**RESEARCH ARTICLE** 



# Spatial and temporal variation of multiple eco-environmental indicators in Erhai Lake Basin of China under land use transitions

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Received: 22 July 2022 / Accepted: 22 September 2022 / Published online: 1 October 2022 © The Author(s), under exclusive licence to Springer-Verlag GmbH Germany, part of Springer Nature 2022

### Abstract

Environmental degradation is a global ecological concern, and land use transitions play a critical role in a region's ecological wellbeing and long-term sustainability. In this paper, indicators related to land use transitions, including the regional eco-environmental quality index (EV), the remote sensing ecological index (RSEI), and soil erosion, are selected to analyze the eco-environmental quality of Erhai Lake Basin from 2000 to 2020. The results showed that (1) from 2000 to 2020, forestland, grassland, and cultivated land were the major land use types in the study region, and also the land use types where land use transition was notable; (2) over the 20 years of study, the EV value of Erhai Lake Basin increased by 0.003, its average RSEI increased by 0.14, and the average soil erosion modulus there decreased by 15.48 t/(km<sup>2</sup>·a), indicating that the eco-environment of the Erhai Lake Basin was improving. Evaluation based on multiple ecological indicators was superior to assessment relying on single indicators; (3) all three ecological indicators showed that the ecological environment of the basin was improving, but with significant regional differences. Forestland had the best ecological quality, while unused land and built-up land had the worst. RSEI was more regionally adaptable than the other two indices. (4) The transition of cultivated land into other land use types was the main reason for the improved ecological quality in the basin, while tourism had accelerated land use transformation. Compared with assessment based on single ecological indicators, evaluation based on a combination of multiple ecological indicators can more accurately reflect the ecological condition of the study area and provide a basis for eco-environmental protection in Erhai Lake Basin.

Keywords Erhai Lake Basin · EV · Land use transition · Soil erosion · RSEI · Spatial and temporal changes

# Introduction

Land use and land cover change (LULC) is an important contributor to regional ecological changes (Du and Huang 2017; Cetin 2020). Land use transition, as a new approach to LULC

Responsible Editor: Marcus Schulz

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research, has been extensively studied in different regions using different data and from different perspectives (Aksoy et al. 2022b, 2022a). Land use transition has become a popular perspective for ecological research (Ren et al. 2021). Land use transition usually causes different degrees of pollution in rivers and lakes, leading to ecological and environmental problems such as non-point source (NPS) pollution, soil erosion, biodiversity degradation, and reduced vegetation cover (Liu et al. 2014b; Guo et al. 2021; Hu et al. 2021). Basins are a unique geographical unit, where human activities such as tourism influence land use transitions, resulting in changes in the water quality of rivers and lakes (Wang et al. 2019; Cetin 2015), and the water quality of basins is the most candid representation of the eco-environment of the study area. Therefore, analyzing the trends and patterns of land use transitions at the basin level, evaluating the spatial and temporal changes in eco-environmental quality, and giving priority to ecological well-being in regional planning and development (Kalayci Onac et al. 2021; Cetin 2019) are key to regional environmental protection and sustainability.

Many existing works on land use transition and the ecoenvironment are performed from such perspectives as rural revitalization (Zhang and Zhang 2022), eco-environmental quality (Li and Wu 2022; Yang et al. 2020), ecosystem service value (ESV) (Cui et al. 2022; Gou et al. 2021), and future land scenario simulation (Diao et al. 2020), involving social humanities, economic development, ecological environment, and other fields. With rapid changes in LULC and tourism, It is urgent to accurately evaluate the ecological quality of studied regions and develop sustainable policies accordingly (Cetin 2019). The adoption of new technologies, methods, and software (Kaya et al. 2019) has also led to new breakthroughs in indicators and methods for evaluating changes in regional ecological quality. Indicators have been a popular tool in research on the relationship between land use transition and the eco-environment. Drought index (DI) (Ashraf et al. 2022), ecosystem condition index (EI) (Sun et al. 2021), remote sensing ecological index (RSEI) and its improved variants (Li et al. 2020b), and regional eco-environmental quality index (EV) (Song et al. 2020) are just a few examples. However, it is difficult to use one single indicator to assess the condition of ecosystems due to the complexity and diversity of contributing factors. Kilicoglu et al. (2020) indicated that site selection of residential areas relying on a single criterion or guideline is unscientific and may result in catastrophic consequences. Johannes et al. (2022) stated that combining two water quality indices provides more accurate assessment of the water quality in the desert than using single indicators. Xu et al. (2021) pointed out that single agronomic parameters can provide one-sided information about the eco-conditions of an area due to the interactive nature between these parameters. Evaluation based on single parameters is, however, unscientific, inaccurate, and incomplete in some cases, because the quality of the ecological environment is often a result of interplay between various contributing factors. Due to the limitations of evaluation based on single parameters, the combination of multiple indicators, such as combining RSEI and EI (Sun et al. 2020), landscape pattern index and EV, or landscape pattern and ESV, is rising to be a dominating trend in studying ecological environments (Liu et al. 2021; Li et al. 2022).

The Erhai Lake is the second largest highland freshwater lake in Yunnan Province in southwestern China and the "Mother Lake" of the people of Dali Prefecture, where human production activities are exceptionally frequent (Zhao et al. 2021). The upper reach of Erhai Lake Basin, featuring a hilly mountain basin landscape, is dominated by the land use type of cultivated land and accounts for an important source of NPS pollution in the basin; the middle reach is a gently sloping landscape with Cang Mountain Range on the west side, which has excellent ecological quality and is the main catchment area of Erhai Lake; and the lower reach of the basin is urban region of Dali, which is densely populated and economically developed. In addition, Erhai Lake is a plateau rift lake and the basin has a large difference in elevation between the upper reach and the lower reach, with Xi'er River as the only outlet. Because of such topological and geographic conditions, Erhai Lake Basin suffer frequently from soil erosion and eutrophication, seeing several cyanobacterial outbreaks and ecological degradation (Zhang et al. 2021a). It is important to analyze spatial and temporal changes in the eco-environmental quality to maintain ecological balance and promote environmental protection in the basin.

