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Research article

Effects of climate change on vegetation dynamics of the Qinghai-Tibet Plateau, a causality analysis using empirical dynamic modeling

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A R T I C L E I N F O

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A B S T R A C T

Given the vital role of the Qinghai-Tibet Plateau (QTP) as water tower in Asia and regulator for regional and even global climate, the relationship between climate change and vegetation dynamics on it has received considerable focused attention. Climate change may influence the vegetation growth on the plateau, but clear empirical evidence of such causal linkages is sparse. Herein, using datasets CRU-TS v4.04 and AVHHR NDVI from 1981 to 2019, we quantify causal effects of climate factors on vegetation dynamics with an empirical dynamical model (EDM) – a nonlinear dynamical systems analysis approach based on state-space reconstruction rather than correlation. Results showed the following: (1) climate change promotes the growth of vegetation on the QTP, and specifically, this favorable influence of temperature is stronger than precipitation's; (2) the direction and strength of climate effects on vegetation varied over time, and the effects are seasonally different; (3) a significant increase in temperature and a slight increase in precipitation are beneficial to vegetation growth, specifically, NDVI will increase within 2% in the next 40 years with the climate trend of warming and humidity. Besides the above results, another interesting finding is that the two seasons in which precipitation strongly influence vegetation in the Three-River Source region (part of the QTP) are spring and winter. This study provides insights into the mechanisms by which climate change affects vegetation growth on the QTP, aiding in the modeling of vegetation dynamics in future scenarios.

1. Introduction

Vegetation has great influence on energy exchange, water balance and terrestrial carbon cycle in seasonal, annual and decadal periods on various spatial scales from regional to global [1–4]. Therefore, in recent decades, the significant change of global climate

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and its influence on vegetation growth have attracted more and more attention [5,6], especially on the QTP which regarded as the Asia's water tower and the regional and even global climate regulator [7], this causal effect analysis is even more important. The existing studies on the influence of climate change on vegetation growth of the QTP mainly include: the regional differences of the response of vegetation dynamics to climate factors were analyzed [8,9]. The main climate control factor for vegetation growth was identified [9–11]. The difference in response lag of vegetation to different climatic factors and the regional difference in this lag were investigated [12,13]. According to different vegetation types or local areas, the relationships between climate factors and vegetation cover in different seasons were tested [14]. The effects of climate on vegetation phenology [15,16] and the sensitivity of vegetation dynamics responses to climate change [17] were examined.

Although there are considerable studies on how vegetation dynamics respond to climate change on the QTP, the following problems still exist: 1) The findings of studies examining the main climate controlling factor (temperature or precipitation) for vegetation dynamics have been mixed, some studies indicated that the factor is temperature while some studies showed precipitation. 2) Most previous studies on the relationship between climate change and vegetation dynamics were conducted by calculating their correlation coefficient rather than estimating their quantitative causal effects. 3) Sensitivity analysis of how vegetation dynamics respond to climate change in previous studies was coarse-grained (e.g., scenarios: temperature increased 2 °C or 4 °C, precipitation increased 10%, 20%, 30% or 40%). Thus, the main climate controlling factor for vegetation dynamics is still controversial, and our understanding of the causal effects over time and the sensitivity of vegetation to climate change remains limited. Here, we investigated the effects of climate change on vegetation dynamics on the QTP. We also examined whether climate warming and humidification promotes vegetation growth. We tested the following hypotheses. First, we hypothesized that temperature is the main controlling climate factor on vegetation dynamics of the QTP compared to precipitation. Second, we hypothesized that there are seasonal differences in the strength of climate effects on vegetation, with temperature effects significantly stronger in spring and summer than in autumn and winter. Finally, we hypothesized that an ongoing warm and humid climate change of the QTP (i.e. significant increase in temperature and slight increase in precipitation) plays a positive role in vegetation growth. These three hypotheses were proposed aims to better understand the mechanisms of climate factors on vegetation dynamics by investigating from the identification of main driving variables, quantification of causal effects to scenario exploration of vegetation variations.

Importantly, linear methods which are based on correlation that may lead to incorrect and contradictory assumptions [18,19]. Of particular note, the lack of correlation does not mean the lack of causality, and vice versa [19]. In essence, the dynamical system can be portrayed as the evolution of a set of states with time according to certain rules that control the motion of states in the state space with high-dimensional (i.e. manifold). The movement on the manifold can be projected onto the coordinate axis to form a time series. On the contrary, time series can be drawn in multi-dimensional state space to restore dynamics, which is called attractor reconstruction [20]. Thus, according to the concept of attractors which can be recovered from time series directly, the empirical dynamic modeling framework (EDM) which focuses on dynamic attractors rather than structural equations can be used for studying dynamical systems [18,21–25]. Compared with fitting a set of hypothetical equations, EDM can reveal the dynamic relationships between variables according to the time series data. By extracting these relationships, EDM can quantify the complex and changing interactions between variables. In short, this method can distinguish causality and correlation in nonlinear dynamic systems.

Our study was based on empirical dynamics model, whereby we randomly sampled in each different vegetation type to ensure the objectivity of this study. We used EDM to identify the effects of climate variables on vegetation dynamics. Our results suggest that temperature has a stronger effect on vegetation than precipitation, meaning that changes in vegetation dynamics are more sensitive to changes in temperature. From the seasonal aspect, the temperature influence is weaker in autumn and winter than in spring and summer. In addition, the warming climate and the increase of precipitation promote vegetation growth. These findings conduce to the understanding that the knowledge of climate control of vegetation growth, how ecosystem responses to climate change and how to manage ecosystem sustainably on the QTP.

2. Materials and methods

2.1. Study area

The Qinghai-Tibet Plateau, with an average elevation of 4500 m, is the highest plateau in the world. It is known as "the roof of the world" and "the third pole of the world". The annual average temperature in the hinterland of the plateau is below 0 °C. The temperature decreases with the increase of height and latitude, and diurnal temperature range is large. The annual precipitation decreases from 2000 mm in southeast to below 50 mm in the hinterland of the plateau [26]. The vegetation types of the QTP are complex and diverse, the main types are forests, meadows, grasslands and deserts, and the vegetation is very sensitive to climate change.

