Sensitivity of net ecosystem exchange and heterotrophic respiration to parameterization uncertainty

Author:

Exbrayat, J; Pitman, Andrew; Abramowitz, Gabriel; Wang, Y

Sensitivity of net ecosystem exchange and heterotrophic respiration to parameterization uncertainty

J.-F. Exbrayat,[1] A. J. Pitman,[1] G. Abramowitz,[1] and Y.-P. Wang[2]

[1]   We examine the uncertainty in net ecosystem exchange due to the model treatment of heterotrophic respiration in a variety of hydroclimatic conditions using a land surface model. Multiple soil temperature-respiration functions and soil moisture-respiration functions are incorporated into the Carnegie-Ames-Stanford Approach with Carbon-Nitrogen-Phosphorus (CASA-CNP) biogeochemical model coupled to the Community Atmosphere Biosphere Land Exchange land surface model. Every possible combination of the newly implemented functions is then used to simulate heterotrophic respiration and net ecosystem exchange at 10 different flux towers covering a large range of global vegetation types. Results show that a large uncertainty in the simulated net ecosystem exchange is attributable to differences in the soil respiration parameterization. No single combination of soil temperature and moisture-respiration functions appears to show superior performance across all sites. Large variations in the simulated evolution of soil carbon storages emphasize the problem that to use an observationally based soil temperature or soil moisture response function requires a land surface model to capture the observed soil temperature and soil moisture mean and variability correctly. Land surface models are known to vary dramatically in their simulation of the soil moisture state and probably in their simulation of soil temperature. Resolving how to simulate heterotrophic respiration and net ecosystem exchange will therefore require an accurate simulation of temperature and moisture combined with a realistic soil heterotrophic respiration parameterization, and these cannot be developed and implemented in isolation.

Citation: Exbrayat, J.-F., A. J. Pitman, G. Abramowitz, and Y.-P. Wang (2013), Sensitivity of net ecosystem exchange and heterotrophic respiration to parameterization uncertainty, *J. Geophys. Res. Atmos.*, *118*, 1640–1651, doi:10.1029/2012JD018122.

1.   Introduction

[2]   With an estimated total of 2400 Gt [*Batjes*, 1996], the soil is the largest terrestrial carbon pool. Understanding the interaction between climate and soil carbon is therefore crucial, since even relatively small changes in soil processes could either contribute significantly to, or compensate for, human emissions [*Kirschbaum*, 2010]. Several studies have shown that a rise in temperature due to climate change is likely to accelerate soil respiration processes [*Cox et al.*, 2000; *Jones et al.*, 2003; *Friedlingstein et al.*, 2006]. This positive feedback has been predicted to contribute to the increase in atmospheric carbon dioxide (CO_2). For example, all 11 models compared by *Friedlingstein et al.* [2006] showed that future climate would

likely reduce the effectiveness of the land surface to absorb human emissions in spite of the CO_2-fertilization effect. However, differences between the projections reported by *Friedlingstein et al.* [2006] illustrate the importance of appropriately parameterizing the soil carbon-climate response to increasing CO_2 [*Kirschbaum*, 1995; *Knorr et al.*, 2005; *Falloon et al.*, 2011] and associated global and regional climate changes.

[3]   Land surface models (LSMs) commonly simulate heterotrophic respiration (HR) as a function of soil temperature, soil moisture, and available substrate. A large variety of functions describing the way soil temperature and moisture control HR is available in the literature. A significant effort has been put into studying the effect of temperature on soil processes based on experimental data [e.g., *Kirschbaum*, 1995, 2000; *Bond-Lamberty and Thomson*, 2010; *Davidson and Janssens*, 2006] and modeling experiments [e.g., *Reichstein et al.*, 2005]. A recent comparative study by *Falloon et al.* [2011] highlighted discrepancies in the parameterization of the soil moisture control on HR as an important source of uncertainty. Similarly, *Chen et al.* [2011] showed how the effect of temperature on HR was sensitive to soil moisture, indicating that these two controlling factors are closely related.

[4]   In this paper, we explore the uncertainty of simulated HR and net ecosystem exchange (NEE) arising from

---

[1]Climate Change Research Centre and ARC Centre of Excellence for Climate System Science, University of New South Wales, Sydney, New South Wales, Australia.

[2]Centre for Australian Weather and Climate Research, CSIRO Marine and Atmospheric Research, Aspendale, Victoria, Australia.

Corresponding author: J.-F. Exbrayat, Climate Change Research Centre, University of New South Wales, Sydney, NSW 2052, Australia. (j.exbrayat@unsw.edu.au)

the choice of the soil temperature-respiration function (STRF) and soil moisture-respiration function (SMRF). We adopt a methodology similar to *Falloon et al.* [2011] by implementing a large range of STRFs and SMRFs into CASA-CNP model [*Wang et al.*, 2010] coupled to the Community Atmosphere Biosphere Land Exchange LSM [*Wang et al.*, 2011], using existing published functions, and examine each possible combination of STRF and SMRF. We use LSM driving and evaluation data measured at 10 different sites reflecting tropical, temperate, and boreal environments. Our aim is to illustrate the uncertainty inherent in the existing range of SMRFs and STRFs but also to determine if any of the existing functions can be excluded within the CABLE and CASA-CNP modeling framework. We evaluate our simulations using observed net ecosystem exchange and estimated ecosystem respiration (RECO) because observations of HR itself do not generally coincide with the meteorological observations required to drive the LSM.

2. Methodology

2.1. Data Sets Used

[5] To assess the uncertainty arising from the differences in SMRFs and STRFs, we chose 10 flux tower sites from the Fluxnet network (http://www.fluxnet.ornl.gov/fluxnet/index.cfm). Required in situ meteorological drivers including temperature, humidity, wind speed, rainfall, and incoming solar and infrared radiation were available via the Protocol for the Analysis of Land Surface Models Web site (PALS; http://www.pals.unsw.edu.au) [*Abramowitz*, 2012]. PALS is a free online evaluation tool currently under development at the Climate Change Research Centre of the University of New South Wales supported by the Global Land Atmosphere System Study (GLASS) of the World Climate Research Program. Besides providing easy access to meteorological forcing data sets and observations at multiple flux towers, PALS allows registered users to upload model outputs obtained with those data sets. Then, automated postprocessing methods are applied to characterize the quality of the simulation in comparison with observed fluxes of net radiation, latent heat, sensible heat, surface ground heat, and net ecosystem exchange. Results are stored online and can be made accessible to other PALS users to allow an easy comparison of model performance.

[6] Table 1 shows the chosen sites and their vegetation types. These 10 sites are broadly distributed geographically and cover a large range of climatic conditions: tropical humid (Howard Springs and Palangkaraya), hot and dry (Audubon, Roccarespampani, Tumbarumba), temperate humid (Cabauw, Harvard Forest, Loobos, Tharandt) and boreal (Boreas).

2.2. Land Surface Model, CABLE, and Biogeochemical Model, CASA-CNP

[7] The CABLE land surface model was developed by the Commonwealth Scientific and Industrial Research Organization (CSIRO) and is used in the Australian Community Climate Earth System Simulator (ACCESS) (http://www.accessimulator.org.au). CABLE is the outcome of several decades of model development and integrates different modules that simulate canopy processes, soil and snow, carbon pool dynamics, and soil respiration. CABLE performs comparatively with other LSMs in simulating latent and sensible heat as well as CO_2 fluxes at the site scale [*Abramowitz et al.*, 2007, 2008; *Wang et al.*, 2011].

[8] CABLE is based on the canopy model developed by *Wang and Leuning* [1998], which differentiates a single canopy layer into sunlit and shaded leaves to calculate fluxes of radiation, heat, water, and CO_2 between each big leaf and the atmospheric boundary layer [*Kowalczyk et al.*, 2006]. The underlying plant turbulence model used to simulate the micrometeorology within the canopy was developed by *Raupach et al.* [1997]. The soil module solves the Richards' equation for soil moisture in each of the six soil layers and computes the corresponding soil temperature based on the heat conduction equation. A three-layer snow module describes snow accumulation, melting, and density. A detailed description of CABLE, including equations, is given by *Wang et al.* [2011].

