Article

The Response of Vegetation to Regional Climate Change on the Tibetan Plateau Based on Remote Sensing Products and the Dynamic Global Vegetation Model

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Abstract: Changes in vegetation dynamics play a critical role in terrestrial ecosystems and environments. Remote sensing products and dynamic global vegetation models (DGVMs) are useful for studying vegetation dynamics. In this study, we revised the Community Land Surface Biogeochemical Dynamic Vegetation Model (referred to as the BGCDV_CTL experiment) and validated it for the Tibetan Plateau (TP) by comparing vegetation distribution and carbon flux simulations against observations. Then, seasonal–deciduous phenology parameterization was adopted according to the observed parameters (referred to as the BGCDV_NEW experiment). Compared to the observed parameters, monthly variations in gross primary productivity (GPP) showed that the BGCDV_NEW experiment had the best performance against the in situ observations on the TP. The climatology from the remote sensing and simulated GPPs showed similar patterns, with GPP increasing from northwest to southeast, although the BGCDV_NEW experiment overestimated GPP in the semi-arid and arid regions of the TP. The results show that temperature warming was the dominant factor resulting in the increase in GPP based on the remote sensing products, while precipitation enhancement was the reason for the GPP increase in the model simulation.

Keywords: dynamic vegetation; gross primary productivity; regional climate change; remote sensing products; Tibetan Plateau

1. Introduction

Terrestrial ecosystems have absorbed 25–30% of anthropogenic carbon dioxide emissions in the past five decades [1]. Vegetation is an essential part of terrestrial ecosystems and plays a crucial role in regulating regional climates and maintaining the surface energy balance [2,3]. Gross primary productivity (GPP) refers to the total amount of organic carbon fixed by plants in the ecosystem by absorbing solar energy and assimilating carbon dioxide through photosynthesis per unit time. GPP determines the total amount of initial energy and material entering terrestrial ecosystems. It reflects the vegetation productivity of terrestrial ecosystems, which profoundly influences the carbon cycle and global climate change.

The Tibetan Plateau (TP), with an average elevation of more than 4000 m, is often called the “third pole” [4]. Previous studies showed that 49% of streamflow in the Yellow
River, 15% of streamflow in the Lancang–Mekong River, and a considerable amount of streamflow in the Yangtze River originate from the TP [5], and the TP is often regarded as the “Asian water tower”. With a large vertical height difference, rich landform types, diverse climatic environments, and complex ecosystem environments, the TP is a vital ecological barrier for China. Due to its unique geographical location, the TP is also a sensitive area of East Asia [6–8]. In particular, the TP shows a significant warming trend and increased precipitation [9,10]. The climate conditions on the TP are extremely variable, and its ecosystem pattern can easily be altered by external disturbances [11].

Land surface observation systems, mainly based on field observation and satellite remote sensing products, are critical for studying changes in land surface variables. With the development of global satellite remote sensing technology, vegetation index products retrieved by satellite remote sensing, such as the leaf area index (LAI), the normalized difference vegetation index (NDVI), and gross primary productivity (GPP), have provided effective support for studying global large-scale vegetation changes. However, due to the high elevation and harsh natural environment, there are few observation sites at high elevation on the TP, especially soil moisture and carbon flux observation sites [12,13]. Affected by high elevation, cloud cover, and auxiliary data, it is doubtful whether remote sensing products can provide a long-term stable vegetation index. Previous studies that included observations, remote sensing products, and simulations have been carried out for carbon flux and its responses to climate change on the TP and China [4,11,14–18]. Empirical models, remote sensing products, and numerical simulations are effective ways to estimate regional and global vegetation distributions. The next generation of land surface models includes the traditional hydrothermal transfer process, biogeochemical processes, and dynamic vegetation [19].

Dynamic global vegetation models (DGVMs) have been coupled with climate models to study the response of vegetation to climate change. In contrast to models of the fixed-satellite vegetation type, some vegetation characteristic parameters in DGVMs are calculated based on temperature, precipitation, and radiation; thus, the vegetation coverage simulated by DGVMs varies with climate change. DGVMs include: (1) simple biogeography rules to delineate the vegetation types based on climate; (2) carbon and nitrogen cycle modules; (3) vegetation dynamics modules. Current DGVMs include the Lund–Potsdam–Jena Dynamic Global Vegetation Model (LPJ DGVM), the Integrated Biosphere Simulator Model (IBIS), the BIOME4 model, the CLM-DGVM, and the Institute of Atmospheric Physics Dynamic Global Vegetation Model (IAP-DGVM). The LPJ model generally describes the temporal and spatial characteristics of regional vegetation, and it has effectively simulated the responses of vegetation patterns and functions to climate change [20]. IAP-DGVM simulations showed that the model could effectively reproduce the global distribution of shrubs, trees, grass, and bare soil, but it overestimated the fraction of temperate forests [21]. Ni et al. [4] used a modified BIOME DGVM to simulate the biome distribution on the TP; vegetation maps confirmed that the modified model did a better job of simulating biome patterns on the TP (grid cell agreement 52%) than the original BIOME4 model (35%). Song et al. [22] evaluated the CLM3.0-DGVM model, showing that the CLM3.0-DGVM predicted a relatively high population density with small individual trees in boreal forests. DGVMs perform differently in simulating vegetation distribution, and the models still have certain defects that cause deviations in simulations.

Vegetation phenology considers the influence of climate and other environmental factors and shows the time pattern of vegetation seasonal growth and decadency. Murray-Tortarolo et al. [23] validated leaf area index (LAI) estimates from multiple land surface models (LSMs) and found that all the LSMs overestimated the mean LAI and the length of the vegetation growing season, primarily due to late dormancy as a result of late summer phenology. A more complete vegetation phenology parameterization in DGVMs is significant for simulating the vegetation distribution and carbon fluxes accurately.

