

Article

# Projection of Net Primary Productivity under Global Warming Scenarios of 1.5 °C and 2.0 °C in Northern China Sandy Areas

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Abstract: Empirical evidence suggests that variations in climate affect the net primary productivity (NPP) across sandy areas over time. However, little is known about the relative impacts of climate change on NPP with global warming of 1.5 and 2.0 °C (GW\_1.5 °C\_2.0 °C) relative to pre-industrial levels. Here, we used a new set of climate simulations from four Inter-Sectoral Impact Model Intercomparison Project (ISI-MIP 2b) datasets, modified the Carnegie-Ames-Stanford approach (CASA) model and assessed the spatio-temporal variation in NPP in sandy areas of northern China (SAONC). Compared with the reference period (RP, 1986–2005), the NPP variation under four emission scenarios showed clear rising trends and increased most significantly under RCP8.5 with an annual average increase of 2.34 g  $C/m^2$ . The estimated annual NPP under global warming of 1.5 °C (GW\_1.5 °C) increased by 14.17, 10.72, 8.57, and 26.68% in different emission scenarios, and under global warming of 2.0 °C (GW\_2.0 °C) it increased by 20.87, 24.01, 29.31, and 39.94%, respectively. In terms of seasonal change, the NPP value under the four emission scenarios changed most significantly in the summer relative to RP, exhibiting a growth of 16.48%. Temperature changes (p > 0.614) had a greater impact on NPP growth than precipitation (p > 0.017), but solar radiation showed a certain negative impact in the middle- and low-latitude regions. NPP showed an increasing trend that changed from the southeast to the central and western regions at GW\_1.5 to GW\_2.0 °C. NPP was consistent with the spatial change in climate factors and had a promoting role in high latitudes in SAONC, but it was characterized by a certain inhibitory effect at middle and low latitudes in SAONC. The uncertainty of NPP under the four models ranged from 16.29 to 26.52%. Our findings suggest that the impact of GW\_1.5 °C is relatively high compared with the current conditions, whereas GW\_2.0 °C implies significantly lower projected NPP growth in all areas.

Keywords: net primary productivity; global warming; CASA model; sandy areas; northern China

# 1. Introduction

Net primary productivity (NPP), which indicates the degree of accumulation of atmospheric  $CO_2$  in terrestrial ecosystems, has an important role in global climate change [1,2]. In addition, NPP is an important indicator of terrestrial carbon (C) and modulator of ecological processes [3]. Recently, many studies have focused on terrestrial NPP at regional to global scales as well as the driving factors of



terrestrial NPP [4–6]. Previous works have estimated NPP based on empirical evidence to further study the terrestrial ecosystem evolution and responses to global change [7,8]. Sandy areas are important within the global C cycle [9–11], and they are believed to represent a large C pool containing the vast majority of C that is missing from terrestrial ecosystems [12–14]. Thus, it is important to understand the amount and variation of NPP in sandy areas [15–17].

However, because of the sparse vegetation and relatively low biological productivity in sandy areas, NPP estimates in these areas over a large scale are difficult to perform using the method of direct harvest [18]. Currently, three types of models are predominantly used to simulate NPP: models based on climate [19], light-use efficiency models [3], and mechanistic ecological process models [20]. Although the parameters of climate-based models are few and easily obtained, simulation results can reflect the zonal distribution of vegetation NPP; however, because climate-based models do not involve biological factors that affect changes in NPP, the estimation errors are relatively large [21–24]. Advances in remote sensing have resulted in the increased development of models that use satellite data to simulate the NPP of terrestrial ecosystems [25–27]. The Carnegie-Ames-Stanford approach (CASA) is a light-use efficiency model that simulates NPP based on its relationships with the characteristics of vegetation and environmental parameters or indicators, including solar radiation, temperature, and precipitation [3,28]. Several researchers have successfully implemented the CASA model to simulate NPP over North and South America, Australia, Eurasia, and Africa at various temporal and spatial scales [22,23,28]. Many studies based on the CASA model have estimated the distribution of China's terrestrial NPP and the responses of NPP to global climate change [23,27,29–31]. However, fewer studies have applied this model to sandy areas with sparse vegetation distributions and low precipitation, especially to estimate the potential variation in NPP in sandy ecosystems when global warming is stabilized at 1.5 or 2.0 °C.

Climate change will have extremely adverse impacts on ecosystems and humans [32]. Recently, signatories to the Paris Agreement agreed to hold "the increase in the global average temperature to well below 2.0 °C above preindustrial levels and to adopt measures to limit further increases in temperature to no more than 1.5 °C above preindustrial levels" [33]. The lowered median Mediterranean region water availability resulting from 2.0 °C warming was predicted to be almost twice that resulting from 1.5 °C warming [34,35]. However, regional impact assessments targeting global climate policy (1.5 and 2.0 °C) remain incomplete [36–38]. In China, sandy land dominates the changes occurring to land use/land use cover in arid and semiarid regions, which account for 18.12% of China's land area [39,40]. Climate change directly affects NPP variations [41,42], which in turn affect the extent of desertification in northern China. Therefore, to predict and evaluate the impact of future global C cycles on human social development and formulate scientific climate policies, investigations of the total and spatial changes of NPP in sandy areas under future climatic changes are of great importance.