[9] The version of CABLE we used here includes the biogeochemical model CASA-CNP [*Wang et al.*, 2010]. CASA-CNP has three vegetation, three litter, and three soil pools. Autotrophic respiration includes maintenance and growth respiration of all vegetation pools. Soil heterotrophic respiration is the sum of respired CO_2 from the decomposition of litter and soil organic matter, and decomposition rate also depends on amount of carbon of the decomposing pool, soil temperature, and moisture. The carbon dynamics of each pool is modeled as a first-order kinetics. CASA-CNP can also simulate limitations of nitrogen and phosphorus availability on C turnover processes, canopy photosynthesis, and plant growth [*Wang et al.*, 2010] and has recently been used to explore the dependence of terrestrial carbon uptake due to nitrogen and phosphorous limitation [*Zhang et al.*, 2011]. However, since our study only targets biophysical controls on HR, nutrient interactions are not included. The net ecosystem exchange (NEE) is calculated as the

Table 1. The 12 Selected Flux Tower Sites

Site	Vegetation Type	Latitude	Longitude	Country	Years	Key Reference
Audubon	Grassland	31.59°N	110.51°W	US	2003–2006	*Emanuel et al.* [2007]
Boreas	Evergreen needleleaf	55.88°N	98.48°W	Canada	1997–2004	*Dunn et al.* [2007]
Cabauw	Grassland	51.97°N	4.93°E	Netherlands	2003–2007	*Gilmanov et al.* [2007]
Harvard Forest	Deciduous broadleaf	42.54°N	72.17°W	US	1994–2002	*Urbanski et al.* [2007]
Howard Springs	Shrub	12.49°S	131.15°E	Australia	2002–2005	*Chen et al.* [2003]
Loobos	Evergreen needleleaf	52.17°N	5.74°E	Netherlands	1997–2007	*Dolman et al.* [2002]
Palangkaraya	Evergreen broadleaf	2.35°N	114.04°E	Indonesia	2002–2004	*Hirano et al.* [2007]
Roccarespampani	Deciduous broadleaf	42.41°N	11.93°E	Italy	2002–2007	*Rey et al.* [2002]
Tharandt	Evergreen needleleaf	50.96°N	13.57°E	Germany	1998–2006	*Grünwald and Bernhofer* [2007]
Tumbarumba	Evergreen broadleaf	35.66°S	148.15°E	Australia	2002–2006	*Leuning et al.* [2005]

difference between the ecosystem respiration (RECO; sum of autotrophic and heterotrophic respiration) and photosynthesis. It is positive when RECO exceeds photosynthesis and the ecosystem is a carbon source.

2.3. Soil Temperature and Moisture Response Functions

[10] In existing LSMs, most carbon models calculate the influence of soil moisture and soil temperature on the carbon cycle separately at each time step. The product of these functions is then used to adjust process rates during the corresponding time step [*Falloon et al.*, 2011]. However, differences exist between models in the way these limitations are parameterized potentially leading to large discrepancies in the fluxes predicted. To explore the impact of the differences in the STRF and SMRFs, we implemented the six new STRFs and seven SMRFs into CASA-CNP. The scaling functions computed in the original version of CASA-CNP are also used, as shown in Figures 1 and 2. We note that each of the STRFs and SMRFs used here are represented in existing biogeochemical models (Table 2). For further details, equations used for each STRFs and SMRFs are summarized in Text S1 of the supporting information.

[11] The effect of soil temperature is commonly described in the different STRFs in terms of an increase in HR for warmer temperatures. Along the original CASA-CNP STRF, we implemented six alternative functions (Figure 1) based on previously published equations (Table 2 and Text S1). Usually, while the shape remains the same, the height of a STRF depends on the model structure in which it is embedded (e.g., reference temperature, respiration rate in optimal conditions). Therefore, in order to only address the effect of shape differences between functions, we adjusted our STRF with a multiplicative factor (Text S1 in the supporting information) so that the area under each curve in Figure 1 would equal the area under the curve corresponding to the reference CASA-CNP STRF over temperatures between −30°C and 50°C, which correspond to the feasible range at nonpermanently frozen sites. The same temperature response functions are then used at all modeled
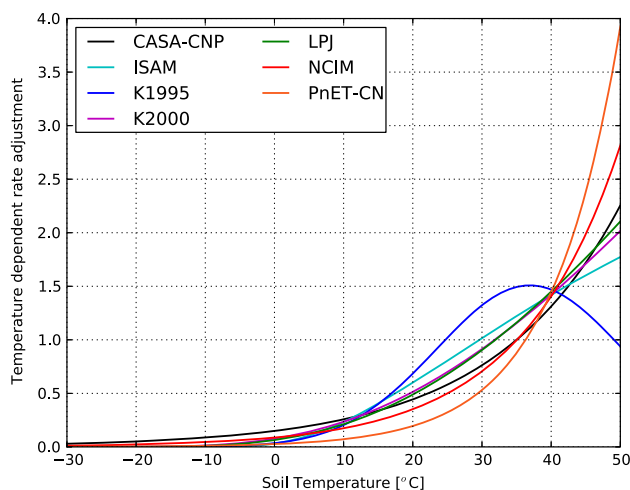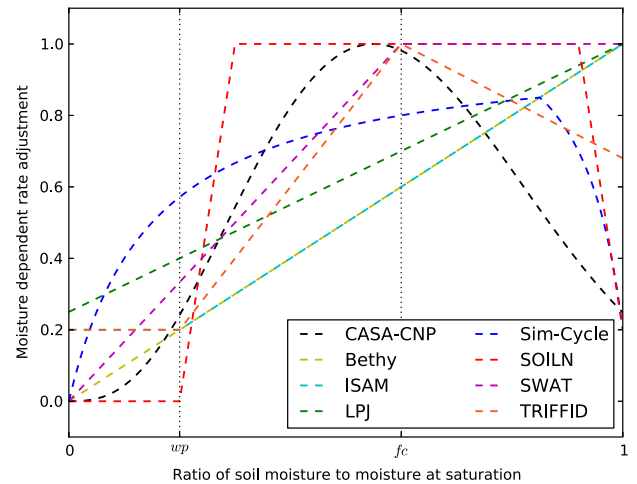

Figure 2. Evolution of the soil moisture-respiration scaling factor as a function of relative soil moisture for the different SMRFs included in this paper.

sites as CASA-CNP only uses one STRF when applied globally. Close examination of Figure 1 shows that with temperatures around 0.0°C, the STRFs differ from less than 0.05 (K1995: *Kirschbaum* [1995]; PnET-CN: *Aber et al.* [1997]) to ~0.25 (CASA-CNP). Maximum spread is observed for soil temperatures around 30°C before STRFs meet around 40°C with values around 1.5. For temperatures below 10°C, the CASA-CNP STRF always gives the highest values, whereas K1995 has the highest values over the range 10°C to 40°C. The PnET-CN STRF is the most generous for soil temperature over 40°C. It is interesting to note that over the full range of temperatures represented in Figure 1, the different STRFs cross several times, e.g., K2000 [*Kirschbaum*, 2000] and Nitrogen Carbon Interaction Model (NCIM) [*Esser et al.*, 2011], revealing different changes of heterotrophic respiration rates simulated for the same change in temperature.

[12] In the case of the SMRFs (Figure 2), a soil water content below the wilting point leads in some SMRFs to either a zero (e.g., SOILN [*Jansson and Berg*, 1985]) or a low but constant scaling of HR (e.g., ISAM). Sim-Cycle's

Figure 1. Evolution of the soil temperature-respiration scaling factor as a function of soil temperature for the different STRFs included in this paper.

Table 2. Soil Moisture-Respiration Functions (SMRFs) and Soil Temperature-Respiration Functions (STRFs) Implemented in CASA-CNP

Model	Reference
SMRFs	
Bethy	*Knorr* [2000]
ISAM	*Yang et al.* [2009]
LPJ	*Sitch et al.* [2003]
Sim-Cycle	*Ito and Oikawa* [2002]
SOILN	*Jansson and Berg* [1985]
SWAT	*Arnold et al.* [1998]
TRIFFID	*Cox* [2001]
STRFs	
ISAM	*Yang et al.* [2009]
K1995	*Kirschbaum* [1995]
K2000	*Kirschbaum* [2000]
LPJ	*Sitch et al.* [2003]
NCIM	*Esser et al.* [2011]
PnET-CN	*Aber et al.* [1997]

SMRF [*Ito and Oikawa*, 2002] increases from a perfectly dry soil rapidly to wilting point; SWAT [*Arnold et al.*, 1998] and LPJ increase linearly with soil moisture toward wilting point. Thus, at wilting point, the range in the SMRFs is from 0.0 (SOILN) to ~0.6 (Sim-Cycle). Similarly, some models indicate that optimal conditions are met at saturation, e.g., Bethy [*Knorr*, 2000], LPJ [*Sitch et al.*, 2003], and ISAM, whereas other parameterizations do not consider saturated soils as being optimal, e.g., Sim-Cycle, SOILN, and TRIFFID [*Cox*, 2001]. Thus, at saturation, SMRFs vary from as low as 0.2 (SOILN, Sim-Cycle) to as high as 1.0 (SWAT, LPJ, Bethy, ISAM), while TRIFFID uses a value 0.7.