2.2. Data and processing

The boundary data of Qinghai-Tibet Plateau in China is from the National Tibet Plateau data Center [27]. Http://data.tpdc.ac.cn/zh-hans/. The boundary data of Three- River Source is from the 1: 1 million national basic geographic database of the National Geographic Information Resources Catalog Service system. The specific boundary data files can be downloaded from Big Earth Data Platform for Three Poles.

Normalized difference vegetation index (NDVI), an important index to characterize plant growth, vegetation coverage, growth status and biomass, has been widely used in vegetation activity studies [28,29]. Here, the NDVI data used in this study covers the period from June 1981 to December 2019, and is obtained from NOAA–AVHRR daily dataset with $0.05^\circ \times 0.05^\circ$ spatial resolution.

The climate data from 1981 to 2019 used in this study is from the CRU TS (Climatic Research Unit gridded Time Series) dataset with version 4.04, which provides a high-resolution (0.5° × 0.5°), monthly grids of observations [30].

According to the boundary data of QTP, we use the data read and write functions which provided by Python language (functions in netCDF4 package) to read the climate grid data (nc format files) to numerical data (csv format files) within the study area, and similarly operations to NDVI data. In order to keep the temporal and spatial resolution of climate data consistent with that of NDVI vegetation data, the daily NDVI data are reshaped into monthly NDVI data with spatial resolution 0.5° × 0.5° by using the maximum value composite [31] to reduce the influence of uncertain factors (i.e., atmosphere, cloud and solar altitude angle). In this way, we get the monthly data of climate and vegetation (csv format files) with the spatial resolution of 0.5 × 0.5. In addition, due to missing NDVI data from October to December of 1994, we remove the seasonal component from the time series, then perform imputation on the deseasonalized series and afterwards add the seasonal component again for interpolation (call the na_seadec function in imputeTS package of R language). Eventually, long enough continuous time-series data of climate and NDVI ensure the viability of empirical dynamic modeling (EDM).

The data of vegetation type zoning in China is 1 : 1,000,000 China Vegetation Map (Editorial Committee of China Vegetation Map, Chinese Academy of Sciences, 2001), and the vegetation of QTP is divided into 16 sub-zones. Data (shp format) about this can be downloaded from official website of the Resource and Environment Science and Data Center. https://www.resdc.cn.

To facilitate the calculation and take into account all vegetation types on the QTP, we randomly select 49 locations (the size of each location is 0.5° × 0.5°) in all vegetation type area for the analysis of causal effects, and the specific location distribution is shown in Fig. 1.

2.3. Methods

To test our hypothesis, we firstly used Multivariate EDM: Forecast Improvement (multivariate simplex projection) to identify the primary climate-driven variables of vegetation dynamics, while considering potential lagged effects. Next, we then selected the climate variables that most directly affect vegetation dynamics and estimated their quantitative causal effects (direction and strength of effects) at each time step using Multivariate EDM: Effects Estimation (multivariate S-map). Finally, we performed Multivariate EDM: Scenario Exploration for predicting the NDVI values under the assumed scenarios with various warming and humidification conditions to predict the variation of NDVI, Which is the sensitivity analysis of vegetation growth to climate change (see Fig. 2).

One should note that, the climate variables are temperature (T), precipitation (Prcp), diurnal temperature range (Dtr), potential evapotranspiration (Pet), temperature and Precipitation (T + Prcp). In addition, the simplex projection and S-map used in this study are data prediction algorithms in empirical dynamical model (EDM) framework.

2.3.1. Multivariate EDM: forecast improvement

A potential causal (driving) variable is considered when including it as a coordinate in the state space leading to improvement in forecasting. At the same time, a test for causality using multivariate forecast improvement can be done when the driving variable is stochastic [21]. In brief, if stochastic variable Y influenced variable X causally, then a multivariate empirical dynamic model including the Y produces better forecasts of X than without. However, in the case of seasonal vegetation growth, we cannot treat the climate time series as stochastic variables (seasonality generally >0.8, Supplementary Fig. 1). This means that information about causal variables has been included in univariate embedding [18,32]. Therefore, Deyle et al. in Ref. [33] modified the method of Strak et al.in Ref. [32] as follows: the best univariate embedding dimension E* for each target time series was determined according to the work of Glaser et al. [34], and E < E * is used in a univariate embedding will be "under embedding". That is, the univariate embedding at this point could not contain complete information about system state and dynamics. In this case, incorporating information about driving variables into multivariate embedding usually improve the forecast skill.

Here, E = E* - 1, the specific method is as follows for each location:

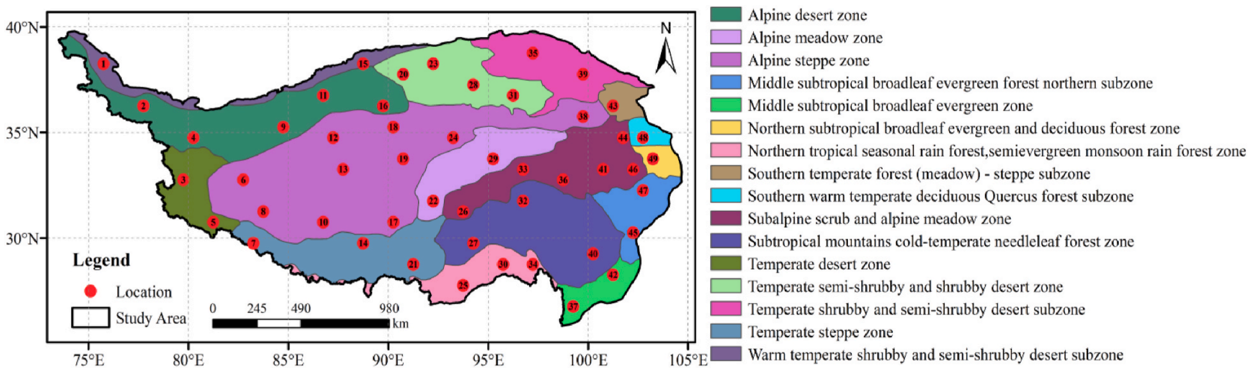

Fig. 1. Spatial distribution of 49 locations of the QTP.

