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Exploration of eco-environment and urbanization changes in coastal zones: A case study in China over the past 20 years

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ABSTRACT

With the rapid development of urbanization and population migration, since the 20th century, the natural and eco-environment of coastal areas have been under tremendous pressure due to the strong interference of human response. To objectively evaluate the coastal eco-environment condition and explore the impact from the urbanization process, this paper, by integrating daytime remote sensing and nighttime remote sensing, carried out a quantitative assessment of the coastal zone of China in 2000–2019 based on Remote Sensing Ecological Index (RSEI) and Comprehensive Nighttime Light Index (CNLI) respectively. The results showed that: 1) the overall eco-environmental conditions in China's coastal zone have shown a trend of improvement, but regional differences still exist; 2) during the study period, the urbanization process of cities continued to advance, especially in seaside cities and prefecture-level cities in Jiangsu and Shandong, which were much higher than the average growth rate; 3) the Coupling Coordination Degree (CCD) between the urbanization and eco-environment in coastal cities is constantly increasing, but the main contribution of environmental improvement comes from non-urbanized areas, and the eco-environment pressure in urbanized areas is still not optimistic. As a large-scale, long-term series of eco-environment and urbanization process change analysis, this study can provide theoretical support for mesoscale development planning, eco-environment condition monitoring and environmental protection policies from decision-makers.

1. Introduction

As a special geographical area connecting the marine and land systems, the coastal zone is not only the most active natural area on the earth's surface, with the most concentrated human activities and the most developed economy, but also the area with the most superior resources and environmental conditions (Crossland et al., 2005). Currently, nearly 60% of the world's population lives in coastal areas, and environmental changes in coastal areas are closely related to human survival and development (Chen and Wang, 2003; Fan et al., 2010). However, since the 20th century, with the development of coastal economy and urbanization, the large-scale population continues to concentrate in coastal areas, the regional environment is increasingly disturbed by human activities, and the natural and eco-environment are facing great pressure (Weston et al., 2009; Zhai et al., 2019; Zhang and Zhu, 1997). Facing increasing ecological disturbances, effective models are increasingly needed to detect the temporal and spatial changes of ecological conditions to ensure the sustainable development of the coastal zone.

The rapid development of remote sensing technology provides data sources and technical support for regional eco-environment monitoring and evaluation, which can effectively reflect the ecological status at different scales (Ivits et al., 2009; Caccamo et al., 2011; Willis, 2015; De Araujo Barbosa et al., 2015). In particular, the frequent application of remote sensing based ecological assessment makes it an important means to monitor the coastal environment, and plays an important role in the global coastal ecological assessment research (Arnous and Green, 2011; Sirirwardane et al., 2015; Wang et al., 2018). In general, remote sensing-based coastal ecological research mainly focuses on landuse/cover change (Zoran et al., 2010; Bui et al., 2014; Vatseva, 2015), landscape pattern analysis (Feng and Han, 2011; (Hepcan, 2013; Li et al., 2015; Chu et al., 2015; Vorovencii, 2015; Xu et al., 2015), coastline change detection (Lo and Gunasiri, 2014; Guneroglu, 2015; Wang et al., 2016; Chen et al., 2016), vegetation change monitoring

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Fig. 1. The location map of coastal zone of China.

(Bird et al., 2004; Stanley et al., 2005; Alatorre et al., 2011; Shibly and Takewaka, 2013; Anwar and Takewaka, 2014; Aslan et al., 2016) and habitat change identification based on indicator system (Qin et al., 2008; Gong et al., 2011; Ning et al., 2016).

In fact, in an ecosystem, the interaction between each environmental indicator affects the whole ecosystem, and they are inseparable (Xu, 2013). However, most of these remote sensing-based coastal ecological environment assessments are based on a single index, such as vegetation index to describe vegetation change (Maselli, 2004; Gillespie et al., 2018) and water body index to represent coastline change (Wicaksono and Wicaksono, 2019). Due to the insufficient ability of these assessment models to reveal the comprehensive ecological status of the region, the detection of ecological change based on the aggregate remote sensing index is still a challenge (Behling et al., 2015). Gradually, some indicators or models that aggregate multiple indicators to monitor ecological conditions have been proposed, such as forest disturbance index (DI) which combines three components of tasseled cap transformation, MODIS global disturbance index (MGDI) which combines the enhanced vegetation index (EVI) and land surface temperature, Ecological Niche Modeling (ENM) which combines the red index, EVI and normalized difference water index (NDWI).

It is worth noting that a recent study on the remote sensing-based ecological index (RSEI) has brought new hope for the realization of long-span and large-scale ecological assessment (Xu, 2013). RSEI is completely based on remote sensing images and can integrate multiple index factors to objectively and quickly evaluate regional ecological quality. It selects four indicators, such as greenness, humidity, heat, and dryness, which can be directly felt by the human body, comprehensively reflects the regional ecological environment, and integrates various indicators through principal component transformation (PCA). RSEI overcomes the shortcomings of a single indicator, makes the aggregation of sub-indicators more reasonable, and has been successfully applied to many regions to provide support for the analysis, modeling and prediction of regional ecological characteristics (Zhang et al., 2015, 2018; Song and Xue, 2016; Hu and Xu, 2018; Yue et al., 2019).

The continuous urbanization process has caused great changes in the natural ecological environment in China's coastal areas since the 1980s. Under the premise of ensuring the sustainable development of the coastal zone, it is of great significance to explore the interaction between the eco-environment and human activities in China's coastal areas in the past few decades. Therefore, based on day-time and nighttime remote sensing images, the interaction between eco-environment and urbanization process in China's coastal areas are explored in this paper. The specific objectives of this study were: 1) monitoring the long-term dynamics of eco-environment in the coastal zone of China under the background of rapid urbanization processes; 2) evaluating the spatiotemporal differences in the intensity of human activity and the level of urbanization in the coastal zone over the last 20 years; 3) assessing the coupling coordination level between the eco-environment and the urbanization level in coastal area, and recognizing the impact of continuous urbanization on local environmental.

2. Study area and data sources

2.1. Study area

Generally, the coastal zone is a belt area that extends to the land and sea sides of the coastline, involving land areas and near-shore waters

(He, 2017). In fact, the coastal zone is commonly defined according to management purposes and research needs, leading to a diversity of coastal zone extent definitions. For example, the United Nations Millennium Ecosystem Assessment project defines coastal zones as lowlands extending 100 km from the coast to the mainland, while scholars usually conduct research based on administrative units (Agardy et al., 2005; Hou et al., 2018).

China's coastal zone is located in the intersection of Eurasia and the Pacific Ocean, with a total length of the continental coastline is more than 18000 km (Cao and Wong, 2007). There are 14 provincial administrative units in the coastal zone, including Liaoning, Hebei, Tianjin, Shandong, Jiangsu, Shanghai, Zhejiang, Fujian, Guangdong, Guangxi, Hainan, Hongkong, Macao and Taiwan (Fig. 1). Although the aforementioned coastal provincial units cover only 13% of China's area, they are concentrated in more than 50% of China's large cities, 40% of its small and medium-sized cities, more than 40% of its population, and more than 60% of its GDP (Luo, 2016). The diversified urban scale and intensity of human activities in the coastal provinces make them an important "window" for recognizing the impact of urbanization on the environment (Di et al., 2014). Besides, considering the higher priority and independence of provincial administrative units in the formulation and implementation of environmental protection and urban development policies, this paper defines the coastal provincial unit as the study area to implement the time-series analysis. In particular, due to the special geographical location of Beijing, it is also included in the study area.

