Spatiotemporal Variation of Vegetation NEP and Its Driving Factors in Qinghai Province: Postprint

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Date: 2022-12-20T00:00:00+00:00

Abstract

To investigate the spatiotemporal evolution of vegetation carbon sequestration and its driving factors in Qinghai Province, vegetation Net Ecosystem Productivity (NEP) was calculated based on Net Primary Productivity (NPP) data from 2000 to 2020 and a soil respiration model. Quantitative analysis of the spatiotemporal evolution of vegetation NEP and its driving factors in Qinghai Province was conducted using trend analysis, partial correlation analysis, and Geodetector. The results indicate that vegetation NEP in Qinghai Province exhibited a fluctuating upward trend over the past 20 years, with an average annual increase of 1.54 g C · m-2 · a-1. The spatial variation of annual average vegetation NEP was substantial, decreasing from southeast to northwest, with 71.08% of the area remaining unchanged or increasing. NDVI demonstrated the strongest explanatory power for vegetation NEP, while climatic and anthropogenic factors such as precipitation, temperature, and population density also exhibited strong explanatory power for the spatial differentiation of NEP. Since two-factor interactions enhance the explanatory power for the spatial differentiation of vegetation NEP, multi-factor synergy should be considered when enhancing the carbon sequestration capacity of Qinghai Province in the future.

Full Text

Spatiotemporal Variation and Driving Factors of Vegetation NEP in Qinghai Province

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Abstract

To investigate the spatiotemporal evolution of vegetation carbon sequestration and its driving factors in Qinghai Province, this study calculated vegetation Net Ecosystem Productivity (NEP) based on 2000–2020 Net Primary Productivity (NPP) data and a soil respiration model. Trend analysis, partial correlation analysis, and geographical detector methods were employed to quantitatively analyze the spatiotemporal dynamics of vegetation NEP and their driving mechanisms. The results indicate that vegetation NEP in Qinghai Province exhibited a fluctuating upward trend over the past 20 years, with an average annual increase of 1.54 g $C \cdot m^{-2}$. Spatial variation was substantial, decreasing from southeast to northwest, with 71.08% of the region maintaining stable or increasing NEP. The Normalized Difference Vegetation Index (NDVI) demonstrated the strongest explanatory power for spatial differentiation of vegetation NEP, while climatic and anthropogenic factors such as precipitation, temperature, and population density also showed significant influence. Notably, two-factor interactions substantially enhanced the explanatory power for NEP spatial differentiation, suggesting that future efforts to enhance carbon sequestration capacity in Qinghai Province must consider multi-factor synergistic effects.

Keywords: Qinghai Province; vegetation NEP; spatiotemporal variation; driving forces

Introduction

Terrestrial ecosystems represent a core component of global climate change research and play a crucial role in global carbon balance. Quantifying spatiotemporal variations in terrestrial carbon sinks is fundamental to climate change prediction and greenhouse gas control protocol implementation. Comparative analysis of regional carbon budgets is essential for understanding inter-regional carbon cycling processes. Implementing ecological restoration projects to enhance vegetation carbon sequestration constitutes a primary approach for regional carbon sink enhancement. Net Ecosystem Productivity (NEP), which quantifies carbon budget status per unit area and time, serves as a key parameter for qualitative and quantitative analysis of terrestrial vegetation carbon cycling and has become a research hotspot in recent years. Methodological approaches include statistical models based on climate variables, parameter models related to light use efficiency, and process models based on ecosystem mechanisms. Advances in remote sensing technology for retrieving surface parameters and vegetation information have propelled mechanism-based ecosystem models to the forefront of current research.

Qinghai Province, located in the northeastern part of the "Third Pole" and known as the "Source of Three Rivers" and "China' s Water Tower," is one of the most sensitive regions to global climate change. Consequently, changes in vegetation carbon sequestration capacity in Qinghai have substantial implications for greenhouse gas emission control and carbon cycling across the Tibetan Plateau and globally. During urbanization and industrialization, population distribution and land cover have undergone transformations that inevitably affect terrestrial vegetation carbon cycling. Although terrestrial ecosystems are projected to continue functioning as carbon sinks, significant controversies remain regarding the driving mechanisms of vegetation carbon sequestration changes and how to clarify vegetation dynamics and their driving mechanisms in climate-sensitive regions under complex environmental changes.

