

## Article

# Modeling the Collaborative Evolution of Urban Land Considering Urban Interactions under Intermediate Intervention, in the Urban Agglomeration in the Middle Reaches of the Yangtze River in China

Chun Li <sup>1</sup>, Jianhua He <sup>2</sup> and Xingwu Duan <sup>1,\*</sup>

<sup>1</sup> Institute of International Rivers and Eco-Security, Yunnan University, Kunming 650500, China; lichun@ynu.edu.cn

<sup>2</sup> School of Resources and Environment Science, Wuhan University, Wuhan 430079, China; hjianh@whu.edu.cn

\* Correspondence: xwduan@ynu.edu.cn

Received: 9 May 2020; Accepted: 28 May 2020; Published: 3 June 2020



**Abstract:** As the dominant area in regional competitions, the urban agglomeration has experienced a dramatic urban land evolution, which has had a significant impact on regional socio-economic development and ecological environment. Conventional simulation models mainly explore the dynamic change of urban land based on the situation of a single city. The urban interactions, which linked separate cities into an organic urban agglomeration area, have not been sufficiently concerned, especially the urban interaction in the context of intermediate intervention. In this paper, we employ the radiation model to measure the urban interaction under intermediate intervention, and further spatially explicitly express the spatial network and influence of such an interaction. A simulation model coupling improved urban interaction is proposed to model the collaborative evolution of urban land in urban agglomeration by considering the influence of improved urban interactions into the basic framework of the cellular automata model. Taking the urban agglomeration in the middle reaches of the Yangtze River in China as a case study, the validity and suitability of the model are evaluated. The results show that, the proposed simulation model exhibits better performance in capturing the networked evolution of urban land. Considering urban interactions under intermediate intervention is necessary for modeling the collaborative evolution of urban land in urban agglomeration areas. The distribution of the urban interaction's influence can be a beneficial reference for guiding the optimal allocation of urban land in a networked way.

**Keywords:** urban interaction; intermediate intervention; urban land evolution; urban agglomeration

## 1. Introduction

Urban land is a significant spatial carrier for human production and living activities. In the process of rapid urbanization, the dramatic quantity growth and spatial expansion of urban land can be observed and has had a profound impact on regional socio-economic development and the ecological environment [1–3]. On the one hand, disordered expansion of urban land triggers the non-intensive use of land resources and promotes the decline of land-use efficiency [4–6]. On the other hand, the loss of cropland, grassland, forest, etc., that results from urban expansion, poses a threat to sustaining food production and maintaining the sustainability of the ecological environment [7–9]. Notably, for urban agglomeration, the new spatial unit participating in global competitions, the dynamic change of urban land in these areas not only impacts their developing pattern, but also influences the improvement of regional competitive power. Furthermore, more rapid urbanization and a more striking evolution of urban land have been widely observed in urban agglomeration areas [10]. Exploring evolution rules

of urban land, as well as identifying and simulating the urban evolution process in these areas are the effective way to analyze the developing trend of urban land, which are vital contents for guiding the optimal allocation of urban land in the future and supporting the sustainable development of the regions.

Urban land evolution is a complex process driven by diverse forces from a natural environment, anthropogenic movement, etc. Adopting simulation models to explore urban evolution is a wide-used and valid approach. The simulation of urban land evolution mainly relies on four types of models. The first type is the empirical-statistical model. This type of model employs regression models, difference equations, differential equations, etc. to describe the related patterns among diverse driving factors and urban land evolution, such as the logistic regression model [11,12], structural equation modeling [13], ordinary least squares regression model [14,15], etc. However, adopting a simple equation is not sufficient to depict the complex urban system, which limits the application of these models. Furthermore, these models explore urban evolution in a quantitative way, and the spatial characteristic of urban evolution cannot be captured. The second type is the model based on system behaviors. Through analysis of the feedback mechanism among urban land evolution and driving factors, these models build a sequence of differential equations to integrally delineate the urban evolution process, herein, the system dynamics (SD) model is the most representative one [16–18]. These models focus on the long-term, dynamic, and comprehensive change of the urban system to analyze urban evolution to better explain the complex and nonlinear issues of urban systems. However, they still focus on the quantity change of urban evolution and have a poor ability to express urban spatial features. The third type is the model based on the discrete stochastic process. Time and space are viewed as discrete in this type of model. These models simulate the evolution of urban space following a bottom-up dynamic mechanism through the exploration of micro-individual interactions. In this type of model, urban space can be expressed from a spatiotemporal dynamic perspective, which covers the shortage of conventional models in a spatially explicit expression of urban evolution, with the cellular automata model (CA) [19], multi-agent system (MAS) [20], etc. as being representative. The two-dimensional lattice of CA, which is similar to a geographical raster grid, makes CA well-suited to represent the geographical process of urban spatial evolution and can be viewed as one of the most powerful tools in relevant researches [21–24]. The models that focus on the transition rules of micro individual cells, however, cannot well address the influence derived from macro-level socio-economic forces. In order to better identify the evolution process of urban space and improve upon current models, the fourth type of model-hybrid models, were developed. For example, the combination of econometric model or SD model with the CA model realizes the integration of quantity change and spatial evolution of urban space [25–27]; the combination of the field model and CA model takes both macro and micro influence into consideration [28]; the combination of distinct artificial intelligence algorithm with CA improves the simulation accuracy when modeling urban dynamic change, e.g., the neural network-CA, ant colony algorithm-CA, decision tree-CA, etc. [29–32]. Hybrid models offer a better inability to simulate urban spatial evolution and have been widely used in guiding the optimal allocation of urban land for implementing the efficient and sustainable development of urban areas.

Urban agglomeration is the region with the closest intra interactions, where frequent flowing of urban elements can be observed, including the flow of people, materials, information, capital, etc. Under such a rapid element flow, the predominant pattern of urban spatial evolution has transformed from a static “Space of Place” pattern into a dynamic “Space of Flow” pattern [33,34]. The dynamic, flowing, and multi-center reconstruction of urban space is increasingly more prominent in these urban agglomeration areas [35,36]. However, the influence of urban interactions stimulated by such flow has not been well considered in the simulation of urban land evolution in urban agglomerations. Some studies have partially concerned such influence. However, they often measured urban interactions based on regional complementarity and accessibility, such as developing a simulation of urban land considering the interaction measured by the field model [28] or gravity

model [37]. According to the theory of spatial interaction, there are three preconditions for the emergence of urban interactions: Complementarity, intervening opportunity, and transferability [38,39]. Neglecting to consider the intermediate interference may halt the accurate identification of urban interactions and create some obstacles in modeling the urban spatial collaborative evolution impacted by urban interaction.

