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Distinct magnitude asymmetries of daily extreme anomalies in gross primary productivity between forests and non-forests

Li, Jianying ; Kug, Jong-Seong ; Park, So-won ; Zhai, Panmao ; Huang, Mengtian ; Kim, Jin-Soo

Abstract: The magnitude asymmetry between positive and negative extreme anomalies in gross primary productivity (GPP) and the underlying mechanism have been investigated based on daily records from the data-driven and in situ datasets. Distinct magnitude asymmetries of daily GPP extreme anomalies (DGEAs) have been identified between forested and non-forested areas. Forested areas are dominated by negative asymmetries, manifesting as the magnitude of negative DGEAs significantly larger than that of their positive counterparts; while non-forested areas are dominated by positive asymmetries. These distinct asymmetric features are due to the different climatic constraints between forests and non-forests. We found that solar radiation is the dominant climatic controller of the daily variation in GPP of forests. Due to the existence of a light saturation point, vegetation productivity is less sensitive to extremely high values of solar radiation than it is to the extremely low, thus leading to the negative asymmetries. For the non-forested areas, however, the daily variation in GPP depends on the preceding 3 6-day soil moisture conditions. Heavy precipitation is more effective at causing strong and persistent soil moisture anomalies, as soil water can penetrate to deeper soil layers. Therefore, strong positive asymmetry of precipitation anomalies results in the positive asymmetry of soil moisture anomalies and thus leads to the positive asymmetry of DGEAs. Due to the significant asymmetry in the DGEAs, the cumulative effect of DGEAs further rectifies the interannual variability of annual GPP, implying the importance of asymmetry in the DGEAs to changes of terrestrial carbon cycle.

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**Distinct Magnitude Asymmetries of Daily Extreme Anomalies in Gross
Primary Productivity between Forests and Non-Forests**

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25

Abstract

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45 **Keywords:**

46 Daily Gross Primary Productivity Extreme Anomaly, Asymmetry, Forest and Non-forest,
47 Terrestrial Ecosystem, Interannual Variation

1. Introduction

Terrestrial gross primary productivity (GPP) plays a critical role in offsetting the anthropogenic CO₂ emissions (Friedlingstein et al. 2020). Studying the spatial-temporal variations in GPP and their underlying mechanisms are thus key to understanding the global carbon cycle (Jung et al. 2017; Wang et al. 2016; 2018; 2021; Zhu et al. 2019). GPP is highly sensitive to short-term extreme climatic variations. Large precipitation pulses could lead to significant GPP increases in water-limited ecosystems (Heisler-White et al. 2008; Guo et al. 2016). For temperature-limited ecosystems, extremely high temperature could impair electron transport and RuBisCo enzymatic capacities severely, thus resulting in a dramatic GPP decline (Larcher 2003; Schulze et al. 2005; Huang et al. 2019). In addition to the immediate variation, daily GPP extremes, with the GPP values exceeding a certain percentile, also play an important role in the interannual variation of terrestrial carbon exchange (Zscheischler et al. 2016). Therefore, studying the daily GPP extremes is not only crucial for understanding the impacts of short-term climatic variations but also beneficial for further understanding the interannual variability of terrestrial carbon exchange.

Note that the response of vegetation productivity to daily climatic variations is nonlinear (Turner et al. 2003; Medvigy et al. 2010; Oliphant et al. 2011; Ahlstrom et al. 2015). For example, the light-use efficiency of vegetation is high when solar irradiance is low but strongly decreases when irradiance becomes excessively high (e.g., Turner et al. 2003), indicating that GPP is more sensitive to reductions in shortwave radiation (SR). In semi-arid and arid ecosystems, the response of GPP increases with precipitation (Guo et al. 2016; Knapp et al. 2017), implying that heavy precipitation influences vegetation productivity more efficiently. Therefore, for the daily GPP extreme anomalies (DGEA), defined as the large-magnitude GPP anomalies in the tails of its probability distribution (Zscheischler et al. 2014), we speculate that

an asymmetry in the magnitude might exist between the positive DGEAs and their negative counterparts (see detailed definitions in section 2.2).

Previous works studied the short-term climatic drivers of positive DGEAs (Zscheischler et al. 2016) and negative DGEAs (Teuling et al. 2010; Frank et al. 2015), separately. However, whether the magnitudes of positive and negative DGEAs show any significant asymmetry is still unclear. What mechanism leads to such an asymmetry of DGEAs also remains elusive. With the magnitude asymmetry, the accumulation of DGEAs could further lead to interannual variation of annual GPP. Therefore, studying the asymmetry of DGEAs is also beneficial to understand the interannual variation of annual GPP. Moreover, as the intensity of daily climatic variations is projected to significantly increase in the future (Alexander et al. 2006; IPCC 2012; Sillmann et al. 2013; Im et al. 2017; Dahl et al. 2019), the asymmetry of DGEAs might also be amplified and become increasingly important in understanding the change of terrestrial carbon exchange. Therefore, one objective of the present study is to analyze the magnitude asymmetries of DGEAs, reveal the underlying mechanism and then explore the contribution of asymmetry in DGEAs to the interannual variation of annual GPP. Since the response of vegetation productivity to climatic variations varies with ecosystem (Seddon et al. 2016), the asymmetric features of DGEAs might differ among different ecosystem types. Thus, comparing the asymmetric features of DGEAs and the underlying mechanism in different ecosystem types is another objective of the present study.

