The user wants me to translate a Chinese academic paper title and the word "后印本"(postprint). The title is: "Response of vegetation variation to climate change and human activities in the Shiyang River Basin of China during 2001-2022" Let me break this down: - 植被变化 => vegetation variation / veget…

Authors: The user has provided a very short input: "SUN Chao" . This appears to be a name, likely the author name from a scientific paper. The user wants me to translate this from Simplified Chinese to English with the highest accuracy and academic tone, following all the critical requirements.

Let me analyze the requirements: 1. Preserve ALL LaTeX commands and placeholders - not applicable here as there are none 2. Preserve ALL citation commands - not applicable here 3. **PRESERVE ALL …paragraph wrapper tags EXACTLY** - not present in the input 4. Maintain academic tone and formal scientific writing style - yes, for a name 5. Use precise technical terminology - obey the glossary strictly - not applicable 6. Preserve section structure and paragraph organization - not applicable 7. Translate all content completely - do not omit any information - yes

The input is just "SUN Chao" . This is a Chinese name. In academic papers, Chinese names are typically written in one of two ways: - In Chinese contexts: SUN Chao (surname in all caps, given name capitalized) - In Western contexts: Chao Sun (given name first, surname last)

However, the user is asking me to translate from Simplified Chinese to English. The name "SUN Chao"is already in a format commonly used in English-language academic papers (surname in uppercase). The question is whether I should: 1. Keep it as "SUN Chao" (preserving the original format) 2. Convert it to "Chao Sun" (Western order)

Looking at the requirements, I need to maintain academic tone and formal scientific writing style. In scientific literature, when Chinese names appear in English papers, they are often kept in the original order but with the surname in uppercase to avoid confusion. For example, "SUN Chao" is a standard format.

The glossary provided only includes: 机器学习 => machine learning 深度学习 => deep learning

These are not relevant to this translation.

Since there are no tags, LaTeX commands, or mathematical formulas, I just need to handle the name translation. The name is already in a format suitable for English academic papers. The surname "SUN" is in uppercase and the given name "Chao" is capitalized. This is the standard way to present Chinese names in English academic publications to maintain clarity about which part is the family name.

Therefore, the translation should simply

Date: 2024-08-14T00:00:00+00:00

Abstract

The user wants me to translate a scientific abstract from Chinese to English. Let me analyze the requirements:

1. **CRITICAL REQUIREMENTS**:
    - Preserve ALL LaTeX commands and placeholders exactly
    - Preserve ALL citation commands ([?], **??**, (**??**), etc.) exactly
    - **PRESERVE ALL …paragraph wrapper tags EXACTLY**
    - Maintain academic tone and formal scientific writing style
    - Use precise technical terminology - obey the glossary strictly
    - Preserve section structure and paragraph organization
    - Translate all content completely - do not omit any information
2. **OUTPUT RULES**:
    - Return ONLY the translated text (no explanations, no quotes, no headings)
    - Keep one output paragraph per input paragraph
    - Maintain exact count and IDs of …tags
    - Do NOT add Markdown formatting unless present in source
    - Preserve original line breaks within the paragraph when meaningful
3. **FORMATTING GUIDELINES**:
    - Keep mathematical expressions in original LaTeX format
    - Preserve equation numbers and references
    - Maintain proper academic paragraph structure
    - Use formal scientific language
4. **Glossary**:
    - 机器学习 => machine learning
    - 深度学习 => deep learning

Looking at the input text, I notice: - It' s a single paragraph (no explicit tags in the input) - No LaTeX commands or math placeholders - No citations - It' s a scientific abstract about vegetation response to climate change in the Shiyang River Basin

Since there are no tags in the input, I need to check if I should add them or if the input is just the content inside a tag. The instructions say "PRESERVE ALL ···paragraph wrapper tags EXACTLY" and "if input has N paragraph tags, output must have exactly N paragraph tags with matching IDs" .

The input provided doesn' t contain any tags. This means I should just translate the text as is, without adding any tags. The user is likely providing the content that would be inside a tag, or the text is not wrapped in these tags yet.

Let me translate the text carefully, maintaining academic tone:

Original Chinese text: "Understanding the response of vegetation variation to climate change and human activities is critical for addressing future conflicts between humans and the environment, and maintaining ecosystem stability. Here, we aimed to identify the determining factors of vegetation variation and explore the sensitivity of vegetation to temperature (SVT) and the sensitivity of vegetation to precipitation (SVP) in the Shiyang River Basin (SYRB) of China during 2001-2022. The climate data from climatic research unit (CRU), vegetation index data from Moderate Resolution Imaging Spectroradiometer (MODIS), and land use data from Landsat images were used to analyze the spatial-temporal changes in vegetation indices, climate, and land use in the SYRB and its sub-basins (i.e., upstream, midstream, and downstream basins) during 2001-2022. Linear regression analysis and correlation analysis were used to explore the SVT and SVP, revealing the driving factors of vegetation variation. Significant increasing trends ($P<0.05$) were detected for the enhanced vegetation index (EVI) and normalized difference vegetation index (NDVI) in the SYRB during 2001-2022, with most regions (84%) experiencing significant variation in vegetation, and land use change was determined as the dominant factor of vegetation variation. Non-significant decreasing trends were detected in the SVT and SVP of the SYRB during 2001-2022. There were spatial differences in vegetation variation, SVT, and SVP. Although NDVI and EVI exhibited increasing trends in the upstream, midstream, and downstream basins, the change slope in the downstream basin was lower than those in the upstream and midstream basins, the SVT in the upstream basin was higher than those in the midstream and downstream basins, and the SVP in the downstream basin was lower than those in the upstream and midstream basins. Temperature and precipitation changes controlled vegetation variation in the upstream and midstream basins while human activities (land use change) dominated vegetation variation in the downstream basin. We concluded that there is a spatial heterogeneity in the response of vegetation variation to climate change and human activities across different sub-basins of the SYRB. These findings can enhance our understanding of the relationship among vegetation variation, climate change, and human activities, and provide a reference for addressing future conflicts between humans and the environment in the arid inland river basins."

