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Visualization and Analysis of Transport Accessibility Changes Based on Time Cartograms

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Abstract: Visualization of the spatial distribution pattern of transport accessibility and its changes can be crucial for understanding and assessing the performance of transportation systems. Compared to traditional maps representing geographic space, time cartograms modify geographic locations and spatial relationships to suit travelling times and thereby emphasize time–distance relationships in time-space. This study aims to facilitate a better understanding of the evolution of the spatial distribution pattern of accessibility by presenting a novel visualization and analysis methodology based on time cartograms. This is achieved by combining a visual qualitative display with a quantitative indicator analysis from multiple perspectives to show transport accessibility changes. Two indicators, namely, the shortest railway travel time (STRT) and spatiotemporal con-version parameter (STCP), are proposed to measure accessibility changes. Our work consists of the construction of time cartograms, the analysis of indicators, and the use of multiple views to show changes in transportation accessibility from multiple perspectives. The methodology is applied on the railway data of Beijing and selected 226 cities in China and to analyze changes in railway accessibility in 1996, 2003, 2009 and 2016. The results show that the development of transportation technology has continuously shortened the travel time, the time-space is gradually compressed, However, the difference in transport accessibility is getting bigger and bigger because of the uneven transportation development speeds between the regions.

Keywords: time cartograms; accessibility; accessibility changes; time-space; geovisualization

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1. Introduction

Accessibility is a fundamental concept in transport geography, urban planning, and other related fields [1]. It refers to the ease with which activity locations or urban services can be reached from a particular location using a particular transport system [2]. The spatial distributions of accessibility, particularly changes in accessibility, are direct indicators from which planners or policy analysts can determine who are the "winners" and "losers" in a given scenario [3]. Visualizing and analyzing spatial distribution patterns of accessibility and their changes are therefore crucial to support decision-making.

Distance is an important indicator of accessibility. The definition of distance is diverse depending on different contexts. Regarding road network, the distance between two places in the network can be measured as the length of road, the travel time or the travel cost that connect the two places. In geographic space, the distance between any two objects is determined by their geographic locations. However, with the continuous transformation and rapid development of modern transportation methods, the basic concepts of space and distance are being re-understood and re-expressed. Travel time has become an important measure in respect of people's perception of global distances. The focus of people's attention has changed from "how many kilometers are there between Beijing and Shanghai?" to "how long does it take to get from Beijing to Shanghai?". Therefore, it is more appropriate to understand the world from the perspective of time-space. Obviously, from the perspective based on time-distance can help us better understand the relationship between space and time. Time-space can provide a synoptic visual summary of time-distance relationships in a given environment, indicating areas where the transportation system is performing well and other areas where it is inefficient [4]. Furthermore, innovations in transportation technology have increased travel speeds and shortened time-distance between cities, so the original spatial distance seems to have been converged, which is called time-space convergence. The time-space convergence model greatly facilitates the understanding of the various geographical implications of a "shrinking world" [5]. Time geography allows the researcher to examine the complex interaction between space and time and their joint effect on the structure of human activity patterns in particular localities [6]. However, it is more focused on understanding and modelling movement and its constraints than on producing a new representation of time-space [7].

As with geographic space, mapping and spatial analysis of time-spaces can be illuminating [4]. However, when we considered mapping the time-space, it is necessary to violate the usual continuous topology in geographic space. For Example, from Los Angeles to New York costs less than many inter-mediate places, for another example, some cities are farther apart in terms of geographic distance, but closer in terms of time-distance. So, Tobler (1961) [8] pointed out that the map may need to be turned inside out. In addition, he applied the theory of map projections, especially azimuthal projections, to create centered time-maps. From a broader perspective of the representation of distances, Bunge (1960) [9,10] has stated that basically two ways to represent time-distance are available either "representing complicated distances on simple maps, or representing simple distances on complicated maps". The former uses irregular isochrones on geographic maps, the latter distorts the geographic space in such a way that the isochrones from a given origin are concentric circles, as shown in Figure 1 [11]. Thus, in the time-space map, the elements are organized in such a way that the distances between them are not proportional to their physical distance as in topographical maps, but proportional to the travel times between them [12]. So, time-space maps which can be seen as deformed maps provide visual summaries of the spatial patterns of warping effect [4].

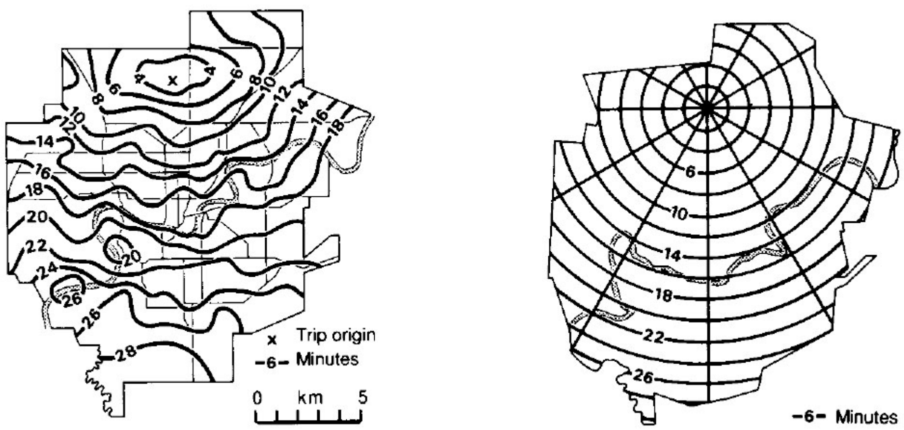

Figure 1. Irregular isochrones and concentric isochrones [11].

After pioneering work by Tobler and Bunge, extensive research has been conducted to visualize time-space. Ewing et al. (1977) [13] described a procedure for interpolating surface features on a map based on a two dimensional time-space configuration of points. Clark (1977) [14] proposed an algorithm for producing a time-distance transformation of the network with respect to a point. Muller (1978) [15] used the displacement vectors to represent deviations between geographic locations and time-distance locations. Shimizu (1992) [16] showed the contraction of Japan due to the development of the high-speed train networks between 1962 and 1992. Spiekermann (1994) [12] used a time-space map of western Europe and France to show the effects of the evolving Europe high-speed rail network. Ahmed & Miller (2007) [4] gave a detailed survey of time-space mapping.

In addition, with the increasing demand for mapping time-space, some cartographers have advanced the application of cartograms in expressing time-distances (travel costs, etc.). This concentric isochrons are also known as centered travel-time cartograms. Another category depicts the travel time between all the pairs of locations, which is called non-centered travel-time cartogram [17–22]. A cartogram is a novel method to represent the geographical distribution of statistical datasets, which uses certain mathematical principles to transform a map so that the areas or distances on the map are proportional to the attribute values [23–25]. There are mainly two types of cartograms: area cartograms and distance cartograms. Obviously, a travel-time cartogram is a typical instance of distance cartogram. In fact, the concepts of time-distance mapping, time-space map and time cartogram have been blended together, all of which are "representing simple distances on complicated maps" through the transformation of geographic space.