2.2. Data and Pre-processing

2.2.1. Daytime remote sensing data

Four ecological components will be involved in the process of constructing RSEI, namely Greenness, Wetness, Heat and Dryness. Accordingly, this paper selects the corresponding standard products from the MODIS product library as the data source based on these four components. The Land Processes Distributed Active Archive Center (LPDAAC) Collections in the USGS United States Geological Survey (USGS, https://earthexplorer.usgs.gov) provides standard data collection for different application scenarios based on level 1B data, including land surface reflectance (LSR), land surface temperature and emission (LST&E), vegetation indices (VI), which can be directly applied to construct RSEI in this paper. For the study area of this paper, we use remote sensing image processing platform to preprocess the tiles images of different components, such as images mosaicing, clipping, resampling and projecting. Also, to reduce the interference caused by the difference of image acquisition time to the ecological components and improve the image quality under the cloud interference, this paper uses the adjacent month as the image acquisition time window for each component (Table 1).

2.2.2. Nighttime remote sensing data

Unlike traditional daytime remote sensing, the nighttime remote sensing can effectively detect the distribution and intensity of artificial light sources. Its image set has been confirmed to be highly correlated with surface human social activities and is widely used in urbanization (Ju et al., 2017; Zhou et al., 2018; Xie et al., 2019), population distribution (Yu et al., 2019; Li and Zhou, 2018), GDP (Ji et al., 2019) and energy consumption (Shi et al., 2019). Considering the time span of this study, the nighttime light image for 2000, 2005 and 2010 were derived from the Stable Light (STL) of Defense Meteorological Satellite Program/Operational Linescan System (DMSP/OLS), while the light image for 2015 and 2019 were derived from the Day/Night Band (DNB) of National Polar-Orbiting Partnership/Visible Infrared Imaging Radiometer Suite (NPP/VIIRS). The detailed parameters of the two types of lighting data used in the paper are shown in Table 2. To avoid the deviations caused by abnormal data fluctuation and sensor difference, in-sensor calibration and sensor-cross calibration is performed referring to the model proposed by Zheng et al. (2019) and Wu and Wang (2019).

3. Methods

3.1. Construction of RSEI

The RSEI consists of four components: Greenness, Heat, Wetness and Dryness, which is often used for ecological assessment (Li et al., 2017; Yuan and Bauer, 2007; Ivits et al., 2009).

Although existing RSEI-based studies use NDVI as the green component, considering the NDVI's saturation problem in high vegetation coverage area, EVI is used as the green component. Since the MOD13A1 V6 image set contains the EVI layer, there is no need to calculate the EVI according to the formula (Index DataBase, 2019).

Different from Landsat image for small scale LST inversion, MODIS thermal infrared image with high temporal resolution (8-days) and medium spatial resolution (1 km) has become an indispensable data source for large-scale regional LST inversion. As listed in Table 1, the heat component was derived from the DLST layer of MOD11A2 V6 Dataset.

Previous studies have confirmed that Kauth-Thomas (K-T) transformation is an effective data compression and de-redundancy technique, and its luminance, greenness, and wet components are directly related to surface physical parameters (Crist, 1985; Huang et al., 2002; Baig et al., 2014) and is widely used for wetness monitoring in eco-environmental assessment (Todd and Hoffer, 1998). As previous studies, the third component of k-t-transformed multispectral image is used to characterize the wetness component of RSEI. The formula is defined as:

$$Wet = c_1\rho_{red} + c_2\rho_{nir1} + c_3\rho_{blue} + c_4\rho_{green} + c_5\rho_{nir2} + c_6\rho_{swir1} + c_7\rho_{swir2} \quad (1)$$

where ρ_{red}, ρ_{nir1}, ρ_{blue}, ρ_{green}, ρ_{nir2}, ρ_{swir1} and ρ_{swir2} represent the reflectance of the 7 bands of the MOD09A1 images, respectively (Zhang et al., 2002). For MODIS multi-band images, the coefficient of each band is: c_1=0.1147, c_2=0.2489, c_3=0.2408, c_4=0.3132, c_5=-0.3122, c_6=-0.6416, c_7=-0.5087 (Xu et al., 2019).

As surface drying will have a huge impact on living conditions and biological richness, and become an important indicator of the level of eco-environment (Xu, 2008). To quantify the dryness component, the Normalized Difference Build-up and Soil Index (NDBSI) was constructed based on Bare-soil Index (BI) (Rikimaru et al., 2002) and Index-based Built-up Index (IBI) (Xu, 2008). The formula is as follows:

$$NDBSI = \frac{IBI + BI}{2} \quad (2)$$

Table 1
The data source of four ecological components.

Component	MODIS Data collection	Date layer	Spatial/temporal resolution	Data time	Image amount
Greenness	MOD13A1 V6	Enhanced Vegetation Index (EVI)	500 m/16-days	August	85
Heat	MOD11A2 V6	Daytime Land Surface Temperature (DLST)	1 km/8-days	September	45
Wetness	MOD09A1	Corrected surface spectral reflectance for bands 1 to 7	500 m/8-days	October	63
Dryness	MOD09A1	Corrected surface spectral reflectance for bands 1 to 7	500 m/8-days	October	63

Table 2
Data parameters of DMSP/OLS and NPP/VIIRS.

NTL data	Sensors	Spatial resolution	Temporal resolution	Data available interval	Unit
Stable Light (STL)	OLS	Annual	30 arc second (around 1 km at equator)	1992–2013	DN (unitless)
Day/Night Band (DNB)	VIIRS	Monthly	15 arc second (around 500 m at equator)	April 2012-Present	Nano Watts/cm^2/Sr

$$IBI = \frac{\frac{2\rho_{swir1}}{\rho_{swir1}+\rho_{nir1}} - [\frac{\rho_{nir1}}{\rho_{nir1}+\rho_{red}} + \rho_{green}/(\rho_{green}+\rho_{swir1})]}{\frac{2\rho_{swir1}}{\rho_{swir1}+\rho_{nir1}} + [\frac{\rho_{nir1}}{\rho_{nir1}+\rho_{red}} + \rho_{green}/(\rho_{green}+\rho_{swir1})]} \quad (3)$$

$$BI = \frac{[(\rho_{swir1}+\rho_{red})-(\rho_{nir1}+\rho_{blue})]}{[(\rho_{swir1}+\rho_{red})+(\rho_{nir1}+\rho_{blue})]} \quad (4)$$

where ρ_{red}, ρ_{blue}, ρ_{green}, ρ_{nir1} andρ_{swir1} are the surface reflectance of the corresponding bands in the MOD09A1 V6 images, respectively.

In order to compress the information on multidimensional variables and effectively reduce the number of variables, the principal component analysis (PCA) method is used to integrate the above four components. PCA determines the weight of each index manually, but automatically and objectively according to the contribution degree of each index to each principal component, thus avoiding the result deviation caused by the subjective setting of weight in the calculation process (Xu, 2013; Seddon et al., 2016). Specifically, 1) standardize each component; 2) perform PCA analysis based on ArcGIS Pro platform to obtain the first principal component as original value of RSEI; 3) standardize the original values to ensure the comparability of RSEI in different periods.

3.2. Construction of the nighttime light index

Based on the calibrated nighttime light image, this paper utilizes a comprehensive nighttime light index (CNLI) to reflect the level of urbanization and the intensity of human activities on the surface, which can effectively monitor the development of regional urbanization (Chen et al., 2003). CNLI is defined as the product of the light area proportion (LAP) and the mean light intensity (MLI) in a specific area. The formula is:

$$CNLI = LAP \times MLI \quad (5)$$

$$MLI = \frac{\sum_{i=1}^{63} C_i \times DN_i}{\sum_{i=1}^{63} C_i \times 63} \quad (6)$$

$$LAP = \frac{Area_{light}}{Area} \quad (7)$$

where DN_i is the light value of the light pixel and C_i is the number of pixels with a value of DN_i; $Area_{light}$ and $Area$ are the total area of the light patch and the total area of the study area, respectively.