Currently, ecological indicators like RSEI (Xiong et al. 2021), ecological sensitivity (Chen and Wu 2020), and ESV (Li et al. 2020a) are often used alone used to evaluate the eco-environmental quality of Erhai Lake Basin, but comparative research based on multiple ecological indicators is lacking. Most scholars analyze the water quality and ecological condition of the Erhai Lake Basin based on the hydrological factors and water quality and the drivers (Zhang et al. 2021a; Chen et al. 2021; Wen et al. 2021), whereas such indicators as soil erosion and RSEI are rarely used. Therefore, with Erhai Lake Basin as the study case, three indicators, including EV, RSEI, and soil erosion, are employed in the present work to analyze the spatial and temporal changes of eco-environmental quality in the basin under land use transitions. The major research content is as follows: (1) the eco-environmental quality of the study area is evaluated by a combination of various ecological indicators; (2) the spatial and temporal changes in the eco-environmental quality of Erhai Lake Basin from 2000 to 2020 are investigated; (3) the key areas affecting the eco-environment of the studied basin are identified by hotspot analysis. In the present work, multiple ecological indicators are used to assess the spatial and temporal changes of the ecological environment in Erhai Lake Basin, with a vision to make up for the shortcomings of research based on single ecological indicators.

# Overview of the study area

The Erhai Lake Basin is located between 99°  $32'-100^{\circ} 27'$ E and 25°  $25'-26^{\circ} 10'$  N. It is situated in Dali Bai Autonomous Prefecture, Yunnan province, China, and belongs to the watershed region of three major water systems, namely the Lancang River, Jinsha River, and Yuanjiang River, covering an area of 2565.0 km<sup>2</sup> (Liu et al. 2019). Erhai Lake is the largest plateau freshwater lake in northwestern Yunnan, with a surface elevation of 1966.0 m, a surface area of 252.3 km<sup>2</sup>, and a water storage capacity of 29.6 × 10<sup>8</sup> m<sup>3</sup>; the length of the lake is 42.0 km from north to south, and 3.1–8.8 km from east to west; the lake has a maximum depth of 21.5 m and an average depth of 10.8 m (Wu et al. 2021). Erhai Lake Basin, subject to the northern subtropical highland monsoon climate, has a small annual temperature difference, a large daily temperature difference, and distinct dry and wet seasons (Wang et al. 2021). Figure 1 presents a map of the study area.



Fig. 1 Location of the study area

#### Fig. 2 Technical flow chart

# **Materials and methods**

## Data source and processing

The LULC data of the five phases (2000, 2005, 2010, 2015, and 2020) were obtained from the data sharing service system of the Earth Big Data Science Project of the Chinese Academy of Sciences (https://data.casearth.cn/) (Zhang et al. 2021b). The spatial resolution is 30 m, and the overall accuracy of the decoded data reaches more than 80%, and the kappa coefficient reaches more than 0.70. Based on the land classification system (GB/T21010-2017), the land use types are classified into six primary types: cultivated land, forest land, grassland, water bodies, built-up land, and unused land. Soil erosion data are from Chengdu Institute of Mountain Hazards and Environment, Chinese Academy of Sciences (http://www.imde.ac.cn/), at a spatial resolution of 30 m. The RSEI was calculated by Google Earth Engine (GEE) with a spatial resolution of 30 m. The data presented above were processed using ArcGIS 10.5 software and uniformly projected into the CGCS2000\_3\_Degree\_GK\_Zone\_33 coordinate system. The technical flow chart of the present work is shown in Fig. 2.

# **Research methodology**

#### Land use transfer matrix

The land use matrix uses Markov and land use change models to represent the area and distribution of different land use types in the region, which is widely used in studies on



land use change and also reflects the level of land use in the spatial development process (Liu et al. 2022).

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

In the matrix,  $S_{ij}$  represents a  $n \times n$  matrix, S represents the area, n represents the number of land use types, and i and j represent the land use types at the beginning and end of the study period, respectively.

#### Regional eco-environmental quality index

Distribution of different land use types mirrors the ecological differences in a region. With the regional ecological quality and the area of land use types taken into account, the regional eco-environmental quality index (EV) is used to quantify the overall eco-environmental quality in a region (Liu et al. 2021), expressed as follows:

$$EV_t = \sum_{i=1}^n \frac{A_{ti}}{TA_t} \times R_i$$
(2)

where  $EV_i$  represents the eco-environmental quality index in period *t*;  $A_{ti}$  represents the area of land use type *i* in period *t*;  $R_i$  represents the eco-environmental quality index of land use type *i* (Table 1), and the values are taken from a previous study (Hu et al. 2021);  $TA_i$  represents the total area; and *n* represents the number of land use types.

The EV was originally proposed by Li et al. (2003) in a study on the Hexi region in Gansu. After that, the index was used and improved by Hu et al. (2021), Wang et al. (2022), and Liang et al. (2022) to studies on Chongqing, Guangxi, and the Three Gorges, respectively. These study areas, which are all highland

#### Remote sensing ecological index

The remote sensing ecological index (RSEI) has been a comprehensive ecological indicator in recent years, which is specifically used to assess the ecological status using remote sensing data because it is closely related to ecological quality and can be directly perceived by human (Xu 2013; Ji et al. 2020). In this paper, four factors (greenness, wetness, heat, dryness) closely related to eco-environmental quality are employed to establish the index of RSEI:

$$RSEI = f(Greenness, Wetness, Heat, Dryness)$$
 (3)

where *Greenness* can be represented by NDVI; *Wetness* can be represented by WET; *Heat* can be represented by NDBSI; and *Dryness* can be represented by LST.

(1) Greenness index (NDVI): the normalized vegetation index (NDVI) is the most widely used index of vegetation. It is closely related to plant biomass, leaf area index, and vegetation cover (Cetin 2019).

$$NDVI = (NIR - Red) / (NIR + Red)$$
(4)

where *NIR* stands for near infrared and *red* stands for red wavelength.

