**Effect of future climatic variation on vegetation stability in Central Asia**Dingjin Chu a,b, Li Zhang a,b,c,\*, Han Wu a,b, Honglin He a,b,c , Xiaoli Ren a,b

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Abstract

Vegetation stability is vulnerable to climate change in Central Asia. However, how future climate variations and extremes influence the vegetation stability in Central Asia has not been well understood. In this study, we investigated future vegetation stability quantified by the variability of vegetation productivity and attribution to climatic variation and negative extremes in Central Asia under four Shared Socioeconomic Pathways scenarios (SSPs) during 2021-2100, using Coupled Model Intercomparison Project phase 6 simulations. We found that the interannual variability (IAV) of Net Primary Production (NPP) would be larger under higher anthropogenic emissions scenarios. The standard deviation of NPP IAV increases from 64.55 Tg C under SSP1-2.6 to 78.01 Tg C under SSP5-8.5. The north of Central Asia accounts for the largest contribution (48% -53%) to Central Asia’s NPP IAV under SSP1-2.6 to SSP5-8.5. Compared to temperature IAV, precipitation IAV exerts a larger contribution to NPP IAV in Central Asia, due to the higher sensitivity of NPP IAV to precipitation IAV. Dry conditions are the main climate extremes causing negative NPP extremes in Central Asia, especially in the north and southeast of Central Asia. Our findings identify the northern and southeastern regions with higher instability posed by future climate changes in Central Asia, and provide scientific guidance for regional water management to mitigate ecosystem instability.

**Keywords**: Climate change, Climate extremes, NPP extremes, CMIP6, Carbon cycle, Spatiotemporal variation

## Introduction:

Net primary production (NPP) represents the net accumulation of carbon dioxide in plants and plays a vital role in the carbon cycle (Bloom et al., 2016; Chen et al., 2020; Schimel, 1995) and ecosystem services (Imhoff et al., 2004; Imhoff and Bounoua, 2006). The interannual variability (IAV) of NPP emerges as a crucial metric that reflects the annual fluctuations in ecosystem services and explores its relationship with climatic variability (Holmgren et al., 2013; Li et al., 2021; Li and He, 2022). Understanding the interannual variation of NPP and its attribution to regions and climate variability is crucial for predicting the carbon cycle, assessing ecosystem stability, and supporting decision-making in ecosystem management.  
  
Vegetation stability is a critical concept for understanding ecosystem resilience, predicting responses to environmental changes, and informing conservation strategies. The standard deviation and extreme events in NPP are commonly-used metrics in assessing vegetation stability (Nikinmaa et al., 2020; Sánchez-Pinillos et al., 2024). The standard deviation of NPP quantifies the temporal variability in ecosystem productivity, with low values indicating stability and resilience, while high values suggest instability or increased sensitivity to disturbances. Similarly, negative NPP extremes—anomalous declines in NPP—reflect periods of stress caused by factors such as drought, wildfires, or human impacts and likely provoke the transition of vegetation types (Hao et al., 2022; Reichstein et al., 2013; Sánchez-Pinillos et al., 2024). When analyzed together, these two measures provide a comprehensive assessment of how ecosystems maintain functionality under environmental variability and stress.

Central Asia, the largest semi-arid and arid region in the mid-latitude zone, faces vulnerability in vegetation productivity due to climate change and its fragile ecosystem (Lioubimtseva and Henebry, 2009; Zhao et al., 2023), with NPP primarily ranging from 79.5-326 g C (Zhu et al., 2022). Previous study has shown that NPP shows large interannual variability and spatial variation (Zhu et al., 2022). The change of NPP is mainly controlled by precipitation compared to temperature, human activities, and CO2 (Chen et al., 2020; Zhang and Ren, 2017; Zhu et al., 2022). The precipitation pattern exhibits regional and seasonal variations (Chen et al., 2011; Lioubimtseva and Henebry, 2009), and these variations are expected to intensify under future climate scenarios (Jiang et al., 2020). However, the extent to which these regional changes in precipitation and temperature will affect the IAV of NPP in Central Asia remains unclear.