3.3. Coupling coordination model

The coupling and coordination between the eco-environment and the development of urbanization (human activity) are important factors affecting the sustainable development of coastal areas. Based on the capacity coupling system model in physics, a coupling coordination model of urbanization and eco-environment was introduced in this paper (Liu et al., 2005). Firstly, the coupling model is constructed as:

$$CD = 2 \times \sqrt{(U \times E)/(U+E)^2} \quad (8)$$

where U represents CNLI and E represents RSEI; CD is the coupling degree between CNLI and RSEI. The larger the value of CD, the more coordinated the eco-environment and urbanization development.

Secondly, to avoid the "false coordination" of the two systems, the coupling coordination model is introduced to objectively reflect the coordinated development level. The formula is:

$$CCD = \sqrt{(\alpha U + \beta E) \times CD} \quad (9)$$

where CCD is the coupling coordination degree, the higher the value is, the higher the level of coupled and coordinated development of the system. α and β are weight coefficients. Considering that urbanization is the key factor leading to the change of eco-environment, and the impact of eco-environment on urbanization is quite limited, so the urbanization system should be given greater weight ($\alpha = 0.65$; $\beta = 0.35$ (Liao et al., 2018).

4. Results

4.1. Eco-environment in the coastal zone

4.1.1. Coastal zone RSEI and its changes

Fig. 2 shows the distribution of the RSEI index in 2000, 2005, 2010, 2015, and 2019. The results indicate that the RSEI in China's coastal regions showed a significant upward trend from 2000 to 2019. The RSEI mean-value of the coastal zone in 2000 was the lowest, only 0.492, while the RSEI mean-value of 2019 increased by about 17% from 2000 to 0.575. The increase in RSEI over the past 2 decades indicates that the ecological environment in China's coastal zones has improved to some extent. For the 2000 RSEI, the number of low-value RSEI pixels (poor eco-environment status) is large and mainly distributed in the north of the coastal zone. For 2019, the number of low-value RSEI

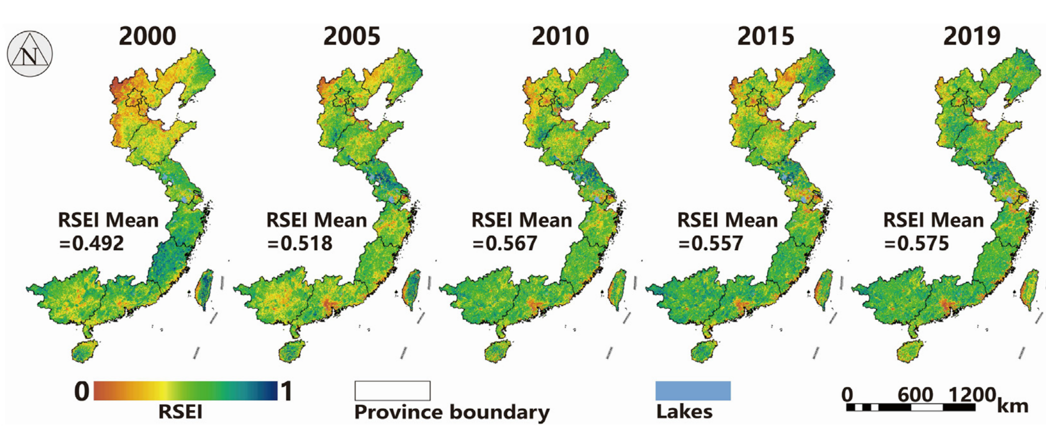

Fig. 2. The RSEI map of China's coastal zone in 2000, 2005, 2010, 2015 and 2019.

Table 3
Area and percentage statistics of the five RSEI levels in different years.

RSEI Level	Very Bad (0–0.2) (×10^2 km^2)	Bad (0.2–0.4) (×10^2 km^2)	Medium (0.4–0.6) (×10^2 km^2)	Good (0.6–0.8) (×10^2 km^2)	Natural (0.8–1.0) (×10^2 km^2)
2000	111.6(0.83%)	2324.5(17.2%)	8977.7(66.6%)	2064.2(15.3%)	5.1(0.04%)
2005	53.1(0.39%)	1360.1(10.1%)	9731.0(72.2%)	2328.1(17.3%)	10.8(0.08%)
2010	49.6(0.37%)	896.2(6.70%)	6970.8(51.7%)	5483.0(40.7%)	83.4(0.62%)
2015	45.6(0.34%)	1218.9(9.04%)	7032.9(52.2%)	5146.4(38.2%)	39.2(0.29%)
2019	68.5(0.51%)	996.2(7.4%)	6172.9(45.8%)	6163.4(45.7%)	82.0(0.61%)
Change (2000–2019)	−43.1(−38.6%)	−1328.3(−57.1%)	−2804.8(−31.2%)	4099.2(198.6%)	76.9(1511%)

pixels is significantly reduced, and most of them are concentrated in built-up areas and estuarine deltas, such as Pearl River Delta, Yangtze River Delta and Beijing-Tianjin areas. Through comparison, it can be found that the change characteristics of RSEI in coastal areas during the past almost 20 years can be summarized as follows: 1) the overall RSEI value shows an increasing trend, especially in the northern coastal zone; 2) the low-value RSEI pixels in urban areas, especially in urban agglomerations, shows an expanding trend. This change characteristic has a close relationship with the ecological civilization construction and green development road that China has continuously promoted in recent years under the development of high-speed urbanization. According to data from the World Bank, China's forest cover increased by 328,630 km^2 between 2000 and 2016, making it the country with the largest increase in forest area in the world (The World Bank., 2019).

In order to better reveal the RSEI changes in the past 2 decades, referring to the ecological classification methods provided by Hu and Xu (2018), the RSEI values of China's coastal areas are divided into 5 grades according to the equal interval of 0.2 to represent 5 different ecological conditions (Table 3). The results show that the area with ecological status of “Very Bad” has decreased by about 38.56% in the past 19 years, and the reduced area has reached over 4300 km^2. The area with the ecological status of ‘Bad’ decreased about 132800 km^2, more than 50% compared with that in 2000. The areas with “Good” and “Natural” ecological status increased significantly, with the growth rate reaching 198.6% and 1511% respectively. In the past almost 20 years, the conversion of RSEI has focused on three levels: Bad, Medium and Good. In year 2000, the ecological conditions of “Bad” and “Good” are relatively close, accounting for about 16% of the coastal area, while the area of ‘Medium’ accounts for about 66%. In year 2019, the proportion of regions in “Bad”, “Medium” and “Good” is 7%, 45% and 45% respectively, which has changed significantly compared to 2000. Changes in the proportion structure indicate that in the past 19 years, about 20%-30% of the areas in the “Medium” have risen to ‘Good’, and about 10% of the ‘Bad’ areas have improved.

4.1.2. Spatial heterogeneity of RSEI

As in most countries, China's administrative divisions have a spatial hierarchy. The social and economic policies formulated or promulgated by the central government can be conveyed through the governments at the provincial, city, county, town, and village levels (Zheng et al., 2019). In the process of regional development and policy implementation, the prefecture-level administrative units have gradually become the core and basic spatial units (Shi et al., 2019). Therefore, based on ArcGIS Pro platform, this paper performed the spatial autocorrelation analysis of RSEI values at prefecture-level cities to reveal the changes and spatial distribution characteristics of coastal eco-environment over the past 20 years.