The rest of the paper is organized as follows. Section 2 describes the data and methods used to explore the DGEAs. The asymmetric characteristics of DGEAs are analyzed in Section 3. Section 4 reveals the nonlinear mechanism causing the negative asymmetries over forested areas. Section 5 explains the positive asymmetries over the non-forested areas. Section 6 presents the contribution of asymmetry in DGEAs to the interannual variation of annual GPP. Finally, a summary and discussion are given in Section 7.

97

98 **2. Data and methods**

99 *2.1. Data*

100 Daily GPP data derived from the FLUXCOM dataset (Jung et al. 2017) were used to
101 calculate the DGEAs globally. This high horizontal resolution ($0.5^\circ \times 0.5^\circ$) dataset was
102 obtained through three machine learning algorithms, with each machine learning algorithm
103 trained on 224 FLUXNET-based GPP estimates. Six versions of FLUXCOM GPP data were
104 derived from the three machine learning algorithms combined with the daytime (Lasslop et al
105 2010) and nighttime (Reichstein et al 2005) partitioning methods. These two partitioning
106 methods were applied to obtain ecosystem respiration and GPP from the measured net
107 ecosystem exchange. Each of the six versions was viewed as an ensemble. DGEAs were first
108 identified and analyzed based on each ensemble, and then the multi-ensemble mean was
109 calculated.

110 Daily precipitation, two-meter air temperature, and SR data from the CRUNCEPv7 dataset
111 (Viovy 2018) were applied to explore the climatic drivers of DGEAs. This dataset has a
112 horizontal resolution of 0.5° longitude $\times$ 0.5° latitude. Daily soil moisture (SM) was calculated
113 as the sum of surface and root-zone SMs, both of which were derived from the high-resolution
114 ($0.25^\circ \times 0.25^\circ$) GLEAM dataset (Global Land Evaporation Amsterdam Model; Martens et al.
115 2017). All the gridded data listed above were extracted for the same period of 1980–2013.

116 To examine the results revealed by the FLUXCOM GPP, two versions of daily GPP records
117 (GPP_NT_VUT_MEAN and GPP_DT_VUT_MEAN) at 15 sites from the FLUXNET2015
118 dataset were also analyzed. In the GPP parameters, NT (DT) indicates that the GPP values were
119 derived through the nighttime (daytime) partitioning method, VUT means that the variable
120 u_{star} (friction velocity) threshold for each year was applied, and MEAN indicates that the GPP

values were derived by averaging among 40 versions of GPP estimates. The 15 sites were selected based on three criteria: (1) the location of the site was within one of the seven targeted domains (as discussed in Section 3); (2) the availability of GPP data spanned at least three years, and more than 70% of the available GPP was flagged as valid (with $NEE_VUT_MEAN_QC \geq 0.8$); and (3) the vegetation type of the site was consistent with that of the target domain. Daily precipitation, temperature and SR derived from the selected sites were used to study the major climatic drivers and nonlinear mechanism inducing the asymmetry of DGEAs at these sites.

2.2. Methods

The daily GPP anomalies were derived via the following procedures. Firstly, as the vegetation productivity of a plant changes with its phenology, the daily GPP anomaly on each calendar day was defined as the deviation from the multi-year average on this day, as done by many previous studies (e.g., Flach et al. 2020; Xu et al. 2020). Considering the probability distribution of daily GPP anomalies may change with the global warming condition, we then removed the long-term trend by subtracting the linear trend for each day through least-squares fitting (Jung et al. 2017). Since vegetation productivity during the non-growing season is very weak, we only analyzed the daily GPP anomalies during the growing season. Following the method of Zhu et al. (2016), the growing season was determined from the daily LAI3g time series using TIMESAT program (Jönsson and Eklundh, 2002; 2004). We firstly applied a Savitzky-Golay filter using a quadratic polynomial in the fitting. Based on the fitted time series, the start (end) day of the growing season was defined as the day when the LAI value is greater than 0.1 and has increased (decreased) by 15% of the amplitude of the growing season. Due to sub-optimal temperatures and low sunlight levels, vegetation may remain green during the dormant season in higher latitudes of the northern hemisphere. Therefore, the above obtained growing season were further refined by excluding the ground-freeze period.

As we focused on exploring the magnitude asymmetry between the positive and negative DGEAs, and how the accumulation of DGEAs contributes to the interannual variation of annual amount, the DGEAs at each grid cell or site were defined according to their probability distribution during the growing season of each year. In this way, the number of positive DGEAs remains constant during the years of 1980–2013 and is always equal to that of negative DGEAs.

The daily GPP anomalies during the 2014 at the site GF-Guy were selected as an example to display the definition of positive and negative DGEAs. This site was chosen because the magnitude asymmetry is stronger than that at the other sites or pixels (Fig. 1, 2a and Tab. 1). The values that exceed the 90th percentile were defined as the positive DGEAs, while the negative DGEAs were defined as the values below the threshold of the 10th percentile (Fig. 1). The magnitude asymmetry of DGEAs was then defined as the arithmetic mean of all the selected positive and negative DGEAs, with positive (negative) asymmetry indicating that the magnitude of positive DGEAs is larger (smaller) than that of their negative counterparts. We conducted the two-sample *t*-test (Cressie and Whitford 1986) between the absolute values of positive and negative DGEAs. When the absolute value of positive DGEAs is significantly larger (smaller) than that of the negative ones, the positive (negative) asymmetry is considered as significant. To examine whether the revealed asymmetries are sensitive to the choice of thresholds, we also used the 95th (5th) percentile as the threshold for positive (negative) DGEAs. The obtained asymmetric features (not shown) are highly consistent with those based on the 90th and 10th percentiles. For brevity, we only present the results with the 90th and 10th percentiles applied as thresholds.