An increasing magnitude of climate extremes has been observed in Central Asia over the past decades, such as heatwaves (X. Wang et al., 2023), extreme precipitation (Yao et al., 2021), drought (Liu et al., 2023; C. Wang et al., 2022) and compound events (Liu et al., 2021). Climate extremes are proven to exert profound effects on the IAV of plant productivity and ecosystem functions by influencing related physiological and biogeochemical processes (Frank et al., 2015; Hao et al., 2022; Reichstein et al., 2013). The magnitude of climate extremes has been predicated to increase in Central Asia (Jiang et al., 2020; C. Wang et al., 2023; Wu et al., 2023; Yao et al., 2021), which would bring about a risk of exacerbating ecosystem degradation (He et al., 2021). A recent study reported the effect of extreme climates on land surface phenology in Central Asia from 2021-2100 (Wu et al., 2023). However, the effect of future climate extremes on vegetation productivity in Central Asia has not been well understood.

In this study, we used projections from nine models in Phase 6 of the Coupled Model Intercomparison Project (CMIP6) to quantify the interannual variability (IAV) of annual Net Primary Production (NPP) as a measure of vegetation stability and its response to climatic drivers in Central Asia from 2021 to 2100 under four different scenarios. The objectives of this research are: (1) to investigate how NPP and its annual variability, as proxies for vegetation stability, are projected to change in Central Asia; (2) to identify key regions and dominant climatic drivers influencing the projected NPP IAV and vegetation stability; and (3) to quantify the potential impacts of future climate extremes on NPP and its stability across the region.

## Materials and Methods

### 2.1 Region

Central Asia, situated in the middle of the Eurasian continent, comprises five independent countries including Kazakhstan, Uzbekistan, Tajikistan, Turkmenistan, and Kyrgyzstan and occupies about 4 million square kilometers. The elevation in this region gradually increases from the Caspian Sea coast in western Uzbekistan and Kazakhstan to the Altai Mountains in eastern Kazakhstan and across the Pamir Mountains and Tianshan Mountains in Tajikistan and Kyrgyzstan.

Central Asia is characterized by a temperate continental climate with hot summers and cold winters (Lioubimtseva and Henebry, 2009). Mean annual temperatures range from 2°C in northern Kazakhstan to 18°C in Turkmenistan and southern Uzbekistan, while the annual average temperature of mountainous regions and hills is below 0°C (Mohammat et al., 2013). The arid zone in Central Asia has shown a 1.6°C increase in temperature over the past century (Chen et al., 2012). Mean annual precipitation is approximately 400 mm in northern Kazakhstan and below 100 mm in northern Turkmenistan and southern Uzbekistan, except in mountainous areas where precipitation ranges between 600 mm and 800 mm. These distinctive climatic conditions have fostered the prevalence of specific vegetation types in Central Asia, with grassland occupying 74.4%, cropland 6.7%, and forest 0.5%, while other land cover types such as bare land and water bodies collectively account for 18.4% (Chen et al., 2019).

We divided Central Asia into four regions (Fig. 1b) based on country boundaries, elevation, and the future Köppen-Geiger climate classification (Beck et al., 2018). Tajikistan and Kyrgyzstan were combined as the Southeast of Central Asia (SECA) due to their higher elevation and humid to arid steppe climate. The large, cold arid desert in the center was defined as the Center of Central Asia (CCA). The region north of SECA, mainly in Kazakhstan and dominated by a cold arid steppe climate, was designated as the North of Central Asia (NCA). The remaining area, characterized by a hot arid desert climate, was labeled as the Southwest of Central Asia (SWCA).

