CHARACTERIZATION OF SPATIOTEMPORAL CHANGES IN SURFACE WATER AREA IN KUNMING, CHINA (1990–2020)

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Abstract. Surface water area is a crucial indicator reflecting the status of water resources and changes in the water environment. Changes in surface water area have a significant impact on ecosystem function, the hydrological cycle, and climate change. In this study, with NDWI (Normalized Difference Water Index), the characteristics and causes of the long-term changes of the surface water area in Kunming were analyzed by PIE-engine remote sensing computing cloud service platform based on Landsat TM/ETM+ remote sensing images. The results suggest that the water area of Kunming demonstrated a W-shaped trend in the past 30 years, with a dynamic fluctuation of first decreasing and then increasing, followed by decreasing and then increasing. The change of water area in Kunming is mainly influenced by natural and anthropogenic factors. Natural factors mainly include climate change. Anthropogenic factors mainly comprise urban expansion, development and utilization of urban water resources, land use changes, water conservancy project construction, and environmental pollution. By analyzing the characteristics of watershed area changes over the past 30 years, this study provides an effective methodology and data support for monitoring and protecting the watershed area in Kunming. The objectives of this study are threefold: (i) to extract and quantify the long-term spatial and temporal changes of surface water area in Kunming from 1990 to 2020 using Landsat imagery on the PIE-Engine platform; (ii) to identify the main natural and anthropogenic drivers influencing these changes; and (iii) to provide scientific references for the management, protection, and ecological restoration of water resources in Kunming.
Keywords: *Landsat time series, NDWI, Otsu thresholding, topographic controls, urbanization*

Introduction

In recent decades, Kunming, as the capital of Yunnan Province, has experienced a remarkable urbanization process (Yangyang et al., 2023). During this process, the utilization and protection of water resources have become vital issues. Since the reform and opening up, the Dianchi basin, as one of the most significant areas of ecological degradation of rivers and lakes in China, has attracted widespread attention (Lee et al., 2024). From the 1990s to the present day, Kunming has been subjected to rapid economic and social development, accompanied by a dramatic increase in water demand (Li et al., 2012a). Concurrently, the region has suffered from persistent droughts, and exacerbating water resource scarcity (Zhang et al., 2024). The ecological degradation of rivers and lakes in Kunming and the subsequent ecological restoration efforts have exerted a considerable impact on the city's domestic and industrial water use (Wu et al., 2024). In this context, monitoring and analyzing the surface water area in Kunming is essential. From another perspective, the Ministry of Water Resources

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(MWR) issued the Guiding Opinions on Recovering the Ecological Environment of Rivers and Lakes and the Implementation Program for Recovering the Ecological Environment of Rivers and Lakes during the 14th Five-Year Plan Period in 2021. They explicitly require that "by 2025 the crowded ecological water use of rivers and lakes in the Haihe River Basin will be returned to a certain extent, and that shrinking and drying up of the key The water surface of lakes that have shrunk and dried up will be restored" (Ministry of Water Resources of the People's Republic of China, 2021). With the purpose of realizing the ecological restoration of rivers and lakes in Kunming, two crucial parameters should be determined. One is the total area of the watershed, that is, how big is the "container of water"; the other is the actual area of the water surface, that is, how much water is in the "container". Water area is one of the land use types, affected by various factors such as precipitation, evaporation, artificial recharge and groundwater level. At present, the scale and size of the water area of rivers, lakes, and ponds in Kunming remain unclear and lacks systematic analysis, especially the change rule of the water surface area of rivers and lakes after carrying out water diversion and recharge projects. Moreover, climatic factors and their changes are essential factors affecting the changes of local waters, thus influencing the local spatial and temporal change characteristics (Dai et al., 2024; Li et al., 2012a; Ling et al., 2023; Miao et al., 2020). Under the requirement of ecological restoration of rivers and lakes, thus, it is of great significance to analyze the change characteristics of surface water area and water surface area in Kunming for the scientific formulation of ecological water recharge and evaluation of water recharge effect.

In this study, the surface water area of Kunming was determined through the fusion of multi-period land use data, the characteristics of water surface area changes in Kunming from 1990 to 2020 were analyzed based on the PIE-Engine platform, and the causes of the changes in surface water area and the driving factors were further investigated. The results provide scientific and technological support for the development of planning programs for the recovery of river and lake ecosystems in Kunming. Yang revealed that the causes of surface water area changes in Zhejiang Province mainly originated from anthropogenic activities and the influence of precipitation upon land use data from 1980 to 2020 (Cao et al., 2021). Zhong discovered that the change in land use type is the primary factor for the change in surface water area on the land surface of inland basins (Wu et al., 2023). Sing employed a land use transfer matrix and other methods to investigate the evolution of watershed spatial patterns and its driving factors in the Jianghan Plain from 2000 to 2020 (Chang et al., 2023). This study suggested that the surface water area of the Jianghan Plain decreased by 36% due to the crowding of cropland and man-made land. Besides, the spatial aggregation of watersheds and connectivity of the Jianghan Plain were also explored, whereas the results were unclear. The spatial aggregation and connectivity of the watershed decreased remarkably, and the boundary density decreased sharply. Concurrently, the "14th Five-Year Plan for Water Safety and Security of Kunming" issued in January 2023 looks ahead to 2035. Specifically, Kunming should fully establish a water security system compatible with the requirements of economic and social development and ecological civilization construction, further highlight the role of the water control front-runner, and basically realize the modernization of water services (Kunming Municipal Water Affairs Bureau, 2022). The study of spatial and temporal changes in the surface water area of Kunming is essential for the investigation of the development, distribution, utilization, circulation, and protection of freshwater resources in Kunming.

With the rapid development of remote sensing technology, the emergence of remote sensing computational cloud platforms in recent years has more advantages, including strong computational performance, fast data processing speed, and simple operation, even though the traditional remote sensing technology can quantitatively reveal the change of water area in a region. Representative remote sensing computing cloud platforms comprise Google Earth Engine (GEE) in the United States and PIE-Engine in China, providing new ideas for long-time series and large-scale remote sensing data processing (Xiaoyan et al., 2023). Meanwhile, the development of remote sensing technology offers more effective technical support for real-time monitoring and environmental protection of lake waters (Batina and Krtalić, 2024; Belgiu and Drăguţ, 2016). Currently, a growing number of researchers around the world have begun to obtain information about water bodies using remote-sensing image data. Donchyts et al. (2016) for the first time adopted the Google Earth Engine (GEE) platform to extract the changes of global surface water bodies for 30 years. They utilized Landsat series satellite remote sensing data, an improved water body classification algorithm, and a deep learning method to improve the classification accuracy. Deng conducted an inversion study on the runoff volume of the river section near Tangnaihe station in the Yellow River source area based on Sentinel-1 and Sentinel-2 image data and DEM provided by GEE (Deng et al., 2020). Zou et al. (2018) evaluated a fully automated water body area extraction framework with the GEE cloud platform and Landsat 8 OLI data by AWEI indices to evaluate the performance and then applied it to monitor and evaluate lakes and reservoirs in New Zealand. These studies have critical theoretical and practical significance in the fields of water resources management and protection, water body pollution control, and ecological environment maintenance.

Materials and methods

Overview of the study area

Kunming is located in the northern part of the Dianchi Basin in the central part of the Yunnan-Guizhou Plateau, with its geographical position ranging from 102°10′ to 103°40′ east longitude and 24°23′ to 26°33′ north latitude (*Fig. 1*). The total topography of the region is high, has a gradual decline from north to south in the form of a ladder, and rises in the center and lower on the east and west sides. Kunming is dominated by the lake basin karst plateau landform, followed by the red mountain plateau landform. Meanwhile, more areas in the region are between 1500-2800 m above sea level. With a total area of 21,012.54 km^2, it is the capital city of Yunnan Province and one of the central cities in the southwest region.