(2) Humidity index (Wet): The humidity component reflects the moisture content of water bodies, soil, and vegetation, and it is closely related to ecology. Therefore, the humidity component is used as a representative (Xiong et al. 2021). For Landsat images, the equations are:

Level 1 type	Eco-environmental Quality Index $(R_i)$	Level 2 type	Eco-environmental Quality Index $(R_i)$
Cultivated land	0.30	Dry farmland	0.25
		Irrigated farmland	0.30
Forest land	0.87	Forestland	0.95
		Shrubland	0.65
		Other forestlands	0.40
Grassland	0.25	Herbaceous cover	0.45
		Sparse grassland	0.20
Water	0.75	Wetlands	0.65
		Water bodies	075
Built-up land	0.20	Impervious surfaces	0.20
Unused land	0.025	Bare land	0.025
		Ice and Snow	0.58

Table 1Land use classificationsystem and the eco-environmental quality index fordifferent land use types

$$Wet - TM = 0.0315 * 0.2021 * b2 + 0.3102 * 0.1594 * b4 +(-0.6806) * b5 + (-0.6109) * b7$$
(5)

Wet - OLI = 0.1511 \* b2 + 0.1973 \* b3 + 0.3283 \* b4 + 0.3407 \* b5 + (-0.7117) \* b6 + (-0.4559) \* b7(6)

where bi (i = 1, ..., 6, 7) is the reflectance of each band of TM/OLI.

(3) Heat index (LST): The heat index is represented by the surface temperature (Cetin 2019), and the calculation equation is:

$$LST = T / \left[ 1 + (\lambda T / \rho) \ln \varepsilon \right]$$
<sup>(7)</sup>

where T is the temperature;  $\lambda$  is the central wavelength of the Landsat TM/OLI thermal infrared band;  $\rho$  is a constant; and  $\varepsilon$  is the emissivity.

(4) Dryness index (NDBSI): The dryness index is a composite of the bare soil index SI and the building index IBI (Xu 2013). The calculation equations are as follows:

$$IBI = \frac{\frac{2b_{swir1}}{b_{swir1} + b_{nir}} - \left[\frac{b_{nir}}{b_{nir} + b_{red}} + \frac{b_{green}}{b_{green} + b_{swir1}}\right]}{\frac{2b_{swir1}}{b_{swir1} + b_{nir}} - \left[\frac{b_{nir}}{b_{nir} + b_{red}} + \frac{b_{green}}{b_{green} + b_{swir1}}\right]}$$
(8)

$$SI = \frac{[(b_{swir1} + b_{red}) - (b_{nir} + b_{blue})]}{[(b_{swir1} + b_{red}) + (b_{nir} + b_{blue})]}$$
(9)

$$NDBSI = (IBI + SI)/2 \tag{10}$$

where  $b_{blue}$ ,  $b_{green}$ ,  $b_{red}$ ,  $b_{nir}$ , and  $b_{swir1}$  stand for blue, green, red, near-infrared, and mid-infrared1 bands, respectively.

After the four indicators, post-normalization can be used to calculate the principal component PC1. To make a large value of PC1 represent higher ecological quality, we subtracted the calculated PC1 by 1 to obtain the initial ecological index RSEI0 (Ji et al. 2020).

$$RSEI0 = 1 - \left\{ PC1 \left[ f(NDVI, Wet, LST, NDSI) \right] \right\}$$
(11)

#### **Revised universal soil loss equation**

The revised universal soil loss equation (RUSLE) has been widely used to simulate soil erosion over large areas (Kabir et al. 2018). The annual soil loss due to water erosion is simulated using the RUSLE model:

$$A = R \times K \times C \times LS \times P \tag{12}$$

where A is the soil loss rate; R is the average annual rainfall erosion force; K is the soil erodibility factor; LS is

the topography (slope length, slope) factor; C is the vegetation cover management measures factor; P is the soil and water conservation measures factor.

Soil erosion data were produced by the Chengdu Institute of Mountain Hazards and Environment, Chinese Academy of Sciences (http://www.imde.ac.cn/), at a spatial resolution of 30 m. In the data, the R-factor is represented by the 40-year average rainfall erosion force from 1981 to 2020; the K-factor is calculated based on the soil map of China at a plotting scale of 1:1 million and soil species information, and it is obtained after interpolation and encryption; the LS factors are represented by the L-factor and S-factor calculated based on the DEM data (AW3D30); the C-factor is calculated based on the GIMMS NDVI and long-term land cover data (Yang and Huang 2021); the P-factor is represented by the land cover data for the C-factor, and the correction factor is calculated based on bare rocky gravelly land correction factors, karstic stone desertification correction factors, etc. (Ju et al. 2015; Liu et al. 2014a). The data was calculated using the improved USLE model and classified according to the "Soil Erosion Classification and Grading Standard" (SL 190-2007). The Chengdu Institute of Mountain Hazards and Environment of the Chinese Academy of Sciences specializes in the study of mountain hazards, mountain environment, and sustainable mountain development, and has complete and accurate meteorological and hydrological data for all regions, with reliable and authoritative data sources. Therefore, the spatial resolution of the calculated soil erosion data is high and accurate, and hence, soil erosion data can be used directly.

#### Ecological contribution rate of land use transitions

The ecological contribution rate of land use transitions is the change in the regional eco-environmental quality caused by the change of a dominant functional land use type, which quantifies the impact of the interconversion between various types of functional land use on the regional ecological environment and is conducive to exploring the dominant factors causing the change in the regional eco-environment (Liu et al. 2014b). The expression is:

$$LEI = (LE1 - LE0) \times LA/TA$$
(13)

where *LEI* is the ecological contribution rate of land use change; *LEO* and *LE1* are the ecological quality index of the initial and final stages of land use change, respectively; *LA* is the area of the change land; *TA* is the total area.

#### **Hotspot analysis**

Hot spot analysis is a type of spatial cluster analysis method that can be used to identify hot and cold spots in the study area. The Getis-OrdGi\* tool in ArcGIS is commonly used to analyze the location relationships in spatial data attributes, using Gi\* as an indicator of local autocorrelation, which helps to determine the extent to which each feature is surrounded by features with similar high or low values (Guo et al. 2021).

