

Terrestrial biosphere model performance for inter-annual variability of land-atmosphere CO₂ exchange

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Abstract

Interannual variability in biosphere-atmosphere exchange of CO₂ is driven by a diverse range of biotic and abiotic factors. Replicating this variability thus represents the 'acid test' for terrestrial biosphere models. Although such models are commonly used to project responses to both normal and anomalous variability in climate, they are rarely tested explicitly against inter-annual variability in observations. Herein, using standardized data from the North American Carbon Program, we assess the performance of 16 terrestrial biosphere models and 3 remote sensing products against long-term measurements of biosphere-atmosphere CO₂ exchange made with eddy-covariance flux towers at 11 forested sites in North America. Instead of focusing on model-data agreement we take a systematic, variability-oriented approach and show that although the models tend to reproduce the mean magnitude of the observed annual flux variability, they fail to reproduce the timing. Large biases in modeled annual means are evident for all models. Observed interannual variability is found to commonly be on the order of magnitude of the mean fluxes. None of the models consistently reproduce observed interannual variability within measurement uncertainty. Underrepresentation of variability in spring phenology, soil thaw and snowpack melting, and difficulties in reproducing the lagged response to extreme climatic events are identified as systematic errors, common to all models included in this study.

Keywords: biosphere-atmosphere interaction, carbon fluxes, carbon sequestration, interannual variability, process-based models, remote sensing

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Introduction

The terrestrial biosphere acts as a net sink for atmospheric CO₂, with global forests absorbing on average 4 Pg C yr⁻¹ (Pan *et al.*, 2011), which, excluding deforestation, offsets roughly half of all anthropogenic emis-

sions from fossil fuel burning and cement production (Pan *et al.*, 2011). Interannual variability in this sink is often on the order of magnitude of the mean (e.g., Zeng *et al.*, 2005; Reichstein *et al.*, 2007; a; Pan *et al.*, 2011), and drives interannual variability in the growth rate of atmospheric CO₂ (Bousquet *et al.*, 2000; Knorr *et al.*, 2007). Carbon fluxes in forest ecosystems are tightly coupled to climate (Richardson *et al.*, 2007; Piao *et al.*, 2008; Chen *et al.*, 2009; Dragoni *et al.*, 2011), and anomalous climatic

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signals generally drive the observed variability in their sink strength (Dunn *et al.*, 2007; Desai, 2010; le Maire *et al.*, 2010). Such signals tend to affect photosynthesis and respiration (the two processes which determine net ecosystem carbon exchange) to different extents (Richardson *et al.*, 2007; Luyssaert *et al.*, 2007), and therefore provide an excellent test-bed to assess the skill of terrestrial biosphere models.

Terrestrial biosphere models are the primary tools used for predicting the impact of climate variability on terrestrial carbon fluxes. Built around the philosophy that a blend of mechanistic and semi-empirical descriptions can capture functional responses to environmental drivers, they have been used in conjunction with remote sensing products (Zhao & Running, 2010) and data mining tools (Papale & Valentini, 2003) to provide regional and global estimates of terrestrial carbon cycling (e.g., Friend, 2010; Beer *et al.*, 2010). They are also commonly used to quantify terrestrial responses to climatic variability, including anomalies, and extreme events (Ciais *et al.*, 2005; Richardson *et al.*, 2007; Vetter *et al.*, 2008; Zhao & Running, 2010). Future model projections of the response of terrestrial carbon cycling to climate change (Heimann & Reichstein, 2008) are necessary to inform policy (IPCC, 2007), although current models show very divergent sensitivity to long-term changes in climate (Friedlingstein *et al.*, 2006).

Biogeochemical models are often shown to capture diel and seasonal dynamics reasonably well (e.g., Braswell *et al.*, 2005). This is not surprising, given the pronounced diurnal and seasonal cycles of climatic drivers. Over yearly and longer time scales, however, studies show poor model performance at reproducing gross fluxes and carbon budgets (e.g., Hanson *et al.*, 2004; Braswell *et al.*, 2005; Siqueira *et al.*, 2006; Richardson *et al.*, 2007; Urbanski *et al.*, 2007). Such comparison studies are typically restricted to a limited number of models and sites, and a relatively short time series length. Nonetheless, the results suggest that although the response of terrestrial ecosystems to mean climatic drivers is relatively well captured, sensitivity to the impact of variability in climatic drivers may not be, leading to the accumulation of high frequency model error (e.g., Dietze *et al.*, 2012) over longer time scales (Schwalm *et al.*, 2010). No study, however, has yet identified systematic errors in model sensitivity to climatic variability.

In this analysis, we use 16 terrestrial biosphere models and 3 remote sensing products, along with eddy-covariance data from a range of sites included in the North American Carbon Program interim site synthesis, to assess model ability to reproduce observed variability in carbon fluxes. We examine the frequency distribution of temporal anomalies in net ecosystem

exchange (NEE), gross primary productivity (GPP), and ecosystem respiration (RE), for two plant functional types. We first assess individual model performance on an annual/interannual scale. As interannual variability can be driven by 'critical' periods within a year (le Maire *et al.*, 2010), we examine monthly systematic model errors (errors consistent across all models and sites). By using data from sites with a regionally coherent anomalous year, we then assess the possible role of extreme within-year climatic events and lagged effects on model performance for interannual variability in terrestrial carbon cycling.

Methods

All models and data used were obtained through the North American Carbon Program (NACP) (<http://www.nacarbon.org/nacp/>). To allow for an ensemble approach and reduce the potential for spurious variability, we selected only sites with at least 5 years of data, from plant functional types that were represented by at least three such sites. This resulted in a total of 11 forested sites distributed through North America (Table 1). Of those, six were deciduous broadleaf, and five evergreen needleleaf. This gave a total of 91 site-years for the analysis.

Eddy-covariance flux data (produced by AmeriFlux and Fluxnet-Canada investigators) from the 11 selected sites was processed according to a common protocol from the NACP site level interim synthesis (<http://www.nacarbon.org/nacp/>). The observed NEE were corrected for storage, despiked (i.e., outlying values removed), and filtered to remove conditions of low turbulence (friction velocity filtered). Flux error estimates were calculated (Barr *et al.*, 2009) by combining random uncertainty (calculated following Richardson & Hollinger (2007)) and uncertainty due to the selection of the friction velocity threshold (Barr *et al.*, 2009). Observed monthly and annual NEE values were then calculated using gap-filled data from each site (Barr *et al.*, 2009). The gap-filled NEE values were also partitioned to gross ecosystem photosynthesis (GPP) and ecosystem respiration (RE). Multiple approaches were used to quantify additional uncertainty introduced by the partitioning (Desai, 2010; Barr *et al.*, 2009).

Gaps in the meteorological forcing data occurred due to instrument failure or quality control. Such gaps were filled using the nearest available climate station in the National Climatic Data Center's Global Surface Summary of the Day (NCDC-GSOD) database. Gaps at sites where no such data were available were filled using DAYMET (Thornton *et al.*, 1997). Daily NCDC-GSOD and DAYMET data were temporarily downsampled to hourly or half-hourly values (see Ricciuto *et al.*, 2009 for details) (http://nacp.ornl.gov/docs/Site_Synthesis_Protocol_v7.pdf).

Sixteen terrestrial biosphere models (Table 2) were run at the sites for the period of available measurements (Table 1). The terrestrial biosphere models simulated carbon cycling with process-based formulations of varying detail for the component carbon fluxes of photosynthesis and respiration.

Table 1 Summary of sites used

Country-site	Name	Lat.	Long.	Elevation (m.a.s.l.)	Years	Biome	Mean NEE	δ NEE	NEE error	Mean GPP	δ GPP	GPP error	Mean RE	δ RE	RE error	Reference
CA-Ca1	BC, Campbell river –Mature forest site	49.87	–125.33	300	1998–2005	EVG	–244	65	32	2310	112	44	2065	130	72	Schwalb <i>et al.</i> , 2007;
CA-Oas	Sask. –SSA Old aspen	53.63	–106.20	530	1997–2005	DBF	–158	100	15	1090	150	24	932	86	35	Barr <i>et al.</i> , 2004;
CA-Obs	Sask. –SSA Old black spruce	53.99	–105.12	629	2000–2005	EVG	–56	20	8	795	55	14	738	41	19	Griffis <i>et al.</i> , 2003;
CA-Ojp	Sask. –SSA Old jack pine	53.92	–104.69	579	2000–2005	EVG	–30	26	9	612	48	16	582	30	22	Griffis <i>et al.</i> , 2003;
CA-TP4	Ontario – Turkey point Mature white pine	42.71	–80.36	219	2001–2005	EVG	–133	72	16	1391	84	20	1258	75	30	Peichl & Arain, 2007;
US-Ha1	MA –Harvard forest EMS tower (HFR1)	42.54	–72.17	303	1992–2005	DBF	–217	117	36	1409	156	87	1192	125	78	Urbanski <i>et al.</i> , 2007;
US-Ho1	ME –Howland forest (Main tower)	45.20	–68.74	60	1996–2004	EVG	–223	53	18	1518	90	22	1295	82	33	Richardson <i>et al.</i> , 2009;
US-MMS	IN –Morgan Monroe state forest	39.32	–86.41	275	1999–2005	DBF	–348	37	23	1331	56	26	983	68	31	Schmid <i>et al.</i> , 2000;
US-NR1	CO –Niwot Ridge forest (LTER NWT1)	40.03	–105.55	3050	1998–2005	EVG	–37	25	15	804	54	25	767	52	38	Bradford <i>et al.</i> , 2008;
US-Pfa	WI –Park falls/ WLEF	45.95	–90.27	485	1995–2005	DBF	45	26	21	1005	49	35	1050	35	45	Davis <i>et al.</i> , 2003;
US-UMB	MI –University of Michigan biological station	45.56	–84.71	234	1999–2005	DBF	–132	65	22	1189	43	32	1057	87	42	Schmid <i>et al.</i> , 2003