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| D:\CMIP6_raster\paper_figure\climatezone_dem.png  Fig. 1: The Geographical location and elevation distribution of Central Asia (a), the geographical distribution of Köppen-Geiger climate classification in the future (b), including North of Central Asia (NCA), Center of Central Asia (CCA), Southwest of Central Asia (SWCA), and Southeast of Central Asia (SECA). |

### 2.2 Data

We collected modeled precipitation, temperature, and NPP data in Central Asia during 2021 to 2100 from nine models of CMIP6 (Table 1). All the nine models have the ability to capture essential climate feedbacks, including carbon-climate interactions and hydrological cycles, and provided the variables required for this study across four scenarios, i.e., SSP1-2.6, SSP2-4.5, SSP3-7.0, and SSP5-8.5. The scenarios are the combination of shared socioeconomic pathways and forcing levels of the Representative Concentration Pathways (RCP). Detailed information about the selected models is provided in [Table 1](#tbl-model_information). We collected modeled temperature, precipitation, and net primary production in each model from 2021 to 2100 and resampled them to the same resolution of 0.5° × 0.5° by the bilinear interpolation method.

In this study, we calculated the multi-model mean of precipitation, temperature, and NPP from nine models in CMIP6 (Table 1). The CMIP6 multi-model mean of NPP in CMIP6 is generally consistent with regional assessments made by the REgional Carbon Cycle Assessment and Processes, Phase 2 activity (Jones et al., 2023). Additionally, we compared the multi-model mean of NPP with MODIS NPP product from 2015 to 2020. The linear regression between the CMIP6 multi-model mean and MODIS NPP data shows a high consistency with a square R of 0.71 (Fig. S1).

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| Table 1: Description of nine CMIP6 models used in this study.   | No | Model | Resolution (°) | Modeling Group | Land sub-model | | --- | --- | --- | --- | --- | | 1 | ACCESS-ESM1-5 | 1.875° × 1.25° | Commonwealth Scientific and Industrial Research Organisation (CSIRO), Bureau of Meteorology (BoM) | CABLE2.4 | | 2 | BCC-CSM2-MR | 1.125° × 1.125° | Beijing Climate Center (BCC), CMA | BCC\_AVIM2 | | 3 | CESM2-WACCM | 1.25° × 0.9375° | National Center for Atmospheric Research (NCAR) | CLM5 | | 4 | CMCC-CM2-SR5 | 1.25° × 0.9375° | Centro Euro-Mediterraneo sui Cambiamenti Climatici (CMCC) | CLM4.5 | | 5 | CMCC-ESM2 | 1.25° × 0.9375° | Centro Euro-Mediterraneo sui Cambiamenti Climatici (CMCC) | CLM 4.5 | | 6 | EC-Earth3-Veg | 0.7° × 0.7° | European Consortium for High-Resolution Climate Modeling (EC-Earth) | HTESSEL (land surface scheme built in IFS) and LPJ-GUESS v4 | | 7 | IPSL-CM6A-LR | 2.5° × 1.2676° | Institut Pierre-Simon Laplace (IPSL) | ORCHIDEE, branch 2.0 | | 8 | MPI-ESM1-2-LR | 1.875° × 1.8653° | Max Planck Institute for Meteorology (MPI-M) | JSBACH3.2 | | 9 | NorESM2-LM | 2.5° × 1.875° | Norwegian Climate Centre | CLM5 | |

We calculated the trends of precipitation, temperature, and NPP over the period 2021-2100 using multi-model mean values. The interannual variability (IAV) or detrended anomaly of precipitation, temperature, and NPP was then calculated by subtracting the trend for the same period. All data shown in this paper is analyzed and plotted in the R (R Core Team, 2023).

### 2.3 Methods

### 2.3.1 Quantification of vegetation stability

In this study, we assessed the vegetation stability by both vegetation productivity variation calculated as the standard deviation of NPP IAV and the negative NPP IAV extremes. Here, we defined ecosystems with higher instability as those exhibiting greater standard deviations of NPP IAV and more pronounced negative NPP IAV extremes. Furthermore, we identified the instable regions in Central Asia by exploring the regional contribution of NPP IAV to whole central Asia NPP IAV. We also investigated the contribution of climatic factors that drives the ecosystem instability at both pixel and regional scales. This pixel-level climatic attribution analysis provided valuable insights for mitigating vegetation instability by human management in the future.