In time–space transformations, the metric nature of time–space is an issue since it is difficult to represent non-metric spaces as a two-dimensional map. The time-distances obtained from a transportation network may violate two of the metric space axioms are included: (1) symmetry ($d(x, y) = d(y, x)$); (2) triangular inequality ($d(x, z) \leq d(x, y) + d(y, z)$). Especially for construction of non-centered time-cartogram, high-dimensional all-pairs origins-destinations travel time matrix as input and the technique of (multidimensional scaling) MDS is usually used to provide a solution. However, the distortion might appear rather significant in this process and the topological properties of the configuration of points could be lost; in which case interpreting the resulting time-cartogram will prove to be difficult. Compared with the non-centered time-cartograms, the centered travel-time cartograms are relatively simpler to construct, and the transformed result can better maintain the topological relationship and is more readable. Moreover, from the relevant literature in recent years, the centered type has received more attention, which is also the focus of this paper.

Some research works are committed to the construction methods of time-cartograms [17,19,21,22,26–28] and their applications in the visualization of transport accessibility [19,26,29–32]. Moreover, the geographical distributions of time-distances of different time series can be effectively represented by multiple time cartograms. Thus, the changes can be perceived at a glance in these series of time cartograms [29]. In specific applications, time-cartograms can visualize the "shrinking world" to reflect the changes of transportation accessibility in a geographic region and reveal the patterns of time-space convergence [33,34].

The rest of this paper is structured as follows. Section 2 presents the study area and data used in this study. Section 3 gives the two measurements of accessibility changes used in the study. Section 4 describes the methods of the travel-time cartogram construction and visualization of accessibility changes used in the study. In Section 5, we present the transformed results and the key findings of this study. Finally, Section 6 presents the conclusions and discussions.

2. Study Area and Data

In this section, we introduce the study area, the collection of related datasets, and data processing methods.

2.1. Study Area

The study area covers almost the entire geographic area of China. More specifically, we investigate the transport accessibility and its change from the capital city of China, Beijing, to other cities in China. Beijing is the most important transportation hub nationwide. In recent years, the continuous development of high-speed railways has accelerated the circulation of capital information and talents, expanded the scope of Beijing's traffic radiation, and strengthened the links between Beijing and other cities. The impact of these changes on time-space may be very uneven.

In order to study the spatial pattern of changes in accessibility from Beijing to various cities, we selected Beijing and other 226 cities in China on a national scale (as shown in Figure 2) and obtained the shortest railway travel time from Beijing to each city in 1996, 2003, 2009, and 2016.

The selection of national cities satisfied the following rules: (1) all cities needed to have corresponding railway time information during the period 1996–2016; (2) we selected cities in each province; (3) the distribution of the selected cities basically covered the whole country, to play a similar role as a "control point". However, due to the influence of geographical environment and population distribution, the distribution of railway networks in China is uneven, showing that the east is dense and the west is sparse [35]. So, in the northwest area where cities are very sparse, we added some counties. Based on the above principles, a total of 226 cities across the country were selected as control points for further time-space transformation.

Figure 2. Beijing and the 226 cities selected in the research.

2.2. Data

The research data primarily include basic geographic data and railway time data for the years 1996, 2003, 2009, and 2016. The geographic data involved in this research originate from China's 1:4 million map data, and the coordinate system is WGS1984. Based on the geographic data, we obtained the latitude and longitude coordinates of each city and calculated the spatial distance between each city and Beijing. We collected the shortest railway traffic time change dataset based on the official data released by the Chinese railway authorities. The railway time data for 2016 was obtained from the official website of China Railway Service Centre (www.12306.cn (accessed on 1 July 2022)), while the time data for 1996, 2003, and 2009 were collected manually from the "National Railway Passenger Train Schedule", which is published by China Railway Publishing House.

Two rules were applied in collecting railway time data:

(1) In our research, the spatial scale was the national scale. All cities and counties were regarded as point features. That means that we did not consider the transfer time and the distance between different stations in the same city. For example, the Zhengzhou East Railway Station and the Zhengzhou Station were both regarded as "Zhengzhou".
(2) Since the high-speed railways in China are not fully covered, the speed of the railways between different cities is different. Therefore, the shortest time counted was the shortest time theoretically; that is, the number of transfers was not considered. For example, for two cities A and B, the direct railway time from Beijing to A is 100 min,

and the non-high-speed rail time from Beijing to B is 230 min, but the time for Beijing–A–B is 200 min; we therefore used 200 min as the shortest railway travel time from Beijing to city B.

2.3. Data Processing

After obtaining the shortest railway time from 226 cities to Beijing, in order to further compare time–space and geographic space, we processed the time data and spatial distance to calculate the transformed coordinates of 226 cities.

The 226 cities serve as the control points in our algorithm. Every control point has its geographic coordinates, and its transformed coordinates are calculated based on travel-time. In order to keep the original and transformed map scale consistent, we followed three design principles in the transformation process. Firstly, Keim et al. (2005) [23] pointed out that the intuitive recognition depends on preserving basic properties (e.g., shape, orientation, and contiguity), the directions from the center point to the other points should not change in order to maintain correct orientation relationships. Secondly, Euclidean distance should be applied to calculate geographical distances [4,25]. Thirdly, the total distance, i.e., the sum of distance from a given origin to each control point, should stay the same after the transformation.

We assume that the set of control points on a map is $\boldsymbol{P} = \{\boldsymbol{p_1}, \boldsymbol{p_2}, \ldots, \boldsymbol{p_n}\}, \boldsymbol{p_i} \in \boldsymbol{P}$. The geographic position of $\boldsymbol{p_i}$ is $\boldsymbol{p_i} = (x_i, y_i)^T$ (this is a row vector), and the position of center point o is (x_o, y_o). s_i and t_i are the geographic distance and travel time from center point o to $\boldsymbol{p_i}$, respectively. The total geographical distance is $S = \sum_{i=1}^{n} s_i$, and the total travel time is $T = \sum_{i=1}^{n} t_i$. d_i is the transformed distance from the center point o to $\boldsymbol{p_i}$ according to the travel time. If the total transformed distance is $\sum_{i=1}^{n} d_i$, and according to the above mentioned third principle, $\sum_{i=1}^{n} s_i = \sum_{i=1}^{n} d_i$, then d_i is calculated according to t_i:

$$d_i = \frac{t_i \sum_{i=1}^{n} s_i}{\sum_{i=1}^{n} t_i} = t_i S/T \tag{1}$$

According to the first and second principles, the -transformed coordinates of $\boldsymbol{p_i}$ are computed by:

$$x_i{}' = x_o + \frac{(x_i - x_o)d_i}{s_i} \tag{2}$$

$$y_i{}' = y_o + \frac{(y_i - y_o)d_i}{s_i} \tag{3}$$

After data processing, we obtained the transformed coordinates of 226 cities in 1996, 2003, 2009, and 2016.

3. Measurements of Accessibility Changes

Accessibility is an intuitive concept used to describe the ease of reaching a destination or accessing a service [1]. Defining appropriate indicators is crucial for the measurement of accessibility and its changes [36]. However, different definitions exist to formalize the concept of accessibility, and the indicators used are not fully comparable [37–39]. In this study, we used the shortest railway travel time (STRT) and spatiotemporal conversion parameter (STCP) as two indicators to measure the impact of traffic development on the evolution of spatial patterns in different years.