# **Results and analysis**

#### **Eco-environmental quality analysis**

#### Analysis of land use change

The land use changes in Erhai Lake Basin were significant between 2000 and 2020 (Fig. 3, Table 2). As shown in Table 2, the land use types in the basin were mainly forest land, followed by grassland and cultivated land, with unused land taking up the least proportion. During the 20 years of study, the area of all land use types in the basin showed an increasing trend, excluding the area of grassland, which decreased. Among them, the area of built-up land witnessed the largest increase by 34.98 km<sup>2</sup>, with a growth rate of 47.12%, followed by cultivated land, which increased by 24.93 km<sup>2</sup> with a growth rate of 7.90%. Grassland was the only area that decreased, by 75.06 km<sup>2</sup>, with a decrease rate of 9.55%. In terms of spatial distribution, forest land and grassland were mainly located along the basin borders; cultivated land was primarily distributed in the upper reach of the basin and the



gentle flat land on the west side of Erhai Lake; built-up land was mainly found in the county seat of Eryuan and the urban area of Dali in the downstream of Erhai Lake; water bodies were mainly concentrated in Erhai Lake, Cibi Lake, and Haixi Lake; and unused land was rarely analyzed for the time being. In terms of sub-basins, the upper reach of the basin was dominated by cultivated land, forest land, and grassland; the middle reaches were dominated by water bodies; and built-up land was concentrated in the lower reaches. Although build-up land encroached on much cultivated land around, the local government could make up for the loss of cultivated land through land improvement initiatives, renovation, and restoration of land use types of low utilization of efficiency, which would lead to an increase in the area of cultivated land.

In 2000–2020, the area of grassland, cultivated land, and forest land witnessed the largest transfer-outs of 120.38 km<sup>2</sup>, 65.66 km<sup>2</sup>, and 34.25 km<sup>2</sup>, respectively (Table 3), while other land use types had smaller areas of transfer-outs. From the perspective of transfer-in, forest land witnessed the largest area of transfer-in, reaching 76.38 km<sup>2</sup>, followed by cultivated land and grassland, with 59.18 km<sup>2</sup> and 45.32 km<sup>2</sup>, respectively. It can be seen that the major shift between land use types during the 20 years as of 2020 was the transfer between forest land, grassland, and cultivated land, which is shown by the marked expansion of built-up land, but the increase in the area of built-up land was primarily from cultivated land. Dali is a tourism-dominated city, where rapid development of tourism has not only boosted economic growth, but accounted



**Fig. 3** Land use distribution in Erhai Lake Basin: the sub-figures **a**, **b**, **c**, **d**, and **e** display the distribution of land use types in 2000, 2005, 2010, 2015, and 2020, respectively

**Table 2**Areas of land use typesin Erhai Lake Basin from 2000to 2020. Unit: km<sup>2</sup>

		2000	2005	2010	2015	2020
Cultivated land	Total area in the basin	315.68	328.65	325.23	333.21	340.61
	Total area in the upper reach	160.17	172.87	171.22	180.09	183.91
	Total area in the middle reach	119.21	119.95	119.37	118.92	121.00
	Total area in the lower reach	36.25	35.77	34.59	34.10	35.59
Forest land	Total area in the basin	1181.58	1172.34	1196.01	1194.88	1192.30
	Total area in the upper reach	630.92	623.21	649.77	651.39	648.88
	Total area in the middle reach	336.35	335.18	332.93	331.65	332.05
	Total area in the lower reach	214.3	213.78	213.29	211.77	211.26
Grassland	Total area in the basin	786.06	769.14	736.53	721.68	711.00
	Total area in the upper reach	449.67	442.56	413.24	404.81	397.6
	Total area in the middle reach	217.53	214.4	211.1	208.78	204.24
	Total area in the lower reach	118.85	116.13	112.01	111.71	109.16
Water	Total area in the basin	253.59	255.87	256.68	254.90	257.26
	Total area in the upper reach	12.48	14.53	15.33	13.68	15.84
	Total area in the middle reach	239.49	239.71	239.80	239.70	239.85
	Total area in the lower reach	1.61	1.63	1.56	1.51	1.57
Built-up land	Total area in the basin	74.24	85.17	96.68	106.39	109.22
	Total area in the upper reach	28.94	31.22	32.51	33.83	34.24
	Total area in the middle reach	24.38	28.52	33.76	38.41	39.82
	Total area in the lower reach	20.93	25.43	30.40	34.16	35.15
Unused land	Total area in the basin	0.04	0.03	0.06	0.13	0.80
	Total area in the upper reach	0.03	0.02	0.05	0.13	0.79
	Total area in the middle reach	0.01	0.01	0.01	0.00	0.01
	Total area in the lower reach	0.00	0.00	0.00	0.01	0.01

for the major reason for quick changes in LULC and substantial increase in the area of built-up land.

# Analysis of regional eco-environmental quality index

According to the ArcGIS natural breakpoint method, the eco-environment quality of the study area was classified into 5 levels (Fig. 4), which were level I (red), level II (orange), level III (yellow), level IV (light green), and level V (dark green), with level V having the highest value. The spatial pattern of eco-environmental quality in Erhai Lake Basin was highly consistent with the spatial distribution of land

use types there, showing lower values in the middle part but higher values along the borders of the basin. The ecoenvironment in the basin was dominated by the high-quality levels of level IV and V. Meanwhile, in the upper-stream, levels II and III were mainly observed in the middle part; in the middle reaches, levels II and III were mainly found on the west of Erhai Lake; and in the lower reaches, level II took up a larger proportion of the area and was primarily found along the lakeside of Erhai Lake. Despite the large differences between regions, the overall pattern remains stable.

The spatial distribution of eco-environmental quality levels in the basin is subject to the topographic and

cm <sup>2</sup>
ŀ

2020	020							
		Cultivated land	Forest land	Grass land	Water bodies	Built-up land	Unused land	Total
2000	Cultivated land	281.43	10.42	10.71	0.26	12.44	0.41	315.68
	Forestland	28.05	1115.92	34.28	1.31	1.89	0.12	1181.58
	Grassland	31.04	65.40	665.68	3.04	20.62	0.27	786.06
	Water bodies	0.08	0.55	0.30	252.63	0.02	0	253.59
	Built-up land	0	0	0	0	74.24	0	74.24
	Unused land	0	0	0.02	0	0	0.01	0.04
	Total	340.61	1192.30	711.00	257.26	109.22	0.80	2611.19

geomorphological characteristics of the basin: the low-elevation and flat middle part, dominated by cultivated land, water bodies, and built-up land, and densely populated, witnessed poor eco-environmental quality and domination by low-quality levels including levels I, II, and III; the borders of the basin, however, were mountainous, dominated by forest land and grassland, and less populated, hence seeing weaker disturbances by human activities, so the eco-environment along the basin borders was good and dominated by high quality levels like levels IV and V.