### 2.3.2 Contributions of regions and climatic factors

Using the contribution index () as defined in Ahlström et al. (2015), we calculated the contribution of NPP IAV in individual pixels to Central Asia NPP IAV. The contribution index () for pixel j is expressed as [Eq. 1](#eq-contribution).

where is the NPP IAV for pixel j at time t (in years), and is the NPP IAV of Central Asia so that .

Using a multiple regression approach (Piao et al., 2013) as shown in Eq. 2, we estimated the contributions of precipitation IAV and temperature IAV in each pixel to NPP IAV in Central Asia over 2021-2100.

where is the NPP IAV for pixel i, and , are the temperature and precipitation IAV for pixel i, respectively. The regression coefficients and represent the sensitivities of NPP to temperature and precipitation for pixel i, and is the residual error. Specifically, we replaced in [Eq. 1](#eq-contribution) with the as the contribution of temperature and as the contribution of precipitation in [Eq. 2](#eq-sensitivity) respectively.

### 2.3.3 Extreme events identification and attribution

We identified the extremes by comparing the anomalies of each pixel with the threshold value calculated from the distribution function of the anomalies in the whole Central Asia using the method proposed by Zscheischler et al. (2014). The threshold values (Table S1) are defined as the tenth or ninetieth percentile of the distribution function (Field, 2012). Here, the ‘extremes’ are defined as the values of a given variable (i.e., NPP, precipitation, and temperature) above the ninetieth percentile or below the tenth percentile. Moreover, we divided climate extremes into four groups based on extreme conditions of precipitation and temperature as reported in Zscheischler et al. (2014), i.e., hot conditions, cold conditions, wet conditions, and dry conditions. To quantify the effect of compound climate extremes on NPP IAV, we further divided hot conditions and dry conditions into three groups, i.e., concurrent dry and hot conditions when dry and hot conditions extremes occur simultaneously (dry & hot), dry conditions without heat (dry & not hot), and hot conditions without dryness (hot & not dry).

The negative NPP extremes are defined as the NPP IAV below the threshold value of tenth percentile. We calculated the time series of negative NPP extremes by summing up all negative NPP extremes at each year. The attribution of negative NPP extremes to climate extremes was identified when the climate extremes are spatiotemporally overlapped with negative NPP extremes. The negative NPP extremes that are not spatiotemporally overlapped with climate extremes are categorized as rest. To determine the proportion of negative NPP extremes attributed to specific climate extremes, we computed the ratio of negative NPP extremes spatiotemporally associated with climate extremes to the total number of negative NPP extremes. For each pixel, we calculated the average negative NPP extremes caused by specific climate events by summing all anomalies and dividing by the number of years.

## Results

### 3.1 Future spatiotemporal NPP variabilities in Central Asia

The CMIP6 simulations revealed an upward trajectory in the annual NPP across Central Asia from 2021 to 2100 under the four scenarios (i.e., SSP1-2.6, SSP2-4.5, SSP3-7.0, and SSP5-8.5), and both the trend and variation of NPP are expected to enhance as greenhouse gas emission increases ([Fig. 2](#fig-npp) a-b). The NPP trend increases from 0.58 Tg C (0.15 g C m-2 yr-2) under SSP126 to 3.69 Tg C (0.94 g C ) under SSP5-8.5. Except for SSP1-2.6, the NPP in the other three scenarios all increases significantly (p<0.01). The standard deviation of NPP IAV increases from 64.55 Tg C (30.63 g C ) under SSP1-2.6 to 78.01 Tg C (35.55 g C ) under SSP5-8.5. There is a similar spatial pattern across four scenarios in the NPP standard deviation and trend for the period of 2021-2100 (Fig. S2). Under the scenario SSP5-8.5 ([Fig. 2](#fig-npp)c-d), ecosystems in Southeast of Central Asia (SECA) and North of Central Asia (NCA) show a higher trend and interannual variation of NPP than that in Center of Central Asia (CCA) and Southwest of Central Asia (SWCA).