Lag-correlations between GPP and climatic variable (SR, precipitation, SM, and temperature) anomalies were calculated for each grid cell or site, with the time lag ranging from 15 to 0 days. We identified the time lag (t_{lag}) when the absolute value of lag-correlation

coefficients reaches its maximum for each climatic variable and then applied these time lags to the multiple linear regression model in the following equation (Eq. (1)).

$$GPP(t) = a*SR(t-t_{lagSR}) + b*Pre(t-t_{lagPre}) + c*Tmp(t-t_{lagTmp}) + d*SM(t-t_{lagSM}) \quad (1)$$

where Pre and Tmp stand for precipitation and temperature, respectively. a–d represent the partial regression coefficients for each climatic variable.

We also used the 10th (90th) percentile as the threshold to select the negative (positive) extreme anomalies of each climatic variable and then evaluated its asymmetry with the same method as GPP. To further examine how the extreme anomalies of climatic variable lead to the asymmetry of DGEAs, composites of GPP anomalies against the positive/negative extreme anomalies of each climatic variable were conducted. The composite of GPP was calculated as the arithmetic mean of GPP anomalies on t_{lag} days after the occurrence of positive (negative) extreme anomalies of the corresponding climatic variable on each grid cell. To quantitatively evaluate the contribution of DGEAs' accumulation to the interannual variation of annual GPP, the variance of annual GPP explained by the accumulation of DGEAs is calculated as the square of their correlation coefficient (Nakagawa and Schielzeth 2013).

3. Asymmetric features of daily GPP extreme anomalies

Figure 2a shows the global pattern of asymmetry in the DGEAs. The DGEAs exhibit distinctive magnitude asymmetries among different regions. Most FLUXCOM ensembles show stronger negative DGEAs over the Amazon (AM; 10°S–7.5°N, 45°–80°W), Maritime Continent (MC; 10°S–7.5°N, 95°–155°E), Korean Peninsula–Japan (KJ; 30°–45°N, 125°–145°E), northeastern America (NEA; 37.5°N–47.5°N, 60°–92.5°W) and northern Europe (NEU; 55°–65°N, 5°–70°E), while larger positive DGEAs are observed over northwestern America (NWA; 25°–40°N, 97.5°–115°W), Australia (AU; 20°–32.5°S, 115°–152.5°E),

central India and some areas of South Africa. Note that larger areas are occupied by the negative asymmetries, accounting for 82.7% of the regions that have significant asymmetries (Fig. 2b).

Based on the plant functional type (PFT) derived from the majority class of annually resolved MODIS land cover product (collection 5, Friedl et al. 2010), we found that areas with negative asymmetries are mainly dominated by four forested PFTs: evergreen needleleaf forest (ENF), evergreen broadleaf forest (EBF), deciduous broadleaf forest (DBF) and mixed forest (MF), accounting for 70.2% of these areas (Fig. 2b). In contrast, the positive asymmetries mainly come from the following five non-forests: open shrubland (OSH), woody savanna (WAS), savanna (SAV), grassland (GRA), and cropland (CRO), occupying 93.9% of the areas with positive asymmetries. Therefore, we mainly focused on exploring the negative (positive) asymmetries in the above four forested PFTs (five non-forested PFTs) in the following sections.

To reveal the mechanism for distinctive asymmetric features of DGEAs between forested and non-forested areas, seven key regions were selected (Fig. 2a). Two criteria were applied to this selection. The occupation of forest (non-forest) biomes is larger than 95%. Moreover, at least one FLUXNET site with valid data spanning longer than three years is located within the selected domain; thus, the results derived from the FLUXCOM dataset could be further examined. Accordingly, the following five regions were selected as representatives for the forested areas with stronger negative DGEAs: AM, MC, KJ, NEA, and NEU. As shown in Fig. 3a, the selected five regions include all the four forested PFTs that feature negative asymmetries of DGEAs, thus they could work as good representatives for the target forested areas. Although significantly positive asymmetries are shown over some areas of South Africa and central India, no site is available within these two domains. As the five non-forested PFTs with positive asymmetries of DGEAs are all included in the NWA and AU (Fig. 3b), these two regions were chosen to represent the non-forested areas.

Table 1 displays the asymmetry of DGEAs derived from the 15 FLUXNET sites within the seven selected regions. Stronger negative DGEAs are observed over the forest-dominated AM, MC, KJ, NEA, and NEU, with most available sites showing negative asymmetry for GPP derived from both the daytime (100%) and nighttime (80%) partitioning methods. These results are consistent with those from the FLUXCOM GPP. For the non-forest-dominated NWA and AU, positive asymmetries are found at all available sites for both partitioning methods (Tab. 1), which is also in agreement with the FLUXCOM dataset.

