Seasonal drivers of carbon cycle interannual variability represented by the Community Earth System Model (CESM2)

W. R. Wieder¹,²*, Z. Butterfield³, K. Lindsay¹, D. L. Lombardozzi¹, G. Keppel-Aleks³

¹ Climate and Global Dynamics Laboratory, National Center for Atmospheric Research, Boulder, CO 80307, USA.
² Institute of Arctic and Alpine Research, University of Colorado, Boulder, CO 80309, USA
³ Department of Climate and Space Sciences and Engineering, University of Michigan, Ann Arbor, MI, 48109, USA

*Corresponding author: William Wieder (wwieder@ucar.edu)

Key Points

- The model simulates low interannual variability of net carbon fluxes due to high covariance of plant productivity and ecosystem respiration
- Dominant modes of variability are characterized by a seasonal amplification and seasonal redistribution of gross primary productivity
- The seasonal redistribution component of carbon cycle variability is a notable feature that appears widespread in the model and observations

Abstract

Earth system models are intended to make long-term projections of carbon pools fluxes in response to climate trends, but they can be evaluated on their ability to realistically simulate appropriate carbon cycle sensitivities to climate variability at interannual and seasonal time scales. The Community Earth System Model (CESM2) showed improvements to the representation of the cumulative land carbon sink over the historical period, relative to its predecessor. Our analysis suggests that the interannual variability (IAV) in net terrestrial carbon fluxes simulated by the model did not show similar improvements. The model simulated low IAV of net ecosystem productivity, that also has a weaker than observed climate sensitivity compared to observations. Low IAV likely resulted from a high covariation in gross primary productivity (GPP) and ecosystem respiration. The IAV of GPP had strong climate sensitivities,
with positive GPP anomalies associated with warmer and drier conditions in high latitudes, and with wetter and cooler conditions in mid and low latitudes. We identified two dominant modes of variability in GPP anomalies that are characterized by seasonal amplification and redistribution. Climate sensitivities associated with the seasonal amplification of GPP were similar to annual climate anomalies. Seasonal redistribution of GPP fluxes is initiated by springtime temperature anomalies, but subsequently negative feedbacks in soil moisture anomalies during the summer and fall result in negligible changes in the annual GPP flux. These two modes of variability are also seen in remote sensing products, suggesting that CESM2 appropriately represents regional-to-global sensitivities of terrestrial carbon fluxes to climate variability.

**Plain Language Summary**

Earth system models that are intended to make climate change projections also represent the global exchange of carbon dioxide (CO₂) between the atmosphere, ocean and land. As such, the growth rate and variability of CO₂ concentrations in the atmosphere provide a robust measurement to evaluate the representation of the terrestrial carbon cycle in models. We looked at the interannual variability of terrestrial carbon fluxes and their sensitivity to variations in temperature and water that were simulated by the Community Earth System Model (CESM2) and compared them to observations. We found that the model underestimates the interannual variability of net terrestrial carbon fluxes. At the same time, we identified two modes of variability that correspond to an increase in summer productivity (amplification) and a change in the seasonal timing (redistribution) of productivity. Notably, the seasonal redistribution was initialized by warmer springs that increased early-season productivity, but subsequent water limitations in the summer and fall resulted in lower than average productivity and negligible changes in the annual carbon flux. Similar patterns of seasonal amplification and redistribution are seen in satellite observations, suggesting that the model is realistically simulating characteristics of terrestrial ecosystems necessary for capturing carbon-climate feedbacks.
1. Introduction

Terrestrial ecosystems continue to provide a sink for about a quarter of anthropogenic carbon dioxide (CO₂) emissions (Ballantyne et al., 2012; Friedlingstein et al., 2019), but the long-term strength and locations of this sink remain uncertain (Gaubert et al., 2019; Tagesson et al., 2020). The net terrestrial flux of CO₂ to or from the atmosphere depends on the balance between much larger carbon fluxes that are driven by plant productivity, ecosystem respiration, and disturbances like fire (Keppel-Aleks et al., 2014). Observational constraints on these gross fluxes are difficult to make globally, which results in persistently high uncertainty in terrestrial carbon cycle projections (Anav et al., 2013; Arora et al., 2020; Friedlingstein et al., 2014). Thus, capturing the appropriate sensitivities to climate driven carbon cycle variability at interannual and seasonal time scales over the observational record may be important to improving longer-term projections of terrestrial carbon balance.

At decadal- to century-time scales, the net exchange of CO₂ between the land and atmosphere remains one of the more robust benchmarks by which to evaluate the representation of terrestrial biogeochemistry in land models (Collier et al., 2018; Hoffman et al., 2014; Keppel-Aleks et al., 2013). Indeed, successive generations of the Community Earth System Model (CESM) and its terrestrial component, the Community Land Model (CLM) show improvements in the globally integrated net terrestrial carbon flux over the historical period (1850-2014; Bonan et al., 2019; Danabasoglu et al., 2020; Lawrence et al., 2019). This suggests that on longer timescales the model adequately represents dominant features influencing in the terrestrial carbon cycle dynamics, namely land-use and land cover change as well as potential CO₂ fertilization effects (Wieder et al., 2019). These longer-term benchmarks, however, offer little insight into the environmental sensitivities of terrestrial CO₂ fluxes, which are important for understanding carbon cycle responses to future climate change.

Measurements of the atmospheric CO₂ growth rate provide an integrated estimate of the interannual variability (IAV) in global carbon cycle (Keeling et al., 1995; Zeng et al., 2005). Since much of the observed IAV is driven by terrestrial processes, variability in the atmospheric CO₂ record provides a top-down constraint on the climate sensitivity of land-atmospheric CO₂ exchange (reviewed by Piao et al., 2020). Specifically, natural climate variability in temperature and precipitation over land are the primary drivers of terrestrial carbon cycle variability that can be inferred from IAV in the atmospheric CO₂ growth rate. This includes the temperature...
sensitivity of gross primary productivity (GPP) and ecosystem respiration ($R_{eco}$) on net ecosystem exchange (NEE, calculated as GPP - $R_{eco}$), especially in the tropics (Anderegg et al., 2015; Ballantyne et al., 2017; Cox et al., 2013; Rödenbeck et al., 2018b; Wang et al., 2013). Meanwhile, other studies emphasize the importance of soil moisture variability on GPP and NEE, especially in arid and semi-arid ecosystems (Anderegg et al., 2015; Humphrey et al., 2018; Poulter et al., 2014). Jung et al. (2017) suggest that compensating moisture driven variation in local-scale gross fluxes (GPP and $R_{eco}$) as well as spatial compensation in moisture anomalies among regions leaves a dominant temperature-driven signal in the IAV of land-atmosphere CO$_2$ exchange. Regardless of the mechanism, these findings emphasize the need to understand the local and regional drivers of carbon cycle variability at finer temporal resolution.