In this paper, we adopt the radiation model [39] to identify urban interactions under intermediate interference. The traffic network and land cover type are considered to improve the ability of the radiation model to measure improved urban interactions. Then, a simulation model coupling improved urban interaction is proposed to model the collaborative evolution of urban land in urban agglomeration areas by embedding the interference-considered urban interaction into the transition rule system of the conventional CA model. Two major hypotheses are embedded in the proposed model: (1) Urban land evolution in the urban agglomeration area not only depends on a self-organizing mechanism, but also on the influence of urban interactions which are derived from the external areas; (2) the consideration of urban interaction regrading intermediate intervention is necessary in identifying the collaborative evolution trend of urban land. Taking urban agglomeration in the middle reaches of the Yangtze River (MYR-UA) in China as a case study, we conduct the implementation, calibration, evaluation, and discussion of the proposed model, the validity of the proposed model, and the necessity of integrating urban interaction under intermediate intervention into urban land simulation have been explored. The rest of this paper is organized in the following manner. Section 2 introduces the study area and the employed data. In Section 3, the construction of the proposed model is illustrated. Section 4 reports the results of the urban interaction exploration and dynamic modeling of urban land in MYR-UA. In Section 5, a further discussion based on the results in the study area is conducted. Lastly, we conclude this paper in Section 6.

## 2. Materials

### 2.1. Study Area

Urban agglomeration in the middle reaches of the Yangtze River (MYR-UA) is the large-scale city group coupled by the Wuhan urban agglomeration, the Chang-Zhu-Tan urban agglomeration, the Poyang Lake eco-economic zone, and their surrounding cities [40], with latitudes of 25°59' to 32°38' N and longitudes of 110°15' to 118°32' E, as shown in Figure 1. There are 31 cities located in the MYR-UA, that are separate from Hubei, Hunan, and Jiangxi province. The agglomeration covers a total area of 0.31 million km<sup>2</sup>, accounting for 3.3% of the total area in China. It is also the most populous and developed area in the middle reaches of the Yangtze River. In 2015, the permanent resident population in the MYR-UA was 128 million, accounting for 9.36% of China's total population. The gross domestic product, fixed investments, and total retail sales of consumer goods in the MYR-UA reached 6.65, 5.87, and 2.67 trillion Yuan, respectively, accounting for 9.77%, 10.37%, and 8.87% of the totals in China [41]. Research on the MYR-UA can be a support for guiding the development of this critical urban area in China.

Moreover, the MYR-UA has experienced a dramatic evolution of its urban land. From 2005 to 2015, the area's urban land increased by 61.28%, with an annual increase of 4.90%. The urban land in the Wuhan urban agglomeration has increased by 70.46%, and that of Chang-Zhu-Tan urban agglomerations and the Poyang Lake eco-economic zone, respectively, increased by 70.46% and 92.29% [42]. Furthermore, the MYR-UA has higher accessibility under the support of its widely distributed traffic infrastructure, which creates frequent element flows and urban interactions. The mileage of the railway open to traffic spans 5440 km, and that of the highway spans 346,000 km [40]. The exploration of the MYR-UA provides a good reference for other areas with similar features of dramatic urban land evolution and frequent urban interactions.

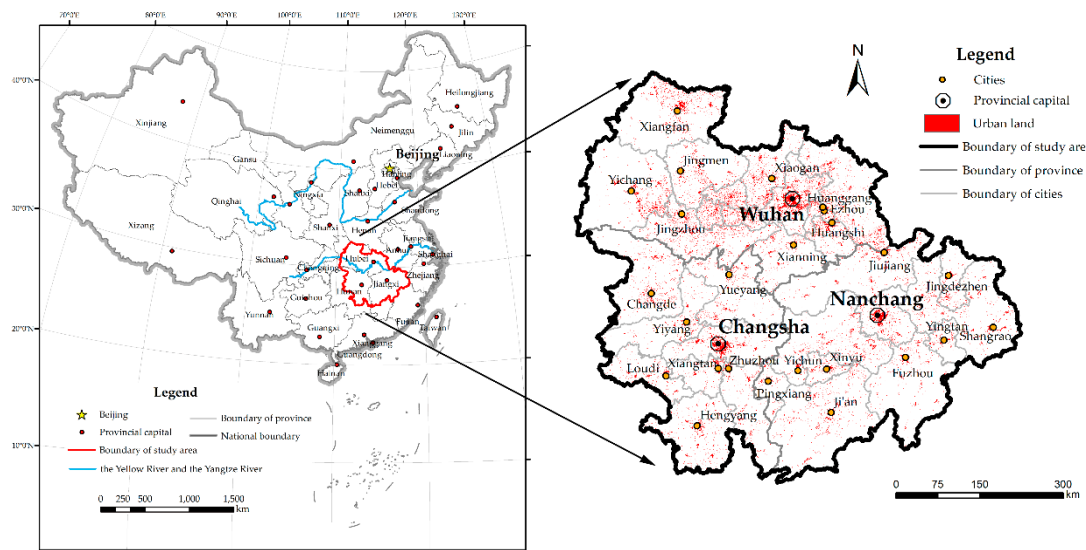


Figure 1. Location of the study area.

## 2.2. Data and Processing

The data used in this paper mainly include land use data, basic geographical information, traffic network data, point of interest data, population data, and a digital elevation model. There into, land use data were derived from the National Land-Use/Cover Database of China (NLUD-C), which has a spatial resolution of 30 m and was produced based on high-quality Landsat 7 ETM+ images and China-Brazil Earth Resource satellite image data [43]. Visual interpretations, geometric corrections, field surveys, and large amounts of auxiliary information were applied during the data-production and updating process. A random sampling of the whole nation confirmed the classification accuracy of NLUD-C to be greater than 90% [44], which demonstrates the accuracy and credibility of this database. Basic farmland, which is protected by national policy and cannot be transformed into urban land, was taken from the dataset of the second land survey of Hubei, Hunan, and Jiangxi province. Basic geographical information was obtained from the National Geomatic Center of China, including the administrative boundaries, the distribution of urban center, the county center, the development zone, etc. The traffic network information was acquired from the transportation network database of Hubei, Hunan, and Jiangxi province, including the distribution of railways, expressways, national roads, provincial roads, town roads, etc. The point of interest was derived from the Gaode open street map [45], which was obtained by the Python-based cyber crawler technology. The population migration data and population density data were collected from the regional statistical bureaus of each city in MYR-UA. The digital elevation model was obtained from the data platform of the Geospatial Data Cloud [46]. The spatial analysis function in ArcGIS 10.2 (Environmental Systems Research Institute, Redlands, USA) was used to obtain the elevation and slope of the region.

