—significantly influence healthcare needs and access opportunities across different groups. In future work, we aim to obtain more detailed demographic data, such as gender distribution, age structure, the proportion of pregnant women, and socioeconomic attributes, to better segment healthcare demand and improve the measures of accessibility. Secondly, the hospital data we used includes only hospitals with a certain number of beds. Thus, actual healthcare accessibility may be higher than our estimates, as many smaller primary healthcare facilities such as community health service centers, village clinics are not covered in our data. Additionally, we assumed all travel occurs under ideal conditions at maximum allowable speeds and shortest paths on all road networks, which is a common limitation of similar datasets.

Code availability

Data processing and analysis were conducted using the Python version 3.8 and code is available for download at the public GitHub repository: https://github.com/uwaovo/hospital_accessibility.

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Author contributions

P.Y., Z.Y. and J.X. proposed the research concept and designed the experiment. Z.Y. and P.Y. implemented the algorithms, produced the data and validated the results. P.Y. performed the analysis and wrote the preliminary versions of the manuscript. M.Z. and L.L. provided expert input on setting the search radius for the Ga2SFCA method. P.Y., J.X., L.Z., M.Z., L.L., W.T., Y.Y. and Q.L. supported the analyses and interpretations. All authors contributed to the writing and revision of the final manuscript.

Competing interests

The authors declare no competing interests.

Additional information

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