2.4. Experimental Design

[13] The original CABLE model was initialized following *Wang et al.* [2011]. A spin-up process reused the in situ meteorological input for each site shown in Table 1 until the maximum difference between simulated soil temperature and soil moisture was less than 0.001°C and 0.001 m³ water/m³ soil at the same time step in two consecutive runs. This quasi-steady state ensures that the choice of initial soil physical conditions does not affect the simulated HR or NEE. Since the implemented functions only affect the carbon balance, we set the initial conditions of soil moisture, temperature, and canopy water content equal to their final value in the spin-up period for each simulation at each site. Then, the CASA-CNP soil carbon pools were initialized to quasi-steady state by running the original biogeochemical module (i.e., with CASA-CNP response functions) with previously equilibrated soil moisture and soil temperature calculated by CABLE over 10,000 loops of available meteorology at each site. Finally, these equilibrated carbon pools were set as initial conditions for all the possible combinations of the eight SMRFs and seven STRFs used to simulate each site over the time periods indicated in Table 1. This resulted in a total of 56 simulations per site between which only the response functions varied. In each case, site-specific International Geosphere and Biosphere Program vegetation type [*Loveland et al.*, 2000], canopy height, and reference heights were used, while soil types were obtained from CABLE's default grid of soil types, based on *Zobler* [1999]. These correspond to values typically used by CABLE and CASA-CNP when run globally [*Wang et al.*, 2011, *Zhang et al.*, 2011]. Parameter sets derived from global data are not calibrated to force CABLE or CASA-CNP to match site-specific observations as we want to mimic the application of these new functions in a climate model framework. Flux tower data are used in an informative manner to place our study in the idealized case where the surrounding climate model would predict unbiased meteorological variables. Furthermore, *Abramowitz* [2005] and *Abramowitz et al.* [2007] demonstrated that the improvement in modeling skill achieved following parameter optimization was relatively small in comparison with model errors in LSMs.

3. Results

[14] Figure 3 shows the averaged seasonal cycle for the 10 sites (Table 1) for simulated heterotrophic respiration (HR, $\mu mol\,m^{-2}\,s^{-1}$). First, note that the original CASA-CNP model run (in blue in Figure 3) is always well bracketed by the other alternatives (in gray). However, while all parameterizations agree on the broad pattern of seasonal variation of HR, they differ significantly on the amplitude of seasonal variation. This is especially true at temperate sites where monthly average HR rate can differ by up to $5\,\mu mol\,m^{-2}\,s^{-1}$ (e.g., Harvard Forest and Tharandt). On the other hand, these differences are less pronounced in tropical sites where the main difference between model versions can be largely explained by the baseline rate of HR at a given soil temperature and moisture, a key parameter in all models (e.g., Howard Springs).

[15] These large differences in simulated HR propagate in the calculation of RECO as shown in Figure 4. The default version of CASA-CNP (blue in Figure 4) captures the seasonal variation in RECO at Audubon, Boreas, Cabauw, Loobos, Tharandt, and Tumbarumba within $2\,\mu mol\,m^{-2}\,s^{-1}$ each month of the year. The default version is less skillful at Harvard Forest, especially between June and September when model bias is greater than $3\,\mu mol\,m^{-2}\,s^{-1}$, but key aspects of the seasonal cycle are still captured. Summer months at Roccarespampani exhibit a bias of up to $4\,\mu mol\,m^{-2}\,s^{-1}$ despite the default version of CASA-CNP being skillful at RECO prediction from January to May and from October to December. The modeled RECO by CASA-CNP reaches a maximum in July, while the observed RECO in July was lower than that in spring or autumn months, possibly as a result of summer water stress. The weakest simulations are at the two tropical sites, Howard Springs and Palangkaraya, where RECO (Figure 4) is always underestimated throughout the year.

[16] Alternative parameterizations of HR provide a first-order uncertainty range of simulated RECO that brackets the observations at Cabauw, Tharandt, and Tumbarumba all year round (Figure 4). While this is not the case at Audubon, Boreas, Harvard Forest, and Loobos, the discrepancy is less than $1\,\mu mol\,m^{-2}\,s^{-1}$. In the summer months at Roccarespampani and throughout the year at Howard Springs and Palangkaraya, all parameterizations fail to capture the broad seasonal patterns of RECO.

[17] Figure 5 presents the annual cycle of simulated NEE. In a similar result to the RECO simulations (Figure 4), the uncertainty range of simulated NEE brackets the flux tower data at Audubon, Boreas, Cabauw, Loobos, and Tumbarumba almost all year round, while a difference of at least $2\,\mu mol\,m^{-2}\,s^{-1}$ is observed between flux tower data and NEE at Harvard Forest and Roccarespampani during the Northern Hemisphere summer. All simulations fail to capture NEE at Tharandt and the two tropical sites (Howard Springs and Palangkaraya). However, even at sites where simulations seem acceptable, there is no globally best model parameterization, with different approaches (gray curves in Figure 5) matching observations (black curve in Figure 5) in different seasons.

[18] Among the existing functions tested here, the performance of CASA-CNP in simulating HR and in turn RECO and NEE clearly depends on the choice of the parameterization of these biophysical controls on HR. However, the effect of different STRFs on HR also depends on the variation of soil temperature. The absolute differences are smallest at cold soil temperatures and at around 40°C as indicated in Figure 1. Figure 6 shows the temperature-dependent respiration rate adjustment used in the calculation of HR (a rescaled version of Figure 1) along with probability
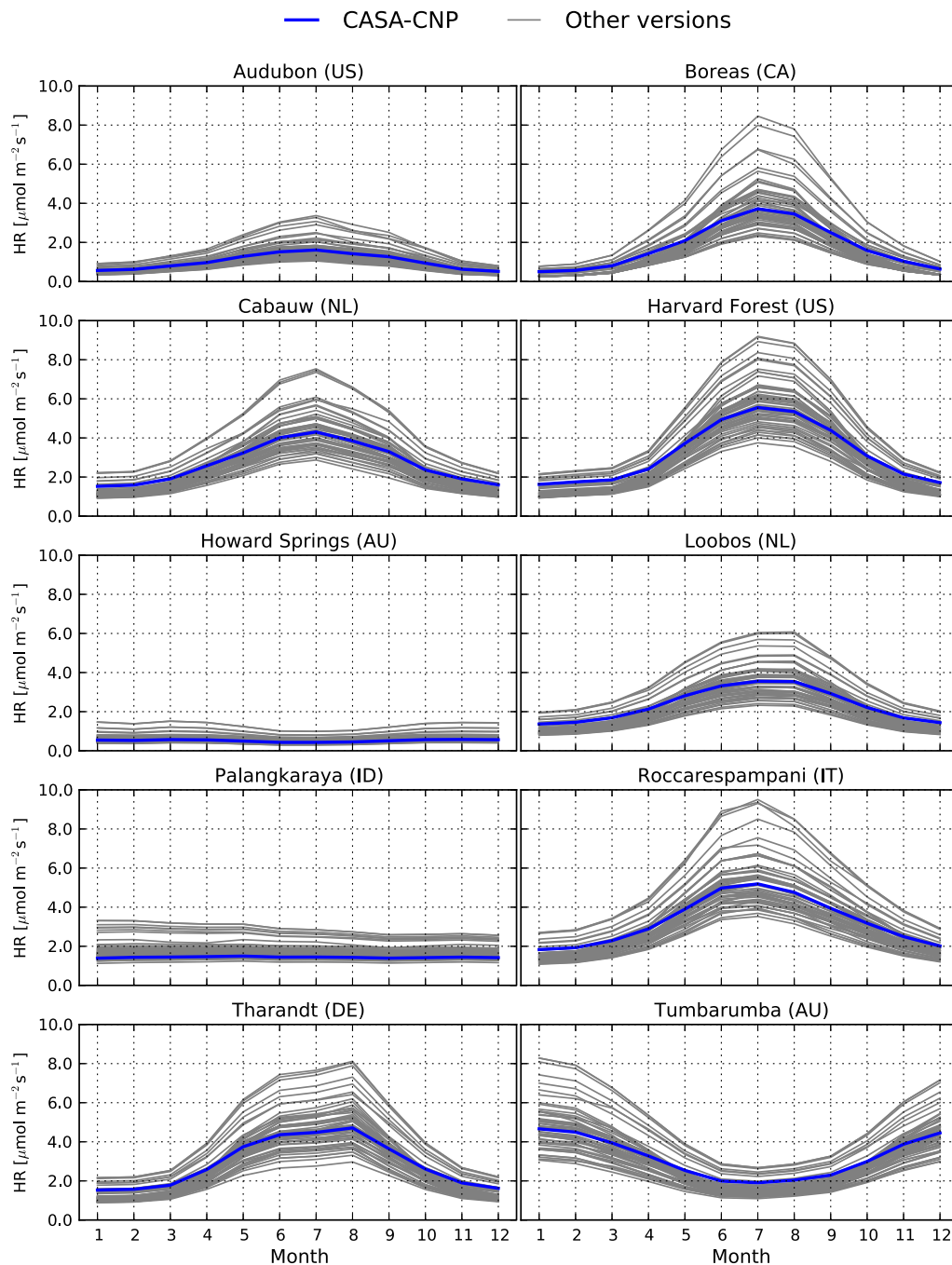
Figure 3. Seasonal simulated heterotrophic respiration ($\mu mol\,m^{-2}\,s^{-1}$). The default version of CASA-CNP is in blue. All alternative combinations of a STRF and a SMRF are in gray.