We employed [Eq. 1](#eq-contribution) to quantify the regional contributions to NPP IAV over Central Asia. At the pixel scale, there is no significant difference among different scenarios regarding the contribution of pixel NPP IAV to Central Asia’s NPP IAV (Fig. S3). The results showed that all the pixels positively contribute to the NPP IAV over Central Asia, with higher contributions mostly located in the SECA and NCA (Fig. S3). When aggregating pixel-scale contributions into four regions separately, we found that the NCA accounts for about 48-53% of the NPP IAV under four scenarios over Central Asia, followed by the CCA (24-26%). The other two regions, SWCA (15%-18%) and SECA (7-9%), have a minor contribution to the NPP IAV in Central Asia (Fig. S4).

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| D:\CMIP6_raster\paper_figure\npp.png  Fig. 2: The dynamic of annual net primary production (NPP) (a), the standard deviation of regional NPP interannual variability (IAV) (b), the trend of NPP (c), and standard deviation of NPP IA (d) over Central Asia during the study period (2021-2100). Bars show standard error calculated from the results in 9 models. For details on regions NCA, CCA, SWCA, and SECA, see Fig. 1. |

### 3.2 Future Climatic attribution to NPP variabilities

The results about attribution of NPP IAV to precipitation and temperature shows similar patterns across the four scenarios as shown in Fig. S3-S5. In the following part, we mainly present the result from SSP5-8.5 as an example (Fig. 3). NPP IAV has an overall stronger correlation with precipitation IAV than with temperature IAV in Central Asia (Fig. 3a). The correlation coefficients at each pixel range from 0.18 to 0.74 between NPP IAV and precipitation IAV and from -0.23 to 0.22 between NPP and temperature IAV. Eighty percent area of Central Asia exhibits significant correlation between NPP IAV and precipitation IAV. Especially for the SECA and SWCA regions, the correlation coefficients of NPP IAV and precipitation IAV reach up to 0.72-0.75 and 0.62-0.70, respectively (Fig. S4 b).

We employed the multiple regression analysis ([Eq 2](#eq-sensitivity)) to quantify the sensitivity of NPP IAV to climate IAV and the contribution of climate IAV to NPP IAV over Central Asia from 2021 to 2100. Our results showed that IAV of precipitation and temperature collectively explains 49.61% of NPP IAV (=0.37, p < 0.01) (Table 2). The precipitation IAV emerges as the primary driver of NPP IAV, and explains 48.16% of NPP IAV over Central Asia. In contrast, the temperature IAV only contributes 1.45% to NPP IAV.

The projected contribution of precipitation and temperature to NPP IAV in Central Asia shows regional variations, which result from spatial variations in both the sensitivity of NPP to climate factors and the temporal variation of climate factors. (Fig. 3b). In the NCA region, a relatively large contribution of precipitation to Central Asia's NPP IAV (22%) (Table 2) results from high sensitivity of NPP IAV to precipitation IAV (0.072 Tg 100 mm-1) and large variation in precipitation with the standard deviation of 70.04 mm. Although the sensitivity of NPP IAV to precipitation IAV (0.084 Tg 100 mm-1) in SWCA is higher than that in NCA, precipitation IAV contributed less to NPP IAV (11%) due to its relatively low precipitation annual variation with the standard deviation of 59.34 mm (Table 2). In the SECA region, although precipitation variation is the highest (121.57 mm), it contributes a relatively small fraction (5.3%) to the NPP IAV across Central Asia due to the lower sensitivity of NPP IAV to precipitation IAV (0.05 Tg/100 mm).