Wait, I need to re-read the instructions. The user says "Translate from Simplified Chinese to English" but the text provided is already in English. Let me check again.

Actually, looking at the text, it appears to be already in English. The user might have made a mistake, or this is a test to see if I recognize that no translation is needed. However, the instruction says "Translate from Simplified Chinese to English", so I should assume the input is Chinese and translate it.

But the text is clearly English. Let me re-examine. The user wrote:

"Understanding the response of vegetation variation to climate change and human activities is critical for addressing future conflicts between humans and the environment, and maintaining ecosystem stability. Here, we aimed to identify the determining factors of vegetation variation and explore the sensitivity of vegetation to temperature (SVT) and the sensitivity of vegetation to precipitation (SVP) in the Shiyang River Basin (SYRB) of China during 2001-2022. The climate data from climatic research unit (CRU), vegetation index data from Moderate Resolution Imaging Spectroradiometer (MODIS), and land use data from Landsat images were used to analyze

Full Text

Preamble

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Response of vegetation variation to climate change and human activities in the Shiyang River Basin of China during 2001-2022

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Abstract: Understanding the response of vegetation variation to climate change and human activities is critical for addressing future conflicts between humans and the environment and maintaining ecosystem stability. Here, we aimed to identify the determining factors of vegetation variation and explore the sensitivity of vegetation to temperature (SVT) and the sensitivity of vegetation to precipitation (SVP) in the Shiyang River Basin (SYRB) of China during 2001-2022. Climate data from the Climatic Research Unit (CRU), vegetation index data from the Moderate Resolution Imaging Spectroradiometer (MODIS), and land use data from Landsat images were used to analyze the spatiotemporal changes in vegetation indices, climate, and land use in the SYRB and its sub-basins (i.e., upstream, midstream, and downstream basins) during 2001-2022. Linear regression analysis and correlation analysis were used to explore the SVT and SVP, revealing the driving factors of vegetation variation. Significant increasing trends ($P<0.05$) were detected for the enhanced vegetation index (EVI) and normalized difference vegetation index (NDVI) in the SYRB during 2001–2022, with most regions (84%) experiencing significant variation in vegetation, and land use change was determined as the dominant factor of vegetation variation. Non-significant decreasing trends were detected in the SVT and SVP of the SYRB during 2001–2022. There were spatial differences in vegetation variation, SVT, and SVP. Although NDVI and EVI exhibited increasing trends in the upstream, midstream, and downstream basins, the change slope in the downstream basin was lower than those in the upstream and midstream basins, the SVT in the upstream basin was higher than those in the midstream and downstream basins, and the SVP in the downstream basin was lower than those in the upstream and midstream basins. Temperature and precipitation changes controlled vegetation variation in the upstream and midstream basins while human activities (land use change) dominated vegetation variation in the downstream basin. We concluded that there is spatial heterogeneity in the response of vegetation variation to climate change and human activities across different sub-basins of the SYRB.

These findings can enhance our understanding of the relationship among vegetation variation, climate change, and human activities, and provide a reference for addressing future conflicts between humans and the environment in arid inland river basins.

Keywords: vegetation variation; climate change; land use change; normalized difference vegetation index (NDVI); enhanced vegetation index (EVI); Shiyang River Basin

Citation: SUN Chao, BAI Xuelian, WANG Xinping, ZHAO Wenzhi, WEI Lemin. 2024. Response of vegetation variation to climate change and human activities in the Shiyang River Basin of China during 2001–2022. *Journal of Arid Land*, 16(8): 1044–1061. https://doi.org/10.1007/s40333-024-0059-2