The Coupled Model Inter-comparison Project Phase 5 (CMIP5), which was facilitated and put into practice by the World Climate Research Programme (WCRP), contributed a key framework for better understanding the mechanism of a changing climate and predicting future scenarios in sandy areas [43]. Previous studies have shown that CMIP5 is to a certain extent able to simulate changes in climate over regional and global scales [44–47] and is also able to predict the spatial-temporal distribution of arid regions worldwide. However, certain uncertainties in drought simulation on some regional scales remain, such as the central region of North America and the western regions of the Amazon and Africa [35,48–51]. The Inter-Sectoral Impact Model Inter-comparison Project (ISIMIP) was initiated in 2010 and is currently in its third phase. In this study, we selected ISIMIP2b datasets with better simulation effects in the typical global semi-arid and arid regions [33], simulated the variations of NPP in the northern sandy areas of China well and analyzed the future NPP variations under the different typical concentration paths (RCPS) of ISIMIP2b. First, we focused on comparing the differences of NPP in sandy ecosystems between global increases in temperature of 1.5 and 2.0 °C and that of the reference year (1986–2005). Additionally, we analyzed the effects of the main meteorological factors (precipitation, air temperature, and solar radiation) on NPP variations in future warming scenarios.

In addition, the response mechanism of the desert ecosystem NPP to future climate change, which was proposed as "the target of temperature control" in the Paris Agreement, is further discussed to provide a theoretical basis for global C cycle research and desertification controlling.

Consequently, our objectives are to (1) document the temporal and spatial variation of NPP in sandy areas of northern China by modified model, (2) determine the climate change impacts on NPP formation when stabilizing global temperatures increases at 1.5 and 2.0 °C, and (3) understand the large gaps remaining in the study of the regional impacts of temperature increases of 1.5 and 2.0 °C (hereafter referred to as the warming scenarios) by analyzing quantifiable sources of uncertainty.

# 2. Data and Methods

# 2.1. Study Area

Northern China's sandy areas are located from are located from 75°–125° E, 35°–50° N (Figure 1) and form a belt of arcuate desert stretching from the Tarim Basin's western edge to the eastern Songnen Plain and extending across northwestern China's warm temperate semiarid, arid, and semi-humid continental climatic zones [40,43]. This zone extends 4500 km from the west to the east and 600 km from the south to the north [44,45], effectively covering 28% of the land area of China while crossing several climate zones, namely, extreme arid, arid, semiarid, and semi-humid climatic areas. The desert zone is one of the eight largest areas of desert globally and a major global source of sandstorms [46–48]. The range of precipitation is 30 mm in the west to 450 mm in the east.



Figure 1. Map showing the location of the sandy areas in northern China.

Northern China's sandy areas consist of several regions, including a transitional zone of desert wilderness; the deserts of Guerbantunggurt, Taklimakan, Qaidam Kumtag, Badain Jaran, Tengger, Ulanbuh, and Kubuqi; and the sandy lands of Mu Us, Otindag, Horqin, Hulun Buir, and Qinghai Gonghe. The SAONC are among the most densely populated areas within the semiarid and arid climatic zones, which are characterized as highly sensitive and vulnerable [49]. Despite substantial reductions in desertification land over the past decade, the net increase has remained high compared with that in the 1950s because of the two regions of the Tengger Desert [50].

2.2. Observed Data and Vegetation Data

Observed meteorological and flux data were collected from five flux sites (Figure 1) administered by the Chinese FLUX Observation and Research Network (ChinaFLUX) (http://www.Chinaflux.org) and the China Ecosystem Research Network (CERN) (http://www.cern.ac.cn), including the Atmospheric Environment Monitoring Station in the Taklimakan Desert (http://www.idm.cn/main.asp). We used the open-path eddy-covariance system to measure the flux [52] at a 10-Hz frequency. Fluxes of CO<sub>2</sub> and H<sub>2</sub>O were calculated and recorded every 30 min, and then traditional data quality control measures were applied [53], including a canopy storage calculation, three-dimensional (3D) rotation [54], the Webb-Pearman-Leuning (WPL) correction [55], and the removal of spurious data.

The soil mechanical composition in northern China corresponds well with the bioclimatic zone distribution [56]. Large differences in soil, vegetation, and climate occur across the sandy regions depending on the bioclimatic zone in which they occur [40,57]. Therefore, we chose five sand flux sites representative of different bioclimatic zones and indicate the distribution of NPP across the sandy regions of northern China (Table 1).

Table 1. Information on the five flux sites in the sandy areas of northern China (SAONC).

Site Name	Lat (° N)	Lon (° E)	Precipitation (mm)	Height (m)	Bioclimate Region	Reference
Naiman	42.93	120.7	366.4	361	Semi-humid	Zheng et al. [58]
Yanchi	37.4	107.12	295	442	Semi-arid	Fu et al. [59]
Shapotou	37.53	105.8	186.6	1227	Arid	Zheng et al. [58]
Fukang	42.28	87.92	160	482	Arid	Yu et al. [52]
Tazhong	38.97	83.65	22.8	1082	Extremely arid	Yang et al. [60]

We used the normalized difference vegetation index (*NDVI*) to trace the vegetation distribution and dynamics. The GIMMS (Global Inventory Modeling and Mapping Studies) 15-day (1982–2015) composite *NDVI*3g dataset, which was applied in the present study, has been shown to have higher accuracy in relation to the GIMMS *NDVI* for phonological change and vegetation activity monitoring [61], and it has a spatial resolution of 8 km (https://glam1.gsfc.nasa.gov). We also adjusted the *NDVI* data for nonvegetative factors to represent the interannual variations in SAONC. The future *NDVI* data (2016–2100) are from http://data.ess.tsinghua.edu.cn; these data are mainly used to evaluate the global land cover under different emission scenarios, and they have been applied in many fields. For vegetation type data, we adopted the 1:100,000 China vegetation type maps, which include statistical information from the Resources and Environment Science Data Center of the Chinese Academy of Sciences of China (http://www.resdc.cn). The type code for major vegetation was regarded as the benchmark for merging and processing [62].