Previous studies have analyzed climate drivers of vegetation on the Qinghai Plateau, demonstrating climate change impacts on NEP evolution. Other research in the Shiyang River basin identified precipitation and temperature as primary factors influencing NEP variation, with solar radiation having negligible effects. Studies in southwestern China have examined spatiotemporal NEP evolution combined with human intensity indices using geographically weighted regression. However, existing research on NEP driving factors has primarily focused on climatic factors, with anthropogenic factor analysis limited to single-factor effects. To explore the impact of dual-factor interactions on NEP, this study applies geographical detectors for quantitative analysis of driving factors, enabling both single-factor and multi-factor interactive effect detection between anthropogenic and climatic factors.

1. Study Area and Data

1.1 Study Area Overview Qinghai Province is located between 89°35 - 103°04 E and 31°9 -39°19 N, characterized by a plateau temperate semi-arid climate with strong winds, long sunshine duration, and low precipitation. Annual precipitation ranges from 50–550 mm, and mean annual temperature varies from -5.1 to 9.0°C. The terrain generally slopes from northwest to southeast. Precipitation is concentrated in spring and summer, with runoff primarily derived from snowmelt and southwestern warm moisture flows.

Forest resources are mainly distributed near river source areas, covering 2.65$\times$10^{4}$ km^2. Grassland types are predominantly alpine meadow and steppe [Figure 2: see original paper], with natural grassland area of 4.2$\times$10^{4}$ km^2 distributed in the northeastern Qilian Mountains and eastern Qaidam Basin regions. Due to special climate conditions, high altitude, and weathered erosion landforms, vegetation in Qinghai Province is highly susceptible to human activities and climate change.

1.2 Data Sources and Processing Net Primary Productivity (NPP) data were obtained from the MODIS MOD17A3 product (https://ladsweb.modaps.eosdis.nasa.gov/) with annual temporal resolution and 500 m spatial resolution for 2000–2020. Normalized Difference Vegetation Index (NDVI) data were derived from MOD13Q1 product with 250 m spatial resolution and monthly temporal resolution, composited into annual maximum values. Land use data were obtained from MCD12Q1 product for 2001-2020. Meteorological data for Qinghai Province were sourced from the China Meteorological Data Service Center (http://data.cma.cn/), with monthly datasets resampled to 0.5°$×$0.5° resolution and interpolated using spline functions. Population density data were obtained from the Chinese Academy of Sciences Resource and Environmental Science and Data Center (https://www.resdc.cn). All data were uniformly processed using Albers conic projection.

For geographical detector analysis of spatial heterogeneity, a 40 km spatial grid was selected to analyze environmental change impacts on vegetation NEP. Precipitation and temperature were classified using natural breaks method, while population density was classified using quantile method.

2. Methods

2.1 NEP Estimation NEP describes regional carbon balance dynamics, indicating vegetation carbon budget status per unit area and time. It serves as a key factor for measuring vegetation activity and can characterize vegetation health and carbon sequestration capacity. Neglecting other natural and anthropogenic factors, NEP values represent the carbon exchange rate between terrestrial and atmospheric ecosystems. NEP >0 indicates that vegetation carbon sequestration exceeds soil respiration carbon emissions, manifesting as a vegetation carbon sink.

The calculation formula is as follows:

$$NEP(t,x) = NPP(t,x) - RH(t,x)$$

where $NEP(t,x)$, $NPP(t,x)$, and $RH(t,x)$ represent vegetation net ecosystem productivity, net primary productivity, and soil respiration for pixel x in year t, respectively, with units of g $\mathrm{C \cdot m^{-2}}$.

Soil respiration (RH) in this study was estimated indirectly from temperature and precipitation using the empirical formula established by Pei Zhiyong et al., which has been validated through field sampling and is applicable for monitoring soil respiration in Qinghai and northwestern China regions. The calculation formula is:

$$RH = 0.22 \times [EXP(0.0913 \times T + 1 \times 0.3145 \times P) + ln(P) \times 12,23] + 30 \times 46.5\%$$

where T represents mean annual temperature (°C), P represents annual precipitation (mm), and RH represents annual soil respiration (g $\mathrm{C \cdot m^{-2}}$).