Fig. 3 shows the RSEI mean-value distribution of urban units and the Local Moran’s I of the change- value of RSEI during the past 20 years. In year 2000, there were 14 RSEI municipal units with lower than 0.4, which were mainly distributed in north-central of Hebei (Shijiazhuang, Zhangjiakou, Chengde, Langfang, etc.), Beijing, Tianjin, western Liaoning (Chaoyang and Jinzhou) and northern Shandong (Dongying). After 19 years of development, the number of RSEI municipal units lower than 0.4 has been significantly reduced, with only 6 remaining, and mainly distributed in the Pearl River Delta (Zhongshan, Dongguan, Foshan, etc.) and southwest Taiwan (Yunlin and Changhua). Meanwhile, the number of RSEI municipal units higher than 0.55 increased from 37 in 2000 to 69 in 2019, with a large increase.

Although the overall ecological status of the coastal zone shows a trend of improvement, it still has spatial heterogeneity. According to the local Moran’s I map, it can be seen that the RSEI rising units (eco-environment has improved) are mainly distributed in Shandong, Hebei, Tianjin and Beijing, the north-central part of the coastal zone. Since these areas are located in northern China and dominated by plains, the vegetation coverage, especially forest resources, is insufficient, unevenly distributed and low quality compared to the southern China. However, after 2000, with the promotion of “Ecological Civilization Construction” and the strengthening of environmental protection awareness, the vegetation coverage in this area has increased significantly (Yan et al., 2019; Li et al., 2017). Then, considering the contribution of EVI to RSEI, the improvement in vegetation coverage has driven the rise of RSEI. Conversely, the number of units that have experienced RSEI attenuation (ecological deterioration) over the past 19 years has been significantly reduced and scattered, including the Yangtze River Delta, the Pearl River Delta, southwestern Hainan, and Taiwan. Due to the better climatic and hydrological conditions, the initial ecological conditions in the above areas are better than those in the northern coastal zone. However, in the past 19 years, with the rapid development of economy and urban expansion, on the urban scale, the impervious surface has occupied more and more ecological land and resulting in the decline of vegetation coverage and ultimately affecting the regional RSEI.

4.2. Nighttime light in coastal areas

4.2.1. The nighttime light intensity distribution and its changes

It is universally acknowledged that the light image after necessary preprocessing and calibration can directly reflect the surface vitality and urbanization intensity. Fig. 4 (a-e) shows the nighttime light images after calibration in China's coastal zone from 2000 to 2019. Obviously, in the past 20 years, the nighttime light in the coastal zone has increased substantially, both from the lighting area and the number of high-intensity light pixels. According to the statistical results of MLI and LAP of coastal light images in different years, it can be seen that the MLI of the light pixel was only 0.26 in 2000, and then it has increased year by year and reached 0.4 in 2019, with a growth rate of 53.8%. Meanwhile, the lighting area has also increased from $33.5 \times 10^4 km^2$ in 2000 to $86.9 \times 10^4 km^2$ in 2019, expanding by about $53.4 \times 10^4 km^2$ (the expansion rate is about 160%), and the LAP has also increased from less than 25% in 2000 to 63% in 2019.

For the spatial distribution of light pixels, it can be found that high brightness light pixels are mainly distributed in coastal cities, especially in the Yangtze River Delta and Pearl River Delta. Another noteworthy feature is that during the study period, the nighttime light pixels continued to expand from the coast to the inland. In year 2000, most of the light pixels were concentrated in coastal cities, while in 2019, the number of light pixels in non-coastal cities increased significantly, especially in North China in the middle and north of the coastal zone. Through comparison, we find that the main feature of the light change

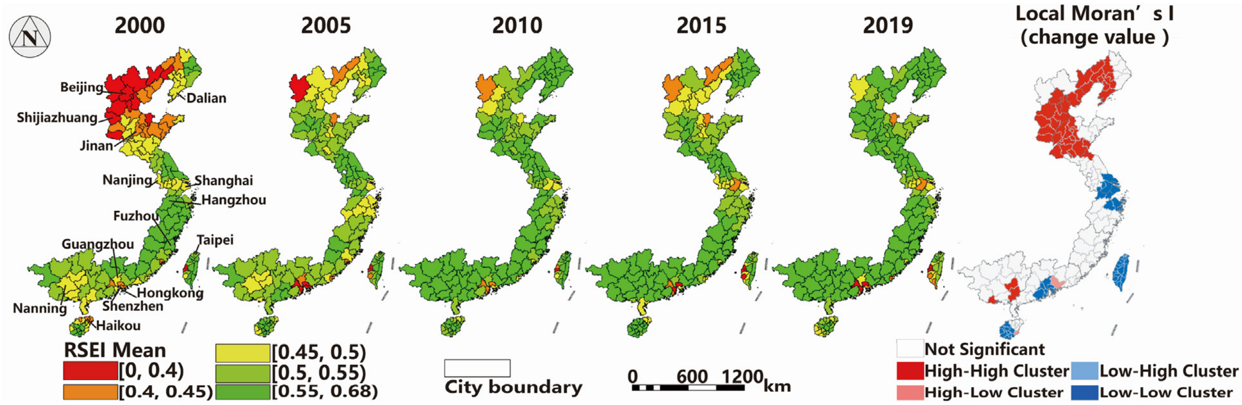

Fig. 3. The RSEI mean-value distribution and local Moran's I map of municipal units.

in coastal cities is the rapid increase of high brightness light pixels, while the main feature of non-coastal cities is the expansion of lighting area and the proliferation of light pixels.

Besides, in order to reveal the internal differences of light intensity changes in the past 20 years, this paper divides the DN value of light image into four levels: Very-low light, Low light, High light and Very-high light. Fig. 4(f) shows the distribution of different levels of light intensity in 2000 and 2019 for the three largest urban agglomerations (the largest light pixel gathering area) in the coastal zone of China. It can be seen that during the study period, the Very-high light area continued to expand outward from the center of the core city, and connected with the center of the surrounding cities, with remarkable area expansion. At the same time, the light intensity in the Very-low light area keeps rising and transforms into Low light on a large scale, continuously extending to the surroundings and shaping the new boundaries of the light area. To quantitatively evaluate the difference in the expansion of light pixels, the number and proportion of light pixels under four levels are counted in this paper (Fig. 4(g)). The results show that the number of light pixels in the four levels keeps substantial growth, of which the growth of Low light pixels is the most prominent, and for the first time exceeds the number of Very-low light pixels in 2019. In terms of the proportion of the light pixels, except the proportion of Very-low light continues to decrease (by 30%), the proportion of the remaining three levels of pixels has increased. It is worth pointing out that the proportion of pixels in Low light and Very-high light has increased markedly (by 21% and 7%, respectively), while the

