# Shrinking or Expanding? City Spatial Distribution and Simulation Analyses Based on Regionalization along the Yellow River

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**Abstract:** In recent years, many cities in China have faced profound and complex shrinkage problems, which have required new perspectives and approaches to improve understanding. In this context, this study built a framework to understand city shrinkage based on the regionalization perspective. By simulating land use with spatial relations and conducting a coupling analysis on land use efficiency and accessibility (by strength) based on the study of urban systems, 96 cities along the Yellow River were analyzed under this framework. The research found that cities with significantly lower land use efficiency tend to exhibit lower accessibility (by strength), and city shrinkage in China may be the consequence of the lower de facto accessibility and mismatch between development rights and development potential. The urban system has proven to be helpful in the research, planning, and administration of city shrinkage. **DOI:** 10.1061/(ASCE)UP.1943-5444.0000605. 

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## Introduction

The study of city shrinkage emerged from the stagnation and loss of population growth in some Westerns cities in the postwar period, with Eastern Europe and the "rust belt" in the northeastern United States as the most typical areas (Olsen 2013). In recent years, case studies and theoretical research around the world have greatly enriched the understanding of the city shrinkage phenomenon (Martinez-Fernandez et al. 2016; Wolff and Wiechmann 2018). Population decline has always been considered an important sign of shrinkage (Turok and Mykhnenko 2007); however, scholars are paying increasing attention to more complex socioeconomic changes like the spatial distribution of economic activities and are searching for innovative insights (Großmann et al. 2013). For example, Haase et al. (2014) established a heuristic model and created an approach for understanding city shrinkage for a specific time and place in a historically specific way.

The increasing research attention attempts to provide strategies for managing city shrinkage (e.g., identification, planning, and administration). However, city shrinkage is such a complex and dynamic phenomenon that no consensus currently exists for its definition. The introduction of mathematical models and application of geographic information systems (GIS) have also stimulated the research on city shrinkage. For example, Schetke and Haase (2008) proposed evaluating shrinking cities with multicriteria indices. Xie et al. (2018) built a multilevel cause-context framework to analyze the shrinking phenomenon in Detroit. Many existing spatial metrics can be applied in shrinking-related research (Reis et al. 2016).

Research on the mechanisms behind city shrinkage found that structural adjustments in economic development and profound social changes to a large extent lead to a population decline (Beauregard 2013). Haase et al. (2016) conducted a case study in Europe and found that economic decline and job losses, suburbanization, and natural population decline may be the three dominating factors of shrinking. However, these factors are always interrelated, as Hartt (2018) expounds. With the theory of growth and decline in population and economy, he points out that globalization can transform temporary cyclical decline into long-term decline where it becomes a spatial characteristic.

City shrinkage is not unusual, even in China, which is still in the process of rapid urbanization (Long and Wu 2016). Wu et al. (2015) found that the phenomenon of "local shrinkage" (e.g., the shrinkage of small and medium-sized countries) is widespread and is even intensifying in both the Beijing–Tianjin–Hebei region and Yangtze River Delta, which are the two most urbanized areas in China according to the latest urbanization ranking released by the Nation Bureau of Statistics of China (National Bureau of Statistics of China 2019). Zhang et al. (2017) proposed that in addition to the trend-type similar to those in developed countries in the West, there are two more types in China: the "overdraft-type," which is due to the blind broadening of the development framework, and the "adjustment-type," which is due to the active setting of the growth boundary in China. These denote that city shrinkage in China is different from the widely known cases in developed countries and is deeply rooted in Chinese city planning and public administration (Zhang 2002), which is far more complex in its performance, mechanisms, and impacts.

Presently, most of the research on city shrinkage in China is in the form of an overall description (Long and Wu 2016) or case studies focusing on a small area (Li et al. 2015; Wu et al. 2015;

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Zhang et al. 2018); it lacks investigation into how planning and administration can impact shrinkage, ignores the systems among cities and fails to take an evolutionary view. Newer perspectives that take into consideration cities and interactions within the entire area are required; this is the area where this research can make progress to reach an improved understanding of city shrinkage in China from a regional perspective and using the concept of urban system. To make it clear, an urban system is *any network of towns and cities, and their hinterlands, which can be seen as a system, since it depends on the movements of labor, goods and services, ideas, and capital through the network* (Mayhew 2009, p. 531). In this study, an urban system refers to a system of cities within the study area.

## Methods and Data

### Methods

This research employs a network analysis that analogizes interactions between cites and urban systems to actors and social networks to study urban systems. To measure interactions within an urban system, current research is usually based on empirical data from practical surveys, like aerial data (Xiao et al. 2013). Though the data is relatively difficult to obtain, when theoretical models are introduced, research can dive deeper into the urban system. For example, Gu and Pang (2008) employed a gravity model (Reilly 1929) to calculate the spatial interactions between cities in China and divided the entire system into different hierarchies. Some important indices that are commonly used to describe networks include the clustering coefficient, characteristic path length, and probability degree distribution (Scott and Carrington 2011).

Different types of networks can be modeled using different topological structures. In a regular network, every node has the same degree, and the clustering coefficient and the characteristic path length are both large (Watts and Strogatz 1998). In a random network, however, the probability of a node degree following a Poisson distribution, characteristic path length, and clustering coefficient are all smaller than those of a regular network (Erdös and Rényi 1959). Watts and Strogatz (1998) constructed the "small-world" network model featuring a larger clustering coefficient and smaller characteristic path length, which falls between the regular and the random networks. Another famous model is the Barabási-Albert (BA) network, or a scale-free network, created by Barabási and Albert (1999), and the probability of each node obeys the power law distribution. These theoretical models have been used in real-world network analyses, including in the study of urban systems. For example, Leng et al. (2011) found that the undirected links in the urban economic network in China conform to the characteristics of the BA network. Wu et al. (2015) found that, in general, the Chinese urban network is in a transition period from a simple random state to a complex ordered position, though scale-free structures already exist in some local small-scale regions.

This study also employs cellular automata (CA) technology to explore the dynamic evolution of each city and the system as a whole. Proposed by Ulam (1950) and used by Von Neumann and Burks (1996) to study self-organizing systems, CA has already been applied to the study of land use change and urban development (Batty and Xie 1994). The basic logic of CA is that a complex system can be generated from simple local rules, and the CA model typically consists of four elements: cell, state, adjacent range, and transition rules. A CA model can effectively simulate urban development tendencies under various conditions, and it presents the dynamic process of urban evolution, regardless of external influences, thus enabling the exploration of the urban development mechanism (Batty and Xie 1997; White et al. 1997), the results of which were often sufficient (Deadman et al. 1993). In recent years, GIS in combination with CA has allowed researchers to introduce various spatial variables to the model, which has greatly promoted the application of CA in land use simulations. Furthermore, the scope of land simulation has gradually expanded from a single city to urban agglomerations (Wang et al. 2016). Exploring the coupling of the CA model and urban spatial interactions is critical for generating improved simulation results considering the increasing complexity of urban development.

