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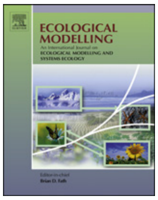

A hierarchical analysis of terrestrial ecosystem model Biome-BGC: Equilibrium analysis and model calibration

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ABSTRACT

The increasing complexity of ecosystem models represents a major difficulty in tuning model parameters and analyzing simulated results. To address this problem, this study develops a hierarchical scheme that simplifies the Biome-BGC model into three functionally cascaded tiers and analyzes them sequentially. The first-tier model focuses on leaf-level ecophysiological processes; it simulates evapotranspiration and photosynthesis with prescribed leaf area index (LAI). The restriction on LAI is then lifted in the following two model tiers, which analyze how carbon and nitrogen is cycled at the whole-plant level (the second tier) and in all litter/soil pools (the third tier) to dynamically support the prescribed canopy. In particular, this study analyzes the steady state of these two model tiers by a set of equilibrium equations that are derived from Biome-BGC algorithms and are based on the principle of mass balance. Instead of spinning-up the model for thousands of climate years, these equations are able to estimate carbon/nitrogen stocks and fluxes of the target (steady-state) ecosystem directly from the results obtained by the first-tier model. The model hierarchy is examined with model experiments at four AmeriFlux sites. The results indicate that the proposed scheme can effectively calibrate Biome-BGC to simulate observed fluxes of evapotranspiration and photosynthesis; and the carbon/nitrogen stocks estimated by the equilibrium analysis approach are highly consistent with the results of model simulations. Therefore, the scheme developed in this study may serve as a practical guide to calibrate/analyze Biome-BGC; it also provides an efficient way to solve the problem of model spin-up, especially for applications over large regions. The same methodology may help analyze other similar ecosystem models as well.

1. Introduction

Climate change due to anthropogenic increases in greenhouse gases has lead to concerns about impacts on terrestrial ecosystems, and has generated an imperative for the understanding of, and the ability to predict, the role of terrestrial ecosystems in the global carbon cycle (IPCC, 2007). In response to this call, a variety of biogeochemical ecosystem models have been developed since the 1980s, including CASA (Potter et al., 1993), CENTURY (Parton et al., 1993), TEM (Raich et al., 1991; McGuire et al., 1992), BGC (Running and Coughlan, 1988; Running and Gower, 1991), and many others. These models are driven by surface climate variables, and employ algorithms to simulate important ecosystem processes such as the exchange of water between the surface and the atmosphere through evaporation and transpiration, the assimilation and release of carbon through photosynthesis and respiration, and the decomposition of organic matter and the transformation of nitrogen in soil. As such, they provide an important means to simulate regional and global carbon/water cycles, and to assess the impacts of climate variability and its long-term change on these cycles (e.g, Randerson et al., 1997; Cramer et al., 1999; Schimel et al., 2000; Nemani et al., 2003).

Early versions of biogeochemical models usually have simple structures; as models evolve to create more realistic simulations, their later versions become increasingly sophisticated. For example, in Forest-BGC, the first member of the BGC family, leaf area index (LAI) of the vegetation canopy is prescribed, and carbon allocation is solely controlled by external parameters (Running and Coughlan, 1988). In the latest BGC model (Biome-BGC, version 4.2), in contrast, LAI is dynamically simulated and updated at daily scales

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with an integrated consideration of both carbon and nitrogen fluxes (Thornton et al., 2002). The current Biome-BGC also treats litter and soil processes in much detail, simulating the transformation of carbon and nitrogen between four different litter pools and four different soil pools (Thornton and Rosenbloom, 2005; Thornton, 1998). (The latest Biome-BGC model and its documentation are available online at http://www.ntsg.umt.edu.)

An indicator of a model's complexity may be the number of parameters that are used in the model to characterize various ecosystem processes or to represent different environmental properties. Currently, the core algorithm of Biome-BGC requires 67 parameters to be specified, of which 23 parameters are assumed constant model-wide, 34 parameters are specific to the plant functional type (PFT), and 10 parameters are specific to the study site. Determining appropriate values for these parameters requires great diligence: White et al. (2000) represents 40 pages of referenced source data to calculate a default set of ecophysiological parameters for Biome-BGC (which are supplied with the distribution of the BGC model). Still, these default parameters are intended for general guidance only: for a model as complex as Biome-BGC, small uncertainties in the parameters may propagate to generate a wide range of variability in the subsequent simulations, and thus model parameters need to be fine tuned for particular applications.

