Assessing the Ecological Quality of Nanjing during Its Urbanization Process by Using Satellite, Meteorological, and Socioeconomic Data

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(Received September 20, 2019; in final form December 25, 2019)

ABSTRACT

Assessing the ecological status of different districts within a city undergoing urbanization is challenging given their complex surface types and fast pace of development. In this study, we utilized satellite data obtained from Landsat 5/TM (Thematic Mapper) and Landsat 8/OLI (Operational Land Imager) images in conjunction with meteorological and socioeconomic data to construct a remote sensing ecological index (RSEI) for monitoring the ecological quality of Nanjing, Jiangsu Province. A higher RSEI value corresponded to better ecological quality. Five ratings were associated with RSEI values of city districts: very poor, poor, average, good, and excellent. In Nanjing, the percentage of areas evidencing good RSEI ratings decreased from 55.9% in 2000 to 48.0% in 2018, whereas there was a slight increase in areas with very poor RSEI ratings during this period. Of the 11 city districts, 16.8%, 21.8%, and 61.4% respectively evidenced the increasing, decreasing, and stable ecological quality relative to their quality in 2000. Of the 11 administrative districts in Nanjing, the main urban districts evidenced increased RSEI values in 2018 compared with those in 2000, with the improved areas exceeding the ones that had deteriorated in these districts. However, the ecological quality of new urban and ecological zones because of the urban expansion, with areas that had deteriorated exceeding the improved ones. Of the three protected ecological zones, the quality of Zijin Mountain National Forest Park was considerably better than that of Laoshan and Jiangxinzhou. Overall, the urbanization rate and RSEI evidenced a high negative correlation coefficient value (−0.76). The urbanization process of Nanjing induced a declining trend for the ecological quality, indicating the need of strong protection measures for the maintenance or improvement of its ecological environment.

Key words: ecological quality, remote sensing ecological index (RSEI), urbanization

Citation: Hang, X., Y. C. Li, X. C. Luo, et al., 2020: Assessing the ecological quality of Nanjing during its urbanization process by using satellite, meteorological, and socioeconomic data. J. Meteor. Res., 34(2), 280–293, doi: 10.1007/s13351-020-9150-6.

1. Introduction

Environmental pollution and ecological deterioration induced by China’s rapidly advancing urbanization and industrialization processes have generated widespread concern (Wang, 2013). Therefore, the monitoring and evaluation of regional ecology and assessments of the effects of urbanization on ecological changes have become imperative to provide a scientific basis for governments to develop active measures to protect the environment and achieve comprehensive, coordinated, and sustainable development of the ecology, economy, and society. The satellite remote sensing technology is one of the most effective and important methods of monitoring dynamic ecological factors to foster a better understanding of ecological patterns and processes and to assess regional ecological changes (Ivits et al., 2009; Badreldin et al., 2015; Murray et al., 2018).

Currently, remote sensing indexes reflecting different ecosystem features are used to characterize and evaluate...
the quality of ecosystems and changes occurring within them (Alberti, 2005). Vegetation indexes and coverage as well as the net primary productivity, which can be calculated by using remote sensing techniques (Li and Pan, 2018), are commonly used as indicators for ecosystems such as the forest, grassland, and farmland (Ma et al., 2006; Ochoa-Gaona et al., 2010; Sullivan et al., 2010; Chen et al., 2015; Lu et al., 2015). The land surface temperature (LST) is generally used to evaluate the heat island effect of urban ecosystems (Han et al., 2012; Zhang et al., 2017; Pan et al., 2018), and the thermal effect of urban surfaces is commonly evaluated by using the impervious surface ratio index (Xu, 2010; Cao et al., 2011; Daramola et al., 2018). These indicators can reveal the characteristics of certain ecosystem features. However, ecosystems are affected by multiple factors, including humans interacting with the environment. Therefore, a single ecological index cannot accurately reflect the entire ecosystem; nor can it yield an objective evaluation of ecological changes. An integrated index is therefore required for comprehensive and objective assessments of urban ecosystems, especially the complex ones such as the urban environments, hills, farmland, woodland, and wetlands.

The remote sensing ecological index (RSEI), which is a new integrated ecological index based on remote sensing, was first proposed by Xu (2013a). It covers the dimensions of greenness, heat, dryness, and wetness of ecosystems. These four natural factors are critical for assessing ecological conditions because they reflect the quality of an ecosystem and changes within it influenced by human activities (Zhao and Zhang, 1998; Nichol, 2005; Yuan and Bauer, 2007; Gupta et al., 2012). The RSEI is an objective and simple technique that can be quickly applied to monitor and evaluate the urban ecological quality and its changes within urban ecosystems (Xu, 2013a, b; Xu and Zhang, 2015; Song and Xue, 2016). This model has been applied in analyses of changes in the ecological quality of areas prone to soil erosion areas, and can be effectively used to evaluate the impacts of ecological restoration (Xu, 2013c; Luo et al., 2014). While these studies have demonstrated its effectiveness, they focused mainly on the quality of ecosystems and changes in them. Few studies have sought to elucidate the causes of these changes. Knowing these causes is crucial for understanding the underlying mechanisms of changes in ecological environments, which can facilitate the design of practical measures for protecting and restoring ecological environments.

We applied the RSEI model by using Landsat 5/TM (Thematic Mapper) and Landsat 8/OLI (Operational Land Imager) images combined with meteorological observations and socioeconomic data for assessing changes in the ecological quality of Nanjing during the period 2000–2018. Our aim was to evaluate the impacts of human activities (e.g., the construction of urban infrastructure) on the ecological environment and to analyze changes in the ecological status of three protected ecological zones (the Laoshan and Zijin mountains and Jiangxinzhou). We also assessed the impacts of urbanization on ecological and environmental changes in Nanjing and sought to identify non-natural factors contributing to ecological changes. Our analysis and findings provide a scientific basis for promoting the “new-type urbanization” pattern for achieving the coordinated development of urban construction and ecological protection.