Located at low northern latitudes on the Yunnan–Guizhou Plateau, Kunming experiences a subtropical plateau monsoon climate, with a multi-year mean air temperature of 15.9°C and a mean annual precipitation of 950 mm, ~85% of which occurs from May to October (Yuan et al., 2025); for clarity, we define the four seasons as spring (March–May), summer (June–August), autumn (September–November), and winter (December–February). Hydrologically, Kunming lies near the watershed divide of three major river basins—the Yangtze (Jinsha), the Pearl (Nanpan), and the Red River—where the north-high/south-low plateau topography directs runoff toward Lake Dianchi and adjacent catchments (*Fig. 1*). Particularly, 134 rivers in Kunming flow through or originate in the city, with a catchment area of more than 50 km^2. Of these, 63 rivers have 50-100 km^2, 60 rivers have 100-1000 km^2, and 8 rivers have greater than or equal to

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1000 km^2. The major rivers consist of the Pudu River, Xiaojiang River, Niulan River, Nanpanjiang River, Panghu River, Muban River, Zhema River, and Ba River. The terrain in Kunming is a mix of mesas, low mountains, plateau trap basins, and trapped river valleys. Among them, there are 10 freshwater lakes, most of which are fracture basin lakes. The most vital lakes are Dianchi and Yangzonghai. Dianchi is the largest freshwater lake in Yunnan Province.

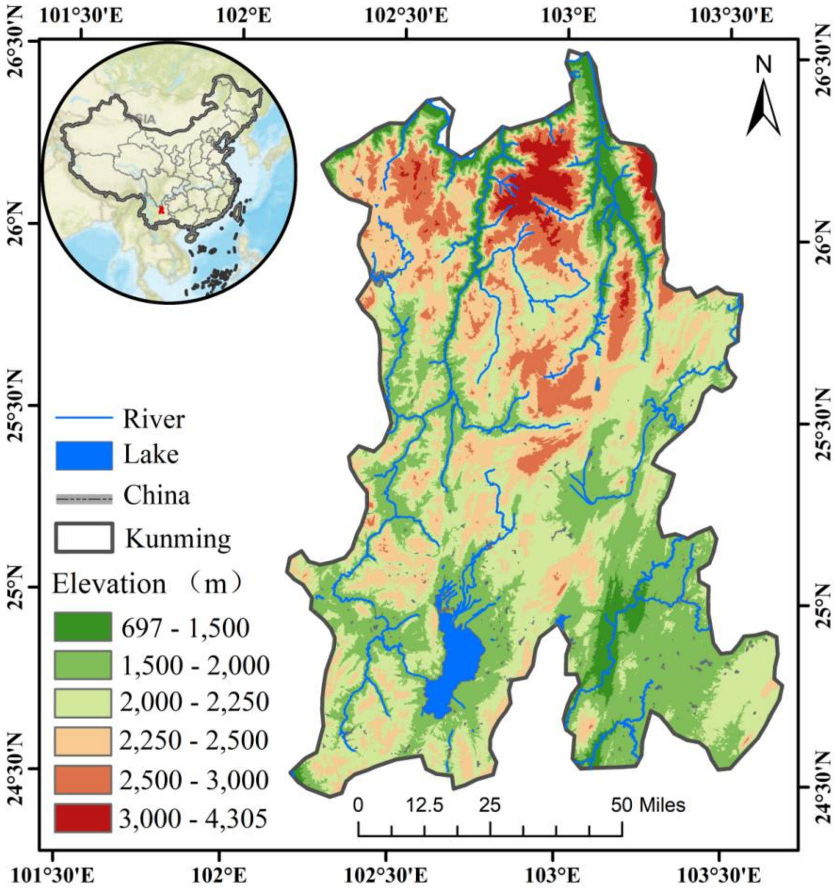

Figure 1. *Distribution of major water systems in Kunming, Yunnan Province, China*

Data sources

Image data sources and image pre-processing

In this study, 30 years of Landsat5 Collection2 TOA, Landsat7 TOA, and Landsat8 TOA satellite image data from 1990 to 2020 are adopted with a spatial resolution of 30 m (*Table 1*). Considering that the PIE-engine cloud platform provides the TOA data after radiometric calibration, only the 7252 images should be preprocessed to remove snow and clouds, image fusion, and image cropping to obtain the data for extracting the water area of Kunming. Since Kunming has a typical temperate climate, some of the Landsat images are easily affected by clouds or cloud shadows. This leads to missing values or outliers in the long time series of Landsat images, thereby considerably influencing the extraction of the water area in Kunming. Hence, Landsat remote sensing images with cloud amounts greater than 10% should be masked. Additionally, clouds and cloud shadows should be identified and removed by establishing rules through the values of

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image quality bands (BQA band in Landsat8 and QA_PIXEL band in Landsat5) obtained by the Cloud Mask algorithm in the PIE-engine cloud platform. This contributes to lowering or eliminating the influence of clouds and cloud shadows on water body extraction in Landsat images. Finally, the images are cropped by the maximum value method to weaken the influence of mountain shadows. In this study, the real value of the water area in the three-survey data of Kunming is compared with the accuracy of the water area extracted from Landsat image data in PIE-engine. The brief introduction of Landsat series satellites is detailed in *Table 1*.

Table 1. *Landsat datasets and acquisition windows used for surface-water mapping in Kunming, China (1990–2020)*

Satellite parameters	Launch time	Number of bands	On-board sensors	Maximum resolution	Data volume	Selected years
LandSat5	1984.3.1	7	MSS; TM	30 m	4860	1990-2011
LandSat7	1999.4.15	8	ETM+	15 m	232	2012
LandSat8	2013.2.11	11	OLI, TIRS	15 m	2160	2013-2020

Meteorological data and pre-processing

The temperature and precipitation data of the meteorological stations (*Table 2*) in and around Kunming for the last 30 years from 1990 to 2020 were obtained from the National Meteorological Science Data Center (http://data.cma.cn/site/index.html). The required meteorological data for the last 30a were extracted in bulk by Python tools.

Table 2. *Meteorological stations in and around Kunming, Yunnan Province, China, and their basic information*

Site name	Area station number	Observed altitude (m)	Average annual precipitation (mm)
Kunming Meteorological Office	56778	1888.1	900.5
Dongchuan Meteorological Office	56688	1254.1	947.8
Anning Meteorological Office	56863	1848.0	826.8
Chenggong Meteorological Office	56882	1906.6	957.9
Jinning Meteorological Office	56871	1893.1	897.2
Fumin Meteorological Office	56772	1692.7	899.4
Songming Meteorological Office	56785	1915.7	971.7
Shilin Meteorological Office	56881	1695.8	835.9

Technology roadmap

As illustrated in *Figure 2*, two interrelated processes are applied: watershed extraction by PIE and land use classification through satellite image data. The PIE watershed extraction process started from Landsat5/7/8 images and adopted NDWI. Otus's thresholding method was employed to separate water and non-water features. Next, watershed extraction was performed and evaluated for watershed extraction accuracy. The land-use classification process started from Landsat surface reflectance data. The NDVI was computed by de-clouding and median synthesis to improve the image quality,

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NDBI, and NDWI. Subsequently, the principal component analysis was conducted to reduce the dimensionality or correlation variables to improve the classification. Furthermore, a support vector machine classification algorithm was employed to assign the land use categories to the image pixels. Moreover, the classification results were evaluated for accuracy to produce the classification results. Finally, the accuracy and consistency of the two processes were verified by comparing the third survey data with the results of the two processes.