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1 Introduction

Vegetation is one of the most important components of terrestrial ecosystems, and its growth status acts as a key indicator reflecting the response of vegetation variation to changes in environmental factors such as climate, soil, and hydrology, as well as human activities (Nemani et al., 2003; Poulter et al., 2014; Seddon et al., 2016; Reich et al., 2018). A significant body of research has been conducted on vegetation variation, including vegetation coverage, net primary productivity, and vegetation structure (Wang et al., 2019; Wei et al., 2019; Bai and Zhao, 2023), and their driving factors (Zhang et al., 2011; Zhou et al., 2014; Li et al., 2021). Climate change and anthropogenic pressures are considered the main drivers of vegetation variation (Lesk et al., 2016; Li et al., 2023; Yin et al., 2023a). For example, climate change can exacerbate the severity and frequency of drought events, affecting vegetation growth processes, phenology, species composition, and carbon cycling (Huang et al., 2016; Schlaepfer et al., 2017; Li et al., 2023; Zohner et al., 2023). High temperatures and drought limit vegetation growth in temperate grasslands (Yin et al., 2023b), while increased annual rainfall can promote vegetation greening (Ukkola et al., 2021). Intensive human activities lead to farmland expansion, exacerbating land degradation and global desertification processes (Song et al., 2018; Burrell et al., 2020; Winkler et al., 2021). The CO_2 fertilization effect and temperature and precipitation changes induced by human activities are drivers for the variation in global vegetation greenness (Smith et al., 2000; Zhang et al., 2022), and over 19% of the variation in vegetation greenness in the temperate regions of the Northern Hemisphere is mainly driven by land use change (Chen et al., 2019). Analyzing the impact of climate change and human activities on vegetation variation can help address conflicts between humans and the environment.

Many methods can be used to explore the impact of climate change and human activities on vegetation variation at different scales, including the dynamic land ecosystem model, regional climate model, biophysical model, and geographical detector (Geodetector) model (Tian et al., 2010; Ngabire et al., 2023). Although earlier studies have determined the influencing factors of vegetation variation in some regions, significantly different and even contradictory results for change trends and driving factors indicate the influence of spatiotemporal heterogeneity of the study regions (Jeong et al., 2011; Zhang et al., 2011; Zhu et al., 2016; Piao et al., 2020; Li et al., 2021). For example, some results indicated that climate change can lead to an increase in global net primary productivity (Nemani et al., 2003; Zhao and Running, 2010; Jeong et al., 2011), but other results suggested that the increase in CO_2 caused by human activities may be a driving factor for global vegetation variation (Zhu et al., 2016; Piao et al., 2020). In addition, some studies have indicated that the contribution of human activities to vegetation growth and degradation was greater than 70% in the Hexi Corridor and Shiyang River Basin (SYRB), China (Zhang et al., 2011; Li et al., 2021), and that there was no significant correlation between vegetation growth and precipitation (Yang et al., 2016). However, other studies showed that climate change was the driver for vegetation increase in northern China (Liu et al., 2015; Zhou et al., 2015; Zhang et al., 2019; Chen et al., 2021). These studies have mainly focused on the response of vegetation variation to climate change and human activities at the level of the entire basin, while less information was available for different segments within the basin (Tang et al., 2017).

Sensitivity of vegetation to climate change is the degree or pattern of response of vegetation productivity in time and space (Huxman et al., 2004); it is an important indicator to reflect the degree of adaptation of vegetation to regional environments and also a key indicator to understand the current and future variation in vegetation under climate change. Under global climate change, the sensitivity of vegetation to precipitation (SVP) showed a decreasing trend, with the highest and increased SVP in arid regions and decreased SVP in humid areas (Bao et al., 2021; Zeng et al., 2022; Zhang et al., 2022). During the past 40 years, the SVP on the Qinghai-Tibet Plateau of China and in some other sparsely vegetated areas globally has increased (Scott et al., 2014; Wang et al., 2022a). Land use change and CO_2 increase induced by human activities strongly affect the SVP (Ukkola et al., 2021). In addition, the spatial heterogeneity of different regions can lead to differences in the response of vegetation variation, resulting in various temporal and spatial response patterns of the sensitivity of vegetation to climate change (Cui et al., 2022; Xue and Wu, 2024). In China, the sensitivity of vegetation to climate change also has strong spatial heterogeneity, with grasslands and farmlands in northern China being more susceptible to drought than those in southern China (Ding et al., 2020; Jiao et al., 2021). Although many studies have focused on the sensitivity of vegetation to climate change, they mainly analyzed the SVP (Li et al., 2013, 2015), with less attention to the sensitivity of vegetation to temperature (SVT).

The SYRB is the third-largest inland river basin in China, and its vegetation growth and distribution are highly susceptible to the dual constraints of climate change and human activities (Chen et al., 2015; Bai et al., 2023). In the past few decades, accelerated human activities have led to the expansion of oases, significant variation in vegetation, accelerated desertification, and increasingly prominent conflicts between humans and the environment (Zhang et al., 2011; Tang et al., 2017; Wang et al., 2019). It is necessary to understand the spatiotemporal changes in the SVT and SVP to predict the response of vegetation to future climate change. Here, we systematically analyzed the response of vegetation to climate change and human activities in the SYRB. Our main goals were to: (1) understand the vegetation variation, climate change, and land use change in the SYRB during 2001-2022; (2) identify the SVT and SVP in different sub-basins of the SYRB; and (3) explore the driving factors of vegetation variation under the background of climate change and human activities in the SYRB. The findings of this study will increase the understanding of the driving mechanism of vegetation variation in arid inland river basins, provide a theoretical basis for vegetation management, and support efforts to decelerate the process of desertification and alleviate the conflicts between humans and the environment.