Disentangling the contributions of gross carbon fluxes and their impact on the IAV of NEE remains a challenge. While GPP and $R_{eco}$ anomalies are strongly auto-correlated, mounting evidence suggests that variance in NEE is more strongly correlated with variance in GPP than $R_{eco}$ (Baldocchi et al., 2018; Schwalm et al., 2010). Globally gridded estimates of net and gross carbon fluxes are derived from upscaled flux tower measurements (Beer et al., 2010; Jung et al., 2011; Jung et al., 2017) or remote sensing (Alemohammad et al., 2017; Köhler et al., 2018; Running et al., 2004) either have low, or questionable representation of IAV that may limit their utility in evaluating simulated carbon cycle variability in models (Jung et al., 2020; Piao et al., 2020; Y. Zhang et al., 2018). These remote sensing products, however, do offer promise for diagnosing seasonal carbon cycle responses to climate variability, especially in the extra-tropics (Buermann et al., 2018). Notably, Butterfield et al. (2020) found that while local to regional-scale IAV was poorly correlated among observational data products, they could identify seasonal modes of variability that shared common features and environmental sensitivities. These included the: 1) Amplification of the seasonal cycle of GPP, which was associated with increases in summertime soil moisture availability, and 2) Seasonal redistribution of GPP that was initially driven by warmer springtime temperatures but followed by higher than average soil moisture stress in the summer and fall.

Given improvements to the representation of the cumulative land carbon sink over the historical period in CESM2, relative to CESM1 (Danabasoglu et al., 2020), we wanted to investigate the representation of carbon cycle variability at interannual and seasonal timescales in the model. Specifically, our aims were to: 1) Quantify both the IAV of land carbon fluxes
simulated by CESM2-esm-hist and their sensitivity to climate variability; 2) Identify modes of seasonal variability in simulated GPP and their likely climate drivers; and 3) Compare the CESM2-esm simulations to results from observational studies, where possible, and identify strengths and weaknesses in the current model implementation.

2. Methods

2.1 Model simulations

We analyzed simulations from the Community Earth System Model, version 2 (CESM2) that couples atmosphere, ocean, land, sea ice, land ice, and river transport components to simulate physical and biogeochemical conditions over historical and future scenarios (Danabasoglu et al., 2020). Of greatest importance for the simulations analyzed here are the atmospheric and land components, which are each briefly described below. The atmosphere model in CESM2 is the Community Atmosphere Model, version 6 (CAM6) which applies the same Finite Volume dynamical core as previous versions of the model, but has numerous changes to the model parameterization (Danabasoglu et al., 2020). Relative to previous versions of the model, CESM2 shows an improvement in its representation of El Niño Southern Oscillation (ENSO) events and their effect on precipitation and temperature anomaly patterns (Meehl et al., 2020). The atmosphere and land models are run at a nominal 1° horizontal resolution (1.25° longitude by 0.9° latitude) and are coupled every 30 minutes.

The terrestrial component of CESM2 uses the Community Land Model, version 5 (CLM5), which includes a number of updates that are summarized in (Lawrence et al., 2019). Briefly, these developments simulate transient agricultural expansion and land management (Lombardozzi et al., 2020), represent plant hydraulic stress (Kennedy et al., 2019), and improve the representation of plant nitrogen limitation (R. A. Fisher et al., 2019; Wieder et al., 2019). We used the CESM2-esm historical simulations that has active biogeochemical representation of terrestrial carbon and nitrogen cycles and that also simulates the prognostic evolution of atmospheric CO₂ concentrations based on fluxes with oceans and terrestrial ecosystems.

As described in Danabasoglu et al. (2020), initial conditions for the land model and ocean model biogeochemical tracers in the non-ESM piControl experiment were generated using spin-up runs of the land and ocean models, respectively. In these spin-up runs, the active atmospheric component was replaced with a data atmosphere that repeatedly cycled through twenty-one years
of surface forcing that were extracted from a fully coupled CESM2 experiment. Twenty-one years of forcing were used in order to capture some aspects of interannual variability. The land model spin-up consisted of an accelerated decomposition (AD) mode segment and a subsequent synchronous spin-up segment. These segments were run for 252 and 1701 years respectively. The ocean model spin-up was applied to biogeochemical tracers. The ocean spin-up was run for 1029 years and also utilized a Newton-Krylov solver, based on Lindsay (2017) to more completely spin up a subset of the biogeochemical tracers, including the carbon pools. The esm-piControl was initialized from the piControl experiment using an incremental coupling approach. In an intermediate experiment, which was initialized from the piControl experiment, the carbon cycle of the surface components was coupled bidirectionally to a CO$_2$ tracer in the atmospheric model. This intermediate experiment was run for 80 years, during which the surface biogeochemical parameterizations adjusted to the prognostic atmospheric CO$_2$. The esm-piControl experiment was initialized with the model state from the end of this intermediate experiment, and the prognostic CO$_2$ was coupled to the radiative computations in the atmospheric model. The esm-hist experiments analyzed here were initialized from the esm-piControl experiment. The CESM2-esm historical simulations used CMIP6 forcings for anthropogenic emissions, biomass burning, and volcanic SO$_2$ emissions from 1850-2014 described in Danabasoglu et al. (2020) as well as land use and land cover change described in Lawrence et al. (2019) following CMIP6 protocols outlined by Eyring et al. (2016).