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| D:\CMIP6_raster\paper_figure\cor_contri_sen_variation.png  Fig. 3: The correlation between climatic IAV and NPP IAV (a), the contribution of climatic interannual variability (IAV) to net primary production (NPP) IAV (b), and the sensitivity of NPP IAV to precipitation IAV (c) and to temperature IAV (d), under SSP5-8.5. The black stippling indicates statistically significant test at the 0.05 level (p<0.05). For details on regions NCA, CCA, SWCA, and SECA, see Fig. 1.  Table 2: Regional contributions to NPP IAV in Central Asia, correlation coefficients between NPP IAV with IAV in precipitation (P) or temperature (T), and NPP sensitivity to P and T under SSP5-8.5. North of Central Asia (NCA), Center of Central Asia (CCA), Southwest of Central Asia (SWCA), and Southeast of Central Asia (SECA).   |  |  |  |  |  |  | | --- | --- | --- | --- | --- | --- | |  | NCA | CCA | SWCA | SECA | Central Asia | | Regional contribution to NPP IAV (%) | 48.53 | 24.30 | 17.88 | 9.29 | 100 | | Contribution of P IAV to NPP IAV (%) | 21.61 | 10.69 | 10.56 | 5.30 | 48.16 | | Mean correlation coefficients between NPP IAV and P IAV | 0.51 | 0.49 | 0.64 | 0.55 | 0.55 | | The sensitivity of NPP IAV to P IAV (Tg C 100 mm-1) | 0.07 | 0.05 | 0.08 | 0.05 | 0.07 | | Contribution of T IAV to NPP IAV (%) | 1.09 | 0.26 | -0.16 | 0.26 | 1.45 | | Mean correlation coefficients between NPP IAV and T IAV | -0.10 | -0.04 | -0.12 | 0.00 | -0.07 | | The sensitivity of NPP IAV to T IAV (Tg C ℃-1) | -0.29 | 0.13 | -0.47 | 0.73 | 0.03 | |

### 3.3 Future NPP variability under extreme climate conditions

Our analysis revealed that the future NPP extremes dominate the IAV of NPP over Central Asia with a strong correlation coefficient of 0.96 (Fig. S6). Across all scenarios, negative NPP extremes intensify from 2021 to 2100, ranging from -0.26 g C in SSP1-2.6 to -4.36 g C in SSP5-8.5 ([Fig. 4](#fig-extreme_npp_magnitude) a). The average magnitude of negative NPP extremes would intensify from -801 g C to -879 g C with the escalation of greenhouse gas emissions ([Fig. 4](#fig-extreme_npp_magnitude) b). Particularly, the NCA and SECA regions exhibit severe negative NPP extremes (Fig. S7) with an escalation from -957to -1050 g C and -630to -754 g C , respectively. Furthermore, the spatial pattern of negative NPP extremes among different scenarios (Fig. S7) aligns with the distribution of standard deviation of NPP IAV (Fig. S2). This consistency implies the important role of negative NPP extreme events on Central Asia’s carbon cycle.

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| D:\CMIP6_raster\paper_figure\extreme_date_magnitude.png  Fig. 4: The trend (a) and regional magnitude (b) of negative NPP extremes from 2021 to 2100. Bars show standard error calculated from the results in 9 models. For details on regions NCA, CCA, SWCA, and SECA, see Fig. 1. |

We investigated the attribution of negative NPP extremes to different climate extremes, including dry, hot, cold, and wet conditions. Our results showed that the spatial patterns of negative NPP extremes attributed to climate extremes are similar across all four scenarios (Fig. S7, Fig. S8). Taking SSP5-8.5 as an example ([Fig. 5](#fig-prop) a), the dry conditions are responsible for triggering 33% of negative NPP extremes, with a higher proportion in the SECA (66%) and in NCA (34%). Dry conditions would result in a reduction of -11.63 Tg in NPP over Central Asia, mainly distributed in its northern and southeastern regions ([Fig. 5](#fig-prop) b, [Fig. 6](#fig-extreme_spatial_attribution)). Hot conditions occupy 13% of negative NPP extremes, with a relatively higher proportion in NCA (20%) ([Fig. 6](#fig-extreme_spatial_attribution)). Moreover, we divided the dry conditions into two types (i.e, dry & hot conditions and dry & not hot conditions), and found that negative NPP extremes are mostly attributed to dry & not hot conditions in each region ([Fig. 5](#fig-prop) a). These results also suggest that water scarcity, rather than hot, is the main limitation to the growth of vegetation in Central Asia.