With their development and improvement, vegetation models have been added to Earth system models to study future changes in the global climate and terrestrial ecosys-
tems. Dynamic vegetation models play a major role in simulating carbon, nitrogen, and water cycle processes in the ecosystem. Improving their accuracy is one of the focuses of vegetation model developers. Due to the high altitude and unique natural environment, DGVMs still encounter great uncertainty in simulating the vegetation distribution on the TP. In this study, we validated the performance of vegetation distribution and ecosystem productivity simulations on the TP by using the CLM5.0-DGVM. The CLM5.0-DGVM runs the CLM biogeochemistry model in combination with the LPJ-derived DGVM introduced in CLM3.0. The accuracy of soil moisture and temperature simulations in the model is significant for improving the ability to simulate ecosystem productivity. Following the work of Deng et al. [24], in which the soil moisture and temperature simulations in CLM5.0 were improved for the TP, the revised soil water and heat transfer schemes were used in all the simulations in this paper. Firstly, we modified the original code in the establishment and survival module, replaced the default vegetation parameters with observations (referred to as the BGCDV_CTL experiment), and evaluated the performance of the BGCDV_CTL experiment. In addition, we modified the vegetation phenology parameterization in the BGCDV_CTL experiment to conduct a comprehensive sensitivity analysis for the modified dynamic vegetation model. Secondly, we evaluated the vegetation productivity and vegetation distribution results from both remote sensing and simulations. Lastly, based on the improved model and the remote sensing GPP products, we investigated vegetation, climate change, and the response of the vegetation to regional climate change on the TP. Following this introduction Section 1, the data and model are briefly described in Section 2. An evaluation of the CLM5.0-DGVM and the GPP remote sensing products is conducted in Section 3. Section 4 analyzes the response of the vegetation to regional climate change on the TP. The conclusions are included in Section 5.

2. Materials and Methods

2.1. Study Area

In this study, we mainly focused on an area 25–40°N and 75–105°E (Figure 1) that covers the whole TP. The TP covers an area of approximately 2.5 × 10^6 km²; with more than half of its area over 4000 m above sea level, it is the highest and largest highland in the world. There are five main plant types on the TP: from southeast to northwest: forests, shrubs, crops, alpine meadows, and sparse alpine grasslands. The alpine meadows and sparse alpine grasslands are the dominant land surface types on the TP.

![Figure 1. Distribution of vegetation and locations of the flux observational sites over the TP (the pentagrams represent the sites with flux observations).](image-url)
2.2. Data

2.2.1. Observation Data

The Maqu site is one of the sites set up by the Zoige Plateau Wetlands Ecosystem Research Station, which is located in the eastern region of the TP [14]. The vegetation type at the Maqu site is typically alpine meadow, with an average height of about 0.2 m. The climate at the Maqu site is a sub-humid climate, with an average annual temperature of 1.9 °C, and the multi-year average precipitation is 593 mm [25]. The soil type at Maqu is silt loam, which is rich in organic matter. The observation data from Dangx and Haibei that are used in this study were derived from the China flux network (http://www.cnern.org.cn/) (accessed on 16 December 2020) [26,27]. The vegetation type at the Haibei and Dangx sites is alpine meadow, and the altitudes are 3148 m and 4250 m above sea level, respectively. The Haibei site has a sub-humid climate, the average annual temperature is −1.2 °C, and the average annual precipitation is 535.2 mm; precipitation in the growing season (May to September) accounts for 82% of the annual precipitation. The vegetation coverage at the end of the growing season can reach more than 98%, and the soil organic matter content is 5.85% in the top 40 cm. The climate at the Dangx site is a semi-arid climate, with an average annual temperature of 1.3 °C; the average annual precipitation is 450 mm, of which 85% is distributed from June to August. The vegetation coverage is 50–80%, and the soil organic matter content is 0.9–2.79%. The Maqu, Dangx, and Haibei sites provide long-term conventional meteorological data and flux data. The carbon flux data include gross primary productivity (GPP), net ecosystem exchange productivity (NEE), and ecosystem respiration (Re) (detailed information of the sites see Table 1).

| Site | Lat (°N) | Lon (°E) | Elevation (m) | Vegetation Type | Years          |
|------|----------|----------|---------------|----------------|---------------|
| Maqu | 33.9     | 102.17   | 3471          | Alpine meadow  | 2010–2016     |
| Dangx| 30.85    | 91.08    | 4250          | Alpine meadow  | 2007–2010     |
| Haibei| 37.62    | 101.3    | 3148          | Alpine meadow  | 2003–2007     |

2.2.2. Remote Sensing Product

The GLASS (Global Land Surface Satellite) GPP product was provided by the Beijing Normal University Center for Global Change Data Processing and Analysis (http://www.bnu-datacenter.com/) (accessed on 5 April 2021). Its time resolution is 8 days, and the spatial resolution is 0.05°. This product has been quality-controlled and had its accuracy verified, and it has the advantages of high accuracy, long time series, and spatial integrity [28,29].

The FLUXCOM GPP product (www.fluxcom.org) (accessed on 12 April 2021) provides carbon fluxes at a high spatial resolution of 0.05°, with a temporal resolution of 8 days, and it is available for the Moderate Resolution Image Spectroradiometer (MODIS, 2000-present). FLUXCOM combines carbon and energy fluxes and meteorological measurements from 224 global FLUXNET sites, using machine learning techniques to scale up these fluxes to a global extent [30,31]. Tramontana et al. [32] evaluated FLUXCOM GPP products against observations and found that the FLUXCOM dataset adequately estimated global carbon fluxes. Long-term time-series GLASS GPP products were used to evaluate the climatology and trend of the GPP simulated using CLM5.0-BGCDV.

