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Evaluation of the Impacts of Land Use on Water Quality: A Case Study in Erhai Lake Basin

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Abstract: Erhai Lake, the second-largest freshwater lake in the Yunnan Province of China, has a flourishing tourist industry. Unfortunately, many problems such as deterioration of water quality and eutrophication were occurred in Erhai Lake, leading to numerous environmental problems. Chlorophyll-a (chl-a) is a critical ecological and environmental parameter for water quality, which plays an important role in the wetland environment and eutrophication of water. Human-induced land-use change can indicate the degree of the interference of anthropogenic activities on the regional ecological environment. Therefore, understanding the relationships between changes in land use and water quality is of great importance to improve water pollution control and for providing guidelines for land use planning. However, the effects of ongoing anthropogenic activities on water quality in Erhai Lake Basin are not well understood. Closing this knowledge gap first requires obtaining accurate chl-a concentration information. The Landsat TM/ETM+/OLI imagery were used to estimate the chl-a concentration in Erhai Lake from 1988 to 2020. Long-term chl-a distributions of Erhai Lake revealed the changing trend of water quality. Besides, a Random Forest classifier could be applied to spectral features extracted from time-series of Landsat TM/ETM+/OLI imagery, ranging from 1988 to 2020, to increase the accuracy of land cover classification. The classification results show the spatiotemporal patterns and characteristics of land-use change in Erhai Lake Basin. The land use change has a direct impact on water quality varied over nearly five decades; both positive and negative effects for certain land-use types were found in Erhai Lake Basin. These findings shed new light on the impact changes of land use on water quality and provide a scientific foundation for land use management and remediation plans.

Keywords: land use; chl-a; Random Forest; Erhai Lake Basin

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1. Introduction

As valuable ecosystem and natural resources, inland lakes not only provide crucial habitats for wildlife including aquatic species and a multitude of mammals[1,2], but also act as hot spots of global carbon cycling and major players of climate change[3], providing critical ecosystem services and mitigating the impact of floods and droughts by their own storage functions[4]. However, a large number of inland lakes have been confronted with severe water quality deterioration[5], such as eutrophication[6]. Erhai Lake, located in the northwestern of Yunnan Province, China (Figure 1), is also facing the problem of cyanobacteria bloom[7]. Therefore, it is vital to monitor the long-term water quality of Erhai Lake.

The Chlorophyll-a (chl-a) concentration is one of the key water quality parameters that play a critical role in affecting ocean biology and ecology[8]. The use of the traditional field sampling methods could only reveal the accurate information for specific sites, which is insufficient in spatial and temporal coverage to derive statistically meaningful results[9]. With better spatial distribution and temporal resolution than the traditional techniques, remote sensing technology can acquire the distribution of chl-a at large spatial scales[10]. Many methods have been proposed to retrieval the chl-a concentration based on remote sensing images in previous studies. The empirical algorithms have been widely used in ocean color remote sensing monitoring as the potential advantage of simple and convenient in application[11,12]. Based on the empirical equations, bio-optical models, and radiation transfer models, the semi-analytical algorithms have been proposed for retrieving optically significant constituents (OSCs), such as the chl-a concentration[13,14]. Machine-learning approaches like random forest (RF) approach performed reasonably well to capture the nonlinear relationship instead of the commonly used methods in previous studies[15].

Many other ocean colour satellites have been launched to monitoring biological parameters of the water environment, such as Sea-Viewing Wide Field-of-View Sensor (SeaWiFS), Moderate Resolution Imaging Spectroradiometer (MODIS), and the Visible Infrared Imaging Radiometer Suite (VIIRS)[16]. However, the spatial and spectral resolutions of current remote sensors can hardly meet the requirements of inland water color parameters' inversion due to the relatively small size of inland waters and their complex optical properties. Considering the limited time span of Medium Resolution Imaging Spectrometer (MERIS), it is difficult to reveal the long-term variation of chl-a concentration. Fortunately, the Landsat TM/ETM+/OLI sensors provided a significant advantage over the ocean colour sensors with long term observations and a higher spatial resolution (30 m full resolution), which has been widely used in inland water monitoring. For example, the 2013–2018 time series of 296 Landsat imageries were used by Markogianni et al. (2020) to quantify the chl-a concentration[17].