Using a single ensemble member of CESM2-esm, we focused our analysis on global, regional, and local carbon fluxes that are simulated during the end of the historical period (1960-2014), which overlaps with atmospheric CO$_2$ measurements. We quantified variability in carbon fluxes at interannual and seasonal time scales and correlated these fluxes with anomalies in climate drivers (temperature and moisture). The model simulates gross fluxes of GPP and R$_{eco}$, with the difference between them representing net ecosystem production (NEP). Positive values for NEP represent net terrestrial ecosystem uptake of carbon. We focused on NEP instead of net ecosystem exchange or net biome production (NEE and NBP, respectively), which include fluxes from fire, land use, and land management, because the CESM2-esm-hist simulations have unrealistically large fire carbon fluxes from land degradation in the tropics at the end of the historical period.
2.2 Statistical Analyses

We summed monthly carbon fluxes (NEP, GPP, and $R_{eco}$) that were simulated from vegetated terrestrial grid cells to calculate accumulated annual fluxes and weighted them by grid cell area and land fraction to calculate global values. We similarly calculated mean annual temperature (TBOT) and terrestrial water storage (TWS) that was simulated by the model. The CESM2-esm results showed strong long-term trends in relevant variables (Fig. S1), so we subtracted linear trends and focused on the detrended anomalies from the climatological mean state for both monthly and annual data. The IAV was calculated as the standard deviation of annual results simulated from 1960-2014. We compared the IAV in global detrended anomalies of simulated CO$_2$ fluxes, simulated land CO$_2$ fluxes, and NEP to those observed in the atmospheric CO$_2$ growth rate reported by the Global Carbon Project (Friedlingstein et al., 2019). As most of the variability in global CO$_2$ fluxes is driven by IAV in terrestrial fluxes (Fig. S2), we focus on the IAV of NEP and its component fluxes.

To characterize relationships in the data we calculated Pearson’s correlation coefficients and regression statistics between detrended anomalies in carbon fluxes, moisture, and temperature. We also calculated the grid cell variance and standard deviation of annual, detrended carbon fluxes to look at covariance between simulated fluxes (as in Baldocchi et al., 2018). We found a robust correlation in the IAV of NEP and its component fluxes, and a strong covariance between GPP and $R_{eco}$ variability. Thus, we focus the remainder of our analysis and discussion on variability in simulated GPP and its environmental sensitivities.

To decompose the annual cycle of GPP simulated in each terrestrial grid cell and identify modes of variability we used a singular value decomposition (SVD; Golub & Reinsch, 1971 as in Butterfield et al., 2020). The SVD decomposed the time series of detrended GPP anomalies into singular vectors (SV$_i$), the elements of which reflect the month (m) of the year (y; Fig. S3). Vectors are ranked by the fraction of variance they explain in the GPP time series. Each singular vector also receives a weight $w_i$, one per year per singular vector, that quantifies the contribution from an individual singular vector to the observed IAV in any given year. Thus, the simulated IAV time series for a grid cell can be fully reconstructed as the weighted sum of singular vectors:

$$IAV(y,m) = \sum_i w_i(y) \times SV_i(m)$$  \hspace{1cm} (1)
Our SVD had 55 singular vectors ($i$, corresponding to the number of years in our analysis). We focused on the first two of these to characterize the dominant modes of variability in GPP that are simulated by CESM2-esm. We also calculated a redistribution metric, $\theta$, as the sum of elements from a singular vector divided by the absolute values of the sum of elements from that vector (Butterfield et al. 2020).

$$\theta = \Sigma_m SV_i(m) / \Sigma_m |SV_i(m)|$$

Thus, when $\theta = 0$, GPP was redistributed within the growing season without changing the annual flux. By contrast, values of $\theta = 1$ (or -1) indicate that every month had a positive (or negative) anomaly in GPP relative to the multi-year mean.

We identified the mode of variability corresponding to a seasonal amplification of GPP as the vector whose elements most strongly correlated with annual climatology of GPP. The other mode of variability corresponded to a seasonal redistribution of GPP, which typically has both positive and negative phases. The $\theta$ values were used to confirm the appropriate identification of amplification and redistribution modes of variability in each grid cell (e.g., $|\theta|$ amplification $>$ $|\theta|$ redistribution). To facilitate our analysis, we reversed the sign of singular vector elements, weights and $\theta$ values so that amplification vectors were positively correlated with the annual climatology of GPP and the redistribution vector started with a positive phase (Fig. S4).

For visualization we calculated regional means for elements in the seasonal amplification and redistribution vectors across high, mid, and low latitude bands in both hemispheres (50-80°, 20-50°, and 0-20°, respectively). Finally, to link modes of carbon cycle variability back to climate anomalies we calculated seasonal means for GPP, air temperature, and terrestrial water storage anomalies. We looked at Pearson’s correlation coefficients between these seasonal anomalies and the SVD weights generated for amplification and redistribution vectors.

### 3 Results

#### 3.1 Interannual variability

Detrended anomalies of terrestrial net ecosystem production (NEP) that are simulated by CESM2-esm have low variability, compared to the atmospheric growth rate of CO$_2$ measured
since 1959 and reported by the Global Carbon Project (Friedlingstein et al., 2019; Figs. 1a, S2). The standard deviation of modeled NEP fluxes (0.47 Pg C y$^{-1}$) is roughly half of the standard deviation in the observed atmospheric CO$_2$ growth rate (0.95 Pg C y$^{-1}$). Note, for convenience we inverted the sign of the atmospheric growth rate so that positive anomalies in Fig. 1a show net land C uptake for both the model and observations. We also note that any temporal correlations between C flux anomalies in CESM2-esm simulations and atmospheric observations here are unintended, because CESM2-esm is experiencing a modeled atmosphere that does not necessarily match local, regional, or global conditions experienced during the historical record of atmospheric CO$_2$ observations. Figure 1b shows detrended annual anomalies of NEP (as in Fig. 1a using a different scale) along with annual anomalies in terrestrial water storage (over vegetated grid cells) and tropical air temperatures over land (23°S - 23°N). The magnitude of terrestrial water storage and tropical air temperature variability simulated in CESM2-esm seems reasonable, compared to observations ($\sigma = 0.82$ Tt H$_2$O and 0.10 K, respectively; Fig. 1b) (Cox et al., 2013; Humphrey et al., 2018). These atmospheric signals, however, do not translate into terrestrial carbon cycle variability.
Figure 1. Detrended annual anomalies of global carbon fluxes, climate drivers, and their correlation. Upper panels show: (a) Atmospheric CO$_2$ growth rate reported by the global carbon project (Friedlingstein et al., 2019) and net ecosystem production (NEP) simulated CESM2-esm (green and black lines, respectively); and (b) NEP, terrestrial water storage (TWS), and tropical air temperature anomalies simulated by CESM2-esm (black, blue, and red lines respectively. Lower panels show correlations between simulated: (c) TWS, which is positively correlated to simulated NEP anomalies; and (d) Tropical air temperature, which is negatively correlated to simulated NEP anomalies. Note, for convenience we inverted the sign of the atmospheric growth rate so that positive anomalies in Fig. 1a show net land C uptake for both the model and observations.