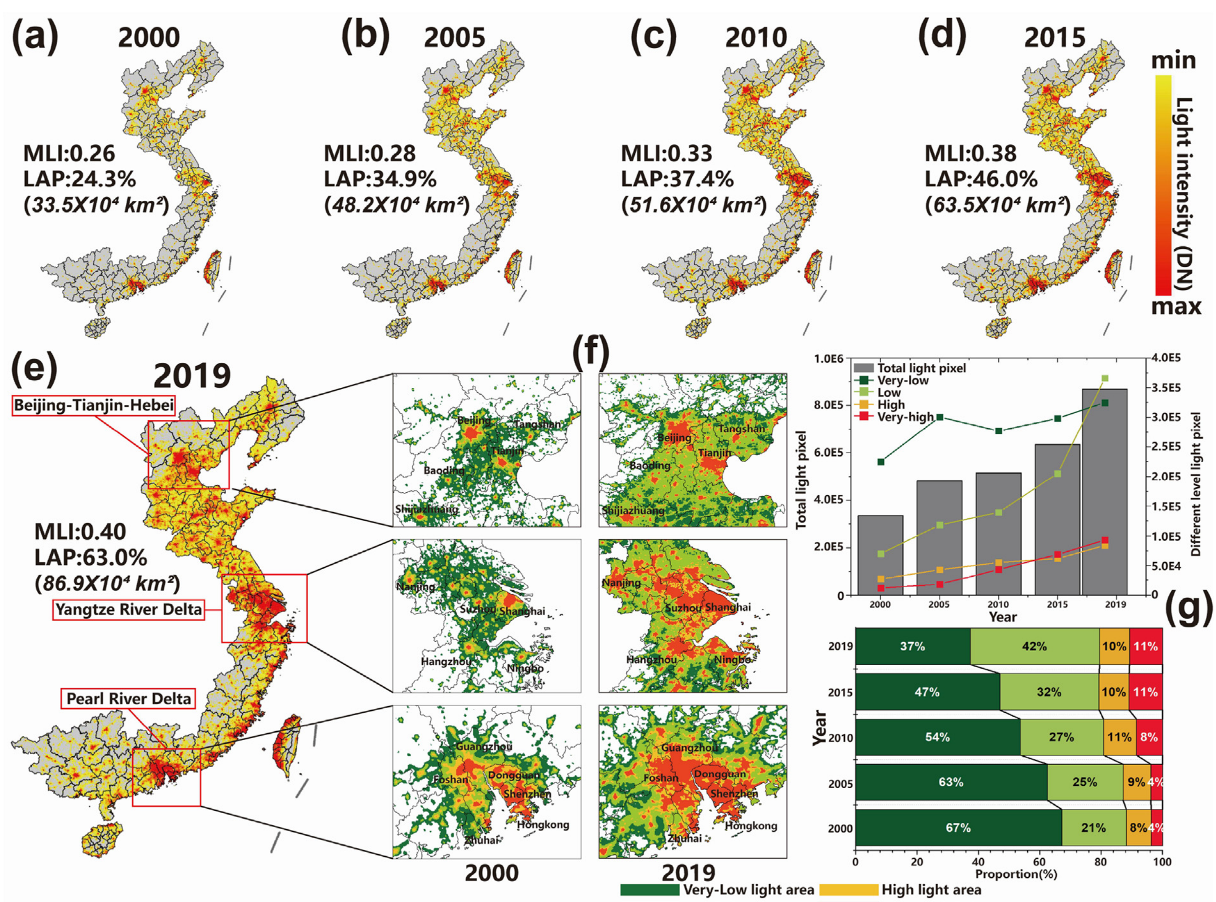

Fig. 4. Coastal zone light images and its changes from 2000 to 2019.

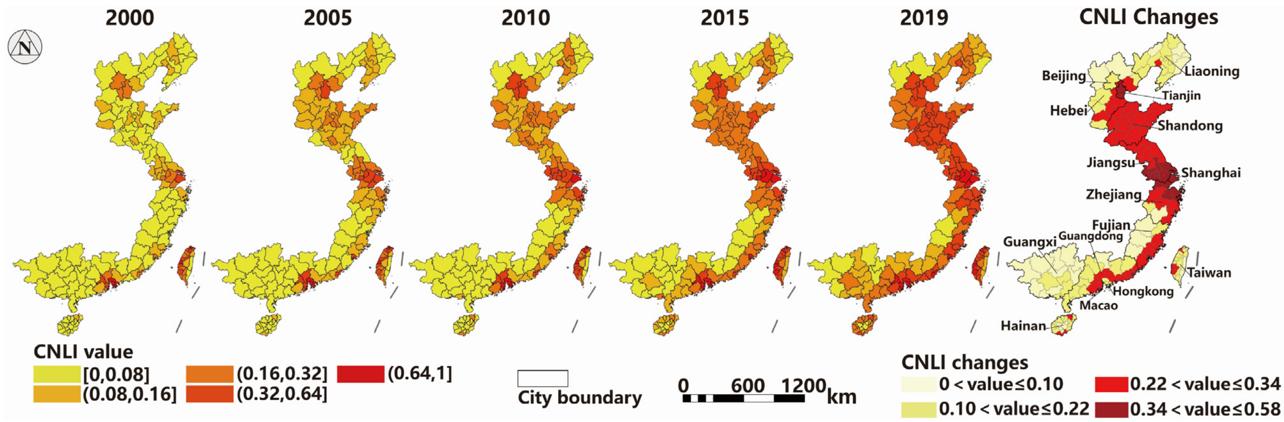

Fig. 5. CNLI in prefecture-level cities and its changes.

proportion of pixels in High light intensity has increased slightly, only 2%.

4.2.2. CNLI changes in prefecture-level cities

According to the constructed CNLI model, the CNLI of each unit and its changes on the scale of the prefecture-level city are calculated, as shown in Fig. 5. Compared with 2000, after 20 years of rapid urban development, CNLI in all coastal cities has increased. The CNLI change gradient of the city units shows that there are 28 CNLI lowest-growth cities ($0 < \text{increased CNLI} \leq 0.1$), accounting for 18.5% of all cities; 51 CNLI low-growth cities ($0.1 < \text{increased CNLI} \leq 0.22$), accounting for 33.8% of all cities; 55 cities with high-increase of CNLI ($0.22 < \text{increased CNLI} \leq 0.34$), accounting for approximately 36.4%; 17 cities with highest- increase of CNLI ($0.34 < \text{increased CNLI} \leq 0.1$), accounting for 11.3% of all units. According to the spatial distribution of four types of cities, the highest and high-growth cities, which growth rate exceeds the average level can be divided into two types, one is coastal cities of each province, and the other is Shandong and Jiangsu Prefecture-level cities. Coastal cities are mostly regional central cities or administrative centers, which have attracted a large number of migrants and investment in the past 20 years, bringing motivation and resources for urbanization. The accelerated urbanization process and the expansion of impervious surfaces cause the rise of CNLI in the region. For Jiangsu Province and Shandong Province, according to the data released by the China Statistics Bureau, Guangdong Province, Jiangsu Province and Shandong Province were the top three provinces in terms of GDP and regional electricity consumption between 2000 and 2018. However, considering the differences in the size of provinces, Jiangsu and Shandong show a faster growth rate of GDP and electricity consumption. The sound economic foundation and geographical advantages have enabled Shandong and Jiangsu provinces to rapidly develop into China's most dynamic regions with close economic levels in the past 20 years (Liu et al., 2019; Guo et al., 2016), which has shown a higher growth rate in CNLI.

4.3. Interaction between eco-environment and urbanization

4.3.1. The CCD and changes in the coastal zone

Based on the calculated RSEI and urbanization characterization factors CNLI of each city, this paper generates CCD of prefecture-level cities in the coastal zone of China according to formula (8–9), as shown in Fig. 6. In general, from 2000 to 2019, the CCD between RSEI and CNLI showed an upward trend, which means that the coupled and coordinated development of the ecological environment and urbanization of coastal zones has improved. Specifically, CDD continued to rise at a rate of approximately 0.01 per year, from 0.39 in 2000 to 0.6 in 2019, an increase of more than 50%. The continuous and steady rise of CCD indicates that the eco-environment and urbanization of coastal cities are undergoing a healthy development process.

To facilitate the analysis of the coupling coordination characteristics of the urban RSEI and CNLI, similarly, we divided the CCD of the prefecture-level city into three levels, namely the Low-level coupling coordination stage, which CCD is lower than 0.45; the Medium-level coupling coordination stage, which CCD is between 0.45 and 0.65; the High-level coupling coordination stage, which CCD is higher than 0.65. In year 2000, there are only 13 cities (9%) in the stage of High-level coupling, while the cities in the stage of Low-level coupling dominated, reaching 76% (Fig. 7). In year 2005, the number of cities in the Low-level coupling stage decreased to 80, accounting for more than 50%, and the number of cities in the Medium-level coupling stage reached 51, an increase of more than double. In year 2010, the number of Low-level coupling cities continued to decline, accounting for less than 50% for the first time, and the Medium-level coupling cities continued to rise and exceeded the Low-level coupling cities for the first time. In year 2019, the portion of High-level coupling cities has increased significantly, accounting for nearly 40%, while the Low-level coupling cities have continued to decrease, less than 20%, and the Middle-level coupling cities has stabilized at about 45%.

