



**Modeling demographic-driven vegetation dynamics and ecosystem biogeochemical cycling
in NASA GISS's Earth system model (ModelE-BiomeE v.1.0)**

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Abstract: We developed a new demographic vegetation model, BiomeE, to improve the representation of vegetation demographic dynamics and ecosystem biogeochemical cycles in the NASA Goddard Institute of Space Studies' ModelE Earth system model. This model includes the processes of plant growth, mortality, reproduction, vegetation structural dynamics, and soil carbon and nitrogen storage and transformations. The model combines the plant physiological processes of ModelE's original vegetation model, Ent, with minor adaptations to fit the new allometry and vegetation structure with the plant demographic and ecosystem nitrogen processes represented from Geophysical Fluid Dynamics Laboratory (GFDL)'s LM3-PPA. For global applications, we added a new set of plant functional types to represent global vegetation functional diversity, including trees, shrubs, and grasses, and a new phenology model to deal with seasonal changes in temperature and soil water availability. Competition for light and soil resources is individual based, which makes the modeling of transient compositional changes and vegetation succession possible. BiomeE will allow ModelE to simulate long-term biogeophysical and biogeochemical feedbacks between the climate system and land ecosystems. BiomeE simulates, with fidelity comparable to other models, the dynamics of vegetation and soil biogeochemistry, including leaf area index, vegetation structure (e.g., height, tree density, size distribution, crown organization), and ecosystem carbon and nitrogen storage and fluxes. Further, BiomeE will also allow for the simulations of transient vegetation dynamics and eco-evolutionary optimal community assemblage in response to past and future climate changes by incorporating core ecological processes, including demography, competition, and community assembly.

Key words: Biogeochemical cycles, Eco-evolutionary optimality, Ecosystem modeling, Plant traits, Vegetation dynamics



1 Introduction

Terrestrial ecosystems play a critical role in the climate system by regulating exchanges of energy, moisture, and carbon dioxide between the land surface and the atmosphere (Sellers, 1997; Pielke et al., 1998; Meir et al., 2006). In turn, climate change has significantly affected vegetation photosynthesis, water use efficiency, mortality, regeneration, and structure through gradual changes in temperature and atmospheric [CO₂] together with shifts in climate extremes (Brando et al., 2019; McDowell et al., 2020; Keenan et al., 2013; Huang et al., 2015). These responses have triggered vegetation structural and compositional shifts. For example, global forest mortality has increased in recent years (Allen et al., 2010; Anderegg et al., 2012), tree sizes have decreased (Zhou et al., 2014; McDowell et al., 2020), and species composition has shifted to more opportunistic species (Clark et al., 2016; Brodribb et al., 2020). The shifts in vegetation function, composition, and structure can change the boundary conditions of the land surface and affect the climate system (Nobre et al., 1991; Avissar and Werth, 2005; Garcia et al., 2016; Green et al., 2017; Zeng et al., 2017). Realistically simulation of these processes is therefore critical for Earth system models (ESMs).

The vegetation dynamics in ESMs are usually simulated using dynamic global vegetation models (DGVMS) (Prentice et al., 2007), most of which are simplified in their representation of ecological processes. The core assumptions of many vegetation models are a big-leaf canopy, vegetation represented by only a few plant functional types (PFTs), single cohort-based vegetation dynamics (“single-cohort” assumption, where the vegetation community at a land unit are simulated as a collection of identical trees), lumped-pool-based biogeochemical cycles and first order decay of soil organic matter. The competition of plant individuals and vegetation types is approximately simulated as a function of productivity or Lotka-Volterra equations to predict



fractional PFT coverage (e.g., SDVGM, HYBRID, TRIFFID) (Friend et al., 1997; Woodward et al., 1998; Sitch et al., 2003). These simplifying assumptions make it possible to simulate the complex interactions of biological and ecological processes at the global scale.

These models are generally successful in reproducing land surface carbon, energy, and water fluxes after extensive tuning against data from sites, observational networks, and satellite remote sensing. However, the uncertainty of model predictions is high, and predictions can diverge substantially across different models (Friedlingstein et al., 2014; Arora et al., 2020). Lack of functional diversity and community assembly processes is one of the key issues in the vegetation modeling of ESMs, which makes the models unable to predict transient dynamics of vegetation composition and structure. A more mechanistic design that uses the fundamental principles of ecology to simulate the emergent properties of ecosystems for predicting ecosystem dynamics may therefore be necessary (Weng et al., 2017; Scheiter et al., 2013).

