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Eco-Environmental Quality Assessment in China's 35 Major Cities Based On Remote Sensing Ecological Index

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ABSTRACT The ecological conditions in urban area are greatly changed during the process of industrialization and urbanization of China. The pressure-state-response (PSR) framework is the most popular method to evaluate the ecological quality by integrating a set of remote sensing and statistical indicators into one index through a weighting method. However, a completely remote-sensed ecological index (RSEI), integrating normalized difference vegetation index (NDVI), Wet, land surface temperature (LST), and the normalized differential build-up and bare soil index (NDBSI) through principal components analysis (PCA) method, has been proposed to assess the regional ecological quality. The publications about urban ecological evaluation by RSEI often focus on only one city or a certain area and there are few types of research on the ecological quality assessment by RSEI of 35 major cities in China. In this paper, we employed RSEI to monitor the changes in the ecological quality in China' 35 major cities. The results of RSEI were compared to that of PSR and stepwise regression method was applied to establish the quantitative relationship among RSEI, NDVI, Wet, NDBSI, and LST. The results show that there are 18 cities with ecological quality deteriorated, mainly located in the east and southwest of China (Shanghai, Guangzhou, Hongkong, Macao, Nanjing, Haikou, Shijiazhuang, and Xi'an), and 17 cities with better ecological quality, mainly located in the north and central area of China (Beijing, Tianjin, Shenzhen, Taipei, Fuzhou, Chongqing, and Jinan), from 1990 to 2015. The 3D-scatter plots of RSEI, NDVI, Wet, NDBSI, and LST demonstrate that the levels of very bad and bad mainly situate in where with a high density of built-up and low vegetation cover and soil water content. The PSR map, acquired from integrating 17 indicators, is quite similar to that of RSEI generated by merging only four remote-sensed indicators. This indicates that RSEI can be adopted to characterize regional ecological quality. Take the quantitative equation of Shanghai in 2015 as an example, every 1.46 decrement in NDBSI or each 3.72 increments in NDVI value can result in one increment in RSEI value and the ecological quality can be improved. Specifically, the expansion of the built-up area can lead to ecological degradation, and vegetation construction can promote eco-environmental quality.

INDEX TERMS Ecological quality assessment, remote sensing-based ecological index (RSEI), 35 major cities in China.

I. INTRODUCTION

The ecological environment is closely related to human health and human life. The industrialization and urbanization of China have been growing rapidly since the government's reform and opening up policy was carried out in 1978, which greatly affected the change of land use and land cover through the expansion of built-up area and urban boundary [1]. However, the change rate of land use and land cover was faster than the self-regulation speed of the ecosystem [2], which caused the enormous pressure and the destruction to the ecological environment [3]. China's major cities have existed a series

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of urban problems, such as heat island effect, water-logging, road traffic and air pollution [4], [5]. The city's ecological environment has changed dramatically with the growth of the economy in China. Therefore, it is becoming the hot spot to quantitatively describe and evaluate the spatiotemporal dynamics of the urban ecological environment.

Remote sensing has become an effective way to evaluate regional ecological environment [1], [5]–[8]. It is difficult to apply a uniform index for assessing the conditions of ecosystems because of its complexity [9]. A number of ecological indicators have been proposed to evaluate the status of ecosystem health. For instances, the Normalized Difference Vegetation Index (NDVI) or leaf area index were used to monitor environmental change [10]–[14]; land surface temperature (LST) was adopted to assess the urban heat island effects [6], [7], [15]–[19]; the normalized difference built-up index (NDBI), an index-based built-up index (IBI) and the normalized difference impervious surface index (NDISI) were applied to delineate the built-up and impervious surface area [20]–[23]; the normalized difference water index (NDWI) and the modified NDWI (MNDWI) were used to extract water bodies [24]–[27]; NDVI and LST were applied to monitor drought or soil moisture [28]–[31]; a bare soil index (BI) [32] and dry bare-soil index (DBSI) [33] was employed to map bare soil areas. It is not sufficient to adopt only one or two ecological indicators to assess the status of the ecosystem due to the complexity and diversity of the influence factors.

The Pressure-State-Response (PSR) framework, initially proposed by the organization of economic cooperation and development (OECD) for environmental policy-making [34], can integrate a set of remote sensing and statistical data into one index through a weighting method, e.g., analytic hierarchy process (AHP) [35], analytic network process (ANP) [36] and Delphi [37]. The selection and measurement of indicators for the PSR model can be grouped into three categories, i.e., indicators of pressures (exerted by human activities), environmental status and societal responses [1], [38]. Subsequently, it has been widely applied to evaluate the health of the eco-environment, such as forest ecosystem [39], [40], soil ecosystem [41], wetland ecosystem [35], agriculture ecosystem [42], [43], water ecosystem [44] and urban ecosystem [45], etc. However, a large number of remote sensing and socio-economic data are employed to construct the PSR framework and the access to the weight of indicators may affect by the subjective experience in practice. For this reason, based on the framework of PSR, a completely remote sensing-based ecological index (RSEI), adopted to evaluate the ecological status in Fuzhou city of China, was generated by integrating four indicators (greenness, wetness, dryness, and heat) through principal components analysis (PCA) method [46]. In recent years, many studies were employed RSEI to assess the urban ecological conditions, e.g., Fuzhou city in China [1], [45], [47], Xiong'an New Area in China [5], Zhengzhou city in China [48], Nanjing city in China [49], Lanzhou city [49], Weinan city in China [50], Hangzhou

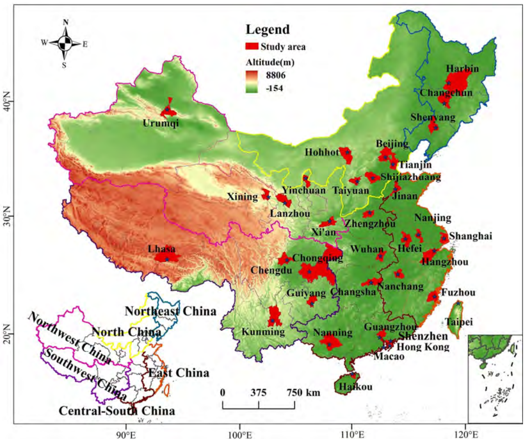

FIGURE 1. Location of the study area.

city [51], Shanghai city in China and New York in America [52], Haidian city in China [53], etc.

As shown above, we can see that the existing research on urban ecological assessment by RSEI only focused on one city or a certain region and few studies are adopted RSEI to assess the ecological quality of 35 major cities in China. The objective of this study was to fill the above-mentioned knowledge gaps by evaluating the temporal and spatial changes of eco-environment in China's 35 major cities based on RSEI. Firstly, four indicators, i.e., NDVI (greenness), Wet (wetness), LST (heat) and the normalized differential build-up and bare soil index (NDBSI) (dryness) combined with IBI and BI, were derived from Landsat data and RSEI maps of 35 major cities in China were generated through PCA embedded in ENVI software in 1990 and 2015, respectively. Secondly, the spatial and temporal changes of urban eco-environment in 35 major cities of China were assessed by RSEI. Thirdly, we adopted the PSR model through the AHP method based on remote sensing and socio-economic data in 2000 and 2015 to evaluate the ecological conditions of Nanjing City, Beijing and Shanghai. The results from RSEI were compared with that of PSR framework to obtain the difference between them and further verify the ability of RSEI in monitoring the health of the city ecosystem. Finally, we employed a stepwise regression method to establish the quantitative relationships among RSEI, NDVI, Wet, NDBSI and LST.

II. IMATERIALS AND METHODS

A. STUDY AREA

We concentrated upon 35 major cities in China (Figure 1). All of them are provincial capitals or municipalities except Hong Kong, Macao and Shenzhen, which are special administrative region and special economic region zone established in 1997, 1999 and 1978, respectively. According to geography of China, 35 major cities were classified into 6 groups [7]: Northeast China (Shenyang, Harbin and Changchun), North China (Beijing, Tianjin, Shijiazhuang, Taiyuan and Hohhot), East China (Shanghai, Hangzhou, Nanjing, Jinan, Nanchang, Fuzhou, Hefei and Taipei), Southwest China (Lhasa, Chongqing, Chengdu, Guiyang and Kunming), Northwest China (Xi'an, Lanzhou, Yinchuan, Xining and Urumqi), and Central South China (Hongkong, Macao, Guangzhou, Haikou, Changsha, Shenzhen, Wuhan, Zhengzhou and Nanning) (Figure 1). The altitude increases gradually from east to west and temperature rises gradually from north to south in winter. The economy of 35 major cities in China have grown rapidly and the built-up area has expanded continuously since the policy of reform and opening up.

B. DATA AND PRE-PROCESSING

A total of 180 Landsat-5 Thematic Mapper (TM) and Landsat-8 Operational Land Imager (OLI) and Thermal Infrared Sensor (TIRS) imageries with cloud free were downloaded from Earthexplorer of the United States Geological Survey (USGS) (https://earthexplorer.usgs.gov/) to obtain RSEI maps in 1990 and 2015, over a period of 25 years. The acquisition time of these images is mainly in spring and autumn. Regarding the same city, the acquisition time of remote sensing data is almost the same (about not exceeding a month) in 1990 and 2015 (Table 1) and the RSEI is season-specific. It can be seen that the vegetation has a similar growing condition and the results are comparable.