To bridge the abovementioned gaps, this study aims to monitor the chl-a concentration from 1988-2020 in Erhai Lake based on the Landsat TM/ETM+/OLI data. We had the following specific objectives:

(1) To obtain accurate results of chl-a concentration between 1988 and 2020.

(2) To explore the driving forces behind the long-term variation of chl-a concentration according to quantitative results of related land-use and land-cover data analyses.

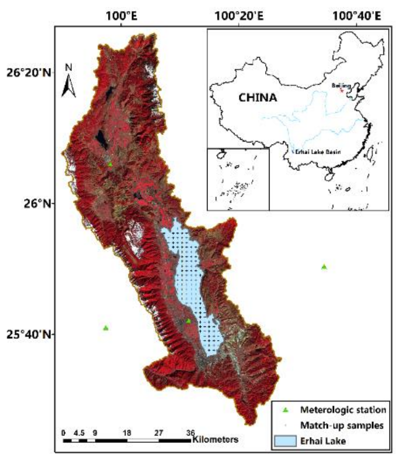

Figure 1. The location of Erhai Lake, match-up samples, and the meterologic stations in Erhai Lake Basin

2. Results

2.1. Chl-a Distributions in Erhai Lake from 1988 to 2020

Derived from Landsat TM/ETM+/OLI images between 1988 and 2020, Figure 2 demonstrated the spatio-temporal variations of chl-a in Erhai Lake. The mean chl-a concentration of Erhai Lake ranges from 11.12 to 13.0 mg/m^3. It went through ups and downs between 1988 and 2020 and reached the highest annual average chl-a (13.0 mg/m^3) in 2000. In the following two decades, the annual average chl-a decreased gradually. From space, the chl-a in the south part of Erhai Lake was higher than that in the northern. The chl-a concentration decreased gradually from nearshore to the center of the lake.

