



The 2020 heatwave led to a larger enhancement in annual gross primary production in West Siberia than in East Siberia

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Key Points:

- The 2020 Siberian heatwave increased annual vegetation production in West Siberia up to 10% more than in East Siberia
- Regional differences were due to the higher sensitivity of annual GPP to spring temperature and stronger warming in the West
- Extreme spring heatwave can outweigh the negative impact of other climate conditions on annual vegetation production

Abstract

Spring and summer vegetation productivity in Siberia showed opposing responses to warmer spring. Spring warming caused excessive vegetation growth and earlier start of photosynthesis, enhancing productivity in spring. However, this led to reduced productivity in the following season (i.e., summer) through soil moisture depletion. To understand how an exceptional spring heatwave (HW) affected ecosystem carbon uptake, we investigated the spatiotemporal cascade of gross primary production (GPP) and multiple climate variables over Siberia in 2020, using a satellite-retrieved GPP product (GOSIF-GPP) and the ERA5-Land reanalysis dataset for 2001–2020. Results showed a positive impact of anomalous spring warming on annual GPP (GPP_{ann}). GPP_{ann} from GOSIF-GPP in West Siberia (55°–70°N, 50°–90°E) was enhanced by up to 10% above the 2001–2019 average despite continued dry conditions from May to August. In East Siberia (55–70°N, 90–130°E), the GPP increases for May and June were sufficient to compensate for marked reduction of GPP in July due to negative anomaly in radiation. In addition, the higher sensitivity of GPP_{ann} to spring temperature in West Siberia than in East Siberia suggests that GPP increase coupled with strong warming and respective excessive vegetation growth might be more pronounced in the western region, as observed in 2020. Our results indicate that the warming trend in spring, combined with possible extreme heat events, could elevate annual carbon uptake in Siberia, particularly in West Siberia. Further, this case study for the extreme HW event that occurred in 2020 can provide useful insight for understanding future change in carbon uptake over Siberia.

Plain Language Summary

Warmer springs can boost plant growth and productivity according to early beginning of photosynthesis in the high-latitudes. However, the early growth can also drain soil moisture,

leading to lower productivity in following summer season. As a result, annual plant production may fluctuate. In 2020, an unusual spring heatwave occurred in Siberia. In West Siberia, plant growth increased by up to 10% compared to the previous two decades (2001-2019), despite dry soil conditions in summer. In East Siberia, despite excessive rainfall in summer that reduced sunlight, there was still an overall positive enhancement in vegetation productivity. These findings highlight the implications of how an extreme spring HW can influence annual carbon uptake and ecosystem productivity in northern high latitude ecosystem.

1 Introduction

The terrestrial ecosystems in the Siberian taiga provide a significant carbon sink by absorbing a large amount of atmospheric carbon dioxide (CO₂) through photosynthesis (Filipchuk et al., 2023; Kasischke, 2000; Loboda & Chen, 2017). Gross primary production (GPP), the total carbon absorbed by ecosystems through photosynthesis is one of the vital indicators of vegetation carbon uptake capacity or vegetation productivity (Anav et al., 2015; Beer et al., 2010). The GPP variability over Siberia is closely connected to the amount of net carbon uptake as well as the variability of atmospheric CO₂ concentration (Lin et al., 2020; Chen et al., 2006). Hence, understanding the variability of GPP over Siberia in response to various climate and environmental conditions across different spatial and temporal scales is necessary for characterizing regional and global terrestrial carbon balance (Chen et al., 2024).

Air temperature is one of the essential factors for regulating vegetation growth and corresponding GPP in Siberia (Beer et al., 2010; Degeffie et al., 2014; Schaphoff et al., 2016; Fan et al., 2023). Numerous observational studies have reported that warming over the northern

latitudes, including Siberia, has become more profound and pervasive relative to other parts of Earth's land surface (Soja et al., 2007; Groisman et al., 2009; Groisman et al., 2016, Overland & Wang, 2021; Rantanen et al., 2022; Post et al., 2019). The strong warming trend in Siberia induced notable changes in vegetation growth and carbon uptake. One of the significant responses of vegetation to the warming trend in Siberia was the advanced start of the growing season, corresponding to earlier leaf onset, which enhanced GPP during spring (Linderholm et al., 2006; Wang et al., 2022; Jeong et al., 2011; Tucker et al., 2001). Spring warming may promote vegetation growth and productivity by advancing the start of the growing season. However, summer heatwave (HW) can suppress ecosystem productivity by causing soil moisture deficits and exceeding the optimal temperature thresholds of vegetation. These contrasting seasonal effects highlights the complex temperature effects, as there is still a lack of consensus on the effect of this advanced vegetation growth on GPP in the following season (i.e., summer). Some studies have suggested that early spring warming enhanced summertime productivity (Ren et al., 2024), while other assessments indicated that soil moisture deficit corresponding to advanced vegetation growth could suppress vegetation productivity in the summer (Buermann et al., 2013; 2018; Gloege et al., 2022; Kwon et al., 2021). Further, heat stress in summer entangled with the soil moisture deficit can exacerbate the reduction in vegetation production. It is still unclear how extremely strong temperatures, events such as HW in spring, impact GPP during both spring and summer.

HWs generally decreased vegetation carbon uptake, particularly in high northern latitudes (Ciais et al., 2005; Bastos et al., 2014; Reichstein et al., 2013; Hegedüs et al., 2024). In recent decades, Siberia has experienced a series of intense HWs that have substantially disturbed vegetation carbon uptake (Degeffie et al., 2014; Zscheischler et al., 2014; Wolf & Paul-Limoges, 2023; Fan et al., 2023; Perkins et al., 2012; Perkins-Kirkpatrick & Gibson, 2017). The GPP in

Siberia could be highly affected by HWs due to the strong temperature dependence of vegetation growth and carbon uptake as well as the HW-induced soil moisture deficit. Among many prior HWs, the 2020 Siberian HW can be an appropriate case for understanding annual and seasonal GPP responses to an anomalously strong HW event that occurred in spring. This event had the strongest intensity and persisted for almost half a year from January to the mid-June (Overland and Wang, 2021; Ciavarella et al. 2020; Hantemirov et al., 2022; Armstrong McKay et al., 2022). In addition, the HW response of ecosystems seems nonlinear and complex (Qu et al. 2024; von Buttlar et al. 2018). Hence, examining GPP responses to the 2020 Siberian HW can give useful insight for understanding the possible impacts of extreme temperature events during spring on annual and seasonal vegetation carbon uptake over Siberia. The objective of this study is to examine the anomalous spatiotemporal patterns of GPP and associated climate variables for 2020, focusing on the difference between the two sub-region in Siberia, West and East Siberia.

2 Data and Methods

2.1 Study region

Our study region encompasses northern Siberia, spanning from 30°-150°E to 55°-75°N, where boreal forests are primarily distributed (Figure. 1). We divided the study region into two sub-regions: West Siberia (55°-70°N, 50°-90°E) and East Siberia (55°-70°N, 90°-130°E), because they have distinct geographical and climatological characteristics (Solomeshch, 2005). West Siberia extends from the Ural Mountains to the West Siberian Lowland, while East Siberia includes the Central Siberian Plateau, the east side of the Lena delta, and the Far East (Solomeshch, 2005). West Siberia is relatively flat compared to the more mountainous terrain of East Siberia (Figure 1a). The annually averaged 2-meter air temperature (T_{2m}) for 2001-2019 was -1.9°C in West Siberia, which is warmer than East Siberia by approximately 5°C despite both regions being

classified under the cold continental climate in the Köppen-Geiger climate classification (Kottek et al., 2006; Peel et al., 2007). Spring mean T_{2m} was warmer in West than in East Siberia (Figure 1b). In the boreal forests of West Siberia, pines and spruces are mainly found, whereas larch species are dominant in East Siberia (Grishin et al., 1995; Xiaodong & Shugart, 2005; Shuman et al., 2011; Sugimoto et al., 2002). The differences in elevation and climate necessitate a regional analysis to understand how vegetation carbon uptake responds to varying climate and environmental conditions across Siberia, as the warming trend in the region has been non-uniform (Wang et al., 2022).