To this end, extensive efforts have been made to improve the representation of transient vegetation dynamics based on ecological theories and conceptual models. Two pivotal advances have been made in ecological vegetation modeling: 1) Demographic processes and trait-based representation of processes have been developed to improve the representation of functional diversity and size structure (Fisher et al., 2015; Weng et al., 2015; Pavlick et al., 2013) and 2) eco-evolutionary optimal and game theoretical approaches have been proposed to predict the flexibility of parameters and processes (McNickle et al., 2016; Weng et al., 2017). These concepts are mainly applied in modeling photosynthesis (Wang et al., 2017; Prentice et al., 2014), allocation (Farrior et al., 2013; Dybzinski et al., 2015), and evolutionarily stable strategy (ESS) of plant traits (Falster et al., 2017; Weng et al., 2017). These ideas for incorporating ecological and evolutionary principles into ESMs have been summarized in several recent review



47 papers (Harrison et al., 2021; Franklin et al., 2020; Kyker-Snowman et al., 2022). Microbial
48 processes have also been added to the decomposition models for soil organic matter (Sulman et
49 al., 2019; Wieder et al., 2014; Lu and Hedin, 2019).

50 There are still major challenges to integrating these more sophisticated ecological modeling
51 approaches into the complex land models of ESMs, where the explicit simulations of energy,
52 water, and carbon fluxes at high frequencies are required for interacting with the atmosphere and
53 climate system. The details of vegetation dynamics, including the key functions from leaf
54 photosynthesis, respiration, biogeochemical fluxes between pools, demographic processes,
55 community assembly, vegetation structure, and competition output, must be well-organized
56 hierarchically and computed efficiently (Fisher and Koven, 2020; Franklin et al., 2020).
57 Representing these processes in ESMs, however, can complicate model structure and behavior,
58 especially for the interaction between physiology and vegetation composition, and cause large
59 increases in the computational burden. Thus, the implementation of detailed vegetation
60 demographic processes and size categories into ESMs would benefit from more parsimonious
61 approaches, such as is the case for the Robust Ecosystem Demography model (Argles et al.,
62 2020).

63 Including highly complex processes does not necessarily increase model predictive skills
64 (Famiglietti et al., 2021; Forster, 2017; Hourdin et al., 2017). On the contrary, it may greatly
65 obscure model transparency and increases uncertainty, and positive feedbacks in these processes
66 may result in large and unanticipated shifts of vegetation states. Any small differences in model
67 setting or even parameter differences can result in distinct predictions, especially in vegetation
68 structure, which is supposed to be predicted by these types of models. These processes make
69 demographic vegetation models often unreliable when compared to the well-tuned “single-



cohort” vegetation models that simplify the reproduction and mortality as growth and turnover of continuous biomass pools. Additionally, the legacy of land models and the technical requirements of reversibility in model development mean developers must often build their new functions on top of their previous assumptions and model structure (Fisher and Koven, 2020), adding up to multiple adjustments on top of previous assumptions and making the model untraceable.

To explicitly model the transient dynamics of ecosystems in ESMs while preserving model traceability, we need clear assumptions, detailed physical processes, and traceable model structure. For the best chance of accurate predictions outside of the model's testing data, model processes should be based on the fundamental biological and ecological principles to predict ecosystem emergent properties, instead of fitting the emergent patterns directly as many models do currently. To achieve this, we need to properly represent the tradeoffs of plant traits, balance the complexity of the model structure and priority for the processes that are required by the general circulation model (GCM), and also make model assumptions transparent and processes robust. These requirements make it difficult to fully implement the modeling approaches that are well-developed in the ecological modeling community.

The NASA Goddard Institute for Space Studies’ Earth system model, ModelE, has a land model for representing land surface hydrology (TerraE) (Rosenzweig and Abramopoulos, 1997; Schmidt et al., 2014) and a vegetation biophysics scheme (from the Ent Terrestrial Biosphere Model)(Ito *et al.* 2020; Kelley *et al.* 2020; Schmidt *et al.* 2014), with fixed vegetation traits (e.g., leaf mass per area, C:N ratio), fixed biomass, canopy height, and plant density, and seasonal leaf area index prescribed from a satellite-derived data set (Ito et al., 2020). The Ent TBM calculates canopy radiative transfer (Friend & Kiang 2005), canopy albedo, canopy conductance,



93 photosynthesis, autotrophic respiration, and some phenological behaviors of leaf biophysics
94 (Kim et al., 2015). The carbon allocation scheme of Kim et al. (2015) is used in ModelE with
95 prescribed canopy structure and LAI, routing the carbon that would otherwise be allocated to
96 plant tissues via growth instead directly as litter into soil carbon pools, thus conserving carbon
97 for fully coupled carbon cycle simulations, but resulting possibly in imbalanced plant carbon
98 reserve pools where the prescribed canopy structure is not in equilibrium with the simulated
99 climate (Ito et al., 2020).

