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Spatiotemporal Change and Landscape Pattern Variation of Eco-Environmental Quality in Jing-Jin-Ji Urban Agglomeration From 2001 to 2015

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ABSTRACT Identifying the changes and relationships between regional eco-environment quality and landscape pattern in an urban agglomeration have a great significance in realizing sustainable development goal. However, limited research has been performed to understand the spatiotemporal change of eco-environment quality, the variation of landscape pattern, and their relationship in an urban agglomeration. This study selected the Jing-Jin-Ji (JJJ) urban agglomeration as the study area. A comprehensive index, the remote sensing ecological index (RSEI), was utilized to understand the eco-environment spatiotemporal change and landscape pattern variation at class-level and landscape-level of JJJ during 2001∼2015, then, their relationship was explored. The major conclusions were as follows: (1) The average RSEI value of JJJ increased from 0.43 to 0.46, which represented that the eco-environment of JJJ had improved in the fourteen years. Among it, the improved region was mainly located in Zhangjiakou city, while the degraded region was mainly distributed in the eastern Hebei plain. (2) The landscape characteristics of entire JJJ eco-environment were becoming more aggregated, connected, diverse, and regular. However, fair, moderate, and good grades were getting more concentrated and continuous; poor grade indicated a more fragmented and disconnected trend; excellent grade displayed an expanded and concentrated situation. (3) Human factors have an increasing influence on regional eco-environment changes. (4) Fair, moderate, and good grades showed a more dominant and stronger influence on the variation of landscape pattern in JJJ. Specifically, the fair grade had a positive correlation with the variation of landscape pattern, while moderate and good grades had a negative one. All of these conclusions could be valuable information for relevant decision-makers in managing or achieving the optimal eco-environment landscape pattern.

INDEX TERMS Jing-Jin-Ji urban agglomeration, landscape pattern, remote sensing ecological index, spatiotemporal change.

I. INTRODUCTION

The eco-environment, defined as "the total quantity and quality of water resources, land resources, biological resources and climate resources that affect human survival and development", is a social-economic-natural compound system. It not only provides human natural resources and living environment service but also is the foundation and core of regional social and economic sustainable development [1]. Its quality can effectively indicate the degree of coordination between human production activities and the environment of a region [2]. Since the implementation of the policy of reform and opening up in 1978, great changes have taken place in mainland China, especially in the aspects of spatial urbanization, population expansion, industrialization, etc. [3], [4]. However, accompanied by the spatial urbanization process, the eco-environment has also been greatly influenced, for example, water and soil loss [5], urban heat

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islands [6], a decrease of vegetation coverage [7], air pollution [8], and so forth, which can pose a threat to the realization of sustainable development goals. Hence, it is of great importance to assess and analyze regional eco-environment quantitatively.

Since the concept of Ekistics was promoted by Doxiadis in the 1950s, developed countries had carried out some researches to analyze and evaluate urban living environment quality [9], [10]. In 1992, Fu evaluated eco-environmental qualities of China systematically [11]. To date, numerous studies have been conducted to assess regional eco-environment at various scales, such as international [12], intercontinental [13], national [14], provincial [15], city [16], etc. As for the evaluation methods, it can be mainly divided into two types, which are qualitative and quantitative evaluation methods [1]. Till now, there has developed several methods, for example, index evaluation method [17], analytic hierarchy process [18], ecological footprint method [19], artificial neural network evaluation method [20], [21], matter element analysis method [22], fuzzy integrated assessment method [23], and so forth [1], [24]. Generally speaking, compared with qualitative evaluation, quantitative evaluation gives more objective judgement about the eco-environment. However, numerous traditional methods could only evaluate the whole regional eco-environment by one calculated value, which is unable to provide the evaluation value of any location.

Advances in remote sensing technology have shown great potential in evaluating numerous aspects of regional eco-environment at various scales, which owes to the principal that remote sensing imagery acquires reflected radiation of the earth surface. For example, regional vegetation situation can be detected by one widely used index—Normalized Difference Vegetation Index (NDVI) [25]; EVI-derived ecosystem functional attributes (EFAs), promoted by Alcaraz-Segura in 2017 [26], could be applied as one important biodiversity variables in species distribution models. Besides, land surface temperature (LST), acquired from remote sensing thermal imagery has also been an important parameter to analyze the urban heat island and the dynamics and evolution of regional thermal environments [27]. Overall, a single remote-sensing index can only reflect a limited aspect. Considering the complexity of an eco-environment, aggregated remote sensing index has drawn the attention of scholars all over the world. He *et al.* [28] developed a comprehensive evaluation index (CEI) to assess urban environment change in China; Wei *et al.* [29] integrated six indexes to evaluate the environment. What's more, numerous researchers combined remote sensing data and other datasets to assess regional eco-environment. Wei *et al.* [30] integrated 23 indices to assess environmental vulnerability; Chang *et al.* [31] constructed an index system combined 14 indices to evaluate the ecological environment; Chai and Lha [32] assessed ecological environmental quality (EEQ) by selecting key indicators; Sun *et al.* [33] evaluated the eco-environmental quality of Hainan island by establishing an eco-environmental quality index (EQI), which was developed and published by the ministry of ecology and environment of China.

Generally, single remote sensing indices or existing aggregated remote sensing indices mostly assess one certain aspect of a regional eco-environment. Constructing one index system is an effective way to comprehensively evaluate a regional eco-environment, however, index system mostly requires multi-source datasets, which is time-consuming and inconvenient, moreover, the establishment of an appropriate sub-index system can exert a great influence on the final evaluation result [34]. So, does there exist one aggregated remote sensing index that can comprehensively evaluate a regional eco-environment? One index promoted by Prof. Xu in 2013 has made some progress [35]. This index is named as remote sensing ecological index (RSEI), it encompasses four sub-indexes representing climatic and land-surface biophysical variables [36]. To be specific, these four sub-indexes are normalized difference vegetation index (NDVI), wetness (WET), normalized difference build-up and soil index (NDBSI) and land surface temperature (LST), respectively. Among it, NDVI represents the greenness aspect of a regional eco-environment; WET represents the wetness aspect; NDBSI represents the dryness aspect; LST represents the heat aspect. Spatial principal component analysis (SPCA) is an effective way to aggregate the most valuable information [37]. By utilizing the SPCA method, RSEI can be acquired. Till now, it has been widely applied in numerous studies, which has proven to be an effective and convenient index in quickly evaluating a regional eco-environment, such as Fuzhou city [38]–[40]; Xiong'an New Area [41]; Nanchang city [42]; Dingcheng district in Changde city [43]; Zhengzhou city [44], etc. However, these existing studies mostly applied RSEI to evaluate regional eco-environment at city level based on medium resolution remote sensing images, like Landsat series image [38], which failed to evaluate at the large region level. The major reason was that at the large region level, it was inappropriate and difficult to apply this index. For instance, one large region mostly requires multiple Landsat images to cover the entire region, however, due to the cloud pollution and the 16 days revisit period, it was extremely hard to acquire all cloud-free images at the same time. To solve this problem, integrating this index with MODIS datasets and Google Earth Engine platform has shown great potential.

Landscape ecology is one subject that aims to study and improve the relationships between specific ecosystems and their ecological processes [45]. Landscape pattern, as one of the key research topics of landscape ecology [46], focuses on the quantification of changes in the land elements' configurations and compositions based on landscape metrics [47]–[49]. Moreover, landscape pattern is considered to be an important indicator of landscape heterogeneity and its effects on a variety of ecological processes [50]. Monitoring land use/cover changes and landscape pattern analysis have drawn much concern from scholars around the world [51]. It was concluded that land use/cover changes and landscape pattern variations have certain ecological effects [52]. A literature review revealed that three main issues had been studied, which were the changes in landscape patterns [53], [54], the influences of these changes on ecological processes [55], [56], and the relationship between landscape pattern changes and their driving forces [57]–[59]. For example, Wang *et al.* [47] found that cultivated land and water bodies had a close relationship with four landscape-level metrics. Besides these studies, the spatial configuration of the urban thermal environment and its relationship with landscape pattern metrics have been investigated by some researchers [45], [60]. To date, however, existing studies seldom investigated the relationship between different eco-environment grades and landscape metrics.