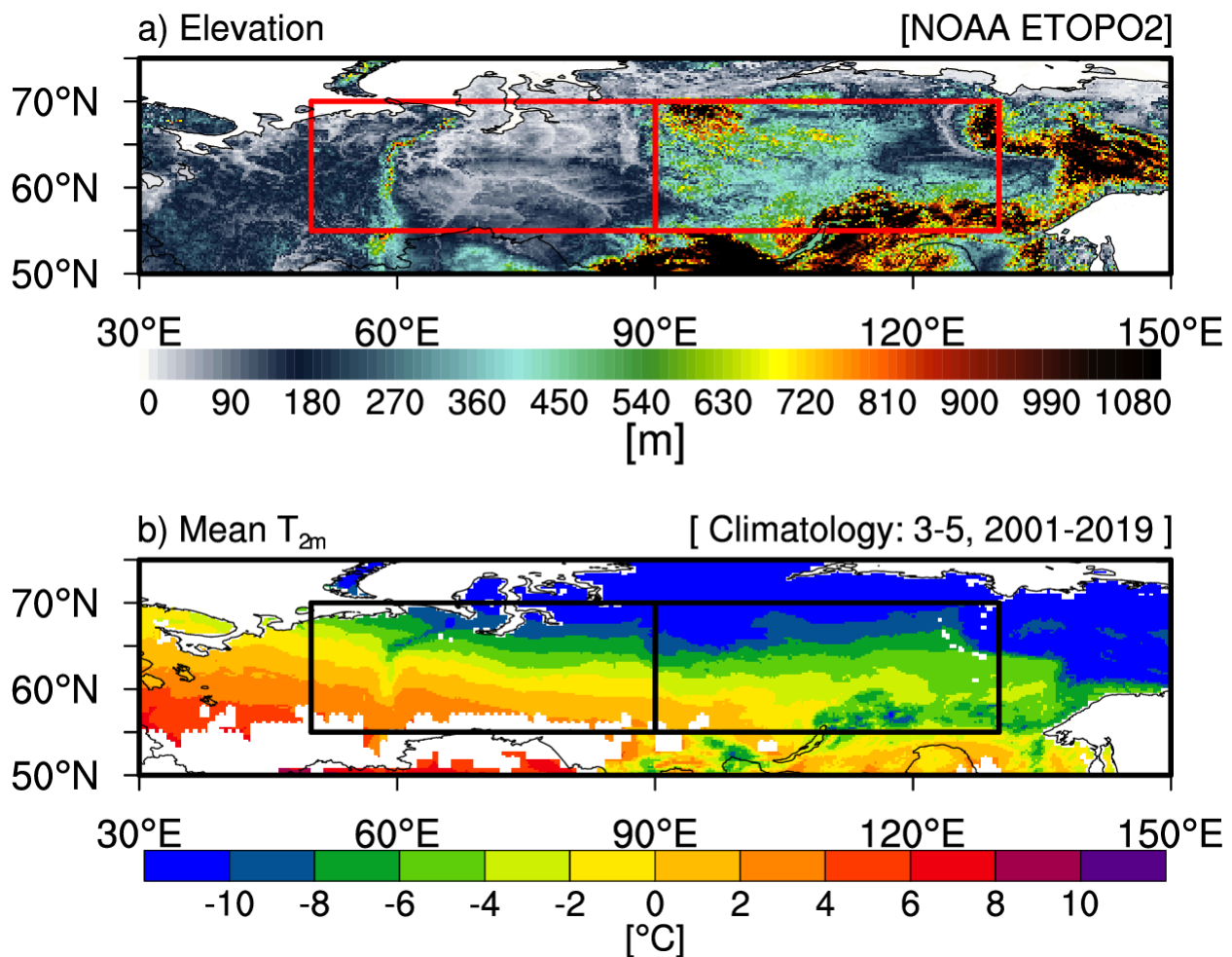


Figure 1. Spatial distribution of (a) elevation and (b) spring (March-April-May) mean T_{2m} over the northern Siberia. Boxes denote the study domains, with the left and right boxes representing for West and East Siberia, respectively.

2.2 Dataset

We used the GPP product derived from Orbiting Carbon Observatory-2 (OCO-2)-based Solar-induced chlorophyll fluorescence (SIF) data with high spatial and temporal resolutions (i.e., 0.05° , 8-day) because it covers the globe and is available from March 2000 to December 2023 (Li et al., 2018, 2022). SIF is recognized as a reliable proxy for vegetation growth and phenological development (Damm et al. 2010; Wu et al. 2012). The latest studies found that SIF showed better performance in quantifying the seasonal dynamics of vegetation productivity compared with the traditional greenness indices (e.g., normalized difference vegetation index and enhanced vegetation index), especially in boreal forests in high-northern latitudes (Walther et al. 2018; Zhang et al. 2022; Peñuelas & Zhang, 2023; Zhang et al. 2023; Karkauskaite et al. 2017). The 8-day, monthly, and annual GOSIF-GPP data were obtained from the Global Ecology Data Repository (<https://globalecology.unh.edu/data.html>). Elevation data shown in Figure 1 was obtained from the NOAA National Geophysical Data Center (2006). We also masked out the cropland area for the analysis based on the GLDAS (Global Land Data Assimilation System) land cover type classification (Rodell et al. 2004) to avoid human influenced cropland management as well as to see the clear HW impact on the natural ecosystem.

To analyze the land surface and near-surface atmospheric variables, we used the land component of the fifth generation of European ReAnalysis, namely, ERA5-Land (Muñoz-Sabater et al. 2021) (<https://cds.climate.copernicus.eu/>). This included monthly 2m air temperature

(hereafter T_{2m} , unit of K), surface solar radiation downwards (hereafter SW_{dn} , unit of $J\ m^{-2}$), and volumetric soil water for a soil layer of 0-7 cm depth (hereafter SMC, unit of $m^3\ m^{-3}$) with a 9 km ($\sim 0.10^\circ$) horizontal resolution. To determine the end-of-snowmelt date ($Snowmelt_{end}$), we used the daily snow cover fraction (%) from the ERA5-Land. A 3-hourly precipitation data (Prep) at 0.1° spatial resolution was obtained from the Multi-Source Weighted-Ensemble Precipitation (MSWEP) (<https://www.gloh2o.org/mswep/>) (Beck et al. 2019). We additionally used the leaf area index (LAI) from the MOD15A2H version 6.1 Moderate Resolution Imaging Spectroradiometer (MODIS) sensor from the Terra satellite as a proxy of net primary production (Myneni et al. 2021). We excluded cloud pixels from the raw data, which was organized on a sinusoidal grid with a 500 m spatial resolution and 8-day interval, based on the quality flag. All data were aggregated to the monthly or annual time step and the spatial resolution of 0.25° for the study period of 2001-2020.

Two GPP products and a SIF dataset are additionally used to assess the reliability of the GOSIF-GPP results. At first, the FLUXCOM-X-BASE GPP products are globally gridded fluxes derived using the Extreme Gradient Boosting (XGBoost) algorithm incorporating MODIS and ERA5 meteorological inputs (Nelson & Walther, 2024). We used the monthly FLUXCOM-X-BASE GPP dataset at a spatial resolution of $0.5^\circ \times 0.5^\circ$. GPP product from Terra/MODIS version 6.1 (MOD17A2H) is the other GPP dataset (Running et al., 2015). For the MODIS GPP, the raw data is regridded into a spatial resolution of $0.05^\circ \times 0.05^\circ$ and a monthly time scale based on the same procedure as MODIS LAI data. Last, we adopted SIF from reconstructed TROPospheric Monitoring Instrument (TROPOMI) SIF retrieved using the XGBoost algorithm (RTSIF) for one of useful proxies for GPP dataset (Chen et al., 2022).

2.3 Calculation of climate and phenological metrics

Snowmelt_{end} was calculated using ERA5-Land daily snow cover data (Muñoz-Sabater, 2019). For each grid cell, we computed an 11-day moving average for snow cover and assigned the resulting value to the middle day of that period (Figure S1). Note that a moving average reduces the noisy signals during the intensive snowmelt period due to temperature fluctuation. For example, the average snow cover from January 1st to 11th was assigned to January 6th (with January 1st to 5th treated as missing values), and so on. We then compared this snow cover with the previous day's snow cover to identify consecutive occurrences of non-snow dates for seven days, indicating complete snowmelt. The first Julian day of this consecutive period was considered the end of snowmelt. All calculations were performed for each grid cell from January 1st to August 31st for every year of the period 2001-2020. Although snow may persist beyond August in some Arctic regions, such cases have no influence on the overall analysis within our study domain. Also, we calculated the anomaly of Snowmelt_{end} in 2020 based on the weekly snow cover extent from NOAA Climate Data Record (CDR), provided on an 88 x 88 Cartesian grid for the Northern Hemisphere (Robinson et al. 2012), to ensure the robustness of the computed ERA5-based Snowmelt_{end} anomaly.