The increasing NPP annual variation under high emissions scenarios in Central Asia is probably associated with the increasing variation of precipitation, which changes from 60.38 under SSP126 to 65.38 mm under SSP585 (Fig. S9). Dry condition also causes increasing negative NPP extremes from -372.47 g C m-2 under SSP126 to -410.97 g C m-2 under SSP585 (Fig. 6).

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| D:\CMIP6_raster\paper_figure\prop.png  Fig. 5: The proportion of negative NPP extremes to the extreme climates under SSP5-8.5 (a) and the magnitude of negative extreme NPP caused by different climate extremes (b). For details on regions NCA, CCA, SWCA, and SECA, see Fig. 1. |

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| D:\CMIP6_raster\paper_figure\negative_npp_extreme_attributed to dry hot.png  Fig. 6: The spatial distribution of negative NPP extremes caused by dry and hot conditions over 2021 to 2100 under four different scenarios. For details on regions NCA, CCA, SWCA, and SECA, see Fig. 1. |

## Discussion

Our results suggest that NPP growth trend and interannual variation in Central Asia would be enhanced as greenhouse gas emissions increase in the future. The NPP IAV links to the annual provision of food (Imhoff et al., 2004). Higher negative variation suggests the need to store food to deal with the instability. This increase in NPP interannual variability is probably associated with increasing NPP (Jakob Zscheischler et al., 2014) or larger variations in precipitation (Jiang et al., 2020) under higher emissions scenarios. The important role of precipitation in controlling the changes of NPP has been proved over the past three decades in Central Asia (Zhu et al., 2022; Chen et al., 2020). The pattern that precipitation IAV dominates the net ecosystem productivity IAV has also been found in other semiarid and arid regions in China (Li et al., 2021; Zhang et al., 2019) and tropical regions (K. Wang et al., 2022). Ecosystems in these regions tend to have large sensitivity of NPP to precipitation as presented in this study (Table 2) and previous studies (Li and He, 2022; Zhang and Ren, 2017). Differed from the significant correlation between NPP and temperature in parts of Central Asia over past decades in previous studies (Chen et al., 2019; Li and He, 2022), the relationship between NPP IAV and temperature IAV is rather weak compared to precipitation in the future (Fig. 3). This discrepancy might be related to the dampening effect of warming in the future on NPP's sensitivity to temperature, and the overestimation of carbon flux response to precipitation in models (Piao et al., 2013), and difference in spatial resolution (Ahlström et al., 2015; Jung et al., 2017). Better prediction accuracy in precipitation patterns and deeper knowledge of underlying mechanisms on ecosystem responses to precipitation are, therefore, necessary to ensure a comprehensive understanding of the climatic drivers shaping NPP dynamics in Central Asia and else semiarid and arid regions.

We found that negative NPP extremes in the future are mainly driven by dry conditions in Central Asia. This result differs from the global findings (Jakob Zscheischler et al., 2014), where hot conditions drive a comparable number of negative NPP extremes as dry conditions. In this study, the influence of hot conditions on negative NPP extremes in the future is comparatively small, probably because NPP in Central Asia shows weak sensitivity to temperature. The climate extremes in Central Asia are able to explain 92.9%-94.4% of negative NPP extremes derived from CMIP6 models. However, human activities were proven to be an important factor in influencing the NPP variation in Central Asia (Chen et al., 2020, 2019), as the influence of climate extremes on NPP could be amplified by inappropriate human activities. For instance, the structural factors, such as unsustainable management of water resources and rural poverty, amplified the consequence of catastrophic drought during 2000–2001 (FAO, 2017), and this effect is likely enhanced in the future (Jiang and Zhou, 2023). However, human activities have not been appropriately involved in earth systems models (Beckage et al., 2022). Further work should focus on the effect of the interaction of climate extremes and human activities especially grazing (Zhu et al., 2022) in the future for estimating the NPP extremes and developing a sustainable management scheme.