4. Negative asymmetry over forested areas

To explore the relative importance of SR, precipitation, temperature, and SM in modulating the daily variation of GPP over the forested areas, multiple linear regression of GPP was conducted against the standardized time series of these four climatic variables. Results from the site observations show that SR predominates over the other climatic variables, with the partial regression coefficient of SR much larger than that of the other climatic variables (Fig. 4b). For the results from FLUXCOM dataset (Fig. 4a), SR also ranks first over the AM, KJ, NEA and NEU. Over the MC, although SM ranks first, its partial regression coefficient is only slightly larger than that of SR, indicating that SR is also an important controller over the MC. The results from FLUXNET show that precipitation has a significantly negative influence on the daily variations of GPP anomalies over all the target forested areas (Fig. 4b). However, the influence of precipitation on GPP is positive and insignificant at most grid cells in the results derived from FLUXCOM dataset. For temperature, the results from both FLUXCOM and FLUXNET datasets suggest that its contribution is weak or insignificant. Although the partial regression coefficients derived from FLUXCOM and FLUXNET datasets show some differences, indicating the large uncertainties in the results; results from both datasets suggest

that SR is a significant and common controller over the daily variation of GPP anomalies over all the target forested areas.

Composites of GPP anomalies against the positive/negative extreme anomalies of each climatic variable were further conducted to examine the results of multiple linear regression, and to reveal how extreme anomalies of climatic conditions lead to the asymmetry of DGEAs (Fig. 5). Over the target forested areas, the influences of climatic variables derived from composite analysis are mainly consistent with those revealed in the multiple linear regression (Fig. 5a and 5b). For example, the result of multiple linear regression suggests that SR is positively correlated with GPP on the daily timescale over the AM. In the composite analysis, we also found that positive (negative) extreme anomalies of SR lead to significant increases (decreases) of GPP in this region. As shown in Fig. 5c, GPP anomalies related to the extreme anomalies of SR show significantly negative asymmetries over all the targeted forested areas. Over the NEU, the negative asymmetry related to temperature seems larger than that associated with SR. However, the influence of temperature on GPP is insignificant in the results of multiple linear regression derived from both the FLUXCOM and FLUXNET datasets (Fig. 4a and 4b). Moreover, while the negative extreme anomalies of temperature could induce significant reductions in GPP, their positive counterparts also tend to reduce the vegetation productivity, thus making the spuriously large negative asymmetries. Over the KJ, although the extreme anomalies of precipitation also lead to a significantly negative asymmetry, its magnitude is smaller than the negative asymmetry related to SR.

Multiple linear regression and composite analyses were further conducted in the ENF, EBF, DBF and MF, respectively (Fig. 6a and 6b). In all these four PFTs, SR predominates over the other climatic variables in controlling the daily variation of GPP and the extreme anomalies of SR also lead to significantly negative asymmetries of DGEAs. Therefore, we suggested that

SR plays a major and common role in inducing the significantly negative asymmetries over all the target forested PFTs.

We also conducted composites of SR anomalies against the positive/negative DGEAs to examine whether the negative asymmetry of DGEAs comes from the negative asymmetry of SR anomalies (not shown). It is found that the SR increases associated with the positive DGEAs are almost a mirror to the SR decreases related to the negative DGEAs, with their residuals close to zero. It is therefore indicated that the dominating SR itself is not characterized by obvious asymmetry.

To explore how the symmetric SR anomalies lead to the negative asymmetry of DGEAs, site GF-Guy was again selected as an example to display how GPP changes with SR (Fig. 7a). We interpolated GPP anomalies against the distribution of SR anomalies. The obtained rectangular hyperbola suggests that the sensitivity of GPP to SR changes with the value of SR anomaly. A steep slope of GPP against SR is found when the SR anomaly is lower than its 10th percentile ($dGPP/dSR_{neg}$; $0.048 \text{ gC W}^{-1} \text{ day}^{-1}$), indicating that vegetation productivity strongly decreases with a large reduction in SR. In contrast, the slope is much smaller when the SR anomaly is larger than its 90th percentile ($dGPP/dSR_{pos}$; $0.019 \text{ gC W}^{-1} \text{ day}^{-1}$), less than half of the $dGPP/dSR_{neg}$, implying that a strong increase in SR is less effective at enhancing vegetation productivity. Therefore, the magnitudes of positive DGEAs are much smaller than those of their negative counterparts, resulting in the negative asymmetry at this tropical forest site.

The results from the other selected forest sites also show that $dGPP/dSR_{neg}$ is much larger than $dGPP/dSR_{pos}$, with the magnitude of $dGPP/dSR_{neg}$ more than twice that of $dGPP/dSR_{pos}$ (Fig. 8b). For the results derived from the FLUXCOM dataset, despite some spread among different versions of FLUXCOM GPP, especially over the middle- and high-latitude forests, most ensembles show that $dGPP/dSR_{neg}$ is larger than $dGPP/dSR_{pos}$ over the target forest regions (Fig. 8a), also verifying the nonlinear response of GPP to SR. Note that the differences

between $dGPP/dSR_{neg}$ and $dGPP/dSR_{pos}$ derived from FLUXCOM GPP are smaller than those derived from the site observations over all the targeted forested areas. It suggests that the nonlinear response of GPP to SR is underestimated in the FLUXCOM GPP; therefore, the identified negative asymmetries of DGEAs are also smaller. CO_2 fertilization effect is not included in this data-driven dataset, which could be a possible reason for the smaller magnitude of daily GPP anomalies, and further lead to the smaller negative asymmetries.