The improvements in GPP products, including near-infrared reflectance (NIRv) and solar-induced chlorophyll fluorescence (SIF), provide a method to estimate global GPP [33]. Limited by its short duration, satellite SIF can hardly be used to monitor long-term GPP [34]. In this study, the global long-term (1982–2018) GPP dataset [35] generated by the proxy of GPP used satellite-based near-infrared reflectance to study the response of vegetation to regional climate change. Previous studies showed that the long-term datasets derived from NIRv better capture the seasonal and inter-annual variations in terrestrial GPP at the global scale [35].
In this study, a GPP dataset derived from the Moderate Resolution Imaging Spectroradiometer (MODIS) instruments on the National Aeronautics and Space Administration (NASA) Terra and Aqua satellites was used (https://search.earthdata.nasa.gov/) (accessed on 15 March 2022). The MODIS GPP product provides global daily estimates of GPP at a 0.05° resolution for the period 2000–2003 [36]. MCD43C4v006 Nadir Bidirectional Reflectance Distribution Function (BRDF)-Adjusted Reflectance (NBAR) products were used as inputs to neural networks that were used to upscale the GPP estimated from the FLUXNET 2015 eddy covariance tower sites.

The fractions of land cover types used in this study were sourced from the Global Vegetation Continuous Fields product (MOD44B, hereafter called MEaSURES), based on observations from the MODIS [37]. This product comprises three different land cover types: (1) bare soil, (2) trees, and (3) non-trees. It can be downloaded from NASA’s Earth data portal (https://search.earthdata.nasa.gov/) (accessed on 10 May 2020). Specific descriptions of the remote sensing products used in this study are presented in Table 2.

Table 2. Detailed information on the remote sensing products used in this study.

| Product | Time Period | Temporal Resolution | Spatial Resolution |
|---------|-------------|---------------------|--------------------|
| NIRv    | 1982–2016   | 8 d                 | 0.05° × 0.05°      |
| GLASS   | 1982–2016   | 8 d                 | 0.05° × 0.05°      |
| FLUXCOM | 2001–2016   | 8 d                 | 0.05° × 0.05°      |
| FLUXCOMI| 1982–2013   | daily               | 0.5° × 0.5°        |
| MODIS   | 2000–2016   | daily               | 0.05° × 0.05°      |
| MEaSURES| 1982–2013   | yearly              | 0.05° × 0.05°      |

2.2.3. Meteorological Data

The observational meteorological datasets used in this study include daily precipitation and temperature with a spatial resolution of 0.5° from 1979 to 2016. The grid precipitation and temperature datasets originated from daily and monthly precipitation and temperature data at 2472 meteorological sites. The data were processed by quality control and then interpolated from station data to grid data, with only stations with data available from 1961 used. A digital elevation model (Global 30 Arc-Second Elevation, GTOPO30) was introduced in order to weaken the effects of elevation on the interpolation precision of temperature and precipitation [38].

2.3. Description of CLM

The land surface model used in this study is provided by the National Center for Atmospheric Research (NCAR) and is the land component of the Community Earth System Model (CESM). The CLM5.0-DGVM is one of the models that simulate the structure and distribution of natural vegetation dynamically, primarily using mechanistic parameterizations of large-scale vegetation processes [39,40]. The dynamic vegetation model of the Lund–Potsdam–Jena model (LPJ) was coupled with the NCAR’s Land Surface Model prior to the first release of the CLM [41]. In addition, the CLM-DGVM has a set of routines that allow vegetation structure and cover to be simulated instead of prescribed from data.

2.3.1. Establishment and Survival

Plant functional type (PFT) survival in a grid cell requires the 20-year running mean of the minimum monthly temperature, $T_c$, to exceed the PFT-dependent 20-year running mean of the coldest minimum monthly temperature, $T_{c,min}$ (Table 3). Existing PFTs that can survive in the current climate continue to exist without change. PFTs do not present in a grid cell unless they can establish. Establishment criteria are stricter than those for survival, additionally requiring that $T_c$ be less than the PFT-dependent 20-year running mean of the warmest minimum monthly temperature, $T_{c,max}$ (Table 3), that growing degree days (GDD$_{23^\circ C}$) be greater than the PFT-dependent GDD$_{min}$ (Table 3), and that GDD$_{23^\circ C}$ be
equal to 0. Establishment also requires the 365-day running mean of precipitation to be greater than 100 mm/year.

### Table 3. Rules that delineate PFT biogeography according to climate.

| PFT                                      | Survival | Establishment |
|------------------------------------------|----------|---------------|
| Tropical broadleaf evergreen tree (BET)  | 15.5     | No limit      | 0             |
| Tropical broadleaf deciduous tree (BDT)  | 15.5     | No limit      | 0             |
| Temperate needleleaf evergreen tree (NET)| −2.0     | 22.0          | 900           |
| Temperate broadleaf evergreen tree (BET) | 3.0      | 18.8          | 1200          |
| Temperate broadleaf deciduous tree (BDT) | −17.0    | 15.5          | 1200          |
| Boreal needleleaf evergreen tree (NET)   | −32.5    | −2.0          | 600           |
| Boreal deciduous                         | No limit | −2.0          | 350           |
| C4                                       | 15.5     | No limit      | 0             |
| C3                                       | −17.0    | 15.5          | 0             |
| C3 arctic                                | No limit | −17.0         | 0             |

#### 2.3.2. Seasonal–Deciduous Phenology

The onset trigger for the seasonal–deciduous phenology algorithm is based on an accumulated growing-degree-day (GDD) approach [42]. The GDD summation is initiated (GDD\(_{\text{sum}} = 0\)) when the phenological state is dormant and the model timestep crosses the winter solstice. Once these conditions are met, GDD\(_{\text{sum}}\) is updated at each timestep as

\[
\begin{align*}
\{ & \text{GDD}^{n-1}_{\text{sum}} + (T_{s,3} - \text{TKFRZ})f_{\text{day}}) & T_{s,3} > \text{TKFRZ} \\
& \text{GDD}^{n-1}_{\text{sum}} & T_{s,3} \leq \text{TKFRZ} 
\end{align*}
\]

(1)

where \(T_{s,3}(K)\) is the temperature of the third soil layer, and \(f_{\text{day}} = \Delta t/86400\) (unit : day). The onset period is initiated if GDD\(_{\text{sum}} > \text{GDD}_{\text{sum, crit}}\) (unit : day), where

\[
\text{GDD}_{\text{sum, crit}} = \exp(4.8 + 0.13(T_{2m,\text{ann,avg}} - \text{TKFRZ}))
\]

(2)

where \(T_{2m,\text{ann,avg}}(K)\) is the annual average of the 2 m air temperature, and TKFRZ is the freezing point of water (273.15 K).