Table 2 Summary of model characteristics

Attribute	Model									
	BEPS	BIOME-BGC	Can-IBIS	CNCLASS	DLEM	ECOSYS	ED2	EDCM	ISAM	LoTEC-DA
Temporal resolution	Daily	Daily	Half-hourly	Half-hourly	Daily	Hourly	Half-hourly	Monthly	Weekly	Half-hourly
Vegetation pools	4	7	3	4	6	9	6	8	5	4
Soil Pools	9	4	7	3	3	9	4	5	8	5
Canopy phenology	Semi-prognostic	Prognostic	Prognostic	Prognostic	Semi-prognostic	Prognostic	Prognostic	Prognostic		Prognostic
Gross primary photosynthesis (GPP)	Enzyme kinetic model	Stomatal conductance model	Enzyme kinetic model	Enzyme kinetic model	Stomatal conductance model	Enzyme kinetic model	Enzyme kinetic model	Light use efficiency	Enzyme kinetic model	Enzyme kinetic model
Heterotrophic respiration (HR)	Temperature (air + soil) precipitation soil evaporation soil carbon + nitrogen	Soil temperature soil moisture soil carbon	First or greater order model	First or greater order model	Air temperature soil temperature litter and soil carbon soil nitrogen soil moisture	Dissolved carbon loss soil temperature soil moisture shortwave & long wave radiation soil carbon vegetation carbon soil nitrogen leaf nitrogen	Soil temperature soil moisture soil carbon soil nitrogen	Soil temperature soil moisture soil carbon dissolved carbon loss vegetation carbon soil nitrogen	First or greater order model	Soil temperature soil moisture soil carbon
Autotrophic respiration (AR)	Air temperature GPP	Air temperature vegetation carbon leaf nitrogen	Air temperature soil precipitation soil moisture incident shortwave + long wave radiation vegetation carbon	Fraction of instantaneous GPP	Air temperature vegetation carbon leaf nitrogen GPP	Air temperature soil temperature vegetation carbon leaf nitrogen	Air temperature soil temperature vegetation carbon leaf nitrogen GPP	Proportional to growth	Proportional to growth	Air temperature soil temperature soil moisture vegetation carbon GPP
Ecosystem respiration	AR+HR	Air temperature soil temperature	AR + HR	AR + HR	AR + HR	AR + HR	AR + HR	AR + HR	AR + HR	AR + HR

Table 2 (continued)

Attribute	Model									
	BEPS	BIOME-BGC	Can-IBIS	CNCLASS	DLEM	ECOSYS	ED2	EDCM	ISAM	LoTEC-DA
Net primary productivity (NPP)	GPP-AR	Shortwave radiation vapor pressure deficit CO ₂ vegetation carbon leaf nitrogen	GPP-AR	Fraction of instantaneous GPP	GPP-AR	GPP-AR	GPP-AR	Air temperature precipitation soil carbon soil nitrogen soil moisture vegetation carbon leaf nitrogen	GPP-AR	GPP-AR
Net ecosystem exchange	NPP-HR	Soil temperature soil moisture shortwave radiation vapor pressure deficit	NPP-HR	GPP-R	NPP-HR	GPP-R	NPP-HR	NPP-HR	NPP-HR	
Reference	Liu <i>et al.</i> , 1999;	Thornton <i>et al.</i> , 2005;	Williamson <i>et al.</i> , 2008;	Arain <i>et al.</i> , 2006;	Tian <i>et al.</i> , 2010;	Grant <i>et al.</i> , 2005;	Medvigy <i>et al.</i> , 2009;	Liu <i>et al.</i> , 2003;	Yang <i>et al.</i> , 2009;	Hanson <i>et al.</i> , 2004;
Attribute	Model									
	LPJml	ORCHIDEE	SiB	SiB-CASA	SSiB2	TECO	BESS	MODISc5	MODISc5.1	
Temporal resolution	Daily	Half-hourly	Half-hourly	10 min	Half-hourly	Hourly	Daily	Daily	Daily	
Vegetation pools	3	8	0	8	0	3	n/a	n/a	n/a	
Soil pools	2	8	0	5	0	5	n/a	n/a	n/a	
Canopy phenology	Prognostic	Prognostic	Prescribed	Prescribed	Prescribed	Prognostic	Prescribed	Prescribed	Prescribed	
Gross primary photosynthesis (GPP)	Stomatal conductance model	Enzyme kinetic model	Enzyme kinetic model	Enzyme kinetic model	Stomatal conductance model	Stomatal conductance model	Enzyme kinetic model	Light-use-efficiency model	Light-use-efficiency model	

Table 2 (continued)

Attribute	Model				Remote Sensing			
	LPJml	ORCHIDEE	SiB	SiB-CASA	SSiB2	TECO	BESS	MODIS5
Heterotrophic respiration (HR)	Soil temperature soil moisture soil carbon	Soil temperature soil moisture soil carbon	Zero-order model	Soil temperature soil moisture soil carbon	Zero-order model	First or greater order model	n/a	n/a
Autotrophic respiration (AR)	Air temperature soil moisture vegetation carbon	Air temperature vegetation carbon	Fraction of instantaneous GPP	Air temperature soil moisture vegetation carbon	Air temperature soil moisture surface incident shortwave radiation relative humidity LAI fPAR CO ₂ forced annual balance	Air temperature vegetation carbon	n/a	n/a
Ecosystem respiration	AR + HR	AR + HR	Forced Annual Balance	AR + HR	GPP-AR	AR + HR	n/a	n/a
Net primary productivity (NPP)	GPP-AR	GPP-AR	GPP-AR	Air temperature soil moisture CO ₂ relative humidity	GPP-R	GPP-AR	GPP	GPP
Net ecosystem exchange	NPP-HR	GPP-R	GPP-R	GPP-R	Zero-order model	GPP - R	n/a	n/a
Reference	Sitch <i>et al.</i> , 2003;	Krinner <i>et al.</i> , 2005;	Baker <i>et al.</i> , 2008;	Schaefer <i>et al.</i> , 2009;	Zhan <i>et al.</i> , 2003;	Weng & Luo, 2008;	Ryu <i>et al.</i> , 2011;	Running <i>et al.</i> , 2004;
								Zhao <i>et al.</i> , 2005

Simulated NEE was based on model specific runs using gap filled observed weather at each site and locally observed values of soil texture according to a standard protocol (Ricciuto *et al.*, 2009). Each model used species or plant functional type specific parameterizations as defined by the individual model teams, with the exception of LoTEC where parameters were optimized using data assimilation (Ricciuto *et al.*, 2008). Three remote sensing products of terrestrial gross primary productivity (MODISc5 (Running *et al.*, 2004), MODISc5.1 (Zhao *et al.*, 2005), BESS (Ryu *et al.*, 2011)), not included in the North American Carbon Program, were also used to provide annual estimates of GPP for each site.

To assess interannual variability, we normalized the measured/modeled values of NEE, GPP, and RE by subtracting the long-term calendar year measured/modeled mean for each site from individual site-year flux values, giving F_{obs} and F_{sim} for each flux and year. By comparing the long-term calendar year mean of measured and modeled fluxes, we also identified biases in model estimates of NEE, GPP and RE. Model-data agreement for interannual variability in annual flux sums was assessed in terms of the normalized root mean squared error (NRMSE) and the χ^2 statistic.

The NRMSE is the root mean square error of model-data mismatch normalized by the magnitude of observed variability at each site:

$$\text{NRMSE}_{ijk} = \frac{\sqrt{\frac{1}{n} \sum l (F_{\text{obs}} - F_{\text{sim}})^2}}{\sigma(F_{\text{obs}})} \quad (1)$$

where F represents the observed (obs) or modeled (sim) value of a particular flux, i (NEE, GPP, or RE), for a particular year, l . Note that each flux here is represented as the interannual variability (F_{obs} and F_{sim}), not the mean flux. $\sigma(F_{\text{obs}})$ is the standard deviation of observed interannual variability at site k . NRMSE values are calculated for each model j at site k . The NRMSE thus reports the mean difference between the simulated and observed flux, relative to the variability in the observed flux.

The χ^2 statistic complements the NRMSE by incorporating measurement error. Here it is calculated for each model and PFT as the squared residual between paired model and data points for each flux (after normalization to the long-term mean as described above), relative to the observational error:

$$\chi^2_{ijk} = \frac{1}{n} \sum_{ijkl} \left(\frac{F_{\text{obs}} - F_{\text{sim}}}{2\delta(F_{\text{obs}})} \right)^2 \quad (2)$$

where $\delta(F_{\text{obs}})$ is uncertainty related to the annual observed value of that flux, 2 normalizes the uncertainty in the observed flux to correspond to a 95% confidence interval. A χ^2 value of less than one indicates that the model agrees with the data relative to data uncertainty. That is interannual variability for a model with a χ^2 value of less than one will always fall within one standard deviation of data error. Above one, the χ^2 scales model error relative to observation uncertainty.

Interannual variability in observed fluxes commonly stems from specific, short-lived, periods of anomalous fluxes within the year (Krishnan *et al.*, 2008, 2009; Chen *et al.*, 2009; le Maire *et al.*, 2010). We therefore also assessed model performance for

variability on a monthly scale. The variability of monthly fluxes between years was calculated in the same way as annual variability, as the difference between the observed or modeled monthly value and the associated long-term mean for the month in question.