2. Data and methodology

2.1 Study region

Nanjing (31°14′–32°37′N, 118°22′–119°14′E), the capital of Jiangsu Province, is a mega city located in the Yangtze River Delta. Its total area is 6587 km², encompassing 11 administrative districts, with the urbanization rate of 82% in 2017. Nanjing has a subtropical monsoon climate, characterized by the relative humidity of 76% and annual average precipitation of 1106.5 mm. The average, high, and low peak temperatures over the year are 15.4, 39.7, and −13.1°C, respectively. The topography comprises a complex landform of low hills, mounds, plains, and islands. Lakes and rivers are dispersed throughout the city, and the proportion of water areas is more than 11.0%. Nanjing is one of China’s four main garden cities, with the forest coverage rate of 22.0%. Ecological resources, national forest parks, and lake wetlands are abundant in this city, making it be awarded the UN-Habitat Special Honor Award in 2008.

We selected the following three protected ecological zones for the study: the Laoshan and Zijin mountains and Jiangxinzhou sandbank (Fig. 1). Laoshan National Forest Park, known locally as “Nanjing Green Lung, Jiangbei Pearl,” is the largest national forest park in Jiangsu Province. Zijin Mountain National Forest Park was the first large-scale urban forest park to be developed in China. Jiangxinzhou, which is an alluvial sandbank situated in the lower reaches of the Yangtze River, has been jointly developed by the Chinese and Singaporean governments as the Sino–Singapore Nanjing Eco Hi-Tech Island.
2.2 Data collection

We used two images (a Landsat 5/TM image taken on 10 October 2000 and a Landsat 8/OLI image taken on 28 October 2018) to minimize errors caused by differences in vegetative growth conditions or seasonal differences in this study. The cloud coverage in both images was below 10%. Each image was subject to the radiometric calibration, geometric correction, and atmospheric correction. We applied the radiometric calibration model and parameters proposed by Chander et al. (2009) to convert the images’ digital number (DN) values to reflectance. The quadratic polynomial and nearest pixel methods were applied to reduce the root-mean-square error to within 0.5 pixels. The atmospheric correction was based on the 6S model (Wang et al., 2013).

Meteorological observation data were mainly sourced from the Jiangsu Meteorological Bureau. We selected data on the average annual temperature and precipitation during the period 2000–2018, obtained from six national basic meteorological stations in Nanjing. Socioeconomic data were mainly sourced from the Nanjing Statistical Bureau. Data on areas of the cultivated land and new buildings, the landscape coverage rate, and urbanization rate for Nanjing during the period 2000–2017 were selected.

2.3 Methods

RSEI was used to represent the ecological condition of a particular region, integrating four key natural indicators (wetness, dryness, heat, and greenness) that reflect the quality of an ecosystem based on the principal component analysis (PCA; Hillger and Ellrod, 2003). To omit the influence of large water bodies on the PCA load distribution, we applied the modified normalized difference water index, thereby masking the water information before calculating RSEI. The wetness component (WET) which was transformed by the tasseled cap transformation, LST, and normalized differential vegetation index (NDVI) represented wetness, heat, and greenness respectively. Dryness was represented by the index-based built-up index (IBI) and soil index (SI).

(1) Wetness: Because the images selected for the present study were obtained by using two different sensors, the formulae used for calculating the WETs obtained through the tasseled cap transformation also differed (Li et al., 2016):

$$WET(TM) = 0.0315b_1 + 0.0202b_2 + 0.3102b_3 + 0.1594b_4 - 0.6806b_5 - 0.6109b_7; \quad (1)$$

$$WET(OLI) = 0.1511b_1 + 0.1973b_2 + 0.3283b_3 + 0.3407b_4 - 0.7117b_5 - 0.4559b_7; \quad (2)$$

where $b_1, b_2, b_3, b_4,$ and $b_7$ denote the reflectance of bands 1–5 and 7 of the Landsat 5/TM image and bands 2–7 of the Landsat 8/OLI image, respectively.

(2) Dryness: Dryness, which was expressed by Normalized Differential Building-Soil Index (NDBSI), was represented by the weighted average results for SI and IBI.

$$NDBSI = (SI + IBI)/2; \quad (3)$$

in which

$$IBI = [2b_5/(b_5 + b_3) - (b_4/(b_4 + b_3) + b_2/(b_2 + b_3))]/[2b_5/(b_5 + b_4) - (b_4/(b_4 + b_3) + b_2/(b_2 + b_3))]; \quad (4)$$

$$SI = ([b_5 + b_3] - (b_4 + b_1))/([b_5 + b_3] + (b_4 + b_1)); \quad (5)$$

where $b_1, b_2, b_3, b_4,$ and $b_5$ represent the reflectance of bands 1–5 of the Landsat 5/TM image and bands 2–6 of the Landsat 8/OLI image, respectively.

(3) Heat: LST, which indicated the heat index, was represented by the emissivity-corrected temperature. The following algorithm was applied:

$$LST = T/[1 + (AT/\rho)\ln e],$$

$$T = K_2/\ln(K_1/L_{6/10} + 1),$$

$$L_{6/10} = \text{gain} \times \text{DN} + \text{bias}, \quad (6)$$

where $L_{6/10}$ is the radiation value of the TM/TIRS.
(Thermal Infrared Sensor) thermal infrared band, DN is the pixel gray value, and gain and bias denote the band gain value and the offset value, respectively. For TM, the gain value was 0.055 and the bias value was 1.18243. For TIRS, the gain value was $3.342 \times 10^{-4}$ and the bias value was 0.1. $T$ denotes the brightness temperature. $K_1$ and $K_2$ are the calibration parameters. For TM, $K_1 = 607.76 \text{ W m}^{-2} \text{ sr}^{-1} \text{ μm}^{-1}$ and $K_2 = 1260.56 \text{ K}$. For TIRS, $K_1 = 774.89 \text{ W m}^{-2} \text{ sr}^{-1} \text{ μm}^{-1}$ and $K_2 = 1321.08 \text{ K}$. The variable $\lambda$ denotes the central wavelength of the thermal infrared band, $\rho = 1.438 \times 10^{-2} \text{ m K}$, and $\varepsilon$ is the specific emissivity which was obtained with reference to the NDVI threshold proposed by Sobrino et al. (2004).