Based on the nearest-neighbor re-sampling and a second-order polynomial methods, the TM images were co-registered to the OLI/TIRS with a mean of RMSE less than 0.5 pixels in the Environment for Visualizing Images (ENVI) software. Then, the Fast Line-of-Sight Atmospheric Analysis of Spectral Hypercubes (FLAASH) module was adopted to convert the raw digital number of 180 Landsat images into land surface reflectance by ENVI software [26].

The socio-economic data, such as gross domestic product (GDP), the population, the density of population and investment in fixed assets, derived from the Nanjing, Beijing and Shanghai yearbook in 2000, 2004, 2006 and 2015, respectively. The amount of $SO_2$and NO_x was acquired from Nanjing, Beijing and Shanghai Municipal Environmental Protection Bureau. Moreover, the TM images of Nanjing City in 2000, Beijing in 2004 and Shanghai in 2006 were also obtained.

C. CONSTRUCTION OF RSEI

RSEI is the function of four indicators (greenness, wetness, dryness, and heat) which can be completely derived from remote sensing data [1], [5], [46]. NDVI represents the greenness indicator and is employed to manifest the environmental state in PSR model. The wet component came from Tasseled Cap transformation stands for wetness and LST represents heat indicators, which are selected as indicators of the local climate changes in response to environmental changes in the PSR model. NDBSI is the indicator of dryness which is adopted to indicate the pressures generated from human activities on the environment in the PSR model. Thus, the expression of RSEI can be rewritten as:

$$RSEI = f(\mathrm{NDVI}, Wet, LST, NDBSI) \tag{1}$$

1) RETRIEVAL OF VEGETATION

NDVI is widely employed to indicate vegetation growth and coverage status [54], [55], which can be expressed as:

$$NDVI = \frac{\rho_{\mathrm{nir}} - \rho_{red}}{\rho_{nir} + \rho_{red}} \tag{2}$$

where ρ_{nir} and ρ_{red} represent the reflectance of the near-infrared and red bands, respectively.

2) RETRIEVAL OF LAND SURFACE MOISTURE

Kauth-Thomas Transformation (K-T Transformation) can generate three components, i.e. wetness, greenness and brightness, have been widely adopted to assess the ecological environment. The water content of soil and vegetation can be reflected by the wetness component [1], [5], [46]. The wetness component of the TM [56] and OLI [57] can be obtained by the following formula, respectively:

$$\begin{aligned} Wet_{TM} &= 0.0315\rho_{blue} + 0.2021\rho_{green} + 0.3102\rho_{red} \\ &\quad + 0.1594\rho_{nir} - 0.6806\rho_{swir1} - 0.6109\rho_{swir2} \end{aligned} \tag{3}$$

$$\begin{aligned} Wet_{OLI} &= 0.1511\rho_{blue} + 0.1973\rho_{green} + 0.3283\rho_{red} \\ &\quad + 0.3407\rho_{nir} - 0.7117\rho_{swir1} - 0.4559\rho_{swir2} \end{aligned} \tag{4}$$

where ρ_{bule}, ρ_{green}, ρ_{swir1} and ρ_{Swir2} are the reflectance of blue band, green band, short-wave infrared band1 and band 2, respectively.

3) RETRIEVAL OF LAND SURFACE TEMPERATURE

Land surface temperature (LST) was evaluated as follows [58], [59]:

$$LST = \frac{T_{sensor}}{\left[1 + \left(\lambda \times T_{sensor}/\rho\right) \ln \varepsilon\right]} \tag{5}$$

where λ is the wavelength of the emitted radiance (11.435μm for Landsat 5/7 and 10.9μm for band 10 of Landsat 8); ρ is a constant (1.438×10^{-2} m K); ε is the land surface emissivity, which can be expressed as [60]–[62]:

$$\varepsilon = \begin{cases} 0.995 & \mathrm{NDVI} \leq 0 \\ 0.970 & 0 < \mathrm{NDVI} \leq 0.157 \\ 1.0094 + 0.047 \ln \mathrm{NDVI} & 0.157 < \mathrm{NDVI} \leq 0.727 \\ 0.986 & \mathrm{NDV} > 0.727 \end{cases} \tag{6}$$

$T_{\mathrm{sensor}}$is the at-satellite brightness temperature in Kelvin and can be computed as follows:

$$T_{sensor} = \frac{K_2}{\ln(K_1/L_\lambda + 1)} \tag{7}$$

$$L_\lambda = Gain \times DN + Bias \tag{8}$$

where L_λ is the at-sensor spectral radiance. Gain and Bias are the band-specific multiplicative rescaling factor and the

TABLE 1. The acquisition time of images.

	Path/Row	Date			Path/Row	Date	
Shanghai	118/38	7/3/1990	27/2/2016	**Beijing**	123/32	18/9/1990	4/9/2014
	118/39	7/3/1990	27/2/2016		123/33	18/9/1990	4/9/2014
Jinan	122/34	29/10/1990	2/10/2015	**Nanjing**	120/37	31/3/1998	28/3/2016
	122/35	13/10/1990	2/10/2015		120/38	31/3/1998	28/3/2016
Yinchuan	129/33	24/4/1994	12/5/2015	**Shijiazhuang**	124/33	1/11/1992	24/10/2018
	129/34	24/4/1994	12/5/2015		124/34	1/11/1992	24/10/2018
Shenzhen	121/44	20/11/1989	16/12/2016	**Hongkong**	121/45	20/11/1989	25/11/2014
	122/44	11/11/1989	7/12/2016		122/44	11/11/1989	16/11/2014
Nanchang	121/40	30/9/1991	24/20/2014	**Guiyang**	127/41	17/9/1991	29/9/2013
	122/40	25/10/1991	15/10/2014		127/42	17/9/1991	29/9/2013
Xining	132/34	29/4/1991	3/5/2016	**Haikou**	123/46	11/4/1990	5/4/2013
	132/35	29/4/1991	3/5/2016		124/46	2/4/1990	5/42013
Fuzhou	118/42	5/5/1994	1/3/2017	**Shenyang**	119/30	31/10/1992	13/10/2015
	119/42	12/5/1994	11/3/2018		119/31	31/10/1992	13/10/2015
Changchun	118/29	24/4/1990	13/4/2015	**Guangzhou**	122/44	3/3/1996	7/2/2016
	118/30	24/4/1990	13/4/2015	**Hefei**	132/35	23/7/1992	25/7/2016
Tianjin	122/32	29/10/1990	2/10/2015	**Urumqi**	142/30	26/9/1991	30/9/2016
	122/33	29/10/1990	2/10/2015		143/29	1/9/1991	21/9/2016
	123/33	20/10/1990	9/20/2015		143/30	1/9/1991	21/9/2016
Lanzhou	130/35	6/9/1991	10/10/2015	**Taiyuan**	125/33	16/9/1990	23/9/2016
	131/34	13/9/1991	1/10/2015		125/34	16/9/1990	23/9/2016
	131/35	13/9/1991	1/10/2015		126/34	22/8/1990	30/9/2016
Changsha	123/40	31/10/1994	25/10/2015	**Xi'an**	126/36	24/11/1995	25/11/2013
	123/41	31/10/1994	25/10/2015		127/36	15/11/1995	6/11/2013
	124/40	22/10/1994	16/10/2015		127/37	15/11/1995	6/11/2013
Kunming	129/42	16/4/1994	23/4/2014	**Nanning**	125/44	4/1/1996	28/12/2016
	129/43	15/3/1994	23/4/2014		125.45	4/1/1996	28/12/2016
	130/42	7/4/1994	14/4/2014		126/44	10/12/1995	3/12/2016
Chengdu	129/39	4/11/1992	30/11/1992	**Chongqing**	128/39	9/8/1992	2/9/2018
	130/38	11/11/1992	7/12/1992		128/40	9/8/1992	2/9/2018
	130/39	11/11/1992	7/12/1992		127/38	3/9/1992	2/9/2018
Hangzhou	119/39	29/10/1992	3/11/2017		127/39	3/9/1992	26/8/2018
	119/40	29/10/1992	3/11/2017		127/40	3/9/1992	26/8/2018
	120/39	20/10/1992	25/10/2017		126/38	8/6/1992	19/8/2018
	120/40	20/10/1992	25/10/2017		126/39	8/6/1992	19/8/2018
Hohhot	126/31	29/10/1990	3/11/2017		126/40	11/8/1992	20/8/2018
	126/32	29/10/1990	3/11/2017	**Harbin**	118/28	2/11/1990	3/10/2014
	127/31	20/10/1990	25/10/2017		117/28	26/10/1990	28/10/2014
	127/32	20/10/1990	25/10/2017		117/29	26/10/1990	28/10/2014
Taipei	117/43	8/11/1989	16/11/2015		116/28	19/10/1990	21/10/2014
Macao	122/45	14/9/1991	18/9/2016		116/29	19/10/1990	21/10/2014
Wuhan	122/39	5/10/1993	18/10/2015	**Lhasa**	137/39	9/10/1991	27/10/2015
	122/38	5/10/1993	18/10/2015		138/39	16/10/1991	18/10/2015
	123/38	12/10/1993	25/10/1993		138/40	16/10/1991	18/10/2015
	123/39	12/10/1993	25/10/1993		139/39	23/10/1991	25/10/2015

band-specific additive rescaling factor, respectively, which are available in the head file of the used image. DN represents the digital number of a given pixel. K_1 and K_2 are calibration coefficients for TM/ETM+/OLI sensor thermal band.