density functions of soil temperatures simulated by CABLE for each site (in gray). Adjustment values are represented as a function of the maximum value achieved by any of the STRFs at the temperature indicated on the x axis. The actual soil temperatures simulated by CABLE are insensitive to the choice of parameterization in CASA-CNP. The range and density of temperatures are critical as they determine which parts of each STRF are active at each site. For example, at the Boreas site, all soil temperatures lie in the range of soil temperature functional space that produce low adjustment values (Figure 1), but the lowest STRF always has a value less than or equal to 30% of the highest STRF over the

relevant temperature space (Figure 6). At the other extreme, for warmer sites such as Palangkaraya and Howard Springs, while all soil temperature values lie in the range of soil temperature functional space that results in high adjustment values, the relative range of temperature respiration adjustments is narrower, with the lowest STRF being always greater than 30% of the highest one. Hence, Figure 5 shows less variation in HR at Howard Springs and Palangkaraya than at Boreas because it matters less which temperature adjustment function is used at those sites. In between are temperate sites where some soil temperature values lie within the range where they trigger very large relative differences in the
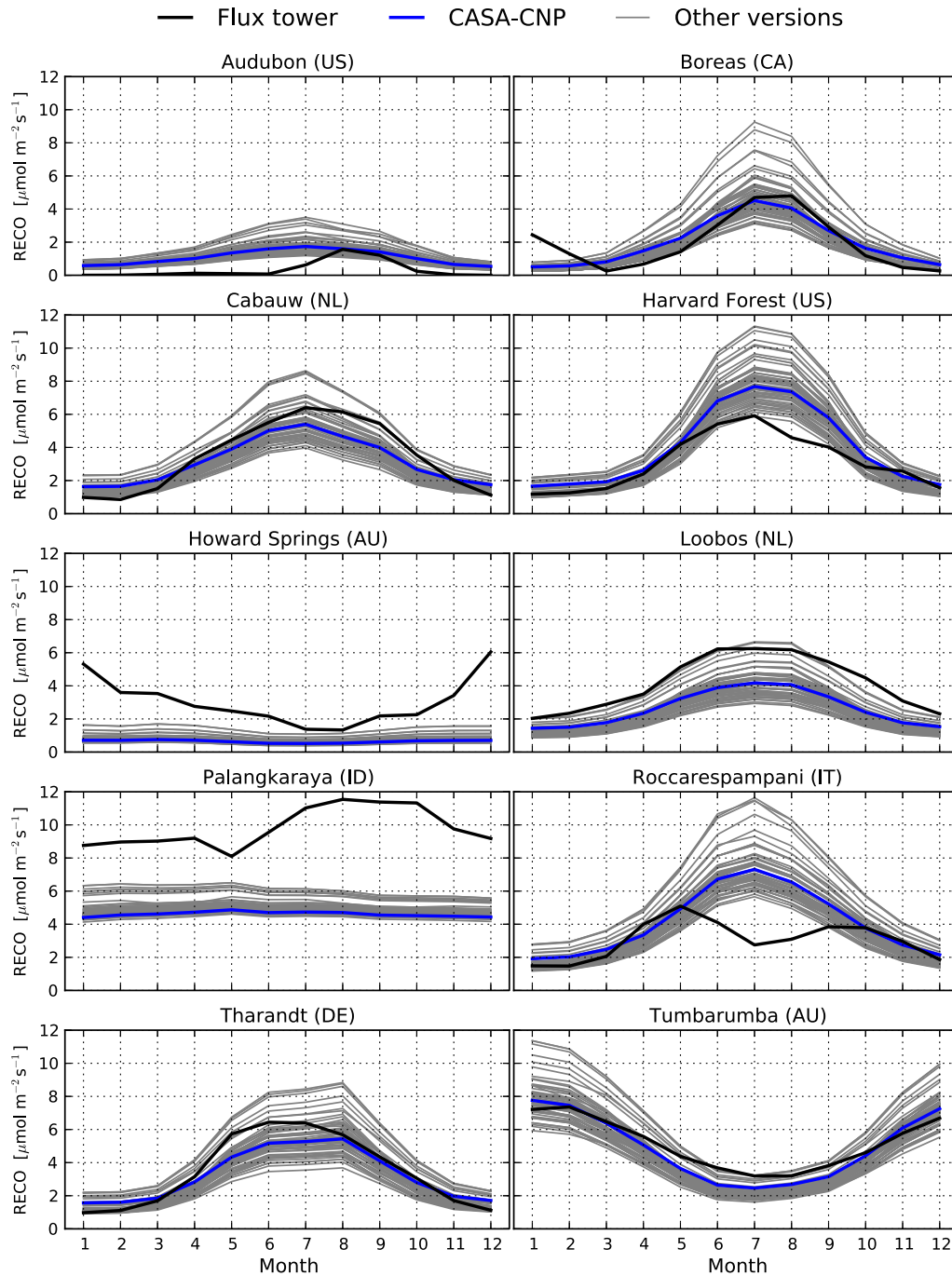
Figure 4. As in Figure 3 but for ecosystem respiration ($\mu mol\,m^{-2}\,s^{-1}$), with observations in black. The default version of CASA-CNP is identified in blue, and simulations using the alternative parameterizations are in gray.

temperature adjustment, but a significant fraction of temperatures lie within a range of soil temperature where the absolute differences among the different STRFs is small (e.g., at Tharandt where the most frequent soil temperature is around $0°C$).

[19] Figure 7 shows the soil moisture adjustment (as in Figure 2) expressed as a fraction of the maximum value obtained by any of the SMRF for each moisture content value, along with the distribution of actual soil moisture values simulated by CABLE. As in Figure 6, a value of 1 is assigned to a SMRF if it is greater than all the others for

a particular moisture value. The shaded area represents the probability density function of the soil moisture as simulated by CABLE and used by CASA-CNP. As with temperature, these soil moistures are insensitive to the choice of STRFs and SMRFs, and only the default values are shown. The SMRFs are more diverse than the temperature dependencies and, except for CASA-CNP and Sim-Cycle, are usually composed of several linear segments meeting at sharp angles. There is some interesting behavior: note that the shape of the functional form for the SMRF can be
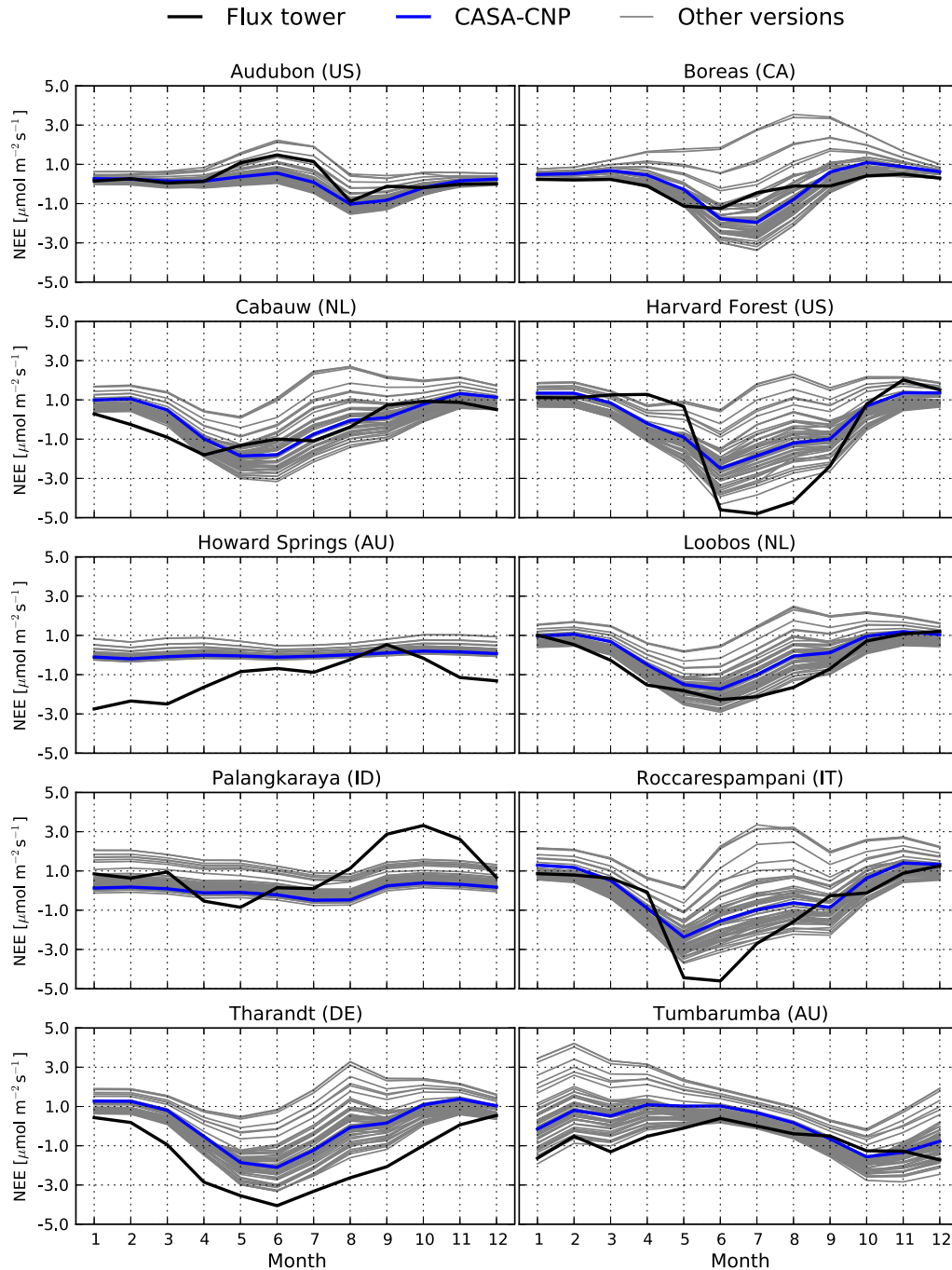
Figure 5. As in Figure 4, but for net ecosystem exchange (μmol m^{-2} s^{-1}). Negative values indicate that the ecosystem is a net carbon sink, while positive values indicate a net carbon source.