The overall eco-environmental quality of Erhai Lake Basin showed an upward trend between 2000 and 2020, from 0.5837 in 2000 to 0.5867 in 2020, despite minor fluctuations in between (Table 4). It increased by 0.003 in the 20 years, with an average annual growth rate of 0.015%, indicating that the eco-environmental quality of the basin was improving. However, the total EV in the upper reach increased in fluctuations, whereas that in the middle and lower reaches were constantly moving downwards, which indicates the improving eco-environment in the upper reach but degrading eco-environment in the middle and lower reaches of the basin.

#### Analysis of remote sensing ecological index

It was verified that the study area witnessed positive values of NDVI and WET, but negative values of NDBSI and LST, and the analysis results of RSEI were consistent with reality (Table 5) (Zheng et al. 2022). The average RSEI of Erhai Lake Basin in 2000, 2005, 2010, 2015, and 2020 was

**Fig. 4** EV distribution in Erhai Lake Basin. Sub-figures **a**, **b**, **c**, **d**, and **e** represent the distribution of EV values in 2000, 2005, 2010, 2015, and 2020 in the basin, respectively

0.56, 0.70, 0.73, 0.74, and 0.70, respectively, and the average RSEI increased by 0.14 during the 20 years (Fig. 5, Table 6). Meanwhile, the average RSEI of the upper, middle, and lower reaches of the basin also increased with fluctuations, with an overall increase of 0.17, 0.12, and 0.09, respectively. This indicates that the overall eco-environmental quality of the basin improved continuously from 2000 to 2020.

In the 20 years of study, the middle part of the upper stream of the basin and the lakeside of Erhai Lake in the mid- and down-stream of the basin had the worst eco-environmental quality levels, while the remaining areas had a higher ecological rating. The most apparent changes in ecological quality were found in the areas with the worst and best ecological ratings, both of which were increasing in spatial distribution. This means that ecological protection initiatives have been put in place along with efforts made to economic development, and the improved water quality in Erhai Lake is ample proof in this regard. Poor eco-environmental quality was mainly observed in the upper

 Table 4
 Regional EV values in Erhai Lake Basin in 2000–2020

Year	Total EV of Erhai Lake Basin	Total EV in the upper reaches	Total EV in the middle reaches	Total EV in the lower reaches
2000	0.5837	0.5650	0.6055	0.5925
2005	0.5814	0.5614	0.6047	0.5910
2010	0.5880	0.5766	0.6029	0.5894
2015	0.5861	0.5745	0.6018	0.5864
2020	0.5867	0.5757	0.6021	0.5857



reaches of the basin, the eastern lakeside of Erhai Lake, and the urban area of Dali in the lower reaches of the basin. This is because grassland accounts for the dominating land use type in these regions, and close to water bodies like Erhai Lake and Cibi Lake, these regions have a lower elevation and accommodate cities and towns with frequent human activities. The good and excellent eco-environmental quality levels were primarily distributed in a circular pattern on the high mountains surrounding the basin, especially Cang Mountain in the western part of Erhai Lake, with high altitudes and high forest coverage. As the central part of Cang Mountain National Geopark, the Cang Mountain is primarily for sightseeing purposes only.

#### Soil erosion analysis

Calculations by the RUSLE model showed that soil erosion in Erhai Lake Basin decreased significantly from 2000 to

 Table 5
 Principal component analysis of RSEI in Erhai Lake Basin from 2000 to 2020

Year	Indictors	PC1	PC2	PC3	PC4
2000	NDVI	0.982	0.075	0.173	-0.018
	WET	0.001	-0.509	0.303	0.806
	NDBSI	-0.128	-0.304	0.804	-0.494
	LST	-0.139	0.802	0.481	0.326
	Eigenvalue	0.043	0.021	0.003	0.002
	Percent eigenvalue	61.99	30.03	4.89	3.08
2005	NDVI	0.970	0.193	-0.057	-0.101
	WET	0.082	-0.403	-0.839	0.073
	NDBSI	-0.097	-0.253	-0.280	-0.531
	LST	-0.208	0.858	-0.464	0.383
	Eigenvalue	0.054	0.021	0.003	0.001
	Percent eigenvalue	68.82	26.22	3.22	1.74
2010	NDVI	0.964	0.069	-0.027	-0.257
	WET	0.035	-0.556	-0.827	0.070
	NDBSI	-0.194	-0.422	0.203	-0.862
	LST	-0.180	0.712	-0.523	-0.431
	Eigenvalue	0.059	0.025	0.004	0.002
	Percent eigenvalue	65.86	27.67	4.16	2.30
2015	NDVI	0.987	0.158	-0.019	0.012
	WET	0.020	-0.199	0.011	0.980
	NDBSI	-0.135	0.878	0.425	0.176
	LST	-0.084	0.406	-0.905	0.095
	Eigenvalue	0.115	0.046	0.008	0.000
	Percent eigenvalue	67.66	27.38	4.70	0.27
2020	NDVI	0.956	0.273	-0.098	-0.035
	WET	0.047	-0.247	0.115	-0.961
	NDBSI	-0.278	0.745	-0.542	-0.270
	LST	-0.075	0.556	0.826	-0.047
	Eigenvalue	0.083	0.026	0.005	0.000
	Percent eigenvalue	72.63	22.78	4.39	0.19

2020. In 2000, 2005, 2010, 2015, and 2020, the average soil erosion modulus in the basin was 105.34, 97.18, 92.90, 92.94, and 89.86 t/(km<sup>2</sup>·a) (Fig. 6, Table 7), and the average soil erosion modulus decreased by 15.48 t/(km<sup>2</sup>·a) in 20 years, with an average annual decrease rate of 14.70%. In terms of sub-basins, the average modulus in the upper reaches decreased from 121.37 t/(km<sup>2</sup>·a) in 2000 to 105.88 t/ (km<sup>2</sup>·a) in 2020; in the middle reaches, the average modulus fell from 75.75 t/(km<sup>2</sup>·a) in 2000 to 61.78 t/(km<sup>2</sup>·a) in 2020; and in the lower reaches, the modulus fell from 124.47 t/ (km<sup>2</sup>·a) in 2000 to 105.29 t/(km<sup>2</sup>·a) in 2020. In sum, the mean soil erosion modulus of all sub-basins of the study area showed a decreasing trend, indicating that the eco-environment of the sub-basins has kept improving over the years of study (Li et al. 2020a).