Given the low carbon cycle variability simulated by CESM2-esm (Fig. 1a-b), the model also shows weaker than observed climate sensitivity to global and regional climate anomalies (Fig. 1c-d). The anomalies between NEP and terrestrial water storage are statistically significant ($r = 0.63$, $p<0.001$), but with relatively modest effect on carbon cycle variability (slope = 0.36 Pg C y$^{-1}$ Tt H$_2$O$^{-1}$), which is weaker than observational estimates from Humphrey et al. (2018; $r = 0.85$, slope = 1.3 Pg C y$^{-1}$ Tt H$_2$O$^{-1}$). We similarly find significant correlations between simulated...
anomalies of NEP and tropical temperature \((r = -0.58, p < 0.001, \text{slope} = -2.6 \text{ Pg C y}^{-1} \text{K}^{-1})\), which is also weaker than observed estimates [Cox et al. (2013), \(r = -0.65, \text{slope} = -5.1 \text{ Pg C y}^{-1} \text{K}^{-1}\); Wang et al. (2013), \(r = -0.7, \text{slope} = -3.5 \text{ Pg C y}^{-1} \text{K}^{-1}\)] (see also, Ballantyne et al., 2017; Rödenbeck et al., 2018a).

The aggregated use of globally integrated carbon cycle and climate metrics are convenient for comparing atmospheric CO\(_2\) observations, but they do not provide much insight into the mechanism responsible for carbon cycle variability or its spatial structure. The mean of grid cell standard deviations in detrended NEP anomalies simulated from 1960-2015 in CESM2-esm \((40.5 \text{ g C m}^{-2} \text{y}^{-1})\) was large, relative to the mean of grid cell NEP simulated over this time \((39.5 \text{ g C m}^{-2} \text{y}^{-1})\). Observed mean and standard deviation of net carbon fluxes from a synthesis of FLUXNET observations by Baldocchi et al. (2018) are much larger than those that are estimated by CESM2-esm \(\text{observed net ecosystem exchange} = 153 \pm/\pm 230 \text{ g C m}^{-2} \text{y}^{-1}; \text{mean} \pm \sigma \text{ of annual anomalies}\). Although the network’s data coverage is improving, the mismatch in aggregated statistics for the CESM2 and FLUXNET data potentially highlight biases in the spatial distribution of FLUXNET observations to relatively mesic temperate environments (Pastorello et al., 2017).

Observed and simulated variability in NEP is driven by variability in component fluxes gross primary productivity (GPP) and ecosystem respiration (R\(_{\text{eco}}\)). The mean standard deviation of detrended GPP and R\(_{\text{eco}}\) anomalies \((102 \text{ and } 83.8 \text{ g C m}^{-2} \text{y}^{-1}, \text{respectively})\) in CESM2 were about 10% of the mean fluxes \((950 \text{ and } 910 \text{ g C m}^{-2} \text{y}^{-1}, \text{respectively})\). The grid cell variance of NEP was strongly and positively correlated with the variance of component fluxes (Fig. 2a).

Although variance in NEP is slightly better explained by GPP variance \((r = 0.79, \text{slope} = 0.77)\) than R\(_{\text{eco}}\) variance \((r = 0.74, \text{slope} = 0.72; \text{Fig. 2a})\), the anomalies of the component fluxes are highly correlated with each other \((r = 0.94, \text{slope} = 0.80; \text{Fig. 2b})\). By contrast, observations from FLUXNET show lower correlations between GPP and R\(_{\text{eco}}\) anomalies \((r = 0.70, \text{slope} = 0.42; \text{Baldocchi et al. 2018})\). The strong simulated correlation between simulated GPP and R\(_{\text{eco}}\) likely accounts for some of the low interannual variability in land carbon uptake in CESM2, since years with large GPP fluxes are necessarily compensated by R\(_{\text{eco}}\) fluxes that are of nearly the same magnitude. Given strong correlations between GPP and R\(_{\text{eco}}\) fluxes, we focus the remainder of our analysis on patterns in GPP variability and its response to moisture and temperature anomalies.
Figure 2. Correlations of grid cell carbon fluxes simulated by CESM2-esm from 1960-2015: (a) Variance in NEP versus GPP and R_{eco} (shown in black and green, respectively); and (b) Autocorrelation of anomalies in R_{eco} and GPP. Pearson correlation coefficients and regression slopes from each relationship are provided in each panel, all correlations are significant (p < 0.001).

The standard deviation of detrended annual GPP anomalies shows high variability in tropical savannah regions, but relatively low variance in highly productive tropical forests (Fig. S5a). When normalized for mean annual GPP, the low productivity regions show higher coefficient of variation (CV), while higher productivity forests show relatively low CV in plant productivity (Fig. S5b-c). In Table S1 we compared the coefficients of variability (defined as the ratio of the interannual standard deviations to the seasonal amplitude of the multi-year mean) in four ecoregions of North America as defined in Butterfield et al. (2020) from CESM2 and several remote sensing products. The various remote sensing products show a factor of two difference in the range of variability in regional GPP estimates, and the magnitude of GPP variability simulated by CESM2 is comparable to these observationally derived estimates. This finding contradicts results reported by Wozniak et al. (2020), who found lower than observed variability in land-only simulations conducted with CLM5 at flux tower sites.