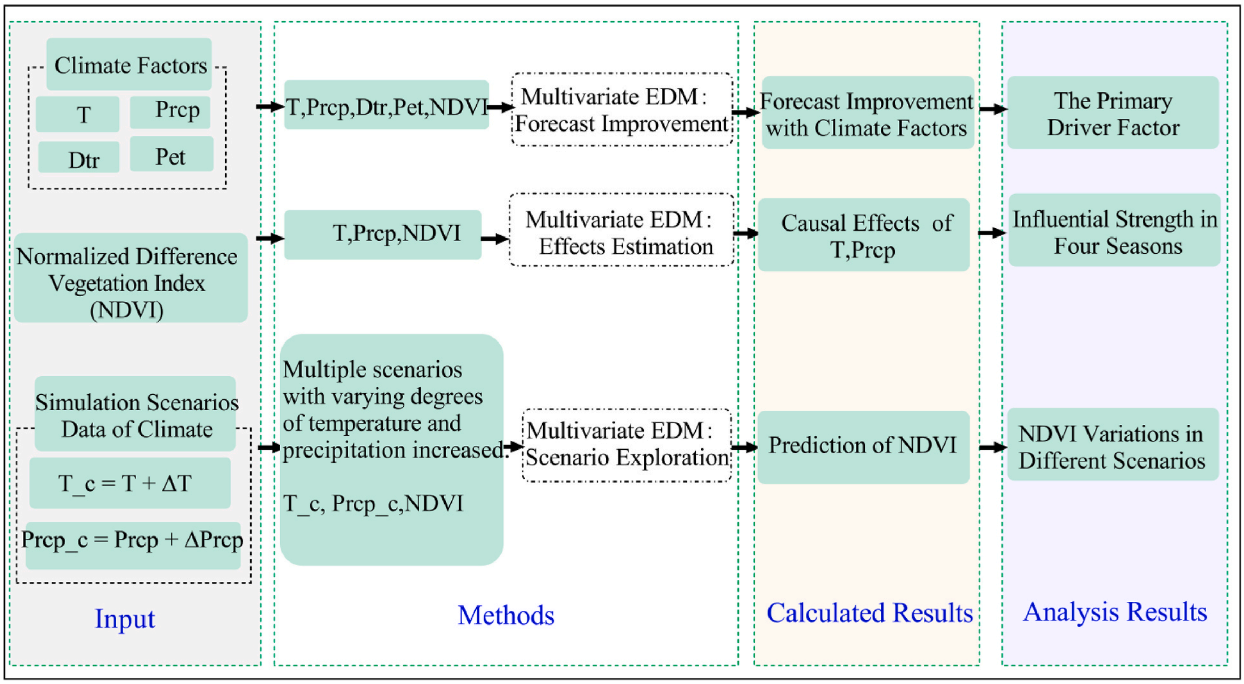

Fig. 2. Flowchart of the study.

1) Use simplex projection to calculate the forecast skill ρ_{univar} of univariate embedding based on NDVI time series:

$$(\mathrm{NDVI\_}t, NDVI\_t-1, NDVI\_t-2, \ldots, NDVI\_t-E+1).$$

2) Use simplex projection to calculate the forecast skill $\rho_{multivar\_1}, \rho_{multivar\_2}, \rho_{multivar\_3}$ of multivariate embedding based on NDVI and climate variable time series:

$$(NDVI\_t, NDVI\_t-1, NDVI\_t-2, \ldots, NDVI\_t-E+1, driver\_t\_lag).$$

3) Calculate $\rho_{multivar} = \max(\rho_{multivar\_1}, \rho_{multivar\_2}, \rho_{multivar\_3})$, and the optimal lag is obtained at the same time.
4) Calculate $\triangle\rho = \rho_{multivar} - \rho_{univar}$.

Note: *driver_t_lag* represents the climate variable with time delay (lag = 1, 2, 3). E^* is the best univariate embedding dimension for each location (see Supplementary Table 1).

Previous studies have mentioned that there is a delay in the effect of climate on vegetation, that is, vegetation growth may be mainly caused by earlier climatic conditions rather than current climatic conditions [35,36]. Relevant studies have shown that the time lag in response of vegetation to climate mainly occurs within 3 months [37,38]. Thus, three time lags are used: one-month lag (lag1), two-month lag (lag2) and three-month lag (lag3). It should be noted that tp (a parameter of EDM) means how many steps ahead to make forecasts. The parameter tp valued at 1 in our study, that is, use current data to predict next. Therefore, when lag = 1, the data of the driving variable (climate variable) uses the data of the current month (i.e., $driver\_t$). When lag = 2, use the data of last month (i.e., $driver\_t-1$). When lag = 3, use the data of the month before last month (i.e., $driver\_t-2$). The delay corresponding to the maximum forecast skill is the best delay, which will also be considered as the delayed response time of vegetation to climate.

2.3.2. Multivariate EDM: Effects Estimation

First, it is important to distinguish the interaction coefficients (which are usually constant in difference or differential equations) from real-time (time-varying) interaction strengths [22,39]. The multivariate S-map method enables the calculation of partial derivatives in state space at each time point, and partial derivatives provide a good approximation of the interactions between causal variables, capturing the real-time dynamics of interaction strengths [22]. Effects of driver variables on vegetation can be calculated for each location as follows:

1) Multivariate state space is reconstructed with $(NDVI\_t, NDVI\_t-1, NDVI\_t-2, \ldots, NDVI\_t-E+1, driver\_t\_bestlag)$.
2) The optimal nonlinear coefficient (θ_{best}) is determined using the S-map by trial-and -error.
3) Partial derivatives are calculated using S-map method with θ_{best} at each time point.

2.3.3. Multivariate EDM: scenario exploration

We used multivariate S-map for sensitivity analysis of vegetation response to climate change, predicting NDVI values based on the original data of temperature and precipitation and the changed data, respectively. The steps are as follows:

1) Determine the increment of the driving variable values $\Delta driver$.
2) If the driver variables are multiple, determine their combinations, and then do followings for each combination.
3) Reconstruct multivariate state space S_0: $(NDVI\_t, NDVI\_t-1, \ldots, NDVI\_t-E+1, driver1\_t\_bestlag, driver2\_t\_bestlag)$ and then the optimal nonlinear coefficient (θ_{best}) is determined using S-map by trial-and -error.
4) Use S-map to predict NDVI with θ_{best} on S_0, denoted as $NDVI_{ori}$.
5) Reconstruct multivariate state space S_1:

$(NDVI\_t, NDVI\_t-1, NDVI\_t-2, \ldots, NDVI\_t-E+1, driver1\_t\_bestlag+\Delta driver1\ ,\ driver2\_t\_bestlag+\Delta driver2)$, and then use S-map to predict NDVI with θ_{best} on S_1, denoted as $NDVI_{add}$.