2.2.1 Trend Analysis The Mann-Kendall test was employed to analyze interannual variation patterns and dynamic changes, calculated as:

$$S = \sum_{i=1}^{n-1} \sum_{k=i+1}^{n} \operatorname{sgn}(x_k - x_i)$$

where x_k and x_i are consecutive data sequences and n is the number of years. The standardized test statistic ZC was computed, where $ZC > 0$ indicates an upward trend and vice versa. Since Mann-Kendall detects monotonic trends that are not necessarily linear, the Theil-Sen slope estimator was introduced to represent change magnitude Q:

$$Q = \text{Median}\left[\frac{x_k - x_i}{k - i}\right], \quad i < k < n$$

When $Q > 0$, it reflects an upward trend, and vice versa.

2.2.2 Correlation Analysis (1) Partial Correlation Coefficient

Partial correlation analysis quantifies NEP response to influencing factors while controlling for other variables. The partial correlation coefficient formula is:

$$P_{ij,k} = \frac{P_{ij} - P_{ik}P_{jk}}{\sqrt{(1 - P_{ik}^2)(1 - P_{jk}^2)}}$$

where $P_{ij,k}$ is the partial correlation coefficient between variables i and j controlling for variable k; P_{ij}, P_{jk}, and P_{ik} are pairwise correlation coefficients.

(2) Geographical Detector

Geographical detector is a statistical method for detecting spatial heterogeneity and revealing underlying driving forces. Based on research needs, this study applied factor detector and interaction detector to analyze NEP driving forces and multi-factor interactions. The explanatory power of factor X on attribute Y spatial heterogeneity is measured by q value:

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

where q represents the explanatory power of a factor on NEP spatial differentiation, with values ranging [0,1]. Larger q values indicate stronger spatial differentiation. In extreme cases, $q = 1$ indicates complete control of NEP spatial distribution. h indexes strata of factor X (range [1, L]), σ_h^2 and σ^2 are variances of stratum h and entire region, respectively; N_h and N are unit numbers; SSW and SST are within-stratum variance sum and total variance.

Interaction detector evaluates interactive effects between different factors on NEP differentiation. The method calculates individual q values for two factors and their interaction q value for comparison. Judgment criteria are shown in .

Table 1 Basis of interaction judgment

Interaction Type	Judgment Criterion
Nonlinear weakening	$q(X_1 \cap X_2) < \text{Min}[q(X_1), q(X_2)]$

Interaction Type	Judgment Criterion
Single-factor nonlinear weakening	$\text{Min}[q(X_1), q(X_2)] < q(X_1 \cap X_2) < \text{Max}[q(X_1), q(X_2)]$
Dual-factor enhancement	$q(X_1 \cap X_2) > \text{Max}[q(X_1), q(X_2)]$
Nonlinear enhancement	$q(X_1 \cap X_2) > q(X_1) + q(X_2)$

3. Results

3.1 NEP Accuracy Evaluation Since measured NEP data are difficult to obtain, this study validated estimates using: (1) measured RH data from other scholars in Qinghai Province, (2) measured RH results from meteorological stations in the Three Rivers Source Region from the Tibetan Plateau Data Center, and (3) simulated NEP results from station meteorological data. Correlation analysis between measured and estimated data yielded a correlation coefficient of 0.7821 ($p < 0.01$), indicating significant correlation and reliable results.

3.2.1 Spatial Distribution Characteristics of NEP in Qinghai Province The spatial distribution of NEP showed significant differences, characterized by high values in the southeast and low values in the northwest [Figure 3: see original paper]. The multi-year average NEP was 134.69 g $C \cdot m^{-2}$, with NEP > 0 areas covering 74.15% of the province and NEP < 0 areas accounting for 5.07%. High-value regions (312–735.90 g $C \cdot m^{-2}$) were concentrated near the Qilian Mountains, Qinghai Lake wetlands, river source areas, and the upper Yellow River valley. Carbon source areas were mainly located in Golmud City, Zhiduo County, and Zaduo County. The distinct spatial transition primarily relates to local precipitation conditions and vegetation distribution.