An urban agglomeration is a highly developed spatial form of integrated cities, with a research history traced back to 100 years ago [61]. In 2014, the Chinese government issued a development roadmap of "National New Urbanization Plan", which clearly pointed out to optimize and upgrade eastern urban agglomerations, establish a coordinated mechanism for urban agglomerations development, and to achieve the green development goals based on protecting the eco-environment [62]. Till now, China has proposed building a hierarchical urban agglomeration system with five national-level large urban agglomerations, nine regional-level medium-sized urban agglomerations and six sub-regional-level small-sized urban agglomerations [61]. Jing-Jin-Ji urban agglomeration (JJJ), which is one of the five large urban agglomerations and considered as "the three engines of China's economic growth" in the 21st century (the other two are Yangtze Delta urban agglomeration and Pearl River Delta urban agglomeration), was selected as the study area. The aims of this study were to (1) analyze the spatiotemporal changes of RSEI; (2) evaluate the landscape pattern variation of RSEI grades based on class-level and landscape-level metrics; (3) identify the relationship between RSEI grades and landscape pattern.

II. MATERIALS AND METHODS

A. STUDY AREA

JJJ is located in north China (36°05′∼42°40′N, 113°27′∼119°50′E) and covers approximately 218,000 km^2. It includes two municipalities and eleven prefecture-level cities, which are Beijing (BJ), Tianjin (TJ), Shijiazhuang (SJZ), Tangshan (TS), Qinhuangdao (QHD), Handan (HD), Xingtai (XT), Baoding (BD), Zhangjiakou (ZJK), Chengde (CD), Cangzhou (CZ), Langfang (LF) and Hengshui (HS) (Figure 1). This region has a temperate semi-humid and semi-arid monsoon climate with the average temperature in July and annual precipitation of 18∼27 °C and 524.4 mm respectively. In 2017, the total population and gross domestic product of JJJ reached 95.74 million and 8058.04 billion yuan, which accounted for 6.89% and 9.77% of that of the whole country (http://www.stats.gov.cn). However,

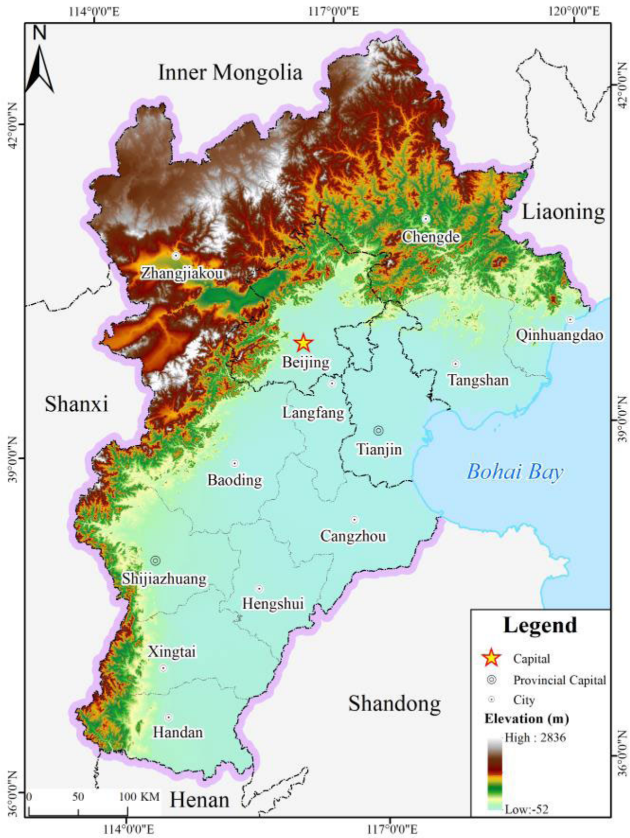

FIGURE 1. Location of the study area.

along with the fast urbanization, quantitatively evaluating the change of JJJ's eco-environment has become a topic of discussion.

B. DATA PREPARATION AND RSEI CONSTRUCTION

In this paper, MOD09A1 and MOD11A2 datasets were utilized to construct RSEI. Specifically, MOD09A1 dataset provides an estimate of the 8-day Terra MODIS seven bands surface spectral reflectance corrected for atmospheric conditions such as aerosols, gasses, and Rayleigh scattering at 500 m resolution; MOD11A2 dataset provides an average 8-day land surface temperature (LST) at 1000 m resolution based on the generalized split-window algorithm [63]. In order to keep the results comparable, both datasets in the time span of 1st June to 31st October were processed on Google Earth Engine (GEE) platform (https://code.earthengine.google.com).

RSEI is composed of four sub-indexes, which are normalized difference vegetation index (NDVI), wetness (WET), normalized difference build-up and soil index (NDBSI) and land surface temperature (LST). Different from previous studies, RSEI integrates MODIS high-temporal datasets, making it possible to assess large-scale regional eco-environment. Except that LST is directly acquired from MOD11A2 dataset, NDVI [25], WET [64] and NDBSI [35] are acquired based on the following formulas, where ρ is the band surface reflectance, blue, green, red, nir, mir1, mir2, mir3 are the MODIS bands at 459-479 nm, 545-565 nm, 620-670 nm, 841-876 nm, 1230-1250 nm, 1628-1652 nm, and 2105-2155 nm respectively.

$$NDVI = (\rho_{nir} - \rho_{red}) / (\rho_{nir} + \rho_{red}) \quad (1)$$

$$\begin{aligned} WET &= 0.1084 \times \rho_{red} + 0.0912 \times \rho_{nir} \\ &\quad + 0.5065 \times \rho_{blue} + 0.4040 \times \rho_{green} \\ &\quad - 0.2410 \times \rho_{mir1} - 0.0.4658 \times \rho_{mir2} \\ &\quad - 0.5306 \times \rho_{mir3} \end{aligned} \quad (2)$$

$$\begin{aligned} NDBSI &= \frac{1}{2}\left\{\frac{\frac{2\times\rho_{mir2}}{\rho_{mir2}+\rho_{nir}} - \frac{\rho_{nir}}{\rho_{nir}+\rho_{red}} - \frac{\rho_{green}}{\rho_{green}+\rho_{mir2}}}{\frac{2\times\rho_{mir2}}{\rho_{mir2}+\rho_{nir}} + \frac{\rho_{nir}}{\rho_{nir}+\rho_{red}} + \frac{\rho_{green}}{\rho_{green}+\rho_{mir2}}}\right\} \\ &\quad + \frac{1}{2}\left\{\frac{(\rho_{mir2} + \rho_{red}) - (\rho_{mir2} + \rho_{blue})}{(\rho_{mir2} + \rho_{red}) + (\rho_{mir2} + \rho_{blue})}\right\} \end{aligned} \quad (3)$$

After acquired all 8-day sub-indexes results during the period, a final average value of each sub-index was firstly calculated and was rescaled to 0∼1, then principal component analysis (PCA) was performed in ArcGIS 10.6 software. Normally, the first component of PCA (PC1) integrates the largest information of the input dataset. Therefore, PC1 was adopted to derive original RSEI value and the expression could be written as follows.

$$RSEI_{origin} = 1 - PC1\,[f\,(NDVI, WET, NDBSI, LST)] \quad (4)$$

Finally, RSEI was obtained by rescaling to 0∼1. The formula of rescaling was as follows.

$$X_{rescale} = (X_i - X_{\min}) / (X_{\max} - X_{\min}) \quad (5)$$

where $X_{rescale}$ represents the rescaled result; $X_{\max}$ and X_{min} represent the maximum and minimum value of X; X_i means X value at the i_{th} pixel. Figure 2 is a flowchart.