### Data

The basic data required for this study include Chinese land use remote sensing data (100 m × 100 m) obtained from the Resource and Environment Data Cloud Platform of the Institute of Geography of the Chinese Academy of Sciences; geospatial data of the 2009 national railways, freeways, and national roads, obtained from the Peking University Geographic Data Platform; 500 m × 500 m China altitude digital elevation model (DEM) spatial distribution data from the Resource and Environment Data Cloud Platform of the Institute of Geography of the Chinese Academy of Sciences. Raster reclassification is based on the land use status classification and research needs, where the raster data is reclassified into six categories (cultivated land, forest land, grassland, water area, urban and rural construction land, and unused land), and the raster size is resampled to 500 m × 500 m, which is suitable for researching technical methods. The total population and gross domestic product (GDP) of the prefectures in 2005, 2010, and 2015 were obtained from the provincial statistical yearbook.

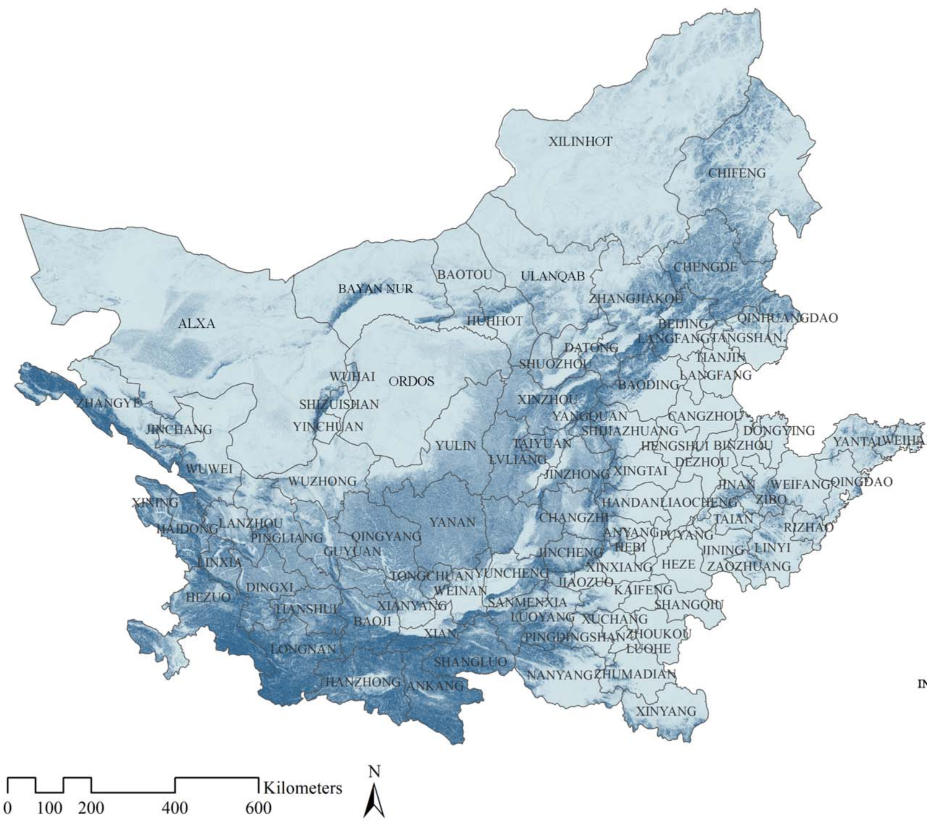
The spatial data extraction and preprocessing, and land use simulations were all completed in ArcGIS 10.2, while the network analysis was conducted using UCINET 6.5, a social network analysis tool. The main steps for performing the network analysis included measuring and analyzing the urban network spatial connections using the gravity model in which the distance data was extracted using the ArcGIS OD Matrix tool. The land use simulation with CA included three stages: data acquisition, rule extraction, and simulation execution or prediction. The required spatial data included land use data interpreted by remote sensing and spatial factors influencing urban growth like traffic accessibility. Data mining methods were employed in rule extraction to capture the laws of urban growth in historical periods. In this study, Logistic-CA is applied to acquire transformation rules, perform simulations, and test the simulation accuracy, which was also carried out in ArcGIS 10.2.

## Research Design

### Study Area

Covering a vast area (almost all of northern China), the topography along the Yellow River is complex and varying. From the mountains in the upstream area to the basins in the middle and the North China Plain in the lower reaches, the complex natural conditions create diverse evolutionary paths for various cities. Apart from the diversification of evolutionary patterns, numerous towns and cities along the Yellow River can fall into different stages of development, which has provided further opportunities for academic research. Therefore, the investigation of cities along the Yellow River is significant because the evolution mechanism of cities of different sizes and stages can be better understood throughout the entire area; the factors potentially influencing the development of cities, including natural conditions, can be thoroughly investigated through comparative analyses; and the structure and evolution of a complex urban system may be better understood.

The period selected for the study was 2005–2015. The 21st century, especially the beginning of it, has witnessed rapid development and dramatic changes in China. In particular, the large amounts of capital invested in infrastructure since the financial crisis has had a profound and widespread impact on not only the




| Province | City Name | Province | City Name |
|---|---|---|---|
| BEIJING | BEIJING | SHANDONG | LAIWU |
| TIANJIN | TIANJIN | | HEZE |
| HEBEI | HANDAN | | LIAOCHENG |
| | XINGTAI | | DEZHOU |
| | SHIJIAZHUANG | | JINING |
| | BAODING | | ZAOZHUANG |
| | HENGSHUI | | LINYI |
| | CANGZHOU | | RIZHAO |
| | LANGFANG | | QINGDAO |
| | LANGFANG | | WEIHAI |
| | ZHANGJIAKOU | | YANTAI |
| | TANGSHAN | | WEIFANG |
| | QINHUANGDAO | | ZIBO |
| | CHENGDE | | TAIAN |
| SHANXI | DATONG | | JINAN |
| | SHUOZHOU | | DONGYING |
| | XINZHOU | | BINZHOU |
| | YUNCHENG | HENAN | JIYUAN |
| | JINCHENG | | XINYANG |
| | CHANGZHI | | ZHUMADIAN |
| | LINFEN | | SANMENXIA |
| | TAIYUAN | | LUOYANG |
| | LVLIANG | | PINGDINGSHAN |
| | JINZHONG | | LUOHE |
| | YANGQUAN | | XUCHANG |
| SHAANXI | YULIN | | ZHENGZHOU |
| | YANAN | | JIAOZUO |
| | BAOJI | | ANYANG |
| | HANZHONG | | HEBI |
| | ANKANG | | XINXIANG |
| | SHANGLUO | | KAIFENG |
| | XIAN | | ZHOUKOU |
| | WEINAN | | SHANGQIU |
| | TONGCHUAN | | PUYANG |
| | XIANYANG | | NANYANG |
| INNER MONGOLIA | ALXA | GANSU | GANNAN |
| | WUHAI | | LONGNAN |
| | ORDOS | | TIANSHUI |
| | BAYAN NUR | | DINGXI |
| | BAOTOU | | LINXIA |
| | HUHHOT | | JINCHANG |
| | ULANQAB | | WUWEI |
| | CHIFENG | | LANZHOU |
| | XILINHOT | | QINGYANG |
| QINGHAI | XINING | | PINGLIANG |
| | HAIDONG | | ZHANGYE |
| NINGXIA | WUZHONG | NINGXIA | SHIZUISHAN |
| | YINCHUAN | | GUYUAN |

**Fig. 1.** The study area. (Map data courtesy of Geographic Data Sharing Infrastructure, College of Urban and Environmental Science, Peking University.)

