Dynamic Changes in Surface Water Area in Xinjiang from 1990 to 2023 and Their Driving Factors (Postprint)

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Abstract

Xinjiang possesses a unique mountain-oasis-desert ecosystem, wherein surface water bodies constitute core elements for maintaining ecological balance and supporting regional economic and social development. This study utilizes Landsat 5/7/8/9 satellite remote sensing imagery and employs a hybrid index algorithm to calculate surface water body area in Xinjiang from 1990 to 2023, analyzing its spatial patterns and variation characteristics. Additionally, the geographical detector method is adopted to reveal factors influencing surface water body area changes. The results indicate that from 1990 to 2023, permanent water body area in Xinjiang increased by 36.25% (2466.20 km^2), dominated primarily by mountain water bodies, particularly the inland river basins of the Qiangtang Plateau, which expanded significantly with an increase of approximately two-thirds (1149.58 km^2). Seasonal water body area increased by 181.90% (1924.84 km^2), dominated by oasis-desert water bodies, among which the main stream of the Tarim River is particularly prominent, with its area increasing by approximately twofold (344.92 km^2). Changes in mountain water bodies are primarily influenced by climatic factors, among which snow water equivalent exhibits the highest average contribution rate at 42.84%; whereas human activities exert a greater influence on oasis-desert water bodies, with average contribution rates of population density and cultivated land being 64.10% and 54.43%, respectively. This study comprehensively analyzes the spatiotemporal variation characteristics of surface water bodies in Xinjiang and their driving factors, providing a scientific basis for assessing Xinjiang' s water resource development potential and formulating rational water resource management strategies.

Full Text

Dynamic Changes and Driving Factors of Surface Water Body Area in Xinjiang from 1990 to 2023

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Abstract

Xinjiang features a unique mountain-oasis-desert ecological system, in which surface water bodies play a crucial role in maintaining ecological balance and supporting regional socioeconomic development. This study utilized Landsat 5/7/8/9 satellite remote sensing imagery and a mixed index algorithm to estimate Xinjiang’ s surface water area from 1990 to 2023, analyzing its spatial patterns and temporal change characteristics. Geographic detector methods were employed to reveal the factors influencing surface water area changes. The results indicated that between 1990 and 2023, Xinjiang’s permanent water body area increased by 36.25% (2466.20 km^2), dominated primarily by mountain water bodies. Notably, the inland river basins of the Qiangtang Plateau expanded significantly by approximately two-thirds (1149.58 km^2). Seasonal water body area grew by 181.90% (1924.84 km^2), dominated by oasis-desert water bodies, with the mainstream Tarim River particularly prominent, nearly doubling in area (344.92 km^2). Changes in mountain water bodies were mainly influenced by climatic factors, with snow water equivalent showing the highest average contribution rate at 42.84%. In contrast, human activities had a more substantial impact on oasis-desert water bodies, with population density and cultivated land exhibiting average contribution rates of 64.10% and 54.43%, respectively. This study provides a comprehensive analysis of the spatiotemporal variation characteristics of Xinjiang’ s surface water bodies and their driving factors, offering critical scientific insights for assessing water resource development potential and formulating effective water resource management strategies in the region.

Keywords: surface water body; Landsat; mountain-oasis-desert; climate change; Xinjiang

1. Introduction

Over the past several decades, global climate change and human activities have profoundly impacted surface water resources. Surface water resources primarily include natural lakes, ponds, rivers, and artificial reservoirs, canals, and ditches, which play vital roles in agricultural production, ecosystem stability, and functional maintenance. Xinjiang represents a typical arid region where water scarcity constitutes a key constraint on economic development. The region' s water resources mainly originate from mountain precipitation and glacier meltwater, making them highly sensitive to climate change. Recent warming trends have not only affected precipitation patterns (e.g., rain versus snow) but also accelerated snow and glacier melting, thereby promoting surface water resource availability. Meanwhile, population growth and socioeconomic development have further increased water demand, intensifying pressure on surface water resources.