(4) Greenness: The most widely used NDVI was selected to represent greenness and was calculated as follows:

$$\text{NDVI} = \frac{(\rho_{nir} - \rho_{red})}{(\rho_{nir} + \rho_{red})},$$

where $\rho_{nir}$ denotes the near-infrared band of the Landsat data and $\rho_{red}$ denotes the red band.

As the dimensions of the above four indicators were not uniform, the weights of all the indicators were unbalanced when the PCA component was calculated directly. Therefore, it was necessary to normalize these indexes to [0, 1] before performing PCA. The following normalization formula was used for each indicator:

$$EI_i = \frac{(I_i - I_{\text{min}})}{(I_{\text{max}} - I_{\text{min}})},$$

where $EI_i$ denotes the result for the normalization of each index, $I_i$ is the value of each indicator at the pixel $i$, and $I_{\text{max}}$ and $I_{\text{min}}$ are the maximum and minimum values, respectively, for each indicator.

(5) Calculation of RSEI: RSEI was constructed on the basis of the principal component transformation. Specifically, main information provided by the four indicators was concentrated in relation to the first one or two principal components to enable its depiction within a single indicator. This method, entailing the integration of information relating to the above four indicators, is advantageous when constructing RSEI. This is because the weight values of the integrated indicators are not determined manually; rather, they are objectively and automatically determined based on the nature of each indicator and its contribution to each component. The first principal component was generally used for positive and negative transpositions. Subsequently, the normalization process was conducted to obtain RSEI.

$$\text{RSEI} = \frac{(\text{RSEI}_i - \text{RSEI}_{i_{\text{min}}})}{(\text{RSEI}_{i_{\text{max}}} - \text{RSEI}_{i_{\text{min}}})},$$

$$\text{RSEI}_i = 1 - \text{PC1},$$

where RSEI is the established remote sensing ecological index. A higher value corresponds to a better ecological situation. RSEI$_{i_{\text{max}}}$ denotes the initial ecological index value at pixel $i$, RSEI$_{i_{\text{max}}}$ and RSEI$_{i_{\text{min}}}$ denote the maximum and minimum values of the initial ecological index respectively, and PC1 denotes the load value of the first principal component.

Figure 2 depicts a flow chart showing the main steps of the ecological quality assessment in Nanjing. Because the methods used to calculate wetness, dryness, heat, and
greenness have already been shown in subsections (1), (2), (3), and (4), the complete flowchart is not presented here. The diagram depicts the overall aim of this study, which was to evaluate and assess changes in the ecological quality of Nanjing by using RSEI values combined with meteorological observations and socioeconomic data.

3. Results

3.1 PCA results for the four indicators

Table 1 shows the PCA results of the WET, NDBSI, NDVI, and LST indicators for Nanjing in 2000 and 2018. These results show that the contribution rates of PC1 of the two images exceeded 90% (96.3% in 2000 and 91.5% in 2018). The data indicate that PC1 concentrates most on the characteristics of the four indicators. Considered independently, the eigenvectors representing greenness (NDVI) and wetness (WET) were positive for both years in the PC1, indicating that NDVI and WET positively influenced the ecological balance, which is consistent with the actual situation (Ke and Mei, 2010; Zhu, 2017). In general, the NDVI value was proportional to the vegetation coverage rate. Further, a larger WET value corresponded to greater wetness of the surface and vegetation, leading to an improvement in ecological conditions. The eigenvectors for dryness (NDBSI) and heat (LST) were negative in the PC1, indicating that they had a negative effect on ecosystems. This result is also consistent with the actual situation. Generally, a larger NDBSI value indicates that the soil and land are less suitable for construction. Conversely, a higher LST value indicates a higher surface temperature and subsequent deterioration of the ecology (Zheng, 2014). However, in the other characteristic components (PC2–PC4), the values of these four indicators were not entirely consistent with the actual situation, which is difficult to explain. Compared with other components, PC1 has obvious advantages because of its ability to integrate information for each indicator. Accordingly, it can be used to construct a comprehensive RSEI.

3.2 An analysis of spatial and temporal changes analysis of the ecological quality in Nanjing

Table 2 presents the results for the WET, NDBSI, NDVI, and LST indicators, mean and standard deviations for RSEI, and PC1 load values in 2000 and 2018. The results indicate that the RSEI value for Nanjing decreased from 0.626 in 2000 to 0.614 in 2018 (2.0%). Values of the four indicators rose between 2000 and 2018, with WET increasing from 0.538 to 0.635 (18.0%), NDBSI increasing from 0.533 to 0.541 (1.5%), NDVI increasing from 0.533 to 0.541 (1.5%), NDVI increasing from 0.533 to 0.541 (1.5%), and LST increasing from 0.449 to 0.489 (8.9%). Table 2 shows that the sum of absolute eigenvalues of NDBSI and LST in 2000 was 0.947 while that of WET and NDVI was 1. The sum of absolute eigenvalues of NDBSI and LST in 2018 was 0.944, and that of WET and NDVI was 1 too. Evidently, the effect of improved vegetation and wetness on the ecological environment in Nanjing was greater than the destructive effect resulting from drying of the soil and buildings as well as the temperature of regional environ-

| Year | Indicator | PC1   | PC2   | PC3   | PC4   |
|------|-----------|-------|-------|-------|-------|
| 2000 | WET       | 0.498 | 0.502 | 0.502 | 0.498 |
|      | NDBSI     | -0.635| -0.312| 0.306 | 0.638 |
|      | NDVI      | 0.502 | -0.494| -0.501| 0.503 |
|      | LST       | -0.312| 0.638 | -0.633| 0.307 |
|      | Eigenvalue| 0.131 | 0.003 | 0.001 | 0.001 |
|      | Eigenvalue contribution rate (%)| 96.250| 2.270| 1.000| 0.480|
| 2018 | WET       | 0.492 | 0.507 | 0.507 | 0.492 |
|      | NDBSI     | -0.637| -0.306| 0.306 | 0.638 |
|      | NDVI      | 0.508 | -0.492| -0.493| 0.507 |
|      | LST       | -0.307| 0.638 | -0.637| 0.306 |
|      | Eigenvalue| 0.083 | 0.005 | 0.002 | 0.001 |
|      | Eigenvalue contribution rate (%)| 91.520| 5.660| 2.110| 0.710|