The IAV of detrended GPP anomalies simulated in CESM2 is positively correlated with terrestrial water storage anomalies in low and mid latitude regions (50°S - 50°N), whereas high latitude systems show a negative correlation between GPP and water storage anomalies (Fig. 3a).
In general, arid and savannah regions on nearly every continent show strong positive correlations in the IAV of GPP with terrestrial water storage, except for parts of the Western United States. These patterns are reversed for correlations between GPP and air temperature anomalies (Fig. 3b). Over cold regions, and especially in boreal forests, the IAV of detrended GPP anomalies are positively correlated with air temperature anomalies. By contrast, over mid and low latitudes, especially in the Amazon, SE Asia, and N Australia, the IAV of detrended GPP anomalies are negatively correlated with air temperature anomalies. Finally, although many regions show strong, negative correlations between terrestrial water storage and temperature anomalies (e.g., the Americas, SE Asia, and Australia), other regions show positive correlations between these simulated climate anomalies (e.g., parts of tropical Africa, tropical Asia, and the high Arctic; Fig 3c).

![Figure 3. Correlations coefficients between detrended annual anomalies that are simulated by CESM2-esm from 1960-2014. Panels show the correlation between (a) GPP and terrestrial water storage; (b) GPP and air temperature; and (c) terrestrial water storage and air temperature. Only statistically significant correlations (p < 0.05, when |r| > 0.226 for 55 years of data) are shown.](image)

### 3.2 Seasonal variability

The first two vectors in the singular value decomposition explained 75% (area weighted mean) of the variance in GPP over the vegetated land surface. In general, the amplification vector explained the greatest fraction of variance in GPP, especially in arctic and arid regions (global area weighted mean = 45%; Fig. 4a). The redistribution vector explained the largest fraction of variation over more mesic regions in the mid latitudes (global weighted mean = 29%; Fig. 4b). Neither vector explained a large fraction of GPP variance over tropical forests, which generally showed low variability in detrended GPP anomalies (Fig. S5).
Figure 4. Fraction of variance in detrended GPP anomalies that was explained by (a) seasonal amplification or (b) seasonal redistribution vectors.

Figure 5 shows the mean annual climatology of the GPP, as well as the monthly values for amplification and redistribution vectors (grey, blue, and red lines respectively) for latitudinal bins. High and mid latitudes are characterized by a strong annual cycle of GPP that is strongly correlated with the amplification vectors describing GPP variability (Fig. 5a, b, e). The amplification vector describes 56%, 45%, and 38% of the GPP variability in arctic, northern hemisphere temperate, and southern hemisphere temperate latitudinal zones, respectively. By contrast, the redistribution vectors in these regions explain 26-31% of the GPP variability and are characterized by positive spring-time anomalies that are followed by negative summer and fall anomalies. In the tropics, the seasonal cycle is more muted, but seasonal amplification and redistribution vectors describe roughly 40% and 30% of the variability in GPP, respectively (Fig. 5 c, d). The $\theta$ values calculated in the SVD show the net impact on the integrated seasonal signal of GPP. The mean $\theta$ values associated with the amplification vector are globally positive (Fig. 5). By contrast, the $\theta$ values associated with a seasonal redistribution of GPP are close to zero, indicating little to no change in integrated seasonal signal of GPP from seasonal redistribution of GPP. Thus, although the seasonal redistribution of carbon variability is a major source of global carbon cycle variability in the model, it would not be evident in more aggregated metrics of variability that only look at annual times-scales (e.g., Fig. 1).
Figure 5. Zonal mean climatology of monthly GPP and singular vectors associated with seasonal amplification and redistribution of GPP (grey, blue, and red lines respectively) for the northern hemisphere and southern hemisphere (top and bottom rows, respectively). Panels show: (a) high latitude ecosystems, 50-80°N; (b) northern temperate mid latitudes, 20-50°N; (c-d) tropics, 0-20°N and 0-20°S, respectively; and (e) southern temperate mid latitudes, 20-50°S. The magnitude of the singular vectors is arbitrary (y-axis). Mean fraction of variance explained and θ values, which indicate the net impact on the integrated seasonal signal of GPP for each singular vector, are also provided. Note x-axis was shifted for southern hemisphere plots to show the climatology for austral summer.
To evaluate the environmental drivers of GPP variability we conducted linear regressions on the weights from the amplification (Fig. 6) and redistribution (Fig. 7) vectors from SVD analysis ($n = 55$, for each year of the simulation) with seasonal anomalies of GPP, terrestrial water storage, and air temperature. The SVD weights for the amplification vector were strongly and positively correlated with the GPP anomalies during the peak of the growing season (Fig. 6, left column). This is expected, since the amplification vector was identified by its correlations with the climatology of GPP, so correlation coefficients are highest in the summer months (JJA and DJF for northern and southern hemispheres, respectively). Strong correlations are evident at other times (e.g., negative correlations between weights and GPP anomalies across high latitudes in DJF), but the magnitude of these anomalies is small relative to the annual cycle (see also Fig. 5a). Although terrestrial water storage and air temperature are auto-correlated (Fig. 3), high-latitude ecosystems generally show SVD amplification weights that are more positively correlated with air temperature anomalies and negatively correlated with water storage anomalies in JJA (Fig. 6, right and middle columns, Table S2). By contrast, SVD amplification weights are more strongly and positively correlated with wetter-than-average conditions across mid and low latitudes, and negatively correlated with air temperature anomalies.
Figure 6. Pearson correlation coefficients between SVD weights from the amplification vector with seasonal anomalies of GPP, terrestrial water storage (TWS), and air temperature (TBOT) simulated by CESM2-esm from 1960-2014. Only statistically significant (p < 0.05) correlations are shown (|r| > 0.26, two-tailed test, n = 55).