3.2.2 Interannual Variation Characteristics of NEP Over the past 20 years, interannual variation was evident, with the carbon sequestration capacity of ecosystems showing a fluctuating increasing trend. The multi-year average NEP ranged from 114.55–155.49 g $C \cdot m^{-2}$, with an average annual increase of 1.54 g $C \cdot m^{-2}$. Based on maximum and minimum values, three periods were identified: (1) 2000–2005, with NEP fluctuating around the multi-year mean; (2) 2006–2015, with fluctuating increases; and (3) 2016–2020, with continuous increases representing the period of maximum growth rate.

3.2.3 Dynamic Changes of NEP To analyze spatial dynamic patterns, pixel-by-pixel Theil-Sen trend analysis was conducted [Figure 5: see original paper]. The spatial pattern of NEP change trends resembled its distribution pattern, showing overall increasing carbon sequestration capacity across Qinghai Province, with negative trends primarily in Haixi and Yushu cities (2.17% of provincial area), mainly in sparsely vegetated regions. High-growth areas (3.17%) were concentrated near Qinghai Lake wetlands, Guinan County, and Gonghe County, where precipitation is relatively abundant and vegetation cover is rich. Superimposing Theil-Sen trends with significance tests revealed that areas passing the $p < 0.05$ significance test covered 3.55$\times10^{4}$ km^2, with significantly increasing areas accounting for 52.95% of the province, mainly distributed in Qaidam Basin desert, Qilian Mountain forest and alpine steppe, and river source meadow steppe ecosystems. Significantly decreasing areas comprised only 0.23%, scattered across Tianjun, Maduo, Qumalai, Huangzhong, Zhiduo, and other counties.

3.3.1 Response of NEP to Climate Factors Climate factors influence NEP by affecting vegetation growth, net primary productivity, and soil respiration. Temperature and precipitation are the primary meteorological factors affecting NEP variation. Over the past 20 years, mean annual temperature in Qinghai Province ranged from -2.35 to -0.70°C, averaging -1.44°C. Areas where NEP negatively correlated with temperature accounted for only 7.37% of the province, scattered across various cities. Positive correlations dominated (71.5% of area), located in foothills, river source areas, and valleys, primarily forest and grassland ecosystems. Significant positive correlations ($p < 0.05$) covered 2.572$\times10^{4}$ km^2 (38.53% of the province).

Annual precipitation ranged from 325–460.85 mm, averaging 395.26 mm. Precipitation-NEP partial correlation coefficients ranged from -0.24 to 0.42, with negative correlations in 23.32% of the province (mainly Yushu, Nangqian, Qumalai, Gande, Jiuzhi, Banma, Zaduo, Henan County). Positive correlations covered 65.75% (mainly Hainan, Haibei, Haixi, Haidong), with significant positive correlations ($p < 0.05$) in 1.142$\times10^{4}$ km^2 (17.1% of area). The correlation analysis indicates that temperature effects on NEP exceed precipitation effects in arid and semi-arid regions.

Spatial analysis revealed high similarity between NEP distribution and temperature/precipitation patterns. High NEP value areas (312–735.90 g $C \cdot m^{-2}$) in Qinghai Lake wetlands, Guinan, and Gonghe counties showed strong positive correlations with both temperature and precipitation. Areas with significant positive precipitation correlations ($p < 0.05$) covered 65.83% of the province, mainly in Hainan, Haidong, and southeastern Haixi.

3.3.2 Human Driving Forces Land use type conversion reveals anthropogenic impacts on NEP. Based on the Land Use Status Classification and MCD12Q1 data, six major categories were identified: cropland, forest, grassland, water body, urban/rural residential land, and unused land. To analyze land use impacts during 2000–2020, the most significant conversion period (2005–2010) was selected, during which conversion area reached 49.48% of the study area, primarily conversion between unused land and grassland (desert to grassland) in Qaidam Basin desert, eastern Kunlun alpine desert steppe, and northern Qiangtang alpine desert steppe regions. Cropland decreased and converted to grassland during 2015–2020 due to government ecological protection policies such as "returning farmland to grassland."

3.3.4 Factor Influence Detection To explore impacts of different factors on NEP spatial differentiation, eight typical factors were selected for geographical detector analysis (with 2001 data missing). Single-factor analysis results [Figure 11: see original paper] showed that NDVI was the dominant factor throughout the study period, with q values around 0.9 and small interannual fluctuations, indicating strong explanatory power. Temperature and precipitation showed strong explanatory power ($q > 0.5$), with precipitation exceeding temperature in 2015 due to low precipitation limiting vegetation growth and carbon sequestration. Land use and per capita GDP showed relatively stable influence.