TABLE 2. Index system of eco-environment evaluation and the weight of each indicator.

Criterion	Pressure Layer						
Indicators	Per unit area GDP	NDBSI	Industrial SO_2 emissions intensity	Population density	Natural population growth rate	Industrial No_x emissions intensity	
No.	X_1	X_2	X_3	X_4	X_5	X_6	
Impact	-	-	-	-	-	-	
Weight	0.0251	0.0801	0.0650	0.0293	0.0228	0.0649	
Criterion	**State Layer**						
Indicators	Vegetation coverage	Grain yield	Per Capita public green space	NDVI			
No.	X_7	X_8	X_9	X_{10}			
Impact	+	+	+	+			
Weight	0.1242	0.0393	0.1101	0.1117			
Criterion	**Response Layer**						
Indicators	Per Capita GDP	Urbanization rate	Per Capita living space	Proportion of tertiary industry	Total investment infixed assets	LST	Wet
No.	X_{11}	X_{12}	X_{13}	X_{14}	X_{15}	X_{16}	X_{17}
Impact	+	-	-	+	-	-	+
Weight	0.0963	0.0308	0.0308	0.0248	0.0172	0.0638	0.0638

For TM, ETM+ and OLI, $K_2 = 1260.56$K, 1282.71 K and 1321.08K, and $K_1 = 607.76$, 666.09 and 774.89 mW cm^{-2} sr$^{-1}\mu$m^{-1}, respectively.

4) RETRIEVAL OF NORMALIZED DIFFERENCE BUILD-UP AND BARE SOIL INDEX

As the urbanization and human activities, the build-up and naked soil have gradually replaced the natural surface of the ecosystem, causing the earth to be "dry", and deteriorate of the environmental quality. Hu and Xu constructed a normalized difference built-up and soil index (NDBSI) to represent the dryness indicator, composed of IBI and BI and the formula is expressed as [1]:

$$NDBSI = {}^{(BI + IBI)}\!/_{2} \tag{9}$$

with (10) and (11), as shown at the bottom of this page.

5) ACQUISITION OF RSEI

PCA included in ENVI software, which can allocate the weight of each factor according to the load of each factor to the principal components, was adopted to integrate four indicators, i.e. NDVI, Wet, LST and NDBSI. The first component of PCA (PC1), usually explains more than 80% of the characteristics of the dataset, was employed to represent RSEI. The expression of RSEI can be written as [5]:

$$RSEI = \text{1-PC1}\ \left[f(\text{NDVI}, Wet, LST, NDBSI)\right] \tag{12}$$

Because of the unit and data range of indicators are different, we need to normalize the value of four indicators between 0 and 1 before performing the PCA. We also rescaled the value of RSEI from 0 to 1, and the closer the value is to 1, the better ecological condition is, and vice versa [1], [5]. With an interval of 0.2, the levels of RSEI were classified into five groups: very bad, bad, acceptable, good, and natural [5].

D. CONSTRUCTION OF PSR

The ecological conditions of Nanjing City, Beijing and Shanghai from PSR model was compared with that from RSEI. PSR framework is composed of pressure layer, state layer and response layer. The pressure layers indicate the impacts of human activities on the environment and the state layer exhibits the status of the environment on the study period [1], [38], [45]. The response layer describes measures and policies that are applied to settle eco-environmental issues [1], [38], [45]. With the help of literatures investigation [1], [38]–[40], [45] and the acceptability of the data, we selected 17 indicators to construct PSR model (Table 2). We adopted AHP method, assigning weights to each indicator, to integrate these 17 indicators as one ecological index [51], [63], which can be expressed as:

$$EI = \sum_{i=1}^{17} W_i \times X_i' \tag{13}$$

where EI is the eco-environmental assessment indicator; $W_i$and X_i' represent the weight and the normalized data of

$$BI = \left[(\rho_{swir1} + \rho_{red}) - (\rho_{nir} + \rho_{blue})\right] \Big/ \left[(\rho_{swir1} + \rho_{red}) + (\rho_{nir} + \rho_{blue})\right] \tag{10}$$

$$IBI = \frac{\{2\rho_{swir1}/(\rho_{swir1} + \rho_{nir}) - [\rho_{nir}/(\rho_{nir} + \rho_{red}) + \rho_{green}/\left(\rho_{green} + \rho_{swirl}\right)]\}}{\{2\rho_{swir1}/(\rho_{swir1} + \rho_{nir}) + [\rho_{nir}/(\rho_{nir} + \rho_{red}) + \rho_{green}/\left(\rho_{green} + \rho_{swirl}\right)]\}} \tag{11}$$

TABLE 3. The average of RSEI in China's 35 major cities in 1990 and 2015.

Index	Year	Cities						
		Yinchuan	Chongqing	Shanghai	Lanzhou	Jinan	Nanjing	Xining
RSEI	1990	0.35	0.49	0.52	0.27	0.41	0.46	0.54
	2015	0.34	0.58	0.39	0.37	0.49	0.30	0.50
Index	Year	City						
		Lhasa	Changchun	Tianjin	Urumqi	Hohhot	Hangzhou	Beijing
RSEI	1990	0.42	0.40	0.44	0.42	0.59	0.51	0.59
	2015	0.37	0.49	0.47	0.41	0.60	0.50	0.63
Index	Year	City						
		Changsha	Taipei	Nanchang	Fuzhou	Macao	Haikou	Guiyang
RSEI	1990	0.52	0.56	0.43	0.51	0.46	0.45	0.51
	2015	0.61	0.59	0.48	0.55	0.40	0.34	0.66
Index	Year	City						
		Shijiazhuang	Kunming	Nanning	Zhengzhou	Guangzhou	Wuhan	Hongkong
RSEI	1990	0.64	0.479	0.49	0.43	0.43	0.44	0.61
	2015	0.60	0.483	0.52	0.44	0.33	0.51	0.59
Index	Year	Cities						
		Chengdu	Harbin	Shenyang	Xi'an	Hefei	Taiyuan	Shenzhen
RSEI	1990	0.54	0.56	0.59	0.61	0.38	0.49	0.495
	2015	0.53	0.37	0.49	0.46	0.32	0.56	0.497

indicator i, respectively; i is the number of indicators and i =1, 2, 3…17.

Before processing the PSR, we also need to rescale 17 indicators between 0 and 1 due to the unit and data range of indicators are different. If the indicators can generate positive impact on ecosystem health, Equation (14) is used, and when they are negative, Equation (15) is used [64].

$$X_i' = (X_i - X_{\min}) / (X_{\max} - X_{\min}) \tag{14}$$

$$X_i' = (X_{\max} - X_i) / (X_{\max} - X_{\min}) \tag{15}$$

where i and X_i' is the same as in Equation (13); X_i is the raw data value of indicator i; $X_{\max}$ and $X_{\min}$ are the maximum and minimum raw date value of indicator i, respectively.

III. RESULTS

A. THE VARIATIONS OF ECOLOGICAL QUALITY IN 35 MAJOR CITIES

Figure 2 and Table 3 show the spatial distribution of eco-environmental variation and the changes of RSEI average in China's 35 major cities from 1990 to 2015, respectively. The eco-environmental quality deteriorates in 18 cities, and what in 17 cities becomes better during 1990-2015. The ecological quality of Changchun in northeast China became better, the average of RSEI increased from 0.40 in 1990 to 0.46 in 2015, and the other two cities got worse. There were one cities' (Shijiazhuang) eco-environmental quality deteriorated in north China, the average of RSEI was declined from 0.64 in

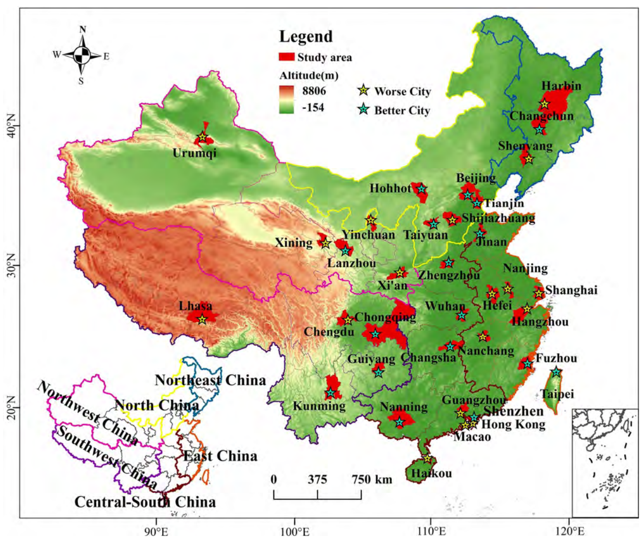

FIGURE 2. Spatial distributions of eco-environmental quality change based on RSEI in China's 35 major cities over the period 1990–2015 (Yellow stars represent the health of eco-environment got worse and cyan stars got better).