By differencing the observed and predicted monthly variability (herein termed variance residuals) specific periods during the year at which the models under- or over-represent the observed monthly variability can be identified. We define periods of systematic model error (statistically common to all models) as times when all models show the same-signed bias in variance residuals with 95% confidence. We also assess persistent biases, which are mean biases of more than 1 month in duration that are not necessarily systematic.

Extreme climatic events, detectable as regionally coherent deviations outside the normal range of variability, provide a strong test of model performance. We identified one such event in our database. At three sites in mid-western Canada, mean spring monthly temperatures in 2002 were between 8 and 10 °C below the long-term mean. We used this event to assess model skill and to identify systematic model error.

Results

Biases and the magnitude of variability

In order to quantify interannual variability, we normalized all models and data by subtracting respective mean annual totals from individual annual totals. This process identified considerable biases in model estimates of all total annual fluxes at all sites (Fig. 1). In particular, biases in annual NEE were commonly of similar magnitude to mean observed annual NEE fluxes. The majority of models were biased toward underestimating ecosystem carbon uptake for both deciduous and evergreen sites (Fig. 1). Note that biases herein are reported relative to the observed mean NEE for each site, and therefore have the potential to be particularly larger for sites with low mean annual NEE. See Table 1 for per-site mean annual NEE values.

The magnitude of modeled interannual variability in each annual flux was on average of the same order of that observed (Fig. 2). A large range in model performance was evident (Table 3), but in general, the models proved 'flexible' enough to reproduce the observed range of variability. Observed interannual variability in NEE for deciduous broadleaved forests was twice that of evergreen needle-leaved forests, a distinction only reproduced by six of the included models. The magnitude of interannual variability in both GPP and RE was greater (55%, 23%) in deciduous broadleaved forests than in evergreen needleleaved forests. The remote sensing products, however, consistently predicted higher GPP variability in evergreen than in deciduous forests.

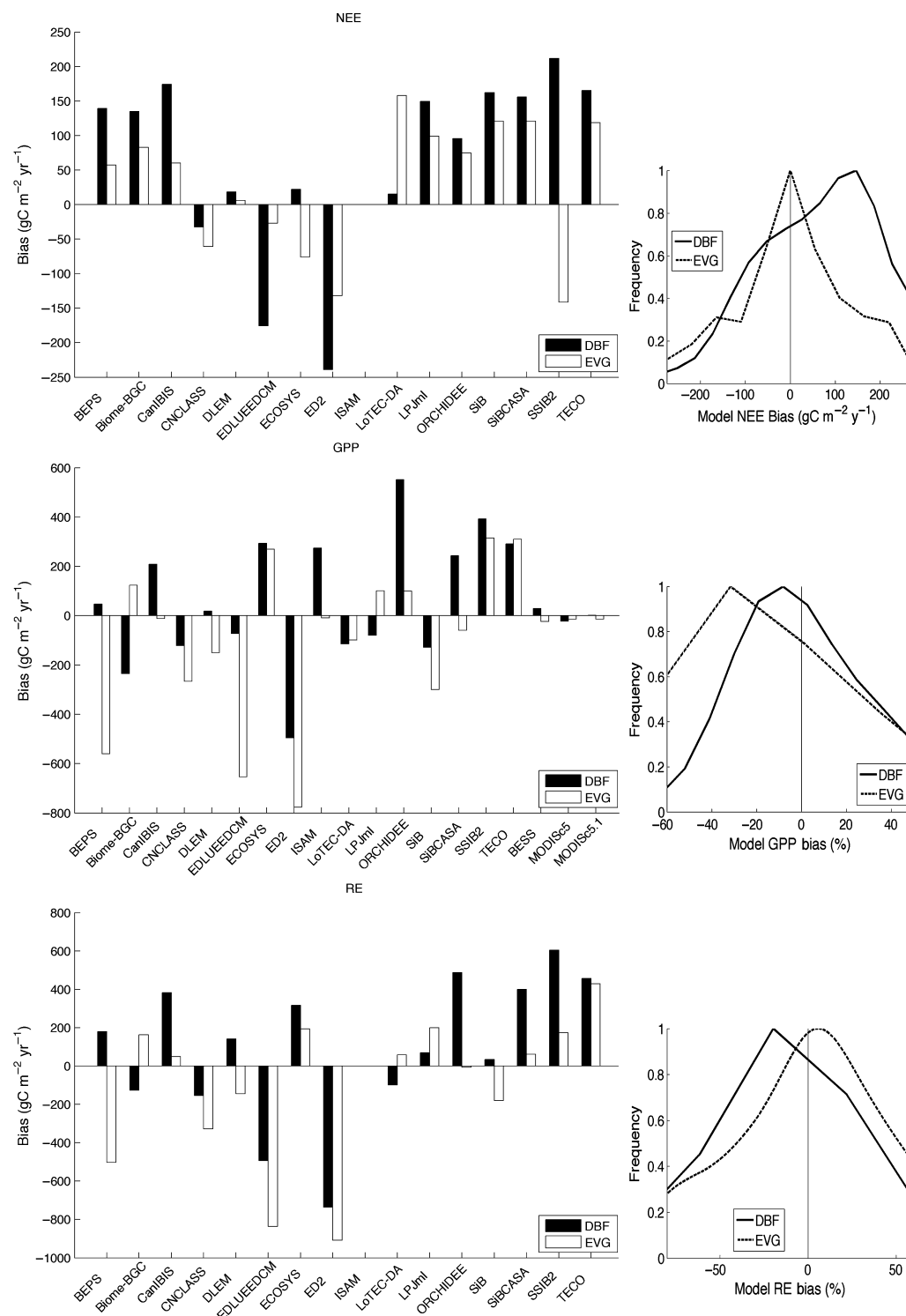


Fig. 1 Mean model bias (Modeled-Measured, $\text{gC m}^{-2} \text{yr}^{-1}$) over all years when compared to annual gap-filled observations of net ecosystem exchange (NEE), gross primary productivity (GPP), and ecosystem respiration (RE). Results are grouped by two plant functional types (EVG: Evergreen needleleaf forest; DBF: Deciduous broadleaf forest). The right panel is the normalized frequency distribution of model biases grouped by plant functional type, showing the distribution of values in the bar charts on the left, reported as a total bias for NEE, and a percentage of the annual total ($|\text{Modeled-Measured}|/\text{Measured}$) for GPP and RE. X-axis ranges are truncated to represent only observed range of biases.

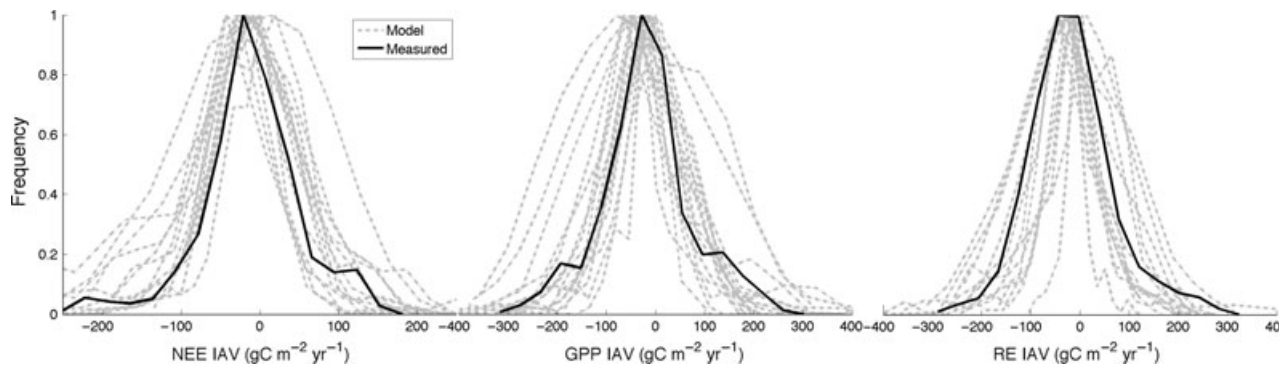


Fig. 2 The distribution of the magnitude of interannual variability (IAV) in annual totals of net ecosystem exchange (NEE), gross primary production (GPP), and ecosystem respiration (RE), over all sites for each model (gray lines) and the data (black line). See Table 3 for individual model values.