Based on the climate change in the past nearly 40 years (see section 3.3), the range of changes in climate variables are determined: the increase in temperature (ΔT) is not greater than the magnitude of $Slope$*40 ('$Slope$' means the slope of the temperature change trend from 1981 to 2019, see Supplementary Table 3), and the increase (or decrease) in precipitation ($\Delta Pr\ cp$) is not greater than 10% of monthly precipitation observations.

Here, $\Delta driver1$ is referred to ΔT, $\Delta driver2$ is referred to $\Delta Pr\ cp$. The values of ΔT are $Slope$*10, $Slope$*20, $Slope$*30 and $Slope$*40. $\Delta Pr\ cp$ values are 1%, 3%, 5%, 7% and 10% of monthly precipitation observations respectively.

Note that the time series of variables should be normalized to unit variance and zero mean before using the EDM-based method for calculation. Besides, EDM methods (S-map and simplex projection) are implemented using the R package rEDM (version 1.2.3).

2.3.4. Statistical analysis

Since the study is on a regional scale of the whole QTP, the calculations of 49 locations needed to be merged before statistical analyses. Significant improvements are calculated using one-sample Wilcox test. And paired two-sample Wilcox test is used to calculate significant differences in the improvement between variables. Similarly, the significant differences in the strength of the effects between seasons, the significance differences in the predicted NDVI between the scenarios with increased climate data and the scenario with original data are also calculated using the two-sample Wilcox test.

2.3.5. Seasonality

A smooth spline (smooth.spline function in the R language stats package) is used in the calculation of the seasonal cycle for climate variables and NDVI, and the Pearson's correlation between the calculated seasonal cycle and observations is used as a quantitative measure for "seasonality" [33].

3. Results

3.1. Driver variables of vegetation dynamics

To examine whether each climate variable (i.e., T, Prcp, Dtr, Pet, T + Prcp) has a stronger causal effect on vegetation dynamics, we use a multivariate EDM approach(see "Methods" section 2.3.1) to look for improvement in forecasting when a climate variable is included. The results show strong evidence that examined variables are drivers of vegetation from a perspective of dynamical system instead of correlation, as including either variable leads to improved forecast skill ($P < 0.001$, one-sample Wilcox test, Fig. 3).

The forecast skill is significantly improved when the temperature variable is added for prediction of NDVI compared to

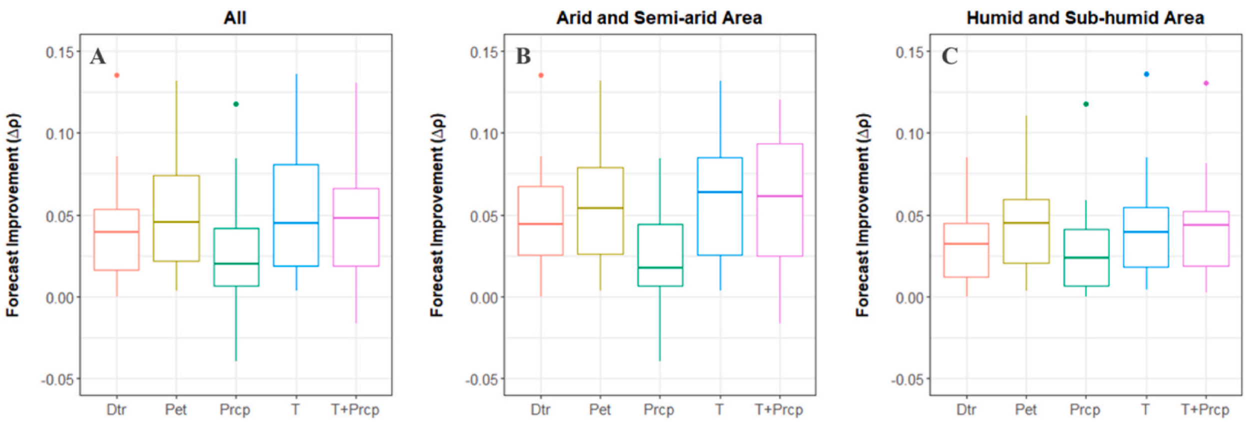

Fig. 3. Forecast improvement with multivariate simplex projection.

precipitation ($p < 0.001$, paired two-sample Wilcox test). We find clear evidence that temperature has more direct and significant effects on vegetation on the QTP than precipitation (Fig. 3A), which supported our first hypothesis that temperature is the dominant influence on vegetation dynamics compared to precipitation on the Plateau. This indicates that vegetation dynamics is more closely related to temperature on a long time scale, which is consistent with the findings of previous studies [9,11]. It also indicates that vegetation dynamics is more sensitive to temperature change.

As shown in Fig. 3B and C, another interesting finding is that the skill in forecasting NDVI when including each climate variable (except precipitation) in arid and semi-arid areas is more significant improved ($P < 0.001$, two-sample Wilcox test) compared to humid and sub-humid areas (The division of dry and wet areas is based on annual precipitation [40]). This suggests that vegetation response is more sensitive to climate change in arid and semi-arid areas. Moreover, this degree of sensitivity exceeded that of the entire QTP ($P < 0.05$).