C. RSEI SPATIOTEMPORAL CHANGE ANALYSIS

Normally, spatiotemporal change includes two aspects, which are spatial change and temporal change. Before analyze RSEI spatiotemporal characteristics, we set 0.2 as the interval to divide RSEI into five grades, which are poor [0.0, 0.2), fair [0.2, 0.4), moderate [0.4, 0.6), good [0.6, 0.8), and excellent [0.8, 1.0], respectively. The dynamic model is one of the frequently used models [47]. It can reflect the change degree of a certain RSEI grade in a certain period quantitively. The formula is as follows.

$$D = \frac{T_{end} - T_{start}}{T_{start}} \times \frac{1}{P} \times 100\% \quad (6)$$

where D is the dynamic degree; T_{start} and T_{end} indicate the area of a certain RSEI grade at the start and end of the comparison period, respectively; P is the time interval.

Besides, the transition matrix method is applied to deeply understand the area transition situation between different

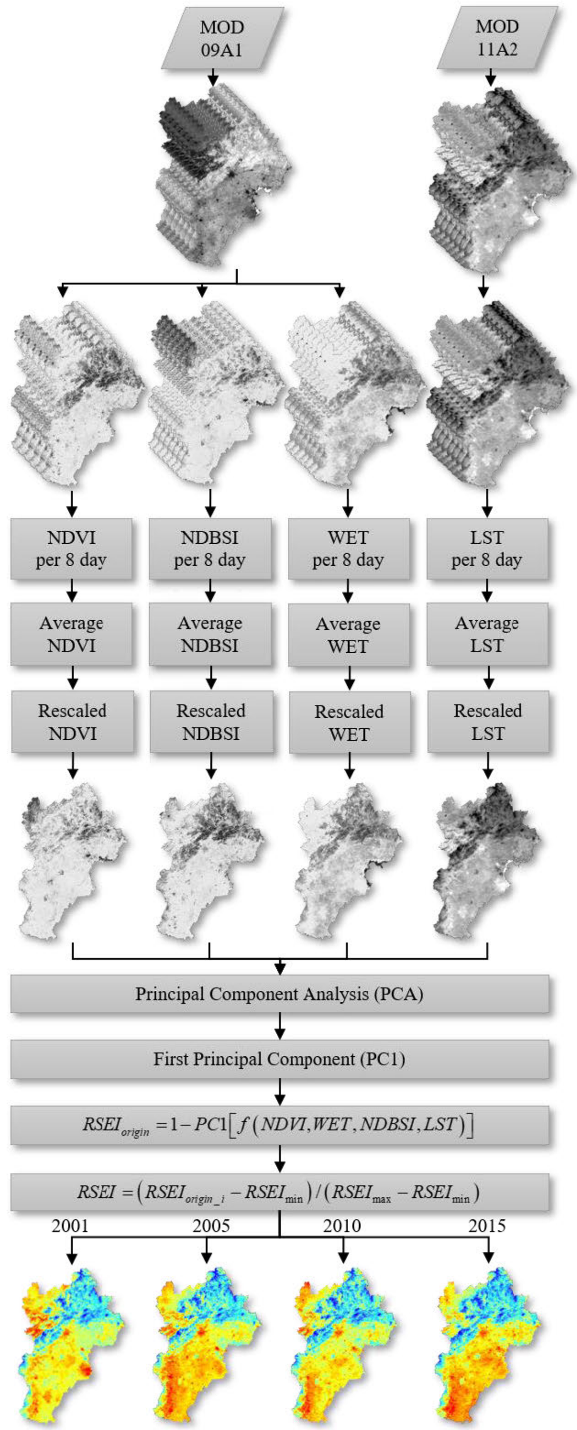

FIGURE 2. RSEI construction flowchart.

RSEI grade [65]. The formula is as follows.

$$S = \begin{bmatrix} S_{11} & S_{12} & \cdots & S_{1n} \\ S_{21} & S_{22} & \cdots & S_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ S_{n1} & S_{n2} & \cdots & S_{nn} \end{bmatrix} \quad (7)$$

TABLE 1. The brief introduction of selected landscape metrics.

Name	Abbreviation	Unit	Level	Computing Equation
Number of Patches	NP	None	Class	$NP = n_i$
Largest Patch Index	LPI	Percent	Class	$LPI = \left[\left(\max_{j=1}^{n}(a_{ij})\right)(100)\right] / A$
Mean Patch Size	AREA_MN	Square kilometre	Class	$AREA\_MN = \left(\sum_{i=1}^{m}\sum_{j=1}^{n} a_{ij}\right) / N$
Patch Cohesion Index	COHESION	None	Class	$COHESION = \left[1 - \frac{\sum_{j=1}^{n} p_{ij}^{*}}{\sum_{j=1}^{n} p_{ij}^{*}\sqrt{a_{ij}^{*}}}\right] \cdot \left[1 - \frac{1}{\sqrt{Z}}\right]^{-1} \cdot (100)$
Contagion Index	CONTAG	Percent	Landscape	$CONTAG = \left[1 + \left\{\sum_{i=1}^{m}\sum_{k=1}^{m}\left[P_i \cdot \frac{g_{ik}}{\sum_{k=1}^{m} g_{ik}}\right] \cdot \left[\ln\left(P_i \cdot \frac{g_{ik}}{\sum_{k=1}^{m} g_{ik}}\right)\right]\right\} / \left[2\ln(m)\right]\right](100)$
Aggregation Index	AI	Percent	Landscape	$AI = \left[\sum_{i=1}^{m}\left(\frac{g_{ii}}{\max \to g_{ii}}\right) P_i\right](100)$
Shannon's Diversity Index	SHDI	None	Landscape	$SHDI = -\sum_{i=1}^{m}\left(P_i \cdot \ln P_i\right)$
Interspersion and Juxtaposition Index	IJI	Percent	Landscape	$IJI = \left\{-\sum_{k=1}^{m}\left[\left(\frac{e_{ik}}{\sum_{k=1}^{m} e_{ik}}\right)\ln\left(\frac{e_{ik}}{\sum_{k=1}^{m} e_{ik}}\right)\right]\right\}(100) / \left[\ln(m-1)\right]$
Mean Patch Shape Index	SHAPE_MN	Square kilometre	Landscape	$SHAPE\_MN = \left[\sum_{i=1}^{m}\sum_{j=1}^{n}\left(\frac{0.25 p_{ij}}{\sqrt{a_{ij}}}\right)\right] / N$
Mean Patch Fractal Dimension	FRAC_MN	None	Landscape	$FRAC\_MN = \left\{\sum_{i=1}^{m}\sum_{j=1}^{n}\left[\frac{2\ln(0.25 p_{ij})}{\ln a_{ij}}\right]\right\} / N$

where S represents the area of a certain RSEI grade; n is the number of RSEI grade; S_{ij} indicates the transformed area from grade i to grade j in a certain period; S_{ii} represents the unchanged area in a certain period.

D. LANDSCAPE METRICS SELECTION AND CALCULATION

Numerous landscape metrics have been promoted to explain the relationships between ecological processes and spatial patterns. Till now, many programs have been developed and promulgated, which acquires numerous landscape metrics become more accessible [47]. Among it, Fragstats 4.2 software is one of the most used platforms, it can compute hundreds of landscape metrics for three levels: patch level, class level, and landscape level [66]. However, previous studies have found that redundancy between various metrics was widely existed [51], [67].