Such a change in the sensitivity of GPP to SR mainly comes from the existence of a light saturation point for photosynthesis (Turner et al. 2003; Alton 2008). Light is an irreplaceable energy source for photosynthesis, with a certain level of light energy required to convert into chemical energy and fuel the Calvin cycle for every species (Bonan 2015). Therefore, photosynthetic carbon uptake usually increases with the level of SR, with a rather high sensitivity of GPP to SR. However, at a high level of SR, vegetation productivity is no longer limited by light; rather, it is limited by other environmental factors, such as CO_2 concentration and water availability, thus decreasing the sensitivity of GPP to SR.

Moreover, the changed fraction of diffuse radiation in concert with the level of SR might further enhance the nonlinear response. A large SR decrease usually occurs under cloudy conditions when diffuse radiation dominates, while a large SR increase mainly occurs under cloud-free conditions when direct beam radiation dominates (Oliphant et al. 2011). Under the diffuse radiation, photons from different angles of the sky share the radiation load more evenly across the canopy, thus strongly reducing the fraction of light-saturated foliage and increasing the overall light-use efficiency. Therefore, diffuse radiation is more effective than direct beam radiation at causing changes in vegetation productivity (Gu et al. 2003; Alton 2008). With the dominance of diffuse radiation, a further SR reduction in weak SR level is well accompanied by a reduction in diffuse radiation; thus, the sensitivity of GPP to SR is high. In contrast, as the fraction of diffuse radiation is small, a further SR increase in strong SR level could not

effectively enhance vegetation productivity, further weakening the sensitivity of GPP to SR. Note that the $dGPP/dSR_{pos}$ drops to near-zero (Fig. 9) for the EBF and ENF, while that for DBF is still comparable with its $dGPP/dSR_{neg}$, indicating that light saturation has a stronger influence on the EBF and ENF.

5. Positive asymmetry over non-forested areas

As the annual precipitation is largely exceeded by the potential evapotranspiration over the NWA, this non-forested area is characterized by sandy and arid soil. Therefore, the vegetation productivity is highly constrained by water availability (Sara et al. 1982; Heisler-White et al. 2008). Results of multiple linear regression derived from both FLUXCOM and FLUXNET datasets show that SM plays a dominating role in the daily variation of GPP over the NWA, with the partial regression coefficient of SM more than twice that of the other climatic variables. In the semi-arid sparsely vegetation area over the AU, vegetation productivity is also predominately controlled by the SM (Fig. 10).

According to the composite analysis, we found that positive (negative) extreme anomalies of SM lead to significant increases (decreases) of GPP over both the NWA and AU (Fig. 11a and 11b), and further result in significantly positive asymmetries of DGEAs (Fig. 11c). As the change in SM is determined by the balance between precipitation input and losses from evapotranspiration and runoff (Bonan 2015), with precipitation leading SM by around 3 days in modulating the daily variation of GPP (not shown), the positive asymmetries of DGEAs are also associated with the influence of precipitation (Fig. 11c). Results from similar analyses in each non-forested PFT also show that SM plays the leading role in modulating daily variation of GPP (Fig. 12a), and extreme anomalies of precipitation and SM make the major contributions to the positive asymmetries of DGEAs (Fig. 12b). Therefore, we suggested that

the positive asymmetries over these two non-forested areas mainly come from the influence of water availability.

Over the NWA, the lag-correlation between GPP and SM peaks when GPP lags the local SM by 3–6 days in most areas (Fig. 13a and 13b), implying that the occurrence of positive (negative) DGEAs is associated with a strong increase (decrease) in SM on the previous 3–6 days. The close correlation between GPP and the 3–6-day preceding SM could also be seen in the scatterplot of GPP versus SM anomalies at the US-Wkg site (Fig. 7b). The curve of the interpolated GPP against the distribution of SM anomalies shows that the sensitivity of vegetation productivity to SM is quite stable, with the slope of GPP against SM when SM anomaly is higher than its 90th percentile being almost identical to that when SM anomaly is lower than its 10th percentile. Note that the SM extreme anomalies at this site exhibit evidently positive asymmetry. While the negative SM extreme anomalies mostly range from -12 to $-8 \times 10^{-2} \text{ m}^3 \text{ m}^{-3}$, their positive counterparts are all larger than $12 \times 10^{-2} \text{ m}^3 \text{ m}^{-3}$. As a result, the associated DGEAs show a significantly positive asymmetry. Figure 13c displays that positive asymmetries of SM extreme anomalies are also found at other pixels in the NWA.

The positive asymmetry of SM anomalies comes from the different characteristics of the hydrologic cycle under the condition of small and heavy precipitation inputs. Small precipitation events (corresponding to the negative precipitation extreme anomalies) could only affect the surface soil water content, most of which is consumed by soil evaporation; thus, the associated SM anomaly is rather weak and short-lived. In contrast, when a heavy precipitation event (corresponding to the positive precipitation extreme anomalies) occurs, water can penetrate to a deeper depth where evaporation is negligible (Sara et al. 1982; He et al. 2012; Lauenroth and Bradford 2012); therefore, heavy precipitation events are always followed by a strong and persistent increase in SM (Heisler-White et al. 2008). Over the NWA, the positive asymmetry of precipitation anomalies (Fig. 13d) leads to that of SM (Fig. 13c) and further

results in the positive asymmetry of DGEAs. A similar situation is found over the AU. The GPP over the AU is also strongly associated with the preceding 3–6-day SM (Fig. 14a and 14b). Due to the significantly positive asymmetries of precipitation and soil moisture extreme anomalies (Fig. 14c and 14d), DGEAs also exhibit strong positive asymmetry (Fig. 2a and Tab. 1).