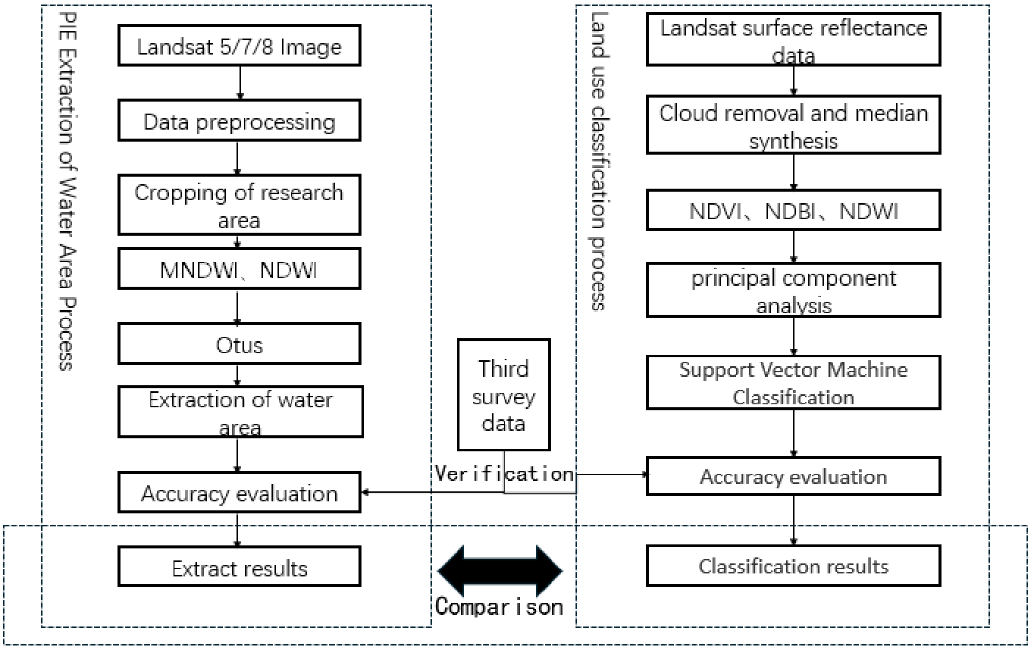

Figure 2. *Research technology roadmap*

Surface water area extraction method

Zhai et al. (2015) and Zhou et al. (2014) include the single-band threshold method, the threshold-based multi-band spectral interrelationship method, the Normalized Difference Water Index (NDWI) method (McFeeters, 1996; Rokni et al., 2014), and the Normalized Difference Water Body Index (MNDWI) method, which is the improved method based on NDWI (Singh et al., 2014). Combining the topography and geomorphology of Kunming and the results of extracting the water area by applying NDWI and MNDWI on PIE-Engine, NDWI achieved a more accurate effect of extracting the area of open water bodies compared to the techniques used for the extraction of the urban water area. In the PIE-engine cloud platform, the NDWI water body index was utilized to extract the area of water bodies in Kunming in comparison with the actual area. The accuracy was 91.2%. Hence the NDWI was adopted to investigate the change in the area of water bodies in Kunming in the past 30 years.

NDWI is a common method to extract water body information from remote sensing images. This method can effectively highlight the water body information in the image by the normalized difference calculation in specific bands. The NDWI method has been widely applied in many studies of water body monitoring and management because water bodies are more reflective in the infrared bands and less reflective in the green bands.

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Difference calculations can better differentiate the categories of water bodies and reinforce the ability to identify the boundaries of the water bodies. The expression is:

$$\text{NDWI} = \frac{p_{Green} - p_{NIR}}{\rho_{Green} + \rho_{NIR}} \quad \text{(Eq.1)}$$

where p_{Green} denotes B3 green light band in Landsat8 TOA image data and B2 green light band in Landsat5 TOA image data; p_{NIR} represents B5 near-infrared band in Landsat8 TOA image data and near-infrared band in Landsat5 TOA image data.

With the purpose of extracting water body information from remote sensing images, determining the optimal threshold is one of the most imperative steps in the NDWI algorithm (Qian et al., 2012). This directly affects the accuracy of water body extraction. Hence, this issue was tackled in this paper by the big law method (Otus) for image segmentation (Che et al., 2025; Wang et al., 2020). This method is an automatic threshold selection method, initially proposed by Japanese scholar Nobuyuki Otsu. In this method, a threshold value that maximizes the inter-class variance of the threshold image is selected to achieve segmentation of the foreground and background of the image. The advantage of Otsu's method is that there is no need to set the threshold value artificially and that the optimal threshold value can be calculated automatically, so as to realize the pixel classification and the accurate extraction of the boundary of the water body. The specific calculation formulas are:

$$\sigma_B^2(t) = \omega_0(t) \times \omega_1(t) \times \left(\mu_0(t) - \mu_1(t)\right)^2 \quad \text{(Eq.2)}$$

$$\omega_0(t) = \Sigma_{\mathrm{i}=0}^{t} P(\mathrm{i}) \quad \text{(Eq.3)}$$

$$\omega_1(t) = \Sigma_{\mathrm{i}=t+1}^{L-1} P(\mathrm{i}) \quad \text{(Eq.4)}$$

$$\mu_0(t) = \frac{1}{\omega_0(t)} \Sigma_{\mathrm{i}=0}^{t} i \cdot P(\mathrm{i}) \quad \text{(Eq.5)}$$

$$\mu_1(t) = \frac{1}{\omega_1(t)} \Sigma_{\mathrm{i}=t+1}^{L-1} i \cdot P(\mathrm{i}) \quad \text{(Eq.6)}$$

where $\omega_0(t)$ and $\omega_1(t)$ denote the pixel ratios of the background image and the target image at threshold t, respectively; $\mu_0(t)$ and $\mu_1(t)$ embody the average gray values of the background image and the target image and the variance between the non-water classes and the water classes, respectively; M represents the gray mean value of the whole water index image; $P(i)$ designates the probability of the occurrence of the gray class i. The threshold value is determined by iterating through all the possible thresholds t. The interclass variance $\sigma_B^2(t)$ corresponding to each t is calculated the interclass variance corresponding to each t, and the one t that maximizes the interclass variance is selected as the most threshold value.

Multiple linear regression analysis method for the effect of meteorological factors on surface water area

There are certain correlations between different meteorological factors. This study aimed to more precisely analyze the effects of temperature and rainfall on the changes of

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water area in Kunming. Specifically, the biased correlation analysis method is adopted to assess the correlation between water area and temperature and precipitation in Kunming, and Pearson's correlation coefficient, P, is used to evaluate the significance of the correlation (Cong and Brady, 2012).

The partial correlation coefficient is expressed as:

$$\gamma_{xy\cdot z} = \frac{\gamma_{xy}-\gamma_{yz}}{\sqrt{(1-\gamma_{xz}^2)(1-\gamma_{yz}^2)}} \quad \text{(Eq.7)}$$

where γ_{xy} denotes the correlation coefficient between x and y; γ_{xy} and γ_{yz} represent the correlation coefficient between x and z, and between y and z, respectively. The correlation coefficient ρ is calculated as:

$$\rho = \frac{cov(X,Y)}{\sigma_x\sigma_y} = \frac{\sum_{i=1}^{n}(X_i-\bar{X})(Y_i-\bar{Y})}{\sqrt{\sum_{i=1}^{n}(X_i-\bar{X})^2\sum_{i=1}^{n}(Y_i-\bar{Y})^2}} \quad \text{(Eq.8)}$$

where $cov(X,Y)$ indicates the covariance of X and Y; σ_x and σ_y denote the standard deviation of X and Y, respectively; $\bar{X}$ and $\bar{Y}$ stand for the mean of X and Y, respectively. The value of the correlation coefficient lies within the range of [-1,1]. The larger the absolute value, the stronger the linear correlation between the two variables. A correlation coefficient of 1 indicates a perfect positive correlation, -1 implies a perfect negative correlation, and 0 specifies no correlation.

Object-oriented random forest method for extracting surface water area

Random forest method, which is a machine learning algorithm based on multiple decision trees, can be applied to classify and regress remote sensing images, enabling the extraction of information such as the area of waters (Belgiu and Drăguţ, 2016). As illustrated in *Figure 3*, multiple feature variables, such as spectral indices, texture features, and shape features, are extracted from remote sensing images to describe the spectral and spatial characteristics of waters and other features. Moreover, several labeled samples are selected from the images to serve as the training data for the random forest model, and each sample contains the values of multiple feature variables and the corresponding categories (such as waters, construction land, and forest land). Using the random forest algorithm, several subsets are randomly selected from the training data, a decision tree is constructed for each subset, and then some decision trees are combined into a random forest model, which can vote for the category of each pixel to acquire the final classification result. With the random forest model, all the pixels in the image are classified to extract the area and range of the watershed, evaluate the accuracy and stability of the model, and analyze the spatial and temporal variations and influencing factors of the watershed.