#### 2.3. Climate Projections under the Warming Scenarios

Four models were selected to generate the daily data considering a single run per scenario from ISI-MIP 2b. Table 2 provides the information on each of the four models, and additional information can be obtained at https://www.isimip.org. The simulations included several variables, such as the minimum and maximum air temperatures, wind speed, relative humidity, atmospheric pressure, precipitation, shortwave and longwave radiation, snowfall flux, and specific humidity. The reference period (RP) of 1986 to 2005 was used to calculate the historical NPP. In addition, the projected changes in NPP from 2006 to 2100 were investigated under the RCP2.6, RCP4.5, RCP6.0, and RCP8.5 scenarios.

Model	Institution	Country	Resolution (Lon $\times$ Lat)
GFDL-ESM2M	Geophysical Fluid Dynamics Laboratory	USA	$144 \times 90$
HadGEM2-ES	Met Office Hadley Center	UK	$145 \times 192$
IPSL-CM5A-LR	L' Institute Pierre-Simon Laplace	France	$96 \times 96$
MIROC5	Model for Interdisciplinary Research on Climate	Japan	$256 \times 128$

Table 2. List of the four ISI-MIP 2b models used in the analysis.

The UNFCCC defines one year of rising temperature as an increase in the global average temperature to values exceeding certain preindustrial temperatures [63], however, disagreement over the specific definition of rising temperature remains [64], and each definition considers multiple variables, including post-stabilization, peak and transition temperatures. Compared with the temperature increase to above preindustrial levels calculated by the UNFCCC, the IPCC Fifth Assessment Report (AR5) (i.e., the first and third working group reports) assessed future temperature changes relative to RP (1986–2005). These temperature changes can therefore be superimposed onto a temperature increase of 0.61 °C relative to the pre-industrialization level based on observations by HadCRUT4 [65]. This computing method has the advantage of consistent changes in the modern climate relative to the preindustrial. Therefore, a large number of studies have adopted this method, which has resulted in high comparability among studies. By adopting the ISI-MIP 2b approach, Warszawski et al. [66] found that the global temperature increases by 0.89 °C in the RCP2.6 scenario relative to RP with global warming of 1.5 °C (GW\_1.5 °C) above the preindustrial level but increases by 1.39 °C with global warming of 2.0 °C (GW\_2.0 °C) above the preindustrial level in the RCP4.5 scenario. Thus, GW\_1.5 °C is likely to occur during the period 2020–2039 under the 2.6 scenario, and GW\_2.0 °C is likely to occur during the period 2040–2059 under the RCP4.5 scenario.

#### 2.4. CASA Model Overview

Potter et al. [3] and Field et al. [28] first developed the CASA model based on the light-use efficiency (LUE) model (Figure 2). The version modified by Zhu et al. [21] was used in the present study. The CASA model incorporates the product of photosynthetic available radiation absorbed by green vegetation (*APAR*) and the actual *LUE* ( $\varepsilon$ ):

$$NPP(x,t) = APAR(x,t) \times \varepsilon(x,t)$$
(1)

where NPP(x, t) is the vegetation NPP in the geographic coordinate system of a given location x and time t.



Figure 2. Framework of the Carnegie-Ames-Stanford approach (CASA) estimation model.

APAR can be described as follows:

$$APAR(x,t) = SOL(x,t) \times FPAR(x,t) \times 0.5$$
<sup>(2)</sup>

where SOL(x, t) represents the total solar radiation at pixel x in month t, FPAR(x, t) represents the fraction of the incident photosynthetic active radiation absorbed by vegetation, and 0.5 represents 50% of the incoming solar radiation within photosynthetic active radiation (with a wavelength range of 0.38–0.71 µm).

FPAR(x, t) is based on the relationship between the *FPAR* and *NDVI* as well as the simple ratio (SR).

$$FPAR(x,t) = \frac{(NDVI(x,t) - NDVI_{min})}{(NDVI_{max} - NDVI_{min})} \times (FPAR_{max} - FPAR_{min}) + FPAR_{min}$$
(3)

where  $NDVI_{max}$  and  $NDVI_{min}$  are the maximum and minimum values of the NDVI, respectively, and  $FPAR_{max}$  and  $FPAR_{min}$  are defined as constants of 0.001 and 0.95, respectively.

Meanwhile, a linear function between FPAR and SR also exists:

$$FPAR(x,t) = \frac{(SR(x,t) - SR_{min})}{(SR_{max} - SR_{min})} \times (FPAR_{max} - FPAR_{min}) + FPAR_{min}$$
(4)

where  $SR_{max}$  and  $SR_{min}$  represent the 95 and 5% values of *NDVI*, respectively, for different vegetation types. SR(x, t) is defined as a linear function of the *NDVI*:

$$SR(x,t) = \frac{1 + NDVI(x,t)}{1 - NDVI(x,t)}$$
(5)

The light-use efficiency algorithm can be expressed as follows:

$$\varepsilon(x,t) = T_{\varepsilon 1}(x,t) \times T_{\varepsilon 2}(x,t) \times W_{\varepsilon}(x,t) \times \varepsilon_{max}$$
(6)

where  $T_{\varepsilon 1}(x, t)$  denotes the limitations of extreme low and high temperatures on LUE, and  $T_{\varepsilon 2}(x, t)$  denotes the decreasing trend of LUE when the environmental temperature deviates from the optimum temperature  $T_{opt}(x)$  to extreme low and high temperatures.