3.1. The Shortest Railway Travel Time (STRT)

As an absolute numerical indicator, STRT is widely used in transport accessibility research [40]. In this study, we used the STRT between a city and Beijing to measure the transport accessibility of the city. We used this indicator and considered it effective mainly based on the following considerations. First, the process of counting the STRT involves comparing multiple possible routes from Beijing to a certain city and choosing the shortest one, then considers the travel time to the city and surrounding cities. Second, Beijing is the national transportation center, so the STRT from Beijing to a city can represent the degree of accessibility of that city. Third, the results based on the STRT data were consistent with the actual urban traffic level [21], which also proves that STRT can be used as an indicator of accessibility.

3.2. Spatiotemporal Conversion Parameter (STCP)

To show the expansion and shrinking patterns of administrative boundaries and control points, here we introduce the indictor STCP r. The value of $\boldsymbol{r_i}$ indicates the degree of expansion or shrinking for a certain point in the direction of the center point after transformation:

$$\boldsymbol{r_i = \frac{d_i}{s_i}} \tag{4}$$

where $\boldsymbol{d_i}$ and $\boldsymbol{s_i}$ represent the transformed distance and the geographic distance of a certain point I, respectively. When $\boldsymbol{0 < r_i < 1}$, that is, $\boldsymbol{d_i < s_i}$, shrinking is indicated; when $\boldsymbol{r_i = 1}$, that is, $\boldsymbol{d_i = s_i}$, the pattern is unchanging; when $\boldsymbol{r_i > 1}$, that is, $\boldsymbol{d_i > s_i}$, expansion is indicated.

In order to study the variation characteristics of r values, we further explore the meaning of r by introducing two concepts $\boldsymbol{\overline{V}}$ and $\boldsymbol{v_i}$. The concept of $\boldsymbol{\overline{V}}$ represents the average speed from Beijing to all cities in a certain year at the national average level (NAL), and $\boldsymbol{v_i}$ means the speed from Beijing to a certain city i in a certain year. $\boldsymbol{\overline{V}}$ and $\boldsymbol{v_i}$ are calculated using the Euclidean distance S, $\boldsymbol{s_i}$, and the travel time T and $\boldsymbol{t_i}$ in Formula (5).

$$\boldsymbol{\overline{V} = \frac{S}{T}, \ v_i = \frac{s_i}{t_i}} \tag{5}$$

By substituting $\boldsymbol{d_i = \frac{t_i S}{T}}$ (see Formula (1) into Formula (4)), we can obtain the relationship between $\boldsymbol{r_i}$, $\boldsymbol{\overline{V}}$, and $\boldsymbol{v_i}$.

$$\boldsymbol{r_i = \frac{d_i}{s_i} = \frac{t_i S}{s_i T} = \frac{v_i}{\overline{V}}} \tag{6}$$

In this way, $\boldsymbol{r_i}$ not only directly indicates the degree of expansion or shrinking of the control point (city) at a certain time, but also shows the comparison between the changing speed of the control point and of the NAL. $\boldsymbol{r_i}$ is a relative numerical indicator. Its size reflects the traffic speed advantage or potential of the control point (city) relative to all control points (cities) in the country at a certain point in time. Since the NAL changes in different years, a change in the $\boldsymbol{r_i}$ value indicates a change in the accessibility advantages of this point (city) relative to the NAL.

4. Methodology

This section introduces the methodology for understanding the spatial distribution pattern of accessibility. The methodology is demonstrated by the workflow shown in Figure 3, including the construction of time cartograms, the adjustment of topological errors, and the visualization methods of accessibility changes through multiple views.

We conduct this research from three perspectives: (1) horizontal comparisons, (2) changes in multiple horizontal comparisons, and (3) vertical comparisons. Horizontal comparisons mean the comparisons between geographic space and time-space at a special time. We can obtain the spatial distribution pattern of the time distance at a certain time. Changes in multiple horizontal comparisons aim to obtain changes in the spatial distribution of accessibility. Vertical comparisons refer to compare time–space changes under the same time scale, which can effectively express time-space compression effects. This requires normalizing the transformed coordinates and is elaborated in Section 4.3.

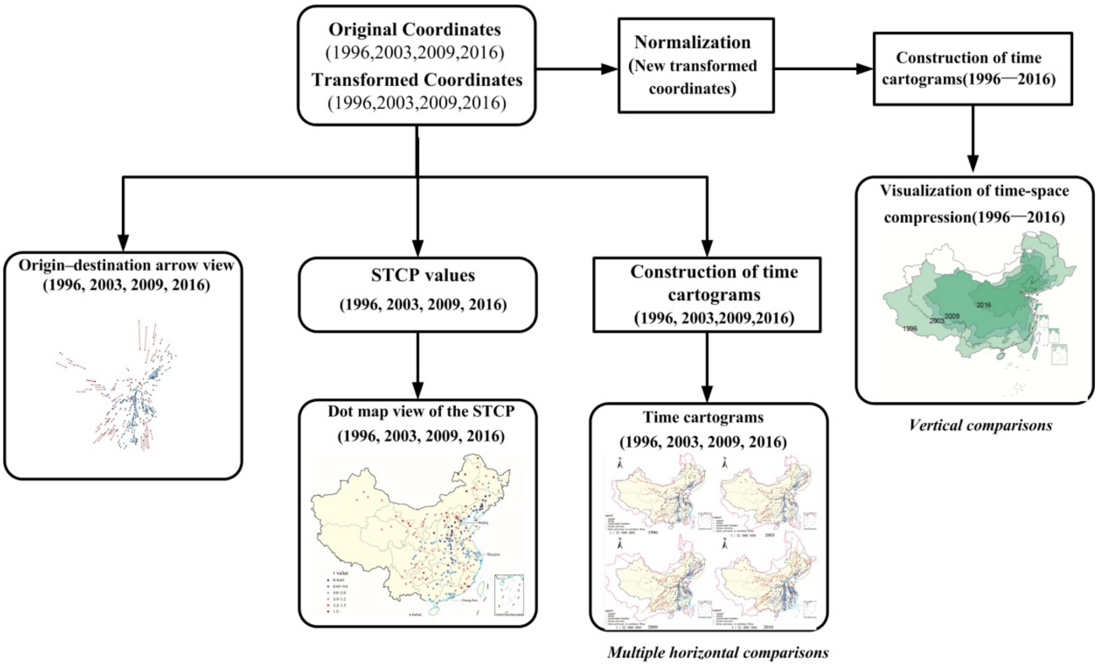

Figure 3. The methodology of this study.

4.1. Construction of Time Cartograms

In this work, we adapt the technique proposed by Wang et al., (2018) [22] for the construction of travel-time cartograms. The construction framework consists of two stages: moving least-squares (MLS) [41] algorithm-based cartogram construction and adjustment of topological errors.