Therefore, the selection of an optimal landscape metrics is the key step for further landscape pattern analyses. Here, correlation analysis of 54 metrics, including 24 metrics at the class level and 30 metrics at the landscape level, was firstly performed, then criterion $|r| \geq 0.9$ was applied to exclude unsatisfied metrics [67]; Next, combined with previous studies [47], [51], [60], [68], [69], ten represented landscape metrics were finally selected to quantitatively evaluate landscape pattern variations at the different period with the support of Fragstats 4.2 (use 8 cell neighbour rule). Table 1 is the brief introduction of ten selected landscape metrics.

III. RESULTS

A. RSEI SPATIOTEMPORAL CHANGE ANALYSIS

Figure 3 illustrates the spatial distribution of four years of RSEI. The average RSEI value of 2001, 2005, 2010 and 2015 were 0.43, 0.42, 0.51 and 0.46 respectively, which

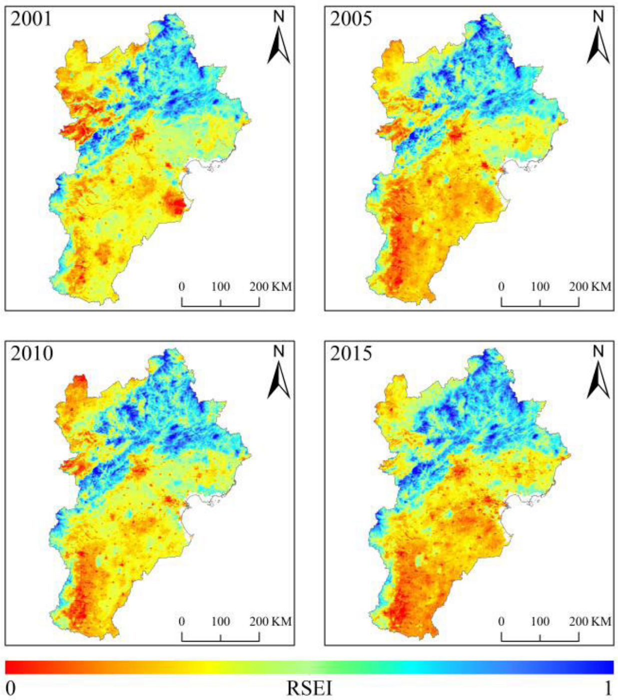

FIGURE 3. Spatial distribution of RSEI in JJJ.

presented an inverted "N" change trend. Generally, the eco-environment of JJJ degraded slightly (2001~2005), then improved sharply (2005~2010), and deteriorated again in the last period (2010~2015); however, from the perspective of the entire period, the eco-environment of JJJ had improved. To be specific, it could be found that the northern part of JJJ had a better eco-environment compared with north-western, central, and south-eastern part, which was following the actual situation, as the northern part was mainly covered with vegetation and belonged to a mountainous area named Yanshan Mountain.

Table 2 displays RSEI five grades statistical result. It could be found that area in poor eco-environment contracted from 2001 to 2010, and slightly expanded towards 2015; The fair grade expanded and contracted alternately, with the greatest shrinkage from 2005~2010 (−28.71%); The area of moderate grade also expanded and decreased alternately from the first (2001) to the last year (2015), with the greatest change from 2005 to 2010 (about +20%); The eco-environment in the good and excellent grades expanded continuously from 2001 to 2010, then slightly declined to 2015. In general, the extent of poor and excellent grades accounted for less than 5% of the study area in four periods, while the area with a fair and moderate eco-environment was dominant.

In order to deeply understand different RSEI grades change situation, dynamic transition analysis was performed (Table 3 and Table 4). Generally, JJJ's eco-environment had undergone a remarkable change. To be specific, in the first period (2001~2005), the area of poor and moderate grade decreased at a rate of 446.94 $km^2 \cdot y^{-1}$ and 2514.38 $km^2 \cdot y^{-1}$, respectively; Among it, poor grade area mainly changed into fair grade (4796.50 km^2), accounting 99.13% of entire poor grade changed area; moderate grade area mainly changed into fair grade (19601.75 km^2) and good grade (6072.00 km^2), accounting 76.34% and 23.65% of entire moderate grade changed area. Fair, good and excellent grade showed similar dynamic degree value, which was 2.28%, 2.57% and 2.55% per year, respectively. Among it, fair grade area mainly changed into moderate and poor grade, accounting 79.13% and 19.84% of entire fair grade changed area; as to good grade, there had 3414.00 km^2 and 458.00 km^2 that changed into the moderate and excellent grade. To excellent grade, the area changing into good grade accounted for 99.77% of the total excellent grade changed area.

In the second period (2005~2010), poor and fair grade displayed negative dynamic degree, which was −18.56% and −11.36%, respectively. Besides, moderate, good and excellent grade showed positive dynamic degree, among

TABLE 2. RSEI grades statistical result.

RSEI	2001		2005	
	Area (km^2)	Percent (%)	Area (km^2)	Percent (%)
Poor	6523.75	3.04	4736.00	2.21
Fair	99370.75	46.31	108418.75	50.53
Moderate	81482.50	37.97	71425.00	33.29
Good	25873.00	12.06	28534.75	13.29
Excellent	1330.75	0.62	1466.25	0.68
RSEI	2010		2015	
	Area (km^2)	Percent (%)	Area (km^2)	Percent (%)
Poor	341.25	0.16	1904.50	0.89
Fair	46817.75	21.82	92125.00	42.93
Moderate	113981.50	53.12	78331.25	36.51
Good	49839.25	23.23	40429.25	18.84
Excellent	3601.00	1.67	1790.75	0.83

TABLE 3. RSEI grades dynamic change of JJJ.

RSEI	2001~2005		2005~2010	
	Area change (km^2)	Dynamic degree (%)	Area change (km^2)	Dynamic degree (%)
Poor	-1787.75	-6.85	-4394.75	-18.56
Fair	9048.00	2.28	-61601.00	-11.36
Moderate	-10057.50	-3.09	42556.50	11.92
Good	2661.75	2.57	21304.50	14.93
Excellent	135.50	2.55	2134.75	29.12
RSEI	2010~2015		2001~2015	
	Area change (km^2)	Dynamic degree (%)	Area change (km^2)	Dynamic degree (%)
Poor	1563.25	91.62	-4619.25	-5.06
Fair	45307.25	19.35	-7245.75	-0.52
Moderate	-35650.25	-6.26	-3151.25	-0.28
Good	-9410.00	-3.78	14556.25	4.02
Excellent	-1810.25	-10.05	460.00	2.47

TABLE 4. RSEI grades transition matrix of JJJ.

Year	RSEI Grade (km^2)	RSEI Grade (km^2)				
		Poor	Fair	Moderate	Good	Excellent
2001~2005	Poor	1685.25	3048.75	2.00	0.00	0.00
	Fair	4796.50	84001.50	19601.75	19.00	0.00
	Moderate	42.00	12162.25	55806.00	3414.00	0.75
	Good	0.00	158.25	6072.00	21982.00	322.50
	Excellent	0.00	0.00	0.75	458.00	1007.50
2005~2010	Poor	280.50	60.75	0.00	0.00	0.00
	Fair	4395.75	41357.50	1064.50	0.00	0.00
	Moderate	59.75	66984.25	46311.00	626.50	0.00
	Good	0.00	16.25	24049.50	25665.75	107.75
	Excellent	0.00	0.00	0.00	2242.50	1358.50
2010~2015	Poor	294.25	1600.25	10.00	0.00	0.00
	Fair	43.75	40829.00	51246.00	6.25	0.00
	Moderate	3.25	4388.50	60409.70	13529.80	0.00
	Good	0.00	0.00	2315.80	36160.95	1952.50
	Excellent	0.00	0.00	0.00	142.25	1648.50
2001~2015	Poor	676.75	1181.50	24.75	21.50	0.00
	Fair	4820.50	71694.20	15562.30	48.00	0.00
	Moderate	1026.50	25945.05	50504.70	854.25	0.75
	Good	0.00	550.00	15388.50	24243.25	247.50
	Excellent	0.00	0.00	2.25	706.00	1082.50

it, the excellent grade had the highest dynamic degree (+29.12%). To be specific, poor grade area mainly changed into fair grade (4395.75 km^2), accounting 98.66% of the total poor grade changed area; Fair grade area mainly changed into moderate grade (66984.25 km^2), accounting 99.89% of the total fair grade changed area; Moderate grade area mainly changed into good grade (24049.50 km^2), accounting 95.76% of the total moderate grade changed area; As to good grade, it mainly changed into excellent and moderate grade, which accounted 78.16% and 21.84% of the total good grade changed area, respectively; To excellent grade, there has 107.75 km^2 that changed from excellent grade into good grade, accounting 100% of the total excellent grade changed area.

