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Article

Land Use Change and Hotspot Identification in Harbin–Changchun Urban Agglomeration in China from 1990 to 2020

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Abstract: An urban agglomeration is a growth pole of regional development. However, the land uses have changed significantly due to the impacts of intense human activities. Analyzing the overall change characteristics of land use and hotspots has direct reference value for the formulation and implementation of land use management measures. This study used a complex network of analysis methods and a cluster and outlier analysis to study the land use changes and hotspots in the Harbin–Changchun urban agglomeration (HCUA). The results showed that farmland exhibited a high weighted degree of centrality, indicating that it is the key land type in the HCUA land use change network. From 1990 to 2000, the land use change in each city mainly manifested as the loss of ecological land, whereas from 2000 to 2010 it manifested as the restoration of ecological land. From 1990 to 2020, the average path length of the network in 11 cities was less than 1.4, which was reduced in 10 cities, indicating that the stability weakened and land use change more likely occurred. Specifically, the area of ecological land reduction hotspots gradually decreased from 15,237.81 km^2 to 11,533.95 km^2. In the ecological land concentration area, the change hotspots for ecological land use and ecological function had strong consistency. The distribution and changes of hotspots were affected by policies and the terrain. The increase in ecological land around urban built-up areas, however, did not improve the landscape connectivity. Therefore, in the planning of ecological land use, attention should be paid to the landscape pattern.

Keywords: regional land use; landscape; local Moran's I; complex network

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1. Introduction

The urban agglomeration is an evolving concept. The existing definitions and descriptions refer to an urban agglomeration based on the metropolitan area, which has one or two cores, as well as peripheral cities and towns with close economic or social connections [1–3]. The organizational structure of future urban agglomerations will be based on hierarchical transportation and ecological networks, and the goal of urban agglomerations is to promote coordinated regional development [4]. Urbanization has caused drastic changes to the Earth's surface, resulting in a series of problems, such as landscape modification, habitat loss, and climate change [5–7]. The Chinese government attaches great importance to urban agglomerations, and the national and local governments have proposed a series of development plans [8–10]. The development of urban agglomerations will inevitably accelerate regional land use changes and cause further deterioration of the ecological environment. Land use changes should be investigated and monitored to help policy makers learn from past practices to ensure sustainable urban growth and development [11].

Land use change is a complex process affected by many factors due to the interactions of socioeconomic and natural factors [12], and the governance mechanism is not fully prepared to deal with this complexity [8]. Most existing studies use the transfer matrix to represent the quantitative changes between various land use types in a region [13], but it is not enough to represent the role of a single type in the entire change system [14]. In the analysis of complex networks, the global characteristics of the system are captured by modeling them in a graph. The nodes in the graph represent dynamic units, and the links represent their interactions [15,16]. The mutual transformation of land use constitutes a directed network. The research theory and method of a complex network can be used to quantify the system characteristics, analyze the characteristics of the entire network system [17,18], and help understand the complex dynamic changes in the land use system [19,20].

In addition, the intensity of land use change in different regions requires attention. A hotspot can be defined as an area where the frequency of occurrence in space is concentrated compared with similar areas. In risk and disaster management, hotspots are the key areas [21]. Determining the temporal and spatial distribution and hotspots of land use change can help decision makers determine the priority areas for protection and make rational use of limited resources [22]. Researchers have conducted research on the identification of hotspots of land use change [23–25], but the research on hotspots of ecological function changes remains insufficient. The spatial distribution and combination of land use patches with different sizes, shapes, and attributes constitute the landscape pattern, and the landscape index is a widely used method for assessing the side effects of human activities and natural changes on ecosystems [26]. Accordingly, the ecological function can be characterized by landscape index, and then the analysis of its change hotspots can provide a direct reference for ecological protection.

The common methods for hotspot detection include the local indicators of spatial autocorrelation (LISA) and kernel density estimation methods [27]. The intensity-based method basically describes the local density of events on the map, which can be displayed as an isometric map [28]. A contour map can indicate the spatial correlation and hotspot range but cannot quantitatively evaluate the importance of aggregation [29]. For LISA, Anselin stated that the Getis-Ord Gi* index is suitable for detecting geographical phenomena with low global spatial autocorrelation, and the analysis results based on the Local Moran's I index are highly reasonable when the autocorrelation is high [30].

In particular, the urban ecosystem is the result of the dynamic interaction of socioeconomic and biophysical processes, evolving over time and space [31–33]. Shen emphasized the impacts of long-term land use intensity, and specifically evaluated the impact on vegetation change by combining structural equation models [34]. Studying land use change over time helps reveal the general principles of land use change and to promote the formulation of land use policies related to urban development policies [35].

Hence, on the basis of long-term land use data, which were combined with complex networks and a hotspot identification method, this study proposed a research framework to reveal the key types and stability of land use change in a region and identify the hotspots of spatial change. The analysis results of this research framework can provide a reference for clarifying the overall trend of land use change and determining the spatial location for implementing management measures.

2. Materials and Methods

2.1. Study Area

The Harbin–Changchun urban agglomeration (HCUA) is located in Northeast China, mainly including the central and southern parts of Heilongjiang Province and the central part of Jilin Province, including 11 prefecture-level cities, of which Harbin and Changchun are provincial capitals, with a total area of approximately 263,600 km^2. The terrain of the study area is high in the southeast and low in the northwest, and generally tilts from south to north (Figure 1).

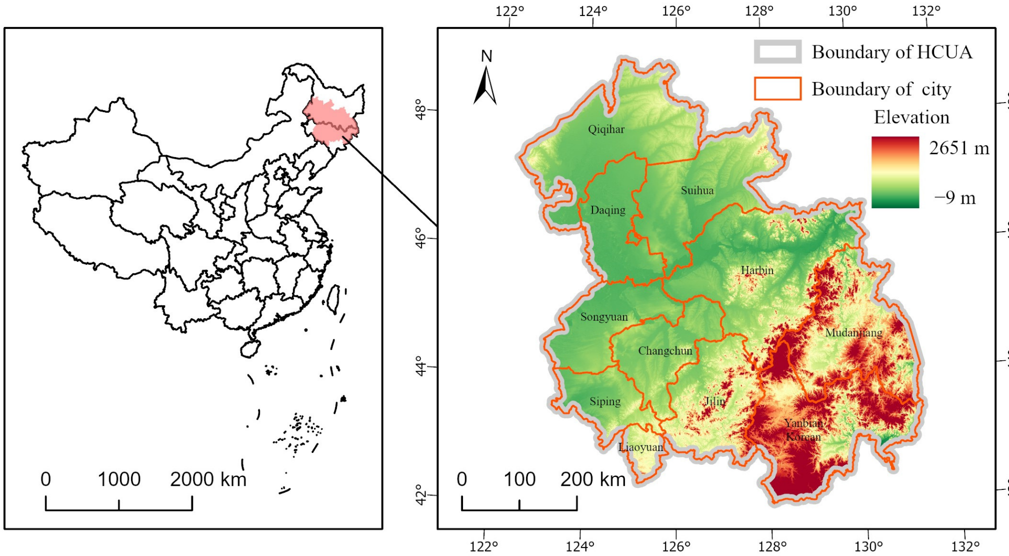

Figure 1. Location of the study area.

The HCUA is an important growth pole for the revitalization of Northeast China and the opening of Northeast Asia. An analysis based on flow data showed that Harbin, Changchun, and Jilin were the centers of HCUA, and other cities in the cluster were the close connection nodes. The intensity and spatial subordination of economic links between cities in the urban agglomeration and between cities in the province were high [36]. By the end of 2015, the population of the HCUA region accounted for 3.4% (47 million) of the total population of the country, and the gross domestic product (GDP) accounted for 3.3% (US $361.38 billion) [37]. However, due to long-term human activities, the urban land has experienced a rapid expansion, with an irrational transformation from farmland to construction land. In 2019, the carrying capacity of the economic land resources was declared to be weak. The average land GDP for HCUA was 6,403,600 CNY/km^2, which was considerably less than that of China's developed urban agglomeration. The ecological environment of HCUA is very fragile, and its ecological recovery capacity is poor [38]. Therefore, The HCUA was selected as the study area to analyze the land use change and its hotspot distribution, which is valuable for efficient land use, ecological protection, and specific spatial planning.

2.2. Land Use Data

The land use data used in this study were obtained through the interpretation of remote sensing images (Figure 2). The remote sensing data sources for 1990, 2000, and 2010 were Landsat images with a 30 m resolution. Meanwhile, Sentinel-2A images were used as the data sources for land use interpretation in 2020. The Sentinel-2A satellite was successfully launched in June 2015, and its data have a higher spatial resolution than Landsat images, in which the spatial resolution of four bands is 10 m. To maintain the continuity of data in each period, the remote sensing interpretation was started from the reference map, and subsequent data processing, change analysis, and classification processes were only carried out at locations of land use change. Meanwhile, to reduce the fragmentation of classification results caused by pixel-based classification, an object-oriented classification method was adopted. The land use types in the study area were divided into six categories: farmland (paddy field and upland field), forest, grassland, wetland, built-up areas, and other land (bare land, sandy land, and saline-alkali land) [39–41]. The overall accuracy rates of the four classification maps were 86% for 1990, 86% for 2000, 88% for 2010, 93% for 2015, and 85% for 2020.