$$T_{\varepsilon 1}(x,t) = 0.8 + 0.2 \times T_{opt}(x) - 0.0005 \times \left[T_{opt}(x)\right]^2$$
(7)

$$T_{\varepsilon 2}(x,t) = \frac{1.184}{\left\{1 + e^{[0.2 \times (T_{opt}(x) - 10 - T(x,t))]}\right\}} \times \frac{1}{\left\{1 + e^{[0.3 \times (-T_{opt}(x) - 10 + T(x,t))]}\right\}}$$
(8)

 $W_{\varepsilon}(x, t)$  represents the monthly water deficit calculated by the comparing actual (EET) to potential (PET) evapotranspiration data.

$$W_{\varepsilon}(x,t) = 0.5 + \frac{0.5 \times EET(x,t)}{PET(x,t)}$$
(9)

The EET and PET values are calculated using the method of Yu et al. [67].  $\varepsilon_{max}$  is the LUE maximum of vegetation under optimal environmental conditions [68], and in the traditional CASA model the  $\varepsilon_{max}$  value was set to 0.389 g C·MJ<sup>-1</sup>. We refer to the results of Piao et al. [23] and Zhu et al. [21] to define the  $\varepsilon_{max}$  values of typical vegetation types in China.

A number of factors, including the observed data and simulation technology, introduce a certain amount of uncertainty into the simulation result [69,70]. To further quantify the uncertainty of the simulation results, a local sensitivity analysis method was used to determine the uncertainty of the simulation results [66]. The method is to calculate the rate of variation (VR + 10% and VR – 10%) of the simulation results with the chosen parameter ( $RUN_P$ ) of the CASA model ±10% (±2 °C) without changing the reference ( $RUN_R$ ). Finally, the maximum value of the two represents the influence of this parameter on the simulation results.

$$VR_{\pm 10\%} = \frac{|RUN_R - RUN_{P\pm 10\%}|}{RUN_R} \times 100\%$$
 (10)

$$RU = \frac{90 \,\% P_u - 90 \,\% P_l}{P_m} \tag{11}$$

where the maximum variation (%) between the VR values was used as a representation of the effect of the initial condition or parameter on the annual NPP. The initial conditions and parameters were then sorted from largest to smallest based on their effect on NPP. All parameters and initial conditions showing effects of >10% (2 °C) on annual NPP were retained for the analysis of uncertainty. In addition, the ratio of 90% of the predicted variation amplitude (predicted upper limit ( $P_u$ )–predicted lower limit ( $P_l$ )) to the predicted mean ( $P_m$ ) was used as the relative uncertainty (RU) to evaluate the amplitude of the variation in *NPP*.

# 2.5. Trend Analysis

The absolute interannual rate of change of the *NPP* residual was calculated based on the pixels using the method of unitary linear regression analysis:

$$\theta_{slope} = \frac{n \times \sum_{i=1}^{n} (i \times \Delta NPP_i) - \sum_{i=1}^{n} i \sum_{i=1}^{n} \Delta NPP_i}{n \times \sum_{i=1}^{n} i^2 - \left(\sum_{i=1}^{n} i\right)^2}$$
(12)

where *n* represents the time scale of the study;  $\Delta NPP_i$  represents the residual NPP of one pixel in year *i*;  $\theta_{slope} > 0$  and  $\theta_{slope} < 0$  represent increasing and decreasing trends, respectively; and  $|\theta_{slope}| \approx 0$  indicates no change in the regional *NPP* residual.

# 3. Results

#### 3.1. Verification of Net Primary Production Estimates

We used the CASA model to compare the NPP simulation (Figure 3a) and the MODIS data product (Figure 3b) for the sandy regions of northern China from 1983 to 2005. According to the spatial distribution, the simulation results can reflect the fluctuation of NPP in SAONC well, and the simulation results are relatively good for certain areas of sparse vegetation. The simulated data fit the MODIS data well under four climate models ( $R^2 > 0.77$ , slope > 0.85). The field monitoring data based on 5 flux observation stations were compared with the simulation results (Figure 3d), and the correlation between the flux observation data and the simulation results was better ( $R^2 > 0.8$ ), indicating that the prediction of NPP based on climate model data was more suitable in SAONC.



**Figure 3.** Simulation and validation of the CASA model; (**a**) represents the CASA simulation of the multi-annual change in mean net primary productivity (NPP); (**b**) represents a multi-annual NPP variation chart based on MODIS data (http://luna.ntsg.umt.edu/data); (**c**) is based on the CASA model simulation of different climate models of the correlation between the model data and MODIS data; and (**d**) is the Taylor diagram between the field monitoring data and the simulated data based on the flux observation site from CASA model.

# 3.2. Temporal Variation in Net Primary Productivity under Different Warming Scenarios

The future NPP values of the four emission scenarios under the temporal variation in NPP showed a rising trend compared with those in RP, and the increase in RCP8.5 was the greatest (Figure 4). Compared with the value in RP, the simulated NPP value of RCP8.5 increased by 26.68%, and the other three emission scenarios (RCP2.6, RCP4.5, and RCP6.0) showed little differences, with increases of 14.17, 10.72, and 8.57%, respectively; however, under GW\_2.0 °C, the simulated NPP values of these RCPs increased by 20.87, 24.01, 29.31, and 39.94% relative to RP, respectively. The NPP changes in different emission scenarios are proportional to the level of the emission path. In a high-emission scenario, the content of NPP is relatively high, whereas in a low-emission scenario, the corresponding NPP content is relatively low. A difference in the corresponding NPP changes was observed between the two warming scenarios. Under GW\_2.0 °C, the NPP contents in the high- and low-emission scenarios increased by 11.33 and 10.47% compared with GW\_1.5 °C, respectively. From 1980 to 2100, the NPP contents in different emission scenarios showed fluctuating and increasing trends, and the values increased by 138.07, 165.75, 192.22, and 252.42 g C/m<sup>2</sup>·a in the RCP2.6, RCP4.5, RCP6.0, and RCP8.5 scenarios compared with that in 1981, respectively. In 2006–2029 and 2037–2042, marked increases in NPP were observed, whereas after 2050, this trend became flat.

