Лесные экосистемы в условиях изменения климата: биологическая продуктивность
и дистанционный мониторинг, №6, 2020

https://doi.org/10.25686/7236.2020.6.58834

ESTIMATION OF URBAN ENVIRONMENT IN TAIPEI LIVING CIRCLE BASED ON REMOTE SENSING ECOLOGICAL INDEX

Yibo Wang
Volga State University of Technology

The development of urbanization affects the natural environment in many fields such as resources, economy, society, culture, and technology. With the continuous development of urbanization, the interference of human activities has greatly changed the structure of the original land. This article takes Taipei Living Circle in the northern part of Taiwan Island as an example. Based on the Remote Sensing Ecological Index (RSEI), the ecological quality of the ground objects from 1988 to 2019 was evaluated. The remote sensing ecological index is divided into five grades and combined with the land use transfer matrix to analyze the impact of land-use changes in the region on the ecology, so as to analyze and evaluate the ecological environment changes in the study area. Research shows that from 1988 to 2019, the remote sensing ecological index was 0.559, 0.571, 0.546, and 0.396 respectively. The areas with improved ecological quality are concentrated in high-altitude areas, in mountainous areas, while the areas with reduced ecological quality are concentrated in the expansion of the city in the Taipei Life Circle. The process of transformation has a significant impact on the ecological environment. From 1988 to 2019, areas with improved ecological quality were concentrated in high-altitude areas in mountainous areas, and areas with reduced ecological quality were concentrated in urban expansion. The forested areas exert significant influence on the quality of environment. Reasonable protection and utilization of mountain forest resources play an important role in the sustainable development of Taipei Living Circle.

Key words: *urbanization, ecological quality, RSEI, sustainable development, Taipei Living Circle, environmental change.*

Introduction

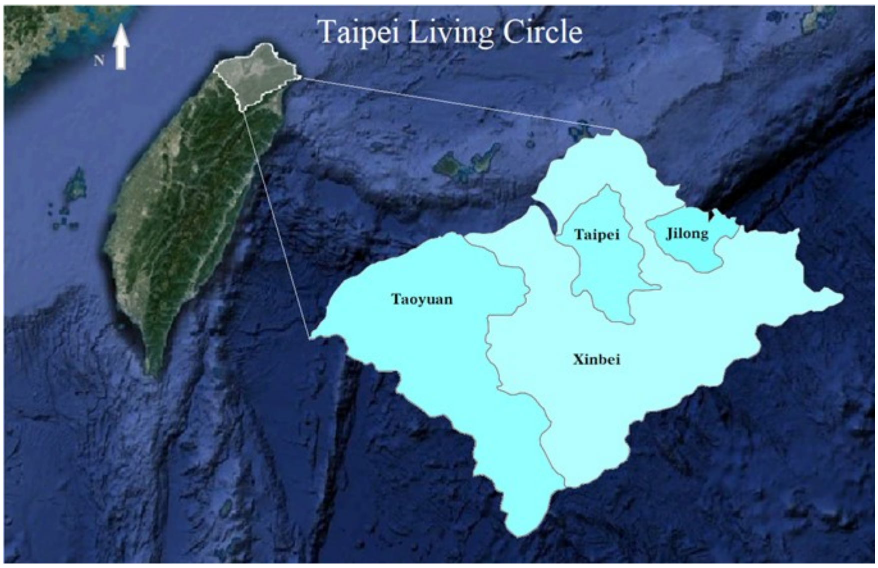
Remote sensing technology has been widely used in the field of ecological environment and has become an effective means of evaluating the regional ecological environment. Land use and land cover changes are often used to explore the impact on the environment (Cooper et al., 2006). The development of urbanization affects the natural environment in many fields such as resources, economy, society, culture, and technology. With the development of human society and the rapid expansion of the scale of cities, people's demand for land resources is increasing (Grimm et al., 2008). The continuous development of urbanization and the interference of human activities have greatly changed the structure of the original land (Jimenez et al., 2018), and have a certain impact on the surrounding ecology. Sustainable urban development is used to coordinate the relationship between people and nature, so as to achieve a relative balance between the various parts of society, economy, and natural environment (Aminzadeh, Khansefid, 2010). In response to the continuous acceleration of global urbanization, remote sensing is used to conduct multi-angle research into the cities. The direct application of remote sensing data has been widely used in the urban thermal environment (Estoque et al., 2017, urban smog (Liu et al., 2017), urban green space (Vorobyev et al., 2015). On this basis, the use of economic (McDonnell, MacGregor, 2016), lighting (Xu et al., 2018) and other data directly reflect remote sensing research of the environment.

The formation and the development of ecosystem are affected by many factors, so the ecological quality status needs to be described from multiple aspects. It is not objective to use only one or two aspects of ecological factors to reflect changes in the ecological environment (Wei et al., 2017). The Remote Sensing Ecological Index (RSEI) is completely based on remote sensing information and integrates a variety of environmental factors including greenness, humidity, heat, and dryness (Xu, 2013). This index is comparable with traditional ecological quality index calculations. Since the data is obtained entirely through remote sensing, the difficulty of data collection is greatly reduced. Data can also be visualized to facilitate comparison between different periods. The principal component analysis method is used to assign weights, thereby improving the objectivity of the evaluation results. And it has been better used in urban (Yang et al., 2019), desert (Jiang et al., 2019), wetland (Wen et al., 2020), and other settings. Combined with the actual situation of Taiwan Island, RSEI, land use and land cover changes, it is possible to understand the impact of different types of ground features on environmental quality.