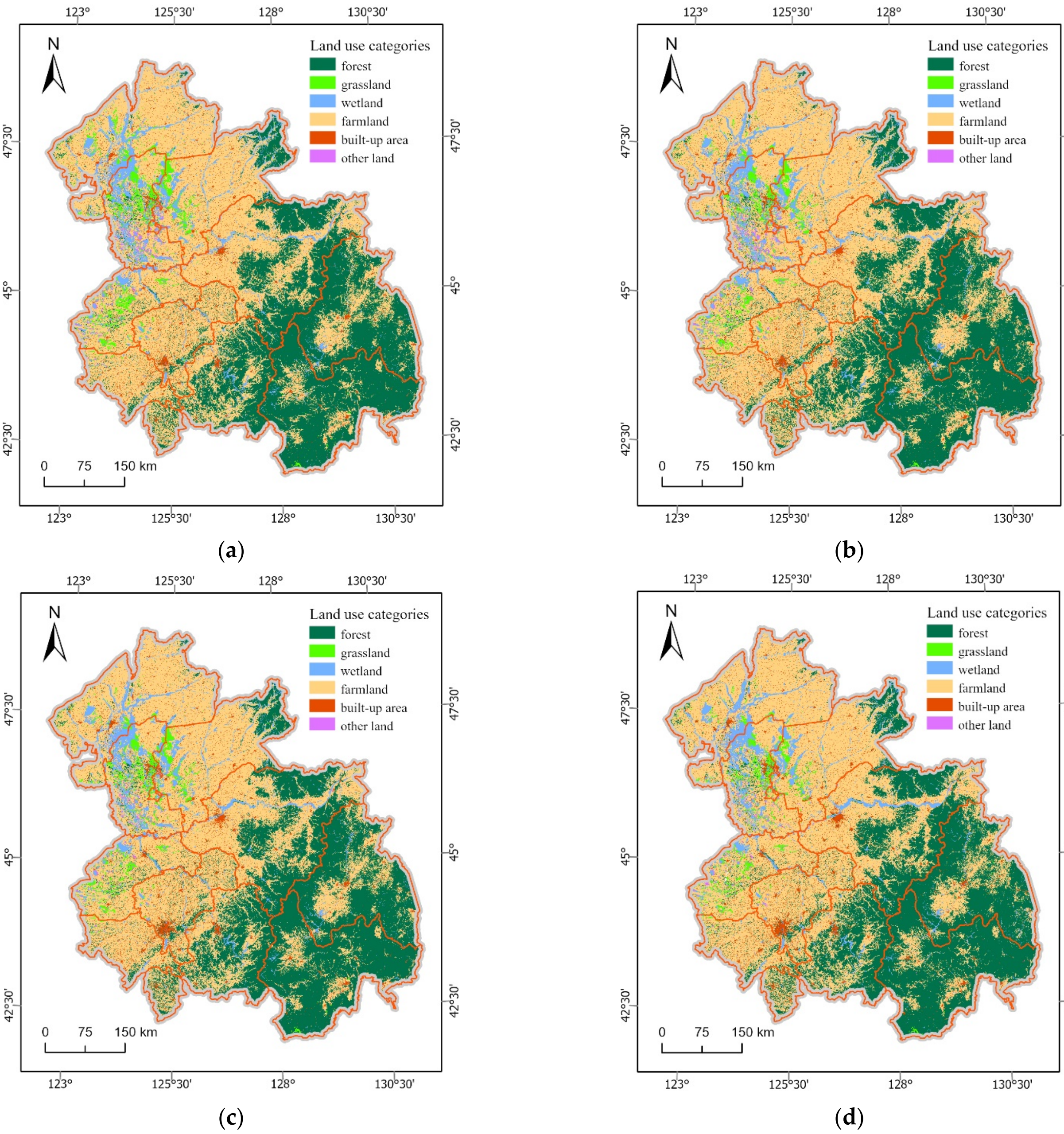

Figure 2. Land use maps in different years: (**a**) 1990; (**b**) 2000; (**c**) 2010; (**d**) 2020.

2.3. Methods

A research framework for the land use change and hotspot analysis in the HCUA was proposed. The main work can be divided into three steps. The first step was the grid processing of land use data, in which the reasonable data grid scale was determined through the sensitivity of landscape index changes in transects at different scales. Then, the transformation characteristics of different land use types were analyzed. The key land use type in the land use transformation network was determined by using the complex network analysis method, and the stability and changes of the network were analyzed. Finally, the cluster and outlier analysis method was used to analyze the hotspots of ecological land and landscape pattern changes; the spatial consistency, the spatial heterogeneity, and the influencing factors were also analyzed (Figure 3).

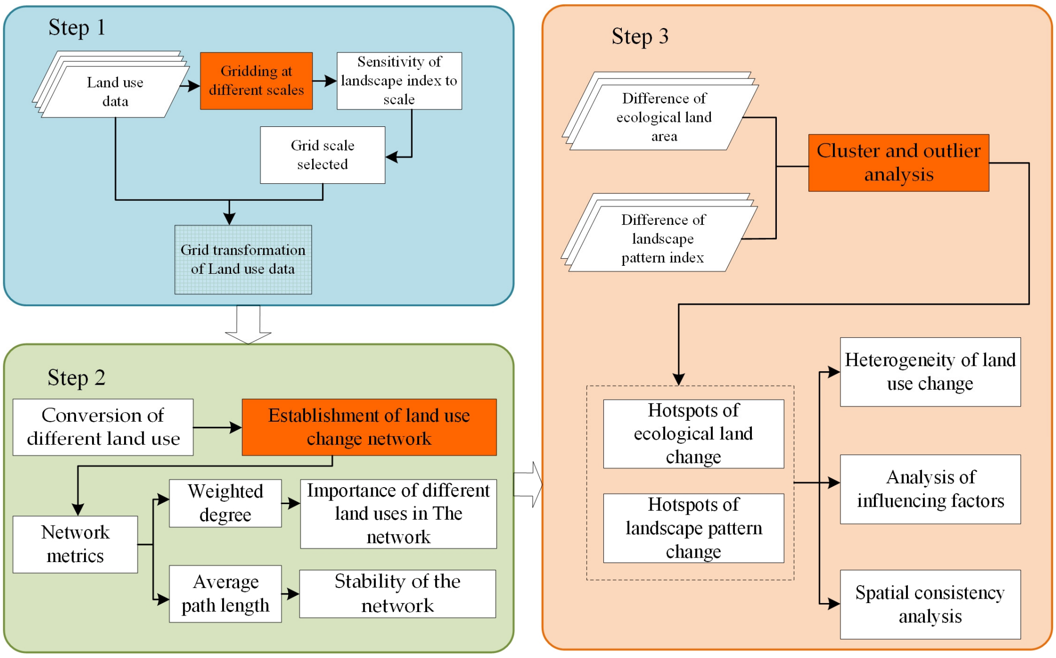

Figure 3. Overall workflow of the land use change and hotspot analysis of the urban agglomeration.

2.3.1. Analysis of Land Use Conversations Based on Complex Network Model

The directed network was constructed by taking the land use type as the node and the transformation area between different types as the edge. The measurement indexes include the weighted degree of centrality and the average path length. The degree of centrality is an important indicator that depicts the status of nodes in the network. In a directed network, nodes are measured by the input and output degrees of centrality. The input degree of centrality is the number of other land use types connected by a certain land use type as the target, and the output degree of centrality is the number of land use types connected by a certain land use type as the source. The weighting degree is based on the area of land use change. The number of direct connections between nodes of a certain land use type and other nodes reflects the breadth and importance of the node connections.

The average path refers to the arithmetic average of the shortest path between all pairs of nodes. If the distance between two nodes is short, then the efficiency of sending information between them is high. Therefore, the average path quantitatively reflects the average efficiency of sending information between nodes in the network [42]. The larger the value, the larger the branch in the network and the stronger the stability of the land use status [19,43]. The above indicators were calculated using Gephi 0.9.

2.3.2. Landscape Pattern Analysis

Many kinds of landscape pattern indexes exist, and a single index can only express the change characteristics of one aspect of the landscape pattern. Selecting an excessive number of indicators will lead to repeated descriptions and redundant information. Therefore, indicators should be selected according to the influencing factors of the landscape index and the characteristics of the data [44]. In this study, four landscape indexes, namely the patch density (PD), mean path size (MPS), patch cohesion index (COHESION), and aggregation index (AI), were selected to evaluate the ecological function changes caused by land use degradation (Table 1).

Table 1. Definition and description of landscape pattern index values.

Landscape Pattern	Index	Abbreviation	Definition	Description
Fragmentation	Patch density [45]	PD	N/A	N is the number of patches, and a is the total area of patches.
	Mean patch size [45]	MPS	A/N	A is the total area of patches, and N is the total number of patches.
Connectivity	Patch cohesion Index [46]	COHESION	$\left\{\left[1-\frac{\sum_{j=k}^{n} P_{ij}}{\sum_{j=1}^{n} P_{ij}\sqrt[n]{a_{ij}}}\right]/\left[1-\frac{1}{\sqrt{Z}}\right]\right\}\times 100$	The smaller the value is, the more dispersed the patches are in a specific range.
	Aggregation index [47]	AI	$\left[\sum_{i=1}^{m}\left(\frac{g_{ii}}{\max\rightarrow g_{ii}}\right)P_i\right]\times 100$	The aggregation index describes the aggregation degree of patches in the landscape and reflects the dispersion of landscape elements. The smaller the value is, the higher the dispersion degree of patches is.