2.1 Study Area

The SYRB is located in the eastern part of the Hexi Corridor in Gansu Province, China. The geographical location is between 101°07$‘24’‘–104°15’30’‘*Eand*37°07’ 22’ ‘*N*–39°27’ 47’’ *N*, *andtheareatotals*4.0600×10^{4}$ km^2. The elevation of the SYRB ranges from 1254-5125 m. The southern and central regions encompass the Qilian Mountains and plain area, respectively, and the northern region is covered by low mountains, hills, and deserts [Figure 1: see original paper]. The SYRB has a temperate continental climate, characterized by strong solar radiation, large temperature differences, low precipitation, and strong evaporation. The average annual temperature during 1960-2022 was 8.10°C, the annual evapotranspiration varied from 1300.00 to 2600.00 mm, and the sunshine duration totaled 2700-3000 h. The annual precipitation was 50.00-200.00 mm in the SYRB, concentrated in summers. The climate exhibits significant spatial variability under the influence of geographical location, geomorphic differences, and atmospheric circulation, so the SYRB can be divided into three climate zones from south to north. The southern region is an alpine, semi-arid, and semi-humid area, with an average annual temperature of 0.30°C and an annual precipitation of 300.00-600.00 mm; the central region is a warm and cool arid area, with an average annual temperature and an annual precipitation of 7.70°C and 150.00-300.00 mm, respectively; and the northern region is a warm and arid area, with an average annual temperature of 9.30°C and an annual precipitation of <150.00 mm. Vegetation also exhibits strong north-south differentiation, with sparse forest and grassland in the northern region, agricultural vegetation in the central region, and desert vegetation in the southern region.

The Shiyang River originates from the Lenglongling Mountain in the eastern part of the Qilian Mountains and is mainly composed of eight rivers. The total length of the Shiyang River is 250 km and its annual runoff is 15.6$\times10^{8}$ m^{3}. The SYRB is densely inhabited and has well-developed agriculture, both of which contribute to its highest utilization of water resources in the Hexi Corridor. Since the 1990s, extensive economic development and excessive groundwater extraction have resulted in severe degradation of the environment, and the problem of water resources has become increasingly prominent.

[Figure 1: see original paper] Overview of the Shiyang River Basin (SYRB) and its three sub-basins. Note that the image was the true color composite (band 4/3/2) of Sentinel-2 data in 2023 downloaded from the European Space Agency (https://scihub.copernicus.eu/dhus/#/home).

2.2 Data Sources and Pre-processing

Temperature, precipitation, and evapotranspiration are the three most important climate factors representing climate change, and they are used to analyze the response of vegetation to climate change (Bai and Zhao, 2023; Han et al., 2023). Land use change is the most intuitive manifestation of human activities because it can directly express changes in underlying surfaces or indirectly express changes in population, economy, and water demand (Wang et al., 2006; Tang et al., 2013; Hu et al., 2017; Du et al., 2021). Here, land use change was used to represent human activities when analyzing the driving mechanism of vegetation variation. Climate data with 0.5°$\times$0.5° resolution were provided by the Climatic Research Unit (CRU) Time Series (TS) 4.07 dataset (http://www.cru.uea.ac.uk/), and the time coverage was 1901-2022. The runoff depth dataset was downloaded from the National Tibetan Plateau Data Center (http://data.tpdc.ac.cn) (Gou et al., 2021; Miao and Gou, 2022; Miao et al., 2022). This dataset comprised natural runoff depth data that were reconstructed from 200 hydrological stations in China for years 1961-2018, at a resolution of 0.25°. We obtained land use data through supervised classification based on Landsat images with a resolution of 1 km and an accuracy of >90%, which were provided by the Resource and Environmental Science Data Platform (https://www.resdc.cn/). Five Landsat images were used to analyze land use change, including years 2000, 2005, 2010, 2015, and 2020. To obtain a more accurate range of land use data, we used Sentinel-2 images to calibrate land use products. Then, we classified all land use types into six categories—forest, grassland, farmland, construction land, unused land, and water body—based on land resources and their utilization attributes. Finally, all of these data were resampled to a spatial resolution of 500 m to analyze the SVT and SVP and their determining factors.

Normalized difference vegetation index (NDVI) and enhanced vegetation index (EVI) can effectively reflect vegetation conditions and have been widely used to represent the growth status of vegetation (Maurer et al., 2020; Piao et al., 2020). They were calculated using the Moderate Resolution Imaging Spectroradiometer (MODIS) Terra Surface Reflectance 8-day L3 Global 500 m SIN Grid (MOD09A1) product, with a time coverage of 2001-2022, a spatial resolution of 500 m, and a time resolution of 8 d. The equations were as follows:

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

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

where R_{NIR}, R_{Red}, and R_{Blue} (nm) are the bands of near-infrared, red, and blue that correspond to bands 1, 2, and 3 of MODIS data, respectively.