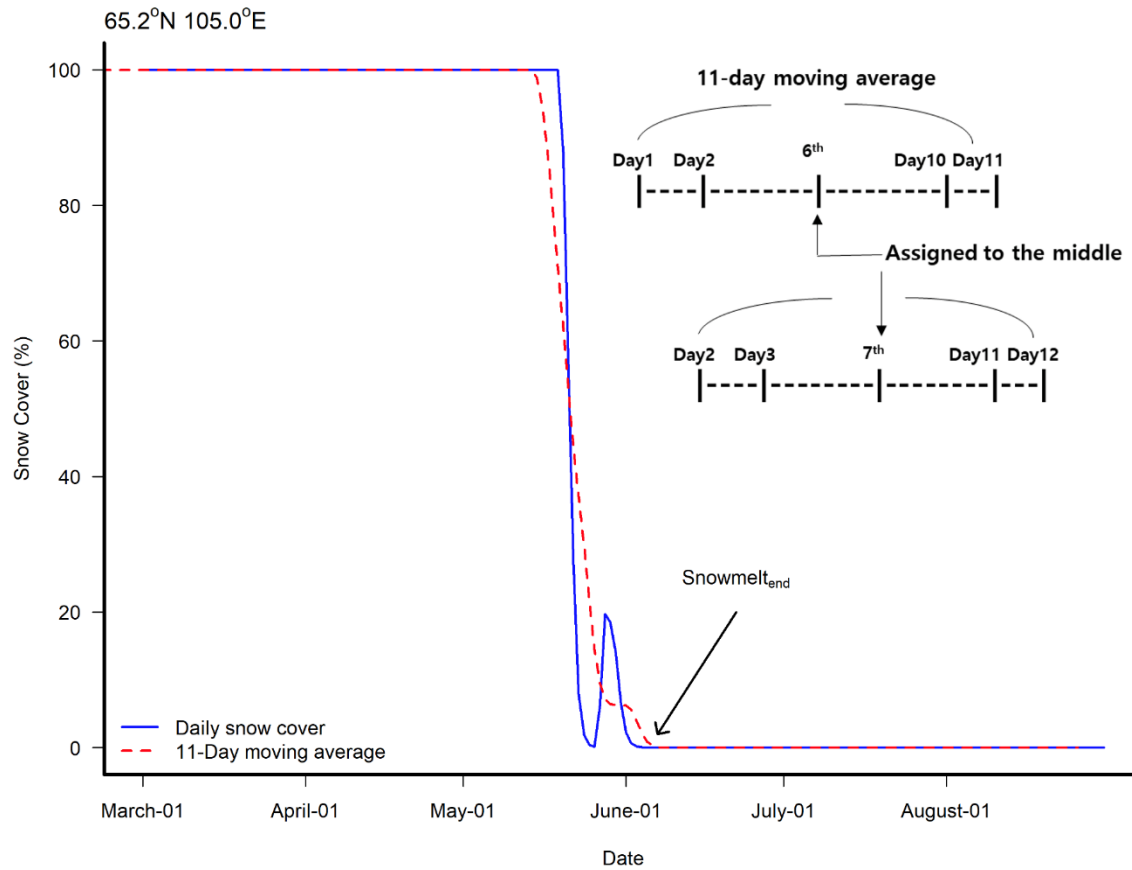


Figure S1. A schematic depicting the calculation of the end-of-snowmelt date (Snowmelt_{end}, unit of DOY). The daily snow cover at 65.2°N 105.0°E in 2020 is shown as an example. The solid blue line and red dashed line denote the daily snow cover and 11-day moving average, respectively. For instance, the average snow cover from March 1st to 11th of the month is assigned to 6th (with 1st to 5th treated as missing values).

We defined the onset and offset dates of GPP (GPP_{onset} and GPP_{offset}) and the carbon uptake period (CUP) to represent the GPP seasonality over the analysis domain. First, we reconstructed the daily GPP time series by applying a spline function to the original 8-day GPP data (a total of 46 data points per year). GPP_{onset} was calculated for every year of 2001-2020 as the first Julian day of the year (DOY) when the GPP value first crosses 15% of the maximum GPP

(GPP_{max}). Similarly, GPP_{offset} was defined as the first day when GPP reached or fell below 15% of GPP_{max} . This calculation was performed the time period from the date of GPP_{max} to December 31st. The CUP was calculated by determining the distance (number of days) between GPP_{offset} and GPP_{onset} . We assumed that the uncertainties in GPP phenology were minimal because reconstructed daily GPP was already smoothed at 8-day intervals.

To investigate the anomalous spatial distributions of GPP responses to climate and phenological variables, we calculated the monthly anomalies of GPP, T_{2m} , LAI, Prcp, SW_{dn} , SMC, GPP_{onset} , GPP_{offset} , CUP, $Snowmelt_{end}$ in 2020. The anomalies were computed by subtracting the long-term mean (2001-2019) from the 2020 values for individual grid cells. To compare regional differences, we computed area-averaged variables from April to August for West and East Siberia, applying cosine-latitude weighting to account for varying grid cell areas. We then calculated the monthly anomalies for these averages. The 2020 anomalies in GPP_{ann} for two sub-regions were processed with the same procedure using the annual GPP data. In addition, we analyzed the 5-month period from April to August by dividing it into two sub-periods: ‘During HW’ (April to May) and ‘After HW’(July to August), according to the following reasons: 1) the start of photosynthesis occurred across most of Siberia between April and May, 2) the 2020 HW ended in the middle of June (Overland & Wang, 2021), and 3) the legacy effect of the 2020 HW was reported in following summer months from July to August (Gloege et al., 2022).

3 Results

3.1 Temperature and snowmelt anomalies in 2020 over Siberia

The 2020 Siberian HW resulted in an anomalous increase in surface air temperature within the event period from January to mid-June. Spring mean T_{2m} anomalies were the most

pronounced in 2020 over both West and East Siberia (Figures 2a and 2b). In West Siberia, the averaged T_{2m} anomaly in 2020 reached 4.6 °C, marking the highest value during the study period (Figure 2a). The 2020 case was also the warmest spring in East Siberia, but the T_{2m} anomaly of 2.9 °C was smaller than that of West Siberia (Figures 2a and 2b). The spring T_{2m} anomalies were extensive in Siberia (Figure 2c), with the largest anomalies up to 7.3 °C concentrated over the West Siberian Plain. Positive T_{2m} anomalies were widely distributed across East Siberia with relatively smaller magnitude.

The anomalously high temperature during spring advanced snow melting in Siberia, indicating early moisture supply to soil and vegetation. Spatial patterns of $\text{Snowmelt}_{\text{end}}$ anomalies showed notable advancement of $\text{Snowmelt}_{\text{end}}$ by up to three weeks or more over West Siberia (Figure 2d). In contrast, the $\text{Snowmelt}_{\text{end}}$ anomalies in East Siberia was much smaller than those in West Siberia.

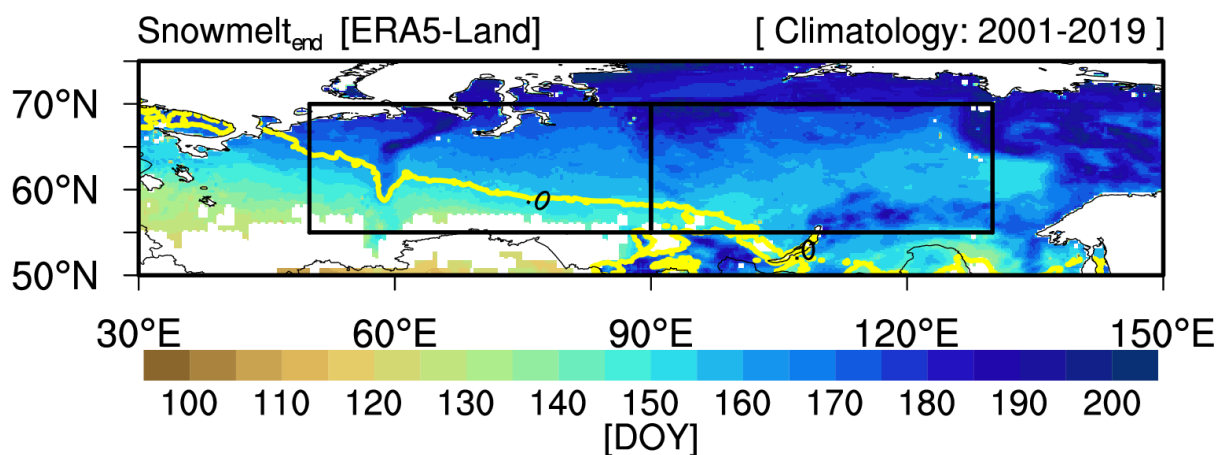


Figure S2. Climatology of the end-of-snowmelt date ($\text{Snowmelt}_{\text{end}}$, unit of DOY) in Siberia for 2001–2019. We masked out cropland areas using the GLDAS (Global Land Data Assimilation System) land cover type. Black boxes indicate West Siberia (left box) and East Siberia (right box).

234 The black line represents the mean annual temperature isotherm of 0°C, which approximates the
 235 southern border of permafrost.