In the third period (2010∼2015), the poor grade had the highest dynamic degree (+91.62%), followed by fair grade (+19.35%); however, different from the second period, moderate, good and excellent grade all had a negative dynamic degree, which was −6.26%, −3.78% and −10.05%, respectively. Combined with Table 4, poor grade area mainly changed into fair grade (43.75 km^2) and moderate grade (3.25 km^2), accounting 93.09% and 6.91% of the total poor grade changed area; Fair grade mainly changed into poor and moderate grade, accounting 26.72% and 73.28% of the total fair grade changed area; Moderate grade mainly converted to fair grade (51246.00 km^2), accounting 95.66% of the total moderate grade changed area; To good grade, the area mainly changed into moderate grade (13529.80 km^2), which accounted 98.91% of the total good grade changed area; As for the excellent grade, there had 1952.50 km^2 that changed into good grade, accounting 100% of the total excellent grade changed area.

During the entire period (2001∼2015), poor, fair and moderate grade all had a negative dynamic degree, while good and excellent grade had positive one, representing the eco-environment of JJJ had improved. According to area transition matrix, poor grade mainly changed into a fair grade (4820.50 km^2) and moderate grade (1027.50 km^2), which accounted 82.43% and 17.57% of the total poor grade changed area, respectively. Different from the former three periods, fair grade mainly changed into a moderate grade (25945.05 km^2), accounting 93.74% of the total fair grade changed area. Moderate grade mainly changed into a fair and good grade equally, which accounted for 50.24% and 49.68% of the total moderate grade changed area, respectively. To good grade, only 6.30% of the total grade area has changed into other four grades, and mainly were moderate grade (853.25 km^2) and excellent grade (706 km^2). As for the excellent grade, it mainly changed into good grade, accounting 99.70% of the total excellent grade changed area.

In general, in a different period, area transition between grades mainly happened in one adjacent grade, which represented that the range of RSEI variation mainly occurred in ±0.2. Moreover, dynamic degree of all grade in the former three periods (2001∼2005, 2005∼2010 and 2010∼2015) demonstrated positive and negative value alternatively. However, in the entire period (2001∼2015), the eco-environment of JJJ represented an improved trend at the change rate

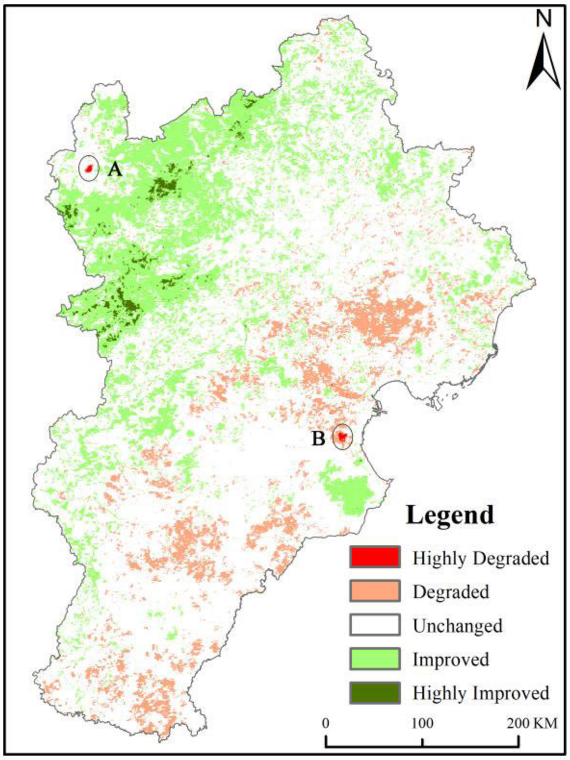

FIGURE 4. Difference results in JJJ during 2001∼2015.

TABLE 5. Four class-level metrics of each RSEI grade in JJJ from 2001 to 2015.

Metrics	Grade	Year 2001	2005	2010	2015
NP	Poor	410	456	106	314
	Fair	1459	976	2047	1150
	Moderate	1778	1122	1539	1427
	Good	721	594	688	648
	Excellent	135	136	276	183
LPI (%)	Poor	0.7036	0.3402	0.0294	0.2309
	Fair	31.4032	40.9970	8.8596	34.3179
	Moderate	27.9824	22.9686	36.9988	29.8528
	Good	2.3086	6.5919	18.6210	8.1951
	Excellent	0.0862	0.1162	0.2517	0.1084
AREA_MN (km^2)	Poor	15.9128	10.3860	3.2264	6.0653
	Fair	68.1095	111.0848	22.8714	80.1087
	Moderate	45.8282	63.6586	74.0621	54.8923
	Good	35.8849	48.0383	72.4411	62.3916
	Excellent	9.8574	10.7813	13.0471	9.7855
COHESION	Poor	96.1902	94.8213	83.4278	91.9118
	Fair	99.8023	99.8487	98.9740	99.7718
	Moderate	99.7457	99.7439	99.8107	99.8121
	Good	98.4708	99.2470	99.7345	99.3607
	Excellent	91.9922	92.0206	94.2412	92.5615

of $-329.95\ km^2 \cdot y^{-1}$ (poor), $-517.55\ km^2 \cdot y^{-1}$ (fair), $-225.09\ km^2 \cdot y^{-1}$ (moderate), $+1039.73\ km^2 \cdot y^{-1}$ (good), $+32.86\ km^2 \cdot y^{-1}$ (excellent), respectively. Here, we set 1∼5 to poor, fair, moderate, good and excellent grade, respectively; then, difference method was performed by using RSEI grade in 2015 minus RSEI grade in 2001; finally, we divided the image into five types based on the pixel value, which were highly degraded $\{-3, -2\}$, degraded $\{-1\}$, unchanged $\{0\}$, improved $\{1\}$, and highly improved $\{2\}$, respectively (Figure 4).

According to Figure 4, we found that improved region was mainly distributed in the northwestern region (Zhangjiakou city). To be specific, these highly improved regions were mostly located in the central and southwestern part of Zhangjiakou city. This had a great relationship with the series policies implemented by the government, such as 'Returning Farmland to Forest (grass) Project', 'Three-North Shelter Forest Program', 'Beijing-Hebei Ecological Water Resources Protection Forest Project', etc. The degraded area was mainly distributed in the eastern Hebei plain, where there had intensive anthropogenic activities. One important reason was that construction land and arable land were mainly located in this region. To be specific, there had two highly degraded regions, which were marked as A and B (Figure 4). By importing these regions' shapefile to Google Earth Pro, we found that Region A was the lake named Angulinao, which was dried since 2004. As for Region B, it belonged to the Beidagang wetland located in Tianjin city. However, in the past years, natural wetlands showed an artificialization trend, while these artificial wetlands were increasing occupied by urban sprawl [70]. Generally, during 2001∼2015, notable effects have been achieved in JJJ by putting a series of environmental protection projects into practice. However, more measures should be promoted to seek a coordinated development between anthropogenic activities and natural environment. Also, we found that these highly degraded and highly improved regions accounted for a larger proportion of JJJ, indicating that the change of JJJ's eco-environment almost occurred in one RSEI grade.