A transect was demarcated from west to east in the study area (Figure 4). The land use types in the transect are complete, and the elevation span of the covered area is large and representative. According to the equidistance interval, the PD and AI values of different scales at the corresponding position of the transect centerline were extracted, and the sensitivity of the landscape index to scale was analyzed to determine the appropriate scale parameters for the moving window analysis of the landscape index. The Landsat image resolution generally used in the interpretation of land use types is 30 m, so an odd multiple of 30 m was used as the size of the moving window, with an interval of 600 m. The land use data for 2020 were used in this process.

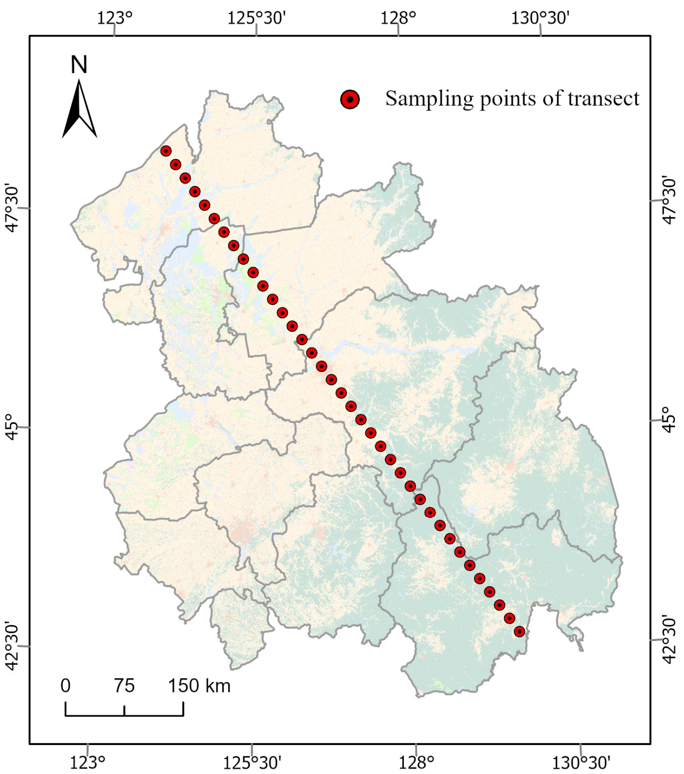

Figure 4. Sampling points of the transect.

2.3.3. Hotspot Identification of Land Use Change

The global Moran's I index is a commonly used indicator and is often used to evaluate whether the global spatial pattern of elements is clustered [48–50]. The statistical significance of the index is determined by the z value and its corresponding p-value. However, the global Moran's I index does not describe the spatial clustering position of high or low values [29]. The local Moran's I, also known as the cluster and outlier analysis method, detects the hotspot distribution of local spatial elements by comparing the relationship between observed and adjacent values and the global situation [27].

First, the global Moran's I index was used to evaluate whether a high spatial clustering pattern existed and then to determine whether the local Moran's I was suitable for hotspot identification in this study [30]:

$$I = \frac{N}{\sum_i^N \sum_j^N W_{ij}} \frac{\sum_{ij}^N \sum_i^N W_{ij}\left(X_i - \overline{X}\right)\left(X_j - \overline{X}\right)}{\sum_i^N \left(X_i - \overline{X}\right)^2} \tag{1}$$

$$Z = \frac{I - E[I]}{\sqrt{Var[I]}} \tag{2}$$

where X_i and X_j are the attribute values of grids i and j, respectively; $\overline{X}$ is the average value of all grids, W_{ij} is the spatial weight matrix defined by spatial proximity, and N is the total number of grids.

The local Moran's I is defined as follows:

$$I_i = \frac{N\left(X_i - \overline{X}\right)W_{ij}\left(X_j - \overline{X}\right)}{\sum_i^N \left(X_i - \overline{X}\right)^2} \tag{3}$$

where I_i represents the local Moran's I of grid i and its correlation with grids in the domain. The local spatial connection between spatial elements and their neighbors can be divided into four types. The high–high type represents a high-value cluster, while low–low represents a low-value cluster. Low–high represents a low-value grid surrounded by a high-value grid, and high–low represents a high-value website surrounded by a low-value grid; that is, an abnormal value. In this study, the grid's attribute is the difference between the value at the next time point and the value at the previous time point. Therefore, high–high and low–low cluster types represent the hotspots with enhanced and weakened values, respectively. High–low and low–high types are helpful in finding outliers.

3. Results

3.1. Selection of Analysis Window Size

The sensitivity of the landscape pattern index to the scale was measured by the PD change of the sampling points under different analysis scales. When the analysis scale was 2850 m, the PD change curve was gentle, so 2850 m was selected as the scale of the landscape pattern analysis in this study (Figure 5).

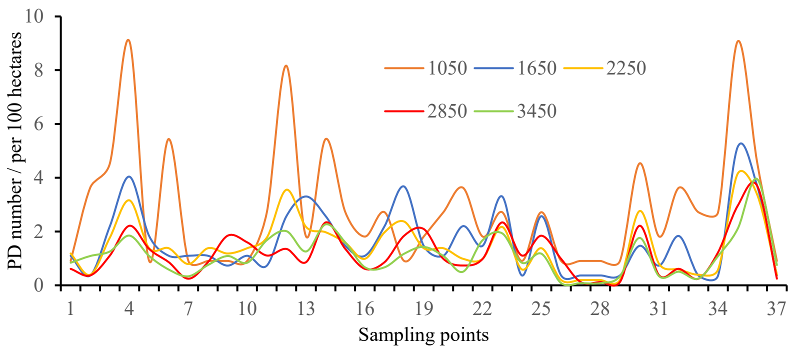

Figure 5. Changes in PD along the transect under different window sizes.

3.2. Transformation between Different Land Use Types

Farmland accounted for the largest proportion of land use types in HCUA, accounting for more than 49% in each year, followed by forest land and wetland. The total proportion of ecological land was 44%, and the ecological condition of this location was superior. According to the interannual changes, the proportion of built-up areas increased annually, from 3.78% to 4.35%, indicating an increase of 15.08%. The proportion of farmland areas first increased and then decreased. The proportion of forest land areas decreased first and then increased. The proportion of grassland areas decreased annually. The wetland areas decreased significantly from 1990 to 2000, and the proportion in 2020 increased compared with that in 2010 but did not recover to the proportion in 1990 (Figure 6).

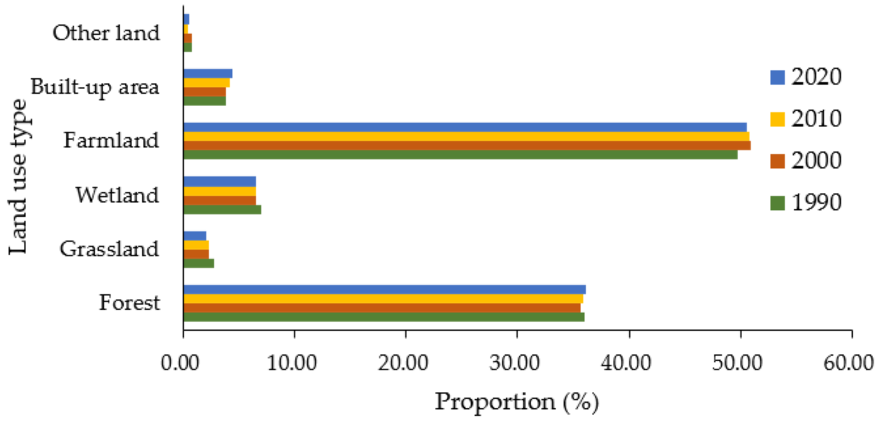

Figure 6. Proportions of land use types in each year.

The land use change in each city from 1990 to 2000 mainly manifested as the loss of ecological land (Figure A1). Except for Changchun City, the maximum value of the output degree in the cities was from forest land, grassland, or wetland areas, and the maximum input degree in each city was from farmland areas. From 2000 to 2010, the land use change in each city was mainly realized as the restoration of ecological land. Among the cities, Harbin and Siping had the largest input degrees of forest land, Daqing and Suihua had the largest input degrees of grassland, Mudanjiang and Qiqihar had the largest input degrees of wetland, and five cities had the largest output degrees of farmland.

Farmland was the main source of ecological land restoration. From 2010 to 2020, the input of ecological land types in four cities was maximal, and the maximum input and output degrees of five cities were from farmland. These phenomena indicated that the amounts of inflow and outflow of farmland in this stage were relatively large, showing that the local government exerted great effort in maintaining the balance between the amount of farmland and ecological protection (Table A1).

Except for Daqing City, the average path length of the land use change network in the remaining 10 cities from 2010 to 2020 was less than that at the beginning of the study period, indicating that the stability of the land use system in the study area decreased (Figure 7).