| Year | Parameter | WEN | NDBSI | NDVI | LST | RSEI |
|------|-----------|-----|-------|------|-----|------|
| 2000 | Mean value| 0.538| 0.533 | 0.560| 0.449| 0.626|
|      | Standard deviation | 0.190| 0.214 | 0.197| 0.144|
|      | Load value for PC1 | 0.498| -0.635| 0.502| -0.312|
| 2018 | Mean value| 0.635| 0.541 | 0.630| 0.489| 0.614|
|      | Standard deviation | 0.182| 0.222 | 0.221| 0.169|
|      | Load value for PC1 | 0.492| -0.637| 0.508| -0.307|
ments. The positive contribution of NDVI was greater than that of WET, indicating that NDVI had a stronger influence on the improvement in the ecological quality. While both NDBSI and LST had negative effects, the effect of NDBSI was more than double that of LST, indicating that NDBSI was the main factor constraining improvements in the ecological quality of Nanjing.

Nanjing comprises four main urban administrative areas (Xuanwu, Qinhuai, Jianye, and Gulou) and seven suburbs (Pukou, Qixia, Yuhua, Jiangning, Luhe, Lishui, and Gaochun). Because of our quantitative analysis of RSEI in Nanjing, we subdivided RSEI into five sets of ratings at intervals of 0.2 (0–0.2, 0.2–0.4, 0.4–0.6, 0.6–0.8, and 0.8–1.0): bad, poor, average, good, and excellent, respectively. Figure 3 depicts changes in RSEI of Nanjing during the period 2000–2018 based on the above five ratings. In 2000, the large red areas in Fig. 3, which represent a bad rating, were mainly distributed in the main urban region while the areas with red dots were mainly located in the suburbs. Areas with poor ratings were mainly located in the northern part of Nanjing, and areas rated as good and excellent covered most of Nanjing. In 2018, there was a significant decrease in areas rated as bad compared with such areas in 2000. However, the number of areas rated as poor showed a significant increase and areas rated as good and excellent decreased slightly. These results indicated that there was a decrease in areas rated as bad and an increase in areas rated as poor, with a slight decrease in areas rated as excellent. Land rated as excellent mainly occurred in forests in the mountains; land rated as good was mainly found in farmland, grassland, and gardens; land rated as average was mainly distributed in the countryside and bare areas; land rated as poor was mainly found in small towns and urban–rural areas; and land rated as bad mainly occurred on the impervious surfaces of buildings in the city.

To develop a better understanding of the quantitative distribution of RSEI in Nanjing, we calculated the areas and proportions of different land categories according to their ratings (Tables 3 and 4). The results showed that the majority of areas in Nanjing had a good RSEI rating in 2000 (55.9%), followed by areas with an average rating (36.8%), with only a few areas having a rating below poor (2.2%). The distribution of RSEI ratings in the main urban region and suburbs evidently differed. An average RSEI rating was predominant in the main urban region, accounting for 42.3% of the area while 38.8% of these areas had a rating of good and excellent. By contrast, the predominant RSEI rating in the suburbs was good (56.9%), and the proportion of areas with a rating of good and excellent was 61.8%. The proportion of areas
with a poor RSEI rating was significantly higher in the main urban region (about 19.0%) than that of such areas in the suburbs (1.6%).

The overall ecological situation in 2018 was still characterized by a good rating, but the proportion of these areas fell to 48.0%, evidencing a decrease of 7.9% compared with that in 2000. In 2018, areas with an average rating increased to 44.2% while the proportion of areas with a poorer rating declined slightly compared with that in 2000. The separate RSEI distribution trends in the main urban districts and in suburbs were similar in 2018 and 2000. Areas rated as average were still predominant in the main urban districts, with their proportion increasing from 42.3% in 2000 to 54.5% in 2018 while that of areas with a rating of good and excellent increased to 42.9% (an increase of 4.1%). A good rating was still predominant in the suburbs, but the proportion of these areas decreased from 56.9% in 2000 to 48.6% in 2018 (a decline of 8.3%). Notably, in 2018, the proportion of main urban districts with an RSEI rating below poor decreased from 19.0% to 2.6% (a decline of 16.4%). These results indicate that the ecology of Nanjing underwent significant changes during the study period. Whereas the ecological quality of main urban districts improved significantly between 2000 and 2018, yet that of suburbs deteriorated. This finding is consistent with the actual situation of Nanjing’s urban development in recent years.

The capacity of urban development to radiate from sub-district centers to surrounding new towns has evidently increased. Nanjing has developed rapidly, with urban expansion evidencing a certain orientation (Xie et al., 2015). The extent of urban expansion is in close agreement with the orange expansion range shown in Fig. 3.

### 3.3 An analysis of spatial and temporal differences in the ecological quality in Nanjing

We analyzed spatial and temporal differences in the ecological quality of Nanjing during the period 2000–2018 based on RSEI values (Fig. 4). The red areas depicted in Fig. 4 represent areas of the deteriorating ecological quality. There was no change in the yellow areas. The green areas represent areas where the ecological quality improved. Evidently, the ecological condition of the main urban region improved while that of the

![Fig. 4. Changes of the RSEI in 2000 and 2018, obtained by subtracting the RSEI value of 2000 from that of 2018.](image)
mountains and cultivated land remained unchanged. Conversely, new urban areas and suburban town centers evidenced the deteriorating quality.

Table 5 shows the results of an analysis of changes in the ecological quality of 11 districts in Nanjing. Evidently, the overall ecological quality of Nanjing had deteriorated slightly in 2018 compared with its status in 2000. The proportion of improved areas was 16.8% and that of deteriorated areas was 21.8% while 61.4% of the city's areas remained unchanged. In the districts of Gulou, Qinhuai, Xuanwu, Jianye, and Luhe, the coverage of improved areas exceeded that of the deteriorated areas. The RSEI value of the main urban region increased from 0.553 in 2000 to 0.592 in 2018. These results indicate an improvement in the ecological quality of the main urban region between 2000 and 2018. Gulou District ranked the highest with 50.2% of its total area showing the improved environmental quality and only 2.6% showing the deteriorating quality, followed by Qinhuai and Jianye. Because of the urban expansion, the RSEI value of new urban and suburban areas decreased from 0.629 in 2000 to 0.615 in 2018, indicating the deteriorating ecological quality. Among them, more areas evidenced the declining ecological quality than improved quality in Qixia, Yuhua, Jiangning, Gaochun, Lishui, and Pukou. The improved urban ecology can be attributed to the national emphasis on developing an ecological civilization and upgrading urban environments in recent years. Moreover, the deterioration in the ecological quality of suburbs also appears to be closely related to the large-scale expansion and construction of cities in these areas.