Overall, the vast majority of the study area showed slight and light intensity of soil erosion. However, the slight, light, and moderate soil erosion was widely distributed, occupying almost the entire Erhai watershed. Areas seeing strong erosion and above accounted for a low percentage of the total area of the basin and were principally distributed in the grasslands in the upper reaches of the basin. Despite the small area of regions with strong soil erosion, the amount of soil erosion was high. Most regions witnessing strong soil erosion were in the hills near cultivated land, and most of them were grassland with low vegetation cover, which were susceptible to disturbances by human activities and could be easily reclaimed into cultivated land. Furthermore, in the case of soil erosion caused by scouring during rainfalls, substances like nitrogen and phosphate will enter the rivers and lakes, resulting in NPS pollution. The average soil erosion modulus of the upper and lower reaches of Erhai Lake Basin were approximately the same, and both showed strong soil erosion, but the area of soil erosion in the upper reaches (1279.91 km<sup>2</sup>) was three times as much as that in the lower reaches (390.75 km<sup>2</sup>), which means that the upper reaches of Erhai Lake Basin suffered stronger soil erosion than the lower reaches of the basin.

# Comparative analysis of measurements by the three indicators

Comparative analyses of the figures and tables above revealed the following findings:

The average values of the EV and RSEI increased during the 20 years of study, both indicating that the overall ecoenvironment of Erhai Lake Basin was improving. The average soil erosion modulus of the basin decreased significantly from 2000 to 2020, which likewise indicated the constantly improving eco-environment in the basin.

The EV was calculated on the basis of land use types, so the calculation result had a high consistency with the spatial and temporal changes of land use types. For instance,



regional eco-environment quality level I corresponded to unused land, level II corresponded to built-up land, level III corresponded to cultivated land, level IV corresponded to grassland and water bodies, and level V corresponded to forest land. The spatial distribution of EV values shows that the eco-environmental quality in the central part of the basin was better than along the borders of the basin, and the quality in the upper reaches was poorer than in the middle and lower reaches of the basin. Analysis of the distribution of RSEI values showed that good eco-environmental quality was mainly observed in the forest land zones along the borders of the basin, whereas poor eco-environmental quality was mainly found in the grassland and built-up land zones in the middle reaches, and the area was expanding. From the viewpoint of soil erosion, slight and mild soil erosion accounted for the dominating intensity of erosion in the study area, mainly found along the borders of the basin,

Table 6	Average	RSEL	in Erhai	Lake	Basin	from	2000	to 2020
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Year	Mean RSEI	Mean RSEI in the upper- stream	Mean RSEI in the midstream	Mean RSEI in the downstream
2000	0.56	0.53	0.58	0.60
2005	0.70	0.69	0.71	0.71
2010	0.73	0.72	0.73	0.73
2015	0.74	0.74	0.73	0.73
2020	0.70	0.70	0.70	0.71

whereas strong soil erosion was mainly distributed in the middle and lower reaches of the basin as well as the lakeside of Erhai Lake.

Analyses of EV values indicate that the eco-environmental quality of unused land and built-up land was poor, whereas the eco-environmental quality of grassland and forest land was good. Analyses of the indicator RSEI showed that the eco-environmental quality of unused land and grassland in the basin was poor, whereas that of forest land was better. Analyses of soil erosion intensity indicated that the strongest soil erosion was found on unused land and grassland, whereas other land use types showed weaker soil erosion. All these three indicators showed that forest land had the best eco-environmental quality, unused land had the worst quality, and cultivated land was somewhere in between. Because the land use type of water bodies was not involved in the calculation of RSEI, comparison with EV and soil erosion indicators for this land use type was not available, and the eco-environmental quality for this land use type thus could not be identified, and it is not analyzed here. Grassland turned out an exception: RSEI and soil erosion modulus of this land use type showed that grassland had poor eco-environmental quality, but its EV did not suggest the same thing. This is because it is widely accepted that grassland could retain water and soil; the grassland in Erhai Lake Basin had poor vegetation cover, but was assigned a high value in evaluation of the eco-environmental quality index, and hence, analysis based on EV revealed that grassland in the study area had high eco-environmental quality.

**Fig. 6** Distribution of soil erosion intensity in Erhai Lake Basin. Sub-figures **a**, **b**, **c**, **d**, and **e** display the distribution of soil erosion intensity in the basin in 2000, 2005, 2010, 2015, and 2020, respectively



 Table 7
 Average soil erosion modulus in Erhai Lake Basin from 2000 to 2020

Year	Mean erosion modulus/t/ (km <sup>2</sup> ·a)	Mean erosion modulus in the upper reaches/t/(km <sup>2</sup> ·a)	Mean erosion modulus in the mid- dle reaches/t/( $km^2 \cdot a$ )	Mean erosion modulus in the lower reaches/t/( $km^2 \cdot a$ )
2000	105.34	121.37	75.75	124.47
2005	97.18	113.48	66.99	116.81
2010	92.90	110.52	63.38	106.61
2015	92.94	106.93	65.20	114.21
2020	89.86	105.88	61.78	105.29

In the present work, the eco-environment of Erhai Lake Basin under land use changes was analyzed on three dimensions: EV, RSEI, and soil erosion, all of which showed that the eco-environment of Erhai Lake Basin was improving, but there were also regional differences between the upper, middle, and lower reaches of the basin. This finding is generally consistent with statements in official documents including "Report on the State of the Environment in China," "Outline of the 13th Five-Year Plan for the Protection and Management of the Erhai Lake and the Ecological Construction of the Basin," and "Report on the State of the Environment in Yunnan Province." For example, in the two reports mentioned above, it is pointed out that the nitrogen and phosphorus content of the Erhai Lake has significantly reduced, and the water quality is close to level II from level III.