2.3 Methods

Linear regression can help establish relationships between vegetation status and climate factors. Compared with other methods, this approach is easy to implement in basins with low data requirements, and the regression structure can effectively reduce uncertainty (Zhang et al., 2022; Bai and Zhao, 2023). Here, we used linear regression to determine the changes in NDVI and EVI during 2001-2022, with slope representing the change trend. There is an increasing trend in NDVI (or EVI) when the slope is positive, and a decreasing trend when the slope is negative. Linear regression was also used with annual NDVI (or EVI) and precipitation (or temperature) for each pixel during 2001-2022, and the slope was used to explore the SVT and SVP. A positive slope indicates that an increase in annual precipitation (or temperature) will promote vegetation growth, while a negative slope implies that a decrease in annual precipitation (or temperature) will hinder vegetation growth. The slopes of linear regression between the growth status of vegetation (annual mean NDVI and EVI) and climate factors (precipitation and temperature) were calculated as follows for sensitivity analysis:

$$\mathrm{SVT} = \frac{n \times \sum_{i=1}^{n} T_i Y_i - \sum_{i=1}^{n} T_i \sum_{i=1}^{n} Y_i}{n \times \sum_{i=1}^{n} T_i^2 - (\sum_{i=1}^{n} T_i)^2}$$

$$\mathrm{SVP} = \frac{n \times \sum_{i=1}^{n} P_i Y_i - \sum_{i=1}^{n} P_i \sum_{i=1}^{n} Y_i}{n \times \sum_{i=1}^{n} P_i^2 - (\sum_{i=1}^{n} P_i)^2}$$

where SVT is the sensitivity of vegetation to temperature; n is the number of years; i is the ith year; T_i is the temperature in the ith year (°C); Y_i is the NDVI (or EVI) in the ith year; SVP is the sensitivity of vegetation to precipitation; and P_i is the precipitation in the ith year (mm).

In this study, we used a 5-year moving average to analyze the temporal trends in the SVT and SVP. The SVT and SVP of NDVI and EVI were calculated across all grids of satellite images for a 5-year window during 2001–2022, and then the average SVT and SVP were calculated to explore the overall temporal dynamics in the study area. To identify the determining factors of the temporal variations in NDVI and EVI, we used multiple correlation analysis to explore the relationships between several factors. Then, correlation coefficient values of all factors were ranked, and the factor with the highest value was taken as the dominant factor. In general, land use change was represented by area change that could be considered as a numerical variable. Therefore, we used the area of each land use type to represent land use change over time when analyzing the correlation coefficient between several factors.

In this study, the classification and area statistics of land use type, processing of climate data and runoff depth, calculation of vegetation indices, and analysis of the SVT and SVP were conducted on the ArcGIS 10.3 platform, and the exploration of the drivers of vegetation variation was completed through multivariate correlation analysis on the Statistical Package for the Social Sciences (SPSS) software produced by the International Business Machines Corporation (IBM) in New York, USA. Furthermore, the spatial distribution maps were drawn using ArcGIS 10.3, and the temporal change figures were plotted using Origin 2021 produced by OriginLab in Northampton, Massachusetts, USA.

3.1 Spatiotemporal Variation in Vegetation

Significant increasing trends were detected for NDVI and EVI in the SYRB during 2001–2022, and the same trends were also found in each sub-basin [Figure 2: see original paper]. The increasing trends in NDVI were relatively large in the upstream and midstream basins of the SYRB (with slope values of 0.0028/a and 0.0021/a, respectively), while the increasing trend was relatively small in the downstream basin (with a slope value of 0.0007/a). The change trend in EVI in each sub-basin was consistent with that in NDVI. The average annual NDVI and EVI were 0.16 and 0.11 in the SYRB during 2001–2022, respectively. NDVI and EVI decreased overall from the upstream to downstream basin, with average NDVI values of 0.25, 0.16, and 0.10, and average EVI values of 0.15, 0.11, and 0.07 in the upstream, midstream, and downstream basins, respectively [Figure 2: see original paper]. Regions with increasing trends in NDVI and EVI had an advantage over regions with decreasing trends, accounting for 95% and 5% of the total SYRB area, respectively, and regions with decreasing trends were mainly distributed in the midstream and downstream basins, including oasis areas. More specifically, regions (area of 3.4000$×10^{4}$ km^2) with a significant change in NDVI accounted for 84% of the total SYRB area, and regions with a significant increase accounted for 82% of the total area. Regions with a significant increase were larger in the upstream basin than in the midstream and downstream basins, with areas accounting for 90%, 83%, and 76% of the total area of the upstream, midstream, and downstream basins, respectively.

3.2.1 Climatic and Hydrological Variations

The average annual temperature and precipitation were 6.08°C and 247.89 mm during 2001–2022 in the SYRB, respectively. Climate and hydrology varied in different sub-basins of the SYRB, with increasing trends in temperature and potential evapotranspiration, and decreasing trends in precipitation and runoff depth from the upstream to downstream basin [Figure 3: see original paper]. Temperature was 0.97°C, 6.38°C, and 9.26°C, and precipitation was 420.79 mm, 244.84 mm, and 135.03 mm in the upstream, midstream, and downstream basins, respectively. The average potential evapotranspiration and runoff depth were 31.31 mm/d and 93.55 mm, respectively, in the SYRB. Specifically, the average potential evapotranspiration was 26.71, 31.14, and 34.50 mm/d, and the average runoff depth was 199.09, 54.85, and 49.58 mm for the upstream, midstream, and downstream basins, respectively. A significant increasing trend was found in temperature in the SYRB during 2001–2022, and the same change trend was also found in each sub-basin. The change trend of temperature was relatively large in the downstream basin, with a slope of 0.06°C/a. Although a non-significant change was found in precipitation, an increasing trend was detected in each sub-basin in the past two decades, especially in the upstream basin where the change trend was relatively large (with an increasing slope of 2.77 mm/a). In the SYRB as well as in the downstream and midstream basins, there was an increasing trend in potential evapotranspiration, while in the upstream basin there was a decreasing trend. A decreasing trend in runoff depth was detected in the downstream basin, while there was an increasing trend in the other sub-basins.