For travel-time cartograms, MLS is used to construct the deformation function f according to the changes between the original coordinates and new coordinates of control points. Suppose the original point is $\boldsymbol{p_i} = (\boldsymbol{x_i}, \boldsymbol{y_i})^{\boldsymbol{T}}$, its transformed location $\boldsymbol{q_i} = (\boldsymbol{x_i}', \boldsymbol{y_i}')^{\boldsymbol{T}}$ can be calculated using Formulas (2) and (3) from Section 2.3. Given any point v on the map, we find the best affine transformation $f(v)$ that minimizes

$$\sum_i \boldsymbol{w_i} |\boldsymbol{f_v}(\boldsymbol{p_i}) - \boldsymbol{q_i}|^2 \tag{7}$$

where the weights $\boldsymbol{w_i}$ have the following form:

$$\boldsymbol{w_i} = \frac{\mathbf{1}}{|\boldsymbol{p_i} - \boldsymbol{v}|^{2\alpha}} \tag{8}$$

where α is a parameter used to adjust the deformation effect, generally taking the value of 1 or 2. Therefore, we have a different transformation function $f(v)$ for each point v on the map. Using the transformed and original coordinates for 226 cities from Section 2, we can calculate changes in the positions of 226 control points and obtain a deformed map, which is the time cartogram corresponding to the original map.

However, some topological errors will inevitably occur during the construction process. The main topological error for polygons is polygon boundary self-intersection, as shown in Figure 4. To reduce topological errors, further constraints are introduced. Bentley–Ottmann algorithm [42] is one of the most common algorithms for intersection detection of multiple line segments. However, when detecting polygon self-intersection, it will consider that polygon vertices are also self-intersection points. Therefore, polygon vertices need to be excluded when applying this algorithm. According to the polygon constraints, the continental boundary data are processed. Figure 5a–c shows the results of three iterations in turn. Topological errors are corrected, and the boundary is smoothed.

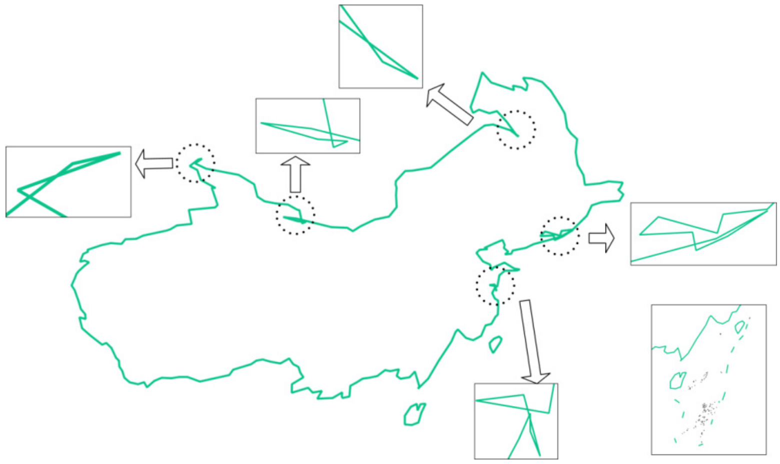

Figure 4. Topological errors in transformed boundary (Maps in this figure are demonstrations of experiment results, not the real territory of the study area).

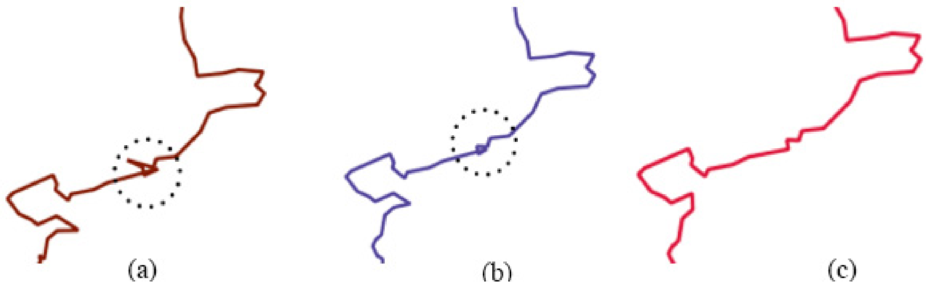

Figure 5. (**a**–**c**) shows the results of three iterations in turn. Corrected boundary topological errors based on constraints.

4.2. Visualization Methods of Accessibility Changes in Multiple Horizontal Comparisons

4.2.1. Origin–Destination Arrow View

The origin–destination arrow view uses the graphic symbol of an arrow to show the positional changes of the control points in time–space and geographic space, and to represent the trend of expansion or shrinking of a certain point. The starting point of the arrow is a certain city node, and the ending point represents the transformed position. The direction of the arrow indicates that the point is expanding outward or shrinking inward by using different colors and the length indicates the difference in position change as well as the degree of expansion or shrinking.

4.2.2. Boundary Change View

Boundary changes are direct reflections of the result of the time cartograms. Changes in the transformed boundary and original boundary can give us the overall deformation trends from geographic space to time-space. This deformation trend can well reflect regional transport accessibility, inwards indicate strong accessibility, outwards indicate weak accessibility. In addition, the transformed boundary changes of time cartograms can effectively represent changes in time-space, present a "shrinking world".

4.2.3. Dot Map View of the STCP

In Section 3.2, we introduced the meaning of the value of the STCP as an indicator for measuring accessibility changes. In order to directly show the changes in the STCP for each city in different years on the map, we use different colors of points (i.e., selected cities) to represent shrinking or expansion(qualitatively) on the map and use the saturation of the color to represent the degree of shrinking or expansion (quantitatively).

4.3. Data Normalization for Visualization of Time-Space Compression

In order to visualize the "shrinking world" in different years on the same time scale and then describe the temporal-spatial changes in accessibility, the datasets for multiple years need to be reprocessed. The key problem is to select a basic data reference benchmark and then normalize the datasets for other years. In our research, we used the dataset in the earliest year (1996) as a reference. That is, the original data and the transformed coordinates in 1996 remained unchanged, and we calculated the deformed coordinates in 2003, 2009, and 2016. The following is an example of the recalculation process for new transformed coordinates in 2003.

First, according to the ratio of the total travel time in 2003 T^{1996} to the total travel time in 1996 T^{1996}, the new total transformed distance in 2003 D^{2003} is recalculated as by D^{1996} in Formula (9). The new transformed distance in 2003 d_i^{2003} for a certain control point according to the corresponding the travel time t_i^{2003} is calculated in Formula (10).

$$\frac{D^{1996}}{T^{1996}} = \frac{D^{2003}}{T^{2003}} \tag{9}$$

$$d_i^{2003} = \frac{t_i^{2003} D^{2003}}{T^{2003}} = \frac{t_i^{2003} D^{1996}}{T^{1996}} \tag{10}$$

Then, the new transformed coordinates of the control points in 2003 are calculated as:

$$X_i^{2003} = x_o + \frac{(x_i - x_o) d_i^{2003}}{s_i} \tag{11}$$

$$Y_i^{2003} = y_o + \frac{(y_i - y_o) d_i^{2003}}{s_i} \tag{12}$$

The same recalculation processes are applied to travel-time data for 2009 and 2016, so the new transformed coordinates of the control points in 2009 and 2016 are, respectively, calculated as:

$$X_i^{2009} = x_o + \frac{(x_i - x_o) d_i^{2009}}{s_i} \tag{13}$$

$$Y_i^{2009} = y_o + \frac{(y_i - y_o) d_i^{2009}}{s_i} \tag{14}$$

$$X_i^{2016} = x_o + \frac{(x_i - x_o) d_i^{2016}}{s_i} \tag{15}$$

$$Y_i^{2016} = y_o + \frac{(y_i - y_o) d_i^{2016}}{s_i} \tag{16}$$

In this way, we calculate the new transformed coordinates for 2003, 2009, and 2016. Next, we construct time cartograms for different times, and then superimpose the time-spaces of different times together. Visual comparison of the superimposed borders of the time cartogram in different years can facilitate interpretation of the "shrinking world".