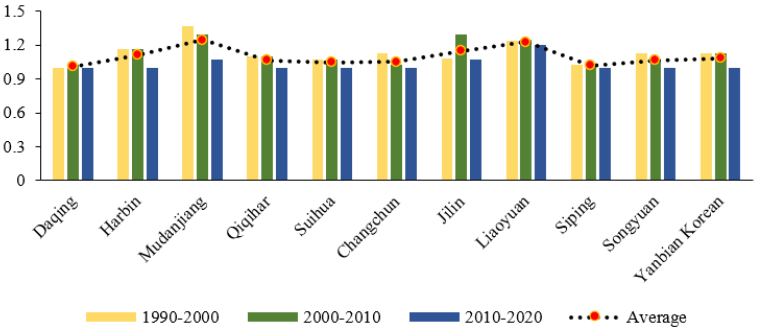

Figure 7. Changes in average path length in each city.

3.3. Spatiotemporal Change Hotspots of Ecological Land

The global Moran's I index of ecological land use change in each time period indicated its high spatial correlation (Table A2). This result showed that the cluster and outlier analysis was suitable for hotspot identification. Figure 8 depicts the results of the cluster and outlier analysis with P values less than 0.05, indicating that the probability that the aggregation was a result of random chance was less than 5%.

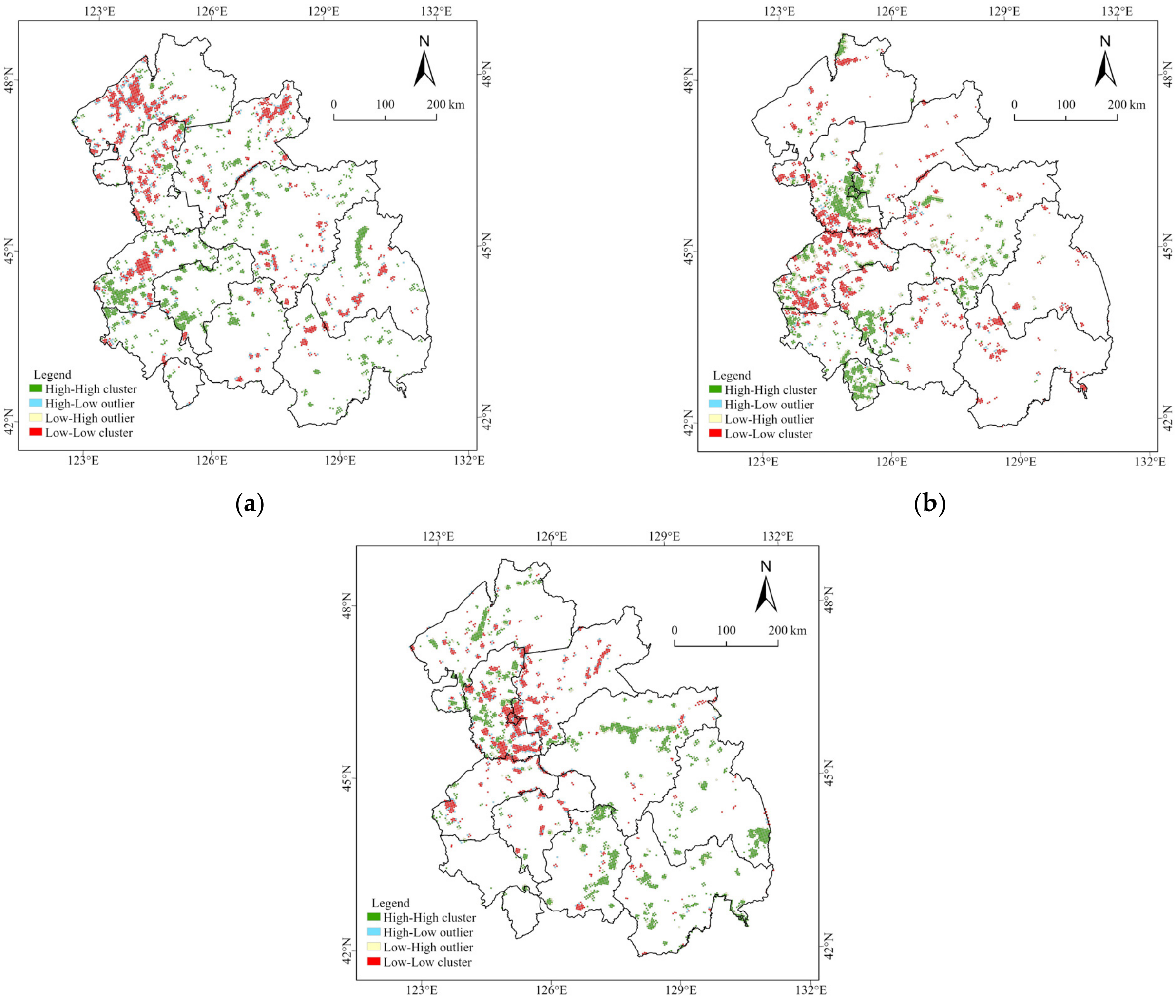

Figure 8. Hotspots of ecological land change: (**a**) 1990 to 2000; (**b**) 2000 to 2010; (**c**) 2010 to 2020.

In the high–high cluster area, namely the hotspot of increasing ecological land use, the distributions were obviously different in diverse periods. The distribution of this type of region was relatively scattered from 1990 to 2000. From 2000 to 2010, the region was mainly distributed in the west of the study area and was widely distributed in Daqing City, Changchun, and Liaoyuan. From 2010 to 2020, the change in ecological land use was manifested as low–low clustering regions; that is, the hotspots of increasing ecological land use area were mainly distributed in the southwest of Daqing.

In 1995–2000 and 2010–2020, the high–high clustering type surrounded the urban built-up areas (Figure 9). This finding indicated that the impact of urban development on the ecological environment is not always negative. Human activities have positively affected the environment with the economic development and the improvement of environmental awareness [51]. The typical areas included the Changchun built-up areas.

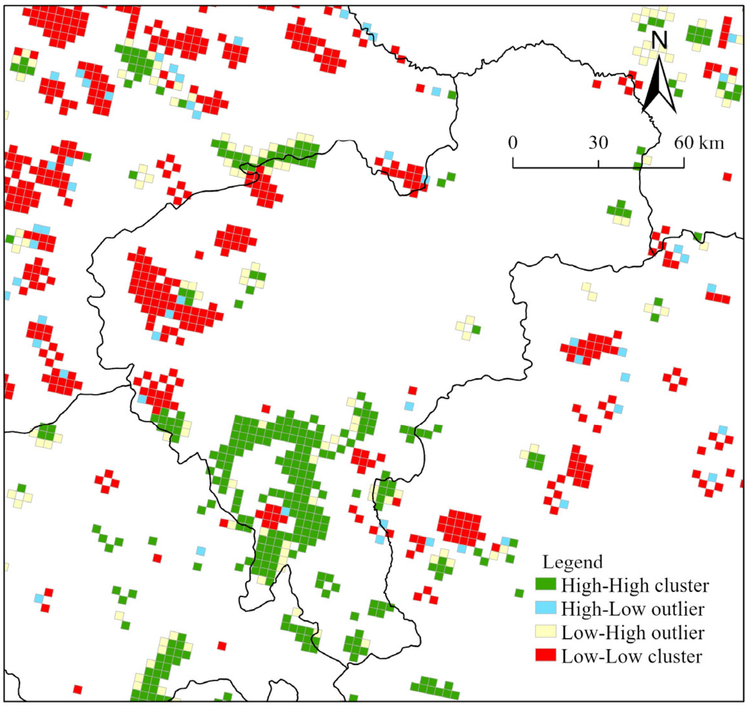

Figure 9. Example of high–high clusters around built-up areas.

In 1990–2020, the area of ecological land reduction hotspots decreased gradually from 15,237.81 km^2 to 11,533.95 km^2. The ecological land hotspot increase at the end of the study was slightly higher than that at the beginning of the study, and the area of the ecological land hotspot increase between 2000 and 2010 was the smallest (Figure 10).

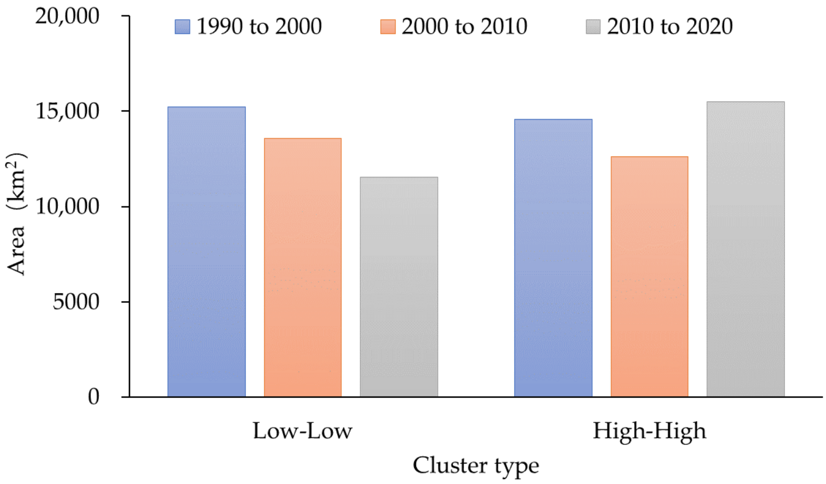

Figure 10. Area changes in high–high clustering and low–low clustering in different periods.