## 3. Method

To construct the simulation model and explore the influence of urban interaction considering intermediate intervening for dynamic change of urban land, three issues should be concerned: First, how to quantify the improved urban interaction considering intermediate intervening; second, how to implement the spatial expression of improved urban interaction influence; third, how to combine such influence into the dynamic simulation of urban land evolution. For the first issue, taking the distribution of traffic infrastructure and land-use type into consideration, the radiation model, which measures urban interaction following the principle of complementarity, intervening opportunity, and transferability, has been improved to quantify the urban interaction; for the second issue, the measuring approach of urban interaction, which is based on the field theory, has been



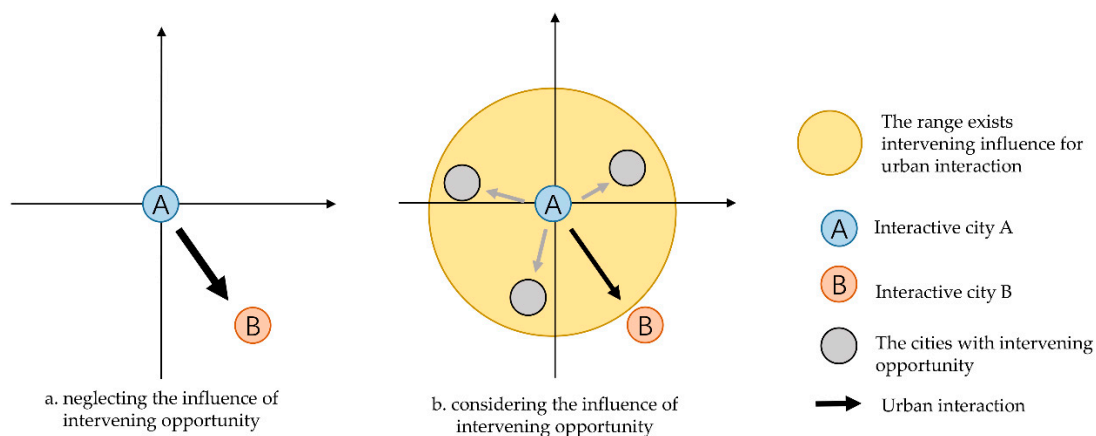
employed to depict the influence of urban interaction in a spatially explicit way; for the third issue, based on the basic framework of the CA model, we introduce the improved urban interaction as a part of CA's transition rules system, adopt the decision-tree learning to excavate the transition rule of urban land, and finally construct the simulation model coupling improved urban interaction.

### 3.1. Improvement of the Radiation Model for Identifying Urban Interaction

The radiation model is a parameter-free model that considers the influence of intervening opportunity in the process of urban interaction in a two-dimensional geographical space [39]. The deficiencies of considering a simple unidimensional distance in the interaction model can be rectified by the radiation model. The intervening interaction opportunities are quantified in the radiation model by measuring the impact produced from the intervening space—a circular area that uses the original city as its center and the influence distance as its radius. Conventionally, the population in the intervening space has been viewed as the key indicator to express potential intervening opportunities [47]. The framework of this model is shown in Figure 2, and the basic formula of the radiation model is included as Equation (1).

$$T_{ij} = T_i \frac{m_i n_j}{(m_i + s_{ij})(m_i + n_j + s_{ij})} \quad (1)$$

where  $T_{ij}$  is the average flux derived from location  $i$  to location  $j$ ;  $m_i$  and  $n_i$  are the total population of location  $i$  and location  $j$ ; setting  $r_{ij}$  is the interaction distance between  $i$  and  $j$ ,  $s_{ij}$  is the total population located in the circular area with original location  $i$  as the center and  $r_{ij}$  as the radius (excluding the population in location  $i$  and  $j$ ); and  $T_i$  is the number of commuters from location  $i$ .



**Figure 2.** Expression of urban interactions without and with intervention.

In this paper, we consider the influence of the traffic network and basic land cover to improve the delimiting of intervening space. First, based on the land use condition and distribution of the traffic network, we measured the time-cost raster of regional accessibility. The required time to travel 1 km is set as the time cost. According to the mileage of different levels of traffic infrastructure (as shown in Table 1), the elapsed time of different traffic modes and land cover was calculated and the time-cost raster was finally acquired.

Second, by calculating the cost-weight distance in ArcGIS 10.2, the least path distance between cities was obtained to quantify the interaction distance  $r_{ij}$ . Taking the objective city as the center, the least path distance between the original city and the terminated city as the limitation, the time-cost raster was used to support the measurement of intervening space, which is an irregular polygon regarding spatial heterogeneity in geographical space. Adopting the basic framework of the radiation model, urban interaction can be better identified under a more appropriate division of the interaction intervening space.

**Table 1.** The speed of different means of transports and land-cover (km/h).

Type	Speed	Type	Speed	Type	Speed
High-speed train	250	National road	80	County road	15
Railway	90	Provincial road	60	Land	5
Expressway	120	Town road	30	Water	1

Note: The definition of speed based on the Technical Standard of Highway Engineering (JTGB01-2019) and Code for Design of High Speed Railway (TB10621-2014) of China.

### 3.2. Measurement of Urban Interaction Influence

#### 3.2.1. Construction of the Interaction Network

Along with the rise of a city network, the networked analytical paradigm has been widely used in urban interaction researches. This paradigm offers a new and alternative technical perspective for quantitatively evaluating the structure and behavior of an intricate urban system [48,49]. In this paper, we constructed a spatial network of urban interaction (UIn) to help explore the influence of urban interactions. Taking cities as the nodes, urban interactions as the links, interaction quantity as the weight of links, the UIn was built under the support of the improved radiation model. In order to eliminate the negative influence from spurious and statistically insignificant links for the analysis and visualization of the urban interaction network, we adopted the global threshold method to extract the major structure of UIn under the no harm principle for urban network connectivity. The social network analysis (SNA) was employed to analyze the UIn. The degree centrality, which is one of the most significant SNA indicators that depicts the impact of network nodes [50], was adopted to demonstrate the urban interaction influence from a directed-network perspective. The formulae of degree centrality are expressed as:

$$C_{RD\_in}(k) = \sum N_k \quad (2)$$

$$C_{RD\_out}(k) = \sum M_k \quad (3)$$

$$C'_{RD}(k) = (C_{RD\_in} + C_{RD\_out}) / (2n - 2) \quad (4)$$

where  $C_{RD\_in}(k)$  is the in-degree centrality of city  $k$ ,  $N_k$  is the number of interaction links inflowing to city  $k$ ,  $C_{RD\_out}(k)$  is the out-degree centrality of city  $k$ ,  $M_k$  is the number of interaction links outflowing from city  $k$ ,  $C'_{RD}(k)$  is the degree-centrality of city  $k$ , and  $n$  is the number of total cities.