5. Visualization and Analysis Results

In this section, we show the visualizations of overall and local changes in the transport accessibilities, then analyze the results in detail.

5.1. Visualization and Analysis of Overall Accessibility Changes

5.1.1. Changes in Time Cartograms in Different Years

Based on the time cartograms construction methods described in Section 4.1, we obtained the time cartogram conversion results for the years 1996, 2003, 2009 and 2016, as shown in Figure 6. We obtained a "horizontal comparison" between time–space and geographic space in a certain year as well as a time series of "horizontal comparisons" from 1996 to 2016.

In Figure 6, we use both origin-destination arrow view and boundary change view to represent the results. The change in the boundary (contraction or expansion) indicate the change of the accessibility of the whole area, and the origin-destination arrow view can more intuitively provide detailed information on the difference in transport accessibility between regions.

From Figure 6 we can perceive a clear pattern that transportation accessibility was predominantly lagging in most cities in west China and a small number of cities in northeast China during the 1996–2016 period. Notably, during the 2009–2016 period, the arrows for some cities in the southeast coastal area shift from red to blue, where the transformed boundary changed from expanding outward to contracting inward. This finding further suggests that the transport accessibility between the region and Beijing has been significantly improved.

The length of each arrow indicates the extent of the change in the location of the city and reflects the extent of the change in the transport accessibility of the city. The changes shown in Figure 6 demonstrate that during the 1996–2016 period, most cities in southeast China remained advantageous in terms of transportation accessibility, and this advantage gradually increased reflected by the continuous increase in the lengths of the blue arrows during the 1996–2016 period. However, unlike southeast China, the transport accessibility of most areas in the west and north are became increasingly worse. This shows that although the traffic was constantly developing, the traffic gap between different regions continued to increase during the 1996–2016 period.

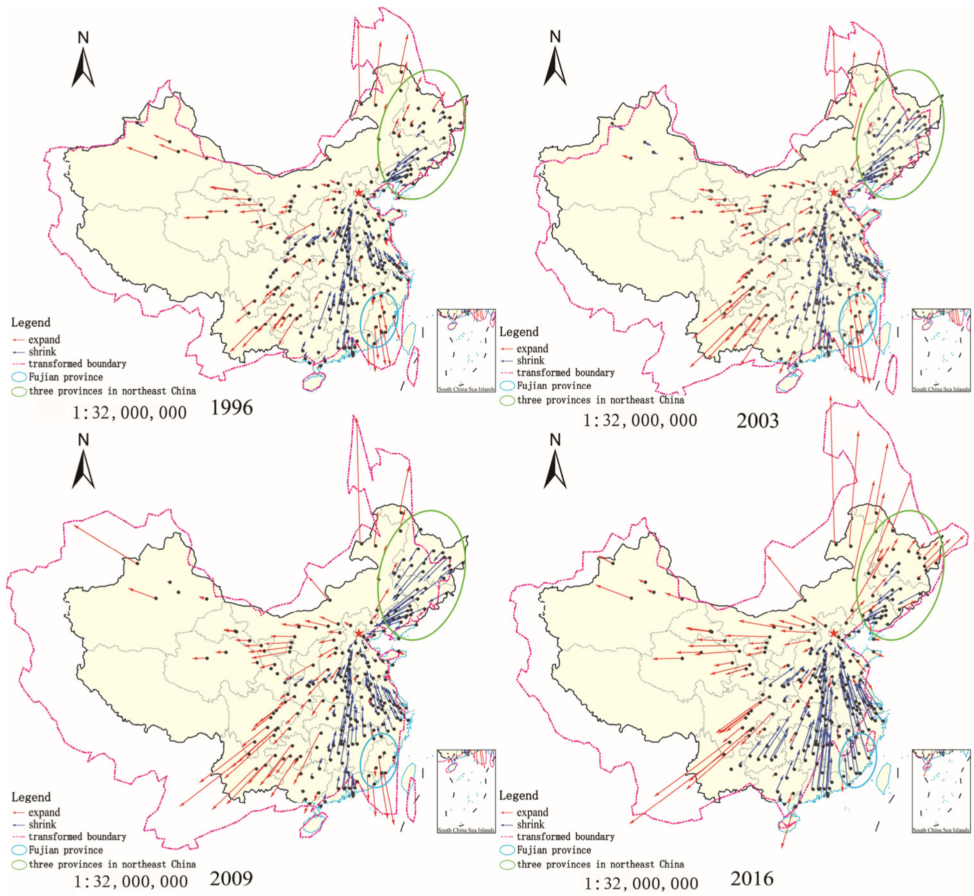

Figure 6. Comparison of transformed results for the years 1996, 2003, 2009 and 2016 (Maps in this figure are demonstrations of experiment results, not the real territory of the study area).

In addition, there was a notable change in the transportation accessibility of the cities in northeast China (in the green circle) and Fujian Province on the southeast coast (in the blue circle). Overall, the transport accessibility between most cities in northeast China and Beijing gradually improved during the 1996–2009 period (as evidenced by the gradual increase in the lengths of the blue arrows) but significantly decreased during the 2009–2016 period (as evidenced by the significant decrease in the proportion and lengths of the blue arrows). Unlike the situation in northeast, the arrows for most cities in Fujian province were red in the period 1996–2009, and changed from red to blue in the period 2009–2016. This can be explained by the railway construction and development in Fujian province and a significant improvement in transport accessibility between the cities in Fujian province and Beijing during the 2009–2016 period.

5.1.2. Changes in the Shortest Railway Travel Time (STRT)

In addition to the visualization, we also performed a statistical analysis of the STRT over the years. The statistical results are shown in Table 1.

The means in Table 1 show that the railway travel time is constantly shrinking due to the continuous development of transportation technology. However, from the coefficient of variation values in Table 1 we can also see that the difference in accessibility between different cities increased overall and was more unbalanced from the travel time perspective from 1996 to 2009, while it declined slightly from 2009 to 2016.

Table 1. Statistical results of STRT from 1996 to 2016 (unit: min).