3.2. Influential strengths of main causal variables

The "heat and water" condition is the key factor and the most direct influence on vegetation growth. After determining the causal variables, we quantify the effects of temperature and precipitation on vegetation dynamics (NDVI) over time using Multivariate EDM: Effects Estimation (multivariate S-map, see "Methods" section 2.3.2, Supplementary Fig. 2). According to our multivariate S-map results, we have the following findings: firstly, the mean values of the causal effects of temperature and precipitation on vegetation dynamics over time are positive (0.335 and 0.199, respectively). The 0.1 and 0.9 quantile regressions are represented by the red lines, which show that the measured effects of temperature and precipitation on vegetation dynamics are almost always positive. (Fig. 4A and B). This indicates that temperature and precipitation promote photosynthesis, and accelerate the release of soil nutrients and thus the growth of vegetation. Secondly, the strength of the effect of temperature is greater than that of precipitation, which further supports our first hypothesis and indicates that temperature has a greater and more direct effect on vegetation than precipitation. Finally, but most importantly, vegetation growth is more influenced by temperature in spring (March to May) and summer (June to August), while precipitation has a greater influence on vegetation in spring and winter (December to Next February) (Fig. 4D, $P < 0.001$). This supports our second hypothesis that there are seasonal differences in the strength of effects that temperature and

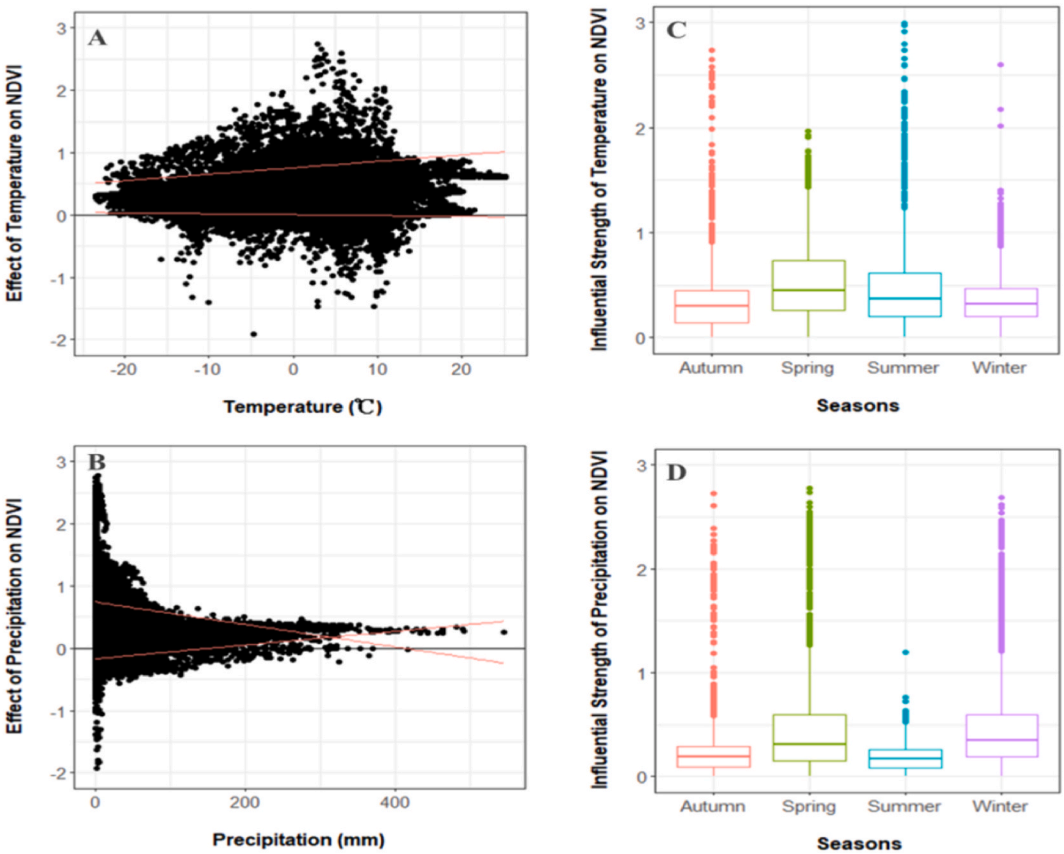

Fig. 4. Effects of climate variables (T, Prcp) on vegetation with multivariate S-map.
(A) Effect of T on vegetation of the QTP. (B) Effect of Prcp on vegetation of the QTP. (C) Influential strengths of T by seasons (ignoring the direction of effects). (D) Influential strengths of Prcp by seasons (ignoring the direction of effects).

precipitation on vegetation, and the temperature effects in spring and summer are much stronger than in autumn and winter (Fig. 4C, P < 0.001).

3.3. Scenario exploration for NDVI variations

By analyzing the climate data during 1981–2019, we find that the temperature shows an increasing trend across the plateau, and the precipitation shows an increasing trend in most areas but a decreasing trend in small localized areas (Fig. 5). The variation rate of annual average temperature of the QTP is 0.284°C-a-10 ($R^2 = 0.4892$, $P < 0.001$), indicating that the entire QTP has experienced a relatively rapid warming process in recent decades. Compared with temperature, annual precipitation shows a slight increase, with a small increase of 7.19 mm per decade ($R^2 = 0.0871$, $P > 0.05$) and a less pronounced linear trend. Thus, the plateau has an overall warming and humidification trend with a significant increase in temperature and a slight increase in precipitation over the past 39 years.

The change of NDVI shows overall increase and local decrease during past decades (Fig. 6A). The annual average NDVI increase with a change rate ranged from −0.0373-a-10 to 0.0385-a-10. The average change rate is 0.0068-a-10 ($R^2 = 0.0767, P > 0.05$, Fig. 6B). Thus, NDVI showed a slight upward trend, but did not reach the level of statistical significance.

Climate variability is critical to the dynamics of vegetation [41], and if the climate continues to warm and humid (i.e., if the climate change stays the same for decades to come), will it be beneficial to plant growth? Based on this question, we conduct a study using the Multivariate EDM: Scenario Exploration (see "Methods" section 2.3.3). We find that the NDVI values increased with the increase in temperature and precipitation (Fig. 6C). From the results, it can be seen that the NDVI values are continuously increasing with the sustained increase in temperature and precipitation. In the "10_01%" scenario, the NDVI values increased but not significantly (averageΔNDVI $= 0.001969$, $P > 0.152$), and the NDVI values increased significantly (averageΔNDVI $= 0.004113$, $P < 0.05$) in "20_07%" scenario. The magnitude of the increase in NDVI values in "40_03%" scenario is very close to the magnitude of the slope of the NDVI change trend per 10-year period. The growth rate of NDVI values in warming and humidification scenarios range from over than 0.5% to less than 2%. The above findings support our third hypothesis that when the climate of the QTP continues to warm and humidify in favor of vegetation growth.