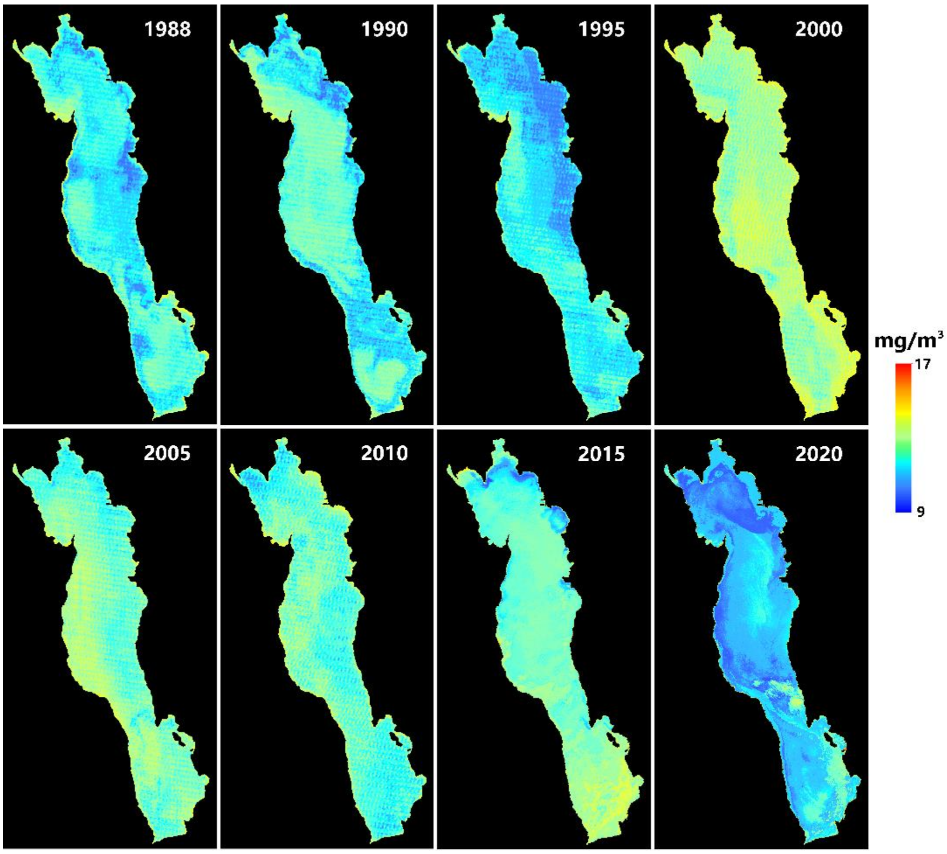

Figure 2. Landsat-derived chl-a distributions in Erhai Lake between 1988 and 2020.

2.2. Land Cover Types changes in Erhai Lake Basin between 1988 and 2020

Figure 3 shows the classification maps for each of the Landsat images between 1988 and 2020s. The spatial distributions of eight land cover types were clearly demonstrated within each panel, and the long-term land cover changes were also revealed. In general, Erhai Lake Basin witnessed the large degradation of grassland, cropland, and mining land, accounting for 15.9%, 4.1%, and 3.8% of the total area in its region. Forest, garden, and building areas were increased in the past 32 years, accounting for 17.4%, 0.9%, and 2.0% of the total area. The Erhai Lake area remained almost unchanged.

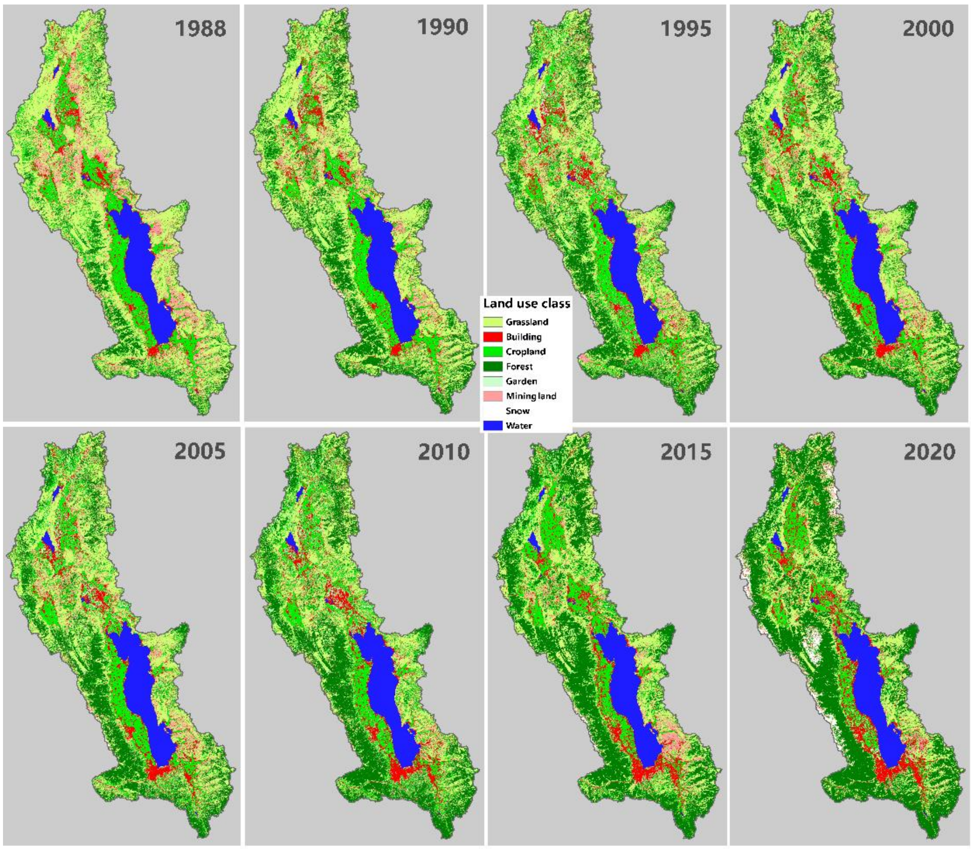

Figure 3. Eight land cover types (including grassland, cropland, forest, garden, building, mining land, snow, and water) changes in Erhai Lake Basin between 1988 and 2020.