	1996	**2003**	**2009**	**2016**
Mean	1386.35	1043.78	837.77	507.37
Median	1302.00	939.00	727.50	430.00
Std. deviation	816.11	599.01	536.86	320.11
Maximum	4420.00	3120.00	3545.00	1729.00
Minimum	68.00	48.000	30.00	21.00
25% percentile	719.50	556.25	419.50	276.50
75% percentile	2010.25	1438.00	1165.25	689.25
Coefficient of variation	58.87%	57.39%	64.08%	63.09%

5.1.3. Changes in Spatiotemporal Conversion Parameter (STCP)

We have summarized and visualized the statistical results of STCP in Table 2 and in the box-plot shown in Figure 7. The mean value is nearly unchanged over these years, and the median decreases slightly, while the standard deviation and coefficient of variation increase significantly. This indicates that although the average travel time has been decreasing due to the development of overall transportation technology, the growth rate of traffic development in different cities is different, and that difference is constantly increasing. This trend of increasing speed differences is clear through the box-plots. In other words, there is a growing disparity in transport accessibility between different regions.

Table 2. Statistical results of STCP from 1996 to 2016.

	1996	**2003**	**2009**	**2016**
Mean	0.975	0.968	0.935	0.953
Median	0.966	0.948	0.890	0.845
Std. deviation	0.197	0.210	0.291	0.411
Maximum	1.867	1.741	2.233	3.137
Minimum	0.604	0.566	0.326	0.495
25% percentile	0.840	0.840	0.739	0.657
75% percentile	1.095	1.075	1.107	1.104
Coefficient of variation	20.21%	21.69%	31.12%	43.13%

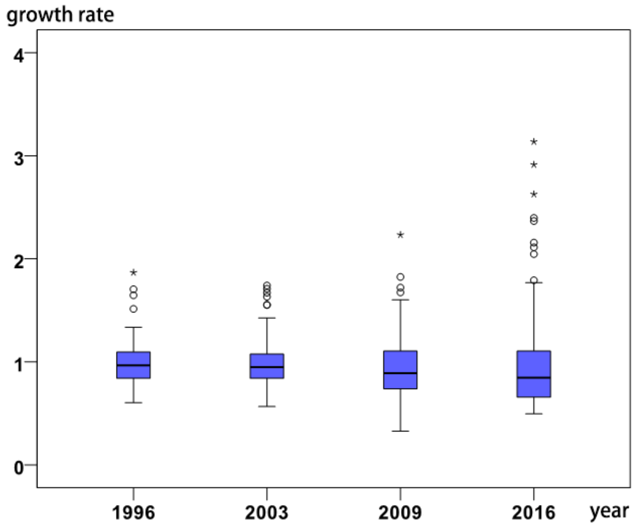

Figure 7. Box-plot of STCP from 1996 to 2016.

In Section 3, we introduced the meaning of the *r* value as STCP. The map visualization results of the changes in spatiotemporal conversion degree for each city in 1996, 2003, 2009, and 2016 are shown in Figure 8. The red dots indicate that the city expands outwards, and the expansion speed is lower than the NAL, while the blue dots indicate that the point shrinks inwards and the speed is higher than the NAL. The darker the color, the larger the degree. We can interpret from the visualizations in Figure 8 the following changes.

(1) Generally speaking, blue points are mostly distributed along the railway line, while red points are mostly located in the western area, and this distribution pattern of points does not change significantly overall. However, some local areas such as Northeast China have changed greatly.

(2) From 1996 to 2016, the differences between red and blue dots gradually increase. The blue color of the cities along the Beijing–Shanghai and Beijing–Guangzhou railways becomes increasingly darker, indicating that the traffic advantages along the Beijing–Shanghai and Beijing–Guangzhou lines have expanded over the past two decades, especially in the period 2009 to 2016, mostly due to the opening of the high-speed railway.

(3) In the northeastern region of China, the proportion of the blue dots increases from 1996 to 2009, and the color of these dots becomes darker. However, in 2016, the color of some points changes from blue to red. This is a good illustration of the changes in traffic conditions in the Northeast; from 1996 to 2009 this region was at the forefront of the country, while by 2016, its dominant position was declining. In contrast, the southeast coastal region was in a disadvantaged position from 1996 to 2009, but it clearly began to be in a dominant position by 2016.

5.2. Visualization and Analysis of Accessibility Changes in Local Regions

In order to further analyze the accessibility changes in detail, we selected three provinces in northeast China (see green circle in Figure 6), comprising Heilongjiang province, Liaoning province, and Jilin province, and one province of Fujian in southeast China (see blue circle in Figure 6) as a demonstration of local regions with large changes.

Table 3 lists travel times and the corresponding STCP values for each city in the three provinces in northeast China from 1996 to 2016. Figure 9 shows the map visualization results of the *r* value for all cities in these three provinces. According to the results, we can divide the traffic development in this region into two main stages. The first stage is the rapid development stage during the period 1996–2009. In this stage, the travel time shortened, and the *r* values of most cities were less than 1 and decreasing. This means that the traffic conditions of the entire northeast region were better than the NAL and the development speed was higher than the NAL. The second stage is the advantage slipping stage during the period 2009–2016. In this stage, the travel time did not change significantly, but the *r* value showed an increasing trend, and even the *r* value of some cities began to reach more than 1. This indicates not only that the traffic development speed was significantly lower than the NAL, but also that the dominant position was shrinking and some cities' traffic conditions had even begun to fall below the NAL.

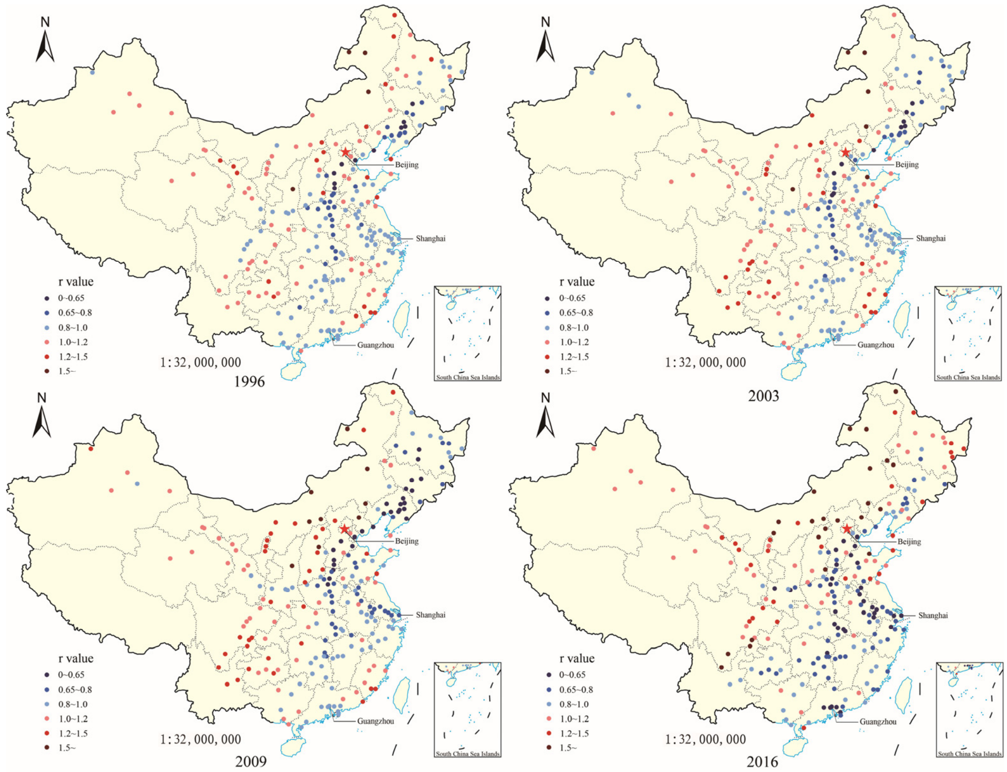

Figure 8. Changes in STCP for cities in China from 1996 to 2016.