Because ecosystem processes tend to be nonlinear, numerical inversion algorithms are usually adopted for parameter tuning. These algorithms generally define a cost function that measures the mismatch between model simulations and the corresponding observations, and search for a set of "optimal" values that minimize the cost function. For instance, a search process usually starts with examining how the cost function responds to small changes in the parameters of interest; it then uses this information to determine new parameter values that decrease the cost function: the procedure is repeated until the minimum of the cost function is reached. Applications and reviews of typical inversion algorithms used in ecosystem model calibration can be found, for instance, in Wang et al. (2001, 2006), Knorr and Kattge (2005), Williams et al. (2005), and Raupach et al. (2005).

There are a few difficulties, or limitations, associated with the inversion of complicated models. First, because the search for an optimal solution is an iterative process, the inversion procedure may consume lots of processing power when the model is complicated and there are many parameters to calibrate (Wang et al., 2001; Raupach et al., 2005). Second, deciding the subset of parameters for calibration itself can be a difficult process. With the computation costs considered, generally we would like to calibrate parameters that are important and mutually independent (Harmon and Challenor, 1997). However, parameters (and the processes they characterize) in complex models preclude easy determination of the relative importance and independence of their component parts. Finally and most importantly, numerical inversion algorithms treat the ecosystem model as a "black-box" process, in which only the tested relationships between inputs (i.e., changes in parameters) and outputs (i.e., usually a few selected variables for which observations are available) are used. Thus the retrieval of optimal parameter values does not necessarily help with insight into the physical processes represented by the model. There are occasions in which we may be more interested in understanding why and how (rather than knowing what) certain values of parameters render the most realistic simulations. Numerical algorithms alone cannot fully address these questions.

Altogether, as today's ecosystem models strive to create more realistic simulations, their increasing complexity induces a major difficulty in tuning parameters and analyzing results, which in turn limits the application of the models themselves. To address this problem, on one hand, simplifications are necessary; on the other hand, the simulation capacity of the models should not be impaired. This creates a dilemma that is faced by anyone seeking to use modern ecosystem models.

Held (2005) discussed a similar dilemma for climate modeling. As suggested by Held (2005), a general solution to problems of this kind relies on the construction of model hierarchies. For instance, suppose there is a set of models that are coherently related to, but less complex than, the model we are working on. By comparing the behavior of the original complex model to that of simpler ones, we can gain understanding of "how the dynamics change as key sources of complexity are added or subtracted" (Held, 2005). Also, parameters can be first tuned on simpler models, and then applied to more complicated systems.

The set of coherently related models (including the original one) that have different levels of complexity forms a "model hierarchy" (Held, 2005). For most ecosystem models, such a model hierarchy is not be readily available, but may be constructed by sequentially removing certain functional components from the original model. Motivated by this approach, in this study we develop a model hierarchy for Biome-BGC and demonstrate its application in model analysis and parameter tuning at four AmeriFlux sites.

The rest of the paper is structured as follows. Section 2 describes the methodology and the dataset. The hierarchical scheme is then applied to analyze and calibrate Biome-BGC at four AmeriFlux sites, and the results are represented and discussed in Section 3. Finally, Section 4 gives the concluding remarks.

2. Methodology and datasets

2.1. Model hierarchy and equilibrium analysis

With a focus on the carbon cycle, we identify three key functional tiers in Biome-BGC: (1) photosynthesis and evapotranspiration at the leaf level; (2) carbon (and nitrogen) allocation and respiration at the whole-plant level; and (3) carbon/nitrogen cycles in litter/soil pools (Fig. 1). The three functional tiers also have a time-scale component to them, with photosynthesis and ET being the fast processes and the first processes whereby carbon enters (and water leaves) the ecosystem, while carbon and nitrogen cycles in litter/soil pools being the slowest processes that depend on the other two tiers (Williams et al., 2005). For simplicity of the text, here we give a qualitative introduction to the derived model hierarchy, but leave detailed mathematic derivations in Appendix B. Tables 1a–1c lists abbreviations and symbols that are frequently used in the following sections.

Photosynthesis (PSN) and evapotranspiration (ET) are two closely related processes that occur at the leaf level (Fig. 1a). PSN represents the start of the carbon cycle in Biome-BGC, which assimilates atmospheric CO_2 into the ecosystem (measured by gross primary production, GPP); during the same process, water is transpired from the soil to the atmosphere. In Biome-BGC, both

Table 1a
List of frequently used abbreviations.

Abbreviation	Description
PSN	Photosynthesis
GPP	Gross Primary Production
NPP	Net Primary Production
NEE	Net Ecosystem Exchange
MR	Maintenance Respiration
GR	Growth Respiration
AR	Autotrophic Respiration
HR	Heterotrophic Respiration
PFT	Plant Functional Type
ENF	Evergreen-Needle-leaf Forest
DBF	Deciduous Broadleaf Forest
LAI	Leaf Area Index
SLA	Specific Leaf Area