Research indicates that under climate change, surface water bodies on the northern slope of the Kunlun Mountains expanded by 71.03% over the past two decades. The Ebinur Lake Basin experienced dramatic fluctuations in water area due to continuous growth in population, irrigation area, and production value. Ecological water conveyance projects in the lower Tarim River significantly expanded the water area of Lake Taitema. Remote sensing technology enables continuous monitoring of Earth' s surface at multiple scales. With the rapid development of Google Earth Engine (GEE) geographic computing cloud platform technology in recent years, global or continental-scale surface cover mapping capabilities based on long-term, massive medium-to-high resolution remote sensing data (Landsat, Sentinel) have achieved leapfrog improvements, facilitating widespread development of spatiotemporal monitoring of surface water dynamics.

Currently, relevant research primarily employs three water extraction methods: (1) threshold methods that enhance water feature information through appropriate band selection and set thresholds for image segmentation, such as the Normalized Difference Water Index (NDWI) proposed by McFeeters and the modified NDWI (mNDWI) subsequently proposed by Xu; (2) classifier methods, which can be divided into spectral feature-based classifiers (e.g., maximum likelihood classification, Mahalanobis distance) and feature fusion-based classifiers (e.g., artificial neural networks, random forest, support vector machine), which can effectively improve classification accuracy but involve time-consuming calculations with extraction precision influenced by training samples and algorithm parameters; and (3) special water classification methods based on big data analysis and information extraction, such as deep learning and empirical optimization techniques, which offer high precision and performance but complex operations.

This study analyzes the spatial patterns and change trends of Xinjiang' s surface water bodies from 1990 to 2023, revealing the impacts of climate change and human activities on water area changes to provide scientific basis for water resource management, optimization allocation, ecological protection policy formulation, and high-quality development in Xinjiang.

1.1 Study Area Overview

Xinjiang is located in northwestern China, between 34°25 ~49°10 N and 73°40 ~96°23 E, covering a total area of approximately 1.6649×10^{6} km^2, making it China' s largest provincial administrative region. Situated in the hinterland of the Eurasian continent and far from oceans, Xinjiang' s terrain descends from southwest to northeast. The Altai, Tien Shan, and Kunlun mountain ranges traverse the region, blocking water vapor from the Pacific and Indian Oceans, resulting in an average annual precipitation of only about 150 mm. Glacier and snow meltwater and mountain precipitation constitute the region' s primary water sources. Rivers originate in mountainous areas, pass through oases with frequent human activity (which are also important agricultural and irrigation zones), and eventually disappear into deserts, forming Xinjiang' s unique mountain-oasis-desert ecosystem. Xinjiang' s water resources exhibit significant spatiotemporal diversity and high sensitivity to climate change. Based on China' s secondary watershed dataset at 1:250,000 scale, this study divides Xinjiang into 8 sub-basins [Figure 1: see original paper] to examine the change characteristics of surface water bodies in different watersheds.

1.2 Data Sources

1.2.1 Image Data

Based on the GEE platform, Landsat imagery was selected. Image quality and quantity are affected by acquisition time and weather conditions. The cloud cover threshold was set to filter images to maintain quality, yielding usable Landsat imagery totaling 3.88×10^{8} pixels, including Landsat 5, Landsat 7, Landsat 8, and Landsat 9. Each image was preprocessed to remove clouds, cloud shadows, and snow pixels. Using the solar azimuth and zenith angles from each image, topographic shadows were calculated and removed with DEM data. The final result provided the number of valid observations per pixel [Figure 2: see original paper]. The missing data proportion in all pixels is very small, indicating sufficient high-quality observation data to support regional surface water dynamic analysis. The spatial distribution of valid observations per pixel in Xinjiang from 1990 to 2023 is shown in [Figure 2: see original paper].

The Digital Elevation Model (DEM) was derived from the Shuttle Radar Topography Mission (SRTM) data released by NASA, primarily used to generate slope data to assist in eliminating topographic shadow effects.

1.2.2 Other Data

Climate data including precipitation, temperature, potential evapotranspiration, and snow water equivalent from the TerraClimate dataset were used to reflect climate change impacts on surface water bodies. TerraClimate combines high-spatial-resolution climate normals from WorldClim with coarser-resolution timevarying data using climate-assisted interpolation, with a spatial resolution of 1/24° and wide application in global ecological and hydrological research.

Population density and cultivated land area were selected to reflect human activity impacts on surface water bodies. Population density data came from the Global Human Settlement Population Dataset (GHS-POP) with 100 m spatial resolution. Cultivated land area data came from the China Land Cover Dataset with 30 m spatial resolution. GRACE gravity satellite data can monitor terrestrial water storage changes and was used as a water resource indicator for comparison with water body area.