1990 to 0.60 in 2015, and what improved in Beijing, Tianjin, Taiyuan and Hohhot. The ecological quality of Fuzhou, Jinan and Taipei in east China became better, the average of RSEI increased from 0.51, 0.41 and 0.56 in 1990 to 0.55, 0.49 and 0.59 in 2015, respectively, and the other five cities got worse. There were two cities' (Chengdu and Lhasa)

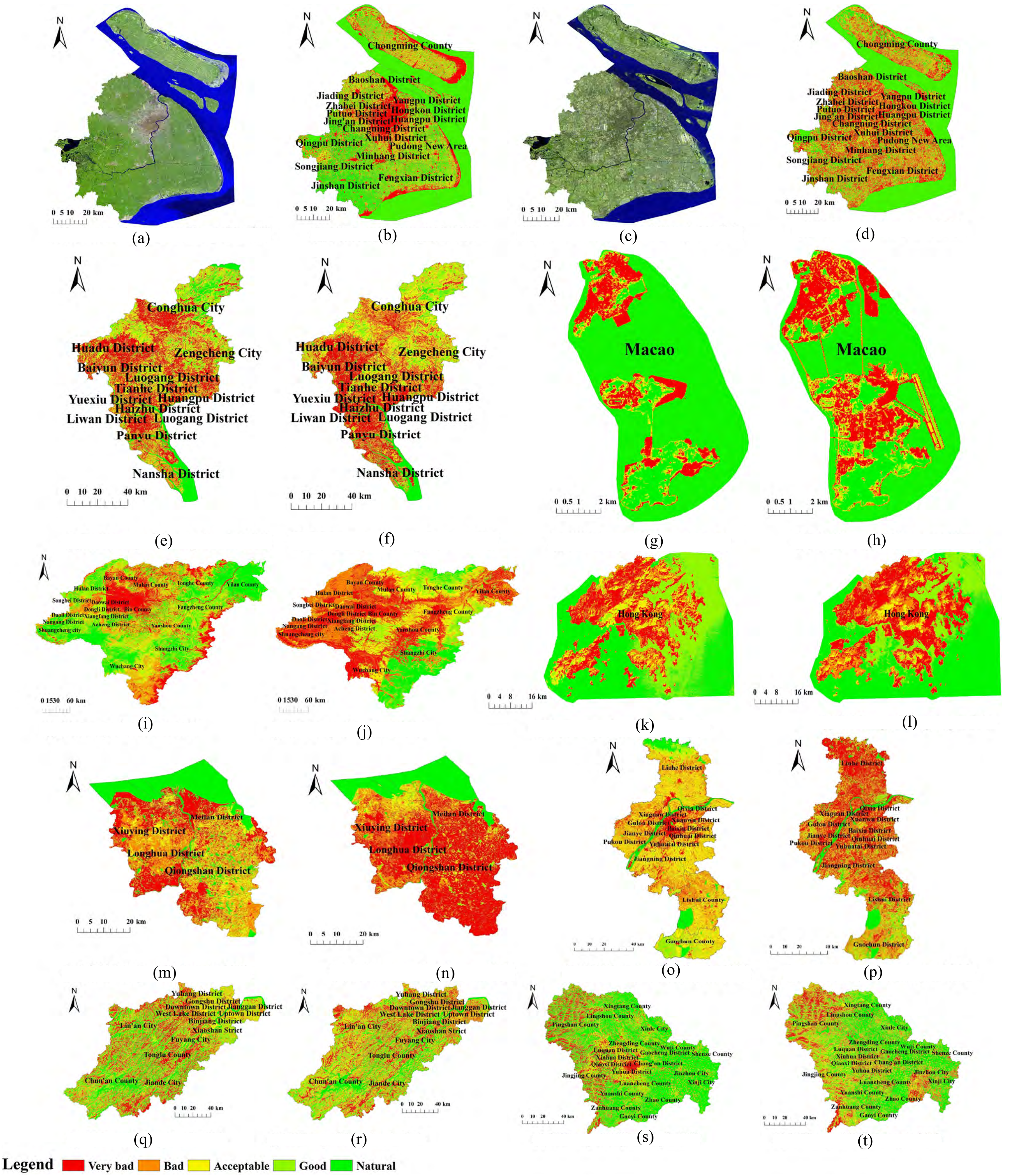

FIGURE 3. RSEI map of some cities with eco-environment got worse. (a) Remote sensing image of Shanghai in 1990. (b) RSEI map of Shanghai in 1990. (c) Remote sensing image of Shanghai in 2015. (d) RSEI map of Shanghai in 2015. (e) RSEI map of Guangzhou in 1990. (f) RSEI map of Guangzhou in 2015. (g) RSEI map of Macro in 1990. (h) RESI map of Macro in 2015. (i) RSEI map of Harbin in 1990. (j) RSEI map of Harbin in 2015. (k) RSEI map of Hongkang in 1990. (l) RSEI map of Hongkang in 2015. (m) RSEI map of Haikou in 1990. (n) RSEI map of Haikou in 2015. (o) RSEI map of Nanjing in 1990. (p) RSEI map of Nanjing in 2015. (q) RSEI map of Hangzhou in 1990. (r) RSEI map of Hangzhou in 2015. (s) RSEI map of Shijiazhuang in 1990. (t) RSEI map of Shijiazhuang in 2015.

TABLE 4. Percentage statistics of the five RSEI levels in cities with eco-environment got worse.

Study area	Level	1990 Percentage (%)	2015 Percentage (%)	Study area	Level	1990 Percentage (%)	2015 Percentage (%)
Shanghai	Very bad	21.5	30.7	Guangzhou	Very bad	26.4	25.7
	Bad	16.4	28.2		Bad	25.7	27.9
	Acceptable	17.5	18.9		Acceptable	21.6	25.1
	Good	20.6	10.5		Good	14.7	14.1
	Natural	24.0	11.7		Natural	11.6	7.2
Macao	Very bad	37.4	39.4	Harbin	Very bad	17.2	30.2
	Bad	15.4	18.9		Bad	16.1	26.4
	Acceptable	9.0	10.7		Acceptable	16.4	19.6
	Good	10.3	10.1		Good	22.3	10.4
	Natural	27.9	20.9		Natural	29.5	13.4
Hongkong	Very bad	17.3	22.1	Haikou	Very bad	23.8	47
	Bad	13.8	14.5		Bad	30.3	24.2
	Acceptable	7.6	3.9		Acceptable	18.4	8.6
	Good	25.9	16.5		Good	4.6	2.4
	Natural	35.4	43		Natural	22.8	17.8
Nanjing	Very bad	4.7	34.7	Hangzhou	Very bad	16.5	15.6
	Bad	31.9	30.2		Bad	18.8	20.8
	Acceptable	49.2	16.7		Acceptable	24.4	26.5
	Good	6.6	8.6		Good	21.6	22.1
	Natural	7.6	9.8		Natural	18.7	15.0
Shijiazhuang	Very bad	11.1	12.4				
	Bad	10.0	12.8				
	Acceptable	14.3	19.9				
	Good	25.5	26.1				
	Natural	39.1	28.8				

eco-environmental quality deteriorated in southeast China, the averages of RSEI were declined from 0.54 and 0.42 in 1990 to 0.53 and 0.47 in 2015, respectively, and it greatly improved in Chongqing and Kunming and slightly improved in Kunming (the average of RSEI was improved from 0.479 in 1990 to 0.483 in 2015). The eco-environmental quality of Lanzhou in northwest China became better, the average of RSEI increased from 0.27 in 1990 to 0.37 in 2015, respectively, and what of Yinchuan, Xi'an, Xining and Urumqi retrograded from 0.35, 0.61, 0.54 and 0.42 in 1990 to 0.34, 0.46, 0.50 and 0.41 in 2015, respectively. There were four coastal cities' (i.e. Guangzhou, Haikou, Hongkong and Macao)