Interaction detector results revealed that interactive q values significantly exceeded single-factor q values, indicating nonlinear enhancement. The dominant interactive factor in representative years was NDVI combined with other factors, with explanatory power exceeding 0.95. Although per capita GDP had small individual influence, its interaction with NDVI could surpass other factors in specific years.

4. Discussion

Validation against crop yield data confirmed the reliability of MOD17A3HGF NPP estimates. The RH model has been validated in the Qinghai Plateau and Tibetan Plateau regions through field observations. This study estimated Qinghai' s 20-year average NEP as 134.69 g $C \cdot m^{-2}$, close to values reported by Zhou Xiafei et al. (120.8 g $C \cdot m^{-2}$) and Liu Feng et al. (128.40 g $C \cdot m^{-2}$). Despite methodological differences and updated time series, the estimates are comparable. Uncertainty primarily stems from soil respiration estimation, as defining RH as a function of meteorological factors may neglect the contribution of substrate decomposition to heterotrophic respiration, potentially overestimating carbon sinks in high vegetation cover areas and underestimating them in low cover areas.

Factor analysis revealed that climate factors (temperature, precipitation) and anthropogenic factors (land use) most significantly influenced NEP. Temperature effects exceeded precipitation because moderate warming promotes NPP more than RH, and above 2000 m elevation, water limitation on plant growth decreases. Negative temperature correlations occurred mainly in desert areas (e.g., Qaidam Basin) where lower temperatures reduce evaporation, alleviating water deficit and promoting NEP accumulation. High spatial similarity between NEP and NDVI distributions indicates that high vegetation coverage areas have high photosynthetic efficiency and carbon exchange.

Geographical detector analysis showed climate factors overall explained NEP spatial heterogeneity more than anthropogenic factors, though situations varied in special years. Under the "warming and wetting" climate trend, vegetation carbon storage capacity responses will present new patterns. While individual anthropogenic factors showed weaker explanatory power, their interactions with other factors exceeded single-factor effects. Dual-factor synergistic interactions far exceed single-factor effects, indicating that future ecosystem carbon sequestration enhancement requires appropriate human intervention alongside climate change adaptation. The relatively low explanatory power of precipitation in 2015 warrants further investigation.

Since carbon fixed by crops during the growing season rapidly enters the atmospheric carbon cycle, and given the large proportion of cropland in the study area, excluding cropland impacts would better guide regional carbon sink enhancement. As one of China' s five major pastoral areas, future studies should incorporate livestock numbers into anthropogenic factor analysis.

5. Conclusions

This study comprehensively analyzed spatiotemporal patterns and driving factors of NEP in Qinghai Province over the past 20 years using geographical detectors. Key conclusions are:

1) **Temporal scale:** NEP showed an increasing trend with an amplitude of 1.07 g $C \cdot m^{-2} \cdot a^{-1}$ and multi-year average of 134.69 g $C \cdot m^{-2}$. Spatially, NEP distribution was consistent with vegetation cover, decreasing from east to west.
2) **Correlation analysis:** NEP was positively correlated with both temperature and precipitation across spatial and interannual scales, with temperature showing stronger correlation than precipitation.
3) **Factor detection:** NDVI dominated NEP spatial differentiation, with temperature showing relatively strong effects. In dry years, precipitation' s influence exceeded all factors except NDVI. Two-factor interactions surpassed single-factor influences. The spatial distribution of NEP in Qinghai Province results from combined climate and anthropogenic factors, with their interactive effects being the dominant driving mechanism.

References

[1] Piao Shilong, Fang Jingyun, Huang Yao. The carbon balance of terrestrial ecosystems in China[J]. China Basic Science, 2010, 12(2): 20-22, 65.

[2] Zhang Mei, Huang Xianjin, Tuo Xiaowei, et al. Spatial distribution and changing trends of net ecosystem productivity in China[J]. Geography and Geo-Information Science, 2020, 36(2): 69-74.

[3] Chang Shunli, Yang Hongxiao, Ge Jianping, et al. Advance and questions in net ecosystem production[J]. Journal of Beijing Normal University(Natural Science Edition), 2005, 41(5): 517-521.