3.4 Assessment of ecological changes of characteristic ecological regions in Nanjing

To develop a deeper understanding of impacts of human activities on ecosystems and urban ecology, it is necessary to examine ecological changes that have occurred in characteristic ecological regions in Nanjing, such as Laoshan and Zijin mountains and Jiangxinzhou. Figures 5–7 depict the distribution of RSEI ratings and their changes between 2000 and 2018 while Table 6 shows statistical results. These results indicate that RSEI values in 2000 and 2018 were respectively 0.794 and 0.752 for Laoshan Mountain, 0.804 and 0.797 for Zijin

![Fig. 5. Changes of the RSEI in the Laoshan Mountain National Forest Park: (a) 2000, (b) 2018, and (c) 2018 minus 2000.](image)

![Fig. 6. As in Fig. 5, but for the Zijin Mountain National Forest Park.](image)
Mountain, and 0.610 and 0.573 for Jiangxinzhou. RSEI values of both Zijin and Laoshan mountains indicated good and excellent ratings. By contrast, the RSEI rating for Jiangxinzhou was predominantly good in 2000 but average in 2018. RSEI values of Zijin and Laoshan mountains far exceeded those of Nanjing and its 11 administrative districts while that of Jiangxinzhou was below the average of Nanjing, being only slightly above that of administrative areas evidencing the poor ecological quality. These results indicate that the ecological quality of Zijin Mountain was the highest and that of Jiangxinzhou was the lowest. Between 2000 and 2018, RSEI values declined to varying degrees in the three regions, with Jiangxinzhou evidencing the greatest decline (6.1%), followed by Laoshan Mountain (5.4%), and Zijin Mountain showing the least decline (0.9%). Our analysis of changes in RSEI values in the three regions indicated that 94.8% of the Zijin Mountain area remained unchanged while Jiangxinzhou showed the smallest proportion of unchanged areas.

Areas of the ecological deterioration exceeded the improved areas in Jiangxinzhou and Laoshan because of the large-scale infrastructure development, whereas the improved area was slightly larger than the area showing deterioration in the Zijin region. In recent years, investments amounting to 150 million RMB have been made for developing the infrastructure and scenic spots in the Laoshan Mountain National Forest Park. Road systems (trunk roads, sub-trunk roads, and walking paths) have been constructed, and 16 scenic spots comprising landscape squares, sightseeing platforms, and bicycle tracks have been developed in the park. According to the revised “Singapore–Nanjing Eco-Technology Island Controlled Detailed Plan” published in 2016, the land area designated for the planned urban construction was 695.0 ha, accounting for 45.7% of the total planned area of Jiangxinzhou. Of this land, 213.4 ha were allocated for residential areas, 59.2 ha for public administration and public service facilities, 141.6 ha for commercial service facilities, 171.85 ha for road and transportation facilities, and 57.7 ha for public facilities. Although the plan includes regulating the scale of urban construction, protecting ecosystems, and preserving the rural ambience, large-scale urban construction and real estate development have affected the ecological environment.

3.5 Effects of urbanization on ecological changes

In recent years, China has undergone a rapid urbanization process that will inevitably have ecological and environmental consequences. Urbanization entails a process of developing the “population–economy–space,” within which humans are the subject, the economy is the driving force, and space is the carrier. Spatial urbanization entails a greater emphasis on the ecological nature of urbanization (Sun and Ding, 2011) and is closely associated with the areas of cultivated and built land as well as

Table 6. RSEI changes in characteristic ecological regions of Nanjing in 2000 and 2018

| Characteristic ecological region | Laoshan Mountain | Zijin Mountain | Jiangxinzhou |
|---------------------------------|-----------------|---------------|-------------|
|                                 | Area (km²)      | Proportion (%) | Area (km²)  | Proportion (%) | Area (km²) | Proportion (%) |
| Worse                           | 13.070          | 15.250        | 0.547       | 2.277          | 4.554      | 31.659        |
| No change                       | 70.300          | 82.050        | 22.781      | 94.773         | 7.953      | 55.290        |
| Better                          | 2.317           | 2.704         | 0.709       | 2.950          | 1.877      | 13.051        |

Fig. 7. As in Fig. 5, but for the Jiangxinzhou Ecological Science and Technology Island.
green coverage. Accordingly, we assessed the effects of urbanization on the ecosystem by analyzing changes in the areas of cultivated land, cumulative area of new buildings, afforestation rate in built-up areas, and urbanization rate of Nanjing.

Figure 8 shows changes in the areas of cultivated land and new buildings in Nanjing from 2000 to 2017. Evidently, the area of cultivated land in Nanjing declined sharply from 3.03 km$^2$ in 2000 to 2.46 km$^2$ in 2004 evidencing a decrease of 18.8%. It subsequently remained stable until 2017 with a decrease of 4.2%. However, the cumulative area of new buildings increased from 12.47 km$^2$ in 2000 to 414.19 km$^2$ in 2017, reflecting annual increases. The decrease in the area of cultivated land is indicative of a decrease in the agricultural population, which inevitably corresponds to an increase in the urban population. Cities need to expand rapidly to accommodate growing urban populations, prompting an increase in the area of urban buildings that leads to a corresponding increase in the NDBSI value because of the hardening of the soil and construction land.

Table 7 shows the urbanization and landscape greening rates of built-up areas in Nanjing during 2000–2017. The urbanization rate increased from 71.1% in 2000 to 82.3% in 2017 and the landscape greening rate of built-up areas increased from 41.0% to 44.9%. The annually increasing urbanization rate reflects the city’s continuous expansion, including a corresponding increase in the area of impervious surfaces, such as buildings. This finding is in agreement with the calculated NDBSI results. The increase in green coverage indicates an annual increase in Nanjing’s greenness that fits with the calculated NDVI results.