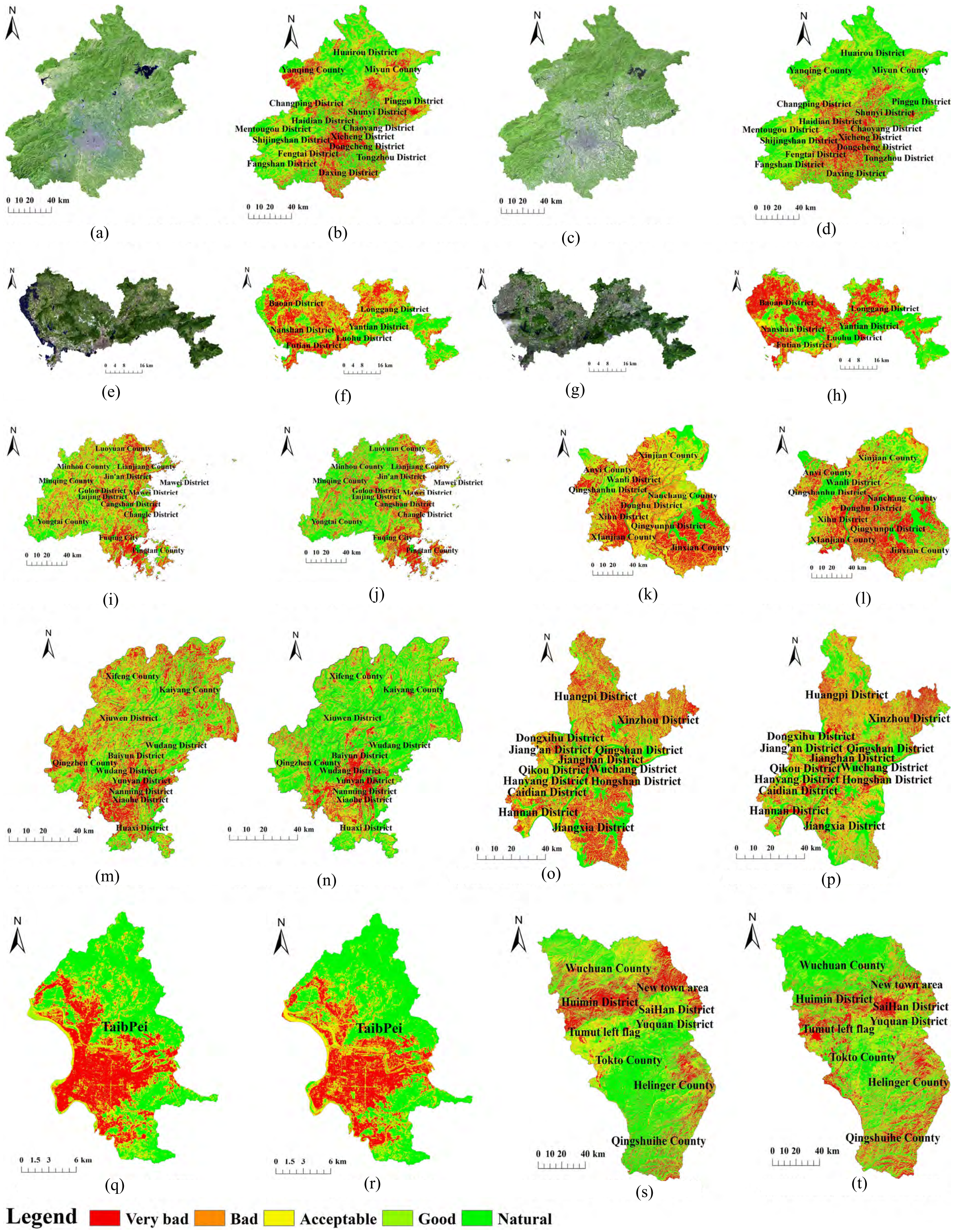

FIGURE 4. RSEI map of some cities with eco-environment became better. (a) Remote sensing image of Beijing in 1990. (b) RSEI map of Beijing in 1990. (c) Remote sensing image of Beijing in 2015. (d) RSEI map of Beijing in 2015. (e) Remote sensing image of Shenzhen in 1990. (f) RSEI map of Shenzhen in 1990. (g) Remote sensing image of Shenzhen in 2015. (h) RSEI map of Shenzhen in 2015. (i) RESI map of Fuzhou in 1990. (j) RESI map of Fuzhou in 2015. (k) RESI mao of Nanchang in 1990. (l) RESI map of Nanchang in 2015. (m) RESI map of Guiyang in 1990. (n) RESI map of Guiyang in 2015. (0) RESI map of Wuhan in 1990. (p) RESI map of Wuhan in 2015. (q) RESI map of Taipei in 1990. (r) RESI map of Taipei in 2015. (s) RESI map of Hohhot in 1990. (t) RESI map of Hohhot in 2015.

TABLE 5. Percentage statistics of the five RSEI levels in cities with eco-environment got better.

Study area	Level	1990 Percentage (%)	2015 Percentage (%)	Study area	Level	1990 Percentage (%)	2015 Percentage (%)
Beijing	Very bad	14.0	13	Shenzhen	Very bad	20.3	27.7
	Bad	12.1	8.7		Bad	20.3	15.2
	Acceptable	17.5	14.9		Acceptable	20.6	13.7
	Good	26.6	29.2		Good	18.9	17.3
	Natural	29.8	34.2		Natural	19.9	26.1
Study area	Level	1990 Percentage (%)	2015 Percentage (%)	Study area	Level	1990 Percentage (%)	2015 Percentage (%)
Fuzhou	Very bad	16.4	16.2	Nanchang	Very bad	23.1	22.8
	Bad	19.3	16.0		Bad	25.3	21.1
	Acceptable	24.6	19.3		Acceptable	26.7	18.9
	Good	22.8	22.8		Good	14.3	17.8
	Natural	16.9	25.7		Natural	10.6	19.4
Study area	Level	1990 Percentage (%)	2015 Percentage (%)	Study area	Level	1990 Percentage (%)	2015 Percentage (%)
Guiyang	Very bad	18.4	10.5	Wuhan	Very bad	23.6	15.3
	Bad	19.0	8.0		Bad	22.3	20.3
	Acceptable	22.0	14.6		Acceptable	26.3	26.7
	Good	20.7	24.6		Good	15.5	18.0
	Natural	20.0	42.3		Natural	12.3	19.7
Study area	Level	1990 Percentage (%)	2015 Percentage (%)	Study area	Level	1990 Percentage (%)	2015 Percentage (%)
Taipei	Very bad	25.1	20.4	Hohhot	Very bad	10.6	14.7
	Bad	10.9	13.3		Bad	9.7	13.6
	Acceptable	11.1	11.0		Acceptable	19.1	14.1
	Good	14.7	12.6		Good	30.8	25.2
	Natural	38.3	42.7		Natural	29.8	32.4

eco-environmental quality deteriorated in the central area of China, the averages of RSEI were declined from 0.43, 0.45, 0.46 and 0.61 in 1990 to 0.33, 0.34, 0.40 and 0.59 in 2015, respectively, and it greatly improved in Changsha and Wuhan and slightly improved in Shenzhen and Zhengzhou (the averages of RSEI were improved from 0.495 and 0.43 in 1990 to 0.497 and 0.46 in 2015, respectively).

B. SPATIAL DISTRIBUTIONS OF RSEI

1) CITIES WITH ECOLOGICAL QUALITY GOT WORSE

Figure 3 demonstrates the spatial distribution of RSEI in some cities with deteriorated eco-environment and the proportions of RSEI levels are shown in Table 4. As shown in Figure 3a and 3c, the built-up area of Shanghai greatly expanded in 2015 than that of in 1990. The levels of very bad and bad were mainly located in central area below the Chongming County of Shanghai in 1990, while the most part of Shanghai was in very bad and bad levels of RSEI and the farmland declined in 2015. The ratio of bad and very bad levels was increased from 37.9% in 1990 to 58.9% in 2015. This demonstrated that the ecological quality got worse during 1990-2015. Table 3 shows that the mean RSEI of Shanghai is declined from 0.52 (corresponding to level acceptable) in 1990 to 0.39 (corresponding to level bad) in 2015. This also indicated that the overall ecological quality of the area was good in 1990 and became worse in 2015. The most part of Guangzhou was in levels bad and very bad except the south, which accounted for 52.1% in 1990 and 53.6%

TABLE 6. Percentage statistics of the five RSEI and PSR levels in Nanjing.

Study area		Level	1990 Percentage (%)	2015 Percentage (%)		Level	1990 Percentage (%)	2015 Percentage (%)
Nanjing	RSEI	Very bad	21.2	34.7	PSR	Very bad	2.1	29.4
		Bad	23.3	30.2		Bad	27.1	34.8
		Acceptable	27.4	16.7		Acceptable	43.9	14.5
		Good	16.5	8.6		Good	21.4	10.8
		Natural	11.7	9.8		Natural	5.5	10.5
Beijing	RSEI	Very bad	14.0	13.0	PSR	Very bad	0.1	0.2
		Bad	12.1	8.7		Bad	9.4	10.4
		Acceptable	17.5	14.9		Acceptable	32.2	27.7
		Good	26.6	29.2		Good	55.4	56.0
		Natural	29.8	34.2		Natural	2.9	5.7
Shanghai	RSEI	Very bad	21.5	30.7	PSR	Very bad	0.7	0.9
		Bad	16.4	28.2		Bad	5.2	8.5
		Acceptable	17.5	18.9		Acceptable	23.1	50.6
		Good	20.6	10.5		Good	53.6	34.9
		Natural	24.0	11.7		Natural	17.4	5.1

in 2015. It showed a bad ecological quality in Guangzhou. The very bad and bad levels of RSEI (water was extracted), accounting for 52.1%, mainly lied in the south, central part and north of Macao. The central area combined with the south and connected with the North of Macao by three roads, whose built-up area significantly expanded and the proportion of very bad and bad levels increased to 53.6% in 2015. As shown in Figure 3, the levels bad and very bad are mainly distributed in the area of built-up and covered with bare soil, while the area with levels good and excellent is mainly covered with vegetation.