In the past 20 years, the city's CCD has not only changed in absolute value and proportion, but also have differences in their spatial distribution. In year 2000, the Low-level coupling of coastal cities accounted for the vast majority, while the number of High-level coupling cities was small and mainly distributed in the Yangtze River Delta, Pearl River Delta and Taiwan. In year 2019, the High-level coupling cities reached about 40%, and the distribution area has expanded significantly, including the Pearl River Delta, Yangtze River Delta, Beijing-Tianjin-Hebei, Zhejiang-Fujian, and western Taiwan, while the Low-coupling cities that account for only 16% are mainly distributed on the west side (far-sea side) of the coastal zone, including northwestern Guangxi, western Fujian, and northern Hebei Province. Furthermore, the distribution of CCD change values shows that there is a significant spatial concentration of CCD growth values between cities, that is, areas with substantial growth (Level 3) are concentrated in Jiangsu, Shandong, Zhejiang and Fujian, while the low slight growth (Level 1) cities are mainly located in Liaoning and Taiwan Province.

4.3.2. Response of RSEI to nighttime light change

This paper analyzes the characteristics of the RSEI and its components with the light intensity gradient to explore the impact of urbanization on eco-environment in coastal areas. Fig. 8(a)–(e) shows the fluctuation of the mean values of RSEI and environmental components under different light intensity in 2000, 2005, 2010, 2015 and 2019. The results show that: 1) the average values of RSEI and EVI have the same fluctuation characteristics under the light gradient, that is: with the increase of light intensity, the regional eco-environment conditions and vegetation coverage have a downward trend; 2) with the increase of

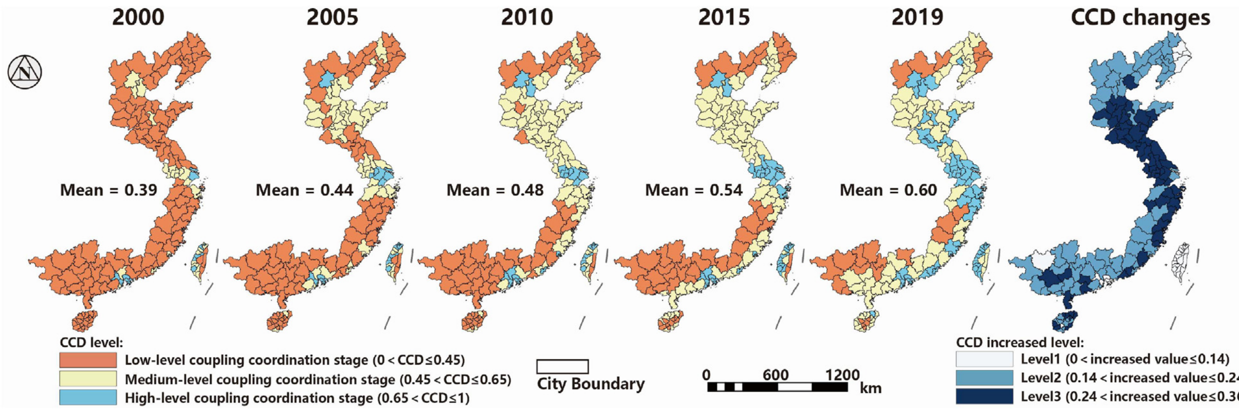

Fig. 6. The CCD and its changes in the coastal zone.

light intensity, LST, NDBSI and Wetness all show a synchronous upward trend. Furthermore, Fig. 8(f) shows the R^2 and absolute coefficients of RSEI and its components linearly varying with the intensity gradient from 2000 to 2019. On the one hand, the results of R^2 indicate that RSEI, EVI, and LST are highly linearly correlated with light intensity (both above 0.8), followed by humidity (about 0.7), and the correlation between NDBSI and light intensity is increasing during the study period. On the other hand, the upward trend of the absolute value of the coefficient indicates that the influence of human activities on the composition and RSEI has deepened during the study period.

In addition, this paper further compares the mean value and change of RSEI under the light gradient in the study period to reveal the interference of different urbanization levels on the eco-environment (RSEI). Fig. 9(a) compares the mean value of RSEI under light gradient in 2000 and 2019, and the result shows that although the RSEI in 2019 is higher than that in 2000, the growth of RSEI decreases with the increase of light intensity. Fig. 9(b) depicts the RSEI changes in the weakest and strongest light intensity regions in different years, indicating that during the study period, the RSEI in the region with the weakest light intensity increased relatively steadily, while the region with the highest light intensity changed slightly. In general, the results of RSEI and its components changes with the light gradient can reflect the impact of urbanization level on the eco-environment. Especially for RSEI, which represents the comprehensive ecological situation of the region, although the overall ecological environment of the coastal zone has been improved in recent 2 decades, the inhibition of urbanization process on the eco-environment still exists, which is not optimistic.

5. Discussion

5.1. Improvement of coastal ecological environment

Through the statistics of the average RSEI of the provinces and cities in the past 2 decades, it is an indisputable fact that the overall eco-environment of the coastal zone of China is gradually improving. During the study period, the average RSEI value has increased by 17%, and the area with the ecological status of “Good” and “Natural” has increased by nearly 200% and 1500%, respectively. The negative effects that urbanization and the expansion of impervious surfaces will have on regional ecosystems have been well documented in numerous studies (Du and Huang, 2017; Chithra et al., 2015). However, the results of this paper show that the coastal zone, as one of the most rapidly urbanizing areas in the world, is showing some improvement in ecological conditions with urbanization, which is a deviation from the previous perception. Generally, the relationship between human activities (urbanization) and eco-environment is not always a simple negative correlation, but there is a complex interaction when human intervention is involved (Ariken et al., 2020). As urbanization and environmental pressures rise worldwide, sustainability development has become one of the key themes around the world. The successive formulation of the Millennium Development Goals (MDGs) and the Sustainable Development Goals (SDGs) has prompted efforts to balance regional development and environmental protection, especially for rapidly developing and emerging developing countries (Griggs et al., 2013; Hickel, 2019). As the largest developing country and a fast-growing economy, China promulgated a series of guidelines and policies after the millennium to protect and restore the eco-environment

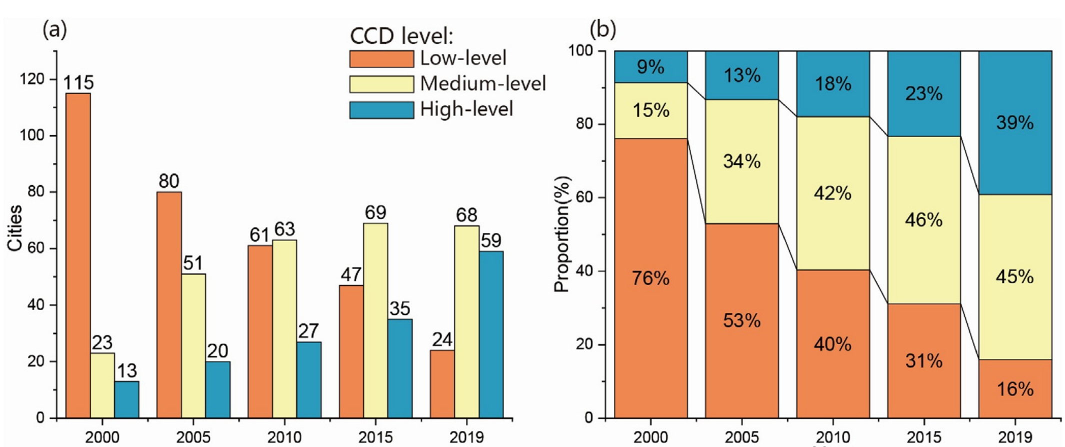

Fig. 7. The quantity and proportion change of graded CCD.