1.3 Methods

1.3.1 Water Extraction

This study employed a mixed index method for water extraction. Remote sensing imagery was used to calculate the Normalized Difference Vegetation Index (NDVI), Modified Normalized Difference Water Index (mNDWI), and Enhanced Vegetation Index (EVI). Water bodies were extracted using the rules mNDWI > NDVI, mNDWI > EVI, and EVI < 0.1, which have been widely used in water extraction. The formulas are:

$$mNDWI = \frac{Green - SWIR}{Green + SWIR}$$

$$NDVI = \frac{NIR - Red}{NIR + Red}$$

$$EVI = 2.5 \times \frac{NIR - Red}{NIR + 6 \times Red - 7.5 \times Blue + 1}$$

where Blue, Green, Red, NIR, and SWIR represent the blue, green, red, near-infrared, and shortwave infrared bands, respectively. The rules mNDWI > EVI and mNDWI > NDVI classify pixels where water signals are stronger than vegetation signals as water. Using EVI < 0.1 further removes water-vegetation mixed pixels. Only pixels satisfying all rules are classified as water, with the remainder classified as non-water.

Slope data were generated using NASA DEM, with pixels having slopes >15° defined as topographic shadows to further exclude non-water factors affecting extraction accuracy. Finally, water occurrence frequency was calculated for each image to distinguish seasonal and permanent water bodies. Water Frequency (WF) is the proportion of times a pixel was observed as water relative to total valid observations during a period:

$$WF = \frac{1}{N} \sum_{i=1}^{N} w_i$$

where N is the number of valid observations within a year and w is a binary variable (1 for water, 0 for non-water). Pixels with WF < 0.25 were excluded to reduce potential errors. Based on existing research, pixels with WF ≥ 0.25 are classified as valid water bodies, which are further divided into seasonal water bodies ($0.75 >$ WF ≥ 0.25) and permanent water bodies (WF ≥ 0.75).

To assess extraction accuracy, a confusion matrix was used to measure remote sensing identification accuracy. High-resolution Sentinel-2A imagery from 2023 served as reference samples, with 500 test samples randomly generated in the study area (250 water samples and 250 non-water samples). The confusion matrix results show overall accuracy of 98.57% and Kappa coefficient of 94.18%, indicating high accuracy suitable for further analysis.

1.3.2 Trend Analysis Methods

This study employed the Theil-Sen trend analysis method, a non-parametric statistical trend analysis that does not require samples to follow a specific distribution and is resistant to noise and outliers. The slope is calculated as:

$$Slope = median\left(\frac{X_j - X_i}{j - i}\right), \forall i < j$$

where n is the number of study years, X_i and X_j are values for years i and j, and Slope represents the trend magnitude. When Slope < 0, values decrease over time; when Slope > 0, values increase.

The Mann-Kendall test is a non-parametric method to assess trend significance:

$$S = \sum_{i=1}^{n-1} \sum_{j=i+1}^{n} sign(X_j - X_i)$$

where sign() is the sign function. The standardized test statistic Z is:

$$Z = \begin{cases} \frac{S-1}{\sqrt{Var(S)}} & S > 0 \\ 0 & S = 0 \\ \frac{S+1}{\sqrt{Var(S)}} & S < 0 \end{cases}$$

At significance level $\alpha = 0.05$, $|Z| \geq 1.96$ indicates statistical significance.

1.3.3 Geographic Detector

Geographic detector is a spatial statistical method that quantitatively reveals the explanatory power of environmental factors and their interactions on geographic phenomena. The factor detector quantifies climate change and human activity impacts:

$$q = 1 - \frac{\sum_{h=1}^{L} N_h \sigma_h^2}{N\sigma^2} = 1 - \frac{SSW}{SST}$$

where q is the explanatory power (0-1), with larger values indicating stronger influence; h = 1,⋯,L represents strata; N_h and N are unit numbers for stratum h and the entire region; σ_h^2 and σ^2 are variances; SSW and SST are within-stratum and total variance sums.