100 This paper describes a parsimonious vegetation demographic and soil organic
101 decomposition model that can be incorporated into the GISS ModelE ESM. Our goal is to
102 develop a parsimonious, transparent model that 1) allows ModelE to simulate the ecological
103 dynamics of terrestrial ecosystems and vegetation at the global scale and 2) sets up a modeling
104 framework for solving some of the major challenges for incorporating important ecological
105 mechanisms into ESMs. For (1), we have incorporated core ecosystem processes, including plant
106 growth, demography, community assembly, and ecosystem carbon and nitrogen cycles. For (2),
107 we have developed PFTs that are plant trait-based and a competition scheme that is individual-
108 based. In this paper, we describe this model in detail, and evaluate its performance compared to
109 both observations and other state-of-the-art DGVMs.

110

111 **2 Model Description**

112 **2.1 BiomeE Structure and Overview**

113 BiomeE is a standalone simulator derived from the LM3-PPA (Weng et al., 2015). It is a
114 demographic vegetation model that simulates plant physiology, vegetation demography, adaptive
115 dynamics (eco-evolutionary adaptation), and ecosystem carbon, nitrogen, and water cycles (Fig.



116 1) (Weng et al., 2017, 2019). In this model, a PFT is defined by a set of combined plant traits
 117 with their values sampled from the observed ranges to represent a specific plant type. The
 118 individual is the basic unit to carry out physiological and demographic activities, e.g.,
 119 photosynthesis, respiration, growth, reproduction, mortality, and competition with other
 120 individuals. Individual plants are categorized into cohorts and arranged in different vertical
 121 canopy layers according to their height and crown area following the rules of the Perfect
 122 Plasticity Approximation model (PPA, Strigul et al., 2008). Sunlight is partitioned into canopy
 123 crown layers according to Beer's law. With the PPA model, a key parameter for light
 124 competition, the height of canopy closure (i.e., critical height, H^*), is defined; all the plants
 125 above this context-dependent height get full sunlight and all trees below this height are shaded
 126 by the upper layer trees.

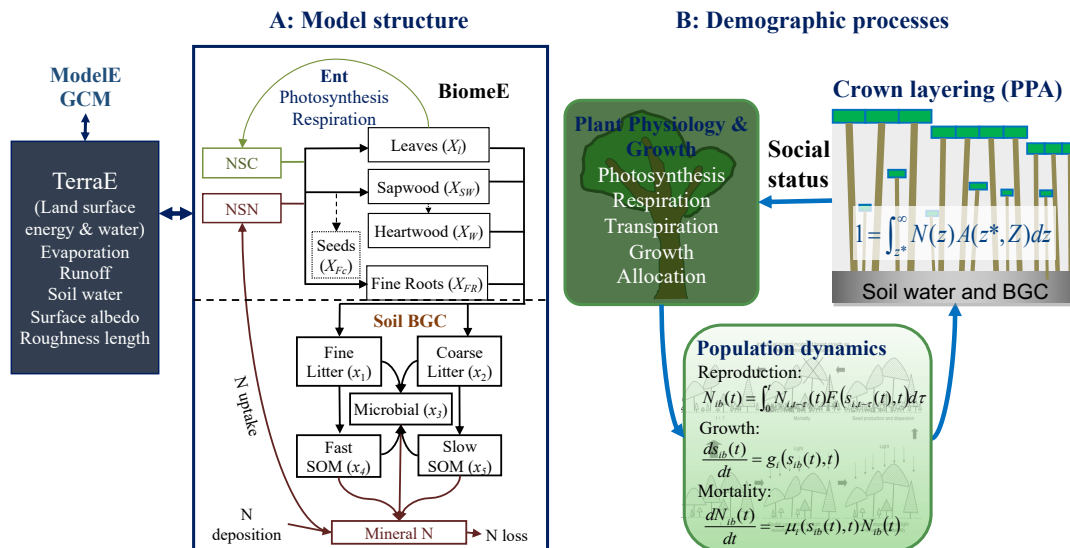


Figure 1 Schematic diagram of the coupling of BiomeE into ModelE

129 Panel A shows the structure of carbon and nitrogen pools and fluxes, and the interactions of
 130 BiomeE with TerraE, the land surface model in ModelE. The lines are the flows of carbon
 131 (green), nitrogen (brown), and coupled carbon and nitrogen (black). The green box is for carbon
 132 only. The brown boxes are N pools. The black boxes are for both carbon and nitrogen pools. The



133 C:N ratios of leaves, wood, fine roots, and microbes are fixed and those of liters and SOM pools
134 are dynamic with input and output. Panel b shows the demographic processes of BiomeE and the
135 key processes of population dynamics.