#### 3.2.2. The Spatially Explicit Expression of Interaction Influence

In order to better address the influence of urban interaction on urban spatial evolution, we adopted the spatially explicit approach of interaction [35] to implement the spatial expression of urban interaction influence. Based on field theory, geographical space was abstracted as a geographical field in this approach. The influence of urban interaction can be expressed as:

$$U_{(k,i)} = \frac{P_k \cdot \lambda_k}{L^a_{(k,i)}} \quad (5)$$

where  $U_{(k,i)}$  is the interaction influence derived from city  $k$  resulting at point  $i$ ;  $P_k$  is the field potential of city  $k$ , defined by its degree centrality, which quantifies the impact of cities from a networked perspective;  $\lambda_k$  is the impact weight of city  $k$ ; and  $L^a_{(k,i)}$  is the distance between city  $k$  and point  $i$ , which is the cost-weight distance calculated based on the time-cost raster of the region.

### 3.3. Construction of the Simulation Model Coupling Improved Urban Interaction for Urban Land Evolution Dynamic

#### 3.3.1. Composite Function of Transition Probability

Urban land change is an intricate process driven by diverse factors simultaneously. In this paper, based on the framework of cellular automata, we constructed the simulation model coupling improved urban interaction for urban land evolution dynamics regarding the influence of urban interaction, which is measured under the impact of intermediate intervention. The driving forces of urban land evolution in this model are divided into three parts: Neighborhood interactions, the suitability and accessibility of regional cells, and the interaction influences. These three parts jointly impact the evolution of urban land in the macro and micro dimension. By assessing the comprehensive transition probability of each regional cell, the evolution rules of urban land can be explored. The composite function of the transition probability for a regional cell in this model can be expressed as:

$$P(i) = \prod_{n=1}^3 P_n(i) = f(\Omega, s, a, ui) \quad (6)$$

where  $P(i)$  is the composite probability of converting unit  $i$  into urban land, which is composed of three parts:  $P_1$ , is the transition probability derived from the impact of neighborhood interactions ( $\Omega$ );  $P_2$  is the transition probability derived from suitability ( $S$ ) and accessibility ( $A$ ); and  $P_3$  is the transition probability derived from urban interaction influence ( $ui$ ).  $f$  is the learning function of transition rules. The formulae of  $P_1$ ,  $P_2$ , and  $P_3$  can be expressed as:

$$P_1(i) = \frac{\sum_{3 \times 3} con(S_i = urban)}{3 \times 3 - 1} \quad (7)$$

where  $con(S_i = urban)$  is the condition function. When the specific cell is urban, the value is equal to 1, otherwise, the value is equal to 0; the Moore's neighborhood ( $3 \times 3$ ) was employed in this model to depict the transition influence from the cell's neighborhood.

$$P_2(i) = f(s_i, a_i) \quad (8)$$

where  $s_i$  is the suitability of transferring cell  $i$  into urban land, which is defined by the natural and socio-economic conditions of cell  $i$ ; and  $a_i$  is the accessibility of cell  $i$ , which is measured based on the distribution pattern of the traffic infrastructure, urban center, sub-center, etc.

$$P_3(i) = f(U_{(i)}) = f\left(\sum_{k=1}^n U_{(k,i)}\right) \quad (9)$$

where  $U_{(i)}$  is the total interaction influence received by cell  $i$ . According to the cumulative effect of urban interactions, the total impact of urban interaction on cell  $i$  is obtained through the superposition of all spatial interaction influences derived from diverse cities on cell  $i$ . The other notations take the same definitions used in Equation (5).

#### 3.3.2. Learning of Transition Rule of Urban Land Evolution

In this model, we employed a decision-tree learning to excavate the transition rule of urban land evolution and construct the function  $f$  in the composite function of urban land transition (Equation (6)). Decision-tree learning can automatically determine the threshold values and create a knowledge base from observational data to explicitly identify the retrieved rules of urban evolution [51]. This is the most efficient form of inductive learning and has been considered competent for exploring the transition rule of urban land evolution [52,53]. According to the maximum information gain ratio principle, the training data set is recursively and continuously split to ensure the gain ratio reaches its

maximum. A series of threshold values with the greatest gain ratio values is selected at each node to help form the decision tree and excavate the explicit transition rules of urban land. A more detailed introduction to this method can be found in [53].

### 3.3.3. Indexes for Model Evaluation

The fuzzy kappa index was used to evaluate the preformation of the proposed simulation model at a cell scale. Fuzzy kappa is considered an effective index for the assessment of model accuracy [54]. Compared to the initial kappa index, the slight displacement of a simulated land-use type compared to the observed map was accepted and classified as correct in the fuzzy kappa index, which makes the fuzzy kappa more credible for the evaluation of model precision.

In order to better explore the need to consider urban interactions under intermediate intervention in the simulation of urban land evolution, the area-weighted mean expansion index (AWMEI) was used to conduct a comparison from the perspective of landscape expansion pattern. The AWMEI is a variant of landscape expansion index (LEI), which is the index that characterizes the changing patterns of urban growth. Through the consideration of the weight of area for each new patch, the AWMEI can be measured by coupling the location and area of the expanded urban patch [55].

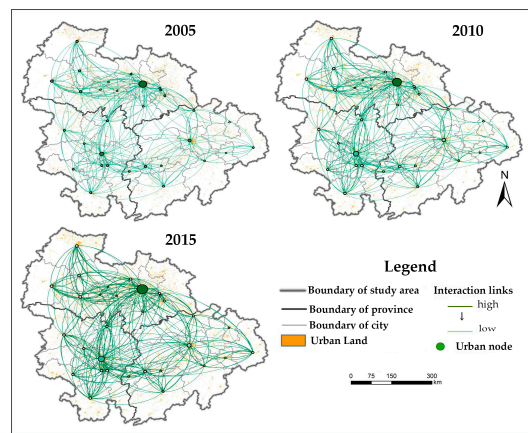
## 4. Results

### 4.1. Interaction Network in the MYR-UA

Based on the results of the improved radiation model, urban interaction between cities can be measured. Through the introduction of a social network analysis, the urban interaction networks of MYR-UA in 2005, 2010, and 2015 were built to explicitly express urban interactions and help evaluate the urban interaction influence, as shown in Figure 3. A networked pattern of urban interaction clearly appears in the MYR-UA. Accompanied by the growth of urban land, the spatial interaction between cities have been reinforced and the networked pattern has become more complex. The degree centrality of each city was calculated with the UCINET software (Analytic Technologies, Lexington, KY, USA), as shown in Table 2. During 2005 to 2015, the cities with increased degree centrality accounted for 93.33% of the total, while the rest presented unaltered degree centrality. An obvious increase in urban connectivity and interaction influence is shown here.