2) CITIES WITH ECOLOGICAL QUALITY BECAME BETTER

Figure 4 and Table 5 show the spatial distribution of RSEI and the proportions of RSEI levels in some cities with improved eco-environment, respectively. As shown in Figure 3a, 3b, 3c and 3d, the built-up area mainly lies in central part and south-east of Beijing, whose RSEI level is very bad or bad, and the north and southwest of Beijing are covered with vegetation, corresponding to level good or excellent. Table 4 indicates that the levels acceptable, good and natural account for 76.9% in 1990 and 78.3% in 2015 of the area, while another two levels make up only 23.1% in 1990 and 21.7% in 2015. Table 3 manifests that the mean RSEI of Beijing is 0.59 (corresponding to the level acceptable) in 1990 and increases to 0.63 in 2015 (corresponding to the level good). This indicates that the overall ecological quality of the area is good although the urban area enlarged in 2015. The built-up area with very bad and bad levels located in west, central area and north of Shenzhen, while the south and southeast of area covered with vegetation (corresponding to level good or excellent) (Figure 4e∼4h). Table 3 indicates that the average of RSEI in Shenzhen is 0.495 (corresponding to level acceptable) in 1990 and that is 0.497 (corresponding to level acceptable) in 2015. It supports that an acceptable ecological quality exists in the area. The proportion of level natural increased from 19.9% in 1990 to 26.1% in 2015 (Table 4), which explained why the ecological quality of Shenzhen slightly got better. Figure 4q and 4r demonstrate that the levels very bad and bad lie in central area and northwest of Taipei. Table 3 exhibits that the average of RSEI increases from 0.56 in 1990 to 0.59 in 2015 (corresponding to the level acceptable), indicating the ecological quality of area improved. Figure 4, Table 3 and Table 5 show that the ecological quality in all other cities is acceptable and is improved during 1990-2005.

IV. DISCUSSION

A. COMPARISON OF ECOLOGICAL QUALITY FROM RSEI AND PSR

We obtained the raster image of socio-economic data in Table 1 by the inverse distance weighted method combined in GIS software [26]. The PSR map was derived by Equation (13) and compared with the results of RSEI in Nanjing, Beijing and Shanghai. Figures 5(a) ∼ (b) show that the levels very bad and bad of RSEI, accounting for 44.4% (Table 6), are mainly distributed in the central area and north of Nanjing in 2000. As shown in Figure5(c), the levels of very bad and bad, only accounting for 29.3% which are apparently less

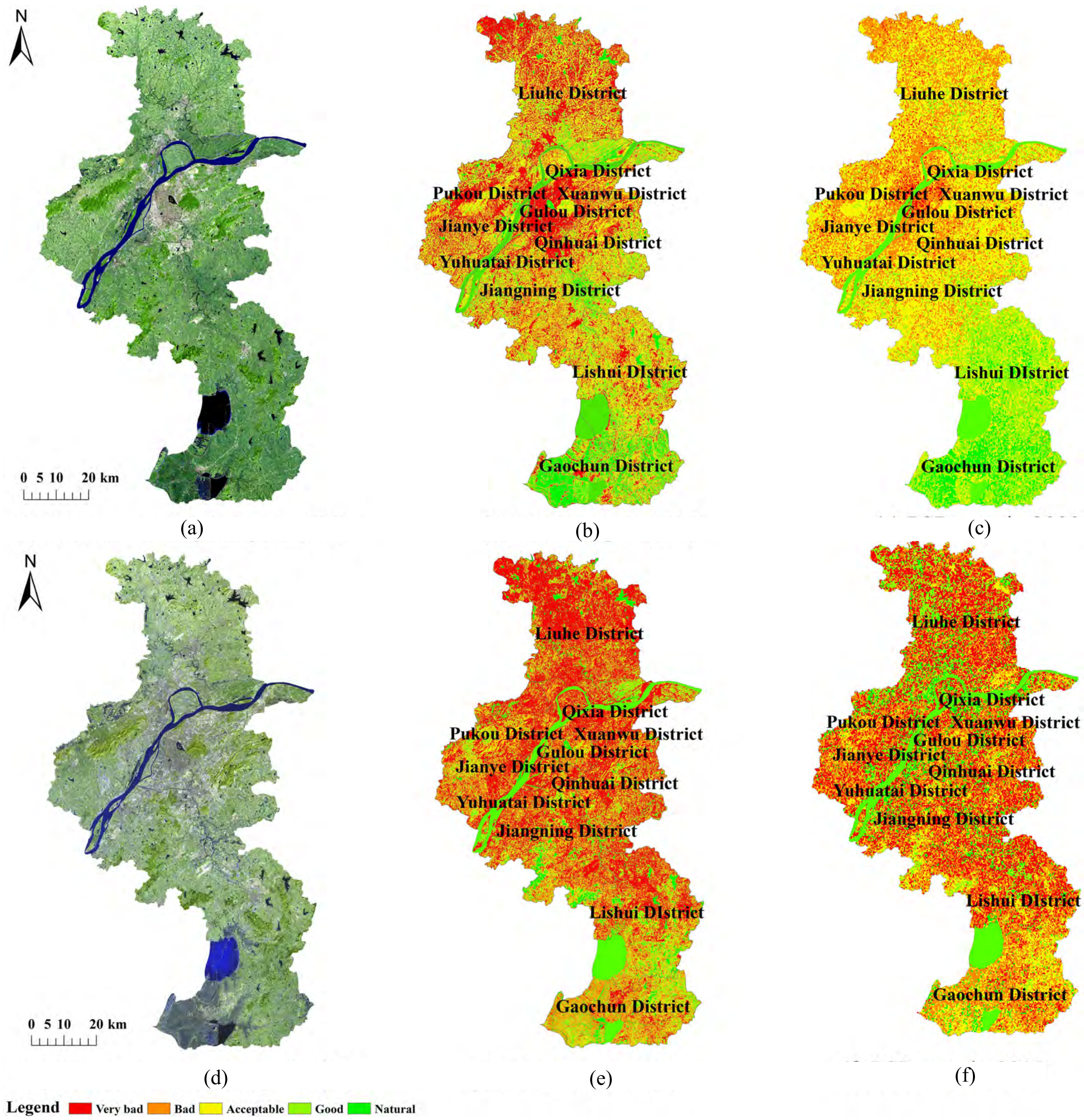

FIGURE 5. The maps of RSEI and PSR in Nanjing. (a) Remote sensing image in 2000. (b) RESI map in 2000. c) PSR map in 2000. (d) Remote sensing image in 2015. (e) RESI image in 2015. (f) PSR map in 2015.

than that of RSEI, are also located in the central part and north of Nanjing. The results of PSR are quite similar with RSEI in south of Nanjing where with better the ecological environment than what is in central part and north in 2000. Figures 5 (e) $\sim$ (f) exhibit that the PSR map is quite consistent with RSEI and the levels of very bad and bad have spread to the south and north of Nanjing in 2015. The ecological conditions in Liuhe, Pukou and Lishui district became worse. Table 6 demonstrates that the proportion of levels very bad and bad of RSEI is 64.9%, while 64.2% of PSR. As shown in Figure 6, we can see that the levels of good and natural of RSEI (accounting for 56.4% in 2004 and 63.4% in 2015) and PSR (accounting for 58.3% in 2004 and 61.7% in 2015) mainly lie in the north and east of Beijing, while the other three levels of RSEI and PSR locate in south, central area and southeast of Beijing. Figures 7(a) $\sim$ (b) show that the levels very bad and bad of RSEI, accounting for 37.9% (Table 4), are mainly distributed in the central area of Shanghai in 2000. As shown in Figure7(c), the levels very bad and bad, only accounting for 5.9% which are apparent less than that of RSEI, are also located in the central part of Nanjing. Figure 7(e) demonstrates that the levels of bad and very bad have expanded to south and north of Shanghai in 2015, while Figure 7(f) describes the level of acceptance have spread and the levels of bad and very bad extends to south of Shanghai.

Although the proportion of each levels from PSR is different with RSEI, the spatial distribution of the ecological quality is quite similar with each other. A total of 17 indicators were employed to generate PSR, while only four remote-sensed indicators were adopted to calculate RSEI. This indicates that RSEI, a completely remote sensing-based ecological index, can be applied to evaluate the urban ecological conditions.