On a seasonal scale, the NPP contents in the four emission scenarios changed to the greatest extent in summer, with an increase of 16.48% compared with that in RP under GW\_1.5 °C. Compared with the NPP content in RP, the range of variation in winter was the smallest and tended to represent a straight line. Under GW\_1.5 °C, the NPP contents in spring and autumn of the four emission scenarios were similar to those of RP and increased by 13.16 and 14.72%, respectively, compared with those in RP. Under GW\_2.0 °C, the seasonal variation in NPP in the four emission scenarios was similar to the annual change, and the increase tended to be gradual. The most typical performances in summer were 15.23 and 33.27% higher than that in RP. Overall, the variation ranges of NPP in SAONC will occur mainly between 2017 and 2036 (465–518 g C/m<sup>2</sup>, except RCP8.5) and 2042 and 2100 (527–614 g C/m<sup>2</sup>, except RCP8.5). The fluctuations in NPP under the RCP8.5 scenario increased significantly; however, after 2052 the increase tended to be gradual (634–668 g C/m<sup>2</sup>·a). In the future, seasonal variations in NPP in SAONC will occur in spring and autumn (287–418 g C/m<sup>2</sup>·a), summer (69–104 g C/m<sup>2</sup>·a), and winter (11–19 g C/m<sup>2</sup>·a).

# 3.3. Spatial Variation in Net Primary Productivity under Warming Scenarios

The spatial distribution of the annual NPP estimated by the four climate models was compared with that in RP at GW\_1.5 °C (Figure 5). The areas showing relative decreasing trends in NPP contents accounted for <20% of the study area and were predominantly located in the northwest and northeast, whereas the areas showing increasing trends accounted for 45% of the study area and were mainly observed in the southeast; they presented relative increases between 0 and 50 g C/m<sup>2</sup>. The relative NPP contents simulated by the four climate models in spring mainly showed increasing trends, with increases ranging between 0 and 25 g C/m<sup>2</sup>, and these areas were mainly distributed in the central and eastern regions of the study area. The regions showing relative decreasing trends were predominantly located in the northwest and southeast. The IPSL-CM5A-LR model showed the greatest relative decrease, with the area experiencing a decreasing trend accounting for 37.52% of the study area. In summer, the range of relative NPP contents simulated by the four climate models was mainly concentrated between 0 and 50 g C/m<sup>2</sup> and distributed throughout the study area, and this region accounted for >68% of the study area. The ranges of relative NPP contents simulated in autumn and winter by the four climate models were 0–25 g C/m<sup>2</sup> and 0–10 g C/m<sup>2</sup>, respectively; however, the area showing a relative decreasing NPP content in autumn had a wider distribution than that in winter.



**Figure 4.** Temporal variation in NPP changes under GW\_1.5 °C\_2.0 °C levels from 1980 to 2100 and the difference in NPP between warming levels for the whole year, spring (March, April, and May), summer (June, July, and August), autumn (September, October and November), and winter (December, January, and February). The horizonal lines in each boxplot represent the minimum, 25th percentile, median, 75th percentile and maximum NPP, respectively, and the stars represent the average NPP. All results were derived from CASA model simulations.

The spatial distribution of the relative NPP contents was simulated by the four climate models under GW\_2.0 °C (Figure 6). The interannual variation shows that the primary range of the relative increase in NPP was 50 to 100 g C/m<sup>2</sup>, and these values were mainly located in the central and western regions of the study area. The region showing a relative decrease was mainly located in the northeastern region of the study area, especially in Heilongjiang province. The relative spatial variation in the NPP contents in spring, summer, and autumn decreased in the east and increased in the west, with relative increases mainly ranging from 25–50, 50–100, and 25–50 g C/m<sup>2</sup> respectively. During winter the

increases mainly ranging from 25–50, 50–100, and 25–50 g C/m<sup>2</sup>, respectively. During winter, the MIROC5 model simulated relative decreases in NPP contents covering a proportional area of 11.90%, whereas the other three models mainly showed relative increases and only observed relative decreases over <1% of the study area.



**Figure 5.** Spatial distribution of NPP changes under GW\_1.5 °C for the whole year, spring (March, April, May), summer (June, July, August), autumn (September, October, November), and winter (December, January, February). Each letter represents a different climate model; G represents the GFDL-ESM2M model, H represents the HadGEM2-ES model, I represents the IPSL-CM5A-LR model, and M represents the MIROC5 model.

Relative to GW\_1.5 °C, the spatial distribution of estimated annual NPP under GW\_2.0 °C showed a regular change from the east to the west in the total area. This pattern may occur because the spatial heterogeneity of the NPP content becomes more obvious with the further increase in temperature, thus exhibiting a certain longitudinal zonality.



**Figure 6.** Spatial distribution of the changes in NPP under GW\_2.0 °C for annual and seasonal projections. Notation used for climate models and definition of seasons—as in caption to Figure 5.