B. LANDSCAPE PATTERN VARIATIONS OF DIFFERENT RSEI GRADES

Class-level landscape metrics can provide addition aggregate properties at the class level that result from the unique configuration of patches across the landscape. In this study, after a careful selection, the values of four class-level metrics, named NP, LPI, AREA_MN, and COHESION, are shown in Table 5. Besides, four class-level metrics variations across time were analyzed (Figure 5).

NP, a shortened form of 'number of patches', represents the number of patches in each RSEI grade. Based on Table 5, the fair and moderate grade had the largest NP value, indicating that they had higher fragmentation. Combined with Table 2, in 2005 and 2010, the NP of the fair grade was 976 and 2047, however, the area was 108418.75 km^2 and 46817.75 km^2, respectively, indicating that fair grade in 2010 was more fragmented and average patch size was small. From 2001 to 2015, only the NP of excellent grade

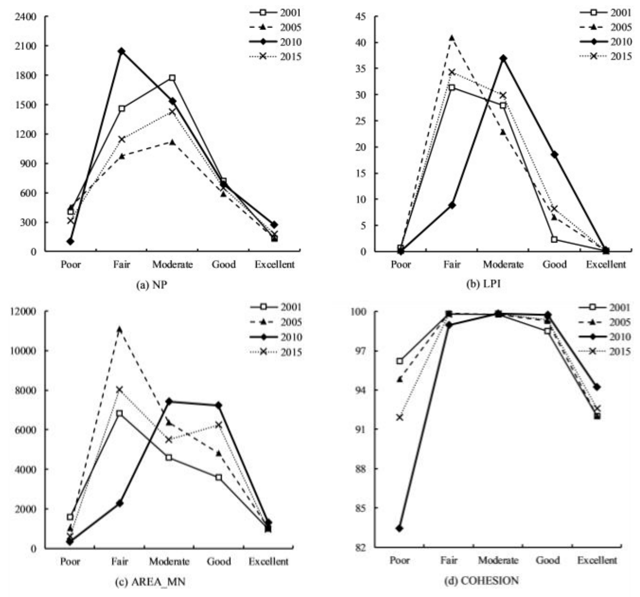

FIGURE 5. Four class-level metrics changes from 2001 to 2015.

increased, further indicating the eco-environment of JJJ had improved.

LPI, the abbreviation of 'largest patch index', interprets the percentage of the landscape comprised by the largest patch of each RSEI grade. In 2001, 2005, and 2015, fair grade all acquired the highest LPI value, followed by moderate grade, indicating there existed large clumpy patch of both grades. The LPI values of poor and excellent grades were less than 1, which meant that both grades patches were dispersed.

AREA_MN, shortened of 'mean patch size', demonstrated the average area of all patches in one RSEI grade. Fair, moderate, and good grade all had higher AREA_MN value. From 2001 to 2015, AREA_MN value of poor grade sharply decreased, excellent grade changed a little, while fair, moderate, and good grade all increased partially. Combined with NP and LPI, during 2001$\sim$2015, fair, moderate, and good grade indicated an expansion and more continuous representation of existing dominant patches, however, the decrease of total fair grade and moderate grade area showed that some small patches changed into other grades. Here, the decrease of NP, the increase of LPI, and the almost unchangeableness of AREA_MN of excellent grade deeply indicated that the improvement of JJJ's eco-environment.

COHESION measures the physical connectedness of the corresponding patch type. In 2001$\sim$2015, the COHESION values of fair, moderate, and good grades were much high (reaching 100%), representing three grades had extremely good connectedness. Besides, the COHESION values of poor and excellent grade in 2015 were lower and higher than that one in 2001, respectively, indicating the decrease of poor grade area and the increase of excellent grade area.

Generally, combined with Figure 5, from 2001 to 2015, fair, moderate, and good grades were dominant. However, we found that fair grade had the highest NP value, lowest LPI, AREA_MN, and COHESION value in 2010, indicating that fair grade achieved the most fragmented situation. As to moderate grade, it had the highest LPI and AREA_MN value, and the second-highest NP and COHESION value in 2010, representing that moderate grade accounted for the largest percentage of JJJ. Compared with 2001, in 2015, fair, moderate, and good grades showed an increase of LPI and AVER_MN, and a decrease of NP, indicating that patches were getting more concentrated and continuous; however, the decrease of four metrics of poor grade indicated the more fragmented and disconnected situation. Besides, the increase of NP, LPI, and COHESION value of excellent grade conveying the expanded and concentrated situation, more importantly, the improvement of JJJ eco-environment. As mentioned above, the acquisition of these changes had a relationship with the implementation of those environmental improvement projects, such as 'Returning Farmland to Forest (grass) Project', 'Three-North Shelter Forest Program', 'Beijing-Hebei Ecological Water Resources Protection Forest Project', etc.

TABLE 6. Six landscape-level metrics of each RSEI grade in JJJ from 2001 to 2015.

Year	CONTAG (%)	AI (%)	SHDI	IJI (%)	SHAPE_MN (km^2)	FRAC_MN
2001	55.41	91.71	1.1170	44.20	1.3282	1.0316
2005	57.47	93.20	1.0976	48.28	1.3273	1.0317
2010	56.63	91.99	1.0862	41.77	1.2885	1.0294
2015	56.12	92.78	1.1272	44.63	1.3015	1.0306

C. LANDSCAPE PATTERN VARIATION OF THE ENTIRE JJJ URBAN AGGLOMERATION

Landscape-level metrics can measure the overall structure, function or changes of the entire region by computing all patches. Besides, these metrics can also be used to interpret other characteristics, like fragmentation, connectedness, diversity, etc. In this study, six landscape-level metrics after careful selection were applied to identify these features (Table 6).

CONTAG, the abbreviation of 'contagion index', is inversely related to edge density. For example, when a single class occupies a very large percentage of the landscape, the value of CONTAG is high, and vice versa. From 2001 to 2015, the value of CONTAG increased first, then decreased, but was still higher than the first period, representing the enhancement of aggregation.

AI, shortened of 'aggregation index', measures the level of aggregation of spatial patterns. From 2001 to 2015, the AI value increased by 1.07%, combined with CONTAG, further indicating the improvement of patches' aggregation.

SHDI, the abbreviation of 'Shannon's diversity index', is a popular measure of diversity in community ecology, applied here to reflect the diversity of RSEI grades. Compared with 2001, SHDI increased to 1.1272 in 2015, representing the patches were getting more complex.

IJI, shortened form of 'interspersion and juxtaposition index', measures the patch adjacency and the degree of the interspersion or intermixing of patch types. In the fourteen years, IJI value had increased from 44.2041 to 44.6309, indicating the patches of all RSEI grade in JJJ were integrated gradually.

SHAPE_MN, shortened of 'mean patch shape index', is the ration between the perimeter of a patch and the perimeter of the simplest patch in the same area, which can be used to reflect the shape complexity. Compared with 2001, in 2015, the value of this metric decreased from 1.3182 to 1.3015, representing that the shape of patches was getting more regular.

FRAC_MN, the abbreviation of 'mean patch fractal dimension', also measures the patch shape complexity. Same as SHAPE_MN metric, the value of FRAC_MN metric decreased from 1.0316 to 1.0306, further demonstrating that patches' shape was more regular.

In general, based on six metrics in landscape level, we found that the patches of all RSEI grades in JJJ were getting more aggregated, connected, diverse, and regular.