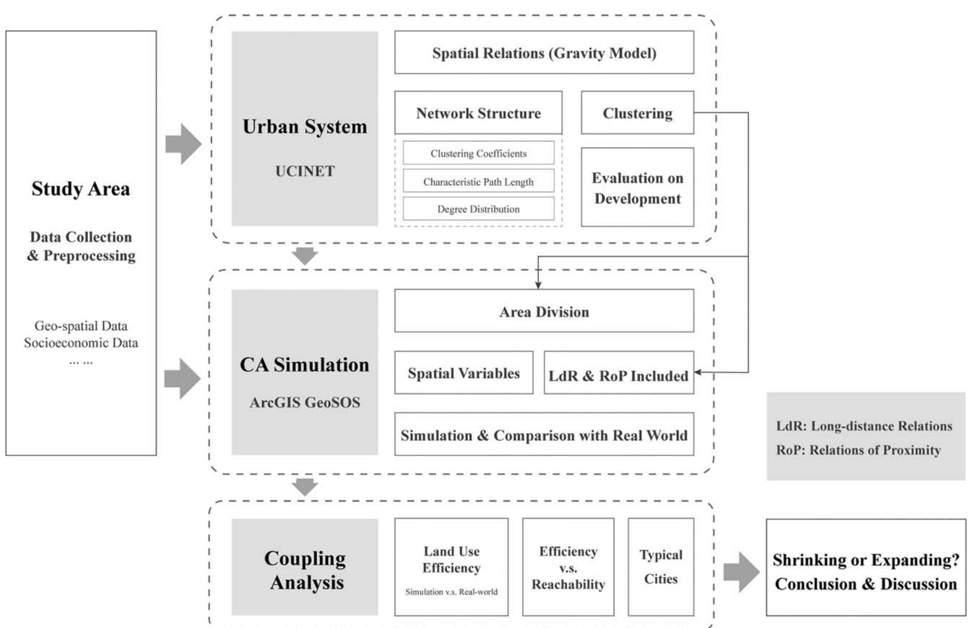
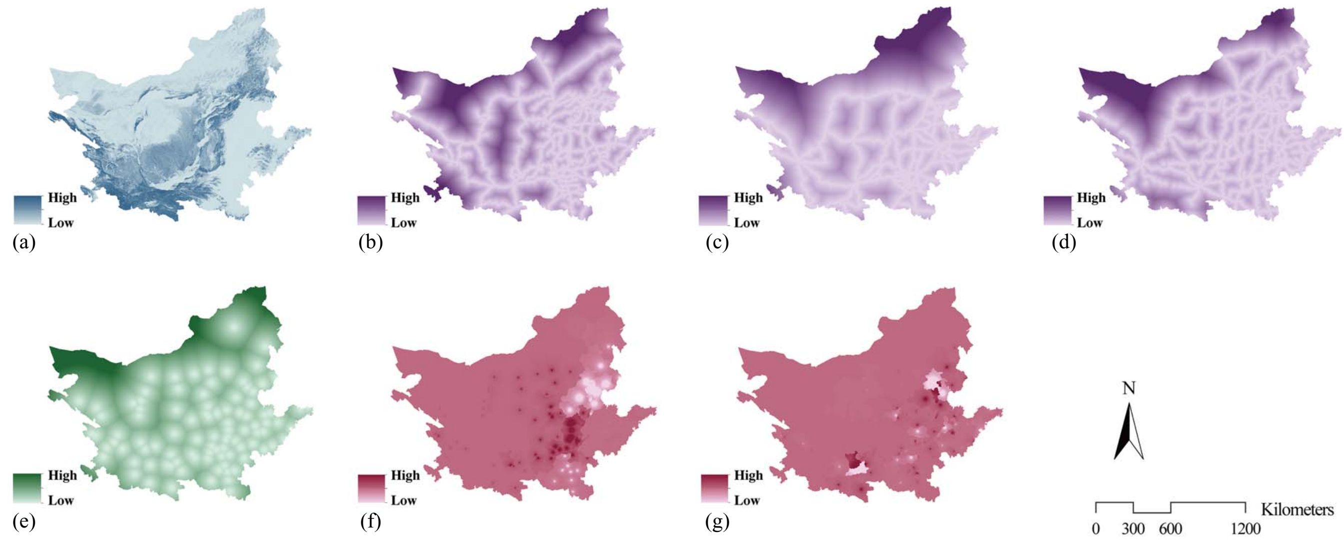
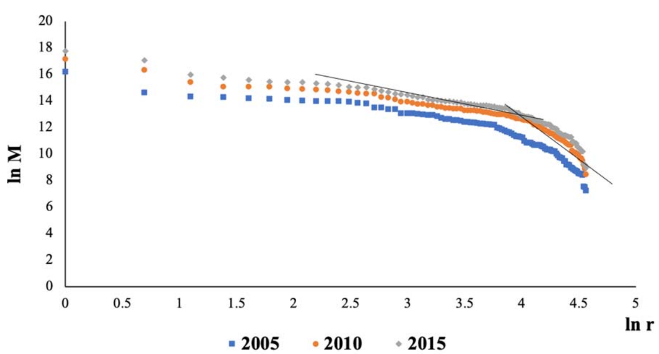



**Fig. 2.** The research process.




| Variables (standardized) | Description |
|---|---|
| (a) slope | The gradient, or rate of maximum change in z-value from each cell of the DEM raster surface, calculated with ArcGIS-3D Analyst Tools-Raster Surface-Slope. |
| (b) dtr (distance to railway) | The distance to railway, calculated with ArcGIS-Euclidean Distance (cell-center). |
| (c) dtf (distance to freeway) | The distance to freeway, calculated with ArcGIS-Euclidean Distance (cell-center). |
| (d) dtn (distance to national road ) | The distance to national road, calculated with ArcGIS-Euclidean Distance (cell-center). |
| (e) dtc (distance to city center) | The distance to city center, specifically, the place where local government is located, calculated with ArcGIS-Euclidean Distance (cell-center). |
| (f) LdR (Long-distance Relations) | Relations with other cities beyond the subgroup and within the whole study area. |
| (g) RoP (Relations of Proximity) | Relations with other cities within the subgroup to which it belongs. |

**Fig. 3.** Variable descriptions (spatial relations included).




**Rank-size Distribution**

| Year | Zipf-dimension | Horsdorff-dimension |
|---|---|---|
| 2005 | 1.829 | 0.547 |
| 2010 | 1.650 | 0.606 |
| 2015 | 1.663 | 0.601 |

**Fig. 4.** Rank size distribution: $M =$ the size of a city measured by total population and GDP; and $r =$ the descending rank of a city according to size in the entire range.

regional development but also the development of each city regardless of its size or location.