# 4. Discussion

# 4.1. Impacts of Climate Variations on Net Primary Productivity in SAONC

The correlations between the changes in NPP and temperature, precipitation, and radiation under different future emission scenarios (2006–2100) under the warming scenarios are shown in Table 3. Temperature had the strongest correlation with the changes in NPP: in both the low (RCP2.6) and high (RCP8.5) emission scenarios, significant positive correlations were observed between NPP and temperature under the four climate models. Precipitation was found to be the second-most important factor (R > 0.017). These results are supported by those of Li et al. [71] and Li et al. [72], who used the Climate Model Intercomparison Project (CMIP5) multipattern to explore the response of global terrestrial NPP to climate change during the historical period from 1850–2005. However, our study also found that as emissions increased, the correlation between solar radiation and alterations in *NPP* content changed from positive under the low-emission scenario (RCP2.6) to negative under the high-emission scenario (RCP8.5).

Emission Scenarios	ISI-MIP 2b	Precipitation	Temperature	Solar Radiation
	GFDL-ESM2M	0.198 *	0.672 **	0.481 **
DCD2 (	HadGEM2-ES	0.505 **	0.812 **	0.493 **
KCP2.6	IPSL-CM5A-LR	0.494 **	0.787 **	0.425 **
	MIROC5	0.555 **	0.847 **	0.647 **
	GFDL-ESM2M	0.355 **	0.853 **	0.215 *
	HadGEM2-ES	0.500 **	0.882 **	0.356 **
KCP4.5	IPSL-CM5A-LR	0.453 **	0.883 **	0.512 **
	MIROC5	0.537 **	0.88 3**	0.352 **
	GFDL-ESM2M	0.017	0.642 **	-0.239
	HadGEM2-ES	0.202	0.702 **	-0.192
KCP6.0	IPSL-CM5A-LR	0.072	0.742 **	-0.325 *
	MIROC5	0.017	0.614 **	-0.490 **
	GFDL-ESM2M	0.390 **	0.863 **	0.062
	HadGEM2-ES	0.674 **	0.850 **	-0.223 *
NCP8.5	IPSL-CM5A-LR	0.598 **	0.850 **	0.213 *
	MIROC5	0.752 **	0.870 **	-0.087

Table 3. Correlation of precipitation, temperature, solar radiation, and NPP.

\* at the 0.05 level; \*\* at the 0.01 level.

The spatial variation analyses of these climatic factors under different warming scenarios can help illuminate the mechanisms driving future NPP changes in terrestrial ecosystems [18,73]. Under the warming scenarios (Figure 7), precipitation mainly increases in SAONC, although certain regions show decreasing trends, predominantly in SAONC and the Mu Us and Tengger Deserts in the central arid zone. Under the warming scenarios, the relative spatial variations in precipitation under the four climate models present a regularly decreasing trend from east to west. The MIROC5 climate model shows a relative trend of decreasing precipitation across the greatest proportion of the study area, reaching values of up to 23.56 and 24.88% under GW\_1.5 and GW\_2.0 °C, respectively. Under the warming scenarios, the relative spatial variation in solar radiation also shows a decreasing trend from east to west. However, the area that shows a decrease in solar radiation under the four climate models accounts for >43.52% of the total study area, and it is mainly located in the central and western regions of the study area.

Differences are observed among the models in terms of the areas that exhibit temperature increases under the warming scenarios (Figure 8). The GFDL-ESM2M model projections show that only small parts of the sandy regions demonstrated lower temperatures under global warming, and they were predominantly concentrated in inner Mongolia in northeastern China. The model results of HadGEM2-ES show temperature increase greater than 1.5 and 2.0 °C for nearly all of SAONC, including the northwestern sandy region of Xinjiang, which will experience the greatest warming, with elevated temperatures predicted to reach 3.0 and 4.0 °C. The results of the IPSL-CM5A-LR model show that areas are predominantly distributed in the southern Tarim Basin and southeast Qinghai province. The results from the MIROC5 model show small areas exhibiting warming below the global aggregated values of 1.5 and 2.0 °C located in northeastern China. Considered collectively, the four model-specific climate patterns under the warming scenarios indicate that the greatest increase in arid areas will occur across northwestern China. In some regions, the increase from the preindustrial temperature is projected to exceed 4.0 °C. These areas are mainly distributed in the northwestern sandy area of the Guerbantunggurt Desert and in the northwestern and central Taklimakan Desert.



**Figure 7.** Spatial variation of precipitation, solar radiation and warming level in SAONC. Each letter represents a different climate model; G represents the GFDL-ESM2M model, H represents the HadGEM2-ES model, I represents the IPSL-CM5A-LR model, and M represents the MIROC5 model.



**Figure 8.** The percentages of areas where the temperature increase is below the global values of 1.5 and 2.0 °C (B1.5\_2.0\_area, Units: %).

Under warming ranging from the current level to the target set by the *Paris Agreement*, the increase in atmospheric  $CO_2$  concentration is the dominant factor driving the increase in the total volume of global NPP, whereas the contributions of temperature, precipitation, and radiation are relatively

weak [74,75]. However, a clear spatial differentiation of changes in NPP with solar radiation occurs under the different warming targets. In the high-latitude regions of SAONC, the spatial changes in solar radiation are consistent with those of NPP, and solar radiation plays a certain role in promoting the change in NPP, whereas in the middle- and low-latitude regions solar radiation shows a certain negative effect. This effect may be explained by the fact that changes in NPP in high-latitude ecosystems in the north are mainly temperature dependent [26]. In these areas, the relatively rapid increase in temperature [32] has eased the temperature limit of vegetation to some extent, thus promoting the growth of NPP in these regions [18,76]. In contrast, the temperature increase at low and medium latitudes may lead to environmental temperatures that exceed the optimum temperature for vegetation growth, thus reducing the resistance of vegetation to drought and limiting the growth of NPP in the ecosystem [41]. With increases in emissions, the correlation between solar radiation and NPP changes gradually weakens, whereas that between precipitation and NPP changes increases, thus reflecting the importance of precipitation. Therefore, precipitation is the key factor dominating vegetation growth and succession in sandy land, which in turn affects the NPP changes [77,78].