Due to the limitation of available sites, we only selected the NWA and AU as the representatives for non-forested areas with significantly positive asymmetry of DGEAs. In the future, numerical experiments based on process-based carbon cycle models need to be conducted to examine the revealed mechanism in other areas.

6. Contribution of asymmetry in the DGEAs to interannual variation of annual GPP

Due to the existence of asymmetry in the DGEAs, the accumulation of DGEAs could further lead to the interannual variation of annual GPP. As shown in Fig. 15, the standardized time series of the accumulation of DGEAs matches well with that of the annual GPP on the interannual timescale, especially over the AM and MC tropical forests. Over all the target forested and non-forested regions, the accumulation of DGEAs explains more than 85% of the interannual variations in the annual GPP, indicating that the asymmetry of DGEAs makes a significant contribution to the interannual variation of annual GPP.

As the asymmetric features of DGEAs are distinguishable between the forested and non-forested areas, changes in the magnitude asymmetry show different rectifications to the annual GPP. The daily variation of GPP in forests is dominated by SR. Due to the existence of a light saturation point, large-magnitude SR decrease is more effective than SR increase of the same magnitude in modulating GPP, thus leading to the negative asymmetry of DGEAs. Therefore,

the stronger daily fluctuations of SR and the consequently stronger negative asymmetry of DGEAs might further decrease the annual GPP in forests. Figure 16 shows the correlation coefficients between the standard deviation of daily GPP anomalies and annual GPP. The standard deviation of daily GPP anomalies quantifies the extent to which the values differ from zero, thus also representing the magnitudes of positive and negative DGEAs. Since positive DGEAs correspond with SR anomalous increase and negative DGEAs correspond with SR anomalous decrease (Fig. 5), the standard deviation of daily GPP anomalies also indicates the strength of daily SR fluctuations. During the years with stronger (weaker) fluctuations of SR anomalies and larger (smaller) variability of daily GPP anomalies, the resultant negative asymmetry of DGEAs is also stronger (weaker), thus strongly (weakly) lower the annual GPP. Therefore, significantly strong negative correlations are found between the standard deviation of daily GPP anomalies and annual GPP over the forested areas.

For the non-forested areas, the daily variation of GPP is mainly controlled by water availability. Since daily precipitation and SM anomalies are both characterized by positive asymmetry, the DGEAs also show a positive asymmetry. In contrast to the forested areas, larger (smaller) variability of daily GPP anomalies in the non-forested areas indicates stronger (weaker) positive asymmetry of DGEAs, and the cumulative effect of these DGEAs further strongly (weakly) increases the annual GPP. As a result, the correlation between the standard deviation of daily GPP anomalies and annual GPP is significantly positive (Fig. 16).

7. Conclusion and discussion

Based on the FLUXNET site observations and FLUXCOM GPP, distinctive magnitude asymmetries of DGEAs are found in the forested and non-forested areas, with forested areas dominated by negative asymmetries and non-forested areas mainly occupied by positive

asymmetries. Such distinctive asymmetries of DGEAs are due to the different climatic constraints for forests and non-forests.

In forested areas, SR is the dominant controller of vegetation productivity on the daily time scale. Due to the existence of a light saturation point, the magnitude of negative DGEAs caused by extremely low SR is much larger than that of the positive DGEAs in association with the extremely high SR, leading to the negative asymmetry. The non-forested areas in NWA and AU are water-limited, with the daily variation in photosynthetic carbon uptake highly dependent on the preceding 3–6-day SM. While small precipitation events lead to only weak and short-lived SM changes, heavy precipitation events are always followed by strong and persistent increases in SM. As a result, the positive asymmetries of precipitation and soil moisture anomalies leads to that of DGEAs. With the interannual variation of daily SR and precipitation fluctuations, the magnitudes of daily GPP anomalies and asymmetry in the DGEAs also show strong interannual variability, and further contribute to the interannual variation of the annual GPP.

Ghil et al. (2011) and Leonard et al. (2014) suggested that a medium anomaly of several climatic variables could exert compound effects on vegetation productivity, thus also leading to GPP extreme anomalies. While the present study focused on the leading climatic controller of daily GPP variation in interpreting the asymmetry of DGEAs, the compounding effect of multiple climatic anomalies should be considered to further understand the cause of the asymmetry in DGEAs in the future. Moreover, as the variability of daily climatic drivers is projected to intensify in a warmer climate (IPCC 2012; Sillmann et al. 2013; Im et al. 2017; Dahl et al. 2019), the variability of daily GPP anomalies and the magnitude asymmetry may also increase. Changes in the global pattern of magnitude asymmetry in the DGEAs and its contribution to the interannual variability in the terrestrial carbon cycle demand further investigation via process-based carbon model projection.