The offset period is triggered when the day length is <39,300 s.

Previous studies found that current DGVMs overestimated the length of the active vegetation-growing season, mostly due to a late dormancy resulting from late summer phenology [23]. The beginning of the growing season in observation is judged when the 5 cm soil temperature is greater than 5 °C. In this study, we modified GDD\(_{\text{sum}}\) as follows:

\[
\begin{align*}
\{ & \text{GDD}^{n-1}_{\text{sum}} + (T_{s,2} - \text{TKFRZ})f_{\text{day}}) & T_{s,2} > \text{TKFRZ} \\
& \text{GDD}^{n-1}_{\text{sum}} & T_{s,2} \leq \text{TKFRZ} 
\end{align*}
\]

(3)

Additionally, the offset period is triggered when the day length of <39,300 s changes to a day length of <42,000 s.

#### 2.4. Experimental Design

In this study, the CLM model we used in simulating ecosystem productivity and vegetation distribution was CLM5.0-BGCDV. To achieve a steady state for the CLM-BGCDV model, we first ran it from a cold state using the “accelerated decomposition spin-up (AD spin-up)” mode for 400 years. Afterward, we saved the last restart file from the AD spin-up simulation and took it as a “finidat” file to use in the normal mode simulations.

To investigate the performance of CLM5.0-DGVM in simulating ecosystem productivity and vegetation distribution over the TP, we conducted the following set of regional simulations on the TP using CLM5.0-DGVM. (1) Following Deng et al. [24], we replaced the soil property data with the Beijing Normal University soil property data, the Ballard
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and Arp, and the virtual temperature schemes were used to replace the original code in the CLM5.0-DGVM. In addition, we modified the establishment and survival code so that PFTs could establish on the TP, and we replaced the vegetation parameters with observations. (2) The seasonal–deciduous phenology parameterization was used to replace the original code (see Table 4 for details). (3) We compared the difference in soil water and heat transfer modeling using CLM5.0-SP and CLM5.0-BGCDV.

Table 4. Designs of the regional experiments by CLM.

| Experiment         | Soil Property Data         | Parameterization                                      | Model          |
|--------------------|---------------------------|-------------------------------------------------------|----------------|
| BGCDV_CTL          | BNU soil property data    | Balland and Arp; virtual temperature; establishment  | CLM5.0-BGCDV   |
|                    |                           | and survival                                          |                |
| BGCDV_NEW          | BNU soil property data    | Balland and Arp; virtual temperature; establishment  | CLM5.0-BGCDV   |
|                    |                           | and survival; seasonal–deciduous phenology           |                |

2.5. Analytical Method

In this study, four statistical features were calculated in order to quantify the differences between the simulated and observed parameters, which were calculated at each station: bias (Bias), root mean square error (RMSE), correlation coefficient (Corr), and ratio of standard deviation (RSD). PBIAS was used to assess the performance of simulations regarding the tendency of the simulated carbon fluxes to be overestimated or underestimated [43]. It is considered unacceptable if PBIAS is greater than 20% [44,45]. When the Corr is high and the RMSE is low, the simulation is considered robust and more desirable [46].

\[
PBIAS = \frac{1}{N} \sum_{i=1}^{N} \left( M_i - O_i \right) / \sum_{i=1}^{N} (O_i) \quad (4)
\]

\[
RMSE = \left( \frac{1}{N-1} \sum_{i=1}^{N} (M_i - O_i)^2 \right)^{1/2} \quad (5)
\]

\[
Corr = \frac{\frac{1}{N} \sum_{i=1}^{N} (M_i - \bar{M})(O_i - \bar{O})}{\sqrt{\frac{1}{N} \sum_{i=1}^{N} (M_i - \bar{M})^2} \sqrt{\frac{1}{N} \sum_{i=1}^{N} (O_i - \bar{O})^2}} \quad (6)
\]

\[
RSD = \frac{\sqrt{\frac{1}{N-1} \sum_{i=1}^{N} (M_i - \bar{M})^2}}{\sqrt{\frac{1}{N-1} \sum_{i=1}^{N} (O_i - \bar{O})^2}} \quad (7)
\]

3. Evaluation of Remote Sensing Products and GPP Simulations

Figure 2 shows the time series of the observed and the simulated GPP, NEE, and Re at the Dangx, Haibei, and Maqu sites. After revising the establishment and survival parameterizations, the simulated vegetation coverage was about 50–80% from 2007 to 2010 at the Dangx site, 70–90% from 2003 to 2010 at the Haibei site, and 90–100% from 2010 to 2016 at the Maqu site, which corresponds to the actual observations at each site. Compared to the seasonal variation in the daily GPP, NEE, and Re at Dangx, the observed GPP, NEE, and Re showed different characteristics. Both the absolute GPP and NEE increased steadily from the beginning of the growing season until July, then increased rapidly from July and reached a peak value at the end of August and the beginning
of September. The simulated GPP generally coincided with the observations, and the simulated GPP of the BGCDV_CTL experiment started earlier and ended later than that of the observed GPP. At the Haibei site, GPP, NEE, and Re showed similar variations during the growing season, increasing beginning in May and reaching a peak value in August (Figure 2). Before modifying the establishment and survival parameterizations, the PFTs in dynamic vegetation simulations could not establish at the Haibei site. After modifying the establishment and survival scheme (BGCDV_CTL experiment), the simulated Re generally coincided with the observations, while the dynamic vegetation model underestimated GPP and NEE from July to September. In addition, the simulated start time of the growing season was advanced, and the end time of the growing season was delayed. The increasing trend of the simulated GPP and NEE was faster than that of the observed GPP and NEE. Seasonal variations in GPP, NEE, and Re at the Maqu site showed a similar pattern to those at the Haibei site. The CLM5.0-DGVM model underestimated Re during the growing season and underestimated NEE. In addition, the model underestimated GPP, NEE, and Re in a vigorous-growth period. In the BGCDV_CTL experiment, variations in the ecosystem productivity simulations were consistent with those in the observations, while the end time of the growing season was delayed.