Meanwhile, the QTP also shows warming and drying trend in some regions, so we conduct scenario explorations on warming and drying. The research findings indicate that in the scenarios of warming and drying, there is a slight increase in NDVI values. However,

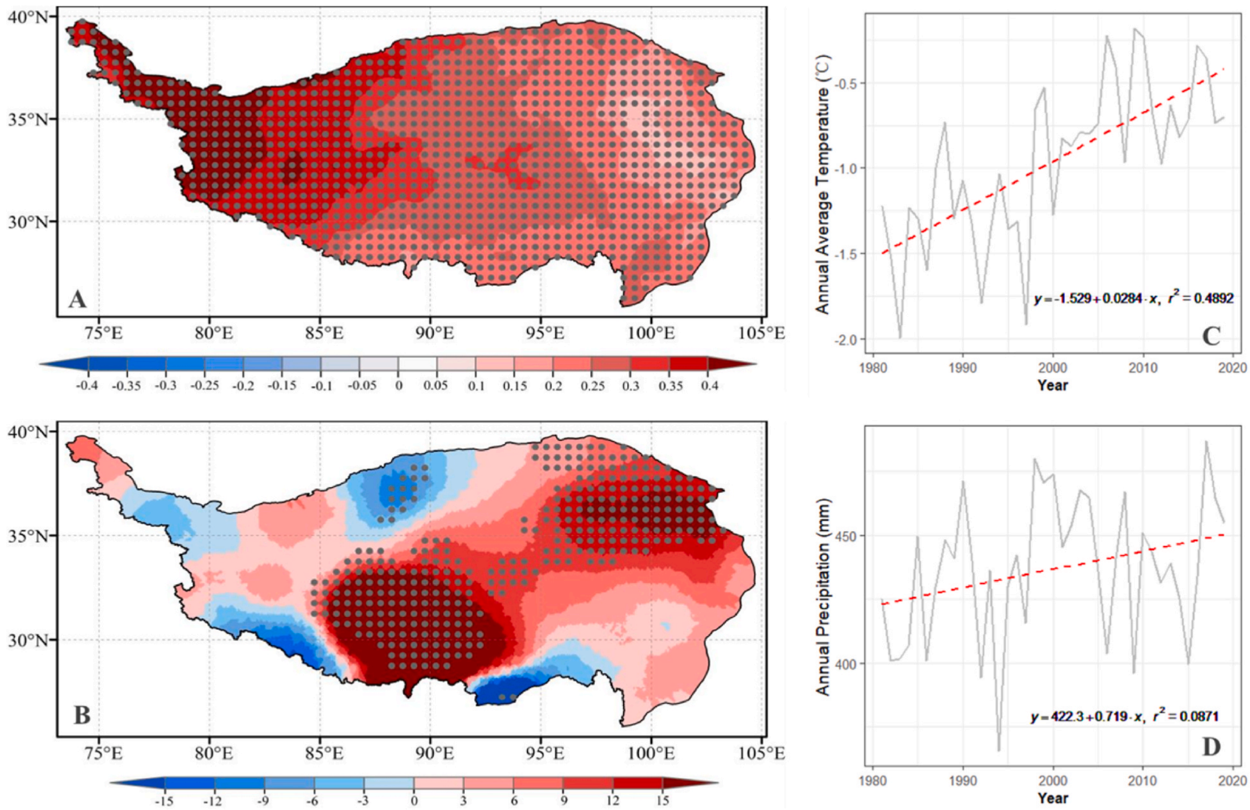

Fig. 5. Changes in annual average temperature and annual precipitation of the QTP from 1981 to 2019.
(A) Trends in annual temperature change. (B) Trends in annual precipitation change. (C) Regional annual average temperature changes. (D) Regional annual precipitation changes.