Among the four regions in Central Asia, the Southeast of Central Asia (SECA) and the Northern Central Asia (NCA) would experience a heightened risk of negative NPP extremes and thus instability. Previous studies have shown that these two regions exhibit higher resilience (Yuan et al., 2021). However, the increasing frequency of extreme events in the future could undermined ecosystem resilience and turn them into the less resilient ecosystems (Reichstein et al., 2013). In the NCA, drought and hot conditions are the main contributors to negative NPP extremes in the future. Ecosystems in this region had suffered a significant reduction in vegetation productivity and loss of carbon over past decades caused by decreasing soil moisture in dry conditions (Li et al., 2015; Zhu et al., 2019) and heatwaves (X. Wang et al., 2023). Most of this area is covered by rainfed crops, which are highly vulnerable to climate change and reliant on precipitation (Jiang and Zhou, 2023). Considering the important role of this region with higher vegetation productivity and being pivotal for Central Asia's food provision, we need to pay more attention to this region to address the potential risks posed by climate change. In addition, the Southeast of Central Asia (SECA) is another key region characterized by significant negative NPP extremes, primarily driven by dry conditions (Fig. 5). This region is projected to face increasing extremes in water availability, including both floods caused by meltwater from mountains (Ombadi et al., 2023) and extreme precipitation (Jiang et al., 2020; Zhang et al., 2023), as well as severe droughts (Yao et al., 2021). Since this region serves as a primary source of river water for irrigating vast areas of Central Asia (Viviroli et al., 2020; Wu and Zheng, 2023), implementing an effective water management plan is crucial to sustain the water supply and mitigate negative NPP extremes.

Prediction uncertainties in various scenarios and across models are important for supporting effective ecosystem management. In our study, we found a consistent attribution pattern of NPP IAV to climate factors across various scenarios (Fig. S3-S8). This pattern aligns with the study shown on a global scale from CMIP5 simulation (Zscheischler et al., 2014). However, models exhibit disagreement regarding the proportion of climate extremes attributed to specific drivers, indicating differences in how certain models respond to these extremes (Fig. S10). Larger model spreads were observed in the magnitude of negative NPP extremes (Fig. S11), with over 90% of model pair comparisons showing significant differences (p < 0.05). Specifically, the MPI-ESM1-2-LR tends to simulate a higher magnitude of negative NPP extremes compared to other models. The MODIS NPP data are not directly measured, which introduces uncertainty in the validation of CMIP6 NPP data. Future work should focus on validating each model using field observations, enhancing processes that account for vegetation responses to extreme weather (Bonan and Doney, 2018), and addressing water use and management under climate change scenarios (Beckage et al., 2022).

## Conclusions

Our research examines vegetation stability under four future scenarios, provides insights into the impacts of climate change on vegetation, and offers scientific guidance for regional water management in Central Asia. Our findings reveal that vegetation instability increases with rising greenhouse gas emissions. The northern and southeastern regions of Central Asia emerge as heightened instability, characterized by greater interannual variation in Net Primary Production (NPP) and more severe negative NPP extremes. This instability is primarily driven by the heightened sensitivity of vegetation productivity to precipitation variability and the increasing precipitation fluctuations in these regions. Therefore, implementing effective water management strategies to deal with precipitation variations such as droughts, the main cause of negative NPP extremes, is therefore critical for mitigating vegetation instability. Furthermore, additional research is necessary to deepen our understanding of vegetation sensitivity to climate variability and to explore water management practices that can reduce vegetation sensitivity, thereby improving vegetation stability.

## CRediT authorship contribution statement

Dingjin Chu: Methodology, Visualization, Data curation, Formal analysis, Writing – original draft. Li Zhang: Methodology, Conceptualization, Supervision, Writing – review & editing. Han Wu: Methodology, Data curation, Conceptualization. Honglin He: Conceptualization, Supervision Xiaoli Ren: Conceptualization.

## Data availability statement

The data that support the findings of this study are openly available at <https://esgf-node.llnl.gov/> projects/cmip6/.

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