Spatiotemporal Dynamics of NPP and Its Driving Forces in the Qinghai Lake Basin (Postprint)

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Abstract

Analyzing vegetation Net Primary Productivity (NPP) and its driving factors in the Qinghai Lake basin can provide valuable references for watershed ecological management and sustainable development. This study estimated NPP values in the Qinghai Lake basin using the Carnegie-Ames-Stanford Approach (CASA) model and quantitatively evaluated the dynamic changes and driving factors of NPP from 2000 to 2018 through methods including trend analysis, Hurst index, and Geographical Detector. The results indicate that: In terms of spatial distribution, the multi-year average vegetation NPP in the Qinghai Lake basin was 218.88 g C·m-2, with high annual average NPP values distributed in the northern and southern parts of Qinghai Lake, reaching a maximum of 375.85 g C·m-2, while low values were distributed on the eastern shore of Qinghai Lake, with a minimum of 0.11 g C·m-2. Temporally, the basin's annual average NPP exhibited an increasing trend from 2000 to 2018, with an increase rate of 1.61 g C·m-2·a-1, reaching the highest value of 247.30 g C·m-2 in 2018. Seasonal variations revealed that NPP peaked in July and reached its minimum in January. Regarding future NPP change trends, areas with Hurst index less than 0.5 accounted for 75.6%, indicating that future vegetation NPP change trends in the Qinghai Lake basin may be opposite to the current trend. Geographical Detector results revealed that in single-factor detection, land use was the primary driving force of vegetation NPP change, while in interaction detection, the strongest dominant interaction factor was elevation and land use. Land use types are significantly influenced by natural factors, and greater attention should be paid to watershed topographic factors and human activities.

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Full Text

Dynamic Changes and Driving Forces of Net Primary Productivity in the Qinghai Lake Basin

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Abstract

Analyzing vegetation Net Primary Productivity (NPP) and its driving factors in the Qinghai Lake Basin provides valuable references for watershed ecological management and sustainable development. This study estimated NPP values for the Qinghai Lake Basin from 2000 to 2018 using the Carnegie-Ames-Stanford Approach (CASA) model, and quantitatively evaluated the dynamic changes and driving factors through trend analysis, Hurst index, and Geographic Detector methods. The results reveal that, spatially, the multi-year average NPP exhibited a pattern of gradually increasing from northwest to southeast. High NPP values were distributed in the north and south of Qinghai Lake, reaching a maximum of 375.85 g $C \cdot m^{-2}$, while low values occurred on the eastern shore, with a minimum of 0.11 g $C \cdot m^{-2}$. Temporally, the annual average NPP showed an upward trend from 2000 to 2018, with an increase rate of 1.61 g $C \cdot m^{-2} \cdot a^{-1}$, peaking at 247.30 g $C \cdot m^{-2}$ in 2018. Seasonally, NPP varied significantly within the year, with the highest values in summer and lowest in winter. Regarding future trends, areas with Hurst index < 0.5 accounted for 75.6% of the basin, indicating that future NPP trends may reverse from current patterns. Geographic Detector analysis identified land use as the primary driving factor of NPP change in single-factor detection, while the strongest interaction effect occurred between land use and elevation. Since land use types are heavily influenced by natural factors, increased attention should be directed toward watershed topographic factors and human activities.

Keywords: vegetation Net Primary Productivity; CASA model; Geographic Detector; Qinghai Lake Basin

1. Methods

1.1 Study Area Overview

The Qinghai Lake Basin is located in northeastern Qinghai Province, China, at the intersection of the northwest arid zone, southwest alpine zone, and eastern monsoon zone. Surrounded by mountains, it contains China's largest inland lake. The basin elevation ranges from 3,159 to 5,279 m, covering an area of approximately 2.97$\times10^{4}$ km^2 with a topography characterized by high elevations in the northwest and low elevations in the southeast. Annual precipitation ranges from 304.3 to 1,605.14 mm, and mean annual temperature varies from -9.27 to 2.77 ℃. The basin features rich vegetation and diverse land use types, including farmland, desert, gravel, bare rock, glaciers, wetlands, lakes, construction land, grassland, and sparse forest.