D. RSEI CHANGE IMPACT ON LANDSCAPE PATTERN

The changes of RSEI grades have a direct influence on landscape pattern. The above content has analyzed the RSEI grade area change situation and the landscape pattern variations in both class-level and landscape-level. Here, the relationship between RSEI grades and landscape-level metrics was analyzed (Figure 6). The order of six metrics average R^2 was CONTAG ($R^2 = 0.0263$) < AI ($R^2 = 0.1397$) < SHDI ($R^2 = 0.2796$) < IJI ($R^2 = 0.5612$) < SHAPE_MN ($R^2 = 0.7921$) < FRAC_MN ($R^2 = 0.8898$). CONTAG metric had an extremely weak correlation with five RSEI grades, with the average R^2 of 0.0263, representing that the changes of RSEI grade area hardly exerted influence on the variation of CONTAG metric; As to AI metric, it had a higher correlation with fair and moderate grades, which were the two dominant grades. The left four metrics (SHDI, IJI, SHAPE_MN, and FRAC_MN) all had a stronger correlation with fair and moderate grades, moreover, poor, good, and excellent grades all had an increasing correlation.

Generally, except those poor correlations, five RSEI grades all had relatively good correlation, representing the changes of RSEI grades influenced the variation of the landscape. However, the effects were different. Poor and Fair grades had a positive correlation with landscape-level metrics, while moderate, good, and excellent grades had a negative one. Besides, taking the small area proportion occupied by poor and excellent grades (total less than 5%) into consideration, the changes of left three grades showed a more dominant and stronger influence on the variation of landscape pattern in JJJ.

IV. DISCUSSION

A. COMPARISON OF ECO-ENVIRONMENT QUALITY FROM RSEI AND EI

In our study, ecological index (EI), announced by the ministry of ecology and environment of China [71], was adopted to compare its result with the RSEI result. Here, to compare EI and RSEI at the same dimension, RSEI value was multiplied by 100, accordingly, the range of five grades was also multiplied by 100. Besides, the grading standard of EI was also given by the ecological index technical criterion, which was poor [0, 20), fair [20, 35), moderate [35, 55), good [55, 75), and excellent [75, 100), respectively. Table 7 was a comparison of thirteen cities' EI and RSEI calculation results. Among it, the changing trend column had two types, the upward-pointing arrow meant the eco-environment of this city during the fourteen years had improved, while the downward-pointing arrow meant the eco-environment of this city had deteriorated. Table 8 was a comparison of EI and RSEI in JJJ during 2001∼2015.

According to Table 7, we found that EI value of each city showed different change trend. To be specific, from 2001 to 2015, Beijing, Tianjin, Shijiazhuang, Tangshan, Handan, Baoding, Zhangjiakou, Chengde, Cangzhou, and Langfang all showed an increasing trend; however, Qinhuangdao, Xingtai, and Hengshui all displayed a decreased trend. As for RSEI, Beijing, Qinhuangdao, Baoding, Zhangjiakou, Chengde, Cangzhou, and Shijiazhuang all displayed an increasing trend, while Tianjin, Tangshan, Handan, Xingtai, Langfang, and Hengshui showed the opposite one. Generally, eight cities showed the same change trend in both EI and RSEI, five cities showed the opposite change trend. This might have a relationship with the difference between the two indexes' data acquisition and calculation methods. The RSEI was purely calculated and derived from remote sensing datasets, therefore, it could reflect the region's eco-environment anywhere. As for EI, it not only relied on part remote sensing data but also relied on statistical data. More importantly, statistical data could not be acquired data the gridded level, therefore using one value to represent the entire region might be inappropriate, which might have led to their difference. Based on the grading standard of each index, we compare them in four periods (Table 8). The grades of EI in 2001, 2005, and 2010 all belonged to fair grade, while the grades of RSEI in the same years belonged to moderate grade. In 2015, RSEI and EI all belonged to the moderate grade. In general, RSEI and EI belonged to different grade in 2001, 2005, and 2010, but the EI value in three years was close to the threshold value (35); moreover, the RSEI value in 2001 and 2015 was just slightly higher than the threshold value (40), which meant that there existed little difference between RSEI and EI. More importantly, during 2001∼2015, RSEI and EI represented the same conclusion that the eco-environment of JJJ had improved, which further validated our findings. Numerous previous studies have validated the RSEI index from several aspects at the city or provincial level. For example, Yue *et al.* [38] constructed one PSR evaluating index system, which integrated remote sensing data, statistical data, meteorological data, and so forth, to compare its results with RSEI result, although the area percentage of five grades was different, the spatial distribution of their results was quite similar with each other; Xu *et al.* [36] also found that RSEI

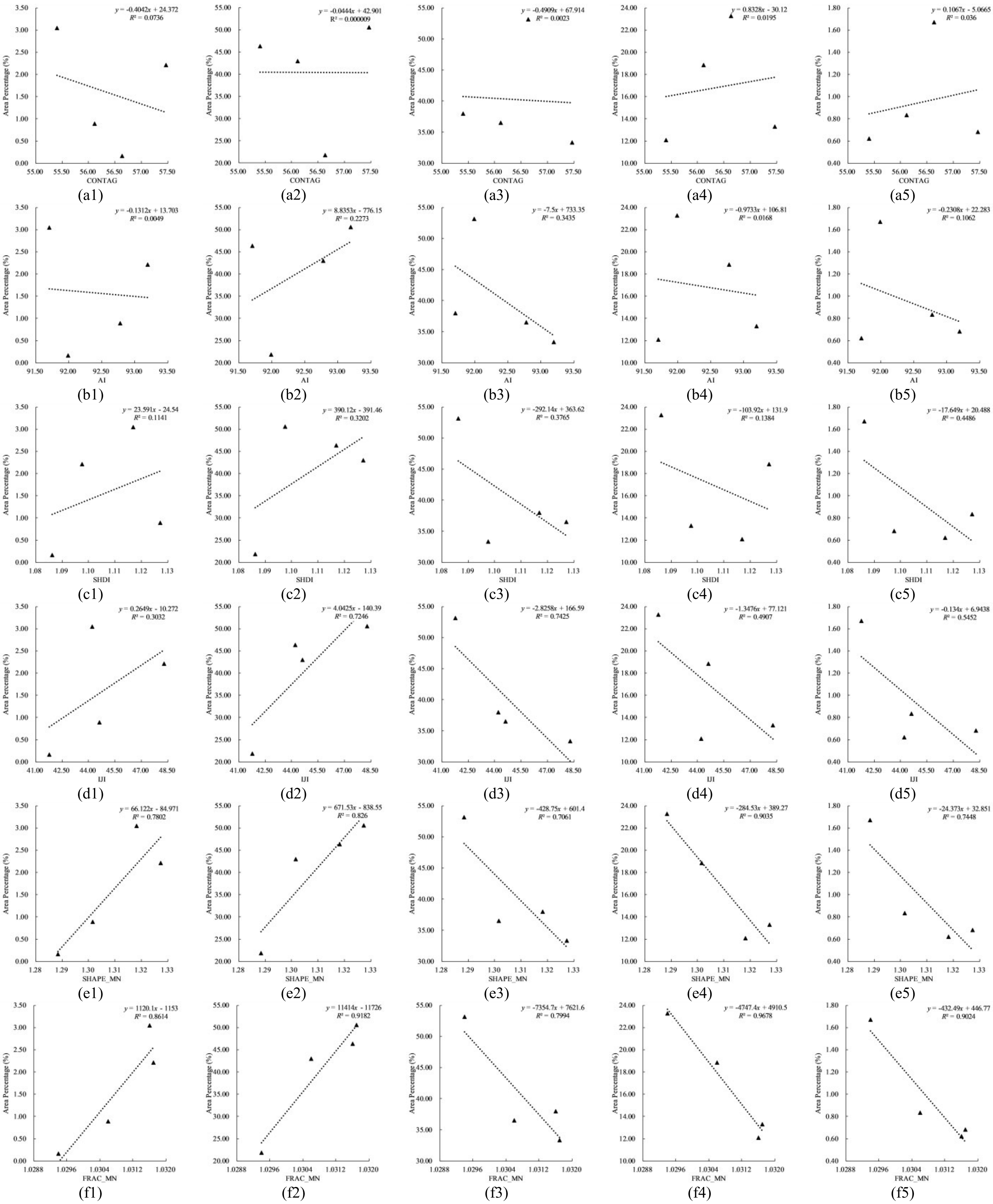

FIGURE 6. Relationships between six landscape-level metrics changes and the area percentage of RSEI poor, fair, moderate, good, and excellent grades. (a1) ~(a5) were five RSEI grades and CONTAG. (b1) ~(b5) were five RSEI grades and AI. (c1) ~(c5) were five RSEI grades and SHDI. (d1) ~(d5) were five RSEI grades and IJI. (e1) ~(e5) were five RSEI grades and SHAPE_MN. (f1) ~(f5) were five RSEI grades and FRAC_MN.