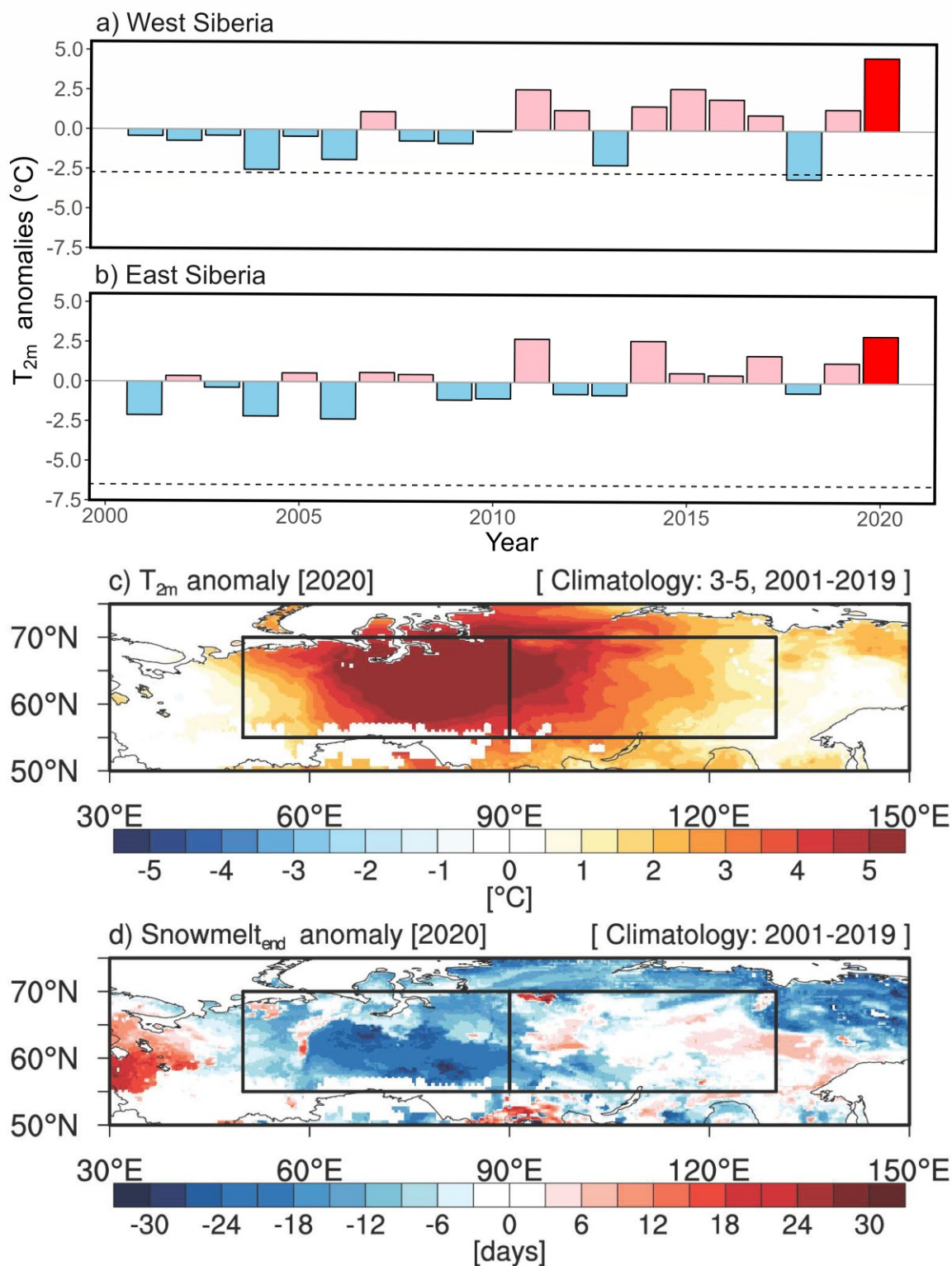


Figure 2. Area-averaged spring (March-April-May) T_{2m} ($^{\circ}\text{C}$) anomalies for a) West and b) East Siberia. Black dashed lines indicate the 2001-2019 mean spring temperatures for each region. c) Spatial distributions of spring T_{2m} anomalies, and d) the end-of-snowmelt date ($\text{Snowmelt}_{\text{end}}$) anomalies (unit of days) anomalies in 2020. We masked out cropland areas using the GLDAS (Global Land Data Assimilation System) land cover type.

3.2 Spatial characteristics of annual GPP and GPP phenology

The climatology of $\text{GPP}_{\text{onset}}$, CUP, and mean annual GPP (GPP_{ann}) for 2001-2019 along with their corresponding anomalies in 2020 revealed the spatial patterns of GPP seasonality and its deviations in 2020 (Figure 3). $\text{GPP}_{\text{onset}}$ climatology showed a progressive delay in the start of spring photosynthesis from West to East Siberia (Figure 3a). $\text{GPP}_{\text{onset}}$ occurred from mid- to late-April in West Siberia, and then gradually delayed as it moved towards East Siberia. $\text{GPP}_{\text{onset}}$ slowed down as it moved northward, demonstrating that spring photosynthesis commenced more slowly in the colder Arctic region. Spatial distribution of CUP and GPP_{ann} were consistent with that of $\text{GPP}_{\text{onset}}$, indicating longer CUP and larger GPP_{ann} in West Siberia and southern areas than in East Siberia and northern areas (Figures 3b and 3c).

The spatial distribution of $\text{GPP}_{\text{onset}}$ anomalies in 2020 was generally consistent with that of T_{2m} anomalies (Figures 2c and 3d). The advancement of $\text{GPP}_{\text{onset}}$ ranged from 12 to 25 days in West Siberia, which was larger than that in East Siberia by 4-7 days (Figure 3d). This indicates that anomalously warm temperatures have a crucial influence on the beginning of photosynthesis. The anomalies of CUP also showed consistent spatial patterns with those of $\text{GPP}_{\text{onset}}$ (Figure 3e), indicating that the early onset of photosynthesis mainly contributed to longer CUP (Figures 3d and 3e). However, GPP_{ann} showed distinct anomalies between East and

West Siberia, contrasting to the consistent advancement of GPP_{onset} and CUP in the two regions (Figures 3d-3f). In 2020, GPP_{ann} increased in most of West Siberia by 10% on area average (Figure 3f). This regional contrast was also apparent in the spatial distribution of the 2020 anomalies based on three other datasets (i.e., GPP products from FLUXCOM-X-BASE and MODIS, and SIF product from RTSIF) (Figure S3). In East Siberia, the sign of GPP_{ann} anomalies was mixed among different regions, resulting in the increment of averaged GPP_{ann} being marginal. Although the advancement of GPP_{onset} and the corresponding longer CUP were favorable conditions for increasing GPP_{ann} , the spatial patterns of their anomalies suggest a need to investigate changes in vegetation and climate variables during the cascading period after the end of the HW to explain the contrast in GPP_{ann} anomalies between the West and East Siberia.

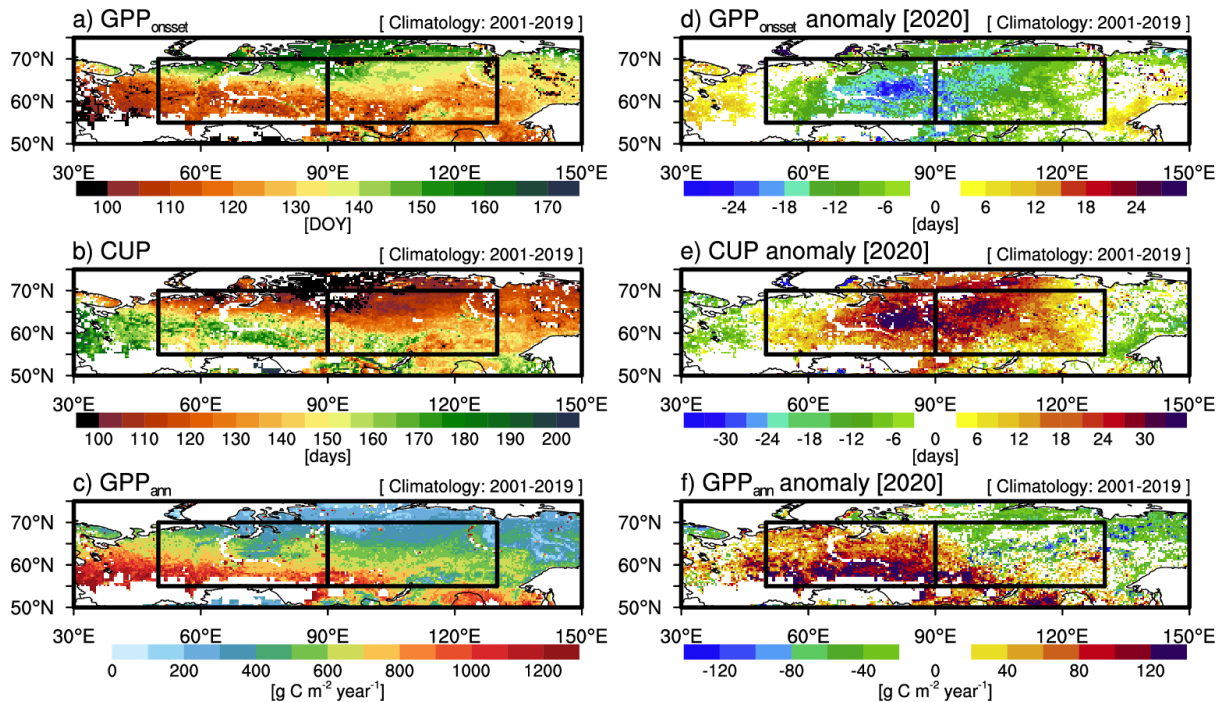


Figure 3. Climatology (2001-2019 average) of a) the onset of GPP (GPP_{onset} , DOY), b) the carbon uptake period (CUP, days), c) annual total GPP (GPP_{ann} , $g\ C\ m^{-2}\ yr^{-1}$), with their respective 2020 anomalies shown in d) GPP_{onset} (days), e) CUP (days), and f) GPP_{ann} ($g\ C\ m^{-2}\ yr^{-1}$)

¹). We masked out cropland areas using the GLDAS (Global Land Data Assimilation System) land cover type.