Table 3. Travel times and STCP values for cities in northeast China.

City Name	Travel Time (min)				*r* Value			
	1996	2003	2009	2016	1996	2003	2009	2016
Shenyang	567	408	239	238	0.609	0.571	0.408	0.657
Dalian	879	577	414	302	1.292	1.105	0.967	1.141
Anshan	619	472	304	282	0.721	0.716	0.562	0.844
Fushun	631	483	296	271	0.633	0.631	0.472	0.699
Benxi	655	478	297	323	0.681	0.648	0.491	0.864
Jinzhou	426	315	170	194	0.679	0.654	0.431	0.796
Yingkou	673	477	308	245	0.892	0.824	0.649	0.836
Fuxin	552	487	279	301	0.761	0.875	0.611	1.067
Panjin	506	381	191	244	0.681	0.668	0.408	0.844
Tieling	630	452	268	256	0.628	0.587	0.425	0.657
Zhaoyang	577	460	309	327	1.026	1.066	0.873	1.495
Dandong	829	634	395	400	0.809	0.806	0.613	1.004
Changchun	802	603	363	350	0.641	0.628	0.461	0.719
Jilin	919	726	458	426	0.657	0.676	0.520	0.783
Siping	757	533	321	330	0.685	0.629	0.462	0.768
Liaoyuan	872	624	418	413	0.736	0.686	0.561	0.897
Baicheng	1198	856	674	613	1.087	1.012	0.972	1.430
Yanji	1394	1109	833	475	0.809	0.838	0.768	0.709
Tonghua	1154	885	587	591	0.928	0.928	0.751	1.223
Harbin	1368	749	484	426	0.906	0.646	0.509	0.725

Table 3. *Cont.*

City Name	Travel Time (min)				*r* Value			
	1996	2003	2009	2016	1996	2003	2009	2016
Jixi	1965	1317	1042	891	0.989	0.863	0.833	1.153
Hegang	1965	1265	1092	827	0.975	0.817	0.861	1.055
Shuangyashan	2046	1311	911	913	0.985	0.822	0.697	1.130
Yichun	2283	1208	991	786	1.209	0.833	0.834	1.070
Jiamusi	1849	1198	822	760	0.927	0.782	0.655	0.980
QItaihe	2070	1382	1121	995	1.034	0.899	0.890	1.278
Mudanjiang	1718	1131	769	690	0.958	0.821	0.681	0.989
Suihua	1469	835	566	511	0.914	0.677	0.560	0.818
Qiqihar	1618	1021	635	572	1.192	0.980	0.743	1.084
Daqing	1497	847	566	527	1.071	0.789	0.644	0.970
Heihe	2163	1432	1062	1031	1.114	0.961	0.870	1.366
Tahe	2489	1686	1574	1081	1.301	1.148	1.307	1.453
Beian	1686	1046	866	689	1.005	0.813	0.821	1.056

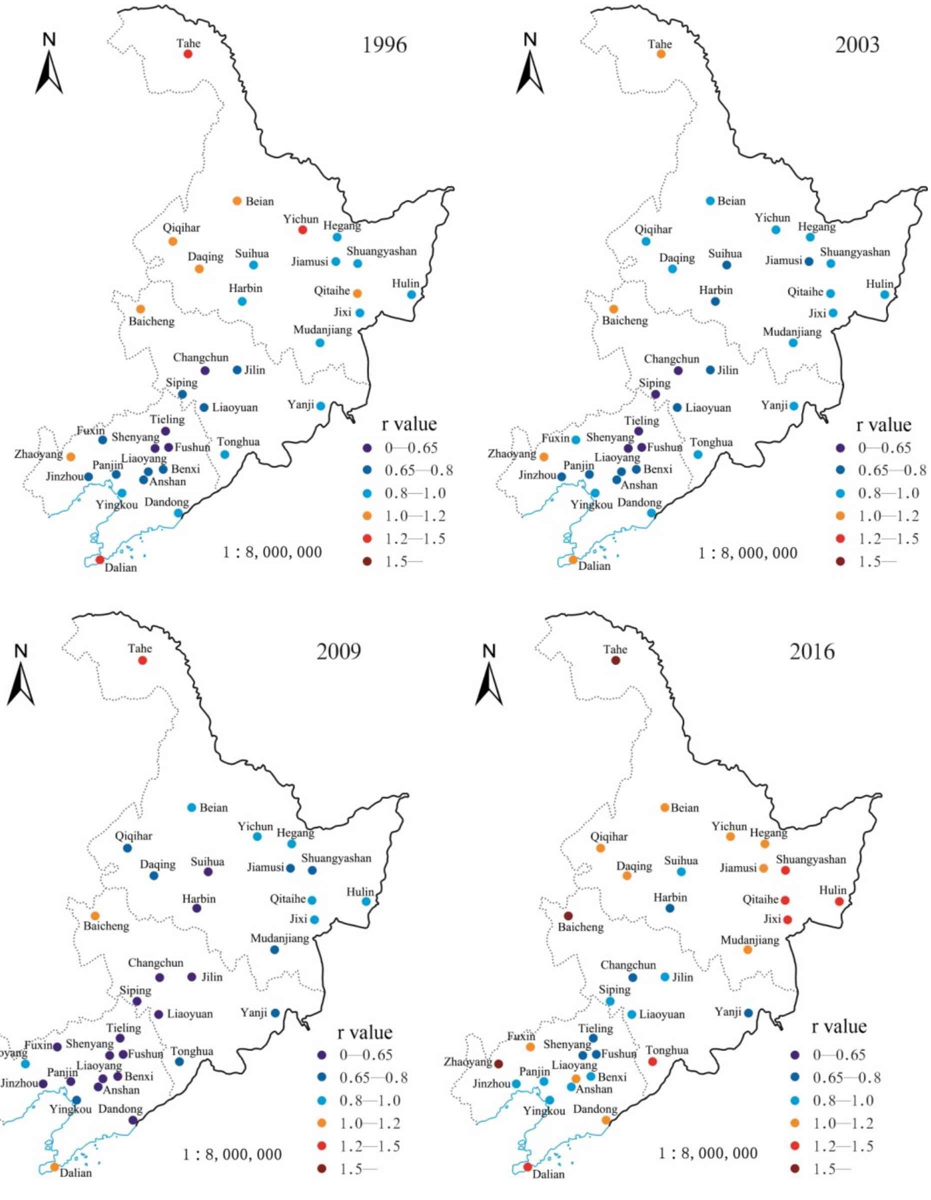

Figure 9. Changes in STCP for cities in northeast China from 1996 to 2016.

Table 4 presents travel times and the corresponding r values for each city in Fujian province in southeast China from 1996 to 2016. Based on the results, we can classify the traffic development in Fujian province into three main stages.