Considering the direct economic relationships with the Yellow River and administrative division integrities, this study selected 96 cities in 11 provinces in the natural basin area including Beijing, Tianjin, Hebei, Shandong, Henan, Shanxi, Shaanxi, Inner Mongolia, Ningxia, Gansu, and Qinghai, as shown in Fig. 1. Several cities in these provinces were excluded from the study such as those in the northwestern part of Qinghai Province and the northeastern part of Inner Mongolia because the development of these cities has little economic relations to that of other cities or the Yellow River. The exclusion of these cities reduces redundancy and disturbance in the study data obtained.

### *Research Process*

The research process of this paper is shown in Fig. 2. The urban system of the study area was first investigated using UCINET and clustered subgroups. The land use simulation employing CA was performed based on the clustering results, with improved spatial variables after considering the spatial relationships between cities. Finally, through a coupling analysis of the relationship between land use efficiency and accessibility (by strength), this study attempts to provide new ideas for how city shrinkage in China may take place.

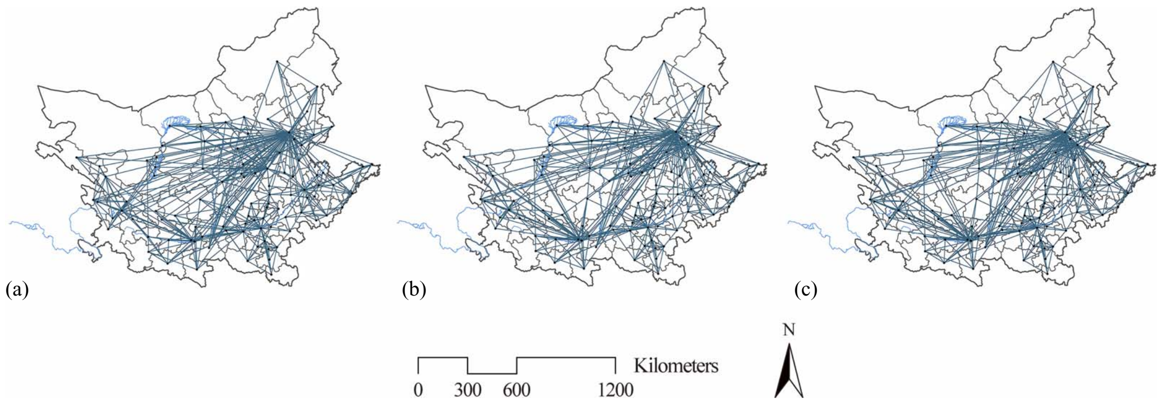
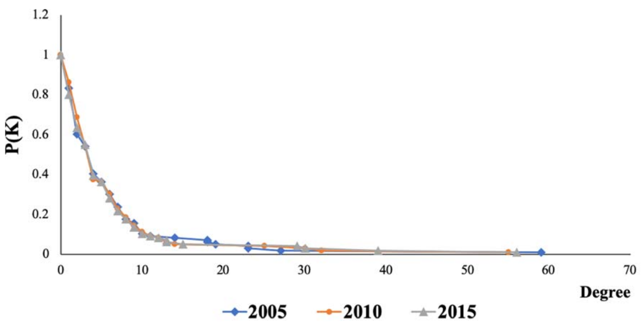



**Fig. 5.** Spatial organization of the urban networks (top five): (a) 2005; (b) 2010; and (c) 2015.




**Degree Distribution**

| Year | Distribution | $R^2$ | Scaling Factor |
|---|---|---|---|
| 2005 | $y = 1.7182x - 1.182$ | 0.9387 | 1.182 |
| 2010 | $y = 1.7419x - 1.202$ | 0.9473 | 1.202 |
| 2015 | $y = 1.5874x - 1.153$ | 0.9502 | 1.153 |

**Fig. 6.** Degree distribution.

**Table 1.** Clustering coefficients and characteristic path length

| Year | C | L |
|---|---|---|
| 2005 | 0.442 | 3.712 |
| 2010 | 0.446 | 4.979 |
| 2015 | 0.453 | 3.952 |
| Random | 0.050 | 3.062 |

Note: C = clustering coefficients; L = characteristic path length.

**Table 2.** Clustering coefficients and average path lengths in eight subgroups

| | 2005 | | 2010 | | 2015 | |
|---|---|---|---|---|---|---|
| Subgroup | C | L | C | L | C | L |
| 1 | 0.575 | 2.067 | 0.531 | 1.86 | 0.525 | 2.298 |
| 2 | 0.575 | 1.837 | 0.583 | 1.685 | 0.606 | 1.676 |
| 3 | 0.558 | 1.816 | 0.497 | 1.733 | 0.546 | 1.6 |
| 4 | 0.645 | 1.611 | 0.6 | 1.5 | 0.63 | 1.464 |
| 5 | 0.601 | 1.612 | 0.683 | 1.5 | 0.683 | 1.5 |
| 6 | 0.643 | 1.543 | 0.531 | 2.269 | 0.482 | 2.388 |
| 7 | 0.49 | 1.781 | 0.616 | 1.417 | 0.533 | 1.671 |
| 8 | 0.557 | 1.658 | 0.65 | 1.578 | 0.631 | 1.306 |

Note: C = clustering coefficients; L = characteristic path length.

### *Urban Network Analysis*

This study first employed a gravity model to measure the strength of connections between cities. The top five linkages in terms of contact for each city were extracted. In UCINET, the main indices for the structural analysis include the clustering coefficient, characteristic path length, point degree, and degree cumulative probability distribution. The clustering analysis was conducted based on the original gravity matrix using the convergence of iterated correlations (CONCOR) method that regards the social system as having interconnected roles (Scott and Carrington 2011). The roles are intertwined in the system, and the social structure in terms of roles and positions was investigated to map the subgroups in the study area. Characteristic indices were also calculated to verify the clustering analysis. In addition, census and economic data were used to test the rank size distribution of the urban system in the study area.

### *Land Use Simulation*

In the land use simulation stage, this study selected 2005–2010 as the training period and 2010 as the starting point for the simulation. The area was divided into six subareas according to the characteristics of the network structure. In addition to traditional spatial variables (such as *distance to city center*, *distance to traffic line*, and *slope*), this study attempted to incorporate the spatial interaction between cities as an improvement to the traditional model. Specifically, the spatial relationships between cities can be divided into long-distance relations and relations of proximity, as proposed by Dematteis (1997), and they are addressed quantitatively. The relations of proximity for each city are the sum of the gravity from all other cities within the subareas (six in total, as mentioned above). The long-distance relations for each city form a weighted distribution of the sum of the gravity from all other cities outside the subarea by the relative relations of proximity values. Due to the distance-decay effect of spatial relations (He et al. 2013), the spatial relations for each cell can be calculated using

$$\boldsymbol{P_i^p(x, y) = \frac{RoP_i}{D(x, y, X_i, Y_i)}}, \quad \boldsymbol{P_i^l(x, y) = \frac{LdR_i}{D(x, y, X_i, Y_i)}} \tag{1}$$

where $i$ = city ($i$) in the urban system; $RoP$ = the relations of proximity; and $LdR$ = the long-distance relations; $(X_i, Y_i)$ = the location of the administration in city $i$; $(x, y)$ = the location of the current cell; and $D(x, y, X_i, Y_i)$ = the distance between the current cell and administration center of the city. All variables are shown in Fig. 3.