[4] Ma Haoxiang, Chen Changcheng, Song Yingqiang, et al. Analysis of vegetation cover change and its driving factors over the past ten years in Qinghai Province[J]. Research of Soil and Water Conservation, 2018, 25(6): 137-145.

[5] Wu J, Chen B, Mao J, et al. Spatiotemporal evolution of carbon sequestration vulnerability and its relationship with urbanization in China' s coastal zone[J]. Science of the Total Environment, 2018, 645: 692-701.

[6] Zhang Bo, Zhou Wei, Zhang Fucun. Remote sensing monitoring and driving force analysis of land degradation in Qinghai Province from 1999 to 2018[J]. Bulletin of Soil and Water Conservation, 2020, 40(2): 120-128, 325.

[7] Piao Shilong, Zhang Xinping, Chen Anping, et al. The impacts of climate extremes on the terrestrial carbon cycle: A review[J]. Science China Earth Sciences, 2019, 49(9): 1321-1334.

[8] Piao Shilong, Yue Chao, Ding Jinzhi, et al. Perspectives on the role of terrestrial ecosystems in the carbon neutrality strategy[J]. Science China Earth Sciences, 2022, 65(6): 1178-1186.

[9] Liu Feng, Zeng Yongnian. Analysis of the spatiotemporal variation of vegetation carbon source/sink in Qinghai Plateau from 2000-2015[J]. Acta Ecologica Sinica, 2021, 41(14): 5792-5803.

[10] Zhou Xiafei, Yu Fang, Cao Guozhi, et al. Spatiotemporal changes of grassland carbon source/sink and its relationship with climatic factors in Qinghai-Tibet Plateau from 2001 to 2015[J]. Research of Soil and Water Conservation, 2019, 26(1): 76-81.

[11] Zhang Xinzhong, Li Yu, Zhang Chengqi, et al. Analysis of the net ecosystem production changes in the Shiyang River basin from 2000 to 2014[J]. Journal of Lanzhou University (Natural Sciences Edition), 2020, 56(4): 486-492.

[12] Liu Chunyu. The Tempo-Spatial Changes and Dynamic Mechanism of Carbon Source/Sink of Provincial Ecosystem: A Case of Gansu Province[D]. Lanzhou: Lanzhou University, 2015.

[13] Pan Jinghu, Wen Yan. Estimation and spatial-temporal characteristics of carbon sink in the arid region of Northwest China[J]. Acta Ecologica Sinica, 2015, 35(23): 7718-7728.

[14] Sun Zhijuan, Xie Shiyou. Spatiotemporal variation in vegetation net primary productivity and factor detection in Yunnan Province based on geodetector[J]. Chinese Journal of Ecology, 2021, 40(12): 3836-3848.

[15] Wen Xuding, Luo Zhaohui, Fu Lianggang. Effects of climate and land use change on NPP in Guangdong-Hong Kong-Macao Greater Bay Area[J]. Guangxi Science, 2021, 28(3): 290-300.

[16] Dai Zijun, Zhao Xia, Li Guanwen, et al. Spatial-temporal variations in NDVI in vegetation growing season in Qinghai based on GIMMS NDVI 3g.v1 in past 34 years[J]. Pratacultural Science, 2018, 35(4): 713-725.

[17] Xi Wentao, Lu Yixiao, Yang Huimin, et al. Spatial heterogeneity of annual precipitation δ^{18}O over the Tibetan Plateau based on the use of a geographical detector[J]. Arid Zone Research, 2021, 38(5): 1199-1206.

[18] Zhang Qiang, Zhu Biao, Yang Jinhu, et al. New characteristics about the climate humidification trend in Northwest China[J]. Chinese Science Bulletin, 2021, 66(28): 3757-3771.

[19] Song Y Z, Wang J F, Ge Y, et al. An optimal parameters-based geographical detector model enhances geographic characteristics of explanatory variables for spatial heterogeneity analysis: Cases with different types of spatial data[J]. GIScience & Remote Sensing, 2021, 57(5): 1-17.

[20] Li J S, Guo X M, Chuai X W, et al. Reexamine China's terrestrial ecosystem carbon balance under land use type and climate change[J]. Land Use Policy, 2021, 102: 105275.

[21] Grosso D S, Parton W, Stohlgren T, et al. Global potential net primary production predicted from vegetation class, precipitation, and temperature[J]. Ecology, 2008, 89(8): 2117-2126.