Table 3 Mean standard deviation of observed and modeled interannual variability for net ecosystem exchange (NEE), gross primary productivity (GPP) and ecosystem respiration (RE). Sites are grouped as deciduous broadleaved forest or evergreen needle-leaved forest. Mean error of observed annual sums is also given for reference (in brackets). IAV: Interannual variability. Model codes, given in brackets, are those used in Fig. 3

	NEE		GPP		RE	
	DBF	EVG	DBF	EVG	DBF	EVG
Observed IAV	85.53	44.49	115.05	74.30	91.56	74.32
Annual error	(24.73)	(17.12)	(47.73)	(24.54)	(50.89)	(37.50)
Models						
BEPS (A)	213.54	40.36	110.54	69.16	234.33	85.04
Biome-BGC (B)	59.66	77.99	115.54	129.05	103.42	78.51
CanIBIS (C)	57.70	71.36	91.42	78.94	66.11	87.81
CNCLASS (D)	76.98	31.34	55.87	55.84	68.36	39.41
DLEM (E)	81.57	39.28	202.73	81.54	224.81	59.75
EDLUEEDCM (F)	169.20	65.57	240.33	93.72	103.86	43.23
ECOSYS (G)	47.79	59.43	110.59	64.85	86.59	64.58
ED2 (H)	134.66	17.69	156.14	23.85	54.08	14.79
ISAM (I)			178.31	98.10		
LoTEC-DA (J)	88.26	92.03	121.13	56.05	57.77	103.90
LPjml (K)	72.97	104.96	127.76	145.35	86.87	93.58
ORCHIDEE (L)	93.58	26.33	175.23	63.33	113.73	47.96
SiB (M)	0.28	0.54	33.23	32.87	33.14	32.90
SiBCASA (N)	37.93	38.81	54.86	40.53	65.39	56.86
SSIB2 (O)	93.55	53.50	74.59	66.23	124.01	95.89
TECO (P)	64.32	38.87	94.41	57.15	121.13	54.89
BESS (Q)			104.32	178.26		
MODIS5 (R)			82.17	136.14		
MODIS5.1 (S)			48.92	52.06		

Statistical performance of models on an interannual scale

Although the mean magnitude of model variability on the interannual scale was similar to the mean observed magnitude of variability (Fig. 2), all models fell outside the data error of the observed for individual site-years ($>1 \chi^2$, Fig. 3, S1). This means that the general magnitude of interannual variability was well reproduced, but not the timing. Interannual variability

in the annual net ecosystem exchange of evergreen forests was better simulated on average than deciduous forests (Fig. 3). A larger range of model performance was observed for variability in annual GPP than that of RE. Our results suggest that on average the inability of models to match the timing of observed variability in GPP is the main cause of errors in the simulation of interannual variability in NEE, although this is very model-dependent (Fig. 3). The

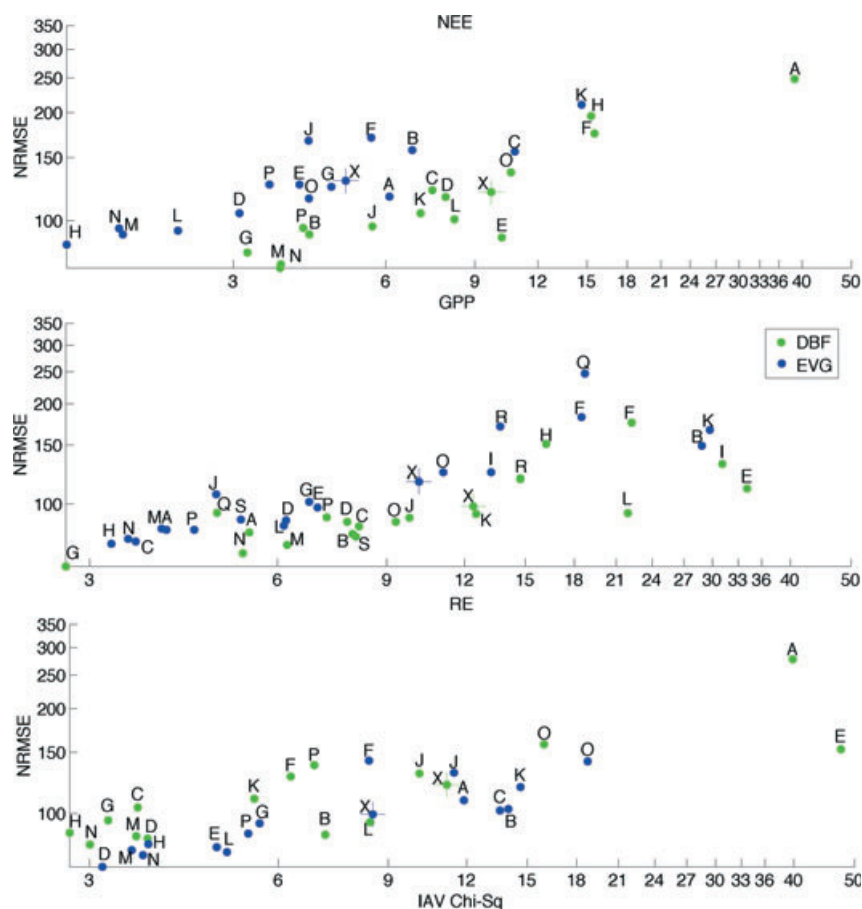


Fig. 3 Statistical comparison (on a log-log scale) of model performance (normalized root mean square error vs. χ^2 statistic) for interannual variability (IAV) in annual totals of net ecosystem exchange (NEE), gross primary productivity (GPP) and ecosystem respiration (RE) for the two plant functional types (DBF (green): Deciduous broadleaved forests; EVG (blue): Evergreen needleleaf forests). See supplementary material for graphs with error bars (Fig. S1, S2).

MODIS5 remote sensing product performed worse than the average model (Fig. 3, Fig. S2). The MODIS5.1 data product proved to be a large improvement over the MODIS5 GPP product. The BESS remote sensing product, a process-based model interpretation of remotely sensed data (Ryu *et al.*, 2011), performed better than either MODIS product for deciduous forests, although that was not the case for evergreens. Although process-based models of different types were represented (e.g., light use efficiency vs. enzyme kinetic model for GPP, Table 2) no model characteristic performed statistically better than any other (data not shown). This could be due to the limited number of models with particular characteristics.

Variability within the year

The models showed persistent systematic biases (see definition in Methods section) for monthly flux variability. In deciduous forests, models consistently underesti-

mated monthly variability in NEE throughout spring (May and June) (Fig. 4). Model underestimation of variability in deciduous spring NEE fluxes was mostly due to underrepresentation of variability in spring GPP (Fig. 4). A smaller peak in the deciduous GPP variance residuals (predicted monthly variability – observed monthly variability) was also evident in September and October. Variability in deciduous RE showed no bias that was consistent across all models.

Systematic underrepresentation of monthly variability during May was also evident for evergreen forests (Fig. 4). Here, however, model error for NEE was dominated by the lack of variability in modeled RE during spring. Although evergreen forests do not exhibit the marked phenological transitions observed in deciduous forests, all evergreen forests included in this study maintain a large snowpack throughout winter. Persistent, non-systematic biases were evidenced throughout the year, in particular an overestimation of winter variability in evergreen NEE and GPP, and a persistent

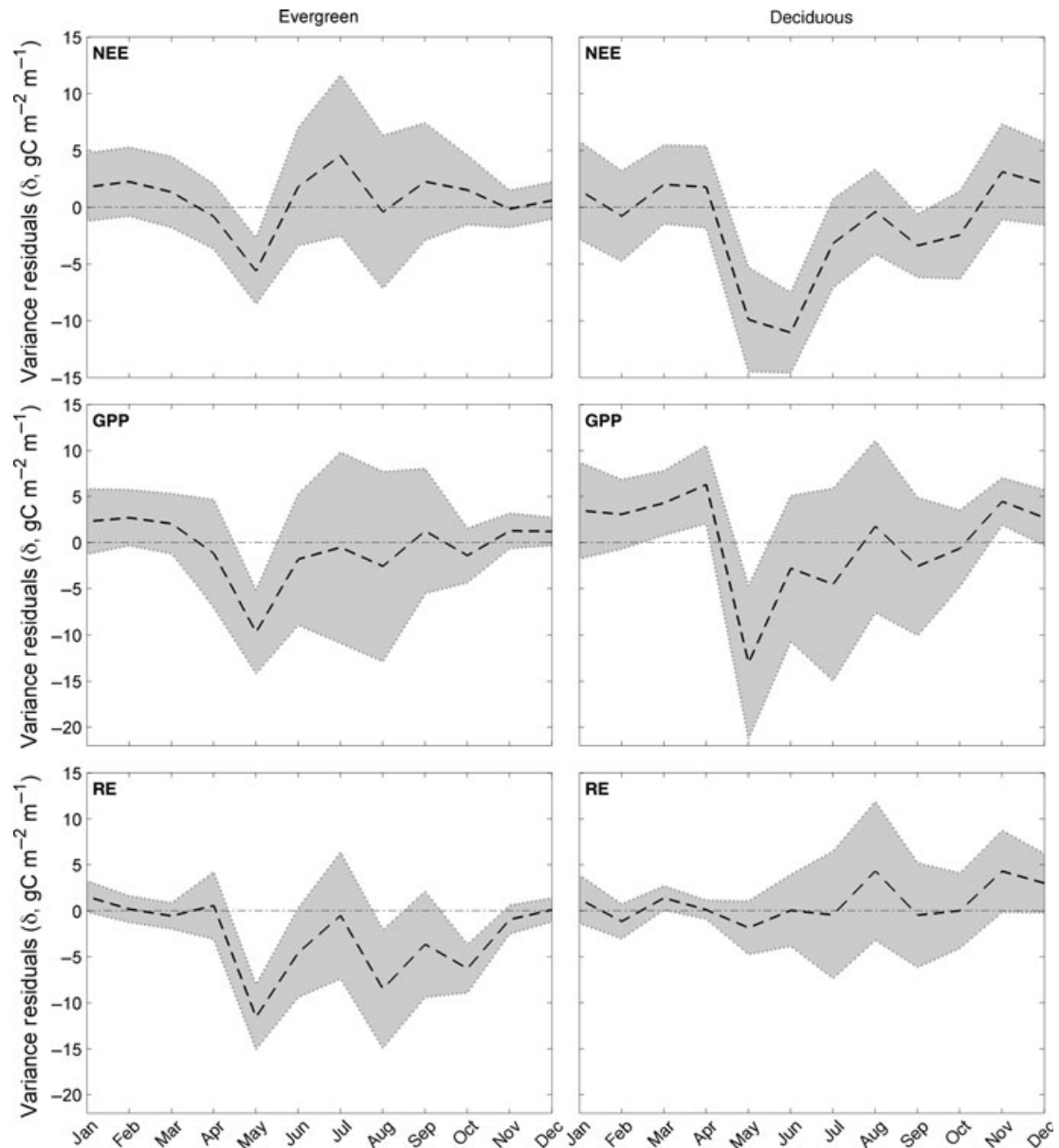


Fig. 4 Residuals (predicted-observed) of monthly variability in net ecosystem exchange (NEE), gross primary productivity (GPP), and ecosystem respiration (RE). Positive values indicate a higher variability in the observations than in a model. The mean model-data residuals are presented as a dashed line. The gray area represents the standard deviation about the mean. Values represent averages over all sites for each plant functional type, and all sites taken together. Model codes – A: BEPS, B: Biome-BGC, C: CanIBIS, D: CNCLASS, E: DLEM, F: EDLUEEDCM, G: ECOSYS, H: ED2, I: ISAM, J: LoTEC-DA, K: LPJml, L: ORCHIDEE, M: SiB, N: SiBCASA, O: SSiB2, P: TECO, Q: BESS, R: MODISc5, S: MODISc5.1, X: Mean

underestimation of variability in evergreen RE during the summer.