Methods for analyzing dynamic land use transfer

The land use transfer matrix is an analytical method applied to quantitatively describe the system state and state transfer. It expresses the land use structure and transfer area in the beginning and end time in the form of a matrix, reflects the structure and area of land categories at a certain moment, and analyzes the transfer of land categories during the

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study period to reveal the evolution process of land use pattern. The method plays a crucial role in land use research, expressed as:

$$\begin{bmatrix} p_{11} & p_{12} & \cdots & p_{1m} \\ p_{21} & \vdots & \ddots & \vdots \\ \vdots & & & \\ p_{m1} & p_{m2} & \cdots & p_{mm} \end{bmatrix} \quad \text{(Eq.9)}$$

where p_{ij} denotes the probability or transfer rate of the ith land use type transferring to the jth land use type in period t, i, j = 1, 2, ..., m, and m represents the number of land use types. In this study, the spatial intersection calculation was performed by ArcGIS Pro software to obtain the land use transfer status of Kunming in different time periods of the past 30 years.

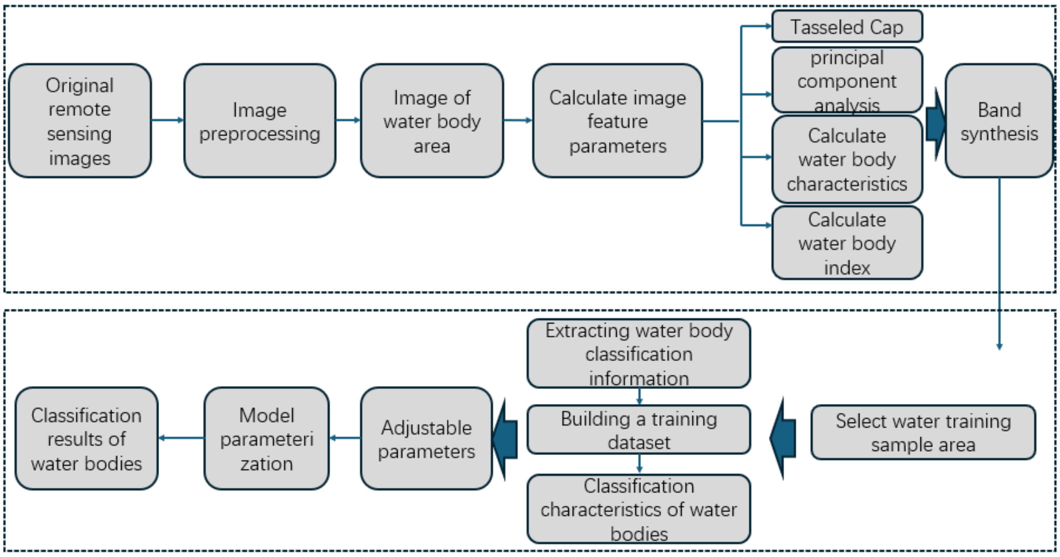

***Figure 3.** Flowchart of random forest extraction of surface water area technique*

Results

Spatial and temporal changes of water area in Kunming

Surface water areas in Kunming from 1990–2020 were extracted using the PIE-Engine cloud platform. As shown in *Figure 4*, the surface water area exhibits significant interannual dynamics and an overall “W-shaped” fluctuation. In detail, the Yunlong Reservoir in the northwest increased from 12.3 km² in 1990 to 15.7 km² in 2020 (+27.6%). A characteristic “increase–decrease–increase” fluctuation occurred near the East Main Drainage Canal, and spatial hotspots shifted over time: in 1990–2000 mainly upstream of Dianchi Lake; in 2000–2010 both upstream and downstream of Dianchi and in the river gorges of Shilin County; in 2010–2020 concentrated again around the upstream and downstream areas of Dianchi.

Between 1990 and 2020, precipitation in Kunming showed a “decrease–increase–decrease–increase” sequence: it increased from the 1990s to the early 2000s, decreased through the 2010s, and then increased again into the 2020s (*Fig. 11*). This pattern is broadly consistent with the overall change in Kunming’s surface water area.

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These spatial–temporal patterns of surface water area likely reflect combined effects of long-term reservoir regulation, urban expansion and drainage management near the East Main Drainage Canal, and decadal hydrometeorological variability. The decade-by-decade migration and persistence of hotspots around Dianchi suggest that shoreline engineering and inflow control mediated where gains and losses were concentrated (*Fig. 4*). By contrast, Qingshui Lake and Yangzonghai show limited interannual variability, consistent with their smaller size and relatively stable watershed settings (*Fig. 5*).

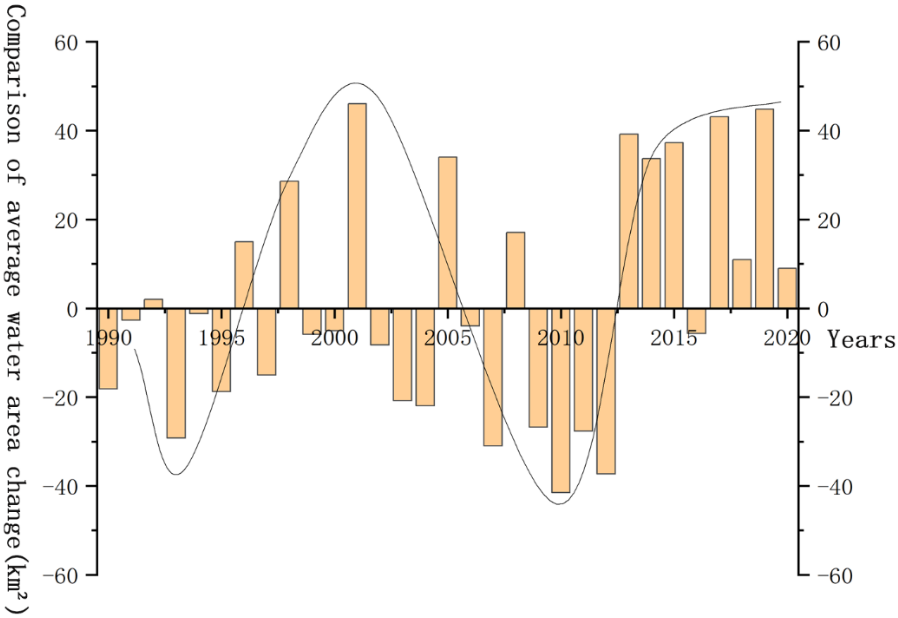

Figure 4. *Temporal trend of surface water area changes in Kunming, Yunnan Province, China, 1990–2020*

Characterization of changes in Dianchi surface water area

In this study, the surface water area of Dianchi Pond was extracted and analyzed with remote sensing image data from 1990 to 2020 by the random forest method (*Fig. 6*). The results suggest that the surface water area of Dianchi exhibited a “W”-shaped trend in the past 30 years, with an overall decrease of about 8.5%. From 1990 to 1993, the water area of Dianchi decreased by 5.4% from 298.61 km^2 to 266.43 km^2. From 1993 to 2001, the water area of Dianchi increased by 6% from 266.46 km^2 to 282.41 km^2. From 2001 to 2009, the water area of Dianchi decreased from 282.40 km^2 to 267.38 km^2. From 2001 to 2009, the water area of Dianchi decreased by 5.6% from 282.40 km^2 to 267.38 km^2. From 2009 to 2019, the surface water area of Dianchi increased by 2.2% from 267.37 km^2 to 273.24 km^2 (*Fig. 7*). The main reasons for the changes in the surface water area of Dianchi are the effects of climate change and human activities. Climate change has brought about a decrease in precipitation and an increase in evapotranspiration, thereby lowering the lake’s inflow and water level. Additionally, human activities, including water conservancy projects, agricultural irrigation, urbanization and industrialization, have induced an increase in outflow and deterioration in water quality, which in turn has affected the lake’s surface water area. For the sake of protecting the water resources and ecological environment of Dianchi Lake, it is recommended to strengthen the monitoring

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and analysis of the changes in the surface water area of Dianchi Lake and to formulate reasonable water resource management policies and measures to control the adverse effects of human activities on the lake.