2.1 Spatial Distribution Characteristics of Xinjiang' s Surface Water Bodies

The spatial distribution of water frequency in Xinjiang from 1990 to 2023 shows significant differences [Figure 3: see original paper]. Permanent water body area was approximately 3129.94 km^2, while seasonal water body area was 8933.88 km^2. Surface water bodies are unevenly distributed, with higher proportions in large lakes and reservoirs, and lower proportions mainly in oasis areas with frequent human activity. Water bodies are primarily distributed between 39°N-40°N latitude and show distinct longitudinal patterns.

Permanent water bodies proportionally dominate in northern basins and the Qiangtang Plateau inland rivers, where they account for over 89.43% of surface water bodies. Conversely, seasonal water bodies dominate the mainstream Tarim River, reaching 59.34% of that basin' s surface water. To characterize stability, coefficient of variation (C_v) and standard deviation (SD) were calculated. The Tarim Basin desert area shows small C_v for permanent water bodies, indicating stable growth; the Qiangtang Plateau inland river shows moderate C_v, indicating substantial but fluctuating increases. Seasonal water bodies in the Gurbantunggut Desert area show steady growth, while those in the Tarim River source area show high variability, indicating strong sensitivity to external factors.

2.2 Temporal Change Trends of Xinjiang' s Surface Water Bodies

From 1990 to 2023, Xinjiang' s permanent water bodies exceeded seasonal water bodies and showed a consistent upward trend [Figure 5: see original paper]. Permanent water bodies exhibited a significant and stable increasing trend ($P < 0.05$), growing from 6803.25 km^2 to 9269.48 km^2 (36.25%). Seasonal water bodies showed a fluctuating upward trend, increasing from 1058.18 km^2 to 2983.02 km^2 (181.90%).

Notable changes include the Ayyakum Lake and Aqikkum Lake areas surging, with Ayyakum Lake surpassing Bosten Lake to become Xinjiang' s largest lake. All basins except the Turpan-Hami Basin small rivers and Tarim River source area showed significant increasing trends, particularly the Qiangtang Plateau inland river basin, which grew at 50.03 $km^2 \cdot a^{-1}$ (67.24%). The mainstream Tarim River seasonal water bodies increased most rapidly at 10.02 $km^2 \cdot a^{-1}$.

Mountain and oasis-desert water bodies both showed significant upward trends [Figure 5: see original paper]. Permanent water bodies were dominated by mountain water bodies, increasing at 25.63 $km^2 \cdot a^{-1}$, led by the Qiangtang Plateau inland river where the entire basin is mountainous. Seasonal water bodies were dominated by oasis-desert water bodies, increasing at 58.56 $km^2 \cdot a^{-1}$, led by the mainstream Tarim River.

2.3 Quantitative Assessment of Surface Water Driving Factors

Geographic detector analysis of climate factors (temperature, precipitation, potential evapotranspiration, snow water equivalent) and human activity factors (cultivated land area, population density) revealed significant differences in factor contributions across basins [Figure 6: see original paper]. Among climate factors, snow water equivalent had the most significant impact with an average contribution rate of 42.84%, followed by precipitation at 41.53%. Temperature and potential evapotranspiration had lower impacts at 28.31% and 24.36%, respectively. Human activity impacts varied substantially, with population density and cultivated land averaging 43.01% and 34.94%, respectively.

Different water body types showed distinct driving factor contributions [Figure 7: see original paper]. Climate change, particularly snow water equivalent (42.84% average contribution), controlled mountain water body changes. Human activities dominated oasis-desert water body changes, with population density and cultivated land contributing 64.10% and 54.43%, respectively. Notably, in some basins like the Central Asian inland river area and Tarim River source area, human activities also significantly impacted mountain water bodies (56.02% and 52.50% contributions), indicating prominent human influence in these regions.

3.1 Impact of Surface Water Dynamic Changes on Terrestrial Water Storage

Regional water resources comprise lakes, rivers, groundwater, and glaciers, playing crucial roles in maintaining social-ecological system diversity. As a key component, surface water dynamics profoundly affect regional water resource stability and sustainability. GRACE data served as a water resource indicator for Xinjiang, with piecewise correlation coefficients quantifying relationships between water body area and terrestrial water storage (TWS) changes [Figure 8: see original paper].