To examine the relationship between the urbanization and ecological index, we calculated RSEI values of administrative districts in Nanjing. Compared with urban areas, the two protected ecological areas, namely Zijin and Laoshan mountains, were less affected by the urban construction and made up a larger proportion of their respective administrative areas. Therefore, when calculating RSEI values, we excluded these two regions from their administrative districts and consequently obtained a new set of values for each administrative district. Figure 9 shows the RSEI fitting curves and urbanization rate of 11 administrative districts in Nanjing in 2018. The curves illustrate the negative relationship between the RSEI and urbanization rate. The correlation coefficient obtained from a Pearson’s correlation analysis of RSEI values and corresponding urbanization rates in the 11 administrative districts was −0.76, which was significant at a level of 0.01. The high level of correlation indicated that urbanization has had a negative ecological impact.

Table 7. The urbanization rate and landscape greening rate for built-up areas in Nanjing during 2000–2017

| Year | Urbanization rate (%) | Landscape greening rate of built-up areas (%) |
|------|-----------------------|---------------------------------------------|
| 2000 | 71.1                  | 41.0                                        |
| 2001 | –                     | 40.0                                        |
| 2002 | 72.0                  | 42.9                                        |
| 2003 | 74.2                  | 43.5                                        |
| 2004 | –                     | 44.5                                        |
| 2005 | 76.2                  | 44.9                                        |
| 2006 | 76.4                  | 45.5                                        |
| 2007 | 76.8                  | 45.9                                        |
| 2008 | 77.0                  | 46.1                                        |
| 2009 | 77.2                  | 44.1                                        |
| 2010 | 78.5                  | 44.4                                        |
| 2011 | 79.7                  | 44.4                                        |
| 2012 | 80.2                  | 44.0                                        |
| 2013 | 80.5                  | 44.1                                        |
| 2014 | 80.9                  | 44.1                                        |
| 2015 | 81.4                  | 44.5                                        |
| 2016 | 82.0                  | 44.8                                        |
| 2017 | 82.3                  | 44.9                                        |

Note: “–” indicates the absence of data for a particular year.
4. Discussion

The climate change is considered to be one of the most important natural factors influencing ecosystems. However, the uncertainty remains regarding the causes of climate change and predictions of future climate change trends and their impacts (Jiang et al., 2014; Flombaum et al., 2017). In this study, we assessed the ecological impacts of climate change in Nanjing in recent years. Figure 10 shows an increasing trend in the annual average temperature and precipitation in Nanjing from 2000 to 2018. A rise in precipitation leads to an increase in the water vapor content, improved soil moisture, and increased moisture in the air, resulting in the improved ecological quality. However, an increase in the annual average temperature may not induce the ecological improvement. Both WET and LST levels increased in 2018 compared with these levels in 2000, which were respectively positively and negatively correlated with ecological changes. This finding is consistent with those of previous studies (Jiang et al., 2003; Su et al., 2014). Although some studies have suggested that the recent warming phenomenon strongly influences terrestrial ecosystems globally (Schmidt, 2018), its impact in China is reportedly slightly different (Wu et al., 2010). Climate changes in recent years do not seem to have exerted a discernible effect on urban ecological functions in Nanjing. Therefore, changes in Nanjing’s ecological quality during the period 2000–2018 are likely to have been mainly caused by urbanization.

The urbanization process has had important effects on the ecosystem and reflects a highly complex relationship among urban economic, social, and ecological processes (Alberti, 2005). The traditional and rapid urbanization process often induces the vegetative damage along with a sharp decline in the cultivated land, increased pollution, and a decline in ecological functions, leading to a heightened need to improve the urban ecological environment (Wang, 2013). The studies have shown that improvements in the quality of ecological environments are constrained during the early stage of a low-quality urbanization process, which has an overall negative impact on
these environments (Ke and Mei, 2010; Li et al., 2014). Our results support this finding. In recent years, the overall ecological quality of Nanjing has declined slightly as a result of processes of urbanization as well as social and economic development. Because of the city’s rapid expansion, the ecological quality of new urban areas and suburbs has shown a discernible downward trend. At the same time, the urbanization model in key urban districts has shifted from the simple extensional expansion to connotative development, which is associated with a clear improving trend relating to the ecological quality. Protection regimes implemented in ecological zones, such as Zijin and Laoshan mountains, have been strictly managed, leading to the sustained high ecological quality. Advanced states of urbanization can contribute to maintaining or even improving the quality of ecological environments (Xing and Fang, 2018; Xiao and Su, 2019).

The changes in urban ecosystems and environments are influenced by various factors. The RSEI model applied in this study comprised only four indicators and was not sufficiently comprehensive to enable a complete evaluation of ecosystems and environmental changes. However, preliminary results indicate that the application of remote sensing techniques to assess changes in urban ecosystems and environments holds a promise. On the one hand, the large-scale urban infrastructure and socioeconomic development exert considerable pressure on ecological systems, with the urbanization generally undermining improvements in ecological environments. On the other hand, higher levels of urbanization can guarantee protection and improvement of the ecology. An important insight of this study is that while urbanization generally impacts negatively on urban ecological systems, strict protection and management measures can help maintain and improve a healthy ecological environment, which supports active promotion of the “new-type urbanization” pattern, entailing the coordinated development of urban construction and protection of ecology.

Since high-resolution and time continuous satellite images are not available, satellite images from only two moments are used to describe the situation in a particular year, which is not representative. In the future, we will consider by using the monthly average data for analyses and research in order to obtain more objective and reliable results.

5. Conclusions

We applied the RSEI model by using the Landsat 5/TM and Landsat 8/OLI imagery combined with meteorological observations and socioeconomic data to assess changes in Nanjing’s ecological quality during the period 2000–2018. We subsequently examined the effects of urbanization on ecological environments and elucidated the relationship between the urbanization rate and RSEI.