Joining the land-use change and remote sensing ecological index in the Metropolitan Taipei in the northern part of Taiwan Island, China from 1988 to 2019, we analyzed the impact of the changes on the ecological environment. It also helps understand the impact of different types of ground features on environmental quality and help urban areas achieve the goal of sustainable development most effectively.

Study area and research methods

The study area was selected as the Taipei Living Circle in the northern part of Taiwan Island. This area is located in the northern part of Taiwan Island, northwest of the Pacific Ocean. Geographical location 24°11′41″N~25°17′59″N, 120°59′10″E~122°01′26″E, including Taipei City, New Taipei City, Keelung City and Taoyuan City (fig. 1). The total area is 3,677 km^2. The climate is subtropical: it is warm and humid all year round, with frequent typhoons (Chang et al., 2013; Jimenez, 2018).



The main remote sensing data used in this article is the Landsat series of satellite images provided by the US Geological Survey (https://eros.usgs.gov/). According to the quality of remote sensing data and cloud conditions, a total of 5 images ranging from 1988 to 2019 were selected. In the period of image data, the selected remote sensing image is of good quality with no cloud coverage or the cloud coverage is less than 5%.

Among them, Landsat 5 data were selected in 1988, 1995, and 2007. Images of 2018, 2019 were acquired from Landsat 8 data. Taiwan carries out a new round of cultivation every February and July-August, at this time the characteristics of the fields are most obvious. In order to better extract the field information, we chose the remote sensing images from that period (table 1).

The images produced in the experiment are processed by ENVI and ArcGIS. Image feature classification is provided by eCognition 9.01. SPSS Modeler 14 for satellite image data mining. In eCognition 9.01, the preprocessed 1988, 1995, 2007, and 2019 remote sensing images are segmented (Florence et al., 2011; Kurtz et al., 2012) and classified according to nine types of ground features: coniferous forest, broad-leaved forest, bamboo forest, field, shrub, water, wetland, city,

Table 1

Image data information in the study area

Years	Satellite	Sensor	Resolution	Date
1988	Landsat 5	TM	30	1988.02.23
1995	Landsat 5	TM	30	1995.07.20
2007	Landsat 5	TM	30	2007.07.21
2019	Landsat 8	OLI	30	2019.07.22

grassland, and bare land. General training sample data sets are used. SPSS Modeler 14 is used to implement data mining. We used the C5.0 model with the Boosting algorithm and set the number of experiments to 10. The interactive verification was selected, and there were 5 folds selected to train the training samples to generate a classification decision tree (Ma et al., 2015). In ENVI 5.3, the decision tree is used to classify the data in 1988, 1995, 2007, and 2019.

The Remote Sensing Ecological Index (RESI) constructed in this paper is to extract the four indicators of humidity, greenness, dryness, and heat from the four aspects of regional humidity, vegetation coverage, surface exposure, and temperature from the remote sensing images to come to the cities in the Taipei metropolitan area Ecological quality. Greenness, humidity, and heat are used for normalized difference vegetation index (NDVI), humidity index (Wet), and land surface temperature (LST), respectively. The land building index (IBI) and the soil index (SI) can respectively express the construction land and bare land conditions. This study uses the average of the two indicators to represent the dryness index (NDBSI). Calculation formula of humidity index is as follows:

$$WET = C_1\rho_B + C_2\rho_G + C_3\rho_R + C_4\rho_{NIR} + C_5\rho_{SWIR1} + C_6\rho_{SWIR2}, \quad (1)$$

In the formula ρ_{NIR}, ρ_R, ρ_B, ρ_G, ρ_{SWIR1}, ρ_{SWIR2} corresponds to the surface reflectivity of 4, 3, 1, 2, 5, and 7 bands in the TM image, and corresponds to the surface reflectivity of 5, 4, 2, 3, 6, 7 bands in the OLI image, respectively. C_1, C_2, C_3, C_4, C_5, C_6 - the coefficients are 0.0315, 0.2021, 0.3102, 0.1594, -0.6806, -0.6109 in TM images. In OLI images, they are 0.1511, 0.1973, 0.3283, 0.3407, -0.7117, and -0.4559.

Green index calculation formula is as follows:

$$NDVI = \frac{\rho_{NIR} - \rho_R}{\rho_{NIR} + \rho_R}, \quad (2)$$

Calculation formula of dryness index is presented below:

$$NDBSI = \frac{IBI + SI}{2}, \quad (3)$$

$$IBI = IBI_{min} * IBI_{max}, \quad (4)$$

$$IBI_{min} = \frac{2\rho_{SWIR1}}{\rho_{SWIR1} + \rho_{NIR}} - \rho_{NIR}(\rho_{NIR} + \rho_R) - \frac{\rho_G}{\rho_G + \rho_{SWIR1}}, \quad (5)$$

$$IBI_{max} = \frac{2\rho_{SWIR1}}{\rho_{SWIR1} + \rho_{NIR}} + \rho_{NIR}(\rho_{NIR} + \rho_R) + \frac{\rho_G}{\rho_G + \rho_{SWIR1}}, \quad (6)$$

$$SI = \frac{[(\rho_{SWIR1} + \rho_{NIR}) - (\rho_{NIR} + \rho_R)]}{[(\rho_{SWIR1} + \rho_{NIR}) + (\rho_{NIR} + \rho_R)]}, \quad (7)$$