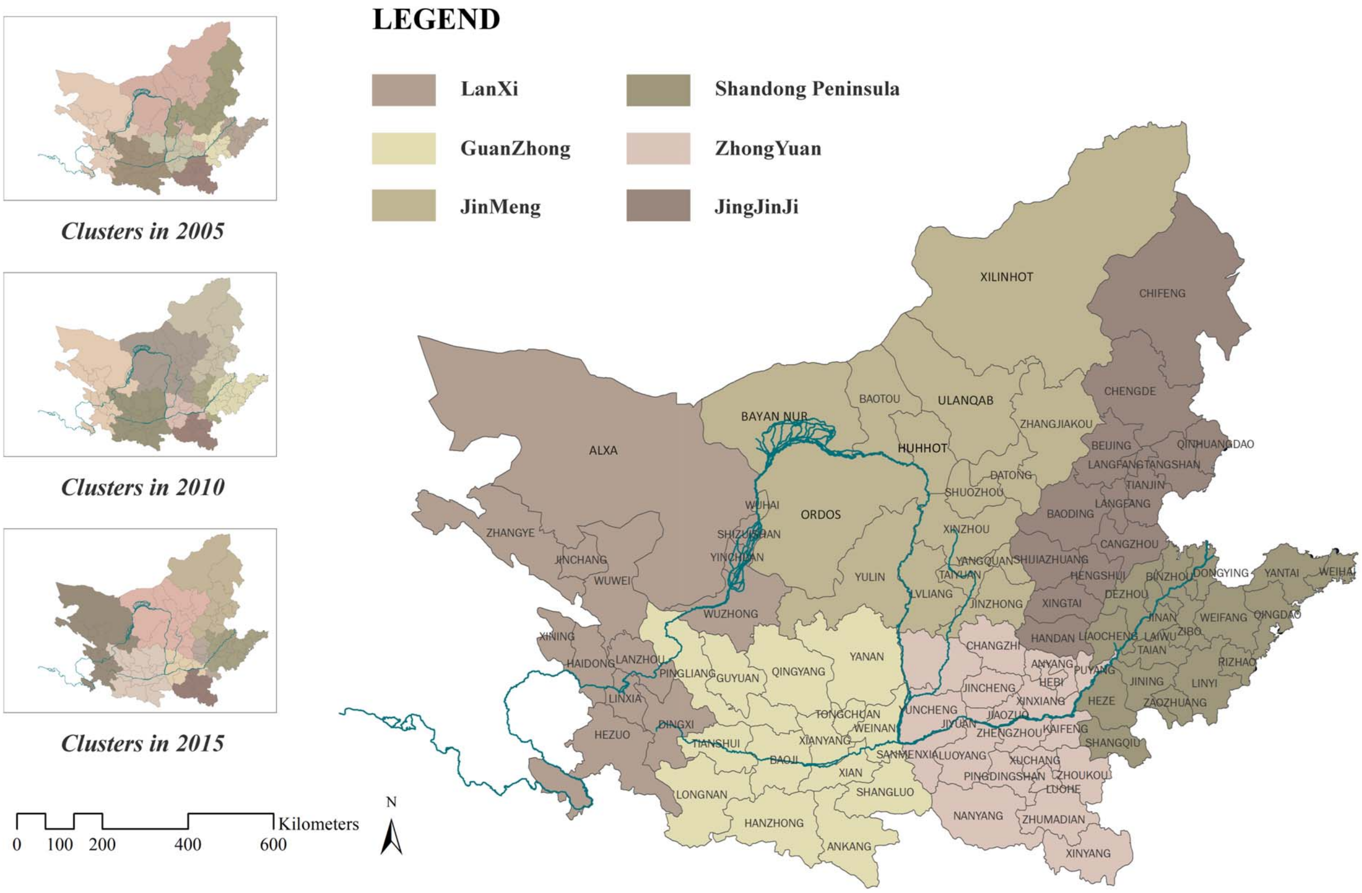



**Fig. 7.** Study subareas. (Map data courtesy of Geographic Data Sharing Infrastructure, College of Urban and Environmental Science, Peking University.)

**Table 3.** Clustering coefficients and average path lengths in six subareas

| | 2005 | | 2010 | | 2015 | |
|---|---|---|---|---|---|---|
| Subarea | C | L | C | L | C | L |
| LanXi | 0.514 | 2.418 | 0.55 | 1.887 | 0.555 | 1.871 |
| GuanZhong | 0.572 | 1.896 | 0.583 | 1.685 | 0.606 | 1.676 |
| ZhongYuan | 0.538 | 2.357 | 0.578 | 2.404 | 0.587 | 2.389 |
| JinMeng | 0.438 | 2.75 | 0.598 | 1.493 | 0.524 | 1.722 |
| JingJinJi | 0.651 | 1.626 | 0.642 | 1.859 | 0.669 | 1.611 |
| Shandong Peninsula | 0.545 | 2.294 | 0.546 | 2.433 | 0.528 | 2.457 |

Note: C = clustering coefficients; L = characteristic path length.

### *Coupling Analysis*

The differences between the real-world situation in 2015 and the simulation results in terms of land use efficiency cannot be investigated until further research is conducted. To understand the improved simulation results that incorporate the effect of the urban system while excluding other disturbing factors in more detail, this study examines the relationship between the land use efficiency of single cities (standardized) and the accessibility (by strength, calculated through UCINET) from the perspective of an urban system. Accessibility refers to the accessibility of one node, and can be used to determine whether a connection exists between two nodes in a binary matrix. Social networks have extended the concept of reachability to allow the fitting of various types of multivalued matrices (Scott and Carrington 2011). The gravity matrix in this study is multivalued with each element representing the connection strength between cities. The accessibility (by strength) performed on the gravity matrix can reflect the expected influence from the counterparts in the urban system for each city. The higher the accessibility (by strength) of the city, the stronger the potential system influence on it. This can be regarded as both a superior status for this city and a stronger connection with its counterparts within the urban system. Therefore, the coupling analysis aims to examine city land use efficiency and its relationship with its urban system.

## Results

### *Network Structure Analysis of Urban Network*

According to the double logarithmic scatter plot, the urban system in the study area can be divided into two scaling ranges. Overall, the primary city holds a monopolistic position. From 2005 to 2015, the Zipf dimension (Chen 2016) shows that the system has a development pattern that is dominated by cities in the middle of ranking. The urban system moves forward in a more organized and ordered direction (Fig. 4).

The visualized representation of the top five linkage networks in the three years is shown in Fig. 5. In general, it is assumed that the network is a scale-free network if the degree probability obeys the power law, and the power exponent of the distribution function is between 2 and 3 (Barabási and Albert 1999). However, the distribution of the degree in the study area does not conform to the characteristics of a scale-free network, although it does obey the power law. Moreover, we are unable to draw a conclusion by comparing the scaling factors in the three years that the study area is moving toward a scale-free network (Fig. 6).