The SVD weights for the redistribution vector were strongly and positively correlated with the GPP anomalies during the spring, with correlation coefficients that are highest in the MAM and SON (for northern and southern hemispheres, respectively; Fig. 7, left column). In the northern hemisphere, the positive phase of the redistribution vector is also more strongly correlated with warmer spring-time air temperatures (Fig. 7, right column) than terrestrial water storage. Subsequent GPP anomalies in the summer and fall, however, show negative correlations with SVD weights (see also Fig. 5). In the summer (JJA) these periods are still characterized by warmer, but also drier than average conditions (Fig. 7, middle column; Table S3). By fall (SON), negative GPP anomalies are only associated with drier than average conditions.
Figure 7. Pearson correlation coefficients between SVD weights from the redistribution vector with seasonal anomalies of GPP, terrestrial water storage (TWS), and air temperature (TBOT) simulated by CESM2-esm from 1960-2014. Only statistically significant (p < 0.05) correlations are shown (|r| > 0.26, two-tailed test, n = 55).

4. Discussion

4.1 Interannual variability

Our results show that the magnitude of global carbon cycle variability simulated by CESM2-esm is low, relative to measurements of IAV in the atmospheric CO₂ growth rate (Fig. 1). Observed variation in the atmospheric CO₂ growth rate shows strong reductions in land carbon uptake during the 1987 and 1998 ENSO events, as well as strong increases in land carbon uptake associated with the 1992 Pinatubo eruption (Fig. 1a). The CESM2 has a good representation of precipitation and temperature anomaly patterns associated with tropical Pacific sea surface temperatures (Danabasoglu et al., 2020; Meehl et al., 2020), and is forced with observed volcanic aerosols during the historical period (Fig. S2). Accordingly, the magnitude of
terrestrial water storage and air temperature variability agrees reasonably well with observations (Fig. 1; Cox et al., 2013; Humphrey et al., 2018). This suggests that the model adequately represents global-scale climate variability, but that this climate variability does not generate enough terrestrial carbon cycle variability in the model.

Since the atmosphere and land models are coupled in the CESM2-esm simulations, we do not expect the timing of ENSO events to line up with observations. As such, the comparison between NEP and terrestrial water storage and NEP and air temperature anomalies are more illustrative of the relationship between observed atmospheric CO$_2$ growth rates and climate variability (Fig. 1c, d). Note, the sign of relationships from previously published work was reversed so that positive carbon flux anomalies reflect terrestrial carbon uptake, as in Figure 1. We appreciate that all of these studies use slightly different time periods for their calculations, but we do not expect this to significantly alter the fundamental sensitivities of land carbon fluxes to climate variability. Indeed, these findings are generally consistent with land-only simulations using the Community Land Model (CLM5), which also shows weaker than observed carbon cycle variability when driven by reanalysis climate forcing data that reflects the historical drivers of the observed carbon cycle variations (Lawrence et al., 2019).

Coupled Earth system models would ideally simulate relationships between the carbon cycle and climate variations over a range of spatial scales. Ultimately, the long-term CO$_2$ forcing reflects the global integral of local to regional carbon-climate feedbacks. To diagnose this global signal, atmospheric CO$_2$ observation and inversion models provide one approach to evaluating model simulations that can provide insight into regional drivers of CO$_2$ variability (Keppel-Aleks et al., 2014), but they are characterized by large uncertainties that limit their utility to detect proximal causes of carbon cycle variability. Our work finds that plant productivity simulated by CESM2-esm shows distinct regional signatures in climate sensitivity and variability at annual and seasonal timescales that imprint onto the net land carbon flux.

In contrast, local-scale observations provide a bottom-up perspective on sources of carbon cycle IAV. Indeed, observations from eddy-covariance towers have long-been used to evaluate land models (Baldocchi et al., 2001; Bonan et al., 2012; Melaas et al., 2013; Pastorello et al., 2017). Measurements from multiple tower sites, therefore, provide another means to evaluate carbon cycle simulations. Syntheses from FLUXNET observations show larger net carbon fluxes and greater variability than CESM2-esm simulations (Fig. 2a; Baldocchi et al.,
A number of factors— including differences in atmospheric conditions, spatial coverage, temporal extent, and potential legacy effects— may lead to mismatches in flux tower observations and coupled Earth system model output (Raczka et al., 2013). Caveats aside, the FLUXNET observations are consistent with atmospheric CO$_2$ measurements and suggest that CESM2 underestimates the IAV of land carbon uptake (Figs. 1-2), prompting us to look more closely at the components of terrestrial carbon fluxes that may be responsible for this feature in the model.

The IAV in net carbon fluxes results from variability in component fluxes (GPP and $R_{eco}$) and their interaction (Baldocchi et al., 2018; Lasslop et al., 2010). Our results suggest that CESM2-esm shows notably low IAV of GPP fluxes in tropical forests (Fig. S5). Similarly, in temperate deciduous forests, Wozniak et al. (2020) found that maximum rates of GPP simulated by CLM were much lower than observations at a number of AmeriFlux sites. Indeed, measurements from flux towers suggest that brief periods of large photosynthetic uptake appear to be an important component of the IAV in net carbon exchange, especially in arid ecosystems (Fu et al., 2019; Kannenberg et al., 2020). The failure of CLM5 to capture this behavior suggests that the model needs parametric or structural changes in its representation of leaf-level photosynthesis, stomatal conductance, or canopy scaling to capture photosynthetic variability. Beyond the site level, however, regional analyses suggest that the variation in GPP fluxes may be appropriate to a suite remote sensing estimates in the northern hemisphere (Table S1; Butterfield et al., 2020). Additional work is needed to evaluate the utility of detecting IAV of carbon cycle metrics in remote sensing products to further evaluate model simulations, especially in the tropics.