logarithmically increasing from 0.0 (Sim-Cycle), linearly increasing (LPJ, Bethy), or zero (CASA-CNP, SOILN) to a threshold value corresponding to the water content at wilting point (0.3 at Audubon, 0.6 at Palangkaraya, and 0.2 at Howard Springs). However, Figure 7 shows that for soil moisture computed by CABLE at these sites, this is an unnecessary complexity because the soil moisture values never drop into this range. The various SMRFs are generally different by at least 0.4 and commonly by 0.5 in the range where soil moisture occurs (Figure 2), which translates to the lowest SMRF generally having half the value of the highest one. However, at Boreas, since saturated conditions

are simulated most of the time, this relative difference leads to a factor 4 difference between the most generous (Bethy and SWAT) and the most constraining functions (CASA-CNP, Sim-Cycle, and SOILN). This is consistent with the roughly fourfold difference between lowest and highest mean monthly respiration rates shown in Figure 3.

4. Discussion and Conclusions

[20] The simulation of the terrestrial carbon budget is one of the key purposes of many terrestrial models. Belowground carbon is strongly affected by HR, which is parameterized in
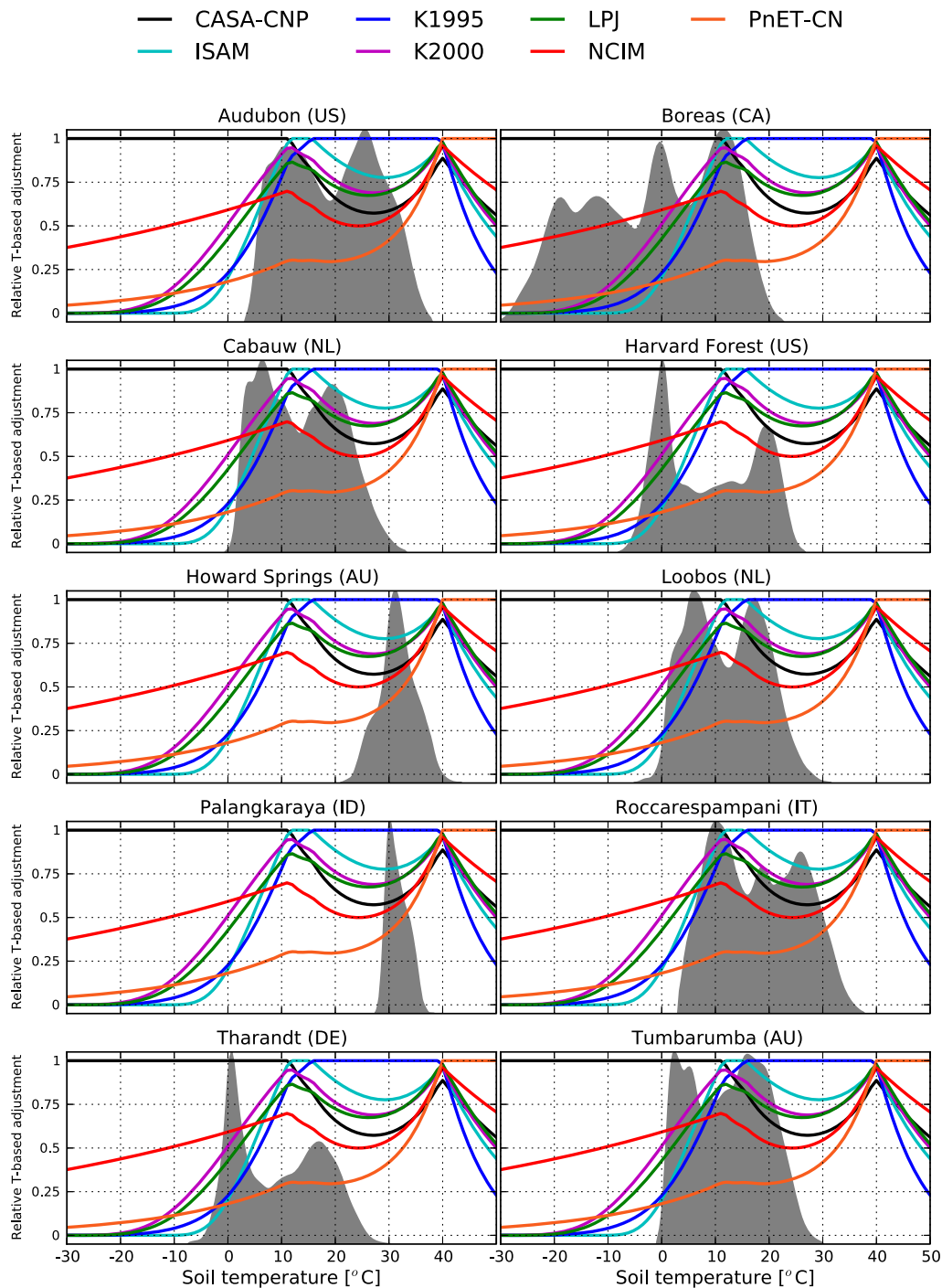
Figure 6. Relative value of each STRF compared to the maximum value at each temperature. STRF with a value of 1 is the maximum for this specific temperature. The shaded area is the probability density function (arbitrary units) of the soil temperature simulated by CABLE.

terrestrial models using a temperature function to accelerate HR as temperature increases and a moisture function that initially increases HR as the soil becomes wetter and then maintains or reduces HR in very wet conditions. These functions depend on the soil moisture and temperature simulated by the terrestrial model. Capturing HR well in a terrestrial model is important in simulating NEE, but it is also a key to understanding how the land-based sinks of CO_2 might change in the future. Will sinks be maintained, increase, or decrease?