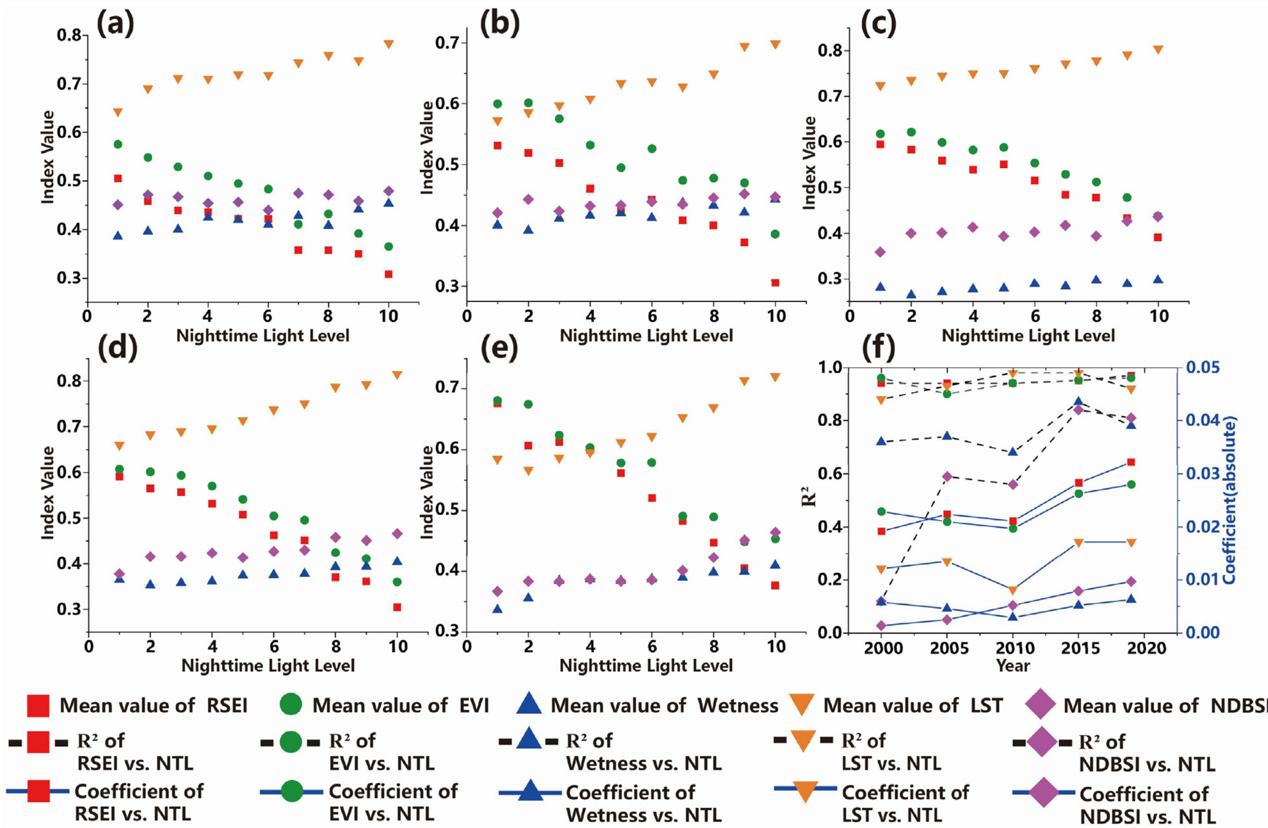

Fig. 8. The mean value of RSEI and 4 factors at nighttime light intensity gradient.

affected by the rapid urbanization process (Wang et al., 2013; Naustdalslid, 2014; Zhao et al., 2016). Therefore, we speculate that the intervention of anthropogenic regulatory measures has fairly reversed the natural trend of regional ecological degradation (with urbanization) and has shaped the upward trend of RSEI in the coastal zone. Also, according to statistics, China's total investment in environmental pollution control is 953.9 billion yuan, 7.2 times higher than that in 2001, with an average annual growth rate of 14.0% (The State Council of the People's Republic of China., 2019), which also supports the above speculation.

Although the overall ecological status of the coastal zone shows a trend of improvement, it still has spatial heterogeneity. It can be seen that the RSEI rising units (eco-environment has improved) are mainly distributed in Shandong, Hebei, Tianjin and Beijing in the north-central part of the coastal zone. Since these areas are located in northern China and dominated by plains, the vegetation coverage, especially forest resources, is insufficient, unevenly distributed and low quality compared to southern China. However, after 2000, with the promotion of "Ecological Civilization Construction" and the strengthening of environmental protection awareness, the vegetation coverage in this area has increased significantly (Yan et al., 2019; Li et al., 2017). Then, considering the contribution of EVI to RSEI, the improvement in vegetation coverage has driven the rise of RSEI. Conversely, the number of units that have experienced RSEI attenuation (ecological

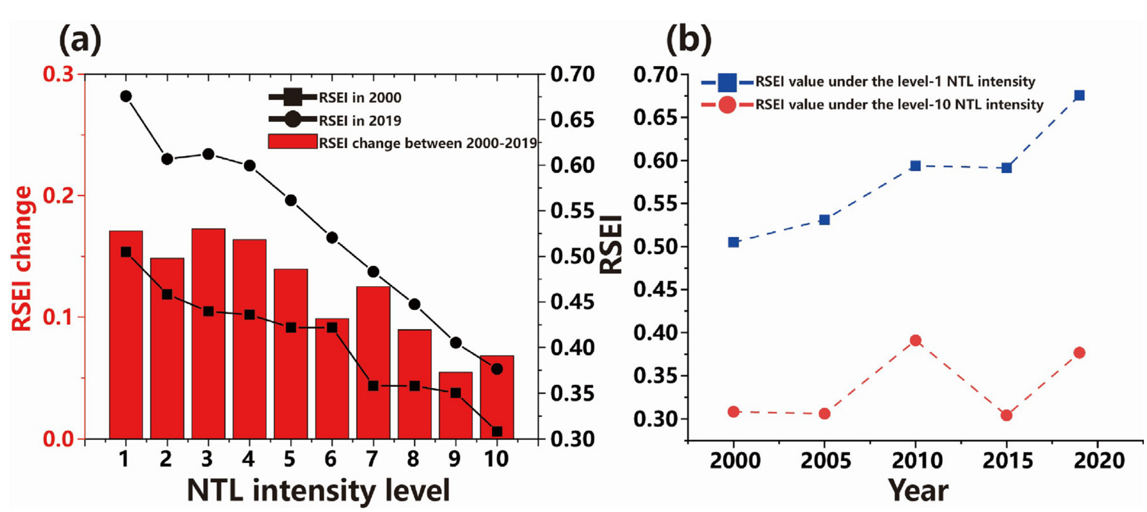

Fig. 9. Comparison of RSEI changes under different light intensity.

deterioration) over the past 2 decades has been significantly reduced and scattered, including the Yangtze River Delta, the Pearl River Delta, southwestern Hainan, and Taiwan. Due to the better climatic and hydrological conditions, the initial ecological conditions in the above areas are better than those in the northern coastal zone. However, during the study period, with the rapid development of economy and urban expansion, on the urban scale, the impervious surface has occupied more and more ecological land and resulting in the decline of vegetation coverage and ultimately affecting the regional RSEI.