Response to anomalous climate forcing

Three sites (CA-Ojp, CA-Obs, CA-Oas; see site description Table 1) experienced a regionally coherent extreme climatic event during 2002, where monthly mean temperatures were between 8 (CA-Ojp, CA-Obs) and 10 °C

(CA-Oas) below the long-term mean. The anomaly largely affected canopy GPP at all three sites, and to a lesser extent RE (Fig. 5). At CA-Ojp and CA-Obs, anomalously low temperatures during the month of April lowered observed GPP by more than twice the normal range of variability for that month (Fig. 5). The models accurately captured the drop in productivity, with the mean of all model projections capturing both the sign and the magnitude of the April GPP anomaly

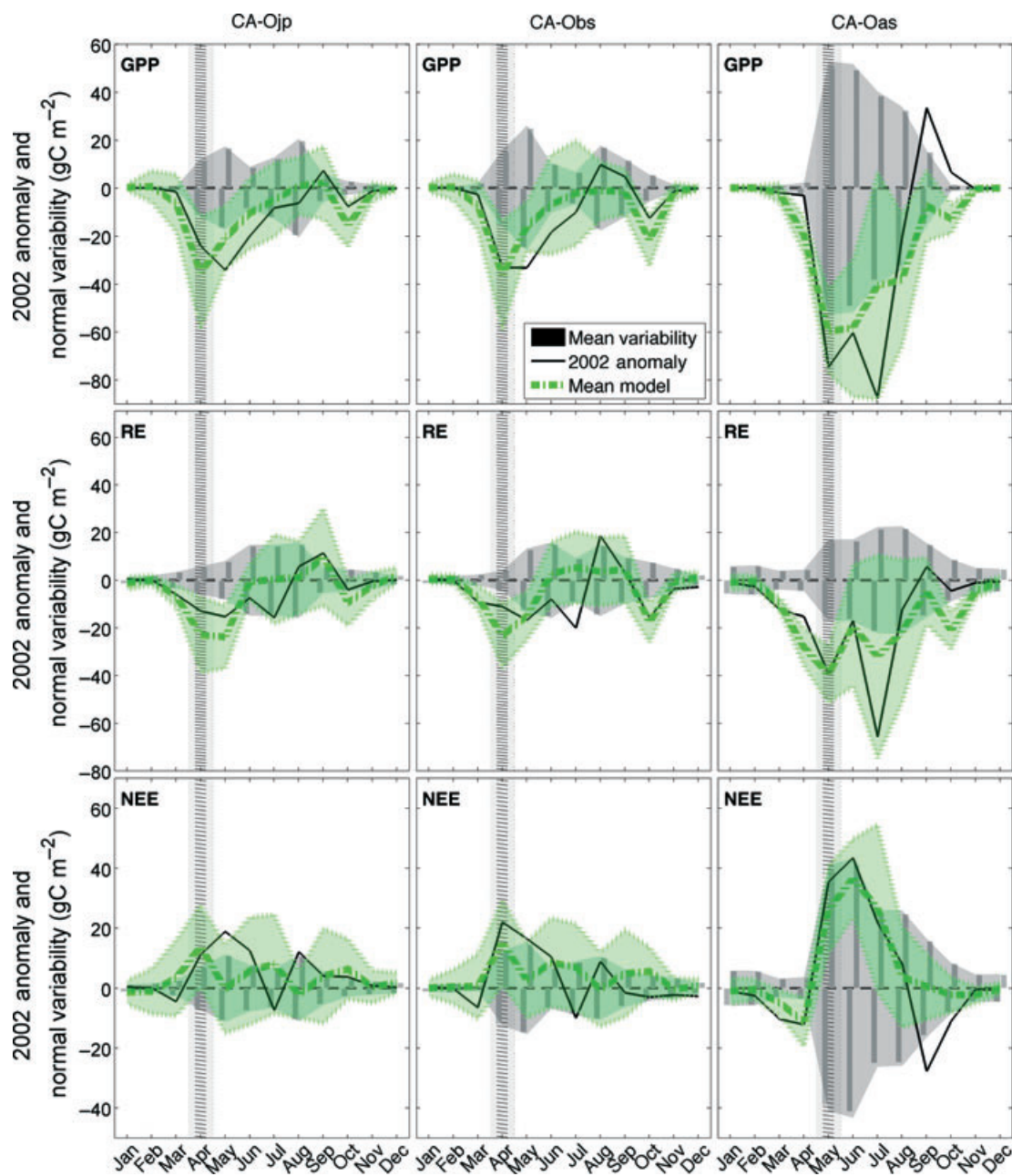


Fig. 5 Monthly modelled and observed anomalies (mean model: green dashed line; standard deviation of models: green shaded area; observed: solid black line) in gross primary production (GPP), ecosystem respiration (RE), and net ecosystem exchange (NEE) for the year 2002 at three sites (Ca-Ojp, Ca-Obs, Ca-Oas) which exhibit a regionally coherent anomaly in that year. The standard deviation of normal observed monthly variability is presented as the gray area with dark gray columns. The duration of the anomalous temperature event is shown in the crosshatched gray area for each site.

at both sites. The temperature anomaly was observed at CA-Oas 1 month later, and again the models accurately reproduced the observed magnitude in anomalous GPP. During the following May, June, and July, observed temperature remained colder than normal but returned to within the normal range of variability for the three sites. Observed GPP, however, remained

anomalously low during those months and did not return to within the normal range of variability until July at each site. This lagged effect between anomalous climate forcing and resulting fluxes was not well reproduced by the models. At CA-Obs, all models returned to within the normal range of GPP variability in the month directly following the temperature

anomaly. The same behavior was apparent at CA-Ojp and CA-Oas, although the average model GPP estimates remained just outside the normal range of variability due to persistent low temperatures. The extended period of low productivity in CA-Oas may be in part also due to consistently low precipitation during the year.

A similar, although smaller anomaly pattern was observable for RE (Fig. 5). Low spring temperatures caused a prolonged anomaly of low ecosystem respiration. The models tended to overestimate the reduction in RE as a result of the colder temperatures. After the initial anomaly, RE as estimated by eddy-covariance measurements took a few months to return to within the normal range of variability. Modeled RE quickly returned to 'normal' at CA-Ojp and CA-Obs. Temporal dynamics at CA-Oas differed from those of the other two sites due to the additional pressure of persistently low temperatures and precipitation during the year.

Discussion

This analysis has shown that, although capable of reproducing the magnitude of interannual variability, terrestrial biosphere models are not consistent with the timing of observations of interannual variability in surface-atmosphere exchanges of CO₂ at mid-latitude forests over North America. By examining interannual variability in measured and modeled monthly fluxes, we show that all the models used for the NACP interim site synthesis systematically fail to reproduce observed variability during spring. Underestimation of spring variability is largest for GPP in deciduous forests, and RE for evergreens, suggesting different processes may be responsible for plant functional type specific model error.

It has been shown that terrestrial biosphere models are typically unable to adequately explain the observed interannual variability in deciduous canopy phenology (Richardson *et al.*, 2012), and that variability in spring GPP often drives observed interannual variability in net ecosystem exchange (Krishnan *et al.*, 2008, 2009). Here we show that this is a systematic cause of the low agreement between modeled and observed interannual variability in terrestrial carbon fluxes.

In a similar fashion, it has been shown that the current available models of snow pack dynamics perform poorly for both spatial and interannual variability. Rutter *et al.* (2009) tested 33 models of snowpack dynamics across a range of sites, and found that although a model could perform well when tuned to a particular site-year, this did not transfer to good performance for other years at the same site, or other sites. Interactions between snowmelt, soil thaw and water table depth are

known to directly affect interannual variability in NEE (Goulden *et al.*, 1998; Dunn *et al.*, 2007; Hu *et al.*, 2010). Results here suggest that this may be a direct systematic contributor to the low agreement between observed and modeled interannual variability in net ecosystem carbon exchange, in particular for evergreen sites. These results do not imply, however, that a lack of phenological variability in canopy or soil dynamics are necessarily the main culprits for the lack of agreement between the observations and output from any one model, as individual models showed large persistent biases at other times of the year (Fig. 3).

The remote sensing products performed comparably to the average process-based model when assessed against interannual variability in GPP. The MODIS5.1 data set is a post-processed version of the MODIS5 data set where corrections are made for poor quality driver data (Zhao *et al.*, 2005). The remote sensing products, which are themselves models, are driven by a global daily meteorological reanalysis dataset not site-specific meteorology and the uncertainties in the meteorological reanalysis can introduce biases in GPP estimates (Zhao *et al.*, 2006). Although estimates of GPP based on remote sensing have been used to evaluate process-based models (e.g., Poulter *et al.*, 2009), results herein suggest that estimates of interannual variability from both approaches are subject to similar magnitudes of error.