Overall, we found that the ecological quality of Nanjing had deteriorated slightly during the study period, with RSEI decreasing from 0.626 in 2000 to 0.614 in 2018 (a 2% decrease). The ecological quality of a large portion of the area (61.4%) remained basically unchanged, 16.8% improved, and 21.8% deteriorated in quality. Of the city’s 11 administrative districts, the main urban districts evidenced higher RSEI values in 2018 compared with those in 2000, with the improved areas in these districts exceeding the deteriorated ones. However, the ecological quality of new urban and suburban areas declined because of the urban expansion, and the areas showing deterioration in these districts were larger than the improved ones. These results indicate that the ecological conditions in the main urban districts improved, whereas the ecological conditions of new urban districts and suburban town centers deteriorated. In 2000 and 2018, the average RSEI values of Zijin and Laoshan mountains were higher than those of other regions. Moreover, because of the strict protection and management regimes, the ecological quality of these areas has remained relatively high, but there are still significant differences among them. Of these areas, the Zijin Mountain ecological region maintained the best quality in 2018 compared with its status in 2000, with 94.8% of the area remaining basically unchanged and 3.0% showing an improvement. However, 15.3% of the area in Laoshan Mountain and 31.7% of the area in Jiangxinzhou deteriorated. The infrastructure construction and real estate development were the main factors accounting for decline in the ecological quality of these two regions. Urbanization has had certain impacts on Nanjing’s ecology. The cultivated land and new buildings are widely used to represent urbanized spatial information. Our results showed a sharp decrease in Nanjing’s cultivated land area (22%) and an increase in the cumulative area of new building area corresponding to rapid growth of the urban population during the period 2000–2017. Simultaneously, the landscape greening rate of the built-up area increased from 41.0% to 44.9%. There was also a significant negative correlation between the urbanization rate and RSEI, indicating that urbanization has constrained improvements in the ecological environment.

Acknowledgments. We thank Mrs. Rongrong Hang for providing IT support. We also thank Radhika Johari and Richard Kelly from Liwen Bianji, Edanz Editing China (www.liwenbianji.cn/ac) for editing work.
REFERENCES

Alberti, M., 2005: The effects of urban patterns on ecosystem function. Int. Regional Sci. Rev., 28, 168–192, doi: 10.1177/0160017605275160.

Badredlin, N., and R. Goossens, 2015: A satellite-based disturbance index algorithm for monitoring mitigation strategies effects on desertification change in an arid environment. Mitig. Adapt. Strateg. Glob. Change, 20, 263–276, doi: 10.1007/s11027-013-9490-y.

Cao, L., H. W. Hu, X. L. Meng, et al., 2011: Relationships between land surface temperature and key landscape elements in urban areas. Chinese J. Ecol., 30, 2329–2334, doi: 10.13292/j.1000-4890.2011.0317. (in Chinese)

Chander, G., B. L. Markham, and D. L. Helder, 2009: Summary of recent radiometric calibration coefficients for Landsat MSS, TM, ETM+, and EO-1 ALI sensors. Remote Sens. Environ., 113, 893–903, doi: 10.1016/j.rse.2009.01.007.

Chen, Q., Y. H. Chen, M. J. Wang, et al., 2015: Ecosystem quality comprehensive evaluation and change analysis of Dongting Lake in 2001–2010 based on remote sensing. Acta Ecol. Sinica, 35, 4347–4356, doi: 10.5886/stxb201403250557. (in Chinese)

Daramola, M. T., E. O. Eresanya, and K. A. Ishola, 2018: Assessment of the thermal response of variations in land surface around an urban area. Mod. Earth Syst. Environ., 4, 535–553, doi: 10.1007/s40808-018-0463-8.

Flombaum, P., L. Yahdjian, and O. E. Sala, 2017: Global-change drivers of ecosystem functioning modulated by natural variability and saturating responses. Global Change Biol., 23, 503–511, doi: 10.1111/gcb.13441.

Gupta, K., P. Kumar, S. K. Pathan, et al., 2012: Urban neighborhood green index—A measure of green spaces in urban areas. Landsc. Urban Plan., 105, 325–335, doi: 10.1016/j.landurbplan.2012.01.003.

Han, X. Z., S. M. Li, and F. L. Dou, 2012: Study of obtaining high resolution near-surface atmosphere temperature by using the land surface temperature from meteorological satellite data. Acta Meteor. Sinica, 70, 1107–1118, doi: 10.11676/qxxb2012.093. (in Chinese)

Hillger, D. W., and G. P. Ellrod, 2003: Detection of important atmospheric and surface features by employing principal component image transformation of GOES imagery. J. Appl. Meteor., 42, 611–629, doi: 10.1175/1520-0450(2003)042<0611:DOIAAS>2.0.CO;2.

Ivits, E., M. Cherlet, W. Mehl, et al., 2009: Estimating the ecological status and change of riparian zones in Andalusia assessed by multi-temporal AVHHR datasets. Ecol. Indic., 9, 422–431, doi: 10.1016/j.ecolind.2008.05.013.

Jiang, T., X. C. Li, Q. C. Chao, et al., 2014: Highlights and understanding of climate change 2014: Impacts, adaptation, and vulnerability. Climate Change Res., 10, 157–166, doi: 10.3969/j.issn.1673-1719.2014.03.001. (in Chinese)

Jiang, X. D., Y. Liu, and B. C. Xia, 2003: Global climate change and its impact on ecosystems. Sun Yatsen Univ. Forum, 23, 258–262, doi: 10.3969/j.issn.1674-3202.2003.05.066. (in Chinese)

Ke, R. P., and Z. X. Mei, 2010: Analysis on the influence of urbanization and greenland-degradation on city thermal environment. Ecol. Environ., 19, 2023–2030, doi: 10.3969/j.issn.1674-5906.2010.09.002. (in Chinese)

Li, B. L., C. P. Ti, and X. Y. Yan, 2016: Study of derivation of tasseled cap transformation for Landsat 8 OLI images. Sci. Surv. Mapp., 41, 102–107, doi: 10.16251/j.cnki.1009-2307.2016.04.021. (in Chinese)

Li, G. Y., S. Chen, C. Yu, et al., 2014: Spatial and temporal variation characteristics of forest biomass in south Jiangsu during the nearly twenty years. Ecol. Environ. Sci., 23, 1102–1107, doi: 10.3969/j.issn.1674-5906.2014.07.002. (in Chinese)

Li, Z., and J. H. Pan, 2018: Spatiotemporal changes in vegetation net primary productivity in the arid region of Northwest China, 2001 to 2012. Front. Earth Sci., 12, 108–124, doi: 10.1007/s11707-017-0621-8.