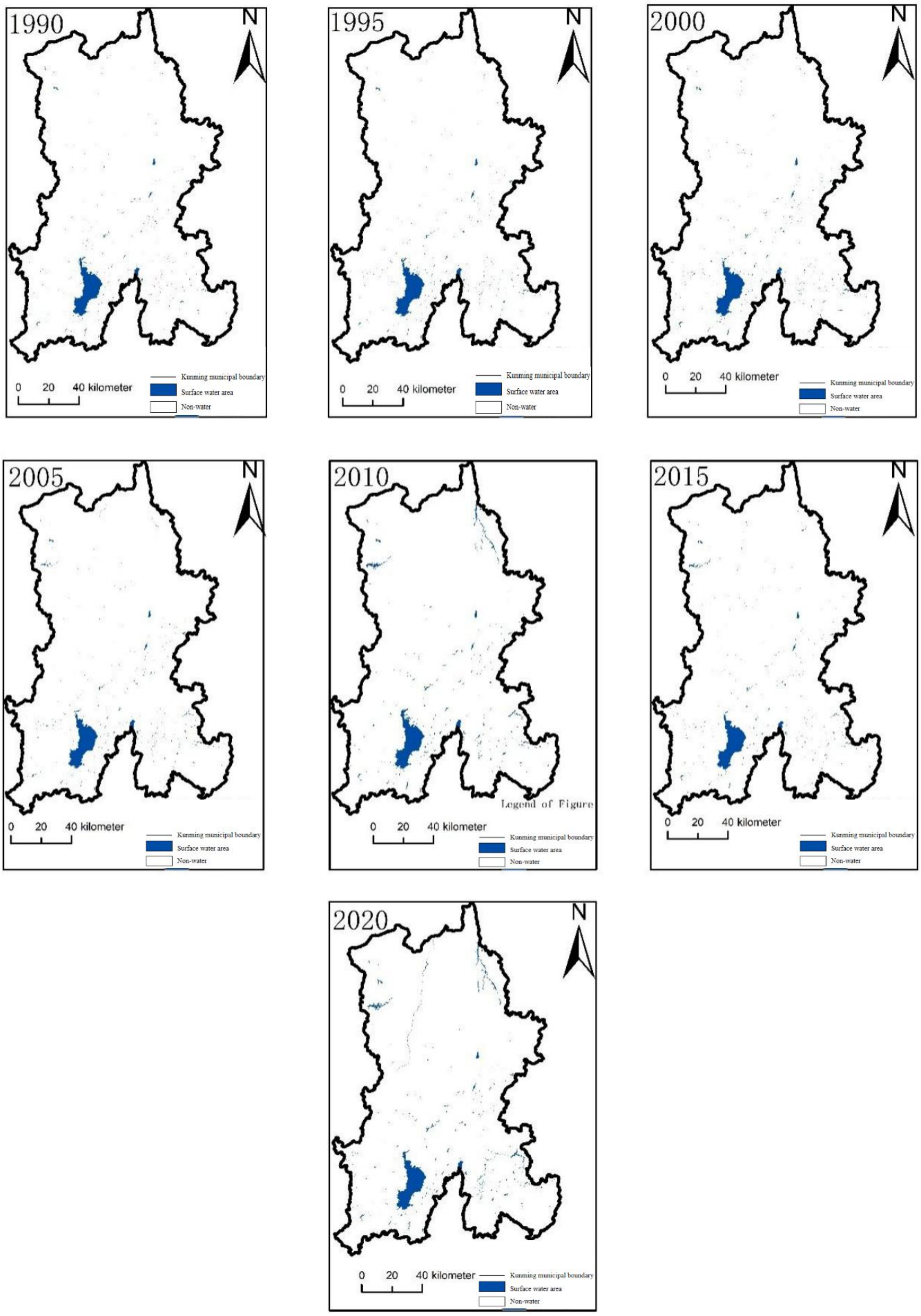

Figure 5. *Spatial distribution of surface water areas in Kunming, Yunnan Province, China, 1990–2020*

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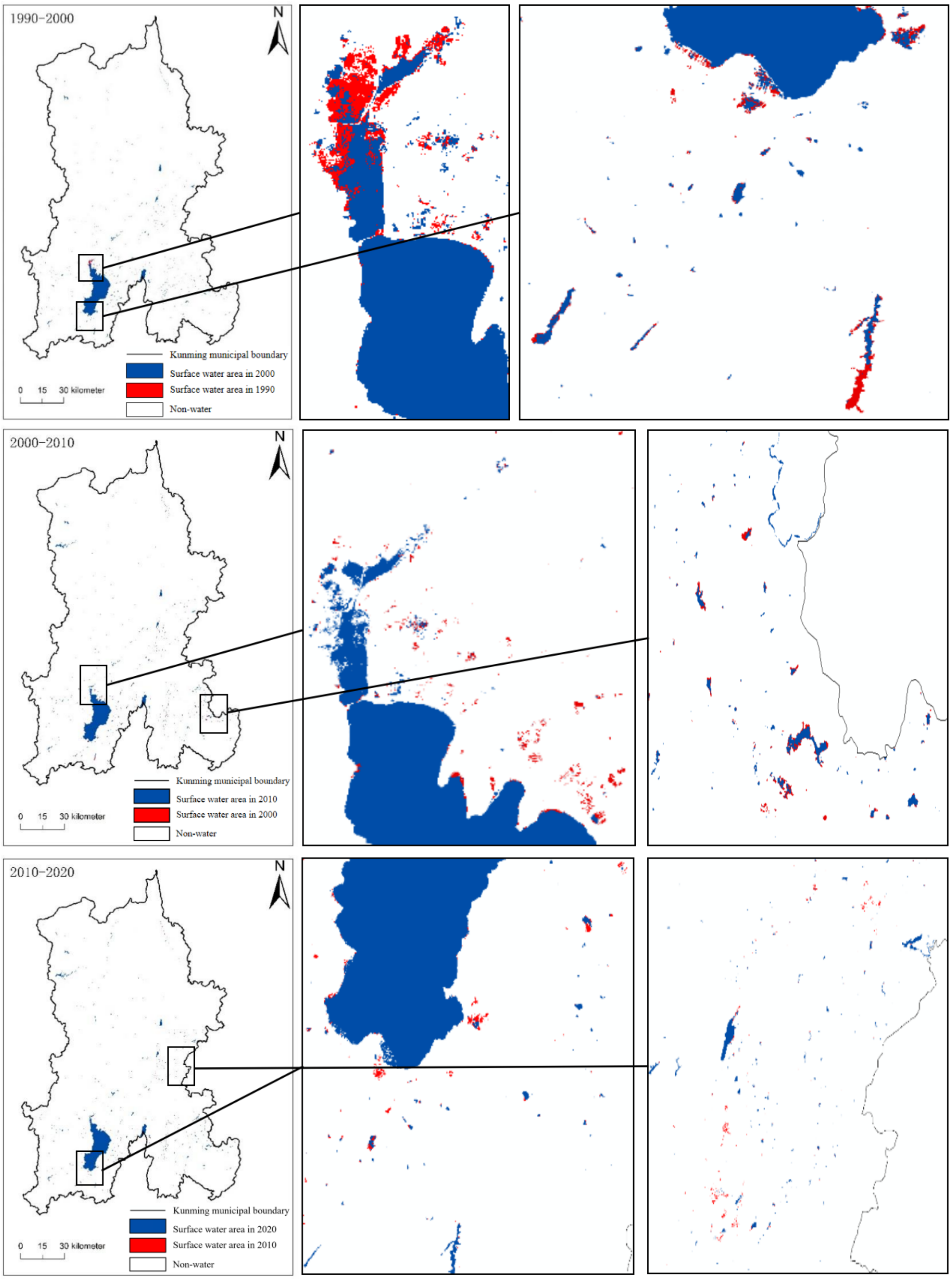

***Figure 6.** Changes in surface water area of Dianchi Lake Basin, Kunming, Yunnan Province, China, 1990–2020*

Changes in the surface water area of Dianchi are significantly associated with precipitation and evaporation yet affected by human activities. Precipitation is the main driving factor for the change in Dianchi surface water area, and this is positively correlated with Dianchi surface water area. Evaporation is the main inhibiting factor for the change in Dianchi surface water area, and this negatively correlated with Dianchi

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surface water area. Human activities primarily influence the water area of Dianchi through water conservancy projects, agricultural irrigation, and urbanization. Among them, water conservancy projects and agricultural irrigation lead to a decrease in Dianchi surface water area, while urbanization triggers the increase in Dianchi surface water area.