[21] We have tested all possible combinations of eight SMRFs and seven STRFs within a single biogeochemical model coupled to a LSM, assuming idealized conditions in which both meteorology and initial conditions would be known. Depending on how we parameterize these functions, very large differences can be simulated in NEE at 10 different sites. Differences in flux results presented in Figures 3, 4, and 5 lead to variations in soil carbon content ranging from a loss of around $800 \, \text{g C m}^{-2} \, \text{yr}^{-1}$ to a gain of $400 \, \text{g C m}^{-2} \, \text{yr}^{-1}$ while
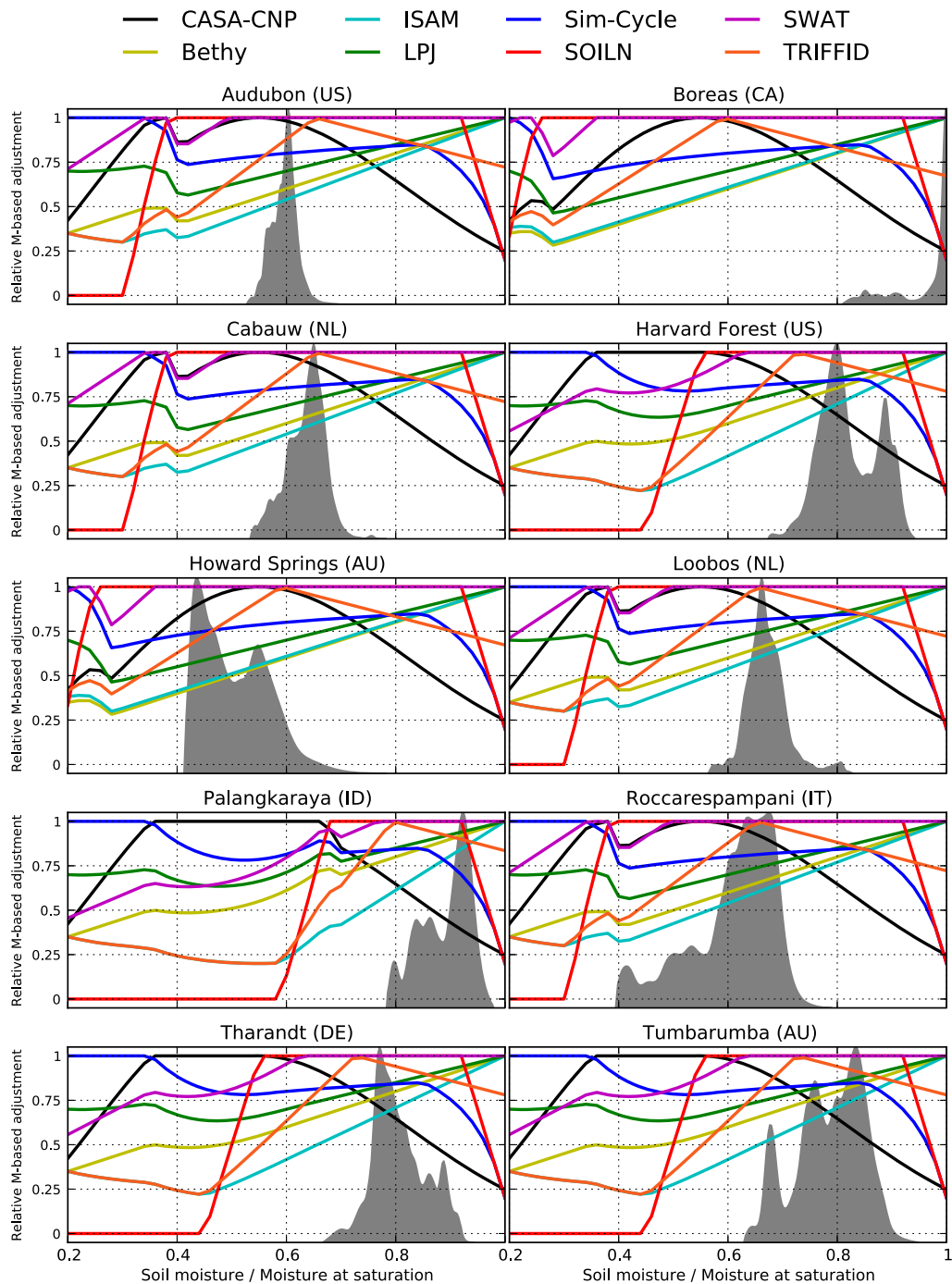
Figure 7. Relative value of each SMRF compared to the maximum value at each soil moisture content. SMRF with a value of 1 is the maximum for this specific moisture content. The shaded area is the probability density function (arbitrary units) of the soil moisture simulated by CABLE.

using the same initial conditions, as illustrated in Figure 8. We have shown that the default version of CASA-CNP implemented functions for the temperature and moisture dependencies of HR that seem at least as plausible as many of the alternative functions (Figures 1 and 2). However, even though the alternative parameterizations all provide a ratio of HR to RECO in agreement with reported values [*Davidson et al.*, 2006], the impact of differences between STRFs and SMRFs was not only clear in the simulation of HR (Figure 5) but could also be identified when summed with other C fluxes in NEE

(Figure 3). At temperate and cold sites, those differences create a spread of seasonal variability of NEE that generally bracket observations, while all model versions fail by up to several $\mu mol\,m^{-2}\,s^{-1}$ in tropical conditions, possibly due to a mismatch between the assumed equilibrium and actual initial conditions at those sites. Further research in that direction is currently undertaken to improve the evaluation of the sensitivity of high-frequency fluxes modeling to the initial carbon pools in the CASA-CNP model. Nevertheless, net differences in soil C content of up to $1200\,g\,C\,m^{-2}\,yr^{-1}$ were simulated
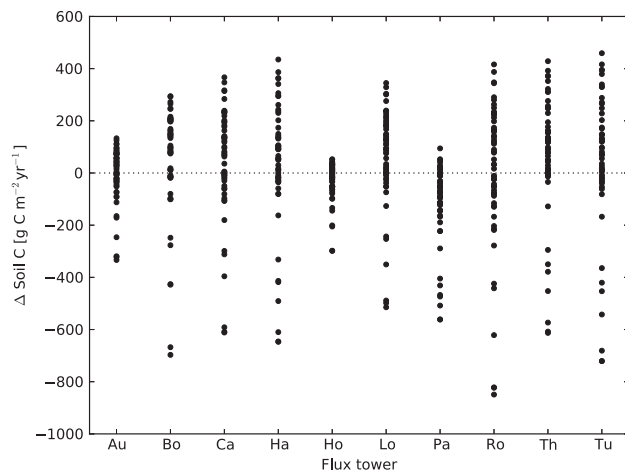
Figure 8. Mean annual change in the soil carbon storage at each station as simulated by each of the alternative parameterizations of soil respiration (Au: Audubon, Bo: Boreas, Ca: Cabauw, Ha: Harvard Forest, Ho: Howard Springs, Lo: Loobos, Pa: Palangkaraya, Ro: Roccarespampani, Th: Tharandt, Tu: Tumbarumba). Positive values indicate an increase in soil carbon content (i.e., sink), while negative values correspond to a depletion in soil carbon (i.e., source).

under the same driving conditions at all stations (Figure 8). This wide range of possible evolution pathways of soil C storages is consistent with global-scale results from *Friedlingstein et al.* [2006] or *Falloon et al.* [2011], for example.

[22] Resolving the representation of STRF and SMRF in LSMs is therefore likely to prove particularly challenging. First, observationally based analyses of HR response to soil temperature [e.g., *Kirschbaum*, 2000, 2010] may provide insight as to the shape of the STRF at many sites, but our results (e.g., Figures 3 and 4) suggest that there are places where all STRFs struggle, likely under very warm conditions which are usually out of range of observational data sets. Developing ways to scale location-specific STRFs to be representative of large spatial areas for LSMs coupled to climate models is a major challenge, but at least the temperature simulated by LSMs in the root zone is based on reasonably well-known physics. In contrast, the soil moisture simulated by LSMs is known to be highly model dependent [*Koster et al.*, 2009]. In Figure 3 of *Koster et al.* [2009], time series of simulated soil moisture for five regions are shown for seven LSMs. Over Europe, the degree of saturation simulated by the models vary from 0.4 to 0.8 in summer; over the Amazon, they vary from 0.7 to 1.0, and over the southern United States they vary in spring and early summer from 0.6 to 1.0. These LSM-specific ranges, mapped onto Figure 7, lead to very different moisture adjustments even if the form of the SMRF was known. Quoting *Koster et al.* [2009], "the soil moisture state simulated by a land surface model is a highly model-dependent quantity, meaning that the direct transfer of one model's soil moisture into another can lead to a fundamental, and potentially detrimental, inconsistency." It follows that a given SMRF will lead to very large differences in the calculation of HR between different LSMs because the "operating range" of soil moisture within LSMs varies.

[23] Our results therefore have a worrying implication. To represent HR well requires a suitable STRF and SMRF to be used. However, the impact of that function is intimately connected with the skill of the LSM to simulate the associated temperatures and soil moistures. Soil moisture has typically been seen as a quantity that can be model dependent, a quantity that needs to reach a model-specific state that enables transpiration and soil evaporation to be accurately simulated. Until standardized observations at flux stations are routinely available with coincident soil temperature and soil moisture observations, taken over the root zone, it seems unlikely that this will be resolvable. We did explore evaluating CABLE's soil moisture and soil temperature simulations using observations at the 10 sites (results not shown), but this proved very challenging due to gaps in the data, inconsistent measurement depths, few measurements below 0.0°C, and some extremely peculiar temperature and moisture observations at some sites. There are simply too few sites with the forcing data required by CABLE, combined with robust measurements of NEE and RECO needed to evaluate CASA-CNP, coincident with observed soil temperature and moisture over the root zone to constrain the model at this time. We also note that there is an implicit assumption that we can choose a STRF based on how well a LSM captures observed NEE, an assumption that needs to be treated carefully because compensations or amplifications of errors in the simulation of the different fluxes respiration and photosynthesis fluxes can provide a good NEE for the wrong reason. For example, while RECO simulations at Palangkaraya are clearly inconsistent with observations, with a bias always greater than 2 (Figure 4), the corresponding NEE simulations bracket the flux tower data almost all year round (Figure 5). Conversely, the RECO simulated at Tharandt by the alternative parameterizations (Figure 4) correctly brackets the observational data, but the corresponding NEE simulations fail to do so with flux tower data (Figure 5). RECO is always underestimated at Howard Springs (Figure 4), but NEE is always overestimated at the same site (Figure 5).