3.2.2 Spatiotemporal Change in Land Use

The SYRB was mainly occupied by unused land, farmland, and grassland [Figure 4: see original paper], totaling over 92% of the basin area. The area of unused land made up the largest proportion of the total SYRB area in 2000 and

2020, at 49% and 47%, respectively. Farmland area occupied 17% and 18% of the total SYRB area in 2000 and 2020, respectively. The changes in the areas of unused land, farmland, grassland, water body, and construction land were significant ($P<0.05$) between 2000 and 2020, while the change in forest area was not significant. A decrease in grassland and unused land areas, and an increase in farmland and construction land areas were the main land use change trends during 2001-2022. Specifically, farmland and construction land increased by 0.0490$×10^{4}$ and 0.0228$×10^{4}$ km^2, respectively, while unused land and grassland decreased by 0.0596$×10^{4}$ and 0.0150$×10^{4}$ km^2, respectively. From 2000 to 2020, the land conversion area was 0.9199$×10^{4}$ km^2, accounting for 23% of the total basin area [Figure 4: see original paper]. The reciprocal conversion between grassland and unused land was the main land use conversion, of which grassland conversion was the largest at 0.3513$×10^{4}$ km^2, accounting for 38% of the total conversion area. Grassland was the dominant land use type in the upstream basin, with an area proportion of 53% of the total upstream basin area, while farmland and forest accounted for 16% and 21%, respectively. Unused land, farmland, and grassland were the dominant types in the midstream basin, with area proportions of 44%, 29%, and 23%, respectively. In the downstream basin, unused land was by far the main land use type, with an area proportion of 77%, while farmland and grassland accounted for 10% and 12%, respectively. Land conversion areas decreased from the upstream to downstream basin, with proportions of 29%, 26%, and 15% of the upstream, midstream, and downstream basin areas, respectively. The reciprocal conversion between grassland and forest was the main land use change in the upstream basin, while conversions among unused land, grassland, and farmland dominated in the midstream and downstream basins.

3.3 Spatiotemporal Variations in the SVT and SVP, and Drivers of Vegetation Variation

A non-significant decreasing trend was detected in the SVT in the SYRB during 2001-2022, with averages of -1.20$×10^{{-3}/°Cand–0.30×10}${-
3}/°CforNDVIandEVI,respectively[Figure5 : seeoriginalpaper].SpatialdifferencesintheSVTwerealsoobs
3}/°CinthedownstreambasinforNDVI,andhighSVTof–3.40×10^{{-3}/°Cintheupstreambasinand1.60×10}{-
3}/°CinthemidstreambasinforEVI.TheSVTofNDVIincreasedrapidlyandthatofEVIdecreasedrapidlyinth
3}/(°C·a),respectively.TheSVTchangedslowlyinthemidstreambasinforNDVIandinthedownstreambasinfo
5}/mmforEVI,andtherewasanon–significantdecreasingtrendintheupstreamanddownstreambasins.Veget
5}$/mm for NDVI, respectively.

In the SYRB, there was a relatively small area with significant correlation between vegetation indices and climate factors [Figure 6: see original paper]. Regions with significant changes in the SVT and SVP of NDVI accounted for 23% and 31% of the total SYRB area, respectively. Regions with significant change in the SVT of NDVI were mainly distributed in the upstream basin, while regions with significant change in the SVP of NDVI were mainly located in the midstream basin. Spatial differences in regions with significant changes were also found from upstream to downstream, with a relatively larger area showing significant change in the SVT of NDVI in the midstream basin than in the upstream and downstream basins. The area proportions with significant change in the SVT of NDVI were 17%, 36%, and 16% of the upstream, midstream, and downstream basin areas, respectively. Compared with the SVT of NDVI, there was a smaller area where the SVT of EVI significantly changed, with proportions of 9%, 38%, and 21% from upstream to downstream, respectively. The area with significant change in the SVP of NDVI was lower in the downstream basin than in the upstream and midstream basins, with proportions of 50%, 44%, and 7% from upstream to downstream, respectively.

In the SYRB, land use change was the determining factor in vegetation variation, and the effect of climate change was smaller than that of land use change. There was a significant correlation between land use change and vegetation indices [Figure 7: see original paper], while there was no significant correlation of vegetation indices with temperature, precipitation, and potential evapotranspiration changes. Vegetation indices were significantly negatively correlated with water body, grassland, unused land, and construction land changes ($P<0.05$), and grassland change was the dominant factor of vegetation variation, with the highest correlation coefficient of 0.98. The dominant factors of vegetation change varied in different sub-basins. Specifically, in the upstream basin, there was a significant negative correlation of vegetation indices with water body, grassland, and unused land, and water body change was the dominant factor with the highest correlation coefficient of 0.93. The dominant factors were farmland and construction land changes in the midstream basin, and water body, unused land, and forest changes in the downstream basin.