Although there was a general tendency for the models to persistently underestimate flux variability in summer, it should be noted that the flux data are subject to random error roughly in proportion to the size of the flux (Richardson & Hollinger, 2007; Richardson *et al.*, 2008). Even if the model were perfect, modeled variability should be smaller than that observed. Carbon fluxes are typically higher in the summer, and subject to larger uncertainty. The apparent higher variability in the data during summer could therefore be due to random errors in the flux measurements generating larger variability in monthly totals.

The analysis of model responses to the regionally coherent climatic anomaly of spring 2002 suggests that models have the potential to correctly reproduce the magnitude of instantaneous biological response to climate anomalies (Desai, 2010). Although the models accurately captured the direct effect of an isolated climate extreme, the models included here failed to accurately reproduce lagged effects of climate anomalies on both gross primary production and ecosystem respiration. Lagged effects of climate variability on ecosystem function have previously been reported (Gough *et al.*, 2009), and our results suggest that such lagged effects are not well incorporated into models. The nature of such lagged effects depends on the type of climatic anomaly. Spring frosts (Gu *et al.*, 2008; Marino

et al., 2011), for example, are known to directly effect canopy structure, an aspect not currently accounted for in models. The affects of other disturbances, such as ice storms, strong winds and insect outbreaks are known to be poorly represented by models (Liu *et al.*, 2011) and affect long-term carbon dynamics. Lagged effects unrelated to disturbances can be caused by changes in nutrient cycling (Richardson *et al.*, 2009) or changes in the size of carbon pools such as litter (Rocha *et al.*, 2008), or non-structural carbohydrates (Gough *et al.*, 2009) due to climatic conditions in previous years. Model aspects related to lagged and cumulative effects can be improved through direct comparisons with observations (e.g., Keenan *et al.*, 2009), although many related issues remain (Liu *et al.*, 2011). Although lagged effects are apparent at the three sites showing a coherent regional extreme event, we did not detect similar lagged events for other climatic anomalies in the database. This is likely due to two confounding effects: that smaller anomalous climate signals do not produce lagged (on monthly scales) ecosystem effects, and that biotic effects could play a role in driving some of the interannual variability in observed fluxes (Richardson *et al.*, 2007).

Open questions remain as to the proportion of interannual variability in land-atmosphere carbon exchange that is directly explainable by variability in climate (Hui *et al.*, 2003; Polley *et al.*, 2010; Richardson *et al.*, 2007). Controls on interannual variability can also be manifest in the form of functional changes in the ecosystem, or lagged effects on pool sizes and dynamics. By contrasting the interannual performance of a simple empirical model with fixed parameters against the same model with interannually varying parameters, Richardson *et al.* (2007) reported that forest functional change at a spruce forest was responsible for 55% of interannual variations in land-atmosphere CO₂ exchange. i.e., 45% of the observed variability was not explainable by the direct impacts of climate. Polley *et al.* (2010) used a similar approach to determine a significant contribution of ecosystem functional change to interannual variability in grasslands. Using an optimized process-based model, however, Desai (2010) found that 81% of interannual variability in annual CO₂ exchange could be explained by variability in climate for five mature hardwood forests, a value that likely underestimates model performance given that it does not account for observational error. This result supports multi-site synthesis efforts that show that ~79% of interannual variability for mid-altitude deciduous broadleaved forests can be explained by variability in temperature (Yuan *et al.*, 2009). Clearly a detailed assessment of the relative roles of climate and functional change on the interannual variability of CO₂ flux across a wide range of sites and climate zones is needed.

We could not distinguish any model structure or characteristic (see Table 2) that tended to give a better model performance. All models are subject to errors resulting from both parameter choice (parameter misspecification) and model structure (process misrepresentation) (Keenan *et al.*, 2011). The fact that no model structure proved consistently better suggests that parameter error was excessively large. In future efforts, model-data fusion techniques (Wang *et al.*, 2009; Keenan *et al.*, 2011) could aid in reducing the relative magnitude of parameter errors, thus allowing for a more rigorous assessment of model structural differences.

Our estimates of the magnitude of observed interannual variability in land-atmosphere CO₂ exchange (DBF: ~85 gC m⁻²; EVG: 44 gC m⁻², Table 3) are roughly 50% and 33% of the mean flux, respectively. Given that this represents one standard deviation about the mean, variability in ecosystem carbon uptake is commonly on the order of magnitude of the mean. This supports previous results from single sites (Richardson *et al.*, 2007; a), and modeling studies (Zeng *et al.*, 2005), across the range of sites included herein. Variability in GPP has been found to be the main contributor to variability in NEE for a variety of terrestrial ecosystems (Luyssaert *et al.*, 2007). Here, we show that for deciduous forests, the interannual variability in GPP is on average 26% greater than that of RE (Table 3). Although on average both GPP and RE show a similar magnitude of variability at the evergreen needleleaf forest sites, four of the six evergreen sites had higher variability in GPP. This suggests that variability in GPP dominates variability in NEE in mid-latitude forests, though this rule is not applicable to all sites included herein.

Using 91 site-years at 11 long-term eddy-covariance forest sites, we show that terrestrial biosphere models have difficulty in simulating land-atmosphere CO₂ exchange at annual and interannual time scales, with the potential for large biases on the interannual scale, and incorrect simulation of the timing of interannual variability. Instead of focusing on model-data agreement, we present a variability-oriented approach of diagnosing systematic and persistent model-data disagreement. Given that studies of the impact of climate variability on terrestrial fluxes are likely to reveal a more informative picture of biosphere-atmosphere interactions (le Maire *et al.*, 2010), such a variability orientated approach should greatly aid modeling teams in future model assessment and development. Our results highlight three potential mechanisms - spring canopy phenology, soil thaw and the melting of the snow pack, and lagged effects - common to all models included in the study, which contribute to the low agreement between the models and the observed interannual vari-

ability in land-atmosphere CO₂ exchange. Addressing these issues in future model efforts will be the first step toward improving the sensitivity of models to climatic variability on interannual time scales.