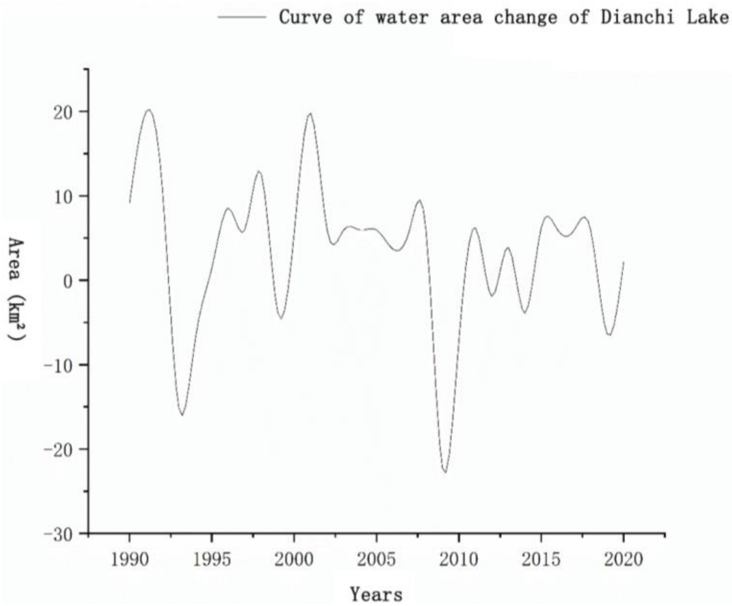

Figure 7. *Trend of Dianchi surface water area change from 1990 to 2020*

Land use dynamic transfer process in Kunming

With the 30 m resolution land use data from 1990 to 2020, the change of surface water area in Kunming in the past 30 years was processed through the land use transfer matrix. The results specify that the surface water area decreased by 27.28 km² from 1990 to 1993, consistent with the time change of surface water area in Kunming in *Figure 7*. From 1993 to 2001, the surface water area rapidly increased by 65.5 km², which majorly originated from the transfer of farmland. From 2001 to 2009, the surface water area entered the stage of decreasing, as observed in *Figure 6*. Additionally, the location of the decrease in surface water area was essentially concentrated in the Dianchi Lake, Yunlong Reservoir, and Nanpanjiang River. In 2009-2019, the surface water area slowly grew to 5.2%. Meanwhile, there is a phenomenon of aggregation in the vicinity of the Dianchi Lake and Yangzonghai, accompanied by a more dispersed distribution trend in other regions. In 2019-2020, the surface water area presented a decreasing state of Kunming, and this was impacted by several large-scale lakes (reservoirs) of Kunming.

The 30-m land use refinement was performed on the Dianchi watershed in Kunming from 1990 to 2020. The results reveal that the land use types of Dianchi watershed are dominated by cropland, forest land, and garden land. Among them, cropland and forest land decreased, while garden land and construction land increased (*Table 3*). In this paper, the land use change data of Dianchi basin from 1990 to 2020 were selected, and correlation and regression analyses were conducted with the area of Dianchi watershed. The results specify that the area of Dianchi watershed is significantly negatively correlated with the area of cultivated land, with a correlation coefficient of -0.77. In other words, the expansion of cultivated land occupies the wetlands, rivers, pits, and ponds around the Dianchi basin, affecting the water level and the area of the Dianchi basin. The area of Dianchi watershed is significantly negatively correlated with the area of forested land, with a correlation coefficient of -0.63. This reflects that the expansion of forested land occupies the wetlands, rivers, pits, and ponds around the Dianchi basin, influencing the water level and the area of Dianchi basin. The correlation coefficient is 0.71, implying that the expansion of garden land increases the demand for irrigation around Dianchi, thereby elevating the runoff into the lake and affecting the water level and water area of Dianchi. The water area of Dianchi has a significant negative correlation with the area of construction land, with a correlation coefficient of -0.76. Hence, the expansion of construction land occupies not only wetlands, rivers, pits and ponds around Dianchi, but also the water area of Dianchi. The correlation coefficient is -0.76, unveiling that the expansion of construction land directly occupies the wetlands, rivers, pits, and ponds around Dianchi while destroying the ecological corridors and buffer zones of Dianchi, influencing the runoff recharge and hydrological regulation of Dianchi.

Table 3. *Land use transfer matrix in Kunming, Yunnan Province, China, 1990–2020*

Topography unit (km^2)		**2020**						
		Wetland	**Woodland**	**Grasslands**	**Waters**	**Building site**	**Unutilized land**	**Shift to**
1990	Cropland	\	156.34	35.72	12.16	138.25	7.56	350.03
	Forest land	153.86	\	89.76	13.23	78.64	13.79	349.28
	Grasslands	26.45	86.75	\	5.56	28.97	6.89	154.62
	Water	12.59	15.64	3.21	\	18.69	1.03	51.16
	Built-up	69.87	46.98	12.85	9.73	\	5.02	144.45
	Unused land	4.67	18.36	8.67	1.68	7.04	\	40.42
	Transfer out	267.44	324.07	150.21	42.36	271.59	34.29	\

To summarize, land use changes exert a significant effect on the change of surface water area in Kunming. Specifically, the expansion of cultivated land and the expansion of construction land are the main reasons for the decrease of surface water area in Kunming, and the expansion of garden land is the main reason for the increase of surface water area in Kunming (*Fig. 8*). After 30 years of land use evolution, the change characteristics of the surface water area in Kunming are more similar to the change characteristics of the surface water area derived from the PIE-engine cloud platform processing.

Discussion

Analysis of causes and drivers of change

Influence of meteorological factors

The fluctuating changes of the surface water area in Kunming are primarily affected by seasonality and interannuality. Seasonal influence is majorly manifested in the fact that the surface water area increases or decreases with the alternation of rainy and dry seasons. Generally, the water area of Kunming is larger in the rainy season (June-September) and smaller in the dry season (October-May) (Lu and Sun, 2023). The inter-annual impacts are mainly manifested in the fact that the water area of Kunming rises or

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falls with the impacts of climate change and human activities (Liu et al., 2020). Generally, the surface water area in Kunming is larger in years with high precipitation, high runoff into the lake, and low evaporation, and smaller in years with low precipitation, low runoff into the lake, and high evaporation. Temperature and precipitation data from eight meteorological stations in and around Kunming were selected to comprehensively analyze the driving factors affecting the change of surface water area in Kunming.