3.4. Hotspot of Spatial and Temporal Changes of Landscape Patterns

The global Moran's I index of landscape change in each time period showed its high spatial correlation (Table A2), and the likelihood that this clustered pattern could be a result of random chance was less than 1%. Hence, the cluster and outlier analysis was suitable for the hotspot identification of landscape change.

From 1990 to 2000, the hotspots of PD change were distributed in a decentralized manner. From 2000 to 2010, the hotspots of PD reductions were concentrated in Daqing City, while the hotspots of PD increases were concentrated around the built-up areas of Changchun City and along the Harbin–Dalian Railway. From 2010 to 2020, the hotspots with increased PD were widely distributed in Jilin and Changchun (Figure A2).

The hotspots of MPS changes were scattered. The hotspots with increased areas were the areas with a good ecological base, such as the wetland-concentrated distribution area in Qiqihar from 1990 to 2000, the wetland- and grassland-concentrated distribution area in Daqing from 2000 to 2010, and the forest-concentrated distribution area in Harbin from 2010 to 2020.

From 1990 to 2000 and 2000 to 2010, the distribution of hotspots increased and decreased by COHESION exhibited an obvious spatial difference, of which the hotspots increased by COHESION were mainly concentrated in the western region. The hotspots reduced by COHESION were mostly concentrated in the eastern region, which were distributed around the existing cities or along the traffic arteries. From 2010 to 2020, the change hotspots of COHESION were distributed in a decentralized manner. The AI hotspot distribution and its changes with time displayed similar spatial characteristics to the COHESION hotspot distribution.

From 1990 to 2020, there were hotspots along the railway from Harbin to Changchun, where the PD, COHESION, and AI values increased. This result indicated that the degree of fragmentation of the patches increased, but the connectivity between patches was enhanced.

4. Discussion

4.1. Spatial Consistency of Ecological Land Use and Landscape Pattern Changes

From 1990 to 2020, the ecological status of the HCUA was improving. The analysis showed that the proportion of farmland first increased and then decreased. At the same time, the area of hotspots for ecological land reduction decreased gradually from 15,237.81 km^2 to 11,533.95 km^2. There were differences in the spatial distributions of changes. For different land use types, the change hotspots of ecological land use and ecological function represented by landscape patterns were not always consistent. Nevertheless, in the ecological land concentration area, the change hotspots of the two showed strong consistency. The increase in ecological land use was accompanied by the decrease in PD, the increase in MPS, and the increase in the COHESION index, and vice versa. The typical area was Daqing City, which had many hotspots for the increase in ecological land, and the landscape pattern index indicated an improvement of the ecological function. In general, the increase in ecological land was conducive to the restoration of ecological functions. However, the situation around the city was the opposite. The built-up area of Changchun was surrounded by hotspots of ecological land increase, but the landscape pattern index indicated a deteriorating ecological function. This research result was consistent with the discovery found by Dadashpoor. Dadashpoor used the landscape index to study the landscape changes in a metropolitan area in Iran. The research showed that urbanization expansion has diverse effects on different spatial locations. In the adjacent built-up and metropolitan central areas, the degree of landscape aggregation continued to increase, while the degrees of fragmentation and heterogeneity continued to increase far from the built-up areas [52].

Given that an ecological network maintains the spatial pattern of urban ecological health and security, paying attention to ecological consistency is conducive to formulating effective ecological protection policies [53]. The artificial disturbance corridor of a railway network affects the connectivity of the urban ecosystem, hinders the material and the energy, and intensifies the spatial and temporal differentiation and dispersion of landscape patches [54]. Moreover, this study found that from 1990 to 2020, along the railway from Harbin to Changchun, there were banded hotspots with increasing patch aggregation index values. This finding showed that the role of railway network in the ecological network is directional.

4.2. Influencing Factors of Hotspot Distribution

According to the analysis of land use changes by using the complex network method, the main process of land use transformation from 2000 to 2010 was the restoration of ecological land. During this period, the hotspots of increasing ecological land were concentrated in the cities of Daqing and Songyuan in the west of the study area, where wetland and grassland areas were concentrated. The strengthening of ecological protection helped increase the ecological land. Heilongjiang Province issued the first wetland protection regulations in 2003, and China announced its ecological function zoning initiative in 2008 [55]. The spatial and temporal distribution of hotspots was related to the ecological protection policies and actions that were implemented. Economic policies can produce significant short-term effects [56]. Changes in land use and management can affect various ecosystem services, with common interests and trade-offs [57]. Meanwhile, hotspots of ecological land increase appeared around the city, indicating that the balance between economic development and ecological protection was considered during this period and human actions were highly targeted.

The ecological landscape change hotspots and landscape hotspots in the study area exhibited obvious spatial differences between the east and the west; that is, areas with high elevations had fewer hotspots than those with low elevations, which indicated that the distribution of hotspots is also related to the geographical environment [58]. The results showed that many settlements along the railway and the high-grade highway had convenient traffic conditions, and the ecological environment was more likely to be affected by human activities. This finding revealed that the traffic condition is one of the main factors affecting urban expansion [59].

Overall, land use change is driven by a combination of synergistic factors, such as increased pressure on resources from production due to resource scarcity, external policy interventions, and changes in social organizations and attitudes [35]. In this study, we performed a qualitative analysis on the influencing factors of land use change. If data reflecting economic and environmental factors are introduced, accurate quantitative research can be carried out on the influencing factors, such as structural equation modeling [34] and geographical weighted regression modeling [60].

4.3. Enlightenment on Balancing Urban Agglomeration Development and Ecological Protection

Urban agglomeration refers to a region that is strongly influenced by human activities and complex human and nature interactions. The complex network method is conducive to finding the key land use types in the control area from a macro perspective. The key land use type in the HCUA was farmland, which had high weighted output and input degrees; that is, it had high centrality in the network. The complex network analysis showed that the input centrality of ecological land in the HCUA increased, but the network stability was not high (i.e., the average network path was less than 1.4) and was even decreasing. The analysis of land use change hotspots based on temporal and spatial changes helps in the placement of specific management measures. The combination of complex network and hotspot recognition methods can describe the characteristics of regional land use change more comprehensively.

This study showed that the increase in ecological land around urban built-up areas did not improve the landscape connectivity. Although ecological land use complementarities can increase the availability of habitats for species in urban areas, they do not necessarily promote species movement, pollination, seed spreading, or other key ecosystem processes [61]. In ecological planning, we should not only pay attention to ecology but should also focus on integrating small land patches to reduce the fragmentation and connectivity of the ecosystem [31]. Reasonable planning steps can be taken to maintain great connectivity with small land use changes and can effectively improve ecosystem functions. This study mainly analyzed the historical changes in land use. In future research, different scenarios could be considered, and land use predictions could be carried out using models, thereby providing more intuitive references for the decision making based on regional land use.

5. Conclusions

An urban agglomeration is a region of intense human activities. Influenced by human and natural factors, the land use pattern has changed significantly, and the analysis of such changes has important practical guiding value for clarifying the key land use types and change hotspots in land use. On the basis of complex network and spatial clustering and anomaly analysis methods, this study proposed a research framework for urban agglomeration land use and hotspot identification, and took the HCUA as the research area for the analysis. The results showed that farmland was the key type in the HCUA land use change network and the main source and target of the land use transformation. The stability of the land use change in this region weakened, whereas the probability of land use change increased. From 2000 to 2010, the hotspots of ecological land increases were concentrated in areas with good ecology and around urban built-up areas, indicating that the problem of balancing economic development and ecological protection required urgent attention, and the policies at this stage were highly targeted. The land use change and hotspot distribution were affected by topographic factors and exhibited obvious spatial differences. The change in the eastern region was gentler than that in the western region, and the changes in ecological land use and landscape patterns had different consistencies for diverse land use types. The planning of ecological land around the city should consider not only the scale but also the spatial pattern to perform ecological functions well. The analysis results have important implications for land use management in urban agglomerations. In future research, through hotspot identification, the introduction of an ecological network construction model would provide a detailed basis for regional ecosystem optimization.

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Data Availability Statement: The data presented in this study are available from the author upon reasonable request.

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Conflicts of Interest: The authors declare no conflict of interest.