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References

- Arain MA, Yuan F, Andrew Black T (2006) Soil-plant nitrogen cycling modulated carbon exchanges in a western temperate conifer forest in Canada. *Agricultural and Forest Meteorology*, **140**, 171–192, doi: 10.1016/j.agrformet.2006.03.021.
- Baker IT, Prihodko L, Denning AS, Goulden M, Miller S, da Rocha HR (2008) Seasonal drought stress in the Amazon: reconciling models and observations. *Journal of Geophysical Research*, **113**, G00B01, doi: 10.1029/2007JG000644.
- Barr AG, Black TA, Hogg EH, Kljun N, Morgenstern K, Nesic Z (2004) Inter-annual variability in the leaf area index of a boreal aspen-hazelnut forest in relation to net ecosystem production. *Agricultural and Forest Meteorology*, **126**, 237–255, doi: 10.1016/j.agrformet.2004.06.011.
- Barr A, Hollinger D, Richardson AD (2009) CO₂ flux measurement uncertainty estimates for NACP. *EOS Transactions, American Geophysical Union*, (Fall Meeting Supplement) **90**, Abstract B54A-04.
- Beer C, Reichstein M, Tomelleri E *et al.* (2010) Terrestrial gross carbon dioxide uptake: global distribution and covariation with climate. *Science*, **329**, 834–838, doi: 10.1126/science.1184984.
- Bousquet P, Peylin P, Ciais P, Le Quéér C, Friedlingstein P, Tans PP (2000) Regional changes in carbon dioxide fluxes of land and oceans since 1980. *Science*, **290**, 1342–1347.
- Bradford JB, Birdsey RA, Joyce LA, Ryan MG (2008) Tree age, disturbance history, and carbon stocks and fluxes in subalpine Rocky Mountain forests. *Global Change Biology*, **14**, 2882–2897, doi: 10.1111/j.1365-2486.2008.01686.x.
- Braswell BH, Sacks WJ, Linder E, Schimel DS (2005) Estimating diurnal to annual ecosystem parameters by synthesis of a carbon flux model with eddy covariance net ecosystem exchange observations. *Global Change Biology*, **11**, 335–355, doi: 10.1111/j.1365-2486.2005.00897.x.
- Chen B, Black TA, Coops NC, Krishnan P, Jassal R, Brümmer C, Nesic Z (2009) Seasonal controls on interannual variability in carbon dioxide exchange of a near-end-of rotation Douglas-fir stand in the Pacific Northwest, 1997–2006. *Global Change Biology*, **15**, 1962–1981, doi: 10.1111/j.1365-2486.2008.01832.x.
- Ciais P, Reichstein M, Viovy N *et al.* (2005) Europe-wide reduction in primary productivity caused by the heat and drought in 2003. *Nature*, **437**, 529–533, doi: 10.1038/nature03972.
- Davis KJ, Bakwin PS, Yi C, Berger BW, Zhao C, Teclaw RM, Isebrands JG (2003) The annual cycles of CO₂ and H₂O exchange over a northern mixed forest as observed from a very tall tower. *Global Change Biology*, **9**, 1278–1293, doi: 10.1046/j.1365-2486.2003.00672.x.
- Desai AR (2010) Climatic and phenological controls on coherent regional interannual variability of carbon dioxide flux in a heterogeneous landscape. *Journal of Geophysical Research*, **115**, 1–13, doi: 10.1029/2010JG001423.
- Dietze M, Rodrigo V, Andrew DR *et al.* (2011) Characterizing the performance of ecosystem models across time scales: a spectral analysis of the North American Carbon Program site-level synthesis. *Journal of Geophysical Research*, **116**, G04029, doi: 10.1029/2011JG001661.
- Dragoni D, Schmid HP, Wayson CA, Potter H, Grimmond CSB, Randolph JC (2011) Evidence of increased net ecosystem productivity associated with a longer vegetated season in a deciduous forest in south-central Indiana, USA. *Global Change Biology*, **17**, 886–897, doi: 10.1111/j.1365-2486.2010.02281.x.
- Dunn AL, Barford CC, Wofsy SC, Goulden ML, Daube BC (2007) A long-term record of carbon exchange in a boreal black spruce forest: means, responses to interannual variability, and decadal trends. *Global Change Biology*, **13**, 577–590, doi: 10.1111/j.1365-2486.2006.01221.x.
- Friedlingstein P, Cox P, Betts R *et al.* (2006) Climate-carbon cycle feedback analysis: results from the C4MIP model intercomparison. *Journal of Climate*, **19**, 3337–3353.
- Friend AD (2010) Terrestrial plant production and climate change. *Journal of experimental botany*, **61**, 1293–1309, doi: 10.1093/jxb/erq019.
- Gough CM, Flower CE, Vogel CS, Dragoni D, Curtis PS (2009) Whole-ecosystem labile carbon production in a north temperate deciduous forest. *Agricultural and Forest Meteorology*, **149**, 1531–1540, doi: 10.1016/j.agrformet.2009.04.006.
- Goulden ML, Wofsy SC, Harden JW *et al.* (1998) Sensitivity of Boreal Forest Carbon Balance to Soil Thaw. *Science*, **279**, 214–217, doi: 10.1126/science.279.5348.214.
- Grant RF, Arain A, Arora V *et al.* (2005) Intercomparison of techniques to model high temperature effects on CO₂ and energy exchange in temperate and boreal coniferous forests. *Ecological Modelling*, **188**, 217–252, doi: 10.1016/j.ecolmodel.2005.01.060.
- Griffis T, Black TA, Morgenstern K *et al.* (2003) Ecophysiological controls on the carbon balances of three southern boreal forests. *Agricultural and Forest Meteorology*, **117**, 53–71, doi: 10.1016/S0168-1923(03)00023-6.
- Gu L, Hanson PJ, Post WM *et al.* (2008) The 2007 eastern US spring freeze: increased cold damage in a warming world. *BioScience*, **58**, 253, doi: 10.1641/B580311.
- Hanson PJ, Amthor JS, Wullschlegel SD *et al.* (2004) Oak forest carbon and water simulations: model intercomparisons and evaluations against independent data. *Ecological Monographs*, **74**, 443–489, doi: 10.1890/03-4049.
- Heimann M, Reichstein M (2008) Terrestrial ecosystem carbon dynamics and climate feedbacks. *Nature*, **451**, 289–292, doi: 10.1038/nature06591.
- Hu J, Moore DJP, Burns SP, Monson RK (2010) Longer growing seasons lead to less carbon sequestration by a subalpine forest. *Global Change Biology*, **16**, 771–783, doi: 10.1111/j.1365-2486.2009.01967.x.
- Hui D, Luo Y, Katul G (2003) Partitioning interannual variability in net ecosystem exchange between climatic variability and functional change. *Tree physiology*, **23**, 433–442.
- IPCC (2007) *Climate Change 2007: The Physical Science Basis* (eds Solomon S, Qin D, Manning M, Marquis M, Averyt K, Tignor MMB, Miller HLJ, Chen Z), pp. 501–586. Cambridge University Press, Cambridge, UK. ISBN-13: 9780521705967.
- Keenan T, Garcia R, Friend AD, Zaehle S, Gracia C, Sabate S (2009) Improved understanding of drought controls on seasonal variation in Mediterranean forest canopy CO₂ and water fluxes through combined *in situ* measurements and ecosystem modelling. *Biogeosciences*, **6**, 1423–1444, doi: 10.5194/bg-6-1423-2009.
- Keenan TF, Carbone MS, Reichstein M, Richardson AD (2011) The model-data fusion pitfall: assuming certainty in an uncertain world. *Oecologia*, **167**, 587–597, doi: 10.1007/s00442-011-2106-x.
- Knorr W, Gobron N, Scholze M, Kaminski T, Schnur R, Pinty B (2007) Impact of terrestrial biosphere carbon exchanges on the anomalous CO₂ increase in 2002–2003. *Geophysical Research Letters*, **34**, 1–6, doi: 10.1029/2006GL029019.
- Krinner G, Viovy N, de Noblet-Ducoudre N *et al.* (2005) A dynamic global vegetation model for studies of the coupled atmosphere-biosphere system. *Global Biogeochemical Cycles*, **19**, GB1015, doi: 10.1029/2003GB002199.
- Krishnan P, Black TA, Barr AG, Grant NJ, Gaumont-Guay D, Nesic Z (2008) Factors controlling the interannual variability in the carbon balance of a southern boreal black spruce forest. *Journal of Geophysical Research*, **113**, 1–16, doi: 10.1029/2007JD008965.
- Krishnan P, Black TA, Jassal RS, Chen B, Nesic Z (2009) Interannual variability of the carbon balance of three different-aged Douglas-fir stands in the Pacific Northwest. *Journal of Geophysical Research*, **114**, 1–18, doi: 10.1029/2008JG000912.
- Liu J, Chen J, Cihlar J, Chen W (1999) Net primary productivity distribution in the BOREAS region from a process model using satellite and surface data. *Journal of Geophysical Research*, **104**, 27375–27754.
- Liu S, Bliss N, Sundquist E, Hungtington TG (2003) Modeling carbon dynamics in vegetation and soil under the impact of soil erosion and deposition. *Global Biogeochemical Cycles*, **17**, 1074, doi: 10.1029/2002GB002010.
- Liu S, Bond-Lamberty B, Hicke JA *et al.* (2011) Simulating the impacts of disturbances on forest carbon cycling in North America: processes, data, models, and challenges. *Journal of Geophysical Research*, **116**, 1–22, doi: 10.1029/2010JG001585.
- Luyssaert S, Janssens IA, Sulkava M *et al.* (2007) Photosynthesis drives anomalies in net carbon-exchange of pine forests at different latitudes. *Global Change Biology*, **13**, 2110–2127, doi: 10.1111/j.1365-2486.2007.01432.x.
- le Maire G, Delapierre N, Jung M *et al.* (2010) Detecting the critical periods that underpin interannual fluctuations in the carbon balance of European forests. *Journal of Geophysical Research*, **115**, 1–16, doi: 10.1029/2009JG001244.