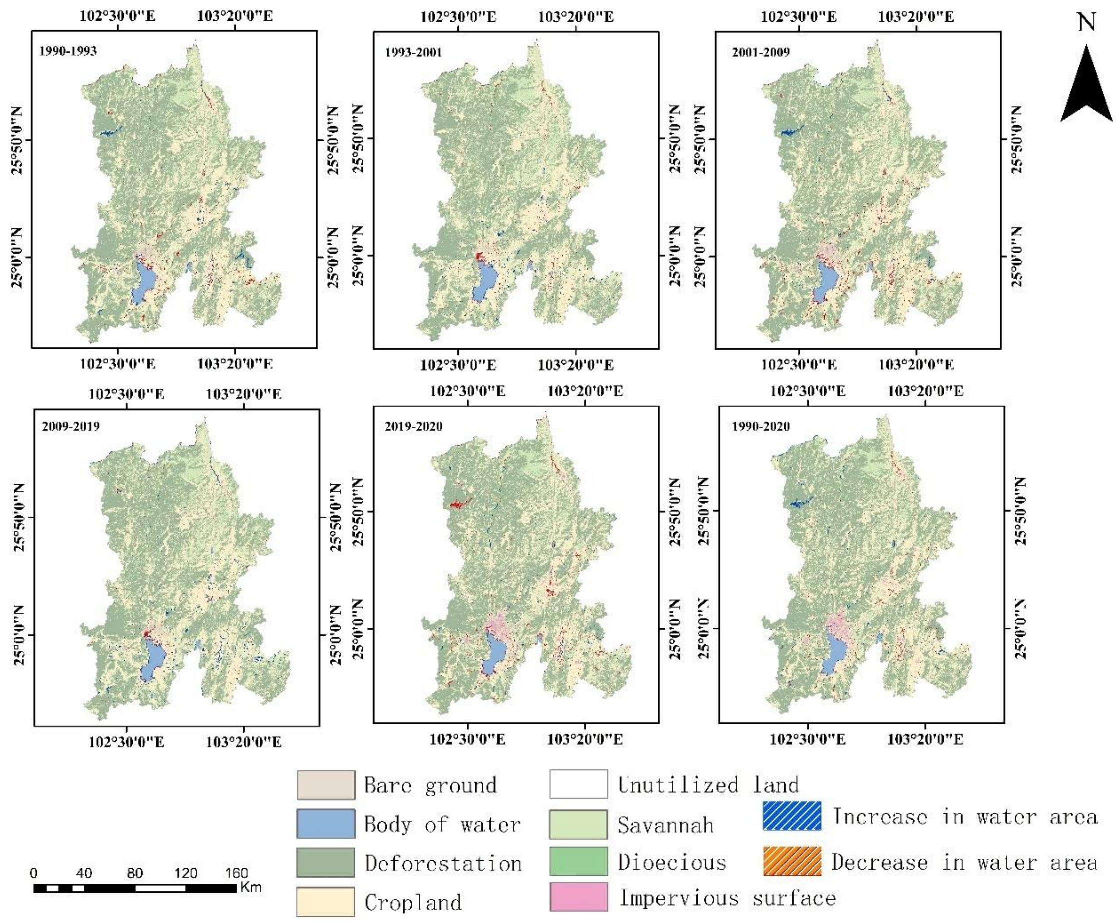

Figure 8. *Thirty-year land-use dynamics and contributions in Kunming, Yunnan Province, China (1990–2020)*

In this paper, the meteorological data such as annual average temperature, annual total precipitation, and annual total evaporation of Kunming from 1990 to 2020 were selected for correlation and regression analysis with the surface water area of Kunming (*Fig. 9*). The results demonstrate that the water area of Kunming is significantly negatively correlated with the average annual air temperature, with a correlation coefficient of -0.67. The regression equation is $y = -39.39x + 1178.86$, with a regression coefficient of -39.39. In other words, a 1°C increase in mean annual air temperature is associated with a 39.39 km² decrease in Kunming's surface-water area. This pattern is consistent with the warming–evaporation mechanism: higher air temperatures enhance evaporation, lowering lake levels and contracting open-water extent—most notably in Dianchi Lake. This interpretation is highly consistent with Peng et al. (2022), who showed that rising

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air/lake-surface temperatures accelerate evaporation and depress lake levels in Chinese lakes, including Dianchi (Peng et al., 2022).

The correlation coefficient is 0.745, and the regression equation is $y = 0.1632x + 388.92$, with a regression coefficient of 0.1632, implying that the water area of Kunming increases by 16 km² for every increase of 100 mm in total annual precipitation (*Fig. 10*). Besides, an increase in precipitation leads to an increase in runoff into the lake, affecting the water level and the water area of Kunming.

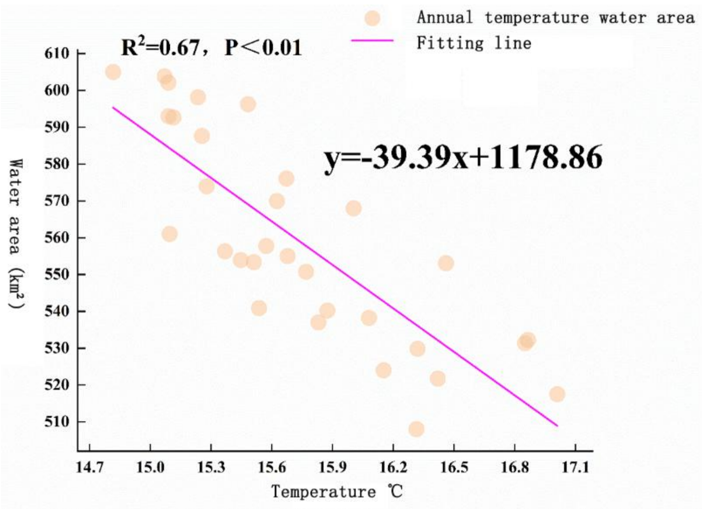

***Figure 9.** Correlation analysis between temperature and surface water area*

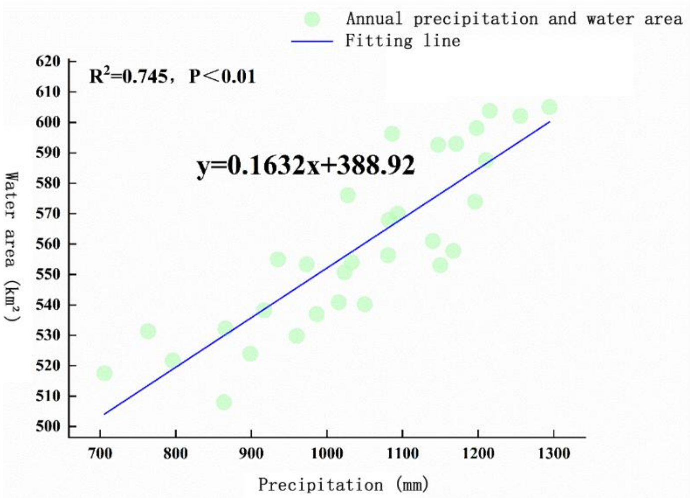

***Figure 10.** Correlation analysis between precipitation and surface water areas*

In summary, climate change exerts a significant influence on the variation of water area in Kunming, with rising temperatures and decreasing precipitation identified as the primary causes of water-area decline. This interpretation is consistent with the findings of Zhang et al. (2022), who demonstrated that inter-annual changes in inflow to Dianchi Lake are strongly driven by precipitation variability and runoff conditions, thereby linking climate variability to reductions in lake water storage and surface extent (Zhang et al., 2022).

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(1) Temperature. The main waters of Kunming are the Dianchi Pond in the southwest of Kunming, the Yangzonghai and the Nanpanjiang River in the south of Kunming, as well as the Jinsha River at the northern border of Kunming. According to the study of the average annual temperature of Kunming in the past 30a, 2009-2013 average temperature is higher than the average temperature and reached the maximum value in 2010. These years are also the period of the great drought in Yunnan Province. The surface water area of Kunming has been going out of the state of shrinkage for 4-5 years and is in the trough of the period of 30a. Following the annual average temperature change, the temperature in the study area was on an increasing trend. The correlation analysis of temperature and water area (*Fig. 9*) reveals that the increase in temperature can bring about an increase in the evaporation of the water body, causing a decrease in the lake area. Consequently, the lake water area and the trend of the temperature change are negatively correlated. The correlation analysis between the total area of the lake water body and the temperature change specifies that the correlation coefficient between the two is negative and significant. This reflects that the decrease in lake area is closely related to the increase in temperature, and the decrease in lake water volume may harm local water resources and ecosystems. Hence, temperature change is a critical indirect driver of the change in water body area.

(2) Precipitation. Precipitation is one of the most imperative drivers of changes in land surface water area and has a considerable impact on changes in the surface area of land surface waters. Attributed to the distinct dry and rainy seasons in Kunming, about 85% of the precipitation in a year is concentrated in the rainy months (May to October), and the total amount of precipitation in the dry months (November to April) only occupies about 15% of the year. The measured precipitation data from meteorological stations around Kunming were collected from 1990 to 2020, and the annual averages of precipitation data were counted. Subsequently, the average of precipitation in these 30 years was calculated (950 mm) (*Fig. 11*). The correlation analysis of precipitation and surface water area is depicted in *Figure 10*. Years with less than average annual precipitation were defined as dry years, and years with more than average annual precipitation were defined as rainy years based on the mean annual precipitation. There were 14 drought years and 16 rainy years from 1990 to 2020 (*Fig. 12*).