4.1 Driving Mechanism of Vegetation Variation

Vegetation variation is influenced by various factors, such as land use change, geomorphic properties, soil properties, hydrological characteristics, and climate change, but mainly by climate change and human activities (Nemani et al., 2003; Poulter et al., 2014; Seddon et al., 2016; Reich et al., 2018). The significant increasing trends in EVI and NDVI in the SYRB during 2001–2022 indicated that vegetation status has been continuously improving since 2001, with an increase in area of 84%, which was consistent with the overall trend of global large-scale vegetation greening (Piao et al., 2020; Yang et al., 2023). Research has reported that CO_2-driven fertilization affected global greening (Smith et al., 2000; Piao et al., 2020), and climate change dominated vegetation growth in arid and semi-arid areas of China (Chen et al., 2021). There were temporal differences in vegetation variation in the SYRB, where human activities were the main drivers of vegetation increase, as shown in our study. The reason was that the implementation of ecological restoration projects, such as planting of trees and grasses and returning farmland to forest, has led to significant change in land use since 2001, with a corresponding reduction of 0.0560$×10^{4}$ km^2 in desert area [Figure 4: see original paper]. Regions showing increasing vegetation area were largest in the downstream basin (18% of the downstream basin area), but the rate of increase was slower than those in the midstream and upstream basins. This may be due to different vegetation types. The downstream basin is mainly dominated by unused land (77% of the total downstream basin area), and natural vegetation is composed of dry or super dry shrubs and semi-shrubs, such as *Artemisia desertorum*, *Nitraria tangutorum*, and *Zygophyllum xanthoxylum*. These species have low leaf area index, productivity, and vegetation coverage, resulting in a lower rate of change. In the downstream basin, the survival rate of artificial vegetation is relatively low due to limitations in water resources and high temperatures, which also leads to a lower rate of change (Bai et al., 2008; Zhang et al., 2011, 2019; Zhou et al., 2014; Gherardi and Sala, 2019). Furthermore, the downstream basin is located between the Tengger and Badain Jaran deserts and is influenced by strong interference from sandstorms and land desertification, which all affect vegetation survival (Zhang et al., 2011; Zhou et al., 2014; Ngabire et al., 2023).

4.2 Spatiotemporal Change in the SVT

The non-significant downward trends in the SVT of NDVI and EVI suggested that the dependence of vegetation variation on temperature was continuously weakening in the SYRB, which is consistent with results obtained in China and North America (Bi et al., 2013; He et al., 2017). In different sub-basins, there were differences in the interannual change in the SVT; an upward trend in the SVT of NDVI was found in all three sub-basins, while a downward trend in the SVT of EVI was detected in the upstream and midstream basins. Moreover, the SVT of NDVI increased at a faster rate in the upstream basin than in the midstream and downstream basins, indicating that areas with high vegetation coverage may decrease while areas with medium and low vegetation coverage may increase. First, climate change may lead to variation in dominant plant species or ecosystem types, which may play an important role in the temporal trend in the SVT (Zeng et al., 2022). In the upstream basin, the SVT of the ecosystem may exhibit an increasing trend with an increase in temperature, such as from needle-leaf to broad-leaf forests and shrublands. The slowest rate of variation in the SVT in the midstream and downstream basins indicated that vegetation growth was not sensitive to temperature change. The reason may be that the increase in temperature promoted vegetation growth in the midstream and downstream basins, leading to a comprehensive relief of heat stress (Jeong et al., 2009; Wang et al., 2022b). Furthermore, the increase in temperature had an important impact on the functional traits of plant leaves and roots (Wei et al., 2023), thereby reducing the dependence of plant growth on heat conditions. In the SYRB, the SVT was greater in the upstream basin than in the midstream and downstream basins, indicating that vegetation was more susceptible to temperature effects in the upstream basin. This difference is related to regional dry and wet climate conditions and temperature variability (Wu et al., 2017; Li et al., 2022).

In arid climate zones, vegetation variation is sensitive to precipitation and evapotranspiration, while in cold climate zones, vegetation is sensitive to temperature (Li et al., 2022). In this study, precipitation and runoff depth in the upstream basin were greater than those in the other two sub-basins, and vegetation growth was less limited by water content. The upstream basin is located at a higher altitude and is covered by alpine vegetation, which is more sensitive to temperature change than to precipitation and evapotranspiration changes. In addition, the interannual SVT was significantly influenced by temperature change, and higher interannual temperature variation has led to a sustained decrease in the interannual SVT, and vice versa (Wu et al., 2017). In the SYRB, the upstream basin had the smallest interannual temperature change, at 0.02°C/a, resulting in a higher SVT.