Formula for calculating the heat index is as follows:

$$L = gain * DN + basi, \quad (8)$$

$$P_V = \frac{NDVI \quad - NDVI_{Soil}}{NDVI_{Veg} - NDVI_{Soil}} \quad , \tag{9}$$

$$\varepsilon_{surface} = 0.9625 + 0.0614P_V - 0.0461P_V^2 \ , \tag{10}$$

$$\varepsilon_{building} = 0.9589 + 0.086P_V - 0.0671P_V^2 \ , \tag{11}$$

$$B(LST) = \frac{[L - L_{up} - T * (1 - \varepsilon)L_{down}]}{T} * \ \varepsilon \ , \tag{12}$$

$$LST = \frac{K_2}{ln\left[\frac{K_1}{B(TS)} + 1\right]} - 273 \quad , \tag{13}$$

The L represents the sensor radiation value obtained by the image calibration of the 6th band of the TM image and the 10th band of the OLI image through ENVI software radiation calibration. DN is the pixel gray value, the gain is the gain value of the band, and bias is the offset value. These three values are obtained through remote sensing image header files. P_V indicates vegetation coverage.

$NDVI_{Soil}$ represents the NDVI value of the area without vegetation coverage, and the empirical value is 0.05. $NDVI_{Veg}$ is the NDVI value of vegetation pixels, and the empirical value is 0.7.

$\varepsilon_{surface}$ and $\varepsilon_{building}$ represent the pixel specific emissivity of natural surfaces and urban areas, respectively, and the water cell pixel specific emissivity takes a value of 0.995 (Yu et al., 2014).

B (LST) is the blackbody radiance value.

L_{up}, L_{down}, T represents the upward radiance of the atmosphere, the downward radiance of the atmosphere and the transmittance of the thermal infrared band.

Because there are many different standards for obtaining weight values, the final image results will also be different, so this experiment uses principal component analysis to obtain the combined value, which can determine the weight according to the value of the data itself. RSEI synthesizes the contents of the four component indicators, and it can determine the only certain value at a certain time point after the change of the main component (Zhang et al, 2019).

RSEI ecological index formula is as follows:

$$RSEI = \frac{RESI_0 - RSEI_{0-min}}{RSEI_{0-max} - RSEI_{0-min}} \quad , \tag{14}$$

$$RESI_0 = 1 - PC1 \ , \tag{15}$$

RSEI is the normalized remote sensing ecological index. $RSEI_0$ is the original ecological index at i pixel. $RSEI_{0-max}$ and $RSEI_{0-min}$, these are the maximum and minimum values of the original ecological index. PC1 is the load value of the first principal component.

In order to further analyze the ecological quality evaluation results, combined with the distribution characteristics of the RSEI index in northern Taiwan, the reclassification is used to divide the RSEI values from 0-1 into equidistant and divided into five grades: poor, fair, average, good, and excellent.

Based on the study of classification of the dynamic changes of the ecological quality in the Taipei Living Circle, this paper makes further analysis of the causes of different ecological quality changes. By combining areas with different ecological qualities in various years and land use types, we explore the changes in land use types under different ecological qualities.

We carried out interpolation analysis and processing of RSEI remote sensing ecological quality value images in 1988 and 2019. The remote sensing images we reclassified after the difference processing in ArcGIS, and divided into five categories: 2, 1, 0, -1, -2. They represent ecological quality significantly improved area, ecological quality improved area, ecological quality constant area, ecological quality deteriorated area, and ecological quality significantly deteriorated area. By combining the areas where different ecological qualities are located each year and the types of land use, the changes in land use types under different ecological qualities are explored.

Results and discussion

Forests occupy the main part of Taipei Living Circle, of which deciduous forests are mainly distributed in mountainous areas (fig. 2). The building area comprising cities, bare land, and grassland is growing year by year. It is mostly concentrated in the Taipei Basin and Taoyuan. Agricultural areas comprising fields and shrubs have also increased. Building areas and agricultural areas have increased by overlapping onto the areas originally covered with bamboo forests, deciduous forests, and coniferous forests. Water and wetlands remain basically unchanged.