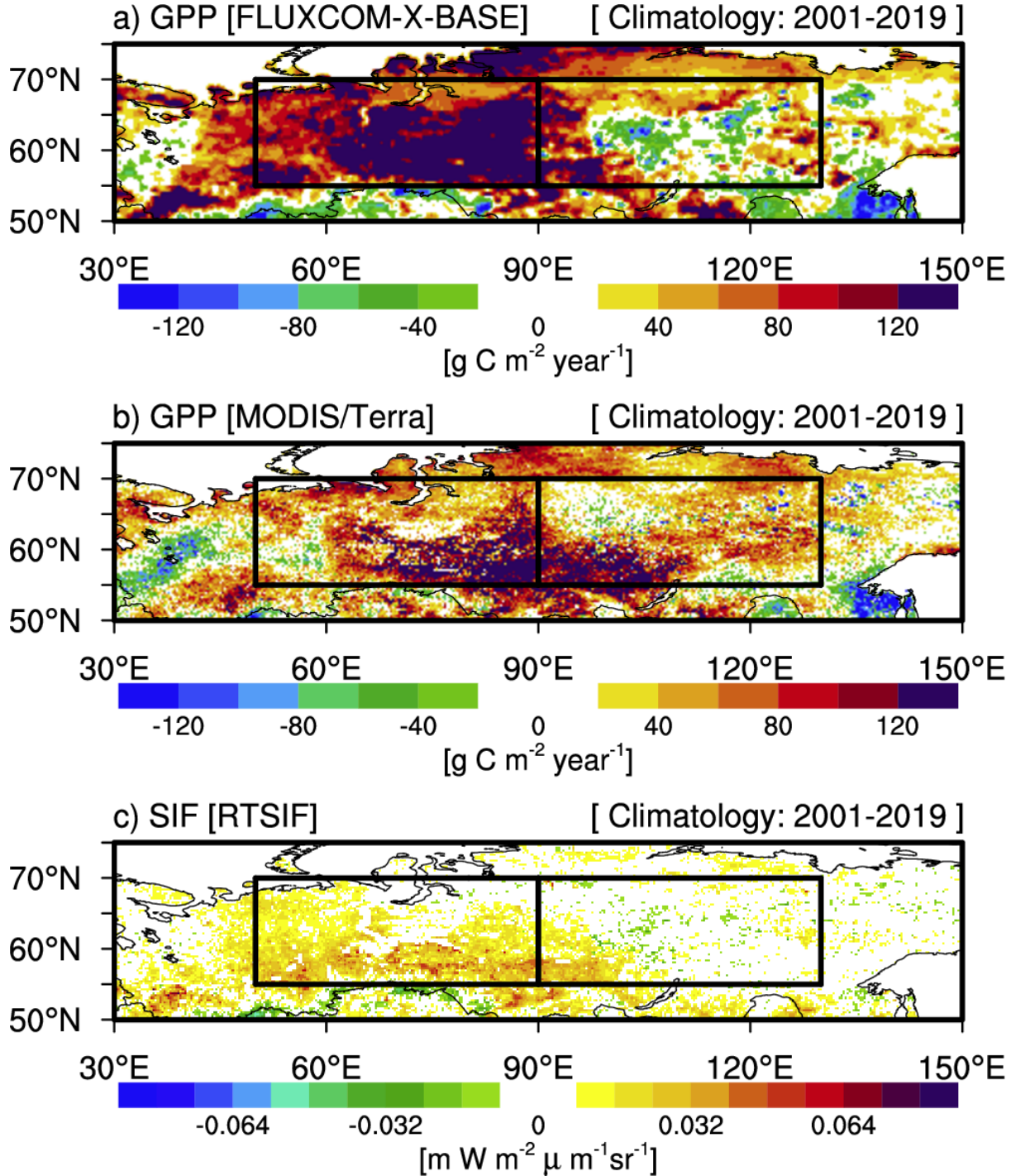


Figure S3. The spatial patterns of annual GPP and SIF anomalies in 2020 over Siberia relative to the climatology of 2001 to 2019. The panels show (a) GPP from FLUXCOM-X-BASE, (b) GPP

from MODIS/Terra, and (c) SIF from RTSIF. Each dataset provides spatial distributions of indicator for vegetation productivity. The black colored boxes indicate the study area in Siberia, focusing on differences in productivity across various regions. Color scales represent GPP in $\text{g C m}^{-2} \text{ year}^{-1}$ for (a) and (b), and SIF in $\text{m W m}^{-2} \mu\text{m}^{-1} \text{ sr}^{-1}$ for (c).

3.3 Temporal evolution of GPP and associated variables

Figure 4 shows monthly anomalies of T_{2m} , GPP, LAI, Prcp, SW_{dn} , and SMC from April to August in 2020 relative to the 2001–2019. Anomalies of T_{2m} , GPP, and LAI were highly positive in West Siberia over the ‘During HW’ period, indicating remarkable enhancement of vegetation growth by the 2020 HW (Figures 4a-4c). Particularly in May, the anomalies of GPP and LAI were $33.3 \text{ g C m}^{-2} \text{ month}^{-1}$ and $0.7 \text{ m}^2 \text{ m}^{-2}$, respectively, which were abnormally high compared to other years (Figures 4b and 4c). Larger Prcp anomalies during this period in 2020 suggest sufficient moisture supply from the atmosphere to the land surface (Figure 4d). Negative anomalies of SW_{dn} in 2020 were relatively small (Figure 4e). The SMC anomaly was positive in April and then became negative in May (Figure 4f). Positive anomalies of T_{2m} , GPP, and LAI, as well as the negative anomaly of SMC in May, tended to continue in the following months from June to August except for T_{2m} anomaly in June (Figures 4a, 4b, 4c, and 4f). For instance, GPP anomalies for the ‘After HW’ period were $8.9 \text{ g C m}^{-2} \text{ month}^{-1}$ in July and $6.1 \text{ g C m}^{-2} \text{ month}^{-1}$ in August. Prcp and SW_{dn} showed negative and positive anomalies in this period, respectively with relatively small magnitudes (Figures 4d and 4e). The results suggest the anomalously high GPP values in the ‘During HW’ period and subsequent summer months contributed to a notable enhancement in GPP_{ann} across West Siberia in 2020, despite a considerable soil moisture deficit in summer.

In East Siberia, the 2020 HW led to anomalous increases of T_{2m} , GPP, and LAI for the ‘During HW’ period, particularly in May, similar to the case in West Siberia (Figures 4g-4l). Consequently, East Siberia also experienced a notable increase in LAI and GPP during the HW period. These positive GPP and LAI anomalies, which were associated with the warming, were sustained in June (Figures 4g-4i). However, in July, when the annual maximum GPP typically occurred, anomalies of individual variables exhibited contrasting patterns. Negative T_{2m} and SW_{dn} , along with positive Prcp and SMC anomalies led to cold and wet climatic conditions (Figures 4g, 4j-4l). As a result, GPP and LAI anomalies in July 2020 were $-11.4 \text{ g C m}^{-2} \text{ month}^{-1}$ and $0.3 \text{ m}^2 \text{ m}^{-2}$, respectively, which were smaller than the respective minimum anomalies for 2001–2019 (Figures 4h and 4i). These negative GPP and LAI anomalies can contribute to marginal increase in GPP_{ann} in East Siberia.