Observations suggest that site-level variance in net carbon fluxes is more tightly correlated with GPP than $R_{eco}$ (Baldocchi et al., 2018). By contrast, the CESM2-esm results show strong correlations between NEP and both of its component fluxes (Fig. 2a). Moreover, the anomalies of GPP and $R_{eco}$ that are simulated by CESM2 are more strongly correlated than observations suggest (Fig 2b, Baldocchi et al., 2018). This high covariation between GPP and $R_{eco}$ offsets variance in either of the component fluxes and dampens the IAV of NEP in the model. These results also suggest that the current structure and parameterization of CESM2-esm, which dictates the high covariance of simulated GPP and $R_{eco}$ should likely be evaluated and revised. We suspect that several changes made to the land model for CESM2 are likely...
responsible for the high covariation of GPP and $R_{\text{eco}}$. First, CLM5 reduced the magnitude of growth respiration fluxes (Atkin et al., 2017) and reduced the total magnitude of growth and maintenance respiration fluxes, relative to previous versions of the model (Lawrence et al., 2019). Second, the incorporation of the Fixation and Uptake of Nitrogen model (FUN) into CLM5 makes plants pay the carbon costs of nitrogen uptake (FUN; J. B. Fisher et al., 2010; R. A. Fisher et al., 2019; Shi et al., 2016). As currently applied in CLM5, the FUN carbon costs make up a large fraction of autotrophic respiration fluxes and are highly correlated with the timing of GPP. Finally, the parameterization for soil organic matter turnover uses a higher minimum water potential, which increases the sensitivity of heterotrophic respiration fluxes to liquid soil water availability (Carvalhais et al., 2014; Koven et al., 2017; Lawrence et al., 2019). Independently, these changes seem justified in their aim to more realistically represent terrestrial ecosystems, but together they likely served to reduce the IAV of net carbon fluxes that are simulated by CESM2.

The IAV of detrended GPP anomalies in CESM2-esm shows strong latitudinal patterns (Fig. 3). Notably, correlations between the IAV of GPP and terrestrial water storage anomalies are particularly strong in many arid, semi-arid and savannah regions (Fig. 3a), a finding that is consistent with work emphasizing moisture and precipitation controls over carbon cycle variability in arid regions (Ahlström et al., 2015; Humphrey et al., 2018; Poulter et al., 2014). Concurrently, correlations between the IAV of GPP and air temperature anomalies are stronger in arctic, boreal and temperate deciduous forests (Fig. 3b), which again is consistent with observations (discussed in section 4.2; Hu et al., 2019; Rödenbeck et al., 2018b). We recognize that inferring the relative importance of climate controls over land-atmosphere carbon exchange remain actively discussed in the literature (Cox et al., 2013; Humphrey et al., 2018; Jung et al., 2017; Piao et al., 2020; Poulter et al., 2014), but given the spatial and temporal heterogeneity of climate anomalies and timescales of ecosystem responses (Rödenbeck et al., 2018b; X. Zhang et al., 2013) we further investigate the seasonal modes of GPP variability that are simulated by CESM2 and their environmental covariates.

### 4.2 Seasonal variability

The timing of climate variations with respect to the climatological annual cycle plays an important role in the resulting interannual variability of terrestrial carbons fluxes (Buermann et
Satellite and flux tower observations in North America suggest that carbon cycle variability can be decomposed into modes of variability that are characterized by the amplification and redistribution of seasonal fluxes (Butterfield et al., 2020; Byrne et al., 2020). Results from our SVD analysis identified similar modes of variability in GPP that are simulated in CESM2; with amplification vectors dominant in high latitude and arid ecosystems (Fig. 4a) and redistribution vectors that are dominant in temperate forests, boreal forests, and agricultural regions (Fig. 4b). Qualitatively, these patterns align with findings from (Butterfield et al., 2020) who found robust patterns in seasonal variability from several satellite datasets that are correlated with regional anomalies of temperature and soil moisture availability. The seasonal redistribution vector explains a significant amount of carbon cycle variability in CESM2-esm (Figs. 4-5) but would not lead to changes in annual C fluxes ($\theta \sim 0$). Thus, climate effects on this mode of variability would be obscured in quantification of variability on annual time scales. This also suggests that the representation of plant phenology and water stress in CESM2 are likely responding in physically and ecologically realistic ways to simulated climate variability.

The nature of carbon cycle variability changes as a function of mean climate, ecosystem type, and the phase of the annual cycle of GPP. In grid cells where the seasonal amplification of GPP characterizes most of the flux variability the second vector from the SVD corresponds to a seasonal redistribution of the fluxes (Figs. 4-5). For example, in high latitude ecosystems the amplification vector describes more than half of the variability in simulated GPP and is associated with a net increase (or decrease) in annual carbon fluxes (Fig. 5a). The weights associated with the amplification vectors are most strongly correlated with summertime GPP anomalies (Fig. 6, top row; Table S2), which is not surprising since we identified the amplification vector from the SVD by its correlation with the mean climatology of monthly GPP fluxes simulated in each grid cell (section 2.2; Fig. S4). The weights from the amplification vectors in high latitude ecosystems show a strong, positive correlation with summertime air temperature anomalies and a weaker, but still significant, negative correlation with terrestrial water storage anomalies. Thus, with warmer (and drier) summertime conditions, CESM2 simulated positive GPP anomalies in Arctic and Boreal ecosystems. Conversely, with cooler (and wetter) summertime conditions CESM2 simulated negative GPP anomalies in these regions. Our analysis cannot diagnose the proximal driver of the GPP anomalies, but given their higher correlation coefficient we assume that summertime temperature anomalies are driving the carbon
cycle response, with declines in soil moisture subsequently resulting from higher evapotranspiration fluxes in warmer, more productive years.

The amplification vector also describes a high fraction of the GPP variability in lower latitudes (Fig. 5b-e). The weights from the amplification vectors in mid and low latitudes shows a strong positive correlation with regional peak growing season GPP anomalies in their respective hemispheres (Fig. 6). In contrast to northern high latitudes, weights from amplification vectors in these regions generally show stronger correlations with terrestrial water storage anomalies than they do for air temperature (Fig. 6, Table S2). Thus, in mid and lower latitudes wetter (and cooler) anomalies during the growing season maxima are associated with positive GPP anomalies, whereas drier (and warmer) anomalies are associated with negative GPP anomalies. While seasonal amplification vectors do explain a majority of the global variability in simulated GPP fluxes, some regions are better characterized by a seasonal redistribution of carbon fluxes that do not necessarily change the annual flux of GPP from the atmosphere onto land, just its timing.