**Table 2.** Degree centrality of each city in the MYR-UA.

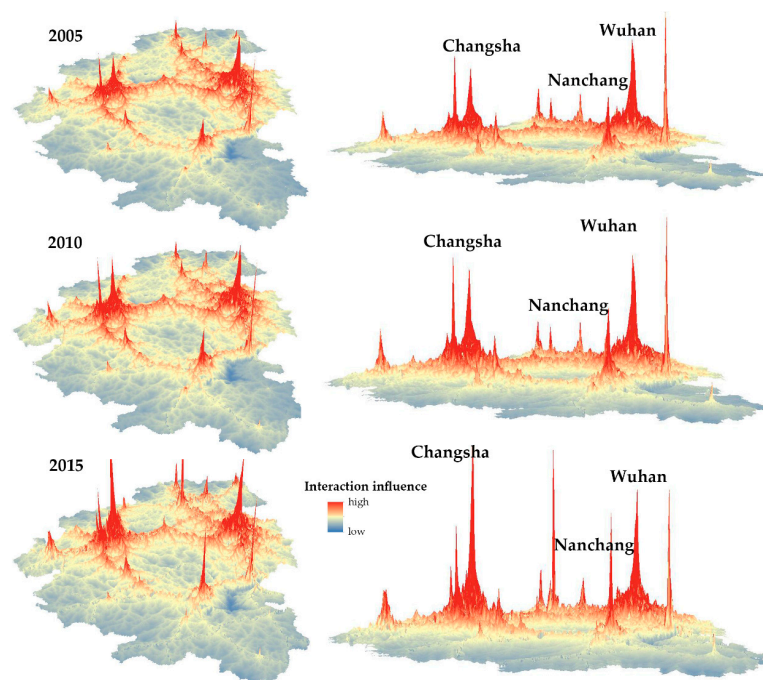
City	2005	2010	2015	City	2005	2010	2015
Wuhan	0.72	0.72	0.75	Loudi	0.2	0.25	0.28
Changsha	0.48	0.6	0.7	Shangrao	0.18	0.25	0.28
Nanchang	0.37	0.45	0.5	Ji'an	0.27	0.28	0.28
Yueyang	0.35	0.45	0.48	Xianning	0.18	0.18	0.25
Yichun	0.38	0.42	0.47	Fuzhou	0.22	0.25	0.25
Xiaogan	0.27	0.35	0.45	Huangshi	0.2	0.2	0.23
Jingzhou	0.38	0.38	0.43	Pingxiang	0.22	0.22	0.23
Hengyang	0.32	0.37	0.4	Xiantao	0.22	0.2	0.22
Zhuzhou	0.35	0.37	0.38	Qianjiang	0.18	0.18	0.22
Huanggang	0.33	0.35	0.37	Tianmen	0.2	0.22	0.22
Changde	0.28	0.35	0.37	Jingmen	0.18	0.22	0.22
Xiangfan	0.25	0.3	0.33	Ezhou	0.12	0.12	0.15
Xiangtan	0.28	0.33	0.33	Xinyu	0.13	0.13	0.13
Yiyang	0.23	0.28	0.33	Jingdezhen	0.08	0.12	0.12
Jiujiang	0.27	0.28	0.33	Yingtan	0.08	0.08	0.08
Yichang	0.27	0.27	0.3				



**Figure 3.** Interaction network in the urban agglomeration in the middle reaches of the Yangtze river in China.

#### 4.2. Interaction Influence in the MYR-UA

With the help of a spatially explicit approach of interaction, the interaction influence from each urban node to the peripheral areas was measured. By overlaying the interaction influence, the total interaction field was finally obtained as shown in Figure 4. There are three interaction peaks in the MYR-UA located in the surrounding area of Wuhan, Changsha, and Nanchang. The Wuhan-surrounding area has the highest interaction influence and the widest high-interaction influence areas, while a moderate interaction influence and high-interaction cover area can be observed in the Changsha-surrounding area. Among the three key areas of the MYR-UA, Nanchang-surrounding area has the lowest interaction influence and the narrowest cover area with a high-interaction. The interaction influence mainly derives from the core city-Nanchang. The influence of Nanchang has not increased the interactions in peripheral areas. From 2005 to 2015, the interaction influence in the study area presented a reinforced trend. The interaction influence in the three key areas of the MYR-UA all increased, but the radiation area showed non-significant expansion.



**Figure 4.** Interaction influence in the urban agglomeration in the middle reaches of the Yangtze river in China.



### 4.3. Simulation of Urban Land Evolution from 2005 to 2015

#### 4.3.1. Model Implementation

The urban landscape in 2005 was set as the initial condition for the model simulation, and that in 2015 was set as the terminal condition. Considering the high cost of transforming urban land into other land, we set that such change only happens in the process of converting other land into urban land. The ecological reservation area and basic farmland were set as the constraints in the modeling. Based on the review of relevant researches and the survey of regional actuality, a sequence of driving factors was selected, including the distance to development zone, the density of commercial residence, the interaction influence, the distance to downtown, the distance to county center, the density of population, the distance to railway station, the distance to expressway, the distance to national road, the distance to provincial road, the distance to town road, the elevation, and the slope. The change of each cell is judged by the transition rules set in Equation (6). Using the ArcGIS 10.2 and See 5.0 systems, a decision tree of urban land evolution was built, and the CA iteration algorithm was implemented.

#### 4.3.2. Model Calibration

Before applying the proposed model to simulate urban land evolution in urban agglomeration areas, the model parameters need to be calibrated. To ensure the efficiency and precision of rules learning, we randomly sampled the initial data and chose 20% of the samples to excavate the conversion rule. Simultaneously, the default value of 25% provided by the See 5.0 system, which aims to avoid the over-fit effect stimulated due to an overly complex decision tree model, was employed to simplify the decision tree and determine the final one. Through the training of massive samples, model precision of the training dataset reached 82.62%, and that of the validation dataset has arrived 90.40%. Adopting the decision tree to identify the conversion rules of urban land evolution can realize the self-correction of model parameters, which is better than the conventional statistic model-based exploration. Parts of the obtained conversion rule are displayed as follows:

Rule 1:

IF population density < 1785.5, elevation > 40.5, slope  $\leq$  0.159, distance to national road > 36,109.21, interaction influence > 37.73

THEN Urban land development is allowed [ $p$ :0.91]

Rule 2:

IF population density > 1785.5, interaction influence > 23.68, distance to railway station  $\leq$  67,043.828125, slope  $\leq$  0.159, distance to provincial road  $\leq$  250

THEN Urban land development is allowed [ $p$ :0.87]

Rule 3:

IF population density > 1785.5, density of commercial residence > 4.618, distance to expressway  $\leq$  17,251.81, distance to provincial road > 4286.58, distance to county center  $\leq$  2524.75, interaction influence > 81.70

THEN Urban land development is allowed [ $p$ :0.90]

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#### 4.3.3. Model Evaluation and Simulation Results

Employing the map comparison kit 3.2.3 software (Netherlands Environmental Assessment Agency, Hague, The Netherlands), we conducted a comparison between the simulated urban land in 2015 and actual urban landscape in 2015. The results show that the precision of the simulation reached 90% and the fuzzy kappa index was 0.89, which is much higher than 0.75—the minimum value indicating the simulation results is effective. The validity of the simulation model coupling improved urban interaction is thus confirmed. The simulation result of the model in 2015 is shown in Figure 5. However, from the perspective of the landscape expansion pattern, AMWEI of the simulation results is 21.81 during 2005–2015, and that of actual urban expansion is 17.81. A slight difference can be observed.