[Figure 1: see original paper]

1.2 CASA Model and Driving Data

1.2.1 CASA Model Description The CASA model, introduced by Potter et al. in 1993, simulates vegetation net primary productivity and has been widely applied in NPP estimation research. The model primarily includes two indicators: Photosynthetically Active Radiation (APAR) and light use efficiency ( ). Light use efficiency is jointly influenced by temperature and moisture factors. This study adopted the parameterization scheme of Zhu et al., which simplifies model parameters and reduces computational complexity. The calculation formula is as follows:

$$NPP(x,t) = APAR(x,t) \times \varepsilon(x,t)$$

where $APAR(x,t)$ represents the photosynthetically active radiation absorbed by pixel x in month t (unit: $\mathrm{MJ} \cdot \mathrm{m}^{-2} \cdot \mathrm{month}^{-1}$), and $\varepsilon(x,t)$ represents the actual light use efficiency of pixel x in month t (unit: $\mathrm{g\ C} \cdot \mathrm{MJ}^{-1}$).

1.2.2 Data Sources and Preprocessing The CASA model requires multiple data inputs including Normalized Difference Vegetation Index (NDVI), temperature, precipitation, radiation, and land use data.

NDVI data were obtained from the MOD13Q1 vegetation index product synthesized by NASA's MODIS sensor, with a spatial resolution of 250 m. Monthly data for the Qinghai Lake Basin from 2000 to 2018 were selected (with 2018 data substituted for 2000 data) and preprocessed through projection (uniformly defined as WGS 1984 UTM), mosaicking, clipping, and removal of invalid values.

Radiation, temperature, and precipitation data were sourced from the China Regional Surface Meteorological Elements Driven Dataset (1979–2018) at the National Tibetan Plateau Data Center. This dataset includes near-surface air temperature, pressure, specific humidity, wind speed, precipitation rate, downward shortwave radiation, and downward longwave radiation in NETCDF format, with a temporal resolution of 3 hours and spatial resolution of 0.1°. This study selected the 2000–2018 data and processed them using Matlab to obtain monthly average values.

Land use data were obtained from the Chinese Land Use Dataset of the Chinese Academy of Sciences Resource and Environmental Science Data Center. The 2000–2018 data were projected, masked, resampled, and reclassified according to CASA model requirements to obtain multi-period land use data for the Qinghai Lake Basin.

This study selected nine factors as Geographic Detector indicators: temperature, precipitation, radiation, slope, aspect, elevation, land use type, Gross Domestic Product (GDP), and population density. GDP and population density data were sourced from the Chinese Academy of Sciences Resource and Environmental Science Data Center as 1 km grid datasets. Digital Elevation Model (DEM) data were obtained from the Geospatial Data Cloud (SRTM 90 m) and processed using ArcGIS to derive slope and aspect data. All other data used annual averages.

1.3 Analysis Methods

1.3.1 Trend Analysis Trend analysis helps understand temporal variation patterns. The calculation formula is:

$$Slope = \frac{n \times \sum_{i=1}^{n}(i \times NPP_i) - \sum_{i=1}^{n} i \times \sum_{i=1}^{n} NPP_i}{n \times \sum_{i=1}^{n} i^2 - (\sum_{i=1}^{n} i)^2}$$

where n is the length of the time series (years), i represents the i-th year, and NPP_i represents the NPP value in year i. $Slope > 0$ indicates an increasing trend over time, while $Slope < 0$ indicates a decreasing trend. Larger absolute $Slope$ values indicate faster change rates. Significance testing was performed based on confidence level P: $P < 0.05$ indicates significant and reliable results, while $P \geq 0.05$ indicates weak significance.

1.3.2 Hurst Index The Hurst index was used to analyze persistence characteristics and predict future trends. When $Hurst \in (0.5, 1]$, the sequence exhibits persistence with long-term correlation, meaning future trends will be consistent with past trends. If $H = 0.5$, the sequence is random. If $Hurst \in (0, 0.5)$, the sequence shows anti-persistence, meaning future trends will oppose past trends, with stronger anti-persistence as values approach 0.

1.3.3 Geographic Detector The Geographic Detector method quantitatively explores spatial heterogeneity and quantifies multi-factor interactions. It detects the spatial heterogeneity of variable Y explained by factor X, measured by the q value:

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

where $h = 1, \ldots, L$ represents categories of variable Y or factor X; N_h and N represent the number of units in category h and the entire study area, respectively; and σ_h^2 and σ^2 represent the variance of category h and the entire area, respectively. The q value ranges from [0,1], with larger values indicating stronger explanatory power of X on Y.

When applying Geographic Detector, numerical variables must first be discretized. This study used the natural breaks method to classify temperature, precipitation, radiation, slope, elevation, GDP, and population density into categories that minimize within-group differences and maximize between-group differences, avoiding artificial interference. A 1 km × 1 km grid was created for the classified data.