# 4.2. Progress of Net Primary Productivity Simulations in SAONC

We have presented a study of the spatial and temporal patterns of and climate controls on NPP obtained from ISI-MIP2b climate models in SAONC from 1980 to 2100 through the use of a carbon model based on remote-sensing data, i.e., the CASA model [3]. This model has been successfully applied worldwide to map NPP patterns, including in mainland China [18,22]. Previous studies have reported similar analyses performed within shorter time periods [24]. Table 4 provides a comparison of the NPP prediction results of the present study with those of previous studies. The previous time scales simulated for SAONC were relatively short, and the results varied widely among simulations and presented an approximate range of 483–843 g C/m<sup>2</sup>·a. The present study simulated a value of 604.52 g C/m<sup>2</sup>·a, which extends beyond the range predicted by other studies that used the CASA model but is lower than the NPP change estimated by Gang et al. [79] using the CMIP5 dataset. This difference may be due to the relatively short time scales employed in previous studies and the absence of future changes in NPP in the context of global warming. However, future climate warming can directly affect future changes in NPP [23], which in turn can affect the average annual NPP.

Methods	Study Periods	NPP Ranges (g C/m <sup>2</sup> )	Reference
LPJ model	1961-1970	686.75	Sun and Mu [80]
CASA model	2000-2012	556.29	Li and Pan [81]
CASA model	1982–1999	510.72	Piao and Fang [82]
LUE model	1990	584.75	Chen et al. [83]
CEVSE model	1981-1998	420.49	Cao et al. [84]
CASA model	1982–1999	523.59	Fang et al. [76]
BEPS model	2001	558.29	Feng et al. [85]
C-Fix model	2003	654.17	Chen et al. [86]
CASA model	1989–1993	483.19	Zhu et al. [21]
GLO-PEM model	1981-2000	710.49	Gao and Liu [30]
CEVSA model	1980-2000	667.45	Gao and Liu [30]
GEOPRO model	2000	683.29	Gao and Liu [30]
GEO-LUE model	2000-2004	724.54	Gao and Liu [30]
LPJ model	1961–2080	564.42	Zhao and Wu [87]
M-SDGVM	1981-2000	537.24	Mao et al. [88]
CASA model	1981–2008	487.69	Chen et al. [89]
BEPS model	2000-2010	684.29	Liu et al. [90]
CASA model	2000-2010	526.47	Pei et al. [91]
CASA model	1982-2010	545.29	Liang et al. [24]
CSCS model	2030 2050 2070	843.27	Gang et al. [79]
CASA model	1980–2100	604.52	This study

Table 4. Summary of studies of NPP in SAONC.

Many studies have focused on how climate change will affect the future terrestrial ecosystem productivity in China; however, these studies have yielded widely different results. Existing studies have indicated that under the B2 scenario the total NPP within China's terrestrial ecosystems will increase from 2.94 to 3.99 Pg C/a in the next 100 years [92]. In contrast, Zhao and Wu [87], who used the Lund-Potsdam-Jena (LPJ) model, observed a declining but fluctuating trend in natural vegetation NPP in China from 1961 to 1980. Wu et al. [93], who used the AVIMI model, found a similarly declining trend in the terrestrial ecosystem NPP in China. Ju et al. [94] used the Integrated Terrestrial Ecosystem Carbon (INTEC) model to predict changes in the forest ecosystem NPP in China under the A2 and B2 scenarios and observed an increasing trend from 2001 to 2100, with NPP increasing by 0.19 Pg C/a for the first 50 years and increasing by 0.15 Pg C/a for the second 50 years. Wen et al. [95] applied the Crop-C model to predict the NPP of China's farmland ecosystem from 2000 to 2050 and predicted that NPP will increase at a rate of 0.0006 Pg C/a under the A1B scenario. Tao and Zhang [96] simulated the changes in China's terrestrial ecosystem NPP until the end of this century under eight climatic scenarios; they observed an initial increase to a maximum in 2090, followed by a decrease, which they attributed to "drought stress".

In conclusion, China's future terrestrial ecosystem NPP may show an initial increasing trend followed by a decrease; however, the results of different regional studies vary widely and even provide contradictory results. The predicted responses of different vegetation types to future climate change also vary. The present study focused on desert vegetation and explored the changes in NPP of SAONC under future scenarios. The results indicate that the NPP in SAONC will initially increase, and then the rate of increase will be slow.