![Figure 2. Model simulations from CLM5.0-DGVM versus observations of daily GPP (unit: gC·m⁻²·d⁻¹), NEE (unit: gC·m⁻²·d⁻¹), and Re (unit: gC·m⁻²·d⁻¹) at Dangx from 2007 to 2010, Haibei from 2003 to 2007, and Maqu from 2010 to 2019; the black, blue, and red lines are the means from observation, the BGCDV_CTL experiment, and the BGCDV_NEW experiment, respectively.](image_url)

After replacing the original seasonal–deciduous phenology scheme (the BGCDV_NEW experiment), the model effectively shortened the growing season length at the Dangx site. The average Bias and RMSE decreased from 0.116 gC·m⁻²·d⁻¹ and 0.321 gC·m⁻²·d⁻¹ to 0.092 gC·m⁻²·d⁻¹ and 0.261 gC·m⁻²·d⁻¹, respectively, and Corr increased from 0.922 to 0.995 (Table 5). At the Dangx site, the simulated NEE tended to underestimate the observed NEE from August to October, mainly caused by overestimating the simulated Re. Compared to the BGCDV_CTL experiment, the simulated NEE in the BGCDV_NEW experiment was smaller. The RMSE decreased from 0.316 gC·m⁻²·d⁻¹ to 0.299 gC·m⁻²·d⁻¹, and Corr increased from 0.572 gC·m⁻²·d⁻¹ to 0.640 gC·m⁻²·d⁻¹. Re began to increase gradually when the growing season started and reached a peak value in August. With the leaves beginning dormancy, Re decreased beginning in September. During the growing season, the simulated Re overestimated the observed Re, and there was a dramatic decline in mid-August in the simulated Re. The average Bias values for the BGCDV_CTL experiment and the BGCDV_NEW experiment were 0.003 gC·m⁻²·d⁻¹ and −0.017 gC·m⁻²·d⁻¹, respect-
tively. After modifying the seasonal–deciduous phenology parameterization, the simulated Re tended to reduce at the Dangx site. The RMSE reduced from 0.323 gC·m\(^{-2}\)·d\(^{-1}\) to 0.300 gC·m\(^{-2}\)·d\(^{-1}\), and Corr increased from 0.899 to 0.915. Compared to the BGCDV_CTL experiment, the simulated GPP in the BGCDV_NEW experiment reduced from −0.136 gC·m\(^{-2}\)·d\(^{-1}\) and 1.227 gC·m\(^{-2}\)·d\(^{-1}\) to −0.109 gC·m\(^{-2}\)·d\(^{-1}\) and 1.127 gC·m\(^{-2}\)·d\(^{-1}\), respectively, and Corr increased from 0.863 to 0.882. The dramatic increase in the simulated GPP from May to June was mainly caused by the increase in the simulated NEE. The simulated NEE from the BGCDV_NEW experiment had a better performance than that from the BGCDV_CTL experiment. At the Haibei site, the simulated Re underestimated the observed Re during the non-growing seasons and overestimated Re in autumn (September to November). The average Bias of the simulated Re by the BGCDV_NEW experiment decreased by 21%, and seasonal variations in the BGCDV_NEW experiment coincided better with observations. The simulated NEE from the BGCDV_NEW experiment had a better performance than that from the BGCDV_CTL experiment. At the Maqu site, the simulated NEE from the BGCDV_NEW experiment tended to overestimate NEE during the non-growing season and reduced the biases of NEE during the growing season at the Maqu site. The average Bias between the BGCDV_CTL experiment simulations and observations was 0.606 gC·m\(^{-2}\)·d\(^{-1}\). In addition, obvious systematic errors existed at the Dangx and Haibei sites from July to September, which may have been caused by the imperfections of the water use efficiency parameterization scheme. The simulated carbon flux of CLM5.0-DGVM is sensitive to water content and less sensitive to temperature. According to PBIAS, the simulated GPP at the Dangx, Haibei, and Maqu sites are considered acceptable. The Re simulations are satisfactory at the Dangx and Haibei sites, and the simulated NEE at the Dangx, Haibei, and Maqu sites are considered unacceptable.

Table 5. Statistical results of the simulated GPP, NEE, and Re.

| Sites   | PBIAS (%) | RMSE (gC·m\(^{-2}\)·d\(^{-1}\)) | Corr  | RSD |
|---------|-----------|----------------------------------|-------|-----|
|         |  CTL      | NEW                |  CTL  | NEW |  CTL  | NEW |  CTL  | NEW |
| Dangx   | GPP       | 20.9               | 16.6  | 0.321 | 0.261 | 0.922 | 0.952 | 1.100 | 1.121 |
|         | NEE       | −71.1              | −87.8 | 0.316 | 0.299 | 0.572 | 0.640 | 0.676 | 0.745 |
|         | Re        | 0.5                | 2.7   | 0.323 | 0.300 | 0.899 | 0.915 | 1.676 | 1.636 |
| Haibei  | GPP       | −6.9               | −5.5  | 1.227 | 1.127 | 0.863 | 0.882 | 0.780 | 0.892 |
|         | NEE       | −45.8              | −40.7 | 0.917 | 0.882 | 0.571 | 0.615 | 0.480 | 0.716 |
|         | Re        | −10.9              | −8.6  | 0.580 | 0.516 | 0.927 | 0.945 | 1.054 | 1.085 |
| Maqu    | GPP       | 18.2               | 11.3  | 1.401 | 1.028 | 0.903 | 0.956 | 0.946 | 1.087 |
|         | NEE       | −82.0              | −79.7 | 1.114 | 0.877 | 0.634 | 0.814 | 0.691 | 0.924 |
|         | Re        | 28.0               | 26.2  | 1.008 | 0.963 | 0.936 | 0.954 | 1.238 | 1.288 |

The Maqu and Haibei sites are located in the eastern and northern regions of the TP, respectively, and both sites are obvious carbon sinks, while the Dangx site is a weaker carbon source that is located in the central region of the TP and at a high elevation. At the Maqu and Haibei sites, with rich soil organic matter, the photosynthetic carbon absorption during the growing season is higher than that of the Dangx site. Compared to the Maqu and Haibei sites, the observed GPP and Re are smaller at the Dangx site.