Appendix A

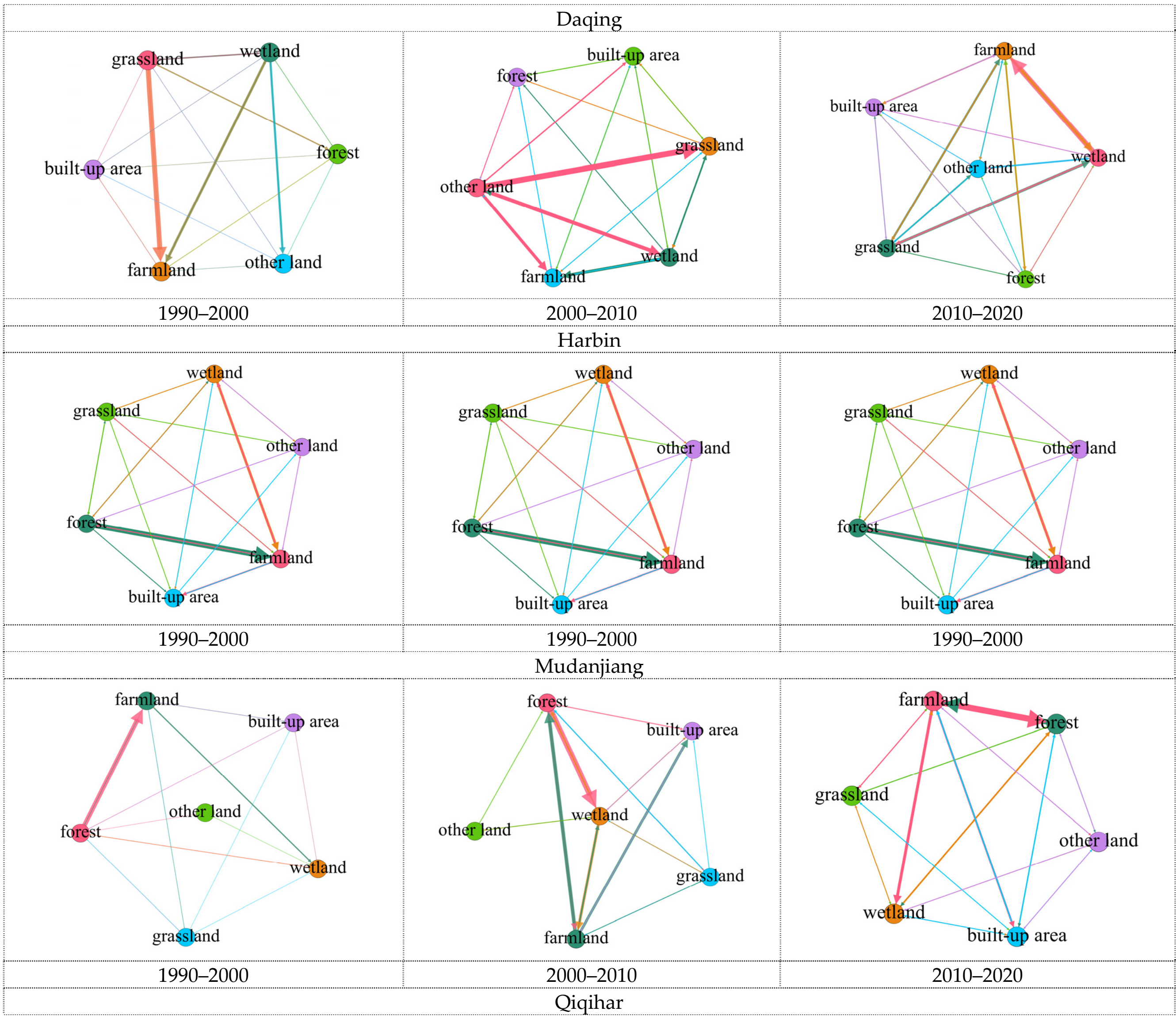

Figure A1. *Cont.*

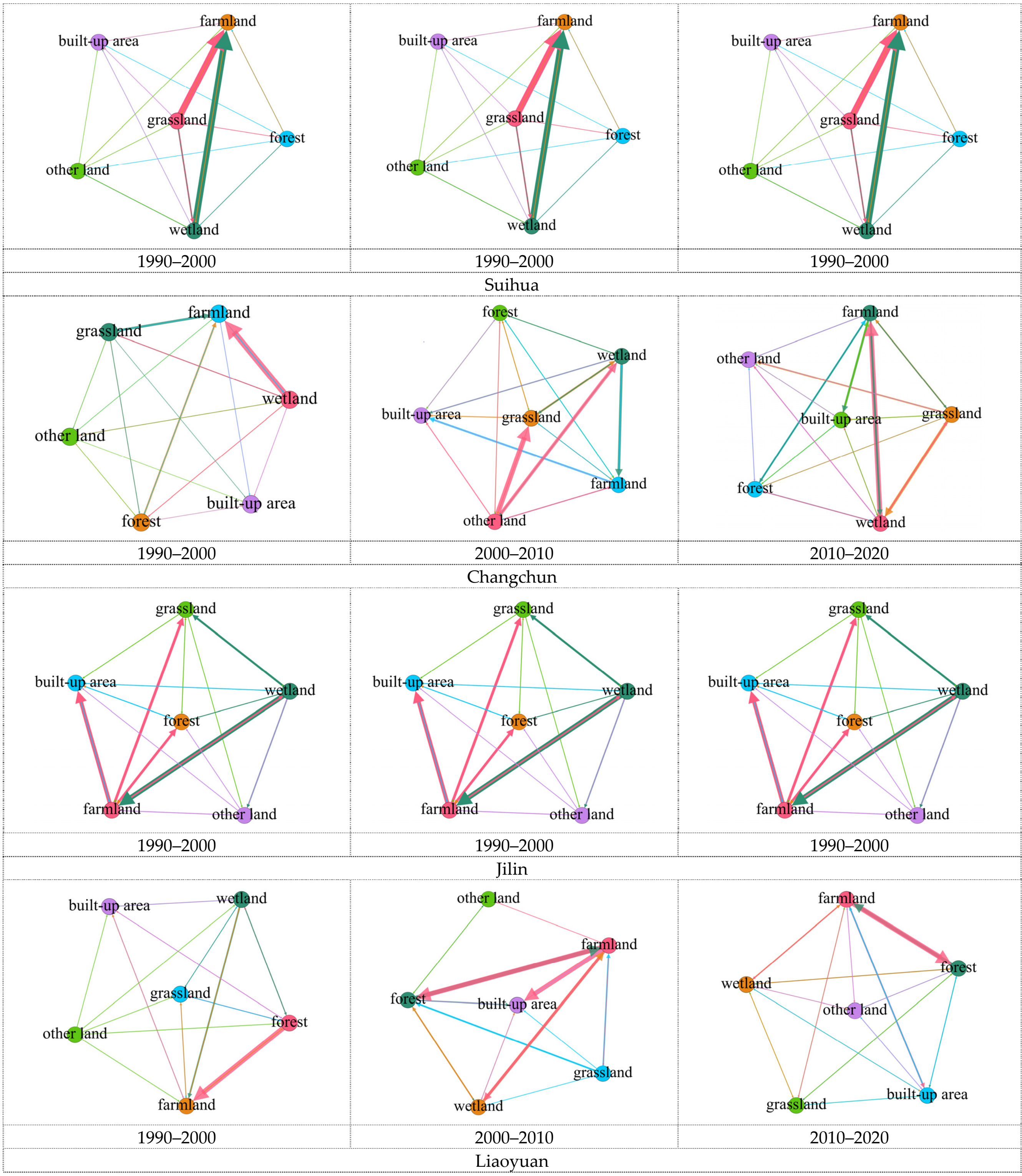

Figure A1. *Cont.*

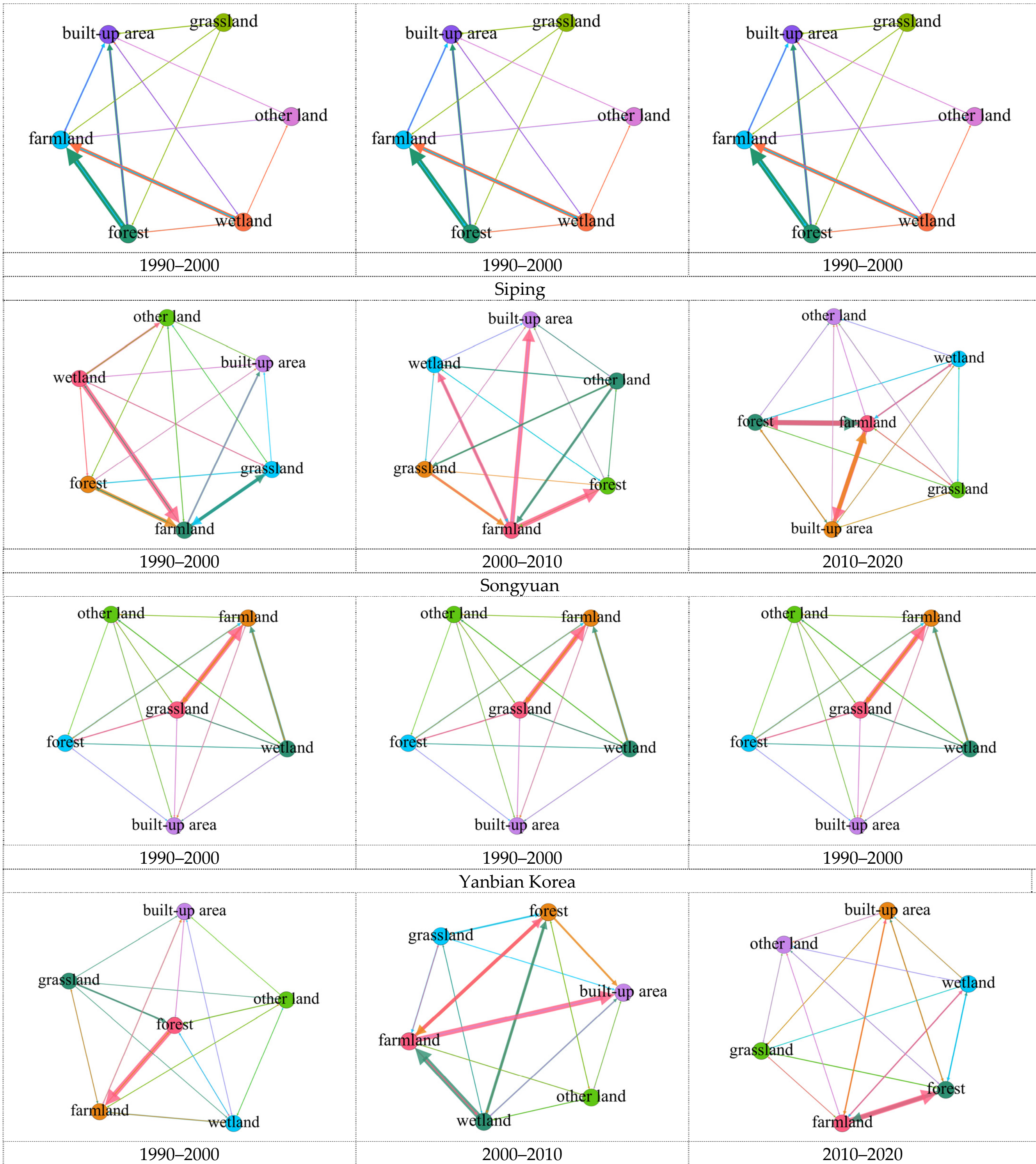

Figure A1. Complex network of land use changes in different periods in different cities.

Table A1. Output and input degrees of nodes in different periods.

Periods	City	Indicators	Land Use Categories					
			Forest	Grassland	Wetland	Farmland	Built-Up Area	Other Land
1990–2000	Harbin	Output	398,875.59	32,603.31	150,446.16	122,689.08	250.29	5494.23
		Input	36,502.65	4583.79	75,858.93	527,696.37	65,126.43	590.49
	Daqing	Output	1518.75	451,855.26	349,921.62	69,010.38	106.11	15,522.84
		Input	83,707.02	58,890.24	121,026.15	471,972.42	21,377.52	130,961.61
	Mudanjiang	Output	429,867.00	6347.97	12,004.20	106,139.16	110.97	121.50
		Input	14,742.00	2387.88	100,013.13	416,973.42	20,126.07	348.30
	Qiqihar	Output	21,895.92	699,136.92	610,521.30	46,300.41	163.62	1458.81
		Input	20,764.35	10,558.35	125,651.25	1,176,733.17	21,633.48	24,136.38
	Suihua	Output	86,566.32	173,146.41	428,279.40	41,312.43	160.38	4510.08
		Input	38,788.47	27,387.72	59,954.58	575,188.29	19,030.95	13,625.01
	Changchun	Output	13,735.98	5172.66	104,212.98	127,977.57	5346.81	2514.24
		Input	37,412.28	54,208.44	13,928.76	87,103.35	58,159.62	8147.79
	Jilin	Output	158,636.07	5317.65	42,276.33	20,727.90	2736.18	3120.93
		Input	22,778.82	15,500.97	5665.95	180,357.84	8511.48	0.00
	Liaoyuan	Output	19,321.74	403.38	10,198.71	4261.41	20.25	20.25
		Input	1070.82	0.00	1304.91	24,917.22	6922.26	10.53
	Siping	Output	42,277.14	39,338.46	79,912.98	52,967.52	311.04	1193.13
		Input	13,156.83	34,945.83	2643.84	133,712.37	13,956.30	17,585.10
	Songyuan	Output	157,818.78	40,530.78	23,413.05	30,402.54	177.39	11,442.06
		Input	55,372.41	1500.12	12,525.03	178,179.75	15,143.76	1063.53
	Yanbian Korean	Output	157,818.78	40,530.78	23,413.05	30,402.54	177.39	11,442.06
		Input	55,372.41	1500.12	12,525.03	178,179.75	15,143.76	1063.53
2000–2010	Harbin	Output	48,743.37	28,239.84	133,546.32	434,891.43	3807.00	6578.01
		Input	248,034.15	350.73	134,464.86	133,718.04	135,588.33	3649.86
	Daqing	Output	1363.23	39,899.79	227,714.49	23,553.18	6196.50	539,485.92
		Input	19,958.40	291,422.61	181,224.54	229,023.45	52,957.80	63,626.31
	Mudanjiang	Output	70,477.29	5101.38	31,207.68	59,534.19	336.96	886.14
		Input	43,442.73	421.20	60,269.67	38,673.45	24,731.73	4.86
	Qiqihar	Output	5893.56	16,472.97	147,202.11	192,537.81	11,868.12	35,860.32
		Input	15,692.94	20,502.72	175,794.30	148,178.16	44,478.72	5188.05
	Suihua	Output	7081.02	46,134.36	74,502.18	39,694.86	2101.14	175,318.83
		Input	13,957.11	112,572.99	95,649.66	63,547.74	52,866.27	6238.62