# 4.3. Quantifiable Sources of Uncertainty

Against the background of global warming, accurate estimations of NPP are relevant to global ecological systems [97]. However, considerable differences are observed among different studies. For example, the estimated value of global NPP is  $56.2 \pm 14.3$  Gt C/a, with an uncertainty of approximately 25% [98]. The main sources of uncertainty in the NPP evaluation process of terrestrial ecosystems are the model structure, model parameters, and data sources. In terms of the data source, an uncertainty analysis of five flux observation sites was conducted in the current study (Figure 9a). The Tazhong station had the largest RU, possibly because it was located in an extremely arid area and was greatly influenced by the climate factors such as rainfall and temperature [60], which is important given that the meteorological conditions are the main factors affecting the change in NPP [99–101]. When using multiple models, the differences in the structures of the models used in different studies have a certain impact on the estimation of NPP [102,103]. Cramer, Kicklighter, Bondeau, Moore, Churkina, Nemry, Ruimy, Schloss, and Participants Potsdam [4] estimated the global NPP; although there was a 20% difference between their estimates, none of the models could explain this difference. Adams et al. [104] studied the relationships between different climate variables such as light, temperature, and moisture in different models with the function of NPP, but they failed to directly connect these differences with differences in NPP. The present study simulated a value of 604.52 g C/m<sup>2</sup>·a, which was close to the mean NPP value obtained by other studies. However, it is noteworthy that the NPP values of global and regional scales exhibit obvious interannual differences [43,105]. Therefore, the annual differences among different studies also introduce additional uncertainties [106,107]. The model parameters exert an important influence on the model simulation results, and a change in one parameter can lead to an obvious increase or decrease in the simulation results [108,109]. With other parameters fixed, the parameters requiring sensitivity analysis increased or decreased. According to Figure 9c,  $\varepsilon_{max}$ , FPAR, NDVI, and SOL are direct linear variables of the model, and they are consistent with the amplitude of NPP. Among them, the value of  $\varepsilon_{max}$  has the greatest influence on the estimated results of NPP. This result is consistent with those of [110], who considered that it was the most important parameter in the LUE model and an important factor in the low accuracy of the vegetation productivity model. The values of  $T_{\varepsilon 1}$ ,  $T_{\varepsilon 2}$ ,  $W_{\varepsilon}$ , and  $T_{opt}$  have a certain influence on the NPP output results. Among them,

the value of  $T_{opt}$  has the greatest influence on the estimated NPP results and leads to higher NPP amplitudes than the direct linear variable of the model.



**Figure 9.** Analysis of uncertainty based on the CASA model. (**a**) the uncertainty based on observation site; (**b**) the results of this study were compared with other studies; (**c**) uncertainty of model parameters.

In the present study, the changes in NPP compared with the changes in RP in the future global warming scenarios were compared and analyzed by synthesizing the simulated results of four climate models. Although the present study improved the accuracy of the research results to some extent, it should be noted that large differences persist among the different model parameters. Based on the above results, an uncertainty analysis of NPP under the four models was implemented (Figure 10), and the values ranged from 16.29 to 26.52%. The uncertainty of the HadGEM2-ES model was the largest, and the uncertainty of the MIROC5 model was the smallest. These results are consistent with those obtained by Li, Lu, Zhang, Liu, Gao, and Ao [71] and Fu et al. [111]. In fact, multiple studies have found large uncertainty associated with the NPP of the global terrestrial ecosystem. However, because of the lack of long-term global NPP data [112,113], the validation of modeled NPP values cannot be as rigorously implemented at regional and global scales as observed for validations of climatic simulations. In the present study, we utilized ChinaFlux data and MODIS NPP data to compare the NPP values of the ISI-MIP2b models, and the results highlighted the need to improve our knowledge of the factors governing variability within model estimations of NPP in sandy regions.

17 of 23



Figure 10. Uncertainty in the estimation of NPP based on CASA model in four climate models.

# 5. Conclusions

We investigated the spatiotemporal features of NPP in SAONC using four ISI-MIP2b datasets and the CASA model. The SAONC exceeded the global warming level at 0-7.1 and 0-12.5%, respectively, with some areas experiencing 4.0 °C increases under GW\_1.5 °C or under GW\_2.0 °C. The spatiotemporal variation in NPP was documented with a modified model, and an assessment of the impacts of climate change on NPP formation when global temperatures were stabilized under the two warming scenarios was carried out using four ISI-MIP2b datasets. The results indicated greater spatiotemporal variation in NPP in SAONC when global temperatures were stabilized under the warming scenarios. The temporal variations in annual NPP showed an increasing trend relative to the reference period. Under GW\_1.5 °C and GW\_2.0 °C, the estimated annual NPP increased by 14.17, 10.72, 8.57, and 26.68% and by 20.87, 24.01, 29.31, and 39.94% in the RCP2.6, RCP4.5, RCP6.0, and RCP8.5 scenarios, respectively. The spatial distribution of the estimated annual NPP under GW\_1.5 °C showed clear increasing trends in the southeast (accounting for 45% of the total area) and decreasing trends in the northwest and northeast (accounting for 20%). Relative to GW\_1.5 °C, the spatial distribution of the estimated annual NPP under GW\_2.0 °C showed a regular change from the east to the west. However, our results showed a robust nonlinear relationship between temperature and NPP growth by accounting for intrayear monthly variability in temperature and precipitation as well as monthly temperature and precipitation maximum and minimum values and outliers. The changes in temperature (R > 0.614) had a greater impact on the NPP growth than did precipitation (R > 0.017), and solar radiation showed a negative impact in the middle- and low-latitude regions.

The projected impacts on NPP under GW\_1.5 °C relative to no additional warming (and relative to 2.0 °C) are uncertain because of the large range of likely outcomes within the model when accounting for both estimation uncertainties regarding climate and NPP. The uncertainty of NPP under the four models ranged from 16.29 to 26.52%. The results imply a large impact of GW\_1.5 °C compared with the current conditions, whereas GW\_2.0 °C leads to a significantly lower growth in projected NPP over all study areas. It must be emphasized that the results solely represent the projected net effect of temperature under the assumption of stable estimated relationships, and large overall uncertainty in NPP growth is observed under the hypothetical temperature scenarios. However, the results suggest that considerable benefits may arise because of the lower warming levels. This finding further motivates efforts to limit GMST warming to 1.5 °C through the use of stringent emission adjustments.

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