[22] Pei Zhiyong, Zhou Caiping, Ouyang Hua, et al. A carbon budget of alpine steppe area in the Tibetan Plateau[J]. Geographical Research, 2010, 29(1): 102-110.

[23] Mou Le, Gao Jing. Spatial and temporal patterns of planting NPP and its driving factors in Qinghai Province[J]. Acta Ecologica Sinica, 2020, 40(15): 5306-5317.

[24] Zhang Z, Ju W, Zhou Y. The effect of water stress on net primary productivity in Northwest China[J]. Environmental Science and Pollution Research, 2021, 28(46): 65885-65898.

[25] Yun Yinjuan. Spatio-Temporal Simulation of Vegetation Carbon Sink and Its Influential Factors in Shiyang River Basin from 2000 to 2015[D]. Lanzhou: Northwest Normal University, 2018.

[26] Zhu Weiwei. Dataset of net primary productivity in Sanjiangyuan region (2000-2015). National Tibetan Plateau Data Center, 2019.

[27] Wang Guibo, Nan Ling. Research on the Spatio-temporal difference of carbon source/sink of arable land resource use in Shannxi Province[J]. Chinese Agricultural Science Bulletin, 2012, 28(2): 245-249.

[28] Wang Jinfeng, Xu Chengdong. Geodetector: Principle and prospective[J]. Acta Geographica Sinica, 2017, 72(1): 116-134.

[29] Lei H M, Yang D W. Interannual and seasonal variability in evapotranspiration and energy partitioning over an irrigated cropland in the North China Plain[J]. Agricultural and Forest Meteorology, 2010, 150(4): 581-589.

[30] Chen Xuejiao, Zhou Wei, Yang Han. Simulation and dynamic change of carbon source/sink in the typical grassland communities in the Three River Source Area from 2001 to 2017[J]. Arid Land Geography, 2020, 43(6): 1583-1592.

[31] Qin Shuqi, Peng Qin, Dong Yunshe, et al. Response of soil respiration to the interaction of rainfall changes and nitrogen deposition: A review[J]. Chinese Journal of Applied Ecology, 2022, 33(16): 1-8.

[32] Zuo Chan, Wang Junbang, Zhang Xiujuan, et al. Changes and influencing factors of vegetation net primary productivity in the Sanjiangyuan National Park[J]. Acta Ecologica Sinica, 2022, 42(14): 1-15.

[33] Zhang J, Hao X, Hao H, et al. Climate change decreased net ecosystem productivity in the arid region of Central Asia[J]. Remote Sensing, 2021, 13(21): 4449.

[34] Piao Shilong, Zhang Xianzhou, Wang Tao, et al. Responses and feedback of the Tibetan Plateau' s alpine ecosystem to climate change[J]. Chinese Science Bulletin, 2019, 64(27): 2842-2855.

[35] Chen H, Bai X, Li Y, et al. Soil drying weakens the positive effect of climate factors on global gross primary production[J]. Ecological Indicators, 2021, 129(12): 1-13.

Spatial-temporal variation and driving factors of vegetation net ecosystem productivity in Qinghai Province

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Abstract: Based on NPP data from 2000 to 2020 and the vegetation net ecosystem productivity (NEP) calculated by the soil respiration model, the spatial-temporal adaptation and driving factors of vegetation NEP in Qinghai Province were quantitatively analyzed via trend analysis, partial correlation analysis, and geographical detector to explore the spatiotemporal adaptation of vegetation carbon sequestration and its driving factors. The results showed that the vegetation NEP fluctuated over the past 20 years, with an average annual increase of 1.54 g $C \cdot m^{-2}$. The spatial variation of annual vegetation NEP varied greatly, decreasing from southeast to northwest, and 71.08% of the area either remained unchanged or increased. Normalized difference vegetation index (NDVI) has the strongest explanatory power for vegetation NEP, and climate and human factors, such as precipitation, temperature, and population density are stronger factors for the spatial differentiation of NEP. Because the two-factor interaction will increase the strength of the argument for vegetation NEP spatial differentiation, it is necessary to pay attention to multi-factor cooperation in the future to enhance the sequestration capacity of carbon in Qinghai Province.

Keywords: Qinghai Province; vegetation NEP; spatial-temporal change; driving force

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