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Variation of parameters in a Flux-Based Ecosystem Model across 12 sites of terrestrial ecosystems in the conterminous USA

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ABSTRACT

Terrestrial ecosystem models have been extensively used in global change research. When a model calibrated with site-specific parameters is applied to another site, how and why the parameters have to be adjusted again in order to fit data well are pervasive yet underexplored issues. In this exploratory study, we examined how and why model parameters of a Flux-Based Ecosystem Model (FBEM) varied across different sites. Parameters were estimated from data at 12 eddy-covariance towers in the conterminous USA using the conditional inversion method. Results showed that optimized values of these parameters varied across sites. For example, the estimated coefficients in the Leuning model, g_l and D_0, exhibited high cross-site variation, but the ratio of internal to air CO_2 concentration (f_{Ci}) and canopy light extinction coefficient (k_n) varied little among these sites. Parameters greatly varied with ecosystem types at adjacent sites where climate conditions were similar. Five parameters (activation energy of carboxylation, E_{Kc}; activation energy of oxygenation, E_{Vm}; ecosystem respiration, R^0_{eco}; temperature sensitivity of respiration, Q_{10}; and stomatal conductance coefficient, D_0) were highly correlated with mean annual temperature and precipitation across sites, which were distributed in different climate regions of conterminous US. Our results indicate that individual parameters vary to different degrees across sites and parameter variation can be related to different biological factors (e.g., ecosystem types) and environmental conditions (e.g., temperature and precipitation). It is essential to further examine magnitudes of and mechanisms underlying the parameter variation in ecosystem models so as to improve model prediction.

1. Introduction

Ecological models that simulate responses of ecosystem photosynthesis and respiratory processes to elevated atmospheric CO_2 and increased temperature are fundamental to projecting carbon balance and impacts of global change on the biosphere (Long, 1991; Lloyd and Taylor, 1994; Sellers et al., 1997; Bernacchi et al., 2001). It has been well noticed that variation in parameters is one of the main sources of uncertainty in model predictions (Luo et al., 2011, 2015; Xiao et al., 2014). Most global biosphere models classify the terrestrial ecosystems with a small number of categories, referred to as plant functional types (PFTs). Parameters are often assigned to some fixed values for a given PFT and may vary among PFTs. For example, Sellers et al. (1996) found that some parameters such as maximum photosynthetic carboxylation rate and minimum stomatal conductance need better parameterizations because they vary strongly with PFTs at the global scale. Even within the same PFT, however, model parameters appeared more variable than assumed. For instance, Groenendijk et al. (2011) found better simulations of photosynthesis and transpiration using site-specific calibrated parameters compared with using fixed vegetation parameters across sites with the same PFT. Xiao et al. (2014) also identified variation of estimated values of parameters both within and across PFTs in a diagnostic carbon flux model, suggesting

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the use of observations from multiple sites for a given PFT provided more representative estimates of parameter values. Although it is recognized that parameters may have to vary with sites, it remains unknown how the parameters vary across sites and what contributed to the parameter variation.

Some studies have shown that parameters vary with both biotic and abiotic factors. For example, maximum rate of carboxylation (i.e., $V_{c,\max}$) is a key parameter in the leaf model of C_3 photosynthesis of Farquhar et al. (1980). Previous studies have identified four factors – species differences, light intensity, seasonal patterns, and water availability – that could cause variability in $V_{c,\max}$ (normalized to 25 °C) (Wullschleger, 1993; Medvigy et al., 2013; Wilson et al., 2000). Despite various factors to influence $V_{c,\max}$, its variation usually can be well represented by $V_{c,\max}$—nitrogen (N) relationships as in many Earth system models (Rogers, 2014). Temperature sensitivity of soil heterotrophic respiration (i.e., Q_{10}) is another critical parameter regulating carbon-climate feedback. Although many ecosystem models commonly use a constant Q_{10} (Tian et al., 1999; Schimel et al., 2000; Chen and Tian, 2005), a small deviation of Q_{10} will significantly change the estimate of the total CO_2 efflux from soil to the atmosphere (Xu and Qi, 2001). In fact, a few studies have shown that Q_{10} varies at site scale with climate variables such as mean annual precipitation and temperature (Zhou et al., 2009; Peng et al., 2009). These examples all illustrate that parameters might have to vary temporally and spatially.

Recently developed techniques of data-model fusion and inversion analysis have emerged as useful tools to gain ecological knowledge about parameter variation in biogeochemical models. For instance, Shi et al. (2015) estimated C–N coupling parameters using Bayesian Markov Chain Monte Carlo (MCMC) technique under ambient and elevated CO_2 in Duke Forests, revealing that C-N coupling parameters exhibited significant changes in response to rising atmospheric CO_2. By using inversion analysis, Zhou and Luo (2008) discovered that estimated carbon residence times were highly heterogeneous over the conterminous United States. Wang et al. (2007) found better predictions of net ecosystem CO_2 exchange (NEE) with seasonally varying $V_{c,\max}$ and maximum rate of electron transport at 25 °C (i.e., $J_{\max}$) in CSIRO biosphere model using a nonlinear inversion approach from eight FLUXNET sites.