[24] Finally, obtaining generalized STRFs and SMRFs suitable for the large spatial scales used in climate models is even more challenging. These functions use observed soil temperatures and observed soil moisture with the associated heterotrophic respiration rates. The LSMs use observed solar radiation, infrared radiation, air temperature, rainfall, and specific humidity to simulate soil temperature and soil moisture. In the case of soil temperature, existing theory allows land surface models to capture heat diffusion reasonably well. However, no similar theory for soil moisture exists, meaning land surface models simulate a soil moisture state that is model specific. Soil moisture varies to support land surface models capturing observed latent heat fluxes and the surface energy balance and as a consequence is not necessarily similar to something that might be observed and called soil moisture. Thus, a "perfect" SMRF implemented into different land surface models would lead to different rates of heterotrophic respiration.

[25] We have shown that the form of the STRFs and SMRFs proposed in the literature vary dramatically, and these lead to major differences in how CASA-CNP simulates heterotrophic respiration. As a consequence, large differences in ecosystem respiration and hence net

ecosystem exchange are also simulated. Of course we could have relied on optimization techniques to adjust the response functions to local conditions. For example, *Bauer et al.* [2012] demonstrated that optimizing the shape of different response functions at a single site led to an almost perfect overlap of the curves over the corresponding ranges of temperature and moisture. These locally optimal responses indicate that regional parameterizations of STRF and SMRF would probably be more suited than global ones. Still, the curves diverge dramatically once outside of the relevant range, introducing a large uncertainty when it comes to study the effect of changing conditions like climate change. Other recent studies have examined the robustness of calibrated models by studying their transferability in both space and time. For example, *Kuppel et al.* [2012] calibrated their model for a specific biome type (broadleaf forest) using alternatively single-site and multisite data streams. They showed that a global multisite optimization often provided as good a simulation as the individual single-site optimizations while narrowing the posterior distribution of the parameters. Similarly, *Keenan et al.* [2012] showed that the uncertainty in future projections of carbon uptake at the Harvard Forest site could be reduced by assimilating data streams at different time resolution. However, by confronting their simulations with transient historical conditions, they showed that time-invariant parameter values are not transferable if key processes are misrepresented, or missing, in the model structure. Care has to be taken therefore when using these automated methods as an apparently good simulation may just be the result of an overfitting procedure that compensates the parameterization inadequacy.

[26] Resolving the form of the STRF and SMRF requires coincident observation at several locations of the following: the meteorological forcing required to simulate land surface fluxes; soil temperature and moisture; heterotrophic respiration; and net ecosystem exchange. The lack of availability of such complete data sets at multiple locations limits our capacity to resolve uncertainty in how to model heterotrophic respiration in land surface models, and Fluxnet data alone remain insufficient to thoroughly evaluate complex models [*Keenan et al.*, 2012]. This fits in a stream of emerging critical research directions [*Treseder et al.*, 2012] such as the uncertainty in the way nutrient availability regulates the carbon cycle, the adaptation of microbial biota and activity distribution to changes in short-term (e.g., rewetting pulses) to long-term (e.g., global warming) conditions [*Evans and Wallenstein*, 2012; *Wallenstein and Hall*, 2012], or simply the correctness of the representation of the soil carbon cycle in coupled models [*Todd-Brown et al.*, 2012]. All are required to resolve beforehand whether soil carbon stores will increase, decrease, or remain the same under future climate change.

References

Aber, J. D., S. V. Ollinger, and C. T. Driscoll (1997), Modeling nitrogen saturation in forest ecosystems in response to land use and atmospheric deposition, *Ecol. Model.*, *101*(1), 61–78, doi:10.1016/S0304-3800(97)01953-4.

Abramowitz, G. (2005), Towards a benchmark for land surface models, *Geophys. Res. Lett.*, *32*, L22702, doi:10.1029/2005GL024419.

Abramowitz, G. (2012), Towards a public, standardized, diagnostic benchmarking system for land surface models, *Geosci. Model Dev.*, *5*, 819–827, doi:10.5194/gmd-5-819-2012.

Abramowitz, G., A. Pitman, H. Gupta, E. Kowalczyk, and Y. Wang (2007), Systematic bias in land surface models, *J. Hydrometeorol.*, *8*, 989–1001, doi:10.1175/JHM628.1.

Abramowitz, G., R. Leuning, M. Clark, and A. J. Pitman (2008), Evaluating the performance of land surface models, *J. Clim.*, *21*, 5468–5481.

Arnold, J. G., R. Srinivasan, R. S. Muttiah, and J. R. Williams (1998), Large area hydrologic modeling and assessment part I: Model development, *J. Am. Water Resour. Assoc.*, *34*(1), 73–89, doi:10.1111/j.1752-1688.1998.tb05961.x.

Batjes, N. H. (1996), Total carbon and nitrogen in the soils of the world, *Eur. J. Soil Sci.*, *47*(2), 151–163, doi:10.1111/j.1365-2389.1996.tb01386.x.

Bauer, J., L. Weihermüller, J. Huisman, M. Herbst, A. Graf, J. Séquaris, and H. Vereecken (2012), Inverse determination of heterotrophic soil respiration response to temperature and water content under field conditions, *Biogeochemistry*, *108*(1), 119–134, doi:10.1007/s10533-011-9583-1.

Bond-Lamberty, B., and A. Thomson (2010), A global database of soil respiration data, *Biogeosciences*, *7*(6), 1915–1926, doi:10.5194/bg-7-1915-2010.

Chen, X., L. B. Hutley, and D. Eamus (2003), Carbon balance of a tropical savanna of northern Australia, *Oecologia*, *137*, 405–416, doi:10.1007/s00442-003-1358-5.

Chen, X., W. M. Post, R. J. Norby, and A. T. Classen (2011), Modeling soil respiration and variations in source components using a multi-factor global climate change experiment, *Clim. Change*, *107*, 459–480, doi:10.1007/s10584-010-9942-2.

Cox, P. M. (2001), Description of the TRIFFID dynamic global vegetation model, *Tech. Note 24*, Met Off. Hadley Cent., Exeter, U. K.

Cox, P. M., R. A. Betts, C. D. Jones, S. A. Spall, and I. J. Totterdell (2000), Acceleration of global warming due to carbon-cycle feedbacks in a coupled climate model, *Nature*, *408*(6809), 184–187, doi:10.1038/35041539.

Davidson, E. A., and I. A. Janssens (2006), Temperature sensitivity of soil carbon decomposition and feedbacks to climate change, *Nature*, *440*(7081), 165–173, doi:10.1038/nature04514.

Davidson, E. A., A. D. Richardson, K. E. Savage, and D. Y. Hollinger (2006), A distinct seasonal pattern of the ratio of soil respiration to total ecosystem respiration in a spruce-dominated forest, *Global Change Biol.*, *12*(2), 230–239, doi:10.1111/j.1365-2486.2005.01062.x.

Dolman, A. J., E. J. Moors, and J. A. Elbers (2002), The carbon uptake of a mid latitude pine forest growing on sandy soil, *Agric. Forest Meteorol.*, *111*(3), 157–170, doi:10.1016/S0168-1923(02)00024-2.

Dunn, A. L., C. C. Barford, S. C. Wofsy, M. L. Goulden, and B. C. Daube (2007), A long-term record of carbon exchange in a boreal black spruce forest: Means, responses to interannual variability, and decadal trends, *Global Change Biol.*, *13*(3), 577–590, doi:10.1111/j.1365-2486.2006.01221.x.

Emanuel, R. E., P. D'Odorico, and H. E. Epstein (2007), Evidence of optimal water use by vegetation across a range of North American ecosystems, *Geophys. Res. Lett.*, *34*, L07401, doi:10.1029/2006GL028909.

Esser, G., J. Kattge, and A. Sakalli (2011), Feedback of carbon and nitrogen cycles enhances carbon sequestration in the terrestrial biosphere, *Global Change Biol.*, *17*(2), 819–842, doi:10.1111/j.1365-2486.2010.02261.x.

Evans, S., and M. Wallenstein (2012), Soil microbial community response to drying and rewetting stress: Does historical precipitation regime matter?, *Biogeochemistry*, *109*(1), 101–116, doi:10.1007/s10533-011-9638-3.

Falloon, P., C. D. Jones, M. Ades, and K. Paul (2011), Direct soil moisture controls of future global soil carbon changes: An important source of uncertainty, *Global Biogeochem. Cycles*, *25*, GB3010, doi:10.1029/2010GB003938.

Friedlingstein, P., et al. (2006), Climate-carbon cycle feedback analysis: Results from the C4MIP model intercomparison, *J. Clim.*, *19*, 3337–3353, doi:10.1175/JCLI3800.1.