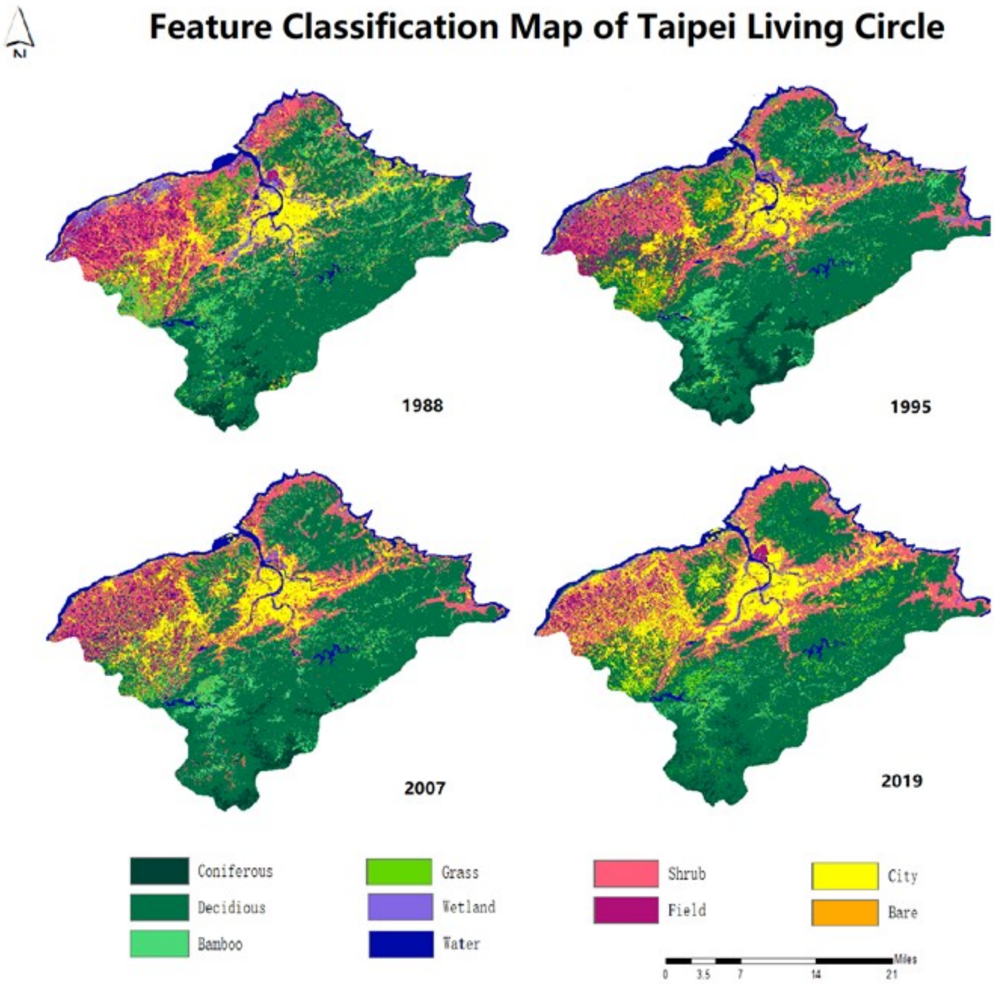


Fig 2. Maps of feature classification for 1988-2019

According to calculations, the RESI values in 1988, 1995, 2007 and 2019 are 0.559, 0.571, 0.546, 0.396 (table 2). The larger the value, the better the quality of the ecological environment in that year. The overall trend in the past four years has been a gradual decline. Based on the four-year data, it can be seen that four ecological indicators have varying degrees of influence on the final RSEI index. Among them, WET, NDVI, NDSI, and LST contributed more evenly to the final results.

Table 2

RSEI index parameter statistics

Date	1988		1995		2007		2019	
Type	**Average**	**SD**	**Average**	**SD**	**Average**	**SD**	**Average**	**SD**
WET	0.722	0.021	0.775	0.018	0.716	0.030	0.642	0.021
NDVI	0.404	0.005	0.524	0.154	0.879	0.042	0.518	0.043
NDBSI	0.145	0.162	0.301	0.333	0.151	0.163	0.121	0.159
LST	0.251	0.283	0.255	0.284	0.207	0.218	0.259	0.294
RESI	0.559	0.059	0.571	0.067	0.546	0.078	0.396	0.117

RSEI ecological quality value is a way of expressing, evaluating, and judging the level of the regional ecological environment. From the perspective of effect, the impact of land-use change on the regional ecological environment mainly includes positive and negative correlations. Among them, the positive correlation is mainly manifested in the improvement of soil quality. Bare land and unused wasteland are converted into cultivated land and forest land by human activities. With the improvement of water resources, the ecological habits of land plants have been further improved (Nakamura et al., 2008). Vegetation coverage has been improved, thereby improving the ecological quality of the natural environment. Correspondingly, the negative correlation mainly includes land quality degradation, desertification, and salinization. The area of cultivated land, garden land, or forest land is gradually reduced or replaced by non-permeable grounds such as urban construction land and urban roads. Water resources pollution and over-exploitation, ecological habits of land plants have further deteriorated, and the vegetation coverage has declined seriously. As a result, the ecological quality of the natural environment deteriorates.

Table 3

RSEI level statistics

Date	1988		1995		2007		2019	
Type	**Area, km²**	**%**	**Area, km²**	**%**	**Area, km²**	**%**	**Area, km²**	**%**
Poor	26,405	0.61	45,430	1.06	67,951	1.59	121,206	2.83
Fair	819,400	19.16	1,148,652	26.85	1,444,596	33.77	1,532,365	35.83
Average	3,329,216	77.83	2,458,707	57.49	2,442,375	57.11	2,362,187	55.22
Good	102,188	2.39	580,764	13.57	320,336	7.48	261,456	6.11
Excellent	87	0.01	43,743	1.03	2,038	0.05	84	0.01

It can be seen that most research areas found within the average interval in 1988, accounted for more than 77% of the total area (table 3). Followed by the fair area, which accounted for about one -fifth. The ecological excellent area and poor area account for a small proportion. The average interval accounted for the largest proportion in 1995, exceeding 57%. Fair area and good area accounted for 26.85% and 13.58% respectively. Ecological Excellent area and poor area account for less. The average interval in 2007 is basically the same as the Average interval in 1995. The Fair area has increased compared to before, with the ratio reaching one third. The good area is reduced by 50%, and the total proportion is 7.5%. The poor region increased slightly, and the excellent region decreased slightly. The region with the largest share in 2019 is still the average region, exceeding 55%.

The fair area and poor area both increased slightly. The proportion of the good area and excellent area has decreased. Comparing the four-year data, we can see that environmental quality has a significant downward trend. Among them, the proportion of poor area and fair area is constantly rising. The corresponding areas in the figure are concentrated on impervious surfaces such as urban roads and agricultural land such as farmland shrubs. Due to the advancement of urbanization, the expansion of urban areas has led to a decline in the value of environmental quality in the region. The average area has been declining continuously in the four-year period. There is also a downward trend in good and excellent region types (fig. 3).