Figure 3 shows the monthly variations in the simulated GPP from CLM5.0-DGVM and the NIRv, GLASS, FLUXCOM, and MODIS products versus observations at the Dangx, Haibei, and Maqu sites. The GPP provided by NIRv underestimated the growing season length at the Dangx site, mostly due to a delayed start of the growing season. At the Haibei and Maqu sites, the NIRv GPP product overestimated GPP in the growing season. FLUXCOM assimilated observations at the Dangx site into the product, but deviations still existed in the descriptions of the GPP characteristics at the Dangx site. The FLUXCOM
product overestimated the length of the vegetation growing season, mostly due to an early start of the growing season. Compared to the FLUXCOM product, the start of the growing season of the GLASS product was closer to the observation, while the product seriously overestimated the observed GPP, especially in 2007, 2009, and 2010. The GPP provided by MODIS overestimated the GPP at Dangx and Haibei at the start of the growing season and the growing season at the Haibei site. At the Maqu site, the MODIS GPP generally coincided with the observed GPP. The simulated GPP from CLM5.0-DGVM displayed better performance and simulated the variation characteristics of GPP. As seen in Table 6, at the Dangx site, the average Bias values of the BGCDV_NEW experiment and the NIRv, GLASS, FLUXCOM, and MODIS products were 0.091 gC·m⁻²·d⁻¹, −0.174 gC·m⁻²·d⁻¹, 0.840 gC·m⁻²·d⁻¹, 0.242 gC·m⁻²·d⁻¹, and 0.370 gC·m⁻²·d⁻¹, respectively. At the Haibei site, the GLASS product overestimated the observed GPP, while the seasonal variations generally coincided with observations. The FLUXCOM product underestimated GPP during the growing season and overestimated the observed GPP during the non-growing season. The bias between simulations from CLM5.0-DGVM and observations was smaller than that between the GLASS and FLUXCOM products. However, there was a valley value in the simulated GPP during the growing season, which did not exist in the observations. Compared to the NIRv, GLASS, FLUXCOM, and MODIS products, the RMSE of the simulated GPP from the BGCDV_NEW experiment decreased by 74%, 36%, 30%, and 39%, respectively. The GLASS product at Maqu generally coincided with observations, while the product overestimated GPP in 2011, 2014, and 2015. The years 2011, 2014, and 2015 were years with less precipitation, which led to lower GPP values. The MODIS GPP product had the best performance in simulating GPP at the Maqu site. Compared to the NIRv, GLASS, FLUXCOM, and MODIS products, the average Bias of the simulated GPP from the BGCDV_NEW experiment decreased by 2.02 gC·m⁻²·d⁻¹, 1.265 gC·m⁻²·d⁻¹, 0.143 gC·m⁻²·d⁻¹, and −0.159 gC·m⁻²·d⁻¹, respectively. Overall, the PBIAS values of the GPP simulations from the BGCDV_NEW experiment at Dangx, Haibei, and Maqu are within 20%, which is considered to be acceptable. In addition, the FLUXCOM and MODIS data are satisfactory at Maqu.

Table 6. Statistical results of the simulated GPP, GLASS GPP, and FLUXCOM GPP against observations at a monthly scale.

| Experiment | PBIAS (%) | RMSE (gC·m⁻²·d⁻¹) | Corr |
|------------|-----------|--------------------|------|
|            | Dangx     | Haibei             | Maqu | Dangx | Haibei | Maqu  |
| NEW        | 16.4      | −11.0              | 11.3 | 0.322 | 1.107  | 1.084 |
| GLASS      | 151.4     | 45.9               | 23.1 | 1.587 | 1.723  | 1.239 |
| FLUXCOM    | 43.6      | 44.1               | 16.8 | 0.520 | 1.582  | 1.472 |
| NIRv       | −31.4     | 118.7              | 89.6 | 0.659 | 4.184  | 3.554 |
| MODIS      | 66.7      | 45.7               | 5.2  | 0.569 | 1.727  | 0.905 |

Figure 4 shows the spatial distribution of the bare soil proportion from the BGCDV_NEW experiment simulations and the MEaSUREs vegetation continuous field in 1982, 1992, 2002, and 2012. Compared to MEaSUREs, the simulated percentage of vegetation from the BGCDV_NEW experiment was greater in the semi-arid region of the TP in 1980. Compared to 1982, the simulated proportion of bare soil from the BGCDV_NEW experiment tended to decrease in the semi-arid and arid regions of the TP. As shown in Figure 4, the simulated proportion of bare soil from MEaSUREs tended to increase in the southeast region of the TP from 1982 to 2012. Overall, the simulated percentage of vegetation from the BGCDV_NEW experiment was greater than that from MEaSUREs.
Figure 3. Model simulations from CLM5.0-DGVM and remote sensing GPP products versus observations of monthly GPP (unit: gC·m⁻²·d⁻¹), NEE (unit: gC·m⁻²·d⁻¹), and Re (unit: gC·m⁻²·d⁻¹) at the Dangx, Haibei, and Maqu sites.

Figure 4 shows the spatial distribution of the bare soil proportion from the BGCDV_NEW experiment simulations and the MEaSURES vegetation continuous field in GPP/(gC/m²).