5.2. Urbanization process of coastal cities

As the pioneer area of China's reform and opening-up policy, the coastal cities of China have been expanding in recent decades, and the transportation network and communication network have developed rapidly (Xu et al., 2018; Duan et al., 2018). According to the CNLI statistics of the coastal zone, the rapid increase in the area and intensity of nighttime lights is a side reflection of eastern China's rapid urbanization process and economic development in the past 20 years. Since the 21st century, China has set up nearly 20 national development strategies in coastal areas, and now the coastal zone has become the "golden zone" of regional social and economic development. Under the one belt, one road development strategy, the coastal zone is the first marine economic zone, which has become a new engine to promote the economic development of our country.

Although the urbanization level of coastal cities is constantly improving, the imbalance of urbanization level among regions is still prominent. An interesting comparison is from Guangdong Province and Jiangsu Province. Since 1989, Guangdong's GDP has consistently ranked first in the country and has become China's largest economic province, with the total economic output accounting for 1/8 of the country (Ye et al., 2008). Jiangsu is located in the Yangtze River Economic Belt, and has been closely following Guangdong in the GDP ranking since 2000, ranking second. However, the growth rate of Jiangsu's CNLI and the area of the lighting area are obviously higher than those of Guangdong Province in the past 20 years. Although Guangdong has the highest GDP, its contribution mainly comes from the core areas (Guangzhou and Shenzhen). The urbanization level in the north, west and east of Guangdong Province is low, and the urban development is unbalanced. For Jiangsu Province, profit by the topographical advantages, multiple urban agglomerations can be formed in the south. Cities can not only be linked in economic ties, but also maintain independence in economic volume, population and geographical space. Compared with Guangdong Province, the level of urbanization in Jiangsu is more balanced, and there is no absolutely dominant area.

5.3. Interaction between urbanization and eco-environment

With the rapid development of the economy, the impact and pressure of urbanization on eco-environment are more obvious, and the constraint and restriction of eco-environment on urbanization are more prominent (Liu and Wang, 2015). Especially for the coastal zone, the excellent economic development foundation and huge employment market have greatly attracted the employment-population from the inland areas of China. It is worth acknowledging that the findings of this paper show that the coupling and coordinated development level between urbanization and eco-environment in China's coastal zone is constantly improving. At present, the sustainable development of cities has become the mainstream. As mentioned earlier, governments at all levels have continuously introduced new policies and measures to strengthen the protection of the ecological environment.

It is worth noting that although the ecological environment quality of the whole coastal zone shows a trend of improvement, our research confirms that the contribution of this improvement is mostly from non-urbanized areas rather than urbanized areas. The decline effect of the increase of RSEI on the light intensity gradient reflects the limitations of the current environmental protection measures in coastal areas. For the urbanized areas, the pressure of population and economic development causes the ecological land to be occupied by impervious surfaces, and gradually leads to a series of urban ecological environment problems including heat island effect, air pollution. For the non-urbanized areas, due to the loss of population, the establishment of ecological protection zones and afforestation, the ecological conditions in areas with low human activity have been gradually restored in recent years.

At present, China's urbanization has entered a period of accelerated development, and the agglomeration of population and industry has put forward greater demand for urban land area, making China one of the countries with the fastest expansion of urban land in the world. Considering the long-term existence of urban–rural differences in China, the urban resource concentration-effect continues to maintain, and spatial expansion is still one of the main trends in the future development of coastal cities. The demand for land in the urban development process is still severe, and the coercive effect of construction land on the eco-environment will not disappear in the short term. Therefore, how to optimize the allocation of limited land resources and realize the coordinated development of urban expansion and urban ecology will be the severe challenges facing land use in China. To realize the sustainable development of the city and construct the ecological city, it is necessary to improve the overall ecological environment while paying more attention to the improvement of the ecological environment within the city, and rationally allocate and optimize the green space within the city (parks, water bodies, greenways, etc.) to coordinated eco-environment and human activities.

5.4. Potentials and limitations

Since RSEI was proposed by Xu (2013), application analysis based on RSEI is being enriched. Due to the advantages in data accessibility and model robustness, RSEI has been steadily applied across a wide range of temperature zones and climatic conditions, such as subtropical monsoon climate (Wen et al., 2019), temperate monsoon climate (Xu et al., 2018), temperate continental climate (Jing et al., 2020). Although the climatic conditions and geographical locations of the above study area are diverse, the studies are mostly focused on small-scale studies due to the resolution of the selected satellite images (Landsat TM/OLI, Sentinel-2). Therefore, the development of new satellite data sources for RSEI-based environmental assessment studies deserves to be further promoted. As a representative of medium resolution satellite imagery, MODIS imagery has good data quality and short revisit intervals, making it the preferred data source for medium scale RSEI-based environmental assessments. This paper validates the stability and feasibility of the RSEI model in a medium-scale environmental assessment scenario by integrating multiple MODIS standard data products for a long time series of ecological and environmental assessments of China's coastal zone.

The RSEI model used in this paper is completely based on remote sensing images and can comprehensively represent the ecological environment of the region by integrating a variety of ecological factors (green, humidity, temperature, dryness). However, the model is completely based on the satellite image, which means that remote sensing images will also produce systematic errors due to different sensors and transit time. Although, to ensure the comparability of the inverted RSEI in different years, the image selection time window is reduced as much as possible to avoid cloud interference, but it still cannot completely guarantee that the acquisition time of images in different years is completely the same.

Although RSEI and CNLI have been widely used in regional eco-environment detection and urbanization research by many scholars, the interaction between urbanization and eco-environment still cannot be explained in essence due to the limited spatial resolution of data and model parameters. We believe that introducing multi-dimensional parameters (including economy, population, environmental protection policies, etc.) to improve the indicator system of ecological environment and urbanization level, which can more comprehensively reveal the relationship between environment and urban development will be the next breakthrough point.

6. Conclusion

Remote sensing technology is of great value to the detection of eco-environment, and has been widely used in recent years. However, long-term large-scale analysis and assessment of ecological-urbanization interactions remain a challenge due to the limitations of data and analytical models. Therefore, this study proposes a detection scheme that combines daytime remote sensing and nighttime remote sensing, which can effectively characterize the regional eco-environment conditions, the intensity of urbanization, and the coupling and interaction between them. Specifically, this paper assesses the ecological condition and urbanization intensity of the coastal zone of China over the past 20 years based on nighttime light data (DMSP/OLS and NPP/VIIRS) and MODIS images, and recognizes the intensity and characteristics of the impact of human activities on the ecological environment through a coupled model. Compared with other ecological evaluation models, the most prominent advantage of this scheme is the diversity of data sources and the less subjective intervention, which is suitable for large-scale time series analysis.

The results of this study show that: 1) in the past 2 decades, the RSEI value of China's coastal areas has increased year by year, and the eco-environment has improved, especially for the cities in the north; 2) the city maintained a high rate of urbanization during the study period, especially for seaside cities and prefecture-level cities in Jiangsu and Shandong, which were much higher than the average growth rate; 3) although the coupling degree of urbanization and eco-environment of coastal cities is constantly improving, the main contribution of environmental improvement comes from the non-urbanization areas with low light intensity, while the eco-environment pressure of urbanization areas with high human activity intensity is still not optimistic.

CRediT authorship contribution statement

Zihao Zheng: Conceptualization, Methodology, Software, Validation, Investigation, Writing - original draft. **Zhifeng Wu:** Supervision, Project administration, Funding acquisition. **Yingbiao Chen:** Writing - review & editing. **Zhiwei Yang:** Software, Validation. **Francesco Marinello:** Conceptualization, Writing - review & editing, Supervision, Project administration.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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