The analysis result of EV was affected by human factors such as the accuracy of land use type interpretation and the

assignment of weights to indicators, which may sometimes fail to accurately reflect the regional eco-environment quality. Calculations of soil erosion are complex, because underlying data are enormous and not easily accessible, and the results are sometimes distorted. However, RSEI is calculated based on remote sensing images, which are easy to obtain; it is easy to calculate, free from influences of human factors, and can authentically reflect the eco-environmental quality of a region. Therefore, RSEI is the most regionally adaptable among all the three indicators.

## Ecological contribution rate of land use transition

From 2010 to 2020, the transition from grassland into forest land was the major form of land use transition and the leading contributor to the improved eco-environmental quality in the basin (Table 8), accounting for 38.73% of the total contribution, followed by the transition of cultivated land to forest land, accounting for 32.54% of the total contribution. The contribution of major land use transitions to ecological improvement was 0.00700, accounting for 98.37% of their total ecological contribution. The main types of land use transitions leading to deterioration of eco-environmental quality were the transitions from forest land into cultivated land, grassland into cultivated land, and grassland into builtup land, which accounted for 32.18%, 28.85%, and 23.65% of the total contribution, respectively. The ecological contribution of major land use transitions to ecological deterioration was 0.01887, accounting for 97.43% of their total ecological contribution.

Land use transition is a double-edged sword for regional ecology, with both advantages and disadvantages. The difference between the rates of contribution to ecological improvement and to ecological deterioration was not significant, and the overall situation of eco-environmental quality was stable. Nonetheless, a stable regional eco-environmental quality index does not mean that there are no changes in the eco-environment. In general, ecological improvement and ecological deterioration coexisted in Erhai Lake Basin, but the trend of ecological improvement was slightly greater than the trend of environmental deterioration. As the ecoenvironment of Erhai Lake Basin is continuously restored and improved, the EV of the basin will continue to rise in the future.

#### **Hotspot analysis**

The data on RSEI and soil erosion modulus were resampled at a resolution of  $1 \times 1$  km, and finally 2350 and 2401 sampling points were selected for hot spot analysis, respectively (Fig. 7 and Fig. 8). As shown in Fig. 7, hotspot analysis of soil erosion in Erhai Lake Basin revealed that most of the study area had no statistical significance, with a few hot spots but no cold spots. Over the last 20 years, the area of spatially concentrated hot spots first increased and then decreased, and mainly distributed in the southern part of the upper reach as well as the lakeside of the middle and lower reaches of the basin. Hot spots with a statistically significant soil erosion confidence level of 99% accounted for the largest proportion of all hot spots in the study area. In terms of spatial distribution, the hot spots overlapped with regions with serious soil erosion, including strong and extreme soil erosion.

Different from the result of hot spot analysis on soil erosion, the hotspot analysis on RSEI of Erhai Lake Basin showed a statistically significant area of cold spots (Fig. 8). Over the 20 years of study, the spatially concentrated area of the hot spots of RSEI exhibited a decrease first and then an increase, whereas the spatially concentrated area of the cold spots exhibited a decrease followed by an increase in the upper reach and a gradual increase in the middle and lower reaches of the basin. The hot spots were mainly found along the basin borders. These areas were distributed in the upper, middle, and lower reaches of the basin, with the western mountains in the middle reaches witnessed the highest concentration of hot spots, followed by the southernmost part of the lower reach of the basin, where mountains were the major land form and forest land was the dominating land use type. Cold spots were distributed throughout the basin, with the highest concentration at the junction of the middle and lower reaches, followed by the upper reaches, and these areas were dominated by grassland and built-up land.

# Discussion

Sometimes single ecological indicator is not enough to fully reflect the eco-environmental situation of the study area. However, combining multiple ecological indicators can make up for the shortcomings of evaluation based on single indicators and thus more accurately represent the eco-environmental condition of the study area (Sun et al. 2020; Liu et al. 2021).

There is a natural coupling between LULC and ecosystem quality (Dong et al. 2021). Indicators including EV, RSEI, and soil erosion, all calculated based on LULC data,

 Table 8
 Major land use transitions and their ecological contribution rates in Erhai Lake Basin in 2000–2020

To ecological improvement			To ecological degradation				
Major land use transitions	Ecological con- tribution rate	Percentage/%	Major land use transitions	Ecological con- tribution rate	Percentage/%		
Cultivated land to forest land	0.00231	32.54	Cultivated land to built-up land	0.00052	2.71		
Cultivated land to grassland	0.00193	27.10	Forest land to cultivated land	0.00623	32.18		
Grassland to forest land	0.00276	38.73	Forestland to grassland	0.00144	7.46		
Total	0.00700	98.37	Forest land to built-up land	0.00050	2.58		
			Grassland to cultivated land	0.00559	28.85		
			Grassland to built-up land	0.00458	23.65		
			Total	0.01887	97.43		



show that the eco-environment in Erhai Lake Basin has been improving. However, EV is not a direct indicator of good ecological quality, and land use types often reflect more obvious ecological differences. Meanwhile, calculation of the overall EV of a study area is considerably subject to the interpretation accuracy of remote sensing images and the EV value of each land use type. Soil erosion is an indicator that visualizes the ecological quality of the study area by the amount of soil erosion, but there are errors. RSEI, an indicator that measures eco-environmental quality based on

the features of remote sensing images alone, is less subject to human influences and reflects the environmental conditions of the study area more accurately than other indicators (Zheng et al. 2022). Methods like ecological evaluation under the pressure-state-response (PSR) framework, weight determination of ecological indicators by the analytical hierarchical process (AHP), and construction of multi-ecological indicator systems (Chang et al. 2019) are approaches that rely on multiple ecological indicators for eco-environmental quality evaluation and have seen wide adoption in ecological quality assessment of towns (Boori et al. 2021), wetlands (Zhang et al. 2021c), plateaus (Li and Wu 2022), mountains (Wu and Zhao 2021), and lake basins (Yu et al. 2020). These multi-indicator approaches are found to perform better in ecological quality assessment than their single-indicator counterparts, which is aligned with the findings of our work here and suggests that multi-ecological indicators are an effective supplement to the EV indicator.