Figure 5 shows the climatology of the GLASS, NIRv, FLUXCOM, FLUXCOM1, and MODIS GPPs and the simulated GPP from the BGCDV_NEW experiment. As shown in Figure 5, a large area of the arid region of the TP has missing values for the NIRv, FLUXCOM, FLUXCOM, and MODIS GPP products. All remote sensing GPP products and the GPP simulated using CLM5.0-DGVM show a similar pattern, with GPP increasing from northwest to southeast and with the maximum at the southeast edge of the TP. Compared to the MODIS GPP product, the NIRv GPP product overestimated GPP in the east of the TP, and the FLUXCOM1 GPP product underestimated GPP in sub-humid regions. The simulated GPP from the BGCDV_NEW experiment was underestimated in the sub-humid regions and overestimated in the semi-arid and arid regions compared to the remote sensing GPP products.
Compared to MEaSURES, the simulated percentage of vegetation from the BGCDV_NEW experiment was greater in the semi-arid region of the TP in 1980. Compared to 1982, the simulated proportion of bare soil from the BGCDV_NEW experiment tended to decrease in the semi-arid and arid regions of the TP. As shown in Figure 4, the simulated proportion of bare soil from MEaSURES tended to increase in the southeast region of the TP from 1982 to 2012. Overall, the simulated percentage of vegetation from the BGCDV_NEW experiment was greater than that from MEaSURES.

Figure 4. Proportion of bare soil (unit: %) on the TP. Left: CLM-BGCDV; right: MEaSURES.

Figure 5 shows the climatology of the GLASS, NIRv, FLUXCOM, FLUXCOM1, and MODIS GPPs and the simulated GPP from the BGCDV_NEW experiment. As shown in Figure 5, a large area of the arid region of the TP has missing values for the NIRv, FLUXCOM, FLUXCOM1, and MODIS GPP products. All remote sensing GPP products and the GPP simulated using CLM5.0-DGVM show a similar pattern, with GPP increasing from northwest to southeast and with the maximum at the southeast edge of the TP. Compared to the MODIS GPP product, the NIRv GPP product overestimated GPP in the east of the TP, and the FLUXCOM1 GPP product underestimated GPP in sub-humid regions. The simulated GPP from the BGCDV_NEW experiment was underestimated in the sub-humid regions and overestimated in the semi-arid and arid regions compared to the remote sensing GPP products.

Figure 5. Climatology and trend of GPP (gC·m$^{-2}$·d$^{-1}$) from May to October.

4. Response of Vegetation to Regional Climate Change on the TP

4.1. Climatology and Trend of Temperature, Precipitation, and GPP

Figure 6 shows the climatology and trend of precipitation and temperature from May to October for the period from 1980 to 2016. As shown in Figure 6, precipitation increased from the northwest to the southeast of the TP, with the maximum in the southeast of the TP. Temperature decreased from the low latitude/altitude region to the high latitude/altitude region, with the maximum in the south of the TP and the Tarim Basin. Both precipitation and temperature showed increasing trends in most regions of the TP. However, precipitation increased in the central region of the TP and decreased on the eastern edge of the TP, while temperature increased in the whole TP.
4. Response of Vegetation to Regional Climate Change on the TP

4.1. Climatology and Trend of Temperature, Precipitation, and GPP

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Figure 7 shows the trend of the GLASS, NIRv, FLUXCOM, FLUXCOM1, and MODIS GPPs and the simulated GPP from the BGCDV_NEW experiment. From 1982 to 2016, the GPP products provided by GLASS and NIRv showed an increasing trend in most regions of the TP, with the maximum in the sub-humid regions. In addition, the increasing trend of the GLASS product was larger than that of the NIRv product. From 1982 to 2013, the GPP provided by the FLUXCOM1 product displayed no significant change trend on the TP. From 2001 to 2016, the FLUXCOM GPP product showed a decreasing trend in the sub-humid and semi-arid regions, while the MODIS GPP product showed an increasing trend in the northeast of the TP. The simulated GPP in the BGCDV_NEW experiment showed an increasing trend in the semi-arid and arid regions of the TP and decreased in the sub-humid regions. In the semi-arid and sub-humid regions of the TP, both the GLASS and NIRv GPP products, as well as temperature, showed consistent trends. However, the GPP simulated using CLM5.0-DGVM, as well as temperature, showed inconsistent trends, with temperature increasing in the whole TP while the simulated GPP decreased in the

Figure 6. Climatology and trend (unit: mm/day, °C) of precipitation (unit: mm/day) and temperature (unit: °C), May to October from 1982 to 2016 on the TP.
Figure 7. Trend of GPP from May to October on the TP.

4.2. Response of GPP to Climate Change

Figure 8 shows partial correlations between different GPP products and precipitation. The results indicated that the GLASS, NIRv, FLUXCOM, FLUXCOM1, and MODIS GPP products did not significantly correlate with precipitation changes in most regions of the TP. Compared to the sub-humid regions of the TP, the remote sensing GPP products showed a relatively high correlation in the semi-arid regions of the TP, especially the FLUXCOM1 GPP product. The GPP simulated using CLM5.0-DGVM significantly correlated with precipitation changes in most regions of the TP. Among all the remote sensing products, the GLASS and FLUXCOM1 GPP products were most sensitive to precipitation in the semi-arid regions.

Figure 8. Partial correlations between GPP and precipitation.

Figure 9 shows partial correlations between different GPP products and temperature. Limited by the period covered by the FLUXCOM and MODIS GPP products, there was
no significant correlation between GPP and temperature for these products. As shown in Figure 9, the GLASS GPP product significantly correlated with temperature changes in most regions of the TP. Partial correlations between the GLASS GPP product and temperature show that the increase in GPP was mainly caused by climate warming on the TP. The NIRv and FLUXCOM GPP data show positive correlations with temperature in the sub-humid and semi-arid regions of the TP, while the CLM5.0-DGVM GPP simulation shows a positive correlation in the arid regions of the TP. The overall results indicate that the increase in the remote sensing GPP was mainly caused by temperature, while the increase in the GPP simulated in CLM5.0-DGVM was mainly caused by precipitation in most regions of the TP.