3. Discussion

The percentages of eight land cover types in Erhai Lake Basin from 1988 to 2020 are plotted in Figure 4 to facilitate visualization. With the increase of cropland, building area, and mining land, the mean chl-a concentration of Erhai Lake was also increasing gradually. The sum of cropland, building, and mining land reached the highest percentage in 2000, which led to the mean chl-a concentration in 2000 was significantly higher than that in other years. After that, with the increase of forest area, the mean chl-a concentration of Erhai Lake gradually decreased. The water quality of Erhai Lake was improved.

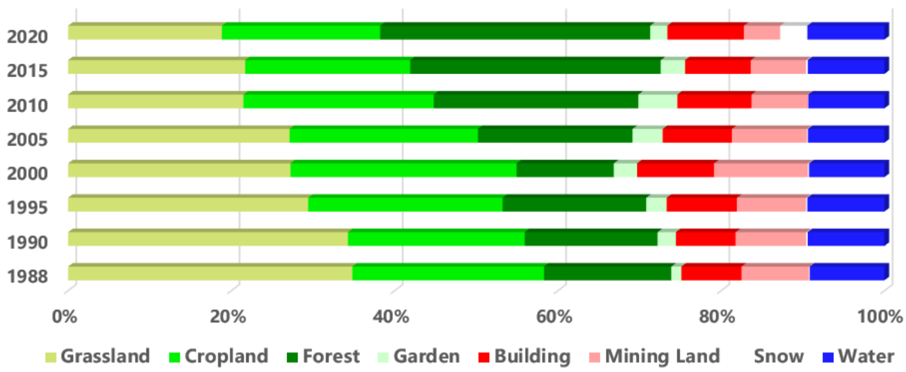

Figure 4. Percentages of eight land cover types in Erhai Lake Basin between 1988 and 2020.

4. Materials and Methods

Landsat TM/ETM+/OLI imagery were downloaded from the United States Geological Survey (http://www.usgs.gov/) with no cloud in Erhai Lake Basin that spanned from 1988 to 2020 (Table 1).

Regarding Landsat TM/ETM+/OLI imagery, data preprocessing include the radiometric calibration and atmospheric correction, which can be completed in ENVI software.

The MERIS satellite is suitable for retrieving chl-a in Erhai Lake. Due to the limited data points, we referred to the chlorophyll retrieval results based on MERIS satellite of Han et al. (2014). To consistent with the MERIS data format, the Landsat data were resampled to 300m by using the bilinear method. Then, 112 match-up points (Figure 1) were randomly selected to conduct point-to-point modeling by using the random forest regression model obtaining the relative true with high spatial resolution[18]. Finally, the median filtering algorithm was applied to remove the noise in chlorophyll retrieval maps. The second task of this study is to discriminate the different land cover types based on Landsat images. High-resolution images are accessible freely from Google Earth™ (http://earth.google.com) and could be used as ground-truth for selecting the different land cover samples. Furthermore, the random forest classification model was employed to build the nonlinear relationship between ground-truth samples with remote sensing images for quantitatively identify the land-use transitions[18]. Then, the land cover of the Erhai Lake Basin was classified into eight major types, including grassland, cropland, forest, garden, building, mining land, snow, and water.

Table 1. Information of Landsat TM/ETM+/OLI images used in this studys.

Sensor	Path/row	Acquisition Date	Resolution
TM	131/42	1988-02-09	30
TM	131/42	1990-12-31	30
TM	131/42	1995-12-13	30
ETM+	131/42	2000-12-02	30
TM	131/42	2005-01-06	30
TM	131/42	2010-12-22	30
OLI	131/42	2015-03-07	30
OLI	131/42	2020-01-16	30

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Author Contributions: The authors undertook different tasks for this paper. Jialin Wang wrote and revised the paper. Jianzhong Lu gave the help for comments and discussions. Xingxing Han designed the research. Zhan zhang analyzed the data. Xiaoling Chen provided direction to the research work. All authors have read and approved the final manuscript.