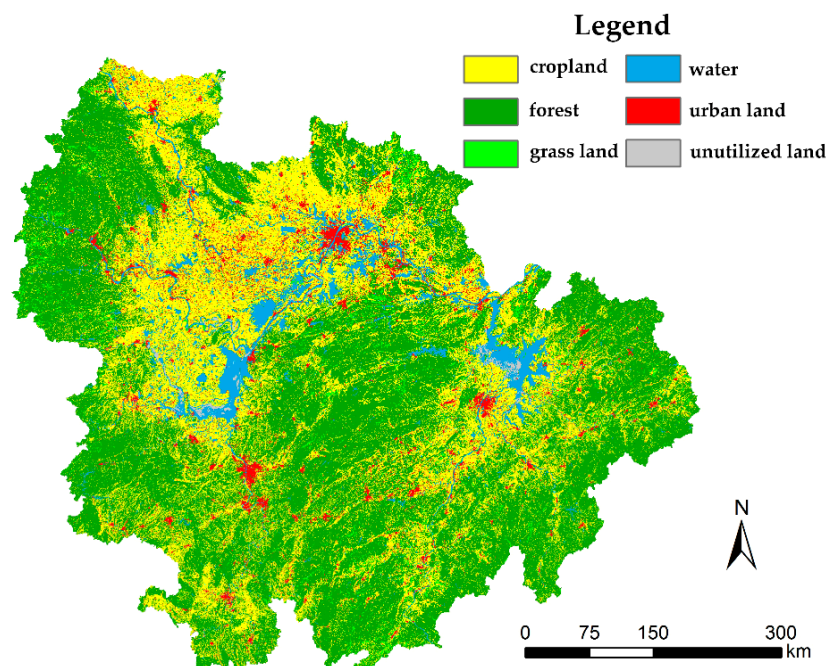


Figure 5. The simulation results in 2015.

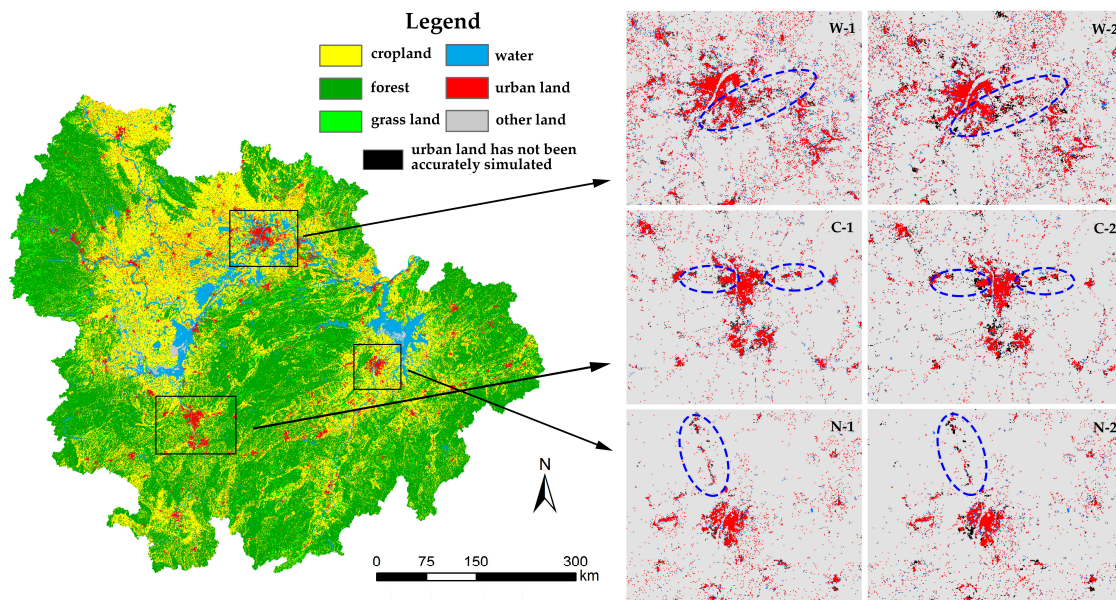
## 5. Discussion

### 5.1. The Comparison between Conventional Model and the Proposed Model

To further identify the advantage of simulation model coupling improved urban interaction, and explore the aforementioned hypotheses embodied in the model, we conduct the comparison between the proposed model and other simulation model. A review on the two hypotheses, for the first one, former studies that focus on the dynamic change of urban land in the “space of flow” has proven that urban land evolution is not an independent process and present a high correlation with the external area through the intercity interaction [28]. For the second hypothesis, the simulation model of urban land evolution, which considers urban interaction but neglects the intermediate intervention in the interaction process, has been constructed (non-intervention model). The comparison between the non-intervention model and the proposed model were conducted. The fuzzy kappa index are adopted to evaluate the simulation results of different models, and the fuzzy kappa of the non-intervention model is 0.86, which can be observed as a decrease than the proposed model, while the superiority of the simulation model coupling improved urban interaction can be identified at a cell scale. From the perspective of landscape expansion pattern, we separately computed the AMWEI of actual urban expansion and the simulation results of the two models. Results show that, during 2005 to 2015, the AWMEI of actual urban expansion is 17.81, and that of simulation results of the proposed model and the non-intervention model are 21.81 and 23.45. A better capability of the simulation model coupling improved urban interaction in capturing the changing pattern of actual urban growth can be depicted. The improvement of capturing the dynamic change of urban land in the axis areas can be clearly observed to confirm the necessity of considering intermediate intervention in the measurement of urban interaction (as shown in Figure 6).

Wuhan, Changsha, and Nanchang are the provincial capitals of the provinces comprising the MYR-UA and the key areas with the most dynamic changes of urban land during the study period in the area. In order to further discuss the suitability of the proposed model, we compared its simulation results with the non-intervention model in these three key areas, as shown in Figure 6. The fuzzy kappa index in these areas have been measured as shown in Table 3. It can be seen that, the fuzzy kappa of the simulation model considering urban interaction under an intermediate intervening opportunity

exhibits a higher value than the non-intervention model. Considering urban interaction, which was impacted by the intermediate intervening opportunity is necessary to capture the evolution trend of urban land in the cities inside the urban agglomeration area.