439

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447 publicly available at the Data Portal of the Max Planck Institute for Biogeochemistry:
448 <https://www.bgc-jena.mpg.de/geodb/projects/Home.php>. The meteorological variables
449 derived from CRUNCEPv7 dataset are available at the NCAR Research Data Archive on the
450 website: <https://rda.ucar.edu/datasets/ds314.3/>. The soil moisture derived from the GLEAM
451 dataset are available on the SFTP-site: hydras.ugent.be. The site observations from
452 FLUXNET2015 dataset are available on the website: [https://fluxnet.org/data/fluxnet2015-](https://fluxnet.org/data/fluxnet2015-dataset/)
453 [dataset/](https://fluxnet.org/data/fluxnet2015-dataset/).

454

Appendix

455

The list of abbreviations in the manuscript

Abbreviation	Full Name
GPP	Gross Primary Productivity
DGEA	Daily GPP Extreme Anomaly
SR	Solar Radiation
SM	Soil Moisture
NT	Nighttime Partitioning Method
DT	Daytime Partitioning Method
VUT	Variable Ustar Threshold
AM	Amazon (10°S–7.5°N, 45°–80°W)
MC	Maritime Continent (10°S–7.5°N, 95°–155°E)
KJ	Korean Peninsula–Japan (30°–45°N, 125°–145°E)
NEA	Northeastern America (37.5°N–47.5°N, 60°–92.5°W)
NEU	Northern Europe (55°–65°N, 5°–70°E)
NWA	Northwestern America (25°–40°N, 97.5°–115°W)
AU	Australia (20°–32.5°S, 115°–152.5°E)
dGPP/dSR _{neg}	Sensitivity of GPP to SR when SR anomaly is lower than its 10 th percentile
dGPP/dSR _{pos}	Sensitivity of GPP to SR when SR anomaly is higher than its 90 th percentile
PFT	Plant Functional Type
EBF	Evergreen Broadleaf Forest
MF	Mixed Forest
DBF	Deciduous Broadleaf Forest
ENF	Evergreen Needleleaf Forest
GRA	Grassland
OSH	Open Shrubland
Pre	Precipitation
Tmp	Temperature

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619 **Tab. 1** The list of FLUXNET sites within the target regions. The asymmetry of DGEAs (gC
620 $\text{m}^{-2} \text{ day}^{-1}$) significant at the 95% (90%) confidence level is labeled with double stars (a single
621 star). The results derived from the nighttime (daytime) partitioning method are shown outside
622 (inside) of the bracket. The abbreviation of PFT means the plant functional type.

	Latitude	Longitude	PFT	Region	Asymmetry	Period
GF-Guy	5.3° N	52.9° W	EBF	AM	-0.65**(-0.53**)	2004–2014
MY-PSO	2.9° N	102.3° E	EBF	MC	-0.17**(-0.11**)	2003–2009
JP-SMF	35.3° N	137.1° E	MF	KJ	-0.16**(-0.14**)	2002–2006
CN-Cha	42.4° N	128.1° E	MF	KJ	-0.11*(-0.04)	2003–2005
US-Oho	41.6° N	83.8° W	DBF	NEA	-0.07(-0.17**)	2004–2013
CA-TP3	42.7° N	80.3° W	ENF	NEA	-0.07(0.16**)	2003–2014
US-MMS	39.3° N	86.4° W	DBF	NEA	-0.33**(-0.02)	1999–2014
FI-Hyy	61.8° N	24.3° E	ENF	NEU	-0.11*(-0.08)	1996–2014
DK-Sor	55.5° N	11.6° E	DBF	NEU	-0.15**(-0.32**)	1996–2014
RU-Fyo	56.5° N	32.9° E	ENF	NEU	-0.07(0.09)	1998–2014
US-Wkg	31.7° N	109.9° W	GRA	NWA	0.16** (0.23**)	2004–2014
US-SRM	31.8° N	110.9° W	GRA	NWA	0.12** (0.23**)	2004–2014
US-AR1	36.4° N	99.4° W	GRA	NWA	0.26** (0.4**)	2009–2012
AU-Emr	23.8° S	148.7° E	GRA	AU	0.31** (0.12)	2011–2013
AU-TTE	22.8° S	133.6° E	OSH	AU	0.54** (0.41**)	2012–2014

624

625 **Fig. 1** Frequency occurrences (bars, %) of daily GPP anomalies ($\text{gC m}^{-2} \text{ day}^{-1}$) at the
 626 GF-Guy site during the year 2014. The red dashed lines show the thresholds of the 10th
 627 and 90th percentiles, respectively. GPP anomaly larger than the 90th (smaller than the
 628 10th) percentile is defined as positive (negative) DGEA.

Fig. 2 (a) The distribution of magnitude asymmetry (shading, $\text{gC m}^{-2} \text{day}^{-1}$) between the positive and negative DGEAs averaged during the growing season of 1980–2013. Shading represents the multi-ensemble mean asymmetry, and stippling indicates the region where more than half of FLUXCOM ensembles consistently show significantly positive or negative asymmetry. The polygons represent the key regions that have significant asymmetry, with name of the region indicated by letters alongside with each polygon. (b) The fraction of pixels that are characterized by significant positive or negative asymmetry, with different PFTs labeled with different color bars.

Fig. 3 (a) The fractions of forested PFTs that are characterized by significant negative asymmetry of DGEAs, with different PFTs labeled with different color bars. (b) Same as in (a), but for the non-forested PFTs feature significant positive asymmetry.