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2. Results and Analysis

2.1 Spatial-Temporal Characteristics of NPP

The spatial distribution of multi-year average NPP in the Qinghai Lake Basin showed a gradual increase from northwest to southeast. NPP values were concentrated between 100–300 g $C \cdot m^{-2}$, accounting for approximately 43.7% of the basin area and primarily distributed in the central and southeastern regions where vegetation types are mainly grassland and meadow. Areas with NPP < 100 g $C \cdot m^{-2}$ accounted for the smallest proportion (15.2%), mainly distributed in the northwestern part of the basin at elevations of 4,000–5,000 m, where vegetation consists primarily of bare rock and gravel with low-coverage grassland.

High NPP values were distributed in the north and south of Qinghai Lake, reaching a maximum of 375.85 g $C \cdot m^{-2}$ in areas dominated by medium- and high-coverage grassland. Low NPP values occurred on the eastern shore of Qinghai Lake, with a minimum of 0.11 g $C \cdot m^{-2}$ in areas dominated by sandy land. Temporally, vegetation NPP showed an overall upward trend from 2000 to 2018, with an annual increase rate of 1.61 g $C \cdot m^{-2} \cdot a^{-1}$ and fluctuation range of 192.91–247.30 g $C \cdot m^{-2}$. The multi-year average NPP was 218.88 g $C \cdot m^{-2}$, with the lowest value (192.91 g $C \cdot m^{-2}$) in 2000 and highest value (247.30 g $C \cdot m^{-2}$) in 2018—11.9% lower and 13.0% higher than the multi-year average, respectively.

Pixel-by-pixel trend analysis revealed NPP change rates ranging from -23.31 to 12.74 g $C \cdot m^{-2} \cdot a^{-1}$. Based on trend analysis and confidence levels, the study area was divided into six categories (Fig. 3). Areas showing an increasing trend accounted for 84.9% of the basin, distributed across most of the region, with significant increases in the northwestern and southern parts (32.2% of the basin) where vegetation is primarily medium- and high-coverage grassland. Decreasing trends accounted for 15.1% of the basin, mainly distributed on the eastern shore of Qinghai Lake in sandy areas.

Monthly data showed substantial intra-annual variation, with NPP peaking in July at approximately 53.71 g $C \cdot m^{-2}$ (25.2% of annual total) and reaching its lowest in January at about 0.31 g $C \cdot m^{-2}$ (0.15% of annual total). The growing season (June–September) contributed 66.2% of annual NPP, with summer NPP reaching 141.21 g $C \cdot m^{-2}$. Spring and autumn NPP values were similar (15.6% and 16.7% of annual total, respectively), while winter NPP was lowest at 3.25 g $C \cdot m^{-2}$.

[Figure 2: see original paper]
[Figure 3: see original paper]
[Figure 4: see original paper]

2.2 Future Trends of Vegetation NPP

The Hurst index for the Qinghai Lake Basin ranged from 0.12 to 0.91. Areas with Hurst < 0.5 (indicating anti-persistence) accounted for 75.6% of the basin, suggesting that future NPP trends may oppose current trends. Areas with Hurst > 0.5 (indicating persistence) accounted for 25.4% of the basin.

Overlay analysis of NPP trend and Hurst index produced six categories (Table 1). The area proportions from high to low were: anti-persistence without significant change (48.1%), anti-persistence with significant increase (26.6%), persistence without significant change (17.4%), persistence with significant increase (4.6%), anti-persistence with significant decrease (2.7%), and persistence with significant decrease (0.6%). The dominant pattern was anti-persistence without significant change, mainly distributed in the northern part of Qinghai Lake. Areas where future trends may shift from increase to decrease accounted for 26.6% of the basin, primarily located northwest of Qinghai Lake, requiring enhanced ecological monitoring.

[Figure 5: see original paper]

2.3 Detection of Driving Factor Influence

Nine factors were selected for Geographic Detector analysis: temperature, precipitation, radiation, slope, aspect, elevation, land use type, GDP, and population density. Single-factor detection revealed that land use was the dominant driving force of NPP change, with the strongest explanatory power (average q value of 0.51). The average q values for 2000–2018 ranked as: land use (0.51) > precipitation (0.23) > temperature (0.18) > elevation (0.15) > aspect (0.12) > radiation (0.11) > slope (0.09) > GDP (0.07) > population density (0.06). This indicates that land use data constitute the primary driver of NPP variation, while temperature and elevation also show relatively high explanatory power.