	Changchun	Output	18,783.90	95,128.83	30,948.48	445,582.62	997.92	11,889.18
		Input	124,234.56	3199.50	120,969.45	100,809.36	247,551.39	6566.67
	Jilin	Output	60,749.19	29,514.78	45,574.65	151,305.57	53.46	404.19
		Input	89,908.38	1073.25	31,771.44	95,502.24	69,229.89	116.64
	Liaoyuan	Output	19,321.74	403.38	10,198.71	4261.41	20.25	20.25
		Input	1070.82	0.00	1304.91	24,917.22	6922.26	10.53
	Siping	Output	12,349.26	40,094.19	19,231.02	223,773.84	427.68	68,438.52
		Input	98,727.66	21,950.19	60,737.04	96,897.06	84,452.22	1550.34
	Songyuan	Output	26,307.18	268,909.47	287,022.69	156,266.82	106.11	217,318.14
		Input	54,160.65	224,536.05	133,157.52	422,065.08	77,162.22	44,848.89
	Yanbian Korean	Output	45,038.43	16,877.97	73,527.75	75,418.29	26.73	3482.19
		Input	56,614.14	1996.65	10,321.02	80,874.45	63,238.32	1326.78

Table A1. *Cont.*

Periods	City	Indicators	Land Use Categories					
			Forest	Grassland	Wetland	Farmland	Built-Up Area	Other Land
2010–2020	Harbin	Output	487,904.31	17,649.90	275,995.35	1,385,581.14	219,552.93	1967.49
		Input	645,611.31	34,134.21	488,666.52	824,171.76	365,293.80	30,773.52
	Daqing	Output	158,349.33	606,177.27	832,604.67	587,095.29	119,456.37	206,498.97
		Input	120,048.48	280,655.28	706,958.28	1,037,661.03	119,671.02	245,187.81
	Mudanjiang	Output	540,994.14	11,369.97	141,312.60	882,242.28	93,474.81	1792.53
		Input	645,546.51	42,377.58	267,706.62	551,544.39	160,608.42	3402.81
	Qiqihar	Output	133,369.74	170,706.69	461,582.55	1,005,417.36	253,187.37	54,764.91
		Input	141,967.89	95,377.50	727,192.89	793,672.83	300,417.66	20,399.85
	Suihua	Output	206,210.61	485,167.32	692,370.99	494,525.25	167,473.98	15,701.85
		Input	137,474.01	147,444.30	493,724.16	906,909.21	220,008.15	155,890.17
	Changchun	Output	395,369.91	12,215.61	150,450.21	700,795.80	297,738.99	5857.92
		Input	389,046.24	19,806.93	76,116.51	658,948.77	400,809.87	17,700.12
	Jilin	Output	495,746.73	7545.96	120,447.81	940,107.87	93,818.25	370.98
		Input	752,515.92	8133.21	87,157.62	611,911.26	196,061.31	2258.28
	Liaoyuan	Output	161,813.70	26.73	14,650.47	218,507.22	54,672.57	34.02
		Input	175,903.65	261.63	18,711.00	203,809.77	50,932.80	85.86
	Siping	Output	247,571.64	19,036.62	49,088.43	461,974.59	189,312.39	11,828.43
		Input	236,855.34	19,593.90	49,020.39	438,991.65	228,142.98	6207.84
	Songyuan	Output	198,905.22	302,651.64	289,905.48	438,248.07	159,694.74	122,298.66
		Input	215,651.16	184,419.18	167,004.99	620,251.02	155,934.72	168,442.74
	Yanbian Korean	Output	443,922.12	37,362.87	103,503.42	699,837.57	113,499.63	4831.65
		Input	683,272.26	11,653.47	128,338.02	451,073.61	119,249.82	9370.08

Table A2. Global Moran's I index values of various change data.