- Marino GP, Kaiser DP, Gu L, Ricciuto DM (2011) Reconstruction of false spring occurrences over the southeastern United States, 1901–2007: an increasing risk of spring freeze damage? *Environmental Research Letters*, **6**, 024015, doi: 10.1088/1748-9326/6/2/024015.
- Medvigy D, Wofsy SC, Munger JW, Hollinger DY, Moorcroft PR (2009) Mechanistic scaling of ecosystem function and dynamics in space and time: ecosystem Demography model version 2. *Journal of Geophysical Research*, **114**, 1–21, doi: 10.1029/2008JG000812.
- Pan Y, Birdsey RA, Fang J *et al.* (2011) A large and persistent carbon sink in the world's forests. *Science*, **14**, 1–11, doi: 10.1126/science.1201609.
- Papale D, Valentini R (2003) A new assessment of European forests carbon exchanges by eddy fluxes and artificial neural network spatialization. *Global Change Biology*, **9**, 525–535, doi: 10.1046/j.1365-2486.2003.00609.x.
- Peichl M, Arain MA (2007) Allometry and partitioning of above- and belowground tree biomass in an age-sequence of white pine forests. *Forest Ecology and Management*, **253**, 68–80, doi: 10.1016/j.foreco.2007.07.003.
- Piao S, Ciais P, Friedlingstein P *et al.* (2008) Net carbon dioxide losses of northern ecosystems in response to autumn warming. *Nature*, **451**, 49–52, doi: 10.1038/nature06444.
- Poulter B, Heyder U, Cramer W (2009) Modelling the sensitivity of the seasonal cycle of GPP to dynamic LAI and soil depths in tropical rainforests. *Ecosystems*, **12**, 517–533, doi: 10.1007/s10021-009-9238-4.
- Polley HW, Emmerich W, Bradford JA *et al.* (2010) Physiological and environmental regulation of interannual variability in CO₂ exchange on rangelands in the western United States. *Global Change Biology*, **16**, 990–1002, doi: 10.1111/j.1365-2486.2009.01966.x.
- Reichstein M, Papale D, Valentini R *et al.* (2007) Determinants of terrestrial ecosystem carbon balance inferred from European eddy covariance flux sites. *Geophysical Research Letters*, **34**, L01402, doi: 10.1029/2006GL027880.
- Riccuto DM, King AW, Gu L, Post WM (2008) Estimates of terrestrial carbon cycle model parameters by assimilation of FLUXNET data: do parameter variations cause bias in regional flux estimates? *EOS Transactions, American Geophysical Union*, (Fall Meeting Supplement) **89**, Abstract B54A-03.
- Riccuto DM, Thornton PE, Schaefer K, Cook RB, Davis KJ (2009) How uncertainty in gap-filled meteorological input forcing at eddy covariance sites impacts modeled carbon and energy flux. *EOS Transactions, American Geophysical Union*, (Fall Meeting Supplement) **90**, Abstract B54A-03.
- Richardson AD, Hollinger DY (2007) A method to estimate the additional uncertainty in gap-filled NEE resulting from long gaps in the CO₂ flux record. *Agricultural and Forest Meteorology*, **147**, 199–208, doi: 10.1016/j.agrformet.2007.06.004.
- Richardson AD, Hollinger DY, Aber JD, Ollinger SV, Braswell BH (2007) Environmental variation is directly responsible for short- but not long-term variation in forest-atmosphere carbon exchange. *Global Change Biology*, **13**, 788–803, doi: 10.1111/j.1365-2486.2007.01330.x.
- Richardson AD, Mahecha MD, Falge E *et al.* (2008) Statistical properties of random CO₂ flux measurement uncertainty inferred from model residuals. *Agricultural and Forest Meteorology*, **148**, 38–50, doi: 10.1016/j.agrformet.2007.09.001.
- Richardson AD, Hollinger DY, Dail DB, Lee JT, Munger JW, Keefe JO, O'keefe J (2009) Influence of spring phenology on seasonal and annual carbon balance in two contrasting New England forests. *Tree physiology*, **29**, 321–331, doi: 10.1093/treephys/tpn040.
- Richardson AD, Anderson RS, Arain MA *et al.* (2012) Terrestrial biosphere models need better representation of vegetation phenology: results from the North American Carbon Program Site Synthesis. *Global Change Biology*, **18**, 566–584, doi: 10.1111/j.1365-2486.2011.02562.x.
- Rocha AV, Potts DL, Goulden ML (2008) Standing litter as a driver of interannual CO₂ exchange variability in a freshwater marsh. *Journal of Geophysical Research*, **113**, 1–10, doi: 10.1029/2008JG000713.
- Running S, Nemani RR, Heinsch FA, Zhao M, Reeves M, Hashimoto H (2004) A continuous satellite-derived measure of global terrestrial primary production. *BioScience*, **54**, 547–560, doi: 10.1641/0006-3568(2004)054.
- Rutter N, Essery R, Pomeroy J *et al.* (2009) Evaluation of forest snow processes models (SnowMIP2). *Journal of Geophysical Research*, **114**, D06111, doi: 10.1029/2008JD011063.
- Ryu Y, Baldocchi DD, Kobayashi H *et al.* (2011) Integration of MODIS land and atmosphere products with a coupled-process model to estimate gross primary productivity and evapotranspiration from 1 km to global scales. *Global Biogeochemical Cycles*, **25**, GB4017, doi: 10.1029/2011GB004053.
- Schaefer K, Zhang T, Slater AG, Lu L, Etringer A, Baker I (2009) Improving simulated soil temperatures and soil freeze/thaw at high-latitude regions in the simple biosphere/carnegie-ames-stanford approach model. *Journal of Geophysical Research*, **114**, 1–18, doi: 10.1029/2008JF001125.
- Schmid H, Grimmer CSB, Cropley F, Offerle B, Su H-B (2000) Measurements of CO₂ and energy fluxes over a mixed hardwood forest in the mid-western United States. *Agricultural and Forest Meteorology*, **103**, 357–374, doi: 10.1016/S0168-1923(00)00140-4.
- Schmid HP, Su H-B, Vogel CS, Curtis PS (2003) Ecosystem-atmosphere exchange of carbon dioxide over a mixed hardwood forest in northern lower Michigan. *Journal of Geophysical Research*, **108**, 4417, doi: 10.1029/2002JD003011.
- Schwalm CR, Black TA, Morgenstern K, Humphreys ER (2007) A method for deriving net primary productivity and component respiratory fluxes from tower-based eddy covariance data: a case study using a 17-year data record from a Douglas-fir chronosequence. *Global Change Biology*, **13**, 370–385, doi: 10.1111/j.1365-2486.2006.01298.x.
- Schwalm CR, Williams CA, Schaefer K *et al.* (2010) A model-data intercomparison of CO₂ exchange across North America: results from the North American carbon program site synthesis. *Journal of Geophysical Research*, **115**, 22, doi: 10.1029/2009JG001229.
- Siqueira MB, Katul GG, Sampson DA, Stoy PC, Juang J-Y, McCarthy HR, Oren R (2006) Multiscale model intercomparisons of CO₂ and H₂O exchange rates in a maturing southeastern US pine forest. *Global Change Biology*, **12**, 1189–1207, doi: 10.1111/j.1365-2486.2006.01158.x.
- Sitch S, Smith B, Prentice IC *et al.* (2003) Evaluation of ecosystem dynamics, plant geography and terrestrial carbon cycling in the LPJ dynamic global vegetation model. *Global Change Biology*, **9**, 161–185, doi: 10.1046/j.1365-2486.2003.00569.x.
- Thornton PE, Running SW, White M (1997) Generating surfaces of daily meteorological variables over large regions of complex terrain. *Journal of Hydrology*, **190**, 214–251, doi: 10.1016/S0022-1694(96)03128-9.
- Thornton PE, Running SW, Hunt ER (2005) *Biome-BGC: Terrestrial Ecosystem Process Model, Version 4.1.1. Data model*. Oak Ridge National Laboratory Distributed Active Archive Center, Oak Ridge, Tennessee, U.S.A., doi:10.3334/ORNLDAAAC/805. Available at: <http://daac.ornl.gov> (accessed 9 March 2012).
- Tian H, Chen G, Liu M *et al.* (2010) Model estimates of net primary productivity, evapotranspiration, and water use efficiency in the terrestrial ecosystems of the southern United States during 1895–2007. *Forest Ecology and Management*, **259**, 1311–1327, doi: 10.1016/j.foreco.2009.10.009.
- Urbanski S, Barford C, Wofsy S *et al.* (2007) Factors controlling CO₂ exchange on timescales from hourly to decadal at Harvard Forest. *Journal of Geophysical Research*, **112**, 1–25, doi: 10.1029/2006JG000293.
- Vetter M, Churkina G, Jung M *et al.* (2008) Analyzing the causes and spatial pattern of the European 2003 carbon flux anomaly using seven models. *Biogeosciences*, **5**, 561–583, doi: 10.5194/bg-5-561-2008.
- Wang Y-PP, Trudinger CM, Enting IG (2009) A review of applications of model-data fusion to studies of terrestrial carbon fluxes at different scales. *Agricultural and Forest Meteorology*, **149**, 1829–1842, doi: 10.1016/j.agrformet.2009.07.009.
- Weng E, Luo Y (2008) Soil hydrological properties regulate grassland ecosystem responses to multifactor global change: a modeling analysis. *Journal of Geophysical Research*, **113**, 1–16, doi: 10.1029/2007JG000539.
- Williamson TB, Price DT, Beverly JL *et al.* (2008) *Assessing potential biophysical and socioeconomic impacts of climate change on forest-based communities: a methodological case study*. Natural Resources Canada, Canadian Forest Service, Northern Forestry Centre. Information Report NOR-X-415E. Available at: http://nrc.cfs.nrcan.gc.ca/bookstore_pdfs/29156.pdf (accessed 9 March 2012).
- Yang X, Wittig V, Jain AK, Post W (2009) Integration of nitrogen cycle dynamics into the Integrated Science Assessment Model for the study of terrestrial ecosystem responses to global change. *Global Biogeochemical Cycles*, **23**, 1–18, doi: 10.1029/2009GB003474.
- Yuan W, Luo Y, Richardson AD, *et al.* (2009) Latitudinal patterns of magnitude and interannual variability in net ecosystem exchange regulated by biological and environmental variables. *Global Change Biology*, **15**, 2905–2920, doi: 10.1111/j.1365-2486.2009.01870.x.
- Zeng N, Mariotti A, Wetzel P (2005) Terrestrial mechanisms of interannual CO₂ variability. *Global Biogeochemical Cycles*, **19**, GB1061, doi: 10.1029/2004GB002273.
- Zhan X, Xue Y, Collatz GJ (2003) An analytical approach for estimating CO₂ and heat fluxes over the Amazonian region. *Ecological Modelling*, **162**, 97–117, doi: 10.1016/S0304-3800(02)00405-2.
- Zhao M, Running SW (2010) Drought-induced reduction in global terrestrial net primary production from 2000 through 2009. *Science*, **329**, 940–943, doi: 10.1126/science.1192666.
- Zhao M, Heinsch FA, Nemani RR, Running SW (2005) Improvements of the MODIS terrestrial gross and net primary production global data set. *Remote Sensing of Environment*, **95**, 164–176, doi: 10.1016/j.rse.2004.12.011.
- Zhao M, Running SW, Nemani RR (2006) Sensitivity of Moderate Resolution Imaging Spectroradiometer (MODIS) terrestrial primary production to the accuracy of meteorological reanalyses. *Journal of Geophysical Research*, **111**, 1–13, doi: 10.1029/2004JG000004.

Supporting Information

Additional Supporting Information may be found in the online version of this article:

Figure S1. Model normalized root mean square error (NRMSE) when compared to inter-annual variability (IAV) of net ecosystem exchange (NEE), gross primary productivity (GPP), and ecosystem respiration (RE), as a percentage of the annual total, grouped by two plant functional types (DBF: Deciduous broadleaf forest; EVG: Evergreen needleleaf forest). Error bars represent the standard deviation from the mean.

Figure S2. χ^2 statistic for modeled vs. observed inter-annual variability (IAV) of net ecosystem exchange (NEE), gross primary productivity (GPP), and ecosystem respiration (RE), grouped by two plant functional types (DBF: Deciduous broadleaf forest; EVG: Evergreen needleleaf forest). Error bars represent the standard deviation from the mean. The dashed line indicates a χ^2 value of 1, below which modeled variability is deemed to fall within the data error of observed variability.

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