Socioeconomic factors (GDP and population density) have minimal impact on NPP.

Interaction detection showed that two-factor interactions produced significantly greater explanatory power than single factors. All interactions between land use and other factors enhanced NPP explanatory power. The strongest interaction effects were land use elevation, land use temperature, and land use radiation, all with q values exceeding 0.55, demonstrating that combined effects of land use and climatic factors strongly influence NPP dynamics.

[Figure 6: see original paper]

3. Discussion

Previous studies by Qiao Kai and Zheng Zhong also simulated NPP in the Qinghai Lake Basin, obtaining multi-year average values of 168.03 g $C \cdot m^{-2}$ and 145.71 g $C \cdot m^{-2}$, respectively. Zhang et al. estimated Tibetan Plateau grassland NPP at 167.52 g $C \cdot m^{-2}$. Our CASA model simulation yielded 218.88 g $C \cdot m^{-2}$, slightly higher than previous results. To verify our findings, we compared them with MODIS NPP (MOD17A3) data, which showed a multi-year average of 215.62 g $C \cdot m^{-2}$ for the Qinghai Lake Basin—consistent with our CASA model result (218.88 g $C \cdot m^{-2}$). Figure 7 further illustrates the temporal consistency between CASA-simulated NPP and MOD17A3 data, confirming the reliability of our results.

Inter-annual and intra-annual NPP fluctuations were substantial but showed an overall upward trend, consistent with findings by Zhang Tao et al. Geographic Detector results indicated that land use is the primary driving factor, with its influence gradually increasing. Essentially, land use impacts NPP because different vegetation types have varying carbon sequestration capacities. In the Qinghai Lake Basin, land use changes were minimal from 2000–2018, with grassland showing the largest variation. Medium- and high-coverage grasslands are concentrated around Qinghai Lake and gradually decrease outward, corresponding to the spatial pattern of decreasing NPP from the lake center to the periphery. The northwestern basin consists mainly of low-coverage grassland and desert, resulting in NPP values below 100 g $C \cdot m^{-2}$.

The Qinghai Lake Basin climate has shifted toward warmer and more humid conditions in recent years, creating favorable environments for vegetation growth. Geographic Detector analysis revealed that interactions between land use and elevation, temperature, and precipitation have the greatest explanatory power. Some studies have found that climate change is the main factor affecting vegetation coverage in the basin, with increased precipitation causing positive vegetation changes. However, excessive precipitation can have negative effects, and rising temperatures may increase evapotranspiration, limiting vegetation growth. Therefore, climate change impacts must be closely monitored.

Elevation increases from southeast to northwest around Qinghai Lake, with temperature and precipitation transitioning from warm-humid to cold-dry conditions along this gradient. Correspondingly, vegetation types shift from temperate steppe to alpine wetland, alpine meadow steppe, desert, and alpine sparse vegetation, explaining why NPP decreases from the lake outward (Fig. 2). This pattern aligns with vegetation distribution 规律.

This study used fused data to estimate NPP and analyze driving factors, but the examination of driving factors remains preliminary. Future research should incorporate evapotranspiration and soil factors, assess NPP changes under different climate scenarios, and evaluate driving factors by season or time period.

[Figure 7: see original paper]

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4. Conclusions

Based on CASA model estimation of Qinghai Lake Basin NPP from 2000–2018, combined with trend analysis, Hurst index, and Geographic Detector methods, this study quantitatively investigated NPP variation trends and driving factors. The main conclusions are:

1) Spatially, vegetation NPP in the Qinghai Lake Basin showed a gradual increase from northwest to southeast from 2000–2018. Temporally, NPP exhibited a fluctuating upward trend with an increase rate of 1.61 g $C \cdot m^{-2} \cdot a^{-1}$ and a multi-year average of 218.88 g $C \cdot m^{-2}$. Inter-annual variation was substantial. Intra-annual variation was significant due to temperature and precipitation influences, with the lowest NPP in winter and highest in summer.

2) The Hurst index ranged from 0.12 to 0.91, with 75.6% of the basin showing anti-persistence (Hurst < 0.5). This indicates that future NPP trends may oppose current trends, with 25.4% of the basin showing strong anti-persistence.

3) Geographic Detector results show that land use is the primary driving factor of NPP change in single-factor detection. In interaction detection, two-factor interactions showed far greater explanatory power than single factors, with land use elevation being the strongest interaction, indicating that land use has substantial influence on NPP, with elevation's impact gradually increasing.

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