Gilmanov, T. G., et al. (2007), Partitioning European grassland net ecosystem CO_2 exchange into gross primary productivity and ecosystem respiration using light response function analysis, *Agric. Ecosyst. Environ.*, *121*(1–2), 93–120, doi:10.1016/j.agee.2006.12.008.

Grünwald, T., and C. Bernhofer (2007), A decade of carbon, water and energy flux measurements of an old spruce forest at the Anchor Station Tharandt, *Tellus, Ser. B*, *59*(3), 387–396, doi:10.1111/j.1600-0889.2007.00259.x.

Hirano, T., H. Segah, T. Harada, S. Limin, T. June, R. Hirata, and M. Osaki (2007), Carbon dioxide balance of a tropical peat swamp forest in Kalimantan, Indonesia, *Global Change Biol.*, *13*(2), 412–425, doi:10.1111/j.1365-2486.2006.01301.x.

Ito, A., and T. Oikawa (2002), A simulation model of the carbon cycle in land ecosystems (Sim-CYCLE): A description based on dry-matter production theory and plot-scale validation, *Ecol. Model.*, *151*(2–3), 143–176, doi:10.1016/S0304-3800(01)00473-2.

Jansson, P.-E., and B. Berg (1985), Temporal variation of litter decomposition in relation to simulated soil climate. Long-term decomposition in a Scots pine forest, *Botany*, *63*, 1008–1016, doi:10.1139/b85-136.

Jones, C. D., P. M. Cox, R. L. H. Essery, D. L. Roberts, and M. J. Woodage (2003), Strong carbon cycle feedbacks in a climate model with interactive CO_2 and sulphate aerosols, *Geophys. Res. Lett.*, *30*(9), 1479, doi:10.1029/2003GL016867.

Keenan, T. F., E. Davidson, A. M. Moffat, W. Munger, and A. D. Richardson (2012), Using model-data fusion to interpret past trends, and quantify uncertainties in future projections, of terrestrial ecosystem carbon cycling, *Global Change Biol.*, *18*(8), 2555–2569, doi:10.1111/j.1365-2486.2012.02684.x.

Kirschbaum, M. U. F. (1995), The temperature dependence of soil organic matter decomposition, and the effect of global warming on soil organic C storage, *Soil Biol. Biochem.*, *27*, 753–760, doi:10.1016/0038-0717(94)00242-S.

Kirschbaum, M. U. F. (2000), Will changes in soil organic carbon act as a positive or negative feedback on global warming?, *Biogeochemistry*, *48*(1), 21–51.

Kirschbaum, M. U. F. (2010), The temperature dependence of organic matter decomposition: Seasonal temperature variations turn a sharp short-term temperature response into a more moderate annually averaged response, *Global Change Biol.*, *16*(7), 2117–2129, doi:10.1111/j.1365-2486.2009.02093.x.

Knorr, W. (2000), Annual and interannual CO_2 exchanges of the terrestrial biosphere: Process-based simulations and uncertainties, *Global Ecol. Biogeogr.*, *9*(3), 225–252.

Knorr, W., I. C. Prentice, J. I. House, and E. A. Holland (2005), Long-term sensitivity of soil carbon turnover to warming, *Nature*, *433*(7023), 298–301, doi:10.1038/nature03226.

Koster, R. D., Z. Guo, R. Yang, P. A. Dirmeyer, K. Mitchell, and M. J. Puma (2009), On the nature of soil moisture in land surface models, *J. Clim.*, *22*, 4322–4335, doi:10.1175/JCLI2832.1.

Kowalczyk, E. A., Y. P. Wang, and R. M. Law (2006), The CSIRO Atmospheric Biosphere Land Exchange (CABLE) model for use in climate models and as an offline model, *Pap. 013*, CSIRO Mar. and Atmos. Res., Aspendale, Victoria, Australia. (Available at http://www.cmar.csiro.au/e-print/open/kowalczykea_2006a.pdf).

Kuppel, S., P. Peylin, F. Chevallier, C. Bacour, F. Maignan, and A. D. Richardson (2012), Constraining a global ecosystem model with multi-site eddy-covariance data, *Biogeosciences*, *9*, 3757–3776, doi:10.5194/bg-9-3757-2012.

Leuning, R., H. A. Cleugh, S. J. Zegelin, and D. Hughes (2005), Carbon and water fluxes over a temperate eucalyptus forest and a tropical wet/dry savanna in Australia: Measurements and comparison with MODIS remote sensing estimates, *Agric. Forest Meteorol.*, *129*(3–4), 151–173, doi:10.1016/j.agrformet.2004.12.004.

Loveland, T. R., B. C. Reed, J. F. Brown, D. O. Ohlen, Z. Zhu, L. Yang, and J. W. Merchant (2000), Development of a global land cover characteristics database and IGBP DISCover from 1 km AVHRR data, *Int. J. Rem. Sens.*, *21*, 1303–1330, doi:10.1080/014311600210191.

Raupach, M. R., K. Finkele, and L. Zhang (1997), SCAM (Soil-Canopy-Atmosphere Model): Description and comparison with field data, *Tech. Rep. 132*, CSIRO Cent. for Environ. Mech., Canberra.

Reichstein, M., J. Subke, A. C. Angeli, and J. D. Tenhunen (2005), Does the temperature sensitivity of decomposition of soil organic matter depend upon water content, soil horizon, or incubation time?, *Global Change Biol.*, *11*(10), 1754–1767, doi:10.1111/j.1365-2486.2005.001010.x.

Rey, A., E. Pegoraro, V. Tedeschi, I. De Parri, P. G. Jarvis, and R. Valentini (2002), Annual variation in soil respiration and its components in a coppice oak forest in central Italy, *Global Change Biol.*, *8*(9), 851–866, doi:10.1046/j.1365-2486.2002.00521.x.

Sitch, S., et al. (2003), Evaluation of ecosystem dynamics, plant geography and terrestrial carbon cycling in the LPJ dynamic global vegetation model, *Global Change Biol.*, *9*(2), 161–185, doi:10.1046/j.1365-2486.2003.00569.x.

Todd-Brown, K., F. Hopkins, S. Kivlin, J. Talbot, and S. Allison (2012), A framework for representing microbial decomposition in coupled climate models, *Biogeochemistry*, *109*(1), 19–33, doi:10.1007/s10533-011-9635-6.

Treseder, K., et al. (2012), Integrating microbial ecology into ecosystem models: Challenges and priorities, *Biogeochemistry*, *109*(1), 7–18, doi:10.1007/s10533-011-9636-5.

Urbanski, S., C. Barford, S. Wofsy, C. Kucharik, E. Pyle, J. Budney, K. McKain, D. Fitzjarrald, M. Czikowsky, and J. W. Munger (2007), Factors controlling CO_2 exchange on timescales from hourly to decadal at Harvard Forest, *J. Geophys. Res.*, *112*, G02020, doi:10.1029/2006JG000293.

Wallenstein, M., and E. Hall (2012), A trait-based framework for predicting when and where microbial adaptation to climate change will affect ecosystem functioning, *Biogeochemistry*, *109*(1), 35–47, doi:10.1007/s10533-011-9641-8.

Wang, Y.-P., and R. Leuning (1998), A two-leaf model for canopy conductance, photosynthesis and partitioning of available energy I: Model description and comparison with a multi-layered model, *Agric. Forest Meteorol.*, *91*(1–2), 89–111, doi:10.1016/S0168-1923(98)00061-6.

Wang, Y. P., R. M. Law, and B. Pak (2010), A global model of carbon, nitrogen and phosphorus cycles for the terrestrial biosphere, *Biogeosciences*, *7*(7), 2261–2282, doi:10.5194/bg-7-2261-2010.

Wang, Y. P., E. Kowalczyk, R. Leuning, G. Abramowitz, M. R. Raupach, B. Pak, E. van Gorsel, and A. Luhar (2011), Diagnosing errors in a land surface model (CABLE) in the time and frequency domains, *J. Geophys. Res.*, *116*, G01034, doi:10.1029/2010JG001385.

Yang, X., V. Wittig, A. K. Jain, and W. Post (2009), Integration of nitrogen cycle dynamics into the Integrated Science Assessment Model for the study of terrestrial ecosystem responses to global change, *Global Biogeochem. Cycles*, *23*, GB4029, doi:10.1029/2009GB003474.

Zhang, Q., Y. P. Wang, A. J. Pitman, and Y. J. Dai (2011), Limitations of nitrogen and phosphorous on the terrestrial carbon uptake in the 20th century, *Geophys. Res. Lett.*, *38*, L22701, doi:10.1029/2011GL049244.

Zobler, L. (1999), Global Soil Types, 1-Degree Grid, http://daac.ornl.gov/SOILS/guides/ZoblerSoil1.html, Distributed Active Arch. Cent., Oak Ridge Natl. Lab., Oak Ridge, Tenn., doi:10.3334/ORNLDAAC/418.