Most of the previous parameter estimation studies with data-model fusion technique have pointed out that only a few parameters in process-based ecosystem models could be well constrained by the measurements of NEE (Wang et al., 2001; Braswell et al., 2005; Xiao et al., 2014). Toward that end, Wu et al. (2009) developed a conditional Bayesian inversion method to maximize the number of constrained parameters by assimilating NEE into FBEM. The conditional inversion method increased the number of constrained parameters from 6 to13 out of a total of 16 eventually. In this study, we used conditional inversion method and separated NEE into gross primary production (GPP) and ecosystem respiration (*Reco*) to fully extract data information to constrain model parameters.

The overall objective of this study is to understand variation of model parameters across different sites. Eddy covariance measurement of carbon dioxide across the canopy-atmosphere interface (Goulden et al., 1996; Baldocchi, 2003), including GPP and *Reco*, from 12 sites in North America were used to constrain the parameters in FBEM. Simulations were carried out from 2003 to 2007 according to the availability of data for each site. With eddy-covariance data and conditional inversion, we attempted to address the following three questions: (1) whether and how the model parameters vary across the 12 sites? (2) Whether model parameters vary within each PFT? (3) Which environmental factors are important in regulating the cross-site variation of the key parameters?

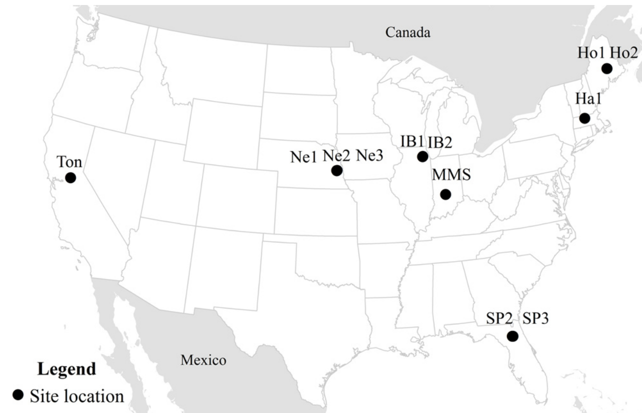

Fig. 1. Locations of the 12 sites in the conterminous United States. Among these sites, there were four clusters of geographically adjacent sites: Ne1, Ne2 and Ne3; Ho1 and Ho2; SP2 and SP3; IB1 and IB2. The sites within each cluster had distinct climate conditions, vegetation types or management strategies except Ho1 and Ho2.

2. Materials and methods

2.1. Site descriptions

The 12 sites in this study were: Harvard Forest (Ha1), Mead Irrigate (Ne1), Mead Irrigate Rotation (Ne2), Mead Rainfed (Ne3), Morgan Monre State Forest (MMS), Tonzi Ranch (Ton), Howland Forest (Ho1), Howland Forest West (Ho2), Mize (SP2), Donaldson Florida (SP3), Fermi Agricultural (IB1) and Fermi Prairie (IB2). Locations of those sites were shown in Fig. 1. The sites belonged to six ecosystem types: two for deciduous broad leaf forest (DBF), four for evergreen needle leaf forest (ENF), four for cropland (CRO), one for grassland (GRA) and one for savanna (SAV). The 12 sites covered four climate types, with mean annual temperature (MAT) varying from 5.13 to 20.25 °C, and mean annual precipitation (MAP) varying from 559 to 1314 mm. Information on the climate type, vegetation type, MAT, MAP and related reference of each site was listed in Table 1.

Among the 12 sites, there were four clusters of geographically adjacent sites. The first cluster included Ne1, Ne2 and Ne3, three fields located within 1.6 km of each other at the University of Nebraska Agricultural Research and Development Center near Mead, Nebraska. The vegetation type in Ne2 and Ne3 were maize soybean rotation while that in Ne1 was maize. Ne1 and Ne2 sites were irrigated while Ne3 site was rainfed. In Howland Forest, there were two eddy covariance towers Ho1 and Ho2 with nearly identical meteorological conditions, vegetation types and site histories. The third cluster included SP2 and SP3. SP2 site was once clearcut and planted with mixed genotype seedlings, and was covered mainly by evenly aged slash pine plantation. SP3 site was also slash pine plantations but established earlier than the new seedlings in SP2 site. The fourth cluster includes IB1 and IB2. IB2 had an eddy correlation system installed on a restored prairie, while there was a corn/soybean rotation agricultural field established in IB1.

2.2. Data sources

The datasets used in this study included climate data (i.e., air temperature at top canopy [*Ta*], photosynthetically active radiation [PAR] and relative humidity [RH]), biometric data (i.e., tower-collected leaf area index [LAI]), and eddy flux data (i.e., NEE, GPP and *Reco*). These datasets were downloaded from the AmeriFlux database at http://public.ornl.gov/ameriflux (AmeriFlux, 2007). Direct LAI measurements were not made or available in many sites.