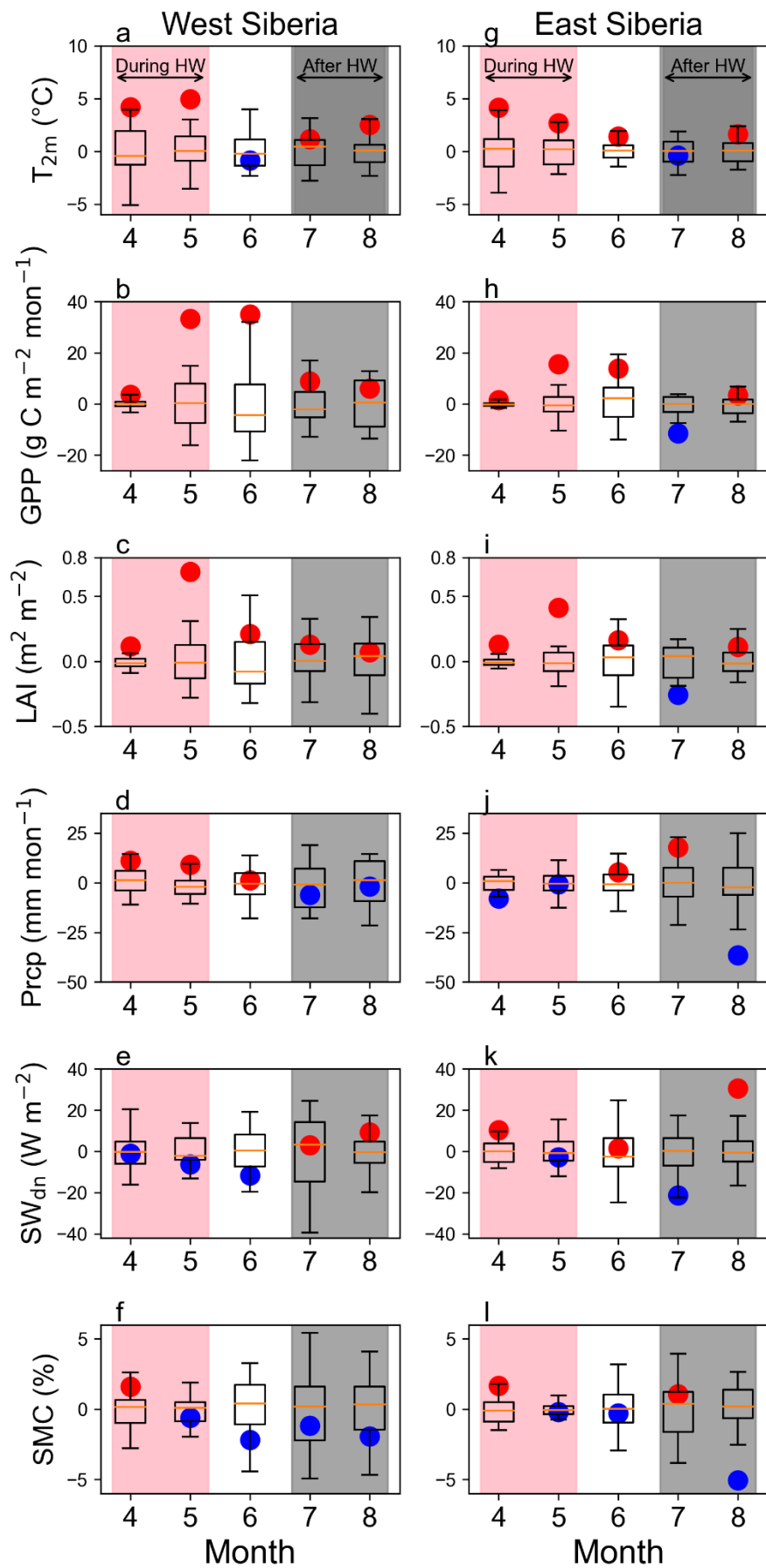


Figure 4. Box plots of monthly anomalies of air temperature a) (T_{2m} , °C), b) gross primary production (GPP, $\text{g C m}^{-2} \text{ month}^{-1}$), c) leaf area index (LAI, $\text{m}^{-2} \text{ m}^{-2}$), d) precipitation (Prcp, mm month^{-1}), e) downward shortwave radiation (SW_{dn} , W m^{-2}), and f) soil moisture content (SMC, %) from April to August relative to the 2001–2019 mean in West Siberia. g-l) same to the a-f), but for East Siberia. Individual boxes represent full ranges of anomalies for 2001–2019, and inner boxes represent 25–75th percentile ranges. The 2020 anomalies are denoted by red and blue star markers representing positive and negative anomalies, respectively. Pink and dark gray shaded areas represent the ‘During HW’ and ‘After HW’ periods, respectively.

3.4 Sensitivity of GPP_{ann} to spring temperature

The sensitivity of GPP_{ann} to spring mean T_{2m} for 2001–2019 was further examined to quantify the contribution of spring temperature to GPP_{ann} (Figure 5). We found that GPP_{ann} was enhanced as increasing spring T_{2m} in both West and East Siberia, which explained 16-20% of the variability in GPP_{ann} , with different sensitivities between the two regions (Figure 5a). The sensitivities of GPP_{ann} to spring T_{2m} in West and East Siberia were $7.9 \text{ g C m}^{-2} \text{ year}^{-1} \text{ }^{\circ}\text{C}^{-1}$ and $5.1 \text{ g C m}^{-2} \text{ year}^{-1} \text{ }^{\circ}\text{C}^{-1}$, which were significant at the 95% and 90% confidence level, respectively, implying a higher GPP sensitivity in West Siberia. The 2020 anomalies of GPP_{ann} and T_{2m} in West and East Siberia were generally aligned with the climatological relationship between GPP_{ann} and T_{2m} for 2001-2019 in both regions (Figure 5a). This indicates different GPP_{ann} sensitivity to spring T_{2m} between West and East Siberia was maintained under an anomalous HW occurred. The spatial distribution of GPP_{ann} sensitivity to spring T_{2m} clearly showed the regional difference (Figures 5a and 5b). In West Siberia, the positive relationship between GPP_{ann} and spring T_{2m} was significant at a 95% confidence level over more than 43.5% of the domain, particularly within 65° - 90°E and 55° - 67°N (Figure 5b). The sensitivities of GPP_{ann} to spring T_{2m} were generally positive in East

Siberia, but only 19.7% of this region show significant (Figure 5b). These results suggest that the enhancement of GPP_{ann} due to spring HW is more notable in West Siberia relative to East Siberia.

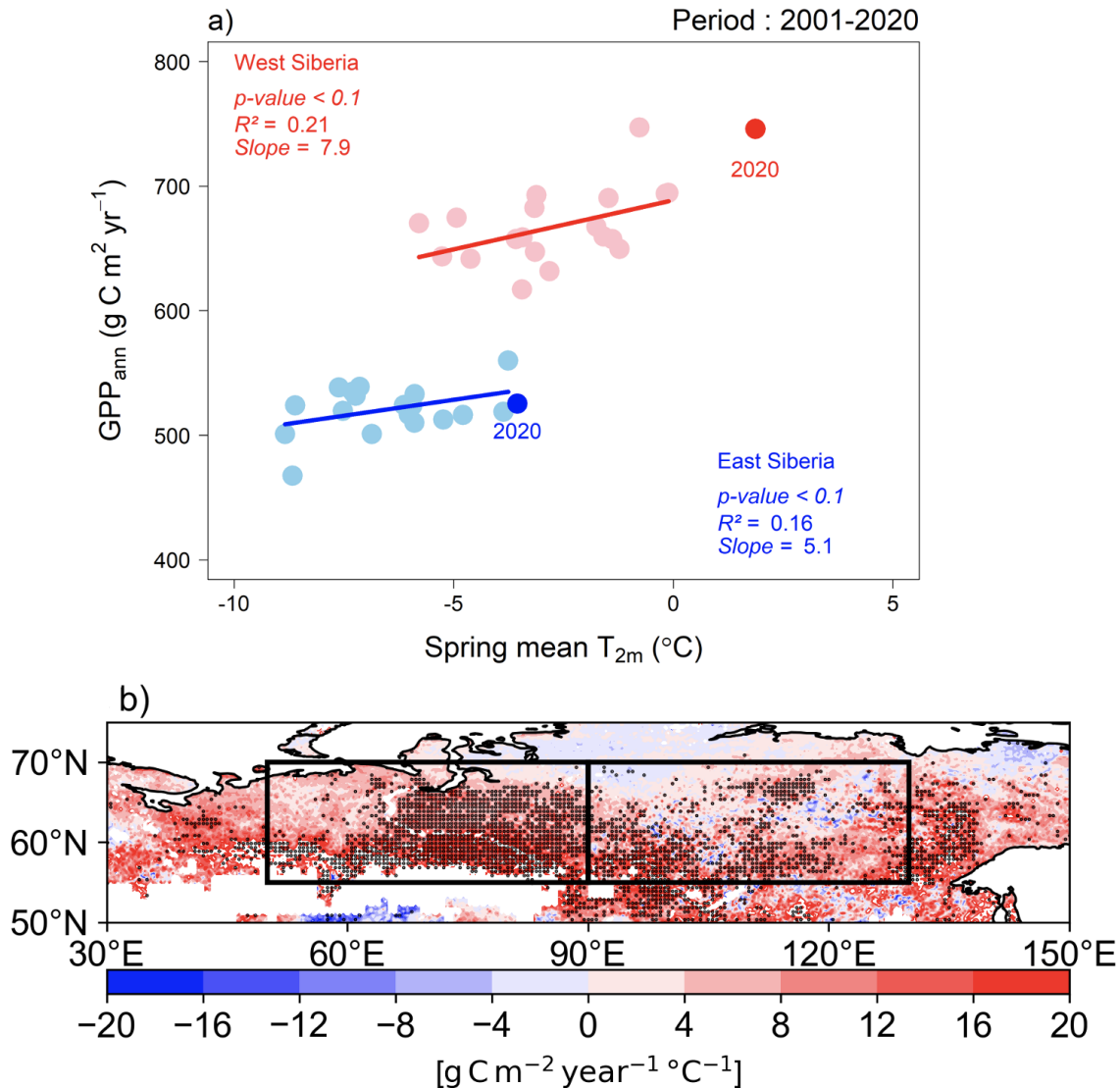


Figure 5. (a) Scatter plots of annual GPP (GPP_{ann} , $g\ C\ m^{-2}\ yr^{-1}$) versus spring temperature (T_{2m} , $^{\circ}C$) in West and East Siberia. Pink and light blue filled circles denote values of individual years for 2001–2019 in West and East Siberia, respectively. The red and blue circles represent values for 2020 in West and East Siberia, respectively. The slopes of the linear regression line were

calculated for the 2001–2019 period. (b) Spatial distribution of regression coefficient for GPP_{ann} and T_{2m} across Siberia. The black hatching indicates that regression coefficients are significant at $p < 0.05$. We masked out cropland areas using the GLDAS (Global Land Data Assimilation System) land cover type.