The first is a backward stage during the period 1996–2003. In this stage, the travel time decreased, but the r value increased slightly and reached more than 1. This indicates not only that the traffic conditions in Fujian province were lower than the NAL, but also that the development speed was less than the NAL.

The second stage is the slightly increasing stage during the period 2003–2009, when the travel time decreased. Although the r values for the cities were still greater than 1, they began to decline slightly. This indicates that the transportation conditions in Fujian province started to develop at this stage, and the development speed was slightly higher than the NAL. However, the transportation level was still below the NAL.

The third stage is the rapid development stage during the period 2009–2016. After the opening of the high-speed railway in Fujian province, the transportation developed rapidly, the travel time was greatly shortened, and the r value sharply reduced and was less than 1. This indicates that the development speed was higher than the NAL and the traffic conditions began to be advantageous.

Table 4. Travel times and STCP values for cities in Fujian Province.

City Name	Travel Time (min)				r Value			
	1996	2003	2009	2016	1996	2003	2009	2016
Fuzhou	2151	1686	1158	468	1.187	1.213	1.016	0.665
Xiamen	2456	2042	1641	552	1.233	1.336	1.309	0.713
Sanming	2017	1615	1235	537	1.145	1.195	1.115	0.784
Zhangzhou	2435	2030	1582	569	1.230	1.337	1.271	0.739
Nanping	1974	1536	1074	514	1.151	1.167	0.995	0.771
Longyan	2342	1896	1221	601	1.234	1.301	1.022	0.814

5.3. Visualization and Analysis of Time-Space Compression

To allow an easy visual comparison of the time-space compression over the study years, we converted the time cartogram results for 1996, 2003, 2009, and 2016 into the same time scale using the method described in Section 4.1, and we overlaid these time cartograms in Figure 10. The continuous shrinkage of the boundary shows the continuous shrinkage of the time-space. In the periods 1996–2003 and 2009–2016, the time-space was shrinking greatly, which coincided with the period of rapid traffic development.

Overall, the continuous upgrading of transportation technology has promoted an increasingly faster average speed. The distance between Beijing and various cities is constantly being "compressed" and the time–space is shrinking. In the past 20 years, time distances between Beijing and cities in the south of China have been greatly reduced, especially during the period 2009–2016. The time distances from Beijing to the northeast were greatly reduced in the period 1996–2003, while the degree of contraction was slight in the period 2003–2016. In addition, the time distances from Beijing to cities in the vast western region of China were also reduced steadily. However, due to the small number of control points in the western area, the time data for these areas that were used in the time cartogram conversion process depended largely on average travel time. Thus, the actual value for the area was not so accurate to a degree on the map.

Table 5 shows the changes in average speed and speed growth rate from Beijing to all cities over the years. It is assumed that the speed in 1996 was 100, and then we could obtain the speed values for the other years. Obviously, the large increase in the speed growth rate from 2009 to 2016 was mainly due to the emergence of high-speed rail.

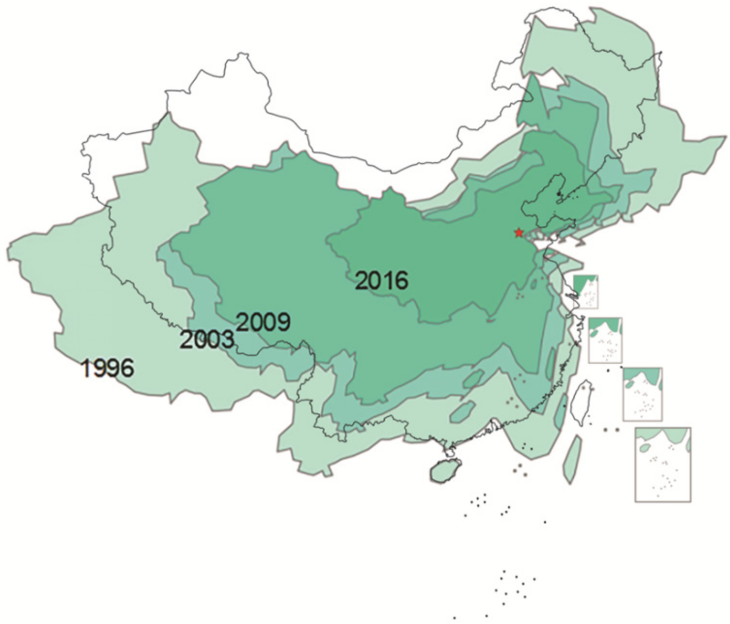

Figure 10. Time–space overlay analysis in the same time scale from 1996 to 2016 (Maps in this figure are demonstrations of experiment results, not the real territory of the study area).

Table 5. Changes of average speed and speed growth rate over the years.

Year	1996	2003	2009	2016
Average Speed	100	132.82	165.48	273.24
Speed Growth Rate	—	32.8%	24.6%	65.1%

6. Conclusions and Discussion

We present the visual analysis of the dynamic spatial pattern of transport accessibility from multiple perspectives using time cartograms. Compared with previous work that focused on either quantitative analysis or visual qualitative expression, we attempt to provide a methodology by combining visual qualitative display with quantitative indicator analysis, and present transport accessibility changes more comprehensively from multiple perspectives. This contributes to a better understanding of the spatial evolution patterns of accessibility.

Our empirical findings highlighted that the development of transportation technology has continuously shortened the travel time, the time–space is gradually compressed. However, the development of transportation in different regions is unbalanced, and the gap in transport accessibility between the southeast and the west in China becomes bigger and bigger. The reasons for the above situation may be that the eastern regions of China tend to be more densely populated and more affluent, their demand for transport is higher and their transport infrastructure is more intensively used. This situation is also similar to the accessibility between the central and peripheral regions in Europe [43]. To bridge the gap, special supports from government policy are needed.

The method in this paper is universal, not only applicable to the Chinese region at the national scale, but also to other regions at different scales. However, although effective analysis is carried out using our proposed methods, our work still has some limitations.

(1) Regarding the selection of measurement indicators for transport accessibility changes, we only used railway data but did not consider road and air transportation.
(2) Although we carefully selected 226 cities as representative control points, due to the limited availability of railway information of different regions, these 226 cities are not evenly distributed throughout China. Especially, there is a lack of city information in western China. This may lead to inaccurate visualization results in this region. In

addition, our analysis ends in 2016, but in fact, after 2016, many high-speed rail lines were opened and the speed was further improved. For example, the speed of the Beijing–Shanghai high-speed rail increased, resulting in a shortened travel time.

(3) As an intuitive result of the time cartogram, the transformed boundary reflects the overall deformation trend. However, it is difficult to effectively display the degree of internal deformation. In the future, we can try to reflect the internal shrinkage/expansion trend through the deformation of the grid covering the area.

(4) This research mainly focuses on the visualization of accessibility changes, but not on an in-depth analysis of the underlying reasons. For example, we did not investigate whether the development and decline of transport accessibility in Northeast China is correlated to its economic development. To verify this, further relevant data are needed. In addition, the research on transport accessibility should be further verified in conjunction with the development of China's railways, especially high-speed railways.

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