![Figure 9. Partial correlations between GPP and temperature.](image_url)

Figure 10 shows the annual change in the GPP anomalies based on the GLASS, NIRv, and FLUXCOM1 products, as well as the BGCDV_NEW experiment, with precipitation and temperature anomalies averaged over the TP. The correlations between the GLASS, NIRv, FLUXCOM, and BGCDV_NEW GPP anomalies and the temperature anomaly were 0.83, 0.80, 0.53, and 0.57, respectively, showing significant positive correlations between the GPP calculated by these products and temperature. The variances in precipitation and temperature were weaker for the GLASS and NIRv GPP products than in the GPP simulation. The correlations between the remote sensing product GPP anomalies and the temperature anomalies were greater than the correlations between the remote sensing GPP products and precipitation. Compared to precipitation, the remote sensing GPP products were more sensitive to temperature. The correlations between the GPP simulation from the BGCDV_NEW experiment and precipitation and temperature were 0.52 and 0.57, respectively. As shown in Figure 10, the correlation between the BGCDV_NEW experiment GPP simulation and precipitation was smaller than that of the GLASS GPP. In addition, the variances in the remote sensing GPPs were weaker than in the simulated GPP from the BGCDV_NEW experiment. The correlation between the BGCDV_NEW experiment GPP and temperature was smaller than those of the GLASS and NIRv GPPs, which indicates that the GLASS and NIRv GPPs were more sensitive to temperature than the simulated GPP from the BGCDV_NEW experiment. A negative precipitation anomaly was recovered from 1998, while the simulated GPP from the BGCDV_NEW experiment dramatically increased from 1996, which mainly caused the significantly positive precipitation anomaly in 1996.
5. Conclusions

According to the CLM5.0 technical note, the DGVM was not tested in the development of the CLM5.0 and is no longer scientifically supported. The Functionally Assembled Terrestrial Ecosystem Simulator (FATES) is an actively developed DGVM for the CLM5.0. FATES was derived from the CLM Ecosystem Demography Model and is a cohort model of vegetation competition and co-existence that is mainly used to study trees of various PFTs, while the study region in this paper is mainly covered by grass. In this paper, after modifying the establishment and survival parameterizations (BGCDV_CTL parameterization), PFTs were able to establish over the whole TP. We evaluated simulations for ecosystem productivity by using CLM5.0-DGVM on the TP. The results showed that the simulated

![Figure 10](image-url). Annual changes in the GLASS GPP anomaly, simulated GPP anomaly in CLM5.0-BGCDV, temperature anomaly, and precipitation anomaly.

Figure 10. Annual changes in the GLASS GPP anomaly, simulated GPP anomaly in CLM5.0-BGCDV, temperature anomaly, and precipitation anomaly.
ecosystem productivity generally coincided with the observations, while overestimating the length of the growing season. Then, we modified the seasonal–deciduous phenology parameterization (BGCDV_NEW experiment) and compared it to the BGCDV_CTL experiment; the BGCDV_NEW experiment simulations reduced the biases in the simulated length of the growing season. Monthly variations in GPP showed that the BGCDV_CTL experiment displayed the best performance at the three sites considered. Compared to the GLASS, NIRv, FLUXCOM, and MODIS GPP products, the average bias of the simulated GPP in the BGCDV_NEW experiments for these three sites was reduced by 0.502 gC·m$^{-2}$·d$^{-1}$, 1.409 gC·m$^{-2}$·d$^{-1}$, 0.424 gC·m$^{-2}$·d$^{-1}$, and 0.376 gC·m$^{-2}$·d$^{-1}$, respectively. Compared to MEaSURES, the percentage of vegetation from the BGCDV_NEW experiment was greater in the semi-arid regions of the TP. The simulated proportion of bare soil from the BGCDV_NEW experiment tended to decrease in the semi-arid and arid regions of the TP. The climatology of the remote sensing GPP products and the simulated GPP showed similar patterns, with GPP increasing from northwest to southeast, while the simulations overestimated GPP in the semi-arid and arid regions of the TP.

From 1982 to 2018, the climate on the TP showed an overall warming and wetting trend, and GPP showed an increasing trend in most regions of the TP. Partial correlations between the remote sensing products and temperature indicated that the increase in GPP on the TP was mainly affected by climate warming. Partial correlations between the simulated GPPs and precipitation indicated that precipitation increased in the central region of the TP, leading to the increase in the simulated GPPs in the central region of the TP. The annual changes in the remote sensing GPP anomalies and the BGCDV_NEW experiment GPP anomaly indicated that the variance in the remote sensing GPPs was weaker than that in the simulated GPP from the BGCDV_NEW experiment. The correlation between the BGCDV_NEW experiment GPP and temperature was smaller than that of the GLASS and NIRv GPPs, which indicates that the GLASS and NIRv GPPs were more sensitive to temperature than the simulated GPP from the BGCDV_NEW experiment.

The simulated ecosystem productivity from the revised CLM5.0-DGVM model generally coincided with the observations, although the evaluation of ecosystem productivity was only conducted at three sites on the TP. There is a lack of validation of the carbon flux caused by using the revised CLM5.0-DGVM model in the northwest of the TP. In addition, the pattern of the simulated GPP from the revised CLM5.0-DGVM model was similar to that of the remote sensing products, while the BGCDV_NEW experiment overestimated GPP in the semi-arid and arid regions of the TP and underestimated GPP on the southeast edge of the TP. Great uncertainty still exists regarding the performance of remote sensing in the high-altitude regions of the TP. We need more carbon flux data to further validate the performance of carbon flux simulations by using DGVMs and by studying the responses of carbon flux to climate change. Otherwise, the BGCDV_NEW experiment was more sensitive to water content than the GLASS or NIRv GPP products. The parameterization of water use efficiency is imperfect in the current CLM5.0-DGVM, and the development of vegetation parameterization is still the main challenge to be faced in further work.

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