The clustering coefficients and the characteristic path lengths of the top five linkage networks in the three years are shown in Table 1. Compared with a random network sharing the same size of nodes, linkages, and overall network density, the characteristic path length (L) increases with an increasing clustering coefficient (C). Comparing the changes over the three years, the compactness of the study area, depicted by the clustering coefficient, has improved overall, but the characteristic path length has not substantially changed, suggesting that the network in the study area does not conform to that of a small-world network. The key to the evolution of a small-world network is the existence of shortcuts, through which the path length can be significantly reduced while the clustering coefficient remains on a relatively high level (Watts and Strogatz 1998). However, according to the analysis results of this study, the network is growing more compact while the path length remains long. One reasonable explanation may be that the compactness occurs in members that are already connected by a short path. If that were true, then several subgroups must exist that are more compact than the average compactness of the entire system. The subgroups analysis results of this study will be displayed in the next section.

### *Clustering Analysis and Subarea Division*

Instead of using the top five linkage networks directly, the clustering analysis is conducted based on the original gravity matrix to avoid information loss and, thus, more accurate results are expected. The clustering analysis generates eight slightly different subgroups for the three studied years. A similar evaluation process is conducted on the eight subgroups for each year, and the results are listed in Table 2.

The results of the clustering analysis allow further division of the entire study area as the latter is too broad to attain a satisfactory simulation otherwise. Existing research shows that higher accuracy is achieved if the simulation is performed in separate subareas with dynamic transition rules (Li and Yeh 2004). In contrast, the administrative system in China has always utilized vertical management, and the central government has increasingly promoted integrated development in specific areas in recent years through the planning of national city clusters. Therefore, based on the result of the clustering analysis that considers the arrangement of city clusters and administrative division, the study area is divided into six subareas as shown in Fig. 7.

Because the division of subareas refers to the administrative units, it is necessary to verify whether the network for each subarea is still compact. Similar measures were taken for the eight subgroups in the clustering analysis as in the previous analysis (Table 3). Compared with the indices of the eight subgroups, the characteristic path lengths for the six subareas increased, with more than two subareas reaching a level over two in 2010 and 2015; however, a decreasing trend from 2005 to 2015 was also clear. Moreover, because the clustering coefficients for each subarea are higher than those of the averages for the entire area, it is safe to conclude that the current division can support further research.

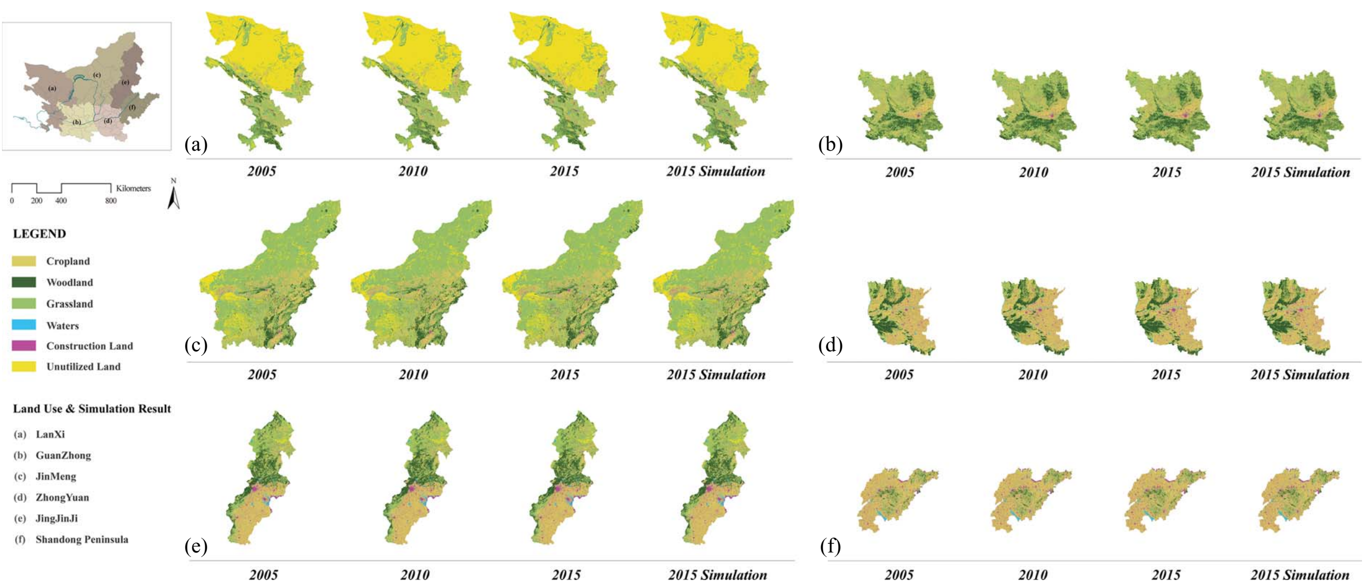



**Fig. 8.** Simulation results of the six subareas. (Map data courtesy of Geographic Data Sharing Infrastructure, College of Urban and Environmental Science, Peking University.)

**Table 4.** Accuracy and the regression coefficients for each variable

| Subarea | General Accuracy | Kappa | dtc | dtr | dtf | dtn | slope | RoP | LdR |
|---|---|---|---|---|---|---|---|---|---|
| LanXi | 98.85% | 0.981 | 0.379 | 2.429 | −5.14 | −5.14 | 1.322 | 127.258 | 122.762 |
| GuanZhong | 91.58% | 0.874 | 246.673 | 1.513 | 1.925 | 0.201 | −1.098 | 0.537 | −398.691 |
| JinMeng | 97.45% | 0.958 | 0.202 | 1.24 | −2.485 | −2.593 | 2.542 | −1,192.658 | −432.956 |
| ZhongYuan | 98.09% | 0.969 | 1.242 | −6.64 | 5.02 | −3.917 | −3.628 | −378.55 | −20.876 |
| JingJinJi | 99.27% | 0.99 | 3.747 | −2.914 | −2.877 | −3.209 | −5.894 | −55.086 | −39.761 |
| Shandong Peninsula | 98.72% | 0.975 | −1.163 | −0.322 | −9.398 | −1.548 | −18.078 | 43.159 | 2,406.476 |

Note: dtc = distance to city center; dtr = distance to railway; dtf = distance to freeway; dtn = distance to national road; RoP = Relations of Proximity; LdR = Long-distance Relations.





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### *Simulation Based on Subareas and Efficiency Calculation*

The real-world situation of land use in 2005, 2010, and 2015 for each subarea and the simulation results of logistic-CA can be seen in Fig. 8. The coefficients for each variable and several simulation accuracy indices are listed in Table 4. The differences between the simulation results and the real situation are mainly reflected in the *new town new area* planning. Hence, the simulation results keep the interactions between cities while ignoring the sporadic effect of *new town new area* planning.

Based on the simulation results, the rasters representing construction land were calculated by the city, and the subarea simulation results were integrated into a whole (Table 5). The land use efficiency for each city was then determined as the GDP (2015) divided by the area of construction land (2015 real-world and 2015 simulation). A further comparison between the simulation results and the real-world situation was conducted using a ratio (simulation/real-world). A ratio greater than one represents a higher land use efficiency in the simulation and a relatively worse performance in the real-world situation.