Impact of land use change

Land use change is one of the most direct and significant anthropogenic factors affecting the change of Dianchi surface water area. The main data bulletin of the Third National Land Survey of Yunnan Province, in the past 30 years specifies that the land used for construction in Kunming and the ecological land have increased and decreased dramatically, respectively. The expansion of construction land directly occupies the waters around Dianchi while destroying the ecological corridor and buffer zone of Dianchi, affecting the runoff recharge and hydrological regulation function of Dianchi. Many water diversion, storage, drainage and other water conservancy projects have been constructed to ensure the security of water supply and economic development of Kunming. These projects not only change the natural flow in and out of Dianchi and the direction of flow but also impact the fluctuation range and cycle of Dianchi, influencing the area of Dianchi waters. Environmental pollution is another vital anthropogenic factor influencing the change of Dianchi's water area. With the rapid development of urbanization, industrialization, and agriculturalization, all kinds of pollutants in the Dianchi basin have been increasing, contributing to the deterioration of water quality in Dianchi, the proliferation of aquatic plants, and the aggravation of eutrophication of the

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water body (Li et al., 2012b). These pollutants and aquatic plants occupy the waterspace of Dianchi while affecting the transparency and reflectivity of Dianchi and thus the watershed extraction accuracy of remote sensing images (Beck et al., 2019).

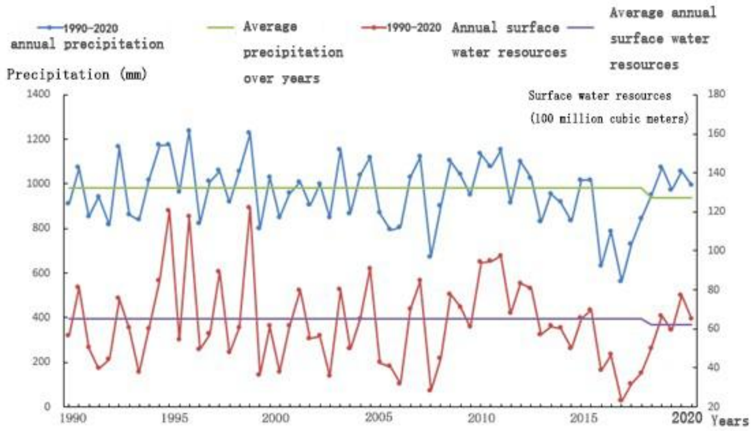

Figure 11. *Trends in annual precipitation and surface water resources in Kunming, 1990-2020*

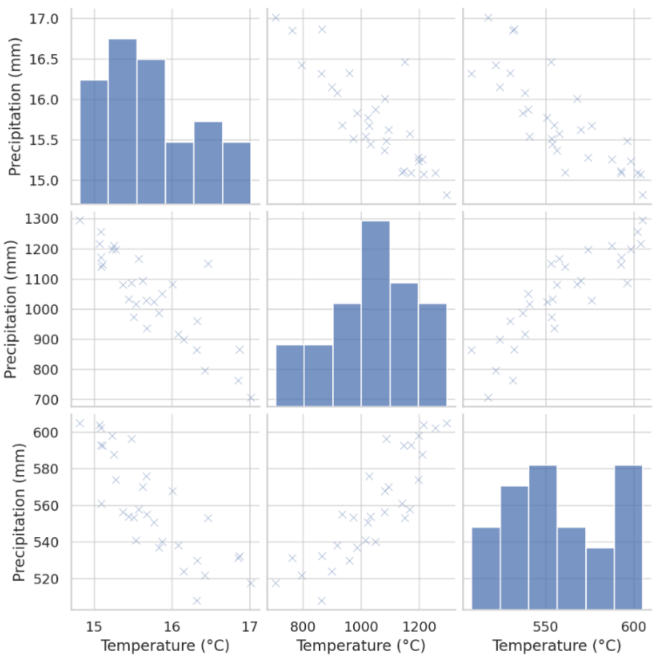

Figure 12. *Scatterplot of temperature, precipitation, and surface water area*

Influence of other factors

Changes in the surface water area of Kunming are affected by both meteorological factors and human activities. During the period of 1990-2020, the influence of human activities on the change of surface water area in Kunming is more prominent. This can be demonstrated from the following perspectives. (1) Due to the rapid expansion of the central urban area of Kunming and the surge of population, the demand for water for the surrounding farmland and domestic use has increased. Concurrently, the Dianchi Pond,

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as its stable source of water, suffers from the excessive development and utilization of water resources, resulting in the shrinkage of the area of the Dianchi Pond and the decline of the water level (Wang et al., 2021). (2) In 1993, Kunming implemented the dredging project of Dianchi Caohai, further reducing the area of Dianchi. (3) In 2003, Kunming proposed the goal of "one lake and four pieces" as the regional center of the city, making the shoreline of Dianchi continue to shrink. (4) In 2007, the water diversion project of the Palm Cove River was put into use, alleviating the problem of water supply in the city and enabling the area of Dianchi temporarily to increase and the water level to rise. (5) The water level of Dianchi was reduced, and the area of Dianchi was further reduced. (5) After 2012, the Qingshuihai Diversion Project and the "Niulanjiang-Dianchi" water replenishment project continue to promote the annual replenishment of water to allow the water area of Kunming to increase year by year, accompanied by the rising water level. Therefore, the protection and management of the ecosystem and water resources in Kunming require scientific and efficient control and planning measures owing to the impacts of various factors.

Conclusions

The change of water area stems from the joint shaping of natural environmental conditions and anthropogenic environmental factors. In this paper, the characteristics and causes of the long time series change of water area in Kunming from 1990 to 2020 were analyzed by the PIE-engine cloud platform and land use data. The results suggest that the NDWI method can improve the accuracy of open water body area extraction compared with other water body extraction. Additionally, the topography and geomorphology of Kunming have a certain impact on the extraction of water area. It has been verified that the remote sensing cloud service platform PIE-Engine combined with the NDWI method can provide a more accurate and efficient technical method for the detection of urban water area. The surface water area of Kunming demonstrates a "W"-shaped trend of change and is subjected to the process of first decreasing and then increasing, and then decreasing and then increasing. Among them, 1993, 2001, 2009, and 2019 are the four inflection points. The change of surface water area is jointly influenced by meteorological factors and human activities. Temperature and precipitation are negatively correlated with surface water area. Human activities mainly include urban expansion and the development and utilization of urban water resources. In this paper, a systematic study was conducted on the change of surface water area in Kunming from three aspects: time series, spatial distribution, and driving force analysis. The results reveal the law and mechanism of surface water area change and lay a scientific foundation and reference for the protection and management of ecosystems and water resources in Kunming.

While this paper provides a preliminary analysis of the changes in the surface water area of Dianchi Pond in Kunming, still some shortcomings need to be further improved in future research.

(1) In this paper, Landsat TM/ETM+ remote sensing images were used as the data source. However, the available image data is less because the orbit period of Landsat series satellites is 16 is days and affected by factors such as clouds and fog. Hence, it is difficult to reflect the high-frequency change of the surface water area in Kunming. In the future, remote sensing images with high resolution and high revisit frequency, such as Gaofen series and Sentinel series, could be adopted to improve the monitoring accuracy and timeliness of the change of water area in Kunming.

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(2) The watershed extraction method applied in this paper is relatively simple based on the spectral differences between water bodies and non-water bodies for discrimination. Moreover, the effects of water body edges, water depth, water quality, and other factors are neglected. In the future, the watershed extraction algorithm based on machine learning and deep learning could be utilized to enhance the accuracy and robustness of surface water area extraction in Kunming.

(3) In this paper, two methods, correlation analysis and regression analysis, were employed for driving force analysis. Nonetheless, both methods were performed following the assumption of a linear relationship, and the ability to portray a nonlinear relationship is weak. In the future, the driving force analysis model based on complex system theory and gray system theory should be designed to reveal the intrinsic mechanism and dynamic process of the change of the surface water area in Kunming.

Additionally, future research directions in the current study, such as data quality, quantitative assessment of influencing factors, and the impact of surface water area change on the ecological environment, can provide reference and inspiration for subsequent studies.

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Conflict of interests. The authors declare no conflict of interests.

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