From 2002 to 2020, Xinjiang’ s TWS changes showed significant spatial heterogeneity. Central Tien Shan showed significant decline (-38.49 $mm \cdot a^{-1}$) due to rapid glacier melting and intensified agricultural water use, while southeastern mountains showed significant increase ($+22.59\ \mathrm{mm \cdot a^{-1}}$) from increased rainfall and glacier melt. Overall, Xinjiang' s TWS declined at -4.15 $\mathrm{mm \cdot a^{-1}}$, while surface water bodies increased at 57.01 $\mathrm{km^2 \cdot a^{-1}}$, showing overall weak correlation. However, their trends were similar in different periods. Before 2010, correlation was low (0.21) as increased precipitation maintained relatively stable water body area while TWS declined. After 2010, correlation reached 0.74, indicating growing influence of surface water dynamics on TWS.

3.2 Attribution Analysis of Surface Water Dynamic Changes

Xinjiang' s surface water bodies increased significantly by 5451.17 $\mathrm{km^2}$ from 1990 to 2023, contrasting with global declines in many arid and semi-arid regions. Studies show climate change and human activities threaten surface water bodies globally, with over 50% of lakes showing decreasing storage. Xinjiang' s contrasting pattern stems from its typical mountain-oasis-desert ecosystem relying on precipitation and alpine snow-ice meltwater. Climate change has caused rapid temperature increases in Xinjiang (0.33-0.39 $\mathrm{°C \cdot a^{-1}}$, exceeding global averages), accelerating glacier, snow, and permafrost melting. Precipitation increased at 9.95 $\mathrm{mm \cdot (10a)^{-1}}$, directly supplementing mountain surface water bodies. Thus, climate change is the primary driver, especially in the Qiangtang Plateau inland river basin where mountain water bodies expanded significantly.

Human activities also significantly impact surface water bodies, particularly in agriculturally intensive oasis-desert areas that depend on mountain runoff. Oasis areas are densely populated with numerous towns and cultivated land, where agricultural irrigation, domestic water use, and water resource management affect surface water changes. Xinjiang' s cultivated land expanded dramatically to 123,569.79 $\mathrm{km^2}$ by 2020, directly increasing water demand. To meet needs, Xinjiang built extensive water supply facilities, with total reservoir capacity reaching 24.12 $\mathrm{km^3}$ in 2020—nearly triple that of 1995. Additionally, ecological water conveyance projects since 2000 raised groundwater levels by 1.38-2.69 m in the lower Tarim River, significantly altering surface water distribution and utilization. Human activities can thus both change surface water status and control change trends, necessitating more scientific and sustainable water resource management strategies.

3.3 Uncertainty Analysis and Future Prospects

This study analyzed long-term dynamics and spatial heterogeneity of Xinjiang' s water body area from 1990 to 2023 using multi-source remote sensing data, facing several uncertainties. First, although CFmask can effectively reduce impacts from clouds, cloud shadows, and snow pixels, thin clouds and topographic shadows may still affect extraction accuracy. Second, Landsat' s 16-day revisit cycle may miss instantaneous surface water changes like floods and rainstorms. Third, despite 30 m resolution being sufficient for regional-scale analysis, it limits detailed analysis of small water bodies and precise water-land boundary changes. Future research should employ weather- and time-independent radar data and higher spatial resolution optical data to improve extraction effectiveness.

4. Conclusions

Based on the GEE platform and multi-source remote sensing data, this study monitored Xinjiang's surface water bodies annually from 1990 to 2023, analyzing spatial patterns and change trends while revealing climate change and human activity impacts. Main conclusions are:

1) Over the past three decades, Xinjiang' s surface water bodies showed a significant upward trend with increasing influence on terrestrial water storage. Permanent water bodies increased by 36.25% (2466.20 km^2), while seasonal water bodies increased by 181.90% (1924.84 km^2).
2) Xinjiang' s permanent water bodies are dominated by mountain water bodies, with the Qiangtang Plateau inland river basin expanding significantly by 1149.58 km^2 (67.24%). Seasonal water bodies are dominated by oasis-desert water bodies, with the mainstream Tarim River increasing by 344.92 km^2 (nearly doubled).
3) Climate factors, particularly snow water equivalent (42.84% average contribution), dominate mountain water body changes. Human activities dominate oasis-desert water body changes, with population density and cultivated land contributing 64.10% and 54.43%, respectively.

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Note: Figure translations are in progress. See original paper for figures.