Conflicts of Interest: The authors declare no conflict of interest.

Abbreviations

The following abbreviation is used in this manuscript:

Chlorophyll-a: chl-a

References

1. Johnson, N.; Revenga, C.; Echeverria, J. Managing water for people and nature. Science 2001, 292, 1071-1072.
2. Beeton, A.M. Large freshwater lakes: present state, trends, and future. Environmental Conservation 2002, 21-38.
3. Tranvik, L.J.; Downing, J.A.; Cotner, J.B.; Loiselle, S.A.; Striegl, R.G.; Ballatore, T.J.; Dillon, P.; Finlay, K.; Fortino, K.; Knoll, L.B. Lakes and reservoirs as regulators of carbon cycling and climate. Limnology and oceanography 2009, 54, 2298-2314.

4. Xie, C.; Huang, X.; Mu, H.; Yin, W. Impacts of land-use changes on the lakes across the Yangtze floodplain in China. Environmental science & technology 2017, 51, 3669-3677.
5. Dai, X.; Zhou, Y.; Ma, W.; Zhou, L. Influence of spatial variation in land-use patterns and topography on water quality of the rivers inflowing to Fuxian Lake, a large deep lake in the plateau of southwestern China. Ecological Engineering 2017, 99, 417-428.
6. Le, C.; Zha, Y.; Li, Y.; Sun, D.; Lu, H.; Yin, B. Eutrophication of lake waters in China: cost, causes, and control. Environmental management 2010, 45, 662-668.
7. Tan, W.; Liu, P.; Liu, Y.; Yang, S.; Feng, S. A 30-year assessment of phytoplankton blooms in Erhai Lake using Landsat imagery: 1987 to 2016. Remote Sensing 2017, 9, 1265.
8. Fijani, E.; Barzegar, R.; Deo, R.; Tziritis, E.; Skordas, K. Design and implementation of a hybrid model based on two-layer decomposition method coupled with extreme learning machines to support real-time environmental monitoring of water quality parameters. Science of the total environment 2019, 648, 839-853.
9. Feng, L.; Hu, C.; Han, X.; Chen, X.; Qi, L. Long-term distribution patterns of chlorophyll-a concentration in China's largest freshwater lake: MERIS full-resolution observations with a practical approach. remote sensing 2015, 7, 275-299.
10. Tyler, A.; Svab, E.; Preston, T.; Présing, M.; Kovács, W. Remote sensing of the water quality of shallow lakes: A mixture modelling approach to quantifying phytoplankton in water characterized by high-suspended sediment. International Journal of Remote Sensing 2006, 27, 1521-1537.
11. E, O.R.J.; S, M.; G, M.B. Ocean color chlorophyll algorithms for SeaWiFS Journal of Geophysical Research: Oceans 1998, 103, 24937-24953.
12. C, H.; Z, L.; B, F. Chlorophyll aalgorithms for oligotrophic oceans: A novel approach based on three-band reflectance difference. Journal of Geophysical Research: Oceans 2012, 117.
13. S, M.; A, S.D.; R, P.A. Optimization of a semianalytical ocean color model for global-scale applications. Applied optics 2002, 41, 2705-2714.
14. E, H.F.; W, W.C.; E, L.P. Inherent optical properties imagery of the western North Atlantic Ocean: Horizontal spatial variability of the upper mixed layer. Journal of Geophysical Research: Oceans 2001, 106, 31129-31140.
15. W, Z.; N, S.; H, L. A spatial downscaling approach for the SMAP passive surface soil moisture product using random forest regression. Journal of hydrology 2018, 563, 1009-1024.
16. McClain; R, C. A decade of satellite ocean color observations. Annual Review of Marine Science 2009, 1, 19-42.
17. V, M.; D, K.; P, P.G. Estimating chlorophyll-a of inland water bodies in Greece based on landsat data. Remote Sensing 2020, 12, 2087.
18. V, S.; A, L.; C, T. Random forest: a classification and regression tool for compound classification and QSAR modeling. Journal of chemical information and computer sciences 2003, 43, 1947-1958.