Lu, C. Y., Z. M. Wang, M. Y. Liu, et al., 2015: Analysis of conservation effectiveness of wetland protected areas based on remote sensing in West Songnen Plain. China Environ. Sci., 35, 599–609. (in Chinese)

Luo, C., H. Liu, and L. Y. Qi, 2014: Ecological changes assessment based on remote sensing indices: A case study of Changning City. Remote Sens. for Land & Rsrc., 26, 145–150, doi: 10.6046/gtzyyg.2014.04.23. (in Chinese)

Ma, D. M., H. Jiang, S. R. Liu, et al., 2006: The preliminary analysis of forest ecosystem site index using remote sensed data. Acta Ecol. Sinica, 26, 2810–2816, doi: 10.3321/j.issn:1000-0933.2006.09.005. (in Chinese)

Murray, N. J., D. A. Keith, L. M. Bland, et al., 2018: The role of satellite remote sensing in structured ecosystem risk assessments. Sci. Total Environ., 619–620, 249–257, doi: 10.1016/j.scitotenv.2017.11.034.

Nichol, J., 2005: Remote sensing of urban heat islands by day and night. Photogramm. Eng. Remote Sens., 71, 613–621, doi: 10.14358/PERS.71.5.613.

Ochoa-Gaona, S., C. Kampichler, B. H. J. De Jong, et al., 2010: A multi-criterion index for the evaluation of local tropical forest conditions in Mexico. Forest Ecol. Manag., 260, 618–627, doi: 10.1016/j.foreco.2010.05.018.

Pan, Y., L. L. Cui, C. M. Liu, et al., 2018: Spatiotemporal distribution of urban heat island effect based on MODIS data in Chongqing, China. Chinese J. Ecol., 37, 3736–3745, doi: 10.13292/j.1000-4890.201812.039. (in Chinese)

Schmidt, D. N., 2018: Determining climate change impacts on ecosystems: The role of palaeontology. Palaeontology, 61, 1–12, doi: 10.1111/pala.12335.

Sobrino, J. A., Jiménez-Muñoz J. C., and L. Paolini, 2004: Land surface temperature retrieval from LANDSAT TM 5. Remote Sens. Environ., 90, 434–440, doi: 10.1016/j.rse.2004.02.003.

Song, H. M., and L. Xue, 2016: Dynamic monitoring and analysis of ecological environment in Weinan City, Northwest China based on RSEI model. Chinese J. Appl. Ecol., 27, 3913–3919, doi: 10.13287/j.1001-9332.201612.024. (in Chinese)

Su, B. D., T. F. Wang, and Y. Z. Yin, 2014: Interpretation of the IPCC fifth assessment report on detection and attribution of observed impacts. Climate Change Res., 10, 203–207, doi: 10.3969/j.issn.1673-1719.2014.03.008. (in Chinese)

Sullivan, C. A., M. S. Skeffington, M. J. Gormally, et al., 2010: The ecological status of grasslands on lowland farmlands in western Ireland and implications for grassland classification and nature value assessment. Biol. Conserv., 143, 1529–1539,
Xie, Z. K., F. X. Li, M. C. Li, et al., 2015: Study on the expansion of new residential land in the Nanjing downtown (south of the Yangtze River). Sci. Surv. Mapp., 40, 92–97, doi: 10.16251/j.cnki.1009-2307.2015.06.0019. (in Chinese)

Xing, L. P., and B. Fang, 2018: Spatial–temporal pattern and coordinated development of urbanization and ecological environment in Jiangsu Province. J. Nanjing Norm. Univ. (Nat.l Sci. Ed.), 41, 131–137, doi: 10.3969/j.issn.1001-4616.2018.03.020. (in Chinese)

Xu, H. Q., 2010: Analysis of impervious surface and its impact on urban heat environment using the normalized difference impervious surface index (NDISI). Photogramm. Eng. Remote Sens., 76, 557–565, doi: 10.14358/PERS.76.5.557.

Xu, H. Q., 2013a: A remote sensing urban ecological index and its application. Acta Ecol. Sinica, 33, 7843–7862, doi: 10.5846/stxb201208301223. (in Chinese)

Xu, H. Q., 2013b: A remote sensing index for assessment of regional ecological changes. China Environ. Sci., 33, 889–897, doi: 10.3969/j.issn.1000-6923.2013.05.019. (in Chinese)

Xu, H. Q., 2013c: Assessment of ecological change in soil loss area using remote sensing technology. Trans. Chinese Soc. Agric. Eng., 29, 91–97, doi: 10.3969/j.issn.1002-6819.2013.07.012. (in Chinese)

Xu, H. Q., and H. Zhang, 2015: Ecological response to urban expansion in an island city: Xiamen, southeastern China. Sci. Geogr. Sinica, 35, 867–872. (in Chinese)

Yuan, F., and M. E. Bauer, 2007: Comparison of impervious surface area and normalized difference vegetation index as indicators of surface urban heat island effects in Landsat imagery. Remote Sens. Environ., 106, 375–386, doi: 10.1016/j.rse.2006.09.003.

Zhang, X., R. C. Estoque, and Y. Murayama, 2017: An urban heat island study in Nanchang City, China based on land surface temperature and social–ecological variables. Sustain. Cities Soc., 32, 557–568, doi: 10.1016/j.scs.2017.05.005.

Zhao, Y. L., and L. J. Zhang, 1998: Study on method of quantitative assessment of fragile environment. Sci. Geogr. Sinica, 18, 73–79, doi: 10.1007/bf02791364.

Zheng, Y., 2014: Eco-environment index extraction and change analysis based on the TM data. Master dissertation, Nanjing Forestry University, Nanjing, 34 pp.

Zhu, Z. R., 2017: Evaluation of ecological environment quality of Nanchang based on remote sensing based ecological index. Master dissertation, East China University of Technology, Nanchang, 27 pp.