TABLE 7. A comparison of EI and RSEI calculation results of four years.

City Name	EI 2001	EI 2005	EI 2010	EI 2015	Change Trend	RSEI 2001	RSEI 2005	RSEI 2010	RSEI 2015	Change Trend
Beijing	32.05	46.16	37.08	42.82	↑	49.04	46.97	56.04	51.35	↑
Tianjin	31.67	34.25	31.03	33.96	↑	42.16	40.13	48.08	38.82	↓
Shijiazhuang	28.05	29.29	29.73	33.22	↑	38.68	31.43	43.76	38.78	↑
Tangshan	26.29	33.94	31.65	40.68	↑	44.23	42.61	50.78	42.09	↓
Qinhuangdao	38.23	32.89	38.95	37.98	↓	47.56	48.80	56.42	49.24	↑
Handan	23.24	23.42	23.30	26.74	↑	37.17	30.87	39.03	31.08	↓
Xingtai	26.38	24.65	25.92	26.24	↓	33.71	29.31	38.77	31.57	↓
Baoding	35.83	32.85	32.08	42.11	↑	40.48	37.55	50.63	44.13	↑
Zhangjiakou	55.61	49.02	56.41	57.15	↑	37.06	43.25	48.58	49.73	↑
Chengde	38.83	35.63	37.17	45.71	↑	57.79	59.97	63.92	62.25	↑
Cangzhou	30.97	33.96	30.56	32.38	↑	31.83	31.24	42.73	33.79	↑
Langfang	23.51	26.93	24.97	26.82	↑	35.04	34.09	45.46	34.85	↓
Hengshui	24.12	24.66	21.14	23.81	↓	37.39	32.75	42.44	33.74	↓

TABLE 8. A comparison of average EI and RSEI during 2001∼2015.

Year	Average EI	Grade	Average RSEI	Grade
2001	31.19	Fair	43.00	Moderate
2005	32.90	Fair	42.00	Moderate
2010	32.31	Fair	51.00	Moderate
2015	36.12	Moderate	46.00	Moderate

TABLE 9. Six driving factors q values in 2001, 2005, 2010, and 2015.

Driving Factors		*q* value 2001	2005	2010	2015
Natural Factors	AT	0.28	0.51	0.31	0.48
	PR	0.25	0.12	0.21	0.08
	EV	0.22	0.39	0.31	0.53
Human Factors	LU	0.15	0.32	0.22	0.42
	GP	0.18	0.31	0.22	0.36
	PD	0.21	0.40	0.31	0.51

showed a small difference in monitoring eco-environment condition by comparing EI and RSEI results. Generally, although there existed a small difference, RSEI was proven to be an effective index to evaluate region eco-environment, whether in the city level, provincial level or large level, like an urban agglomeration.

B. THE DRIVING FORCING OF JJJ'S ECO-ENVIRONMENT CHANGE

To explore the driving factors' influence on JJJ's eco-environment change in a different year, we have carefully selected three natural factors, which were annual average temperature (AT), annual precipitation (PR), and elevation (EV), and three human factors, which were land use (LU), gross regional product per square kilometre (GP), and population density (PD) [72], [73]. The Geodetertor method was one method that could investigate the spatially stratified heterogeneity of the geographic variable Y and explore how factor X explains the spatial pattern of Y [74], [75]. The importance of a factor could be represented by the q value, which ranges from 0 to 1. A higher q value indicates that Y has a stronger spatially stratified heterogeneity and factor X can explain $100 \times q$ of the spatial pattern of Y. In this study, Y represents the RSEI gridded result in 2001, 2005, 2010, and 2015; X represents each driving factor. Table 9 was six driving factors q values in 2001, 2005, 2010, and 2015.

According to Table 9, we found that, in the third natural factors, AT and EV had an increased influence during 2001∼2015, however, PR had a decreased one. Among it, AT and EV could explain a relatively higher spatial stratified heterogeneity of the RSEI, showing that the spatial distribution of AT and EV might be consistent with the RSEI spatial distribution; as for PR, the lower q value represented that it had limited influence on the JJJ's eco-environment changes, In the third human factors, LU, GP, and PD all represented an increased influence from 2001 to 2015. To be specific, three human factors had the highest q value in 2015, which reflected that the intensity of anthropogenic activities was also getting stronger, which might be connected with the urbanization process [7]. Generally, the eco-environment of JJJ in the different years was driven by both natural and human factors, and during the process of urbanization, anthropogenic activities could play an important role in changing the regional eco-environment [76], [77].

C. IMPLICATIONS FOR REGIONAL ECOLOGICAL LANDSCAPE MANAGEMENT

The analysis of investigating the relationship between landscape-level metrics and RSEI grades percentage represented that mostly landscape-level metrics had a positive or negative correlation. Although in the field of region heat islands or LULC studies, the relationship was explored [47], [78], our finding was still interesting. As our finding firstly validated that there existed a relationship between different RSEI grades and landscape-level metrics. Moreover, it provided some implications for regional ecological landscape management. As a better spatial configuration could be achieved based on these relationships. To be specific, if the regional ecological landscape managers want the whole region's landscape pattern more regular, then based on the relationship, they can try to decrease the area of poor and fair grades, and increase the area of moderate, good, and excellent grades. Considering the area percentage of different grades, focusing on the fair, moderate, and good three dominant grades can achieve the regular landscape pattern more efficiently. Generally, our finding may provide new insight for the regional eco-environment landscape management and configuration.

D. LIMITATIONS AND FURTHER STUDY

Even the variations of JJJ's eco-environment and the dynamics of landscape pattern have been investigated, there still exist some limitations. Firstly, only four-time periods have been performed, however, more deep information needs to be studied. For instance, whether the eco-environment exists natural fluctuations in the scale of per year still needs to discover. Secondly, we only selected limited landscape pattern metrics to study the relationship, whether these metrics can appropriately reveal these relationships still needs to explore in the future. Thirdly, more driving factors influencing the eco-environment also needs to investigate. Finally, simulation tools may help achieve the optimal eco-environment landscape pattern and providing useful suggestions for relevant policy-makers.

V. CONCLUSIONS

Four remote sensing ecological index (RSEI) maps of JJJ from 2001 to 2015 were firstly acquired and equally divided. Then spatiotemporal changes of RSEI and landscape pattern variation in class-level and landscape-level were analyzed. Finally, the relationship between the area percentage of five grades and six landscape-level metrics were performed.

This study found that the eco-environment of JJJ had improved in the fourteen years, with the RSEI value increased from 0.43 to 0.46, with the improved region was mainly located in Zhangjiakou city, while the degraded region was mainly distributed in the eastern Hebei plain. We also found that the landscape characteristics of entire JJJ eco-environment were becoming more aggregated, connected, diverse, and regular. Besides, this study found that the eco-environment of JJJ was dominated by three RSEI grades, which were fair, moderate, and good. More importantly, we found that anthropogenic activities exert increasingly importance on the regional eco-environment changes and different RSEI grades had a positive or negative correlation with the variation of landscape pattern, which may provide an view in managing and achieving the optimal eco-environment landscape pattern.

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