**Figure 6.** Land use of study area in 2015 and the comparison of diverse simulation results in 2015. Note: W-1 is the simulation result of the proposed model in Wuhan, W-2 is the simulation result of the non-intervention model in Wuhan (2015); C-1 and C-2 are the same in Changsha; N-1 and N-2 are the same in Nanchang.

**Table 3.** The fuzzy kappa of the simulation results in diverse urban areas.

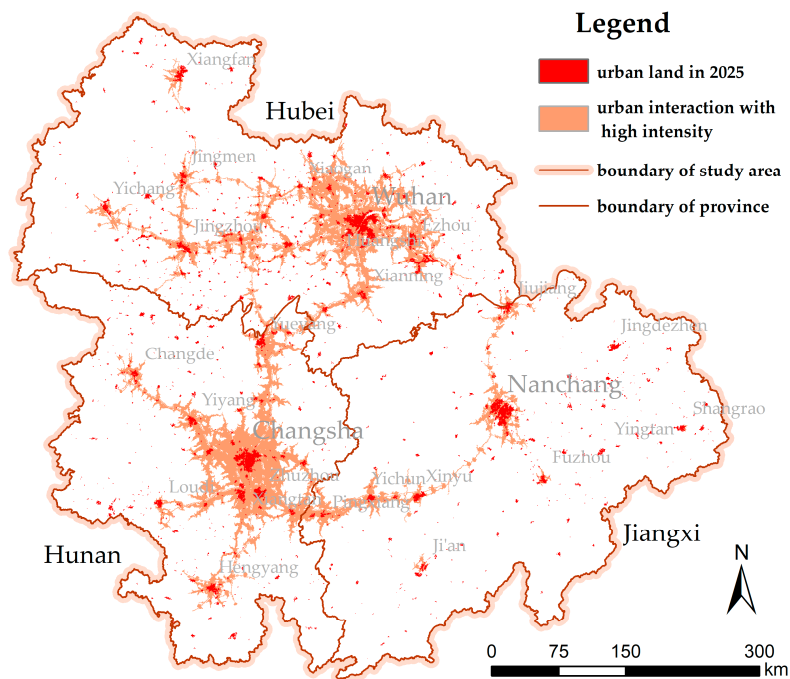
	Wuhan	Changsha	Nanchang
The proposed model	0.873	0.890	0.925
The non-intervention model	0.841	0.862	0.897

## 5.2. The Relationship between Urban Land Evolution and Urban Interaction

Employing the simulation model coupling improved urban interaction, we predicted the spatial patterns of urban land in 2025, as shown in Figure 7. Moreover, the influence of urban interactions in 2015 was measured. The natural break (Jenks) method was adopted to divide the influence area of urban interaction into areas with high, moderate, and low intensity. We extracted the interaction area with a high intensity as shown Figure 7. The spatial patterns of future urban land and high-intensity urban interaction can be analyzed in an overlapping way. It can be observed that, the expansion of urban land closely matches the spatial location of high-intensity interactions, and is distributed in a networked and linked pattern. In the MYR-UA, the networked distribution pattern of urban land in the spatial range of the Hubei and Hunan province is much more significant than that in the Jiangxi Province. In the Hubei-affiliated area, urban interaction and urban land are mainly distributed in the Wuhan urban agglomeration area; in the Hunan-affiliated area, the Chang-Zhu-Tan urban agglomeration is the central region allocated urban land and high-intensity urban interaction. The distribution of urban land is coordinated with the distribution of high-intensity urban interaction influence.

Urban interaction links interior cities of the urban agglomeration and facilitates regional collaborative development. Its considerable significance for urban land evolution is showcased by the spatial match of high-intensity urban interactions and future urban land. The relatively weaker networked pattern of urban land are accompanied by a smaller distribution of high-intensity urban interactions inside Jiangxi province, which may be an impediment to the collaborative construction

of Poyang Lake eco-economic zone. Furthermore, we observed that the linked and collaborative development of urban land occurs in the MYR-UA, but the segmentation produced by provincial boundaries is also prominent. The associated pattern of urban space is mainly located inside the sub-urban agglomeration areas of MYR-UA, typically as a closer interaction inside the Wuhan urban agglomeration area and the Chang-Zhu-Tan urban agglomeration area, where more intensive urban interactions among sub-urban agglomeration areas are essential. In the future, measures aimed at reinforcing the urban interaction among cities in the Jiangxi province and the interactions between sub-urban agglomeration areas should be further concerned to support the optimal allocation of urban land for implementing collaborative development of the large-scale urban cluster areas.



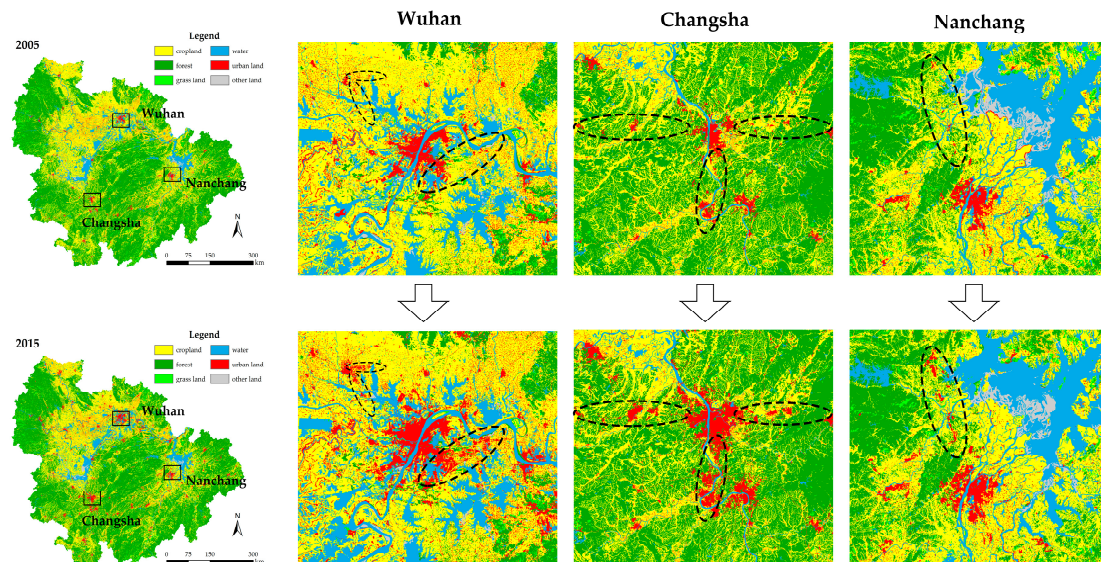
**Figure 7.** Distribution of urban land in 2025 and the urban interaction influence in 2015.