**Table 5.** Comparison of real economic land benefits and simulation results

| City | Real | S | Improved value | City | Real | S | Improved value |
|---|---|---|---|---|---|---|---|
| Wuhai | 2.073 | 2.345 | 1.131 | Gannan | 0.754 | 0.758 | 1.006 |
| Ordos | 2.784 | 3.543 | 1.273 | Dingxi | 0.712 | 0.552 | 0.776 |
| Bayan Nur | 0.567 | 0.449 | 0.792 | Linxia | 0.763 | 0.640 | 0.840 |
| Baotou | 3.352 | 3.404 | 1.016 | Xining | 3.236 | 2.714 | 0.839 |
| Hohhot | 2.545 | 2.475 | 0.973 | Haidong | 1.891 | 1.380 | 0.730 |
| Ulanqab | 0.487 | 0.441 | 0.907 | Jinchang | 1.125 | 1.035 | 0.919 |
| Datong | 1.975 | 1.756 | 0.889 | Alxa | 0.823 | 1.926 | 2.340 |
| Shuozhou | 2.228 | 2.034 | 0.913 | Wuwei | 1.034 | 1.058 | 1.023 |
| Xinzhou | 1.320 | 1.196 | 0.906 | Lanzhou | 3.592 | 4.215 | 1.173 |
| Yulin | 2.547 | 5.983 | 2.349 | Wuzhong | 0.421 | 0.518 | 1.232 |
| Taiyuan | 5.702 | 4.544 | 0.797 | Yinchuan | 4.639 | 3.908 | 0.842 |
| Lvliang | 2.431 | 2.435 | 1.002 | Shizuishan | 1.520 | 1.445 | 0.951 |
| Jinzhong | 2.327 | 2.031 | 0.873 | Zhangye | 0.889 | 0.756 | 0.851 |
| Yangquan | 3.001 | 2.745 | 0.915 | Longnan | 0.961 | 0.927 | 0.964 |
| Zhangjiakou | 0.582 | 0.446 | 0.766 | Tianshui | 1.204 | 1.198 | 0.995 |
| Xilinhot | 0.939 | 1.444 | 1.538 | Yanan | 4.713 | 5.509 | 1.169 |
| Handan | 2.215 | 2.225 | 1.005 | Qingyang | 1.348 | 1.221 | 0.906 |
| Xingtai | 1.471 | 1.472 | 1.001 | Guyuan | 0.695 | 0.684 | 0.983 |
| Shijiazhuang | 3.692 | 3.630 | 0.983 | Pingliang | 0.466 | 0.435 | 0.934 |
| Baoding | 1.501 | 1.469 | 0.979 | Baoji | 3.632 | 3.493 | 0.962 |
| Hengshui | 1.104 | 1.093 | 0.990 | Hanzhong | 3.435 | 3.399 | 0.990 |
| Cangzhou | 1.543 | 1.514 | 0.981 | Ankang | 8.857 | 8.229 | 0.929 |
| Langfang | 2.491 | 2.488 | 0.998 | Shangluo | 5.649 | 5.008 | 0.887 |
| Tianjin | 6.850 | 7.180 | 1.048 | Xian | 4.572 | 4.920 | 1.076 |
| Beijing | 7.963 | 8.009 | 1.006 | Weinan | 1.640 | 1.645 | 1.003 |
| Langfang | 2.491 | 2.488 | 0.998 | Tongchuan | 2.592 | 2.905 | 1.121 |
| Tangshan | 2.549 | 2.544 | 0.998 | Xianyang | 2.537 | 2.618 | 1.032 |
| Qinhuangdao | 2.465 | 2.459 | 0.998 | Jiyuan | 3.746 | 4.139 | 1.105 |
| Chengde | 0.886 | 0.892 | 1.006 | Xinyang | 1.230 | 1.178 | 0.958 |
| Chifeng | 1.074 | 1.074 | 1.000 | Zhumadian | 0.957 | 0.954 | 0.997 |
| Laiwu | 2.746 | 2.830 | 1.031 | Sanmenxia | 3.509 | 3.562 | 1.015 |
| Shangqiu | 0.850 | 0.893 | 1.051 | Yuncheng | 1.215 | 1.160 | 0.954 |
| Heze | 1.059 | 1.039 | 0.982 | Luoyang | 3.448 | 3.534 | 1.025 |
| Liaocheng | 1.651 | 1.646 | 0.997 | Pingdingshan | 1.770 | 1.829 | 1.034 |
| Dezhou | 1.509 | 1.509 | 1.000 | Luohe | 1.838 | 1.821 | 0.991 |
| Jining | 2.452 | 2.494 | 1.017 | Xuchang | 2.397 | 2.388 | 0.996 |
| Zaozhuang | 3.044 | 3.003 | 0.987 | Zhengzhou | 3.821 | 3.976 | 1.041 |
| Linyi | 2.001 | 1.963 | 0.981 | Jiaozuo | 2.684 | 2.627 | 0.979 |
| Rizhao | 3.436 | 3.445 | 1.003 | Jincheng | 4.099 | 3.911 | 0.954 |
| Qingdao | 5.488 | 5.416 | 0.987 | Changzhi | 2.706 | 2.754 | 1.018 |
| Weihai | 4.406 | 4.316 | 0.980 | Linfen | 0.000 | 0.000 | 0.000 |
| Yantai | 4.165 | 4.227 | 1.015 | Anyang | 1.718 | 1.739 | 1.012 |
| Weifang | 2.227 | 2.198 | 0.987 | Hebei | 2.093 | 2.346 | 1.121 |
| Zibo | 4.375 | 4.327 | 0.989 | Xinxiang | 1.483 | 1.484 | 1.001 |
| Taian | 3.025 | 3.043 | 1.006 | Kaifeng | 1.525 | 1.481 | 0.971 |
| Jinan | 4.894 | 4.970 | 1.015 | Zhoukou | 0.958 | 0.949 | 0.991 |
| Dongying | 3.419 | 3.333 | 0.975 | Puyang | 1.680 | 1.651 | 0.982 |
| Binzhou | 1.688 | 1.713 | 1.015 | Nanyang | 1.458 | 1.490 | 1.022 |

Note: Real = land use efficiency in 2015; S = land use efficiency in 2015 by simulation; improved value = the ratio of the simulation land use efficiency and that in the real-world situation for 2015.

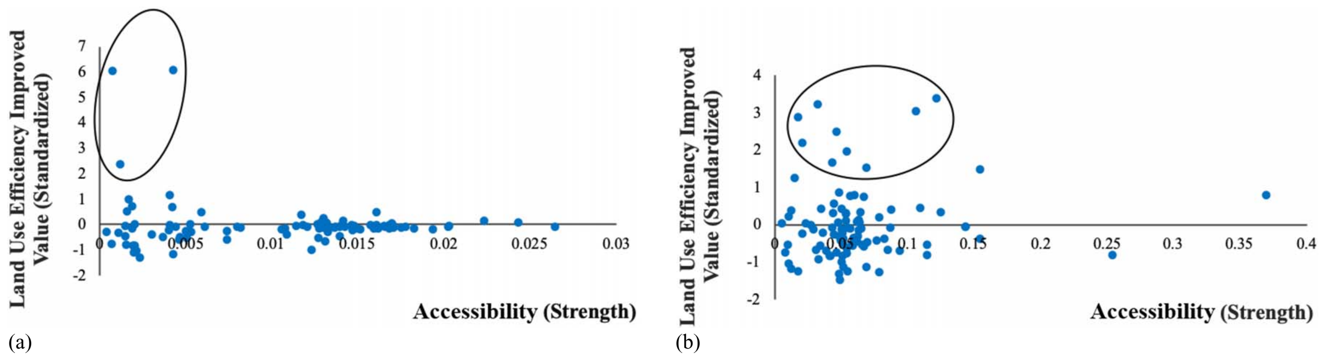


**Fig. 9.** Coupling analyses for the (a) improved value in the study area; and (b) improved value in the subarea.

### *Result of Coupling Analysis*

The improved value was defined as the ratio between the simulation land use efficiency and that in the real-world situation for 2015. The improved values of land use efficiency and the accessibility (by strength) are presented as scatter plots in Fig. 9.