There were land use transitions that lead to ecological improvement, but there were also transitions that result in ecological degradation; these two types of transitions offset each other, and hence sometimes failed to reach accurate reflection of the ecological situation of the study area (Li and Wu 2022; Biswas and Gangwar 2021). However, it is certain that the area of land use transitions that contributed to ecological improvement was larger than that contributing to ecological degradation. The primary reason is that the conservation policies of Erhai Lake have achieved good results (Xu et al. 2014). Xiong et al. (2021) found based on analysis of RSEI that the eco-environment in Erhai Lake Basin was improving, which is consistent with the findings of our work here. Land use transitions in China are profoundly reflected in ecological changes, including improved water quality in lakes and rivers (Yu et al. 2020), increased forest cover, significantly reduced carbon emissions (Tang et al. 2022), and transformation of deserts into oases, which are attributed to adoption and promotion of ecological conservation policies (Gou et al. 2021).

The data on RSEI and soil erosion modulus are raster data, while the EV data cannot be parsed by hotspot analysis because of the agglomeration feature of the data. "The 13th Five-Year Plan for the Protection and Management of the Erhai Lake and the Ecological Construction of the Basin" and Zheng et al. (2021) also have pointed out that the upper reach of Erhai Lake Basin suffered the worst soil erosion and NPS pollution. In some other works, it was found that chromophoric dissolved organic matter (CDOM) concentration (Zhang et al. 2021a) and chlorophyll (Wang et al. 2021) in Erhai Lake were generally high in the north and low in the south, which is consistent with the results of hotspot analysis. The upper reach of the basin accommodates most cultivated land in the basin. Meanwhile, dominated by grassland and with sparse vegetation cover, the upper reach of the basin cannot retain soil and water, which is among the causes of NPS pollution (Zhang

et al. 2021a). NPS pollution is the most serious eco-environmental concern in Erhai Lake Basin (Li et al. 2020a). Though initiatives like ecological restoration and wetland construction have improved the water quality of Erhai Lake, the problem of water pollution remains. Therefore, how to further reduce the discharge of pollutants such as nitrogen and phosphorus is key to eutrophication management of Erhai Lake and ecological protection of Erhai Lake Basin.

Currently, chemical fertilizers and pesticides have been banned throughout the basin, and much cultivated land has been transferred into other land use types or planted with cash crops. Also, production and domestic wastes have been effectively managed, which solved the problem of discharge of pollutants like nitrogen and phosphorus from the source (Zhong et al. 2018). Analyses based on multiple ecological indicators showed that the low vegetation cover of grassland in Erhai Lake Basin is another reason for ecological degradation of the basin. Thus, strengthening vegetation restoration of grassland and removing sloping cultivated land are important measures to reduce soil erosion, decrease discharge of pollutants into the lake, and improve water quality and eco-environment of Erhai Lake Basin (Jin et al. 2017). Despite the good eco-environment in the middle reaches of Erhai Lake, it is necessary to continue increasing vegetation cover, control the expansion of cultivated land, and maintain the achievements of pollution control initiatives of Erhai Lake. In the lower reaches of the basin, it is crucial to control urban expansion and curtail discharge of NPS pollutants.

Evaluating the impact of land use transition on the ecoenvironment principally focuses on its impact on a single ecological factor (Ren et al. 2021), but ecological quality of a region is subject to multiple factors (Wu and Zhang 2021). The initial eco-environmental state of the region also plays a part (Hu et al. 2021). Thus, in future works, it is necessary to explore the following topics: how to make eco-environment quality indicators better aligned with reality, how to select proper evaluation indicators as the studied region differs, and how to measure the impacts of the scale and precision of land use classification on the evaluation result.

# Conclusions

In the present work, quantitative indicators including EV, RSEI, soil erosion, and ecological contribution rate are combined to analyze changes in the eco-environment caused by land use transitions, reveal the correlations between LULC and the eco-environment quality of the basin, and achieve quantitative evaluation of the eco-environment in Erhai Lake Basin.

(1) From 2000 to 2020, the Erhai Lake Basin witnessed an increase in cultivated land, forestland, water bodies, build-up and unused land, but a decrease in grassland. Forestland, grassland, and cultivated land were the main land use types affecting the ecological status of the study area, and were also the land use types that marked the most significant land use transitions, mainly in the upper reaches of the basin.

(2) Over the 20 years of study, the EV value increased by 0.003, the mean value of RSEI increased by 0.14, and the average value of soil erosion modulus decreased by 15.48 t/(km<sup>2</sup>·a). All three indicators suggest that the eco-environment of Erhai Lake Basin was improving and would continue improving in the future. The combination of multiple ecological indicators could provide a more accurate picture of the ecological condition of the study area than assessment based on of single indicators.

(3) Changes in EV, RSEI, and soil erosion all indicated that the ecological environment of the basin was improving, but with significant regional distinctions. Forestland had the best ecological quality, while unused land and built-up land had the worst ecological quality. Meanwhile, the indicator RSEI is simple to calculate, less influenced by human factors, and has stronger regional adaptability. (4) Ecological improvement and ecological deterioration coexisted in Erhai Lake Basin, but the trend of ecological improvement was slightly greater than the trend of environmental deterioration. The transitions of cultivated land into other land use types were the main reason for improved ecological quality of the basin. Tourism has accelerated land use transformation and resulted in rapid expansion of build-up land. The upper part of the basin had the greatest impact on the ecological quality of the study area and hence is a key zone for control.

Author contribution Conceptualization: Yakun Dong, Wei Ma, Yu Wang, Weijun Zeng; methodology: Yakun Dong, Wei Ma, Zhiwei Tan, Weijun Zeng; writing—original draft: Yakun Dong, Wei Ma, Zhiwei Tan; writing—review and editing: Yakun Dong, Wei Ma, Zhiwei Tan, Yu Wang, Weijun Zeng.

**Funding** We thank the National Natural Science Foundation of China (grant No. 41961040) and the Yunnan Province Agricultural Joint Special General Project (grant No. 202101BD070001-101) for providing financial support.

**Data availability** All data generated or analyzed during this study are included in this published article.

# Declarations

Ethics approval and consent to participate Not applicable.

Consent for publication Not applicable.

**Competing interests** The authors declare no competing interests.

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