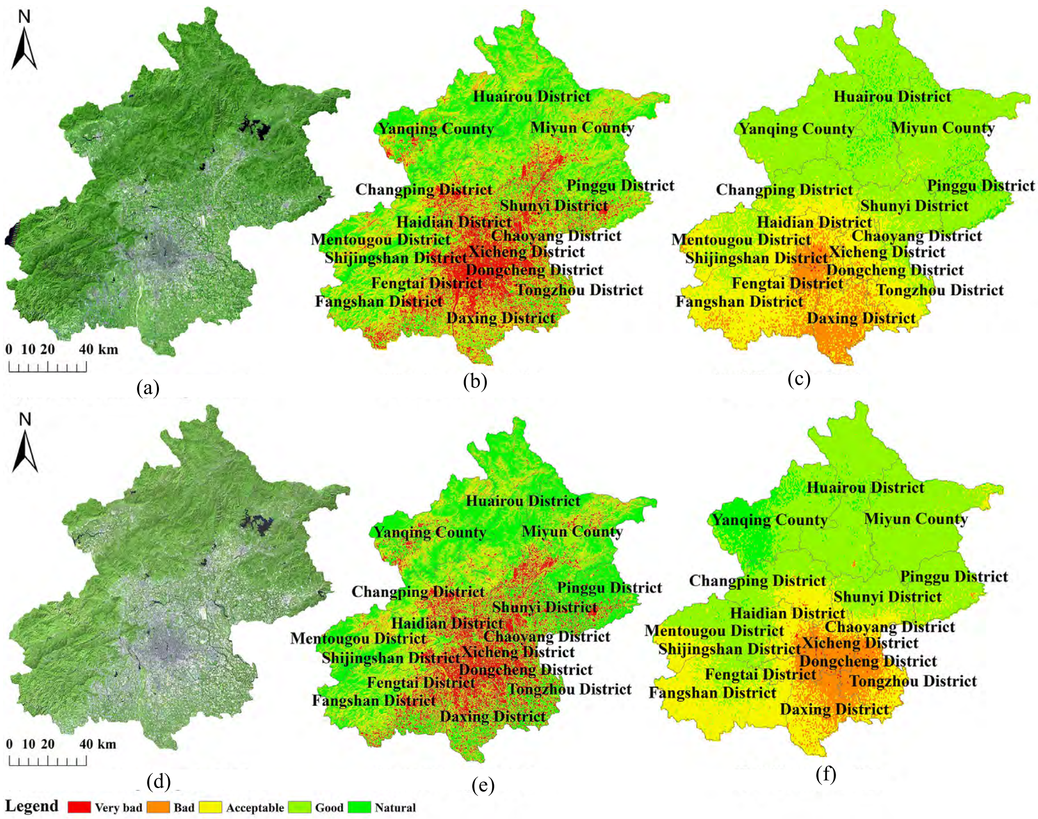

FIGURE 6. The maps of RSEI and PSR in Beijing. (a) Remote sensing image in 2004. (b) RESI image in 2004. c) PSR image in 2004. (d) Remote sensing image in 2015. (e) RESI image in 2015. (f) PSR map in 2015.

B. PREDICTION OF ECOLOGICAL EFFECTS

In order to further quantitatively describe urban ecological conditions, an ecological quality model can be established for simulating and predicting the change trend of urban ecological quality. First, taking Nanjing, Beijing and Shanghai as examples, we randomly sampled with 150m×150m grid across the whole images of Wet, NDVI, NDBSI, LST and RSEI, respectively, and a total of 278954, 728565 and 307088 pixels were sampled for each image of Nanjing, Beijing and Shanghai, respectively. And then, taking RSEI as the dependent variable and NDVI, Wet, LST and NDBSI as the independent variables, stepwise regression [5] with a large number of samples were adopted to quantitatively analyzing the relationships of four indicators with RSEI. The regression was proceeded in Statistical Product and Service Solutions (SPSS) Version 22.0 and yielded the following relationship models (significant at the 0.01 level):

Beijing in 1990

$$RSEI = 0.268Wet + 0.374NDVI - 0.377NDBSI - 0.267LST + 0.561(R^2 = 0.993) \quad (16)$$

Beijing in 2015

$$RSEI = 0.198Wet + 0.326NDVI - 0.394NDBSI - 0.267LST + 0.578(R^2 = 0.997) \quad (17)$$

Shanghai in 1990

$$RSEI = 0.188Wet + 0.391NDVI - 0.687NDBSI - 0.228LST + 0.702(R^2 = 0.999) \quad (18)$$

Shanghai in 2015

$$RSEI = 0.203Wet + 0.269NDVI - 0.908NDBSI - 0.226LST + 0.803(R^2 = 0.995) \quad (19)$$

Nanjing in 1990

$$RSEI = 0.191Wet + 0.252NDVI - 0.487NDBSI - 0.315LST + 0.700(R^2 = 0.991) \quad (20)$$

Nanjing in 2015

$$RSEI = 0.356Wet + 0.331NDVI - 0.642NDBSI - 0.156LST + 0.487(R^2 = 0.990) \quad (21)$$

The equation (16) $\sim$ (21) show that all four indicators have been retained in the stepwise regression procedure ($p < 0.01$). It demonstrates that Wet, NDVI, NDBSI and LST are all important factors in modulating RSEI and can be used as predictor variables in revealing regional ecological condition. Nevertheless, the four indicators work differently by their coefficient of the equation. Table 6 indicates that both Wet and NDVI contribute positively to RSEI, while NDBSI and

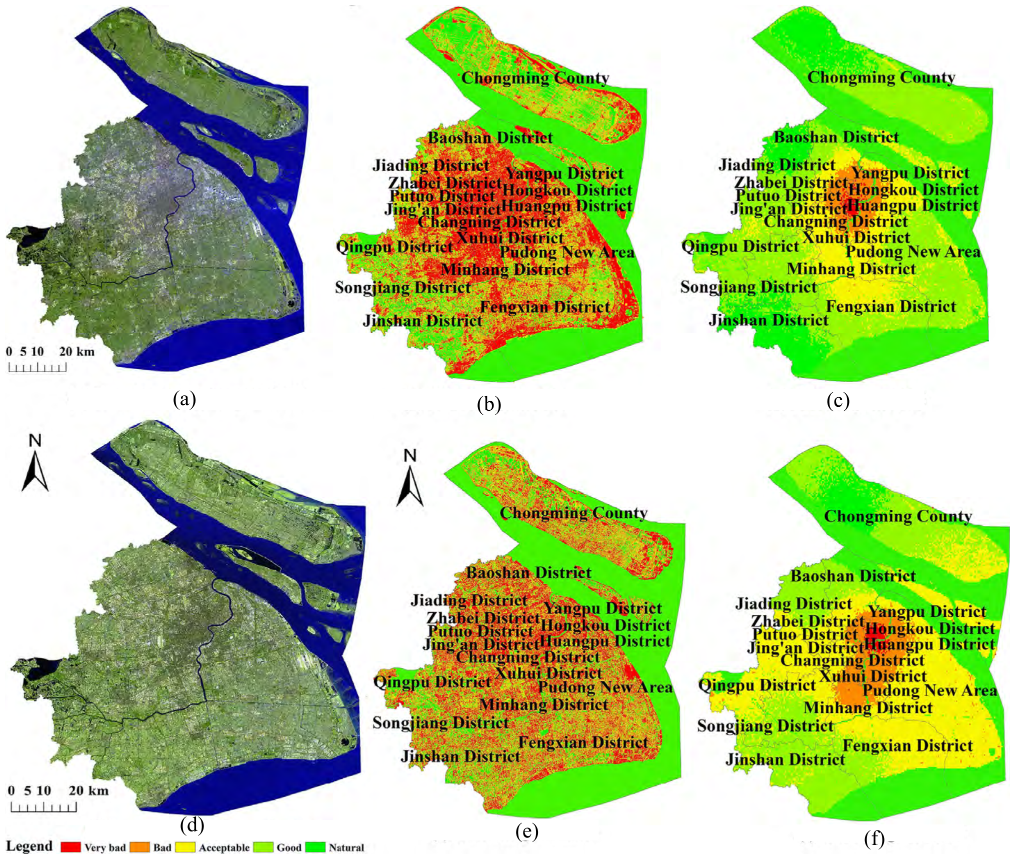

FIGURE 7. The maps of RSEI and PSR in Shanghai. (a) Remote sensing image in 2006. (b) RESI image in 2006. (c) PSR image in 2006. (d) Remote sensing image in 2015. (e) RESI image in 2015. (f) RESI image in 2015.

TABLE 7. Coefficient comparison of regression models.

Cities	Year	Wet	NDVI	NDBSI	LST	Difference
Beijing	1990	0.268	0.374	-0.377	-0.267	0.002
	2015	0.198	0.326	-0.394	-0.267	0.137
	Mean	**0.233**	**0.350**	**-0.386**	**-0.267**	0.070
Shanghai	1990	0.188	0.391	-0.687	-0.228	0.336
	2015	0.203	0.269	-0.908	-0.226	0.662
	Mean	**0.196**	**0.330**	**-0.798**	**-0.227**	0.499
Nanjing	1990	0.191	0.252	-0.487	-0.315	0.359
	2015	0.356	0.331	-0.642	-0.156	0.111
	Mean	**0.274**	**0.292**	**-0.565**	**-0.234**	0.235

Note: Difference=coefficient of (|Wet|+|NDVI|)-coefficient of (NDBSI+ LST)

LST work inversely in these three cities. Table 7 also exhibits that NDBSI has the largest negative influence on RSEI, followed by NDVI with larger positive impacts on RSEI, which are all larger than that of Wet and LST in these three cities. As shown in Table 7, the sum of the absolute coefficient value of NDBSI and LST is larger than that of NDVI and Wet and the difference of Shanghai increases from 0.336 in 1990 to 0.663 in 2015.