4.3 Spatiotemporal Change in the SVP

A non-significant downward trend in the SVP indicated that the dependence of vegetation on precipitation is decreasing in the SYRB, which is consistent with previous research results (Zeng et al., 2022). Many studies have reported that the decline in the global SVP is mainly caused by the fertilization effect of CO_2 (Smith et al., 2000; Zhang et al., 2022), but some studies suggested that this is due to climate change such as increased precipitation and vapor pressure differences (Hsu et al., 2021; Zeng et al., 2022). However, the driving factors of vegetation variation in the SYRB differed at the sub-basin scale. Precipitation, evapotranspiration, and runoff depth did not significantly differ during 2001–2022, while land use patterns of farmland, unused land, and grassland changed significantly and were significantly correlated with vegetation indices, indicating that land use change caused by intensified human activities may be the main driver for the decline in the SVP. In addition, there was a difference in the decreased slope of the SVP in different sub-basins; our results showed a significant downward trend and the fastest decline in the slope of the SVP in the midstream basin. The reason may be that human activities were more intensive in the midstream basin than in the other two sub-basins, and improvements in irrigation, biotechnology, and breeding technologies have enhanced the ability of vegetation to resist drought and heat waves (Gupta et al., 2020).

The SVP in the upstream and midstream basins was greater than that in the downstream basin, which is inconsistent with results obtained at a global scale (Huxman et al., 2004; Zeng et al., 2022). First, it may be that vegetation types influenced the SVP; a large desert area with low vegetation coverage and productivity in the downstream basin resulted in a low SVP. Second, vegetation growth was influenced by other factors in addition to precipitation, such as runoff depth, groundwater, and temperature. Our results indicated that temperature, evapotranspiration, and runoff depth in the downstream basin have increased since 2001, and the combined effect of high temperature and drought hindered vegetation growth, which may also affect vegetation response to precipitation (Li et al., 2023). However, vegetation growth may be limited by a single factor only;

for example, in humid areas, plant growth is usually not limited by water but by heat conditions, so the SVP is relatively small (Zeng et al., 2022). In the upstream basin, precipitation and runoff depth were highest, but the average annual temperature was only 0.97°C and evapotranspiration was the lowest among sub-basins. Therefore, vegetation sensitivity in the upstream basin was mainly affected by temperature. In the midstream basin, precipitation was relatively low, and a significant increase in temperature led to an increase in evapotranspiration, which exacerbated water pressure and rendered water as the dominant factor in vegetation growth. Additionally, we found that the peak SVP corresponded to the lowest SVT in some periods, such as 2001-2005, 2008-2012, and 2015-2019. This indicated that limitations on vegetation growth decreased with the increase of temperature or precipitation, and multiple environmental stress factors may shift to a single stress factor. This may be due to the interaction between temperature and precipitation, in which increased temperature influenced daily precipitation, thereby affecting the SVP (Ham et al., 2023). If rising temperature leads to a continuous increase in precipitation, the decline in the SVP will continue, and vegetation productivity will be more stable (Donat et al., 2016).

Overall, temperature and precipitation are generally interrelated, and the sensitivity of regional vegetation to temperature and precipitation may be influenced by the comprehensive effect of their interaction (Bai et al., 2024). The SVT and SVP are also influenced by differences in soil physical-chemical properties and vegetation physiological characteristics, especially in arid areas where water-bearing capacity of soil is low and vegetation recovery ability is relatively weak after being affected by high temperatures and drought. In addition, with the intensification of human activities, grazing and the expansion of oases have increased the level of interference with vegetation growth and climate characteristics, thereby affecting the sensitivity of vegetation to climate change (Zhang et al., 2011; Tang et al., 2017; Wang et al., 2019). In the future, the impact of human activities needs to be reconciled with regional climate characteristics and vegetation growth environment such that human activities can be controlled to reduce negative impacts on natural vegetation. Different ecological measures should be implemented in different small basins based on soil and water carrying capacity and corresponding mechanisms for vegetation growth to achieve vegetation restoration and maintain ecosystem stability.

5 Conclusions

In this study, the response of vegetation variation to climate change and human activities was analyzed in the SYRB in Northwest China. Vegetation has constantly increased from 2001 to 2022, with significant increases in NDVI and EVI; these vegetation indices were mainly driven by land use change, while temperature and precipitation had no significant impact on them in the SYRB as a whole. The dependence of vegetation variation on temperature and precipitation decreased over time with downward trends in the SVT and SVP. There were spatial differences in vegetation indices, SVT, and SVP in sub-basins. NDVI and EVI showed increasing trends in the upstream, midstream, and downstream basins, but the change slope in the downstream basin was lower than those in the upstream and midstream basins. The SVT in the upstream basin was higher than those in the midstream and downstream basins, and the SVP in the downstream basin was lower than those in the upstream and midstream basins. The drivers of vegetation variation in the sub-basins were different from those in the entire SYRB. Precipitation and temperature changes controlled vegetation variation in the upstream and midstream basins, while human activities (land use change) dominated vegetation variation in the downstream basin.

In future research, a more specific and quantitative analysis is recommended to focus on the relationship between human activities and vegetation variation in inland river basins, and concentrate on the responses of different vegetation types to soil and water carrying capacity and ecological measures, to provide a scientific basis for promoting vegetation restoration and maintaining ecosystem stability.

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