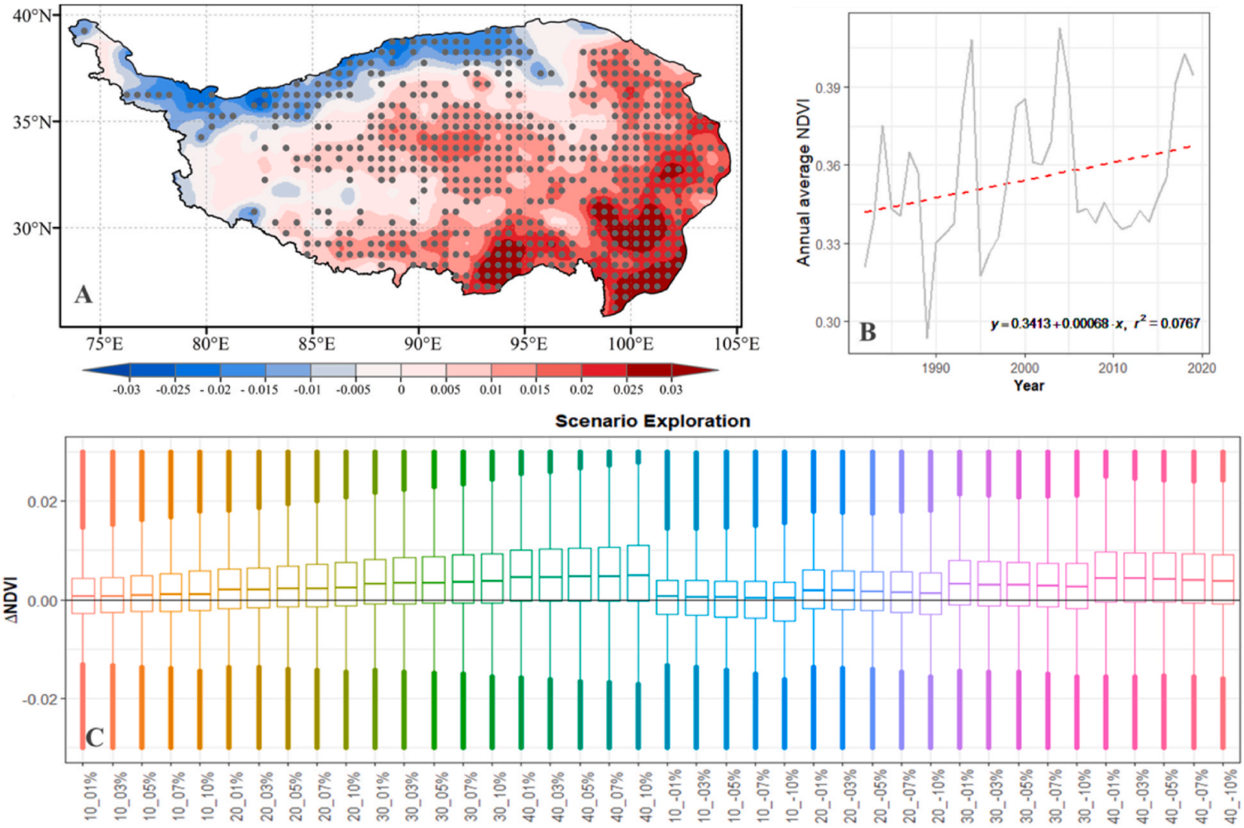

Fig. 6. Changes in annual average NDVI from 1982 to 2019 and scenario exploration with multivariate EDM.
(A) Trends in annual average NDVI change. (B) Regional annual average NDVI changes. (C) ΔNDVI in different scenarios. "10_01%" represents the scenario that temperature and precipitation increasing: Δ T is the magnitude of *Slope**10 ('*Slope*' means the slope of the temperature change trend) and Δ Prcp is 1% of monthly precipitation observations. Similarly, "10_-01%" represents the scenario that temperature increasing and precipitation decreasing: Δ T is the magnitude of *Slope**10 and Δ Prcp is 1% of monthly precipitation observations.

the NDVI values in the warming and drying scenarios are lower than those in the corresponding warming and humidification scenarios. Furthermore, when the temperature increase remains constant, the corresponding NDVI value decreases with the increasing intensity of the decrease in precipitation (Fig. 6C). Therefore, research data evident that warming and humidification is more favorable for the growth of vegetation in the Qinghai-Tibet Plateau compared to warming and drying.

4. Discussion

4.1. The advantage of EDM in analyzing causality of complex systems

Natural systems are usually dynamic and complex, and more importantly, for dynamical systems, the variables are interdependent [18] which makes them difficult to understand using linear statistical approaches (e.g., structural equation modeling or regression). This is because linear methods are essentially based on correlations and assume that the system is additive [18]. Thus, from the perspective of methodology, the research about nonlinear dynamical systems needs nonlinear methods with the acknowledgment of state dependency.

The relationship between climate and vegetation is complex and interdependent [42]. Empirical dynamic modeling (EDM) is an emerging non-parametric framework for studying nonlinear dynamic systems. Currently, there are some studies on the EDM framework, and EDM has been more widely used in ecosystems, climate, epidemiology, financial regulation, medical diagnosis, etc. [22,33,39,43–46]. DeAngelis et al. commented on EDM as "providing a promising quantitative approach for using time series to construct models to successfully map dynamics to the future" [47].

Different methods may yield varying results, and it is crucial to use the appropriate method to obtain reliable results that may challenge our conventional understanding of certain phenomena. We find that the influential strength of temperature on vegetation is stronger in spring and summer than in autumn and winter, while precipitation's is stronger in spring and winter than in summer and autumn at the regional scale of Three-River Source (part of the QTP, Supplementary Fig. 3). This is inconsistent with the existing findings that vegetation in the Three-River Source region is most affected by precipitation and temperature in spring and autumn [48].

There are several possible explanations for the inconsistency. 1) The discrepancy in temporal and spatial scales of datasets used for studies. 2) Spatial differences in the response of vegetation to climate change. 3) Differences in research methods of studies and whether consider the time delay, which we believe could be the main reason. Our results about it challenge conventional knowledge – temperature and precipitation in autumn have a stronger influence on vegetation than in summer and winter.

4.2. Causal effects of climate change on vegetation dynamics

Under the influence of global warming, the QTP has experienced significant climate change. Our study confirms previous reports that temperature has increased significantly in all areas and precipitation has increased slightly in most areas during recent decades. Our findings show strong evidence that climate variables are drivers of vegetation, as including either variable leads to improvement in forecasting.

Our results suggest that the effect of temperature on vegetation is mainly positive and with a few negative. It is probably because that suitable temperature promotes photosynthesis, faster release of nutrients from the soil, and higher nutrient effectiveness [49]. For the negative effect of temperature, one of the possible reasons is that low temperature limits the photosynthesis of vegetation and thus inhibits the growth of vegetation. Another reason may be that high temperature may accelerate the evaporation of soil water, forming a drought trend, and then the vegetation prevents itself from losing water by reducing leaf area and light saturation point, resulting in a corresponding reduction of vegetation cover, and also limiting photosynthesis rate [50], affecting the synthesis of organic matter. Besides, warming increases the autotrophic respiration and transpiration rates of vegetation, which accelerates the consumption of organic matter and causes a decrease in the net productivity of vegetation, which will in turn leads to a suppressive effect on vegetation activities [51].

Similarly, for the positive effect of precipitation, the possible reason is that abundant water resources help photosynthesis of plants, which in turn promotes vegetation growth and development [52]. For the negative effect of precipitation, one of the possible reasons is that when the increase of precipitation exceeds the needs of vegetation, it may indirectly and adversely affect vegetation activities such as growth and development by increasing relative humidity and reducing radiation [53]. Another possible reason is that when moisture is not sufficient, vegetation under reduced moisture conditions can lead to a decrease in photosynthetic rate, lower organic matter production and suppression of vegetation activities such as growth and mulching [54].

Temperature significantly influences vegetation dynamics compared to precipitation on the QTP. This result suggests that temperature is the main factor on vegetation growth. This may be due to the high altitude and relatively low temperature of the QTP, where the increase in temperature over the past decades has been more favorable to vegetation photosynthesis, and thus vegetation activity has responded more strongly to temperature than precipitation [16].

Our findings also suggest that warming and precipitation rising significantly improve vegetation growth by mitigating low temperature limitation and drought levels respectively in arid and semi-arid areas on the QTP [15,55,56]. Importantly, we find that T and Prcp interact nonlinearly (Fig. 3). In other words, the relationships between temperature, precipitation, and vegetation are understood not by separately examining the influence of different variables, but by examining their interdependent effects.

If the climate on the QTP is ongoing warm and humid, we find that this climate trend has a positive effect on vegetation growth. This finding indicates that climate warming can promote vegetation growth by slowing the low temperatures that limit vegetation growth [55,57]. Warming can also accelerate vegetation growth by releasing more nutrients through the decomposition of vegetation litter and reinforced mineralization of soil organic matter and nitrates [56]. Moisture is involved in biochemical and physiological processes such as transpiration and photosynthesis of vegetation, and many minerals and nutrients in the soil can only be taken up by plants under water-soluble conditions, so vegetation under conditions of weakly increased moisture will lead to photosynthetic rate rises and organic matter production increases, promoting vegetation activities such as mulching and growth [54].