Figure 8 is a three-dimensional scatter plot illustrating the relationships of RSEI with Wet, NDVI, NDBSI and LST. It can be found that the most points are well aggregated rather than scattered, indicating a high degree of correlation among the variables. The rod-shaped morphology of the points expresses that the ecological status is relatively homogeneous in Beijing, Shanghai and Nanjing, respectively. Images in the first and the third columns of Figure 8 demonstrate the bottom of the scatter plots represent the area with poor ecological quality, and the samples in these areas are concentrated in where with low humidity and vegetation. Images in the second and the fourth columns of Figure 8 indicate that the top of the scatter plots represent the area with better ecological quality, and the samples in these areas are concentrated in where with low heat and building density. Figure 8 also expresses that the slope between NDBSI, LST

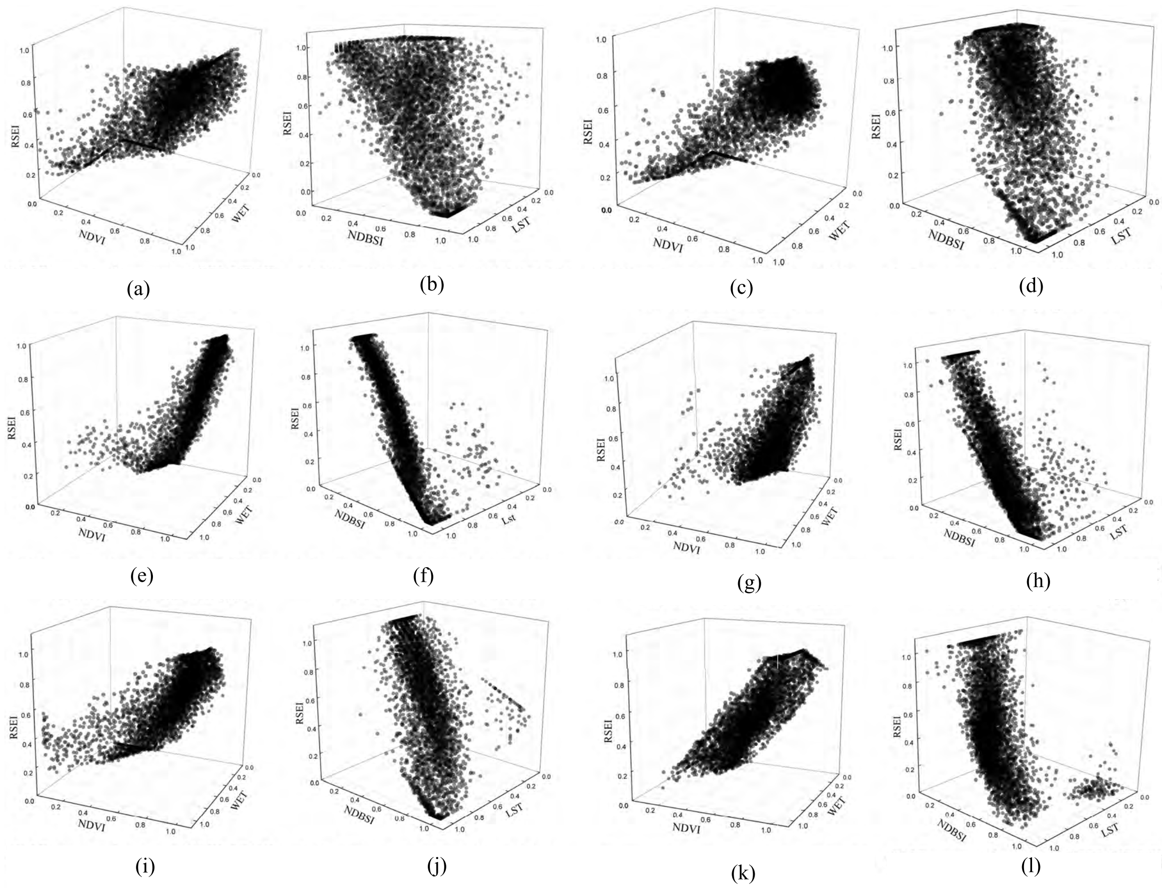

FIGURE 8. 3D-scatter plots showing the relationship among RSEI, NDVI, Wet, NDBSI and LST in Beijing, Shanghai and Nanjing. (a) 3D-Scatter plot among RSEI, NDVI and Wet of Beijing in 1990. (b) 3D-Scatter plot among RSEI, NDBSI and LST of Beijing in 1990. (c) 3D-Scatter plot among RSEI, NDVI and Wet of Beijing in 2015. (d) 3D-Scatter plot among RSEI, NDBSI and LST of Beijing in 2015. (e) 3D-Scatter plot among RSEI, NDVI and Wet of Shanghai in 1990. (f) 3D-Scatter plot among RSEI, NDBSI and LST of Shantghai in 1990. (g) 3D-Scatter plot among RSEI, NDVI and Wet of Shanghai in 2015. (h) 3D-Scatter plot among RSEI, NDBSI and LST of Shanghai in 2015. (i) 3D-Scatter plot among RSEI, NDVI and Wet of Nanjing in 1990. (j) 3D-Scatter plot among RSEI, NDBSI and LST of Nanjing in 1990. (k) 3D-Scatter plot among RSEI, NDBSI and LST of Nanjing in 1990. (l) 3D-Scatter plot among RSEI, NDBSI and LST of Nanjing in 2015.

and RSEI is larger than that of NDVI, Wet and RSEI, further illustrating that the impacts of the former on the ecology is greater than that of the latter.

The very strong fitness of the regression models equation (16) ∼ (21) can be employed to predict RSEI changes in Beijing, Shanghai and Nanjing, respectively. Take the equation (19) as an example, each 0.372 increment in NDVI value or each 0.146 decrement in NDBSI would lead to 0.1 increment in RSEI value and the ecological quality will be improved.

C. LIMITATIONS

There are some limitations of RSEI in assessing urban ecological quality. First, the RSEI is mainly used in terrestrial areas and is not suitable for large water areas (such as oceans). The wet component from K-T Transformation is mainly related to the moisture of vegetation and soil. If there is a large area of water in the study area, it will increase the contribution of water, and the calculated wet component cannot truly reflect the moisture of vegetation and soil. In this case, large areas of water must be masked. Second, if the vegetation in the area was predominantly farmland-based, the ecological quality of the area was sensitive to seasonal changes. The vegetation covered area was changed into bare soil after harvesting of crops, which will significantly affect the area's temporal ecological quality. Xu *et al.* [5] expressed that the RSEI was declined from 0.645 in August 2016 into 0.512 in July 2015 due largely to crops' phenology. Therefore, the acquisition time of remote sensing images in two periods should be similar with each other.

V. CONCLUSION

A completely remote sensing-based ecological index (RSEI) was employed to assess the spatial and temporal distribution characteristics of ecological conditions in China' 35 major cities by Landsat TM and OLI imageries in 1990 and 2015. The results of RSEI were compared with that of the PSR framework and the quantitative relationship among RSEI, NDVI, Wet, NDBSI and LST was constructed by stepwise regression method.

This study shows that ecological quality gets better in 17 cities and degrades in 18 cities during 1990-2015 in China. The cities with ecological quality got worse mainly lie in the east and southwest of China, e.g. Hongkong, Guangzhou, Macao, Haikou, Nanchang, Shanghai, Nanjing, Hefei, Hangzhou, Shijiazhuang, Shenyang, Harbin, Xi'an, Yinchuan, Xining, Chengdu, Lhasa and Urumqi. The cities with ecological quality became better mainly locate in the central area and the north of China, i.e. Changchun, Beijing, Tianjin, Jinan, Taiyuan, Hohhot, Zhengzhou, Lanzhou, Wuhan, Changsha, Chongqing, Guiyang, Kunming, Nanning, Shenzhen, Fuzhou and Taipei. Moreover, the levels very bad and bad of RSEI are mainly distributed in where with high density of building and low vegetation and humidity. The results of PSR in Nanjing, Beijing and Shanghai, obtained by integrating 17 indicators through AHP, are quite consistent with that of RSEI, obtained by integrating 4 indicators through PCA. This supports that RSEI can be applied to monitor regional ecological status. NDBSI and LST can generate negative impacts on RSEI while NDVI and Wet have positive influence. Take the equation (22) as an example, each 3.02 increment in NDVI value or each 1.56 decrement in NDBSI will bring about 1 increment in RSEI value and the ecological quality will become better.

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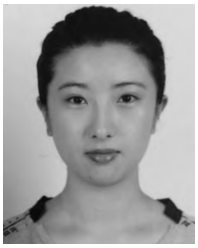

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