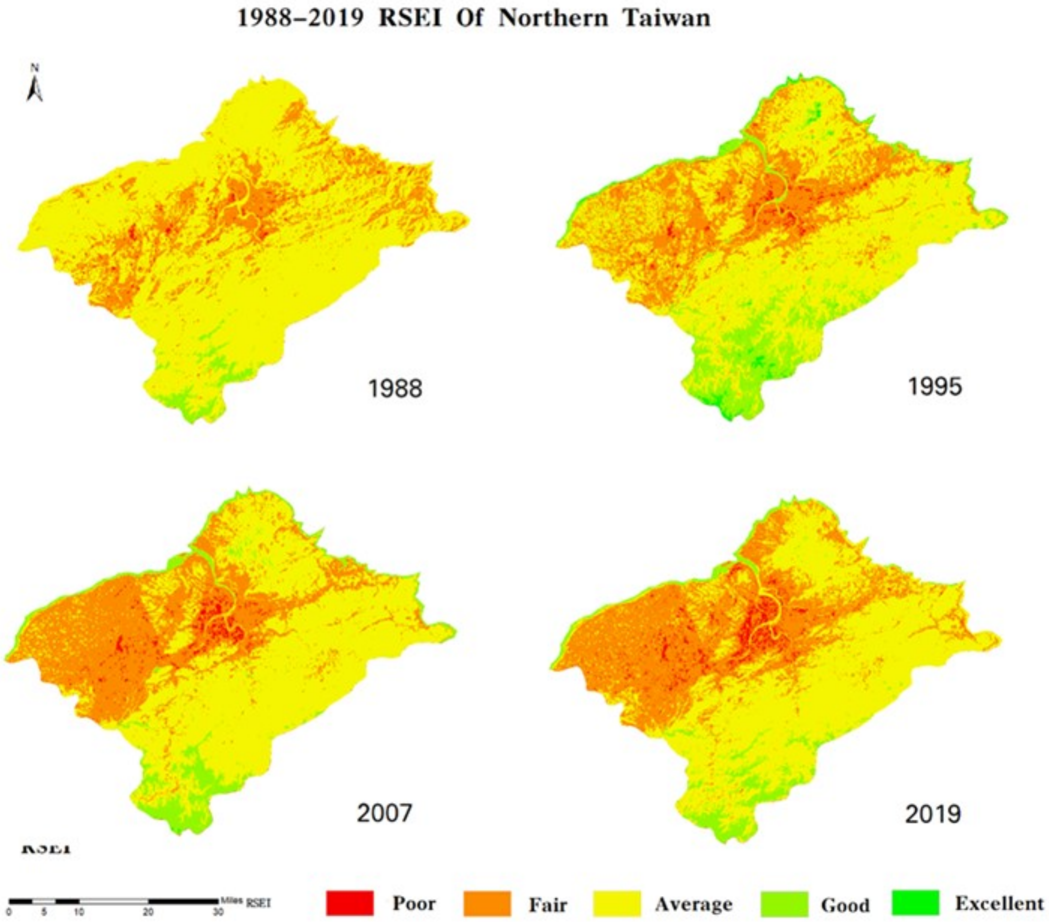


Fig 3. RSEI index area for 1988-2019

The average area occupies the largest area ratio in four years, and the proportion is more than 50%. The poor area and excellent area account for only a small percentage of the four-year data. The area of change is mainly concentrated in the fair area and good area. According to the DEM comparison of the study area, the areas with ecological quality changes are mostly concentrated in plains or hills with a terrain of less than 500 m, which corresponds to changes in urban expansion. The mountainous areas, which account for the largest proportion of the study area, basically maintain good ecological quality.

Through the analysis of the feature type transfer matrix of ecological quality significantly improved area, improved area, constant area, deteriorated area, significantly deteriorated area, the relationship between the ecological quality index and urbanization is obtained (fig. 4). In the ecological quality improved area, broad-leaved forest occupies the largest proportion, indicating that the area of broad-leaved forest plays an important role in ecological quality. At the same time, it is found that although grassland, shrubs, and other areas are all green, their impact on ecological quality is less than that of woodland. According to the invariable areas of ecological regions, the mutual conversion between different types can reach a relative balance of ecological quality. According to the analysis of the ecological quality deteriorated area, the increase in the area of cities and fields has a significant negative effect on ecological quality. Substituting shrub areas for forest areas will slightly reduce the ecological quality. Cities have the most obvious response to ecological quality. The main reason for the loss of wetlands and water bodies is the increase in the urban areas. The main reason is that most wetlands are located in low-altitude areas and the area is close to the city. The area of water loss is mainly the area of shallow waters near the city.