4 Discussion

4.1 Positive impacts of the 2020 Siberian HW on GPP_{ann}

We showed that the 2020 Siberian HW significantly induced larger GPP_{ann} increase in West Siberia than in East Siberia because of a larger GPP_{ann} sensitivity to spring T_{2m} . These regional responses of GPP_{ann} to the 2020 Siberian HW could be a good example of the impact of anomalous warming and respective vegetation growth during spring on seasonal and annual GPP over Siberia. In West Siberia, GPP anomalies were positive even after the end of HW despite a notable decrease in soil moisture, which was contrasting to some previous assessments suggesting summer browning due to early vegetation growth and subsequent soil moisture depletion (Buermann et al., 2018; Gloege et al., 2022; Lian et al. 2024). This result suggests that, as observed in 2020, the negative impact of soil moisture deficit in summer could be less important in West Siberia if the moisture supply from snowmelt during spring is sufficient. In the case of East Siberia, the increased GPP during spring was approximately equivalent to a remarkable GPP decrease in July. This suggests that a possibility that GPP increment due to anomalous spring warming can compensate the GPP variability in the following seasons. Consequently, the GPP_{ann} responses to the 2020 Siberian HW indicate a positive impact of abnormal heat extreme and relevant early vegetation growth on annual vegetation productivity in Siberia for this particular event.

4.2 Regional contrast of the 2020 GPP_{ann} anomalies between West and East Siberia

The 2020 GPP_{ann} anomalies in Siberia was consistent with higher sensitivity of GPP_{ann} to spring temperature in West Siberia than in East Siberia, suggesting that regionally different responses of GPP_{ann} to spring warming are climatological phenomena rather than an instantaneous feature shown in 2020. These regional differences might be fundamentally associated with the contrasting distribution of plant functional types and vegetation species between West and East Siberia in conjunction with topographical characteristics and mean climate (Sato et al. 2020; Fan et al. 2023; Dolman et al. 2012). For example, Scots pine, Siberian pine, and spruce forests are mainly distributed in West Siberia, while East Siberia is characterized by more widespread larch and fewer needle-leaf coniferous species (Kharuk et al. 2021). Hence, further analyses considering the differences in plant functional types or tree species would help to understand the different GPP responses to the warming and relevant HW events as suggested in previous assessments (Flach et al. 2018; Li et al. 2023).

The spatial pattern of GPP_{ann} anomalies was highly consistent with $Snowmelt_{end}$ anomalies in 2020, suggesting that the end timing of snowmelt was one of the important factors determining GPP_{ann} . For 2001–2019, the GPP_{ann} sensitivities to $Snowmelt_{end}$ were $-3.2 \text{ g C m}^{-2} \text{ year}^{-1} \text{ day}^{-1}$ and $-2.9 \text{ g C m}^{-2} \text{ year}^{-1} \text{ day}^{-1}$ in West and East Siberia, respectively, which were significant ($p < 0.05$) (Figure S4). This result aligns with previous studies showing that early $Snowmelt_{end}$, caused by spring warming, and provides favorable conditions for vegetation growth through ample moisture supply (Kwon et al., 2020; Gloege et al., 2022). In addition, the contrasting $Snowmelt_{end}$ anomalies in 2020 between West and East Siberia were explained by the distinct sensitivity of $Snowmelt_{end}$ to spring temperature in the two regions. This pattern was also captured by other satellite-based snow cover product (Robinson et al. 2012) (Figure S5). In West Siberia, the regional mean $Snowmelt_{end}$ advanced by $1.3 \text{ days } ^\circ\text{C}^{-1}$ ($p < 0.05$) as spring

temperature increased, whereas the relationship between $\text{Snowmelt}_{\text{end}}$ and spring temperature was insignificant in East Siberia (Figure S6). This indicates that an increase in spring temperature can amplify the regional contrast in $\text{Snowmelt}_{\text{end}}$ anomalies and respective GPP_{ann} anomalies between West and East Siberia, as observed in the 2020 HW case. Hence, additional studies examining variations in $\text{Snowmelt}_{\text{end}}$ under a future warmer climate would aid our understanding of regional differences in vegetation growth and productivity over Siberia.

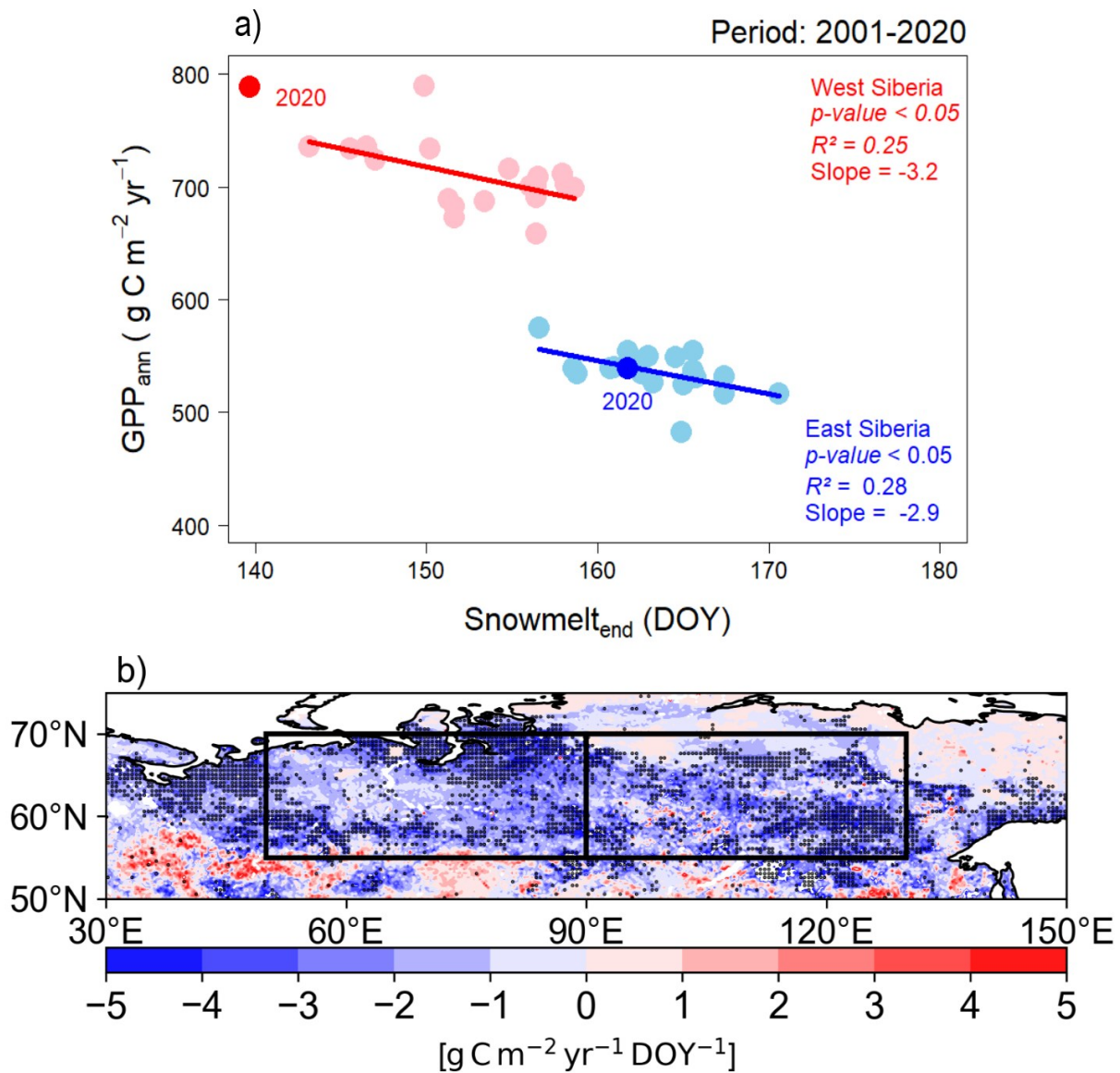


Figure S4. (a) Scatter plots of annual GPP (GPP_{ann} , unit of $g\ C\ m^{-2}\ yr^{-1}$) to the end-of-snowmelt date ($Snowmelt_{end}$, unit of DOY) in West and East Siberia. Pink and light blue filled circles denote values of individual years for 2001–2019 in West and East Siberia, respectively. Red and blue circles represent values for 2020 in West and East Siberia, respectively. The slopes of the linear regression line were calculated for the 2001–2019 period. (b) Same as Figure 5 but for the slope of GPP_{ann} and $Snowmelt_{end}$.