Data	Global Moran's I Index	z-Score	*p*-Value
Change of ecological land from 1990 to 2000	0.49	139.84	0.00
Change of ecological land from 2000 to 2010	0.47	132.72	0.00
Change of ecological land from 2010 to 2020	0.57	160.38	0.00
Change of PD from 1990 to 2000	0.00	3.23	0.00
Change of PD from 2000 to 2010	0.24	70.65	0.00
Change of PD from 2010 to 2020	0.01	2.35	0.02
Change of AI from 1990 to 2000	0.22	67.22	0.00
Change of AI from 2000 to 2010	0.39	109.78	0.00
Change of AI from 2010 to 2020	0.22	62.96	0.00
Change of MPS from 1990 to 2000	0.27	75.13	0.00
Change of MPS from 2000 to 2010	0.32	91.51	0.00
Change of MPS from 2010 to 2020	0.27	75.34	0.00
Change of COHESION from 1990 to 2000	0.03	21.09	0.00
Change of COHESION from 2000 to 2010	0.26	74.99	0.00
Change of COHESION from 2010 to 2020	0.27	75.34	0.00

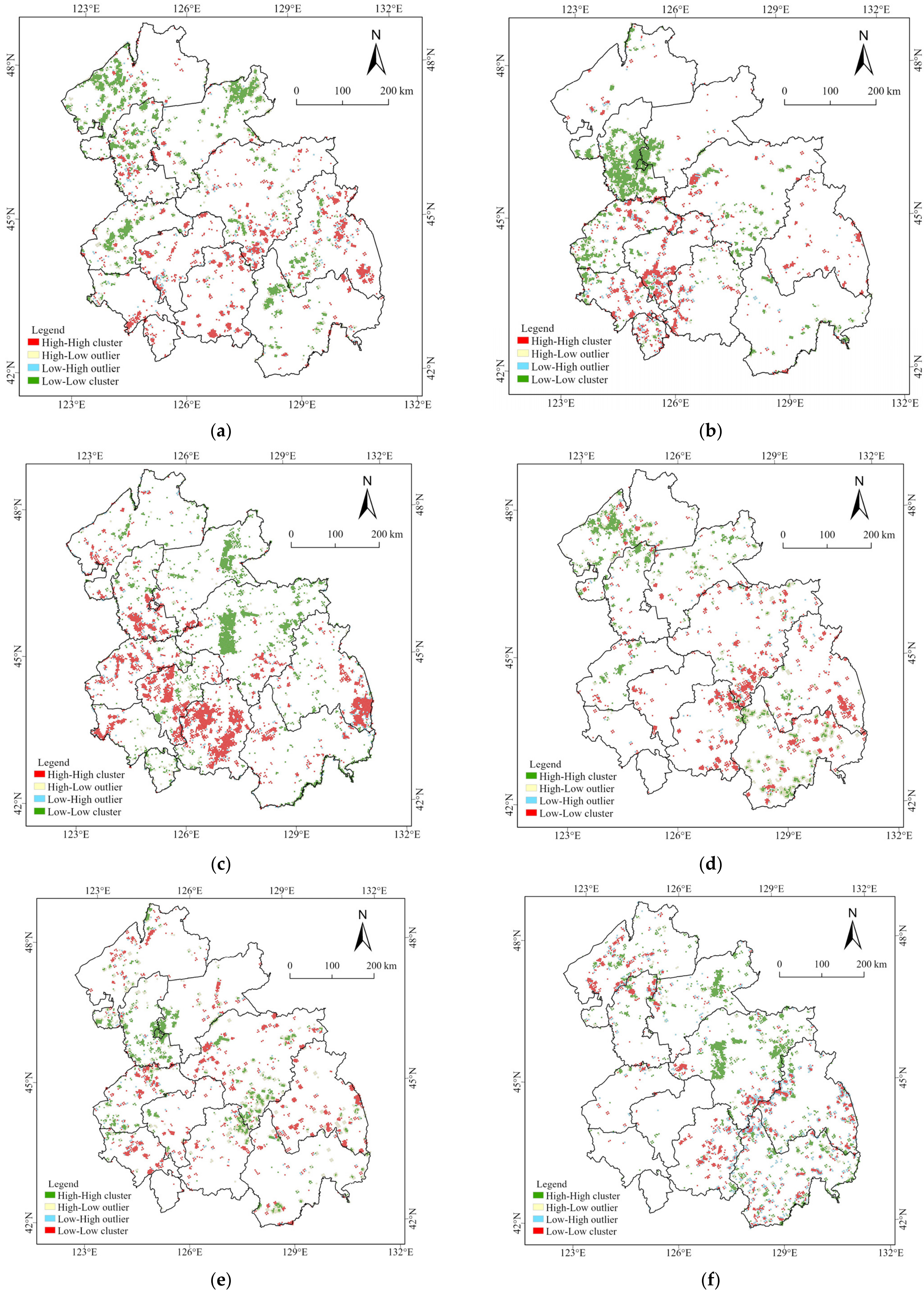

Figure A2. *Cont.*

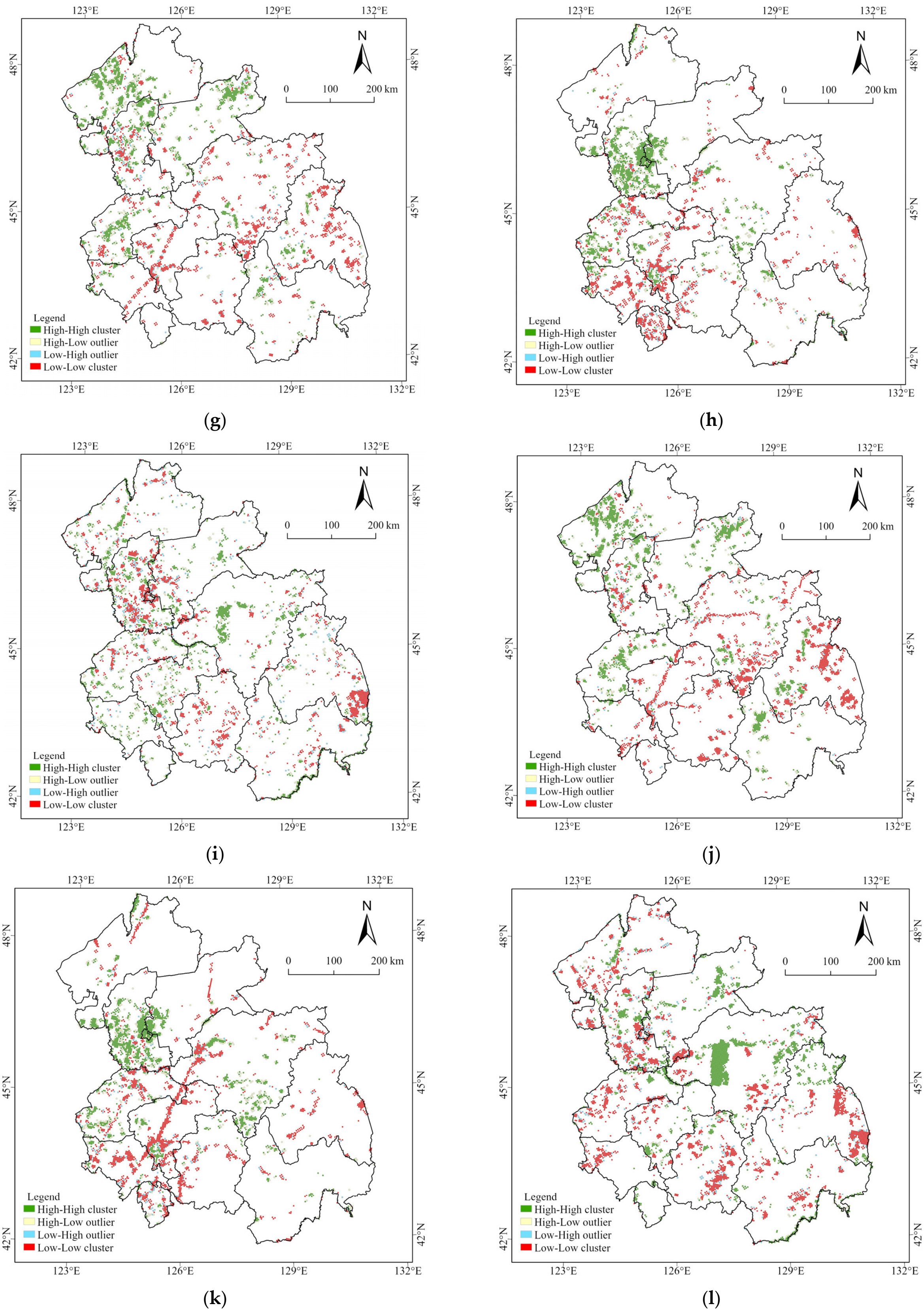

Figure A2. Hotspot identification results of landscape index changes: (**a**) changes in PD from 1990 to 2000; (**b**) changes in PD from 2000 to 2010; (**c**) changes in PD from 2010 to 2020; (**d**) changes in MPS from 1990 to 2000; (**e**) changes in MPS from 2000 to 2010; (**f**) changes in MPS from 2010 to 2020; (**g**) changes in COHESION values from 1990 to 2000; (**h**) changes in COHESION values from 2000 to

2010; (**i**) changes in COHESION values from 2010 to 2020; (**j**) changes in AI values from 1990 to 2000; (**k**) changes in AI values from 2000 to 2010; (**l**) changes in values AI from 2010 to 2020.

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