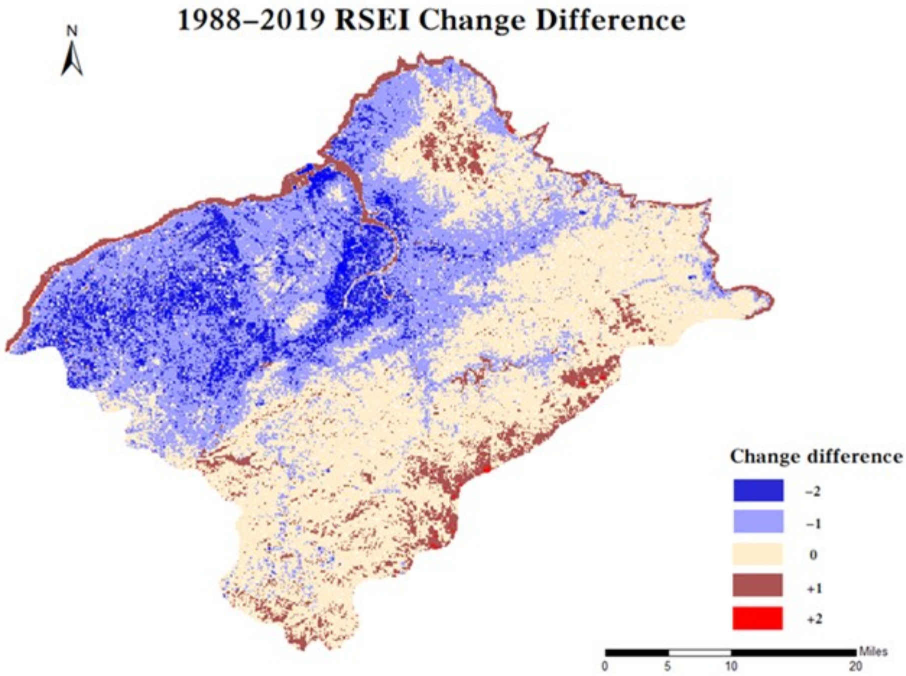


Fig 4. RSEI change difference for 1988-2019

The mountains with higher altitudes are mostly covered by forest, among which broad-leaved forests have a greater influence on the ecological quality than bamboo forests and coniferous forests. And most of the broad-leaved forests are located in areas where human activities are limited, making the broad-leaved forests basically unchanged. Part of the broad-leaved forest near the city turned into shrubs. The reason is that it has become grassland and some trees have been replaced with cash crops under the influence of urban development. The amount of bare land is reduced, and it is transformed into an urban impervious surface, and its impact on environmental quality remains basically unchanged.

The land use/land class maps of 1988 and 2019 years were combined using the spatial connection tool. We generated several matrix tables to estimate the ecological quality: significantly improved area transition matrix (table 4), improved area transition matrix (table 5), constant area transition matrix (table 6), deteriorated area transition matrix (table 7), and significantly deteriorated area transition matrix (table 8).

Table 4

Ecological quality significantly improved area

1988 / 2019	water	field	city	grass	wet-land	shrub	decidu-ous	bam-boo	conif-erous	bare	Output
water		1557	809	0	0	6	0	0	18	1	2391
field	0		1	0	2	0	0	0	0	0	3
city	0	13		0	0	4	0	0	0	0	17
grass	0	0	0		0	1	228	38	0	0	267
wetland	0	1	4	0		0	0	0	0	0	5
shrub	0	3	2	0	1		3	1	0	0	10
deciduous	320	363	287	128	0	23		381	84	0	1,586
bamboo	0	0	0	0	0	0	20		0	0	20
coniferous	0	0	0	0	0	0	9	10		0	19
bare	0	0	0	0	0	0	0	0	0		0
Input	320	1,937	1,103	128	3	34	260	430	102	1	

Table 5

Ecological quality improved area

1988 \ 2019	water	field	city	grass	wet-land	shrub	decidu-ous	bam-boo	conif-erous	bare	Output
water		3,900	1,513	11	310	295	535	74	4,150	4	10,792
field	4		15	4	4	22	0	1	0	0	50
city	1,706	296		22	21	98	54	27	18	6	2,248
grass	38	34	43		0	102	1,305	363	37	0	1,922
wetland	233	106	53	0		12	23	7	17	1	452
shrub	44	100	109	1	7		234	146	16	1	658
deciduous	2,096	940	1,319	2,407	1	2,386		10,948	26,301	44	46,442
bamboo	14	1	2	32	0	7	5,934		374	0	6,364
coniferous	0	1	34	44	0	55	1408	317		0	1,859
bare	3	0	0	0	0	0	0	0	0		3
Input	4,138	5,378	3,088	2,521	343	2,977	9,493	11,883	30,913	56	

Table 6

Ecological quality constant area

1988 \ 2019	water	field	city	grass	wet-land	shrub	decidu-ous	bamboo	conif-erous	bare	Output
water		495	1,226	63	114	445	1,913	391	2,273	9	6,929
field	83		684	318	169	905	448	684	18	291	3,600
city	515	941		1,987	941	6,748	6,226	4,669	561	329	22,917
grass	346	524	1,561		4	5,983	41,806	23,982	349	271	74,826
wetland	236	702	1,878	16		989	1,681	976	228	15	6,721
shrub	314	2,895	8,585	150	3,024		78,676	28,532	2,582	143	124,901
deciduous	1,213	2,893	19,016	40,003	105	44,921		160,249	65,217	1,312	334,929
bamboo	63	16	294	1,342	1	1034	80,865		916	23	84,554
coniferous	3	0	162	819	0	287	37,157	3664		0	42,092
bare	0	0	109	9	0	44	79	2	0		243
Input	2,773	8,466	33,515	44,707	4,358	61,356	24,885	223,149	72,144	2,393	