### 5.3. The Networked Development of Urban form Call for Collaborative Simulation of Urban Land

The efficient and optimal allocation of urban land—the significant carrier of regional socio-economic activity—plays a key role in ensuring the agglomeration economics of urban areas. More and more convenient information transfer, population migration, and cargo transportation produce intensive interactions among urban areas. The polycentric and networked patterns of urban space are gradually being developed and are viewed as a more effective form to stimulate better urban performance, such as improvement of the job-housing balance, mitigation of heat island effects, increase of air quality, etc. As shown in Figures 3 and 4, the networked and polycentric forms developed inside the MYR-UA can be obviously observed and present a gradually increasing trend. There are two predominant centers separately located in Wuhan and Changsha's surrounding areas, and a remarkable sub-center can be identified in the Nanchang-surrounding area. Additionally important are the widely distributed regional sub-centers, such as the sub-centers located in the north part of MYR-UA and in the axis between the Wuhan urban agglomeration and Chang-Zhu-Tan urban agglomeration. Under such background, urban interaction becomes an important part linking distinct urban centers and sub-centers. The area around the interaction lines between diverse cities becomes the key area to construct a functionally integrated urban group. The calculation results of AWMEI in the period of 2005–2010 (value = 23.68) and 2010–2015 (value = 17.81) present that the urban land expansion type has transformed from an edge-expansion growth to an outlying growth. As shown in Figure 8, increasing growth of urban land in the axis area is clearly observable to link diverse urban



centers. Through consideration of improved urban interactions, the dynamic change of urban space in the axis area can be better identified (as shown in Figure 6), such approach can be a helpful tool to predict and allocate urban land under a polycentric and networked form of urban spatial organization, and finally implement the agglomeration economics of cities.



**Figure 8.** Evolution form of urban land from 2005 to 2015.

Under the background of polycentric and networked development patterns, urban interaction, which is the key element that links internal and external urban centers and sub-centers, requires more attention in the optimal organization of urban space. Considering the improved urban interaction influence to dynamically analyze urban land evolution is suitable for areas beyond the MYR-UA. In China, the wide and constituent construction of traffic infrastructure and the proposal of national integrated development strategies have promoted the networked organization forms of urban areas. For instance, the proposed “Guangdong-Hong Kong-Macao Greater Bay Area” in south China aims to develop the already polycentric region into one that “is driven by poles, support by axes and radiating to nearby areas”. Based on the improved and spatially explicit urban interactions to conduct the allocation of urban land can be a beneficial reference for exploring the superior urban performance in these areas. From a global perspective, under the background of globalization, marketization, and decentralization, a city cannot achieve development completely on its own. The positive effect of polycentric and networked develop patterns on enhancing regional economic productivity has been widely accepted [56]. For instance, in the metropolitan areas of US, a higher level of intracity polycentricity with higher labour productivity has been associated [57]. Veneri and Burgalassi [58] similarly found a positive association between urban polycentricity and economic productivity in Italian Cities. Capello and Camagni [59] studied 58 Italian cities and claimed that additional benefits can be brought for the cities located in a functional network through synergies and complementarities between cities. In this context, the comprehensive simulation and prediction of urban land while considering the improved urban interaction, which focus on the impact of external hetero-organization, can be a feasible approach to help determine the synergistic allocation of urban land and support the development of agglomeration economics for global urban agglomeration areas.

## 6. Conclusions

Urban land is the basic spatial carrier supporting regional socio-economic development. Identifying the evolution rule of urban land plays a significant role in promoting the sustainable and synergetic development of such regions. Due to the impact of close interactions, the distribution of



urban land inside an urban agglomeration developed into a more linked pattern. The conventional urban land simulation model, which focuses on the conditions of a single city, is ill equipped to capture the collaborative evolution of urban land in urban agglomeration areas. Based on the spatial interaction theory, intermediate intervention may exist in the interaction process, and these interventions were considered in measuring urban interactions in this paper. A simulation model coupling improved urban interaction was constructed to model the collaborative evolution of urban land in the urban agglomeration area. Taking urban agglomeration in the middle reaches of the Yangtze River as the case study, the validity and suitability of this model in capturing the evolutionary trend of urban land was delineated. Through a comparative analysis with former simulation models that consider urban interaction but neglect the influence of intermediate intervening in the interaction process, we further ascertained the superiority of the proposed model and the necessity of embedding the urban interaction considering an intermediate intervening opportunity into the simulation process. Under the continuous growth of urban interactions inside urban agglomeration, the evolution of urban land presents a networked and polycentric pattern. More attention should be paid to the reinforcement of urban interactions among sub-urban agglomeration areas, urban centers, and urban sub-centers to guide the optimal allocation of urban land for developing the agglomeration economics of cities.

The evolution of urban land and the interactions of urban area are complex and interlaced processes. In this paper, we measured the influence of urban interactions on the dynamic change process of urban land inside urban agglomeration. The simulation model that considers improved urban interactions can offer support for exploring the networked evolution of urban land in urban agglomeration areas. However, it should be noted that implementing an efficient and sustainable urban socio-economic development is a significant objective for urban land allocation. Under the networked and polycentric trends of urban spatial evolution, merging the socio-economic conditions and requirements into the optimal allocation process of urban land is a key issue. Future works can be conducted from two angles: (1) From the perspective of interactions, urban interaction can be expressed by diverse elements, we adopted the population index to quantify urban interactions in this paper. In the future, more socio-economic elements can be considered to explore the interaction pattern of cities, such as the distribution and communication of cross-regional industries. The value chain of industries, which explores the characteristic of urban interactions from the perspective of the market, could be a feasible approach to help explore urban interaction based on the socio-economic condition of cities. (2) From the perspective of urban land distribution, we employed the transition rules identified from current trends to conduct our simulation and prediction of urban land distribution. Further research could take the land-use distribution scenarios that fit the socio-economic requirements as an objective (such as a land-use scenario pursues maximum labor productivity), and design an evolutionary path in a back-stepping way to stimulate the greater potential of urban space in the process of networked spatial reconstruction.

**Author Contributions:** C.L. participated in all phases; J.H. helped in conceiving and designing of the research; X.D. helped in paper organization and language correction. All authors have read and agreed to the published version of the manuscript.

**Funding:** This research was financially supported by the China Postdoctoral Science Foundation (No. 2019M663592).

**Acknowledgments:** The authors sincerely thank the editors and the anonymous reviewers for their constructive suggestions for this manuscript.

**Conflicts of Interest:** The authors declare no conflict of interest. The founding sponsors had no role in the design of the study; in the collection, analyses, or interpretation of data; in the writing of the manuscript, and in the decision to publish the results.

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