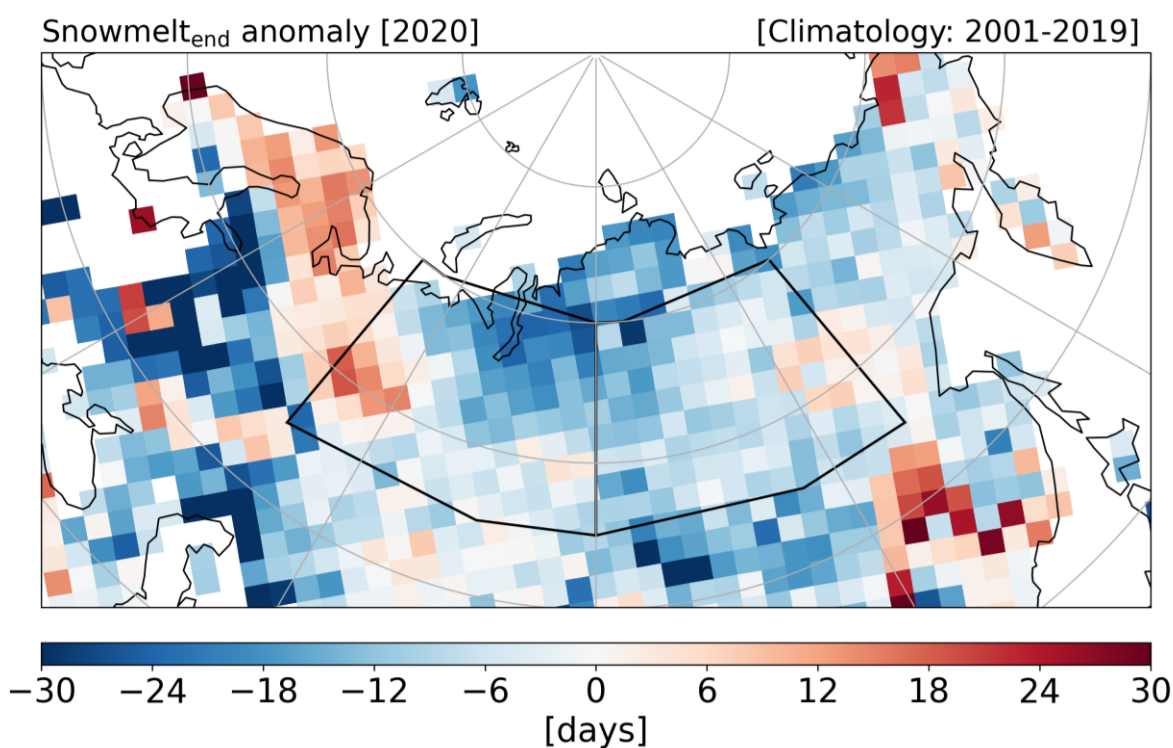


Figure S5. The spatial distributions of the end-of-snowmelt date ($Snowmelt_{end}$) anomaly (unit of days) in 2020 estimated using NOAA snow cover extent data. The weekly data was aggregated into daily to calculate $Snowmelt_{end}$ for each grid cell as explained in Section 2.3.

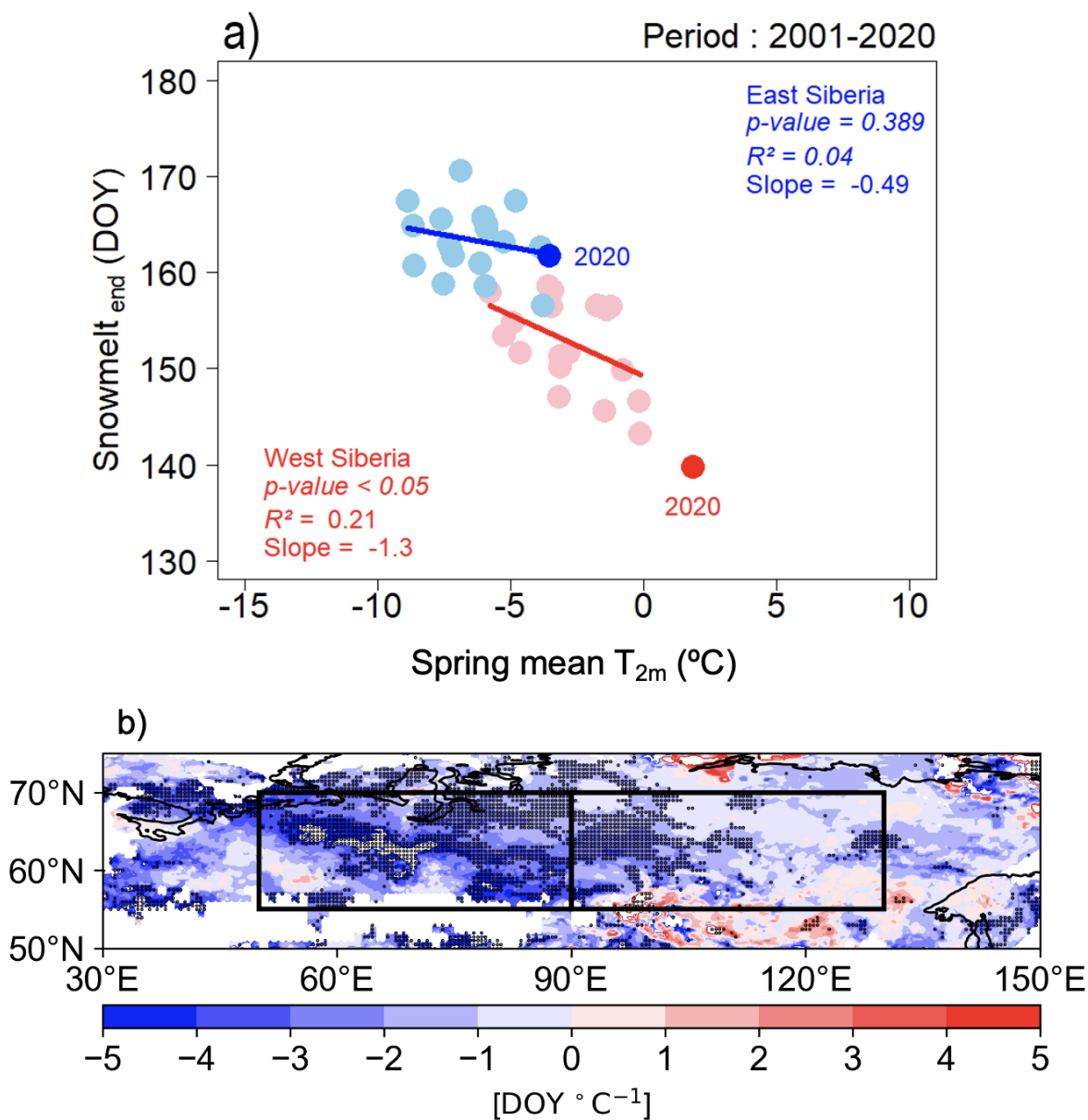


Figure S6. Same as Figure 5 but (a) for the end-of-snowmelt date (Snowmelt_{end}, unit of DOY) to spring mean T_{2m} (March–April–May, unit of °C). (b) for the slope of Snowmelt_{end} and spring mean T_{2m} .

4.3 Role of soil respiration in influencing the net CO₂ uptake

We demonstrated that the 2020 Siberian HW caused anomalous enhancements in GPP across Siberia. However, increased GPP does not necessarily lead to the increase in CO₂ sink capacity because soil respiration generally rises with increasing surface temperature. A previous study indicates that enhanced soil respiration during the shoulder season offset the increased spring carbon uptake, resulting in decreased annual net CO₂ uptake in 2020 (Kwon et al., 2020). In addition, the limited representation of the temperature sensitivity of soil respiration within the carbon cycle model makes the HW impacts on net carbon uptake uncertain, particularly in cold regions. For example, the model with seasonally varying Q₁₀ values significantly reduced the overestimation of soil respiration in cold region especially in winter and spring (Contosta et al., 2013; Kimball et al., 2022).

4.4 Implications for vegetation carbon uptake over Siberia under future climate

Although our results were based on a case study, the observed GPP_{ann} responses to the 2020 Siberian HW provide valuable insights into future GPP_{ann} changes in Siberia. Warming-induced earlier snowmelt and permafrost thawing may increase the frequency and severity of extreme HWs in Siberia (Yang et al., 2023; Zhou et al., 2021; Zittis et al., 2024). The GPP_{ann} in Siberia is likely to increase in the future due to an increasing possibility of HW occurrence in spring and subsequently advanced beginning of photosynthesis. Furthermore, projected spring warming may amplify the differences in GPP_{ann} between West and East Siberia, given the higher GPP_{ann} sensitivity to spring temperature in West Siberia. Therefore, further assessments considering changes in temperature, tree species, and hydro-climate conditions would be necessary to fully understand the Siberian GPP_{ann} responses to future climate change.

5 Conclusions

We examined the impact of extremely high spring temperatures on GPP_{ann} over Siberia by analyzing the 2020 Siberian HW case. The HW increased GPP_{ann} by 10% in West Siberia despite soil moisture deficit, while East Siberia experienced insignificant GPP_{ann} change. These differences in GPP_{ann} anomalies aligned with the higher sensitivity of GPP_{ann} to spring temperatures in West Siberia than in East Siberia. Results suggest that the warming trend in spring, combined with possible extreme heat events, could elevate annual carbon uptake in Siberia by outweighing the negative impact of other climate conditions, such as soil moisture depletion, particularly in West Siberia. Further, as HWs are expected to occur more frequently in a warmer future, our insight into the response of vegetation carbon uptake to extreme HW event during spring can aid in understanding potential changes in carbon uptake over Siberia in future.

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The raw data used in this study were all obtained from the source cited in the reference. Figures were made with R version 4.3.0 (R Core Team, 2023) with dplyr package (Wickham et al., 2023) available under the GPL-3 license at <https://www.r-project.org/>. Maps were generated using NCL version 6.6.2 (NCAR, 2019) and Python 3.8.16 along with xarray 2022.11.0 (Hoyer & Hamman, 2017), numpy 1.24.3 (Harris et al., 2020), pandas 1.5.3 (McKinney, 2010), matplotlib 3.7.1 (Hunter, 2007), and cartopy 0.21.1 (Met Office, 2010–2015).

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