The seasonal redistribution of plant productivity explains roughly a quarter of global GPP variability, but this is the dominant form of variability simulated by CESM2-esm in several regions, including the Canadian Great Plains, temperate forests, and agricultural regions (Fig. 4b). The seasonal redistribution vector is characterized by positive (or negative) GPP anomalies early in the growing season, followed by GPP anomalies of the opposite sign later in the growing season (Fig. 5). The spatial cohesiveness of this pattern is most notable in the northern hemisphere, where SVD weights associated with the redistribution vector are positively correlated with GPP anomalies and air temperature anomalies in the spring (MAM; Fig. 7). The SVD weights are negatively correlated with GPP and terrestrial water storage anomalies by summer and fall (JJA and SON; Fig 7, Table S3). Drier summer and fall conditions could result from higher evapotranspiration in the spring, or also from increased early runoff due to earlier snowmelt during warm springs (Buermann et al., 2013). Thus, the potential increases in plant productivity from an early green-up that were facilitated by warmer spring temperatures are negated by soil moisture stress later in the growing season, leading to negligible net changes in the annual land carbon flux (mean $\mathbf{\theta}$ values close to zero for the redistribution vector; Fig. 5).

The regions where a seasonal redistribution vector dominates GPP variability in CESM2-esm (Fig. 4) are also regions where native vegetation in the model use a stress deciduous
phenology scheme, or they are under agricultural management, which is explicitly represented in
CESM2 (Lawrence et al., 2019; Lombardozzi et al., 2020). Both of these phenology modes use a
growing degree day approach to simulate leaf emergence (or planting date and leaf emergence
for the CLM5 crop model), so the strong correlation between air temperature anomalies and
SVD weights are expected (Fig. 7, Table S3). We were more surprised, however, by the negative
GPP anomalies that emerge later in the growing season. These seem to be driven by drier and
warmer than average conditions that are consistent with satellite observations of vegetation
greenness (Buermann et al., 2013; Buermann et al., 2018). Notably, redistribution vectors in SIF
derived GPP in North America are tightly linked with spring (and summer) temperature
anomalies, and tend to be stronger in temperate forests, the Canadian Prairies, and agricultural
regions (Butterfield et al., 2020; Byrne et al., 2020). The larger influence of seasonal
redistribution at lower latitudes that is simulated in CESM2-esm is also consistent with
observations from forests reported in (Butterfield et al., 2020), but the overall importance of
seasonal redistribution vs. amplification on carbon cycle variability remains uncertain. Indeed,
considering the relative importance of these modes of variability may be important in trying to
infer appropriate sensitivities and interactions between seasonal to interannual variability in
climate, phenology, and ecosystem carbon fluxes from both models and observations.

5. Conclusion

The interannual variability of terrestrial net carbon exchange with the atmosphere in
CESM2-esm is low. Accordingly, the model also simulates a weaker than observed sensitivity of
net carbon exchange to global climate anomalies. This low variability of net carbon fluxes likely
results from a high covariation in component fluxes of NEP, namely gross primary productivity
and ecosystem respiration. The model also may simulate low variability in GPP, especially in the
tropics, which may be caused by missing the brief periods of high productivity that are evident in
flux tower observations and seem to make an important contribution to carbon cycle IAV. The
variability in GPP that is simulated by the model generally shows a latitudinal gradient in climate
sensitivities whereby positive GPP anomalies are driven by warmer and drier conditions in high-
latitude ecosystems but wetter and cooler conditions in mid and low latitudes.
Our analysis decomposes IAV in GPP fluxes into modes of variability, characterized by seasonal amplification and redistribution vectors that together explain three quarters of the global variability in GPP. The seasonal redistribution component to carbon cycle variability is notable because although it is not apparent in more aggregated (annual) measurements of IAV, it does seem widespread in both the model and in observations. Decomposing carbon cycle variability with the SVD allows us to look at regional patterns that may be consistent with observational data. For example, both the model and observations show that wetter and cooler springs and summers lead to an amplification signal in GPP over the western United States, whereas a temporal redistribution of GPP anomalies is more strongly associated with variability in springtime temperatures in the eastern US. Thus, while the total magnitude of net and gross terrestrial carbon flux variability simulated by CESM2 may be too low, the simulated interannual and seasonal variability does qualitatively capture patterns of regional and global sensitivities to climate variability. More broadly, we contend this kind of analysis is useful in diagnosing strengths and weaknesses in biogeochemical models in comparison to observational data.

Acknowledgments, Samples, and Data

The authors declare no conflicts of interests. The CESM project is supported primarily by the National Science Foundation (NSF). This material is based upon work supported by the National Center for Atmospheric Research, which is a major facility sponsored by the NSF under Cooperative Agreement No. 1852977. Computing and data storage resources, including the Cheyenne supercomputer (doi:10.5065/D6RX99HX), were provided by the Computational and Information Systems Laboratory (CISL) at NCAR. We thank all the scientists, software engineers, and administrators who contributed to the development of CESM2. WRW and DLL were supported by the US Department of Agriculture NIFA Award number 2015-67003-23485. WRW, GKA, and ZB would like to acknowledge support from the NASA Interdisciplinary Science Program award number NNX17AK19G.

Previous and current CESM versions are freely available online (see http://www.cesm.ucar.edu/models/cesm2/release_download.html) with code from https://github.com/ESCOMP/CESM). The CESM2-esm-hist data set (doi: 10.22033/ESGF/CMIP6.7575) used in this study are also freely available from the Earth System
Grid Federation (ESGF; at https://esgf-node.llnl.gov/search/cmip6/, search for CESM2.esm-hist)
or from the NCAR Digital Asset Services Hub (DASH; at data.ucar.edu) or from the links
provided from the CESM website (at www.cesm.ucar.edu); CESM2 (2019). Code for the
analyses presented can be found at WRW’s GitHub page
(https://github.com/wwieder/ctsm_py/blob/master/notebooks/esmIAV.ipynb), which has been

Author contribution
WRW conducted the analyses with help from ZB and GKA. WRW wrote the manuscript with
contributions from all other authors.

References