Table 7

Ecological quality deteriorated area

1988 \ 2019	water	field	city	grass	wet-land	shrub	decidu-ous	bam-boo	co-nifer ous	bare	Output
water		2,650	6,925	320	1,427	2,586	965	303	940	109	16,225
field	225		19,665	5,840	12,363	33,384	3,430	1,619	568	2,565	79,659
city	1,815	36,768		19,257	41,462	80,033	13,839	8,549	953	8,553	211,229
grass	437	9,935	7,670		14	35,474	18,456	16,900	235	1,453	90,574
wetland	2,106	11,103	17,089	31		11,920	4,544	2,619	639	579	50,630
shrub	1,987	35,668	28,617	782	31,811		100,119	21,894	2,884	821	224,583
deciduous	1,312	12,255	15,850	44,371	198	46,249		22,929	1,845	1,414	146,423
bamboo	24	27	77	360	4	408	3,015		20	15	3,950
coniferous	0	0	44	71	0	17	536	118		0	786
bare	0	0	83	34	0	22	14	7	0		160
Input	7,906	108,406	96,020	71,066	87,279	210,093	144,918	74,938	8,084	15,509	

Table 8

Ecological quality significantly deteriorated area

1988 / 2019	water	field	city	grass	wet-land	shrub	decidu-ous	bamboo	conif-erous	bare	Output
water		884	770	49	323	608	97	10	96	35	2,872
field	468		13,406	2,048	9,513	21,983	1,685	299	357	1,758	51,517
city	4,830	40,731		4,559	30,540	33,007	3,284	760	721	4,547	122,979
grass	272	7,309	1,415		10	9,705	1,886	373	117	136	21,223
wetland	847	4,553	3,197	0		3,116	417	38	117	149	12,434
shrub	1,107	22,254	2,832	36	3,700		1,535	191	371	111	32,137
deciduous	839	4,827	932	1,602	51	2,795		236	155	77	11,514
bamboo	4	11	4	4	5	16	21		3	1	69
coniferous	0	0	0	1	0	0	49	10		0	60
bare	0	0	7	6	0	3	0	2	0		18
Input	8,367	80,569	22,563	8,305	44,142	71,233	8,974	1,919	1,937	6,814	

In areas with the improved ecological quality, broad-leaved forests account for the largest proportion, which indicates that the area of broad-leaved forests plays an important role in ecological quality. At the same time, it was found that although grassland, shrubs, and other areas are also green areas, their impact on ecological quality is less than that of woodland. Through unchanging ecological regions, we know that the conversion between different types of characteristics can achieve a relative balance of ecological quality to a certain extent. It can be seen from the analysis of areas with degraded ecological quality that the increase in urban and field area has a significant negative correlation with ecological quality. Substituting bush areas for forest areas will result in a slight decline in ecological quality.

The remote sensing image was selected when the field had just been planted. During this period, the crops in the field have not fully grown, and the bare land constitutes a large area, which will greatly reduce the ecological quality. The main reason for the loss of wetlands and water bodies is the increase in urban areas. Most wetlands are located in low-altitude areas and the area is closer to the city. The decrease in the water area is mainly observed in wet areas near cities.

High-altitude mountainous areas are mostly forests, and the number of broad-leaved forests and their impact on environmental quality is greater than that of bamboo forests and coniferous forests. Moreover, human activities in most broad-leaved forest areas are restricted, so broad-leaved forests remain basically unchanged. The broad-leaved forest near the city was partially turned into shrubs. The reason is that due to the impact of urban development, grasslands and some trees have been replaced by cash crops. The number of bare lands has been reduced, and it has become an impermeable surface of the city, which has basically no impact on environmental quality.

Conclusions

Through the Landsat 5/TM and Landsat 8/OLI images of Taipei Living Circle from 1988 to 2019, the RSEI model combined with the Feature classification map was used to quantitatively evaluate the ecological quality and changes of Taipei Living Circle, and monitor the changes. An analysis of the results leads to several conclusions.

1. Taipei Living Circle in 1988, 1995, 2006, and 2019, the remote sensing ecological index was 0.559, 0.571, 0.546, and 0.396 respectively. It showed a slight increase in the early period and a downward trend in the later period. From an overall perspective, ecological quality shows a trend of degradation.

2. From the RSEI level statistics, the average accounts for the majority, exceeding 50%. The comparison of data from 1988 and 2019 revealed that the fair area and poor area increased by 807,766, the average area decreased by 845,805, and the good area and excellent area increased by 102,275. Both the areas with a better environment and the areas with the worse environment have increased, the average area accounting for the largest area has decreased, and the overall environmental performance has decreased.

3. The forest area covered with coniferous forest, deciduous forest, and bamboo forest has reduced by 10% to 252,148 km^2. Agricultural land (fields and shrubs) decreased by 7.7% to 66,958 km^2. The water area comprising water and wetlands decreased by 18.2 % to 67,846 km^2. The building area comprising urban, grass, and bare land increased by 72.7% to 377,547 km^2.

4. Through the transfer matrix of land-use types of different RSEI levels, it can be seen that forests and water bodies have a positive effect on the environment, while agricultural building areas have a negative effect on the environment. Forest has the greatest impact on the ecological index, and the area of broad-leaved species determines the influence of the entire area. Although grasslands, shrubs, and other areas are also green areas, their impact on ecological quality is less visible than that of forest land. Since the remote sensing image was taken at the sawing period, the vegetation in the field has not fully grown, and the reflected ecological index value is low.