In the overall study area scatterplot in Fig. 9, the vertical axis represents the standardized improved value of all cities, and the horizontal axis reflects the relative accessibility of cities. For the subareas, the same procedures, including the standardization of the improved value and the re-calculation of the accessibility (by strength) within each subarea, are performed. Therefore, cities with a positive improved value are distributed in the first quadrant, and the cities with negative improved values fall into the fourth quadrant.

It can be seen from the scatter plot that cities with improved values that are higher than normal demonstrate a lower accessibility (by strength) in the network, and the same scenario for the entire system as well as each subarea. This coupling result is even more significant when the scope is changed from subarea to the entire study area. For the overall study area, cities with a positive improved value include Ordos, Yulin, Alxa, and Xilinhot, and cities with a negative improved value include Bayan Nur, Dingxi, Haidong, Taiyuan, and Zhangjiakou. For the subareas, the cities with a positive improved value include Tongchuan, Hebei, Shangqiu, Yulin, Laiwu, Xi'an, Tianjin, Jiyuan, Alxa, and Xilinhot, and cities with a negative improved value include Qingyang, Yuncheng, Jincheng, Kaifeng, Yangquan, Baoding, Cangzhou, Dongying, Shijiazhuang, and Shangluo.

## Conclusion

This study attempted to tackle the shrinking phenomenon from the regional perspective. The investigation of the urban system first revealed that when considering the influence that the network has on individual cities, proximity may play a more important role geographically, at least in the area along the Yellow River.

The coupling analysis that is based on the network analysis and land use simulation found that cities with lower land use efficiencies feature in relatively lower accessibility (by strength). These cities include Ordos, Yulin, Alxa, and Xilinhot, all of which are typical shrinking cities. Accessibility (by strength) evaluates the relative connection for every city in the entire system. Cities with lower accessibility (by strength) are expected develop less economically compared with other cities in the same system. These results support the shrinking phenomenon in China, and the mismatch between the development potential of and the resources or development rights may play an important role in the shrinkage of some cities in China.

## Discussion

### *The Urban System within Study Area*

This study focused on the cities along the Yellow River. Although the study covered a vast area, the study area is part of China. The indices revealing the characteristics of the urban system structure led to inconsistent conclusions between the study area and China as a whole (Wu et al. 2015). One possible explanation may be the mismatch between the selected research boundary and the real-world situation of the network system because mega-cities such as Beijing were included, whose impact spreads over a wider area. Further evidence is required to find a resolution.

Despite the deviations in the network boundary, the investigation of subgroups provided additional research insights. The characteristic path length of the urban network in the study area, as shown in Table 1, denotes that the overall system increased in compactness; however, this trend primarily took place within smaller subgroups. In the real-world situation where factor flows represent the connection between the cities, frequent and strong connections tend to occur between places in geographic proximity.

### *Shrinking and Expanding in Network*

Urban systems are bottom-up and self-organizing (Batty 2009), and research only focusing on the macrostructure cannot measure and analyze the degree to which one single city can be influenced. Network analyses, actor framework, and relational networks enable researchers to understand the system characteristics while simultaneously investigating. In contrast, the spatial relations between cities can be divided into long-distanced relations and relations of proximity (Dematteis 1997), which is helpful when addressing a vast and dynamic area.

The coupling analysis containing the improved simulation that corporates spatial relation into the variables reveal that the cities with lower land use efficiencies also exhibit lower accessibility (by strength) in the urban system. Accessibility (by strength) evaluates the connection status for each city in the entire system. Cities with lower accessibility (by strength) are expected to potentially be less influenced, and influences in the real-world situation are represented as element flows like labor, capital, information, and technology. Hence, the lower accessibility (by strength) indicates lower potential for economic development compared with other cities in the same urban system. Without delving into the system and investigating the relationships between cities, it is difficult to understand the structure and mechanisms behind the system for all the parties involved, including the decision-makers.

Therefore, the development rights (land, infrastructure investment, capital, etc.) granted by the government, which is common in China, do not always match the development potential which can be measured by accessibility (by strength). This mismatch between developmental rights and the development potential leads to the wasting of resources, insufficient development motivation, and shrinkage.

Some cities in this study are superior in terms of land use efficiency, including Bayan Nur, Dingxi, Haidong, Taiyuan, and Zhangjiakou when analyzing the entire area. However, the coupling analysis fails to attribute their higher land use efficiencies to higher accessibility (by strength). One possible explanation may be that the physical environment limits the disorderliness, but how relationships with other cities can exert influence remains unclear. Future investigations focusing on these cities may help us to better understand the underlying mechanisms.

### *Prescriptions for Regional Planning*

Therefore, combining a land use simulation that incorporates spatial relations and a coupling analysis that bridges the urban system and individual cities has led to profound insights beyond a general understanding of the urban system. By explaining the shrinking phenomenon in China from a regional perspective, our research provides several potential implications for regional planning.

Network analyses assist in identifying city cluster spaces, especially when determining whether cities that are not geographically near are closely related. Additionally, because the formulation of regional policies and distribution of development rights can no longer be based on intercity "games" (although this was a previously normal planning practice in in China), the employment of simulation tools and measurements based on different scenarios can help planners and policy makers to better understand developmental trends in terms of their connections to cities and the entire area. Finally, investigating how different socioeconomic factors and policies can exert influence on cities and the urban system they belong to is a useful topic for further research.

All these questions should be paid attention to when planning for regions, and cities, and management systems. There are still some issues when focusing on the differences between subareas, specifically, how the effect of spatial relations can vary between locations, which should be more comprehensively tackled in future research. From this perspective, an even more detailed investigation on the planning and administration systems of Chinese cities is recommended in addition to conduction studies on revolution and innovation related to the Chinese administrative system.

## Data Availability Statement

The data include: Chinese land use remote sensing data (100 m × 100 m) from the Resource and Environment Data Cloud Platform of the Institute of Geography, Chinese Academy of Sciences; Chinese road network data from the Peking University Geographic Data Platform; Chinese altitude spatial distribution data (DEM 500 m × 500 m) from the Resource and Environment Data Cloud Platform of the Institute of Geography, Chinese Academy of Sciences; and prefectural socioeconomic data in 2005, 2010, and 2015 from the provincial statistical yearbook.

Some or all data, models, or code generated or used during the study are available from the corresponding author by request (list items).

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