Exploration of the warm-dry scenario reveals an increase in NDVI values. The reason why a warm and dry climate may be beneficial to vegetation growth is that warmer temperatures can promote photosynthesis and increase photosynthetic efficiency, thus increasing vegetation growth. In addition, plants under drought conditions usually adjust their growth strategies, such as reducing leaf size and increasing root length, to adapt to the drought conditions. These adaptations sometimes also increase the growth of vegetation. Therefore, when the temperature increases and precipitation decreases slightly (mild drought), it is possible to promote the growth of vegetation.

The analysis of the seasonal effects of climate change reveals that the influential strength of precipitation on vegetation is greater in winter than in summer and autumn. This indicates that the snow in winter, an important water resource for vegetation growth in the growing season, significantly influences vegetation growth by alleviating winter soil drought and reducing soil heat dissipation [58]. We also find that temperature and precipitation in spring have a greater influence on vegetation growth than in other seasons, it is probably because that plants have to enter active photosynthetic process in spring after dormancy phases during winter. Thus, weather conditions in spring are crucial for vegetation growth, and also vegetation is more sensitive to climate change in spring.

4.3. Delayed response of vegetation dynamics to climate variables

Vegetation growth lags behind seasonal weather changes [59–67]. For example, in Central Asia, Yin et al. in Ref. [66] reported that vegetation responses to temperature lagged by one month from June to September during the period of 1982–2012. Wu et al. in Ref. [65] studied the lag of global plant responses to different climatic factors over the past 30 years. Piao et al. in Ref. [67] examined approximately a three-month lag between temperature changes and vegetation activities at both the national and biome scales in China. These previous studies have shown that vegetation changes are driven mainly by earlier climatic conditions. Therefore, it is necessary to consider the lag when testing the causal effects of climate change on vegetation dynamics.

Generally, vegetation can only grow under suitable climatic conditions (e.g., suitable temperature and suitable precipitation) and sufficient nutrients. Plants cannot immediately grow even in the best circumstances because the growth process is relatively slow. Therefore, there is a certain time delay (lag) between vegetation growth response and seasonal climate change. The lag between precipitation and vegetation growth reflects the time between the occurrence of precipitation and the arrival of water to plant roots [68]. Different response delays to precipitation may also be linked to different precipitation distribution patterns, as the precipitation gradient decreases from southeast to northwest across the plateau [69]. The time delay between vegetation growth and temperature is associated with organic matter decomposition, soil temperature, and nutrient availability [70]. Time delay in response to temperature varies among the 49 locations on the QTP (see Supplementary Table 2), which may be related to the spatial differences in climatic characteristics and vegetation types, as well as land use [37,71–73].

4.4. Limitation and future research direction

The interaction between vegetation and climate is considered to be one of many important ecological processes. Apart from temperature and precipitation, there may be other driver factors of vegetation such as solar radiation, wind speed, and human activities [74,75]. One of the advantages of EDM is that these other factors related to the deterministic dynamics of vegetation, are indirectly explained in the reconstructed attractor [25,76]. However, the most comprehensive understanding of vegetation dynamics will come from treating an integrated treatment of all these factors. In addition, our study evaluates the time lag of vegetation response to climate on the monthly scale because of the limitation of the original data. Although NDVI data has been widely used in the study of vegetation dynamics, there may be some limitations in its application due to its uncertainty caused by the influence of atmospheric and surface reflectance characteristics [77,78]. Given the limitations above, future studies may more fully explore vegetation dynamics on the QTP in combination with other datasets (EVI/GPP/higher resolution images, etc.).

5. Conclusions

The purpose of this study is to analyze the causal effects of climate change on vegetation dynamics on the QTP with datasets CRU-TS v4.04 and AVHHR NDVI from 1981 to 2019 using the method based on EDM. Our results confirm that climate variables are drivers of vegetation because including either variable leads to improvement in forecasting. Moreover, the improvement in forecasting is more obvious when temperature variable is included compared to precipitation. This result indicates that the relationship between vegetation and temperature is stronger than that with precipitation. Hence, temperature is the main factor for vegetation dynamics on the plateau. In addition, our findings suggest that the influential strengths of climate on vegetation have significantly varies with seasons. The effects of temperature and precipitation in spring are stronger than in other seasons. Finally, the sensitivity analysis shows that the NDVI increases as temperature grows and precipitation goes up a bit, which revealed that a warm and humid environment promotes the vegetation growth.

In addition to the above results from the regional scale of the entire QTP, we also have some interesting findings. Climate change has more significant influence on vegetation growth in arid and semi-arid areas compared to humid and sub-humid areas. In the Three-River Source region (see Supplementary Fig. 3), the influential strengths of precipitation on vegetation in spring and winter are much more stronger than in other two seasons, which is inconsistent with previous studies that the influential strengths in spring and autumn are stronger. We believe that the main reason for the inconsistent results may be the differences in research methods and if or not the lagged vegetation response to climate is considered.

Our research quantified the influential strengths of climate on vegetation at each time point and conducted statistical analysis on it. In scenario exploration, we first analyzed climate change over the past few decades, and based on assumptions about future climate change, we set the range of changes in temperature and precipitation for a more detailed scenario simulation. Of course, because climate change is simulated, there is a degree of uncertainty in NDVI's predictions.

Taken together, this study reveals the mechanism of how climate change influences vegetation dynamics from the perspective of causality analysis with lagged response, and provides information for sustainable ecological development and ecological management.

Author contribution statement

Zhaoni Li; Hongchun Qu; Lin Li; Jian Zheng; Dianwen Wei; Fude Wang: Conceived and designed the experiments; Performed the experiments; Analyzed and interpreted the data; Contributed reagents, materials, analysis tools or data; Wrote the paper.

Data availability statement

Data included in article/supplementary material/referenced in article.

Additional information

Supplementary content related to this article has been published online at [URL].

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Declaration of competing interest

All authors declare that they have no conflicts of interest.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.heliyon.2023.e16001.

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