References

1. Aminzadeh B., Khansefid M. A case study of urban ecological networks and a sustainable city: Tehran's metropolitan area. *Urban Ecosystems*, **2010**, *13*, 23-36 https://doi.org/10.1007/s11252-009-0101-3
2. Chang C.P., Yang Y.T., Kuo H.C. Large Increasing Trend of Tropical Cyclone Rainfall in Taiwan and the Roles of Terrain. *Journal of Climate*, **2013**, *26*, 4138–4147, https://doi.org/10.1175/JCLI-D-12-00463.1.
3. Cooper A., Shine T, McCann T, Tidane D.A. An ecological basis for sustainable land use of Eastern Mauritanian wetlands. *Journal of Arid Environments*, **2006**, *67*, 116-141 https://doi.org/10.1016/j.jaridenv.2006.02.003
4. Estoque R.C., Murayama Y., Myint S.W. Effects of Landscape Composition and Pattern on Land Surface Temperature: An Urban Heat Island Study in the Megacities of Southeast Asia. *Science of the Total Environment*, **2017**, *577*, 349-359. https://doi.org/10.1016/j.scitotenv.2016.10.195
5. Florence L. Guy F, Olivier A. The morphological pyramid and its applications to remote sensing: Multiresolution data analysis and features extraction. *Image Analysis & Stereology*, **2011**, 21, 49-53.
6. Grimm N.B., Faeth S.H., Golubiewski N.E., Redman C.L. Wu J., Bai X., et al. Global change and the ecology of cities. *Science*, **2008**, *319*, 756-760 https://doi.org/10.1126/science.1150195
7. Jiang C. L., Wu L., Liu D., Wang S. M. Dynamic monitoring of eco-environmental quality in arid desert area by remote sensing: Taking the Gurbantunggut Desert China as an example. *The journal of applied ecology*, **2019**, *30*, 877–883. https://doi.org/10.13287/j.1001-9332.201903.008
8. Jimenez A.A., Vilchez F.F., González O.N., Flores S.M. Analysis of the Land Use and Cover Changes in the Metropolitan Area of Tepic-Xalisco (1973–2015) through Landsat Images. *Sustainability*, **2018**, *10*, 1860.
9. Kurtz C., Passat N., Gancarski P., Puissant A. Extraction of complex patterns from multiresolution remote sensing images:A hierarchical top-down methodology. *Pattern* Recognition, **2012**, 45, 685-706 https://doi.org/10.1016/j.patcog.2011.07.017
10. Liu Y, Arp H.P.H, Song X., Song Y. Research on the relationship between urban form and urban smog in China. *Environment and Planning B: Urban Analytics and City Science*, **2017**; *44*: 328-342. https://doi.org/10.1177/0265813515624687
11. Ma L.G., Deng J., Yang H., Hong Y., Wang K. Urban landscape classification using Chinese advanced high-resolution satellite imagery and an object-oriented multi-variable model. *Frontiers of Information Technology & Electronic Engineering*, **2015**, 16, 238-249.
12. McDonnell M.J., MacGregor-Fors I. The ecological future of cities. *Science*, **2016**, *352*, 936-938 https://doi.org/10.1126/science.aaf3630
13. Nakamura K., Kayaba Y., Nishihiro J., Takamura N. Effects of submerged plants on water quality and biota in largescale experimental ponds. *Landscape and Ecological Engineering*, **2008**, *4*, 1-9.
14. Vorobyev O.N, Kurbanov E.A., Gubayev A.V. Polevshikova Y.A., Demisheva E.N., V.O. Koptelov. Remote sensing monitoring of urban forests. *Vestnik of Volga State University of Technology: Human. Ecology. Nature management*. **2015**, *25*, 5-21.
15. Wei S.R., Jin X., Wang K., Liang H. Response of lake area variation to climate change in Qaidam Basin based on remote sensing. *Earth Science Frontiers*, **2017**, 24, 427-433. DOI: 10.13745/j.esf.yx.2016-10-1
16. Wen X., Ming Y., Gao Y., Hu X. Dynamic Monitoring and Analysis of Ecological Quality of Pingtan Comprehensive Experimental Zone, a New Type of Sea Island City, Based on RSEI. *Sustainability*, **2019**, *12*, 1-14. https://doi.org/10.3390/su12010021

17. Xu H. A Remote Sensing Index for Assessment of Regional Ecological Changes. *China Environmental Science*, **2013**, *33*, 889-897.
18. Xu Y., Knudby A., Côté-Lussier C. Mapping ambient light at night using field observations and high-resolution remote sensing imagery for studies of urban environments. *Building and Environment*, **2018**, *145*, 104-114, https://doi.org/10.1016/j.buildenv.2018.09.002
19. Yang J.Y., Wu T., Pan X.Y., Du H.T., Li J.L., Zhang L., et al. Ecological quality assessment of Xiongan New Area based on remote sensing ecological index. *Chinese Journal of Applied Ecology*. **2019**, *30*, 277–284 https://doi.org/10.13287/j.1001-9332.201901.017
20. Yang JY, Wu T, Pan XY, et al. Ecological quality assessment of Xiongan New Area based on remote sensing ecological index. *Ying Yong Sheng Tai Xue Bao.* **2019**; *30*: 277-284. https://doi.org/10.13287/j.1001-9332.201901.017
21. Yu X., Guo X., Wu Z.. Land Surface Temperature Retrieval from Landsat 8 TIRS-Comparison between Radiative Transfer Equation-Based Method, Split Window Algorithm and Single Channel Method. *Remote Sensing*, **2014**, *6*, 9829-9852. https://doi.org/10.3390/rs6109829
22. Zhang C., Xu H.Q., Zhang H., Tang F., Lin Z. Fractional vegetation cover change and its ecological effect assessment in a typical reddish soil region of southeastern China: Changting County Fujian Province. *Chinese Journal of Natural Resources*, **2015**, *30*, 917-928. DOI:10.1115/1.4031791