Fig. 4 (a) Relative importance of SR (blue bar), temperature (red bar), precipitation (green bar) and SM (orange bar) to the daily variation in GPP anomalies over the target forested regions derived from the FLUXCOM GPP. (b) The results derived from the FLUXNET site observations. Color bars represent the arithmetic mean of different (a) FLUXCOM or (b) FLUXNET ensembles, and error bars reflect the spread between the maximum and minimum of results derived from different ensembles. Star marker indicates that regression coefficients for more than half of grid cells within the region are statistically significant at the 95% confidence level.

Fig. 5 Composite of GPP anomalies ($\text{gC m}^{-2} \text{ day}^{-1}$) against the (a) positive and (b) negative extreme anomalies of SR (blue bar), temperature (red bar), precipitation (green bar), and SM (orange bar) over the target forested regions. Color bars represent the arithmetic mean of different ensembles, and error bars reflect the spread between maximum and minimum of results derived from different ensembles. Star marker indicates that the composite of GPP anomalies is statistically significant at the 95% confidence level for more than half of grid cells within the region. (c) As in (a) and (b), but for the asymmetry ($\text{gC m}^{-2} \text{ day}^{-1}$) between the positive and negative extreme anomalies, calculated as the summation of (a) and (b).

661

662 **Fig. 6** (a) The same as Fig. 4a, but for the four target forested PFTs. (b) The same as

663 Fig. 5c, but for the four target forested PFTs.

664

665 **Fig. 7** (a) Scatter plot (black dots) of SR (X Axis; W m^{-2}) versus GPP anomalies (Y
666 Axis; $\text{gC m}^{-2} \text{ day}^{-1}$) at the GF-Guy site during the period of 1991–2012. Also displayed
667 are the interpolated GPP anomalies against the distribution of SR anomalies (gray dots),
668 obtained by averaging GPP anomalies that coincide with each 15 W m^{-2} bin of SR
669 anomalies. The green (red) line indicates the linear regression slope between GPP and
670 SR when SR anomaly is less than its 10th percentile (larger than its 90th percentile). (b)
671 Scatterplot (black dots) of SM (X Axis; $10^{-2} \text{ m}^3 \text{ m}^{-3}$) versus GPP anomalies (Y Axis;
672 $\text{gC m}^{-2} \text{ day}^{-1}$) at the US-Wkg site during 1 April–30 September of 2004–2014. Also
673 displayed are the interpolated GPP anomalies against the distribution of SM anomalies
674 (gray dots), obtained by averaging GPP anomalies that coincide with each $2 \times 10^{-2} \text{ m}^3$
675 m^{-3} bin of SM anomalies. The red vertical lines in (b) show the 10th and 90th percentiles
676 of SM anomalies.

Solar Radiation Sensitivity

Fig. 8 Sensitivity of GPP to SR ($dGPP/dSR$; $10^{-2} \text{ gC W}^{-1} \text{ day}^{-1}$) at each forested region derived from (a) FLUXCOM and (b) FLUXNET datasets, estimated based on the linear regression slopes between GPP and SR. The $dGPP/dSR$ was calculated first at each pixel or site and then averaged over each target forested region. Red bars show the sensitivity when SR anomaly is larger than its 90th percentile ($dGPP/dSR_{pos}$), and green bars represent the sensitivity when SR anomaly is less than its 10th percentile ($dGPP/dSR_{neg}$). Color bars represent the arithmetic mean of different ensembles, and error bars reflect the spread between maximum and minimum of results derived from different ensembles.

687

688

Fig. 9 The same as Fig. 8a, but for the four target PFTs.

689

690 **Fig. 10** The same as Fig. 4, but for the situation of NWA and AU.

691

692 **Fig. 11** The same as Fig. 5, but for the situation of NWA and AU

693

694 **Fig. 12** The same as Fig. 6, but for the five target non-forested PFTs.

Fig. 13 (a) The multi-ensemble mean maximum lag-correlation coefficient between GPP and SM anomaly at each grid cell over the northwest America (NWA; 25°–40°N, 97.5°–115°W) within the time lag from 15 to zero days. The maximum lag-correlation is displayed only over the region where the positive asymmetry of DGEAs is significant in Fig. 2a. Stippling indicates the region where more than half of FLUXCOM ensembles consistently show a significant lag-correlation coefficient at the 95% confidence level. (b) The time lag corresponding to the maximum lag-correlation coefficients in (a), with negative values implying that SM leads GPP. The time lag is displayed only when the corresponding maximum lag-correlation coefficient is significant. Also shown are the distributions of (c) SM (shading, $10^{-2} \text{ m}^3 \text{ m}^{-3}$) and (d) precipitation (shading, mm day^{-1}) magnitude asymmetries. Stippling indicates the region where positive SM (precipitation) anomalies are significantly larger than their negative counterparts at the 95% confidence level. The SM and precipitation asymmetries at three FLUXNET sites (open circle) are also displayed.

710

711 **Fig. 14** The same as Fig. 13, but for the situation of AU

712

713 **Fig. 15** Standardized time series of annual mean GPP (red line) and accumulation of
 714 DGEAs (green line) area-averaged over the target forested and non-forested regions
 715 during the period of 1980–2013. The value in the bracket is the interannual variance of
 716 annual mean GPP explained by the accumulation of DGEAs.

Fig. 16 Correlation coefficient between the standard deviation of daily GPP anomalies and annual GPP during the period of 1980–2013. Stippling indicates the region where correlation coefficient is significant at the 90% confidence level for more than half of ensembles.