136

137 The demographic processes generate and remove cohorts and change the size and density of
138 plant individuals in the cohorts. With explicit description of cohort size, organization, and
139 composition during a model run, the model simulates competition for light and soil resources,
140 community assembly and vegetation structural dynamics. These processes are hierarchically
141 organized in this model and run at various time steps: half-hourly or hourly for plant physiology
142 and soil organic matter decomposition, daily for growth and phenology, and yearly for
143 demography.

144 We coupled the standalone BiomeE into ModelE's land model for simulating global
145 dynamics of vegetation and biogeochemical cycles and their feedback to the climate systems. For
146 extrapolating this model to the global scale, we designed a new set of PFTs to represent the
147 functional diversity of global vegetation and a new phenological scheme to deal with
148 environmental seasonality and water conditions across the world. Leaf photosynthesis processes
149 are from ModelE's existing vegetation model, Ent (Kim et al. 2015), for calculating carbon
150 budget that drives vegetation dynamics. Plant growth and demographic processes and the soil
151 organic matter decomposition and nitrogen cycle processes are from BiomeE (Fig. 1). The land
152 surface energy and water fluxes are calculated by TerraE with land surface characteristics jointly
153 defined by the vegetation model.

154 **Plant functional types**

155 We defined 9 PFTs in our test runs to represent global vegetation functional diversity
156 (Table 1) according to their life form (tree, shrub, and grass), photosynthesis (C₃ and C₄), and



leaf phenology (evergreen and deciduous). A set of continuous plant traits are used to define the distinctive plant types, because we plan to simulate plant emergent behavior based on their fundamental properties with this model in the future. For example, life forms are along the continuums characterized by wood density (woody vs. herbaceous), height growth coefficient (tree vs. shrub), and leaf mass per unit area (LMA, for evergreen vs. deciduous). Deciduousness is defined by cold resistance (evergreen vs. cold deciduous), and drought resistance (evergreen vs. drought deciduous), and the photosynthesis pathway is predefined as C₃ or C₄. Grasses are simulated as tree seedlings with all stems senescent along with leaves at the end of a growing season. The individuals are reset back to initial size each year and the population density is also reset using the total biomass of current cohort and predefined initial size of grasses.

Table 1 Plant functional types used in BiomeE

Plant functional types	V_{cmax}	LMA (kg C m ⁻²)	ρ_w (kg C m ⁻³)	α_H	$T_{0,c}$	$\beta_{0,D}$	PS pathway
1. Tropical evergreen broadleaf	18	0.07	360	30	15	0	C ₃
2. Temperate/boreal evergreen needleleaf	18	0.14	300	30	-80	0	C ₃
3. Temperate/boreal deciduous broadleaf	22	0.025	350	30	15	0	C ₃
4. Tropical drought deciduous broadleaf	20	0.03	250	30	15	0.2	C ₃
5. Boreal deciduous needleleaf	20	0.03	300	30	15	0.0	C ₃
6. Cold shrub	18	0.025	360	20	15	0.1	C ₃
7. Arid shrub	18	0.03	360	20	15	0.1	C ₃
8. C3 grass	20	0.025	90*	10	5	0.2	C ₃
9. C4 grass	15	0.025	90*	10	5	0.2	C ₄

LMA: leaf mass per unit area, ρ_w : wood density, α_H : Height coefficient, $T_{0,c}$: Critical temperature for phenology offset, $\beta_{0,D}$: critical soil moisture index for the offset of phenology, PS: photosynthesis pathway, E: evergreen, C: cold-deciduous, D: drought-deciduous. *Grass stem density is calculated as tissue biomass divided by stem volume. The tissue density of grass's stems is as high as wood.



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174 All PFTs go through the same set of plant physiological and demographical processes in
 175 the model and derive different emergent properties due to the differences in parameters, rather
 176 than differences in processes (except C_3 and C_4). With these different strategies, they have their
 177 advantages and risks in different environments. An advantage of this continuous parameter
 178 design is that one PFT can switch to another by changing its parameters (except C_3 and C_4
 179 photosynthesis pathways). This opens the way for eco-evolutionary and ecological community
 180 assembly simulation to explore the competitively optimal plant traits as environments change.

181 **Phenology**

182 Phenology types are defined by two parameters, a critical low temperature and a critical soil
 183 moisture index, that are used to trigger leaf fall. These two parameters define 4 phenological
 184 types for all the 9 PFTs: evergreen, drought-deciduous, cold-deciduous, and drought-cold-
 185 deciduous. Evergreen PFTs have high resistances to cold (i.e., very low critical temperature) and
 186 drought (very low soil drought). Cold and drought deciduous PFTs have low critical temperature
 187 and soil drought index, respectively.

188 For the cold-deciduous PFTs (3 and 5), we used the growing degree days above 5 °C
 189 (GDD_5) to control the timing of phenological onset and a critical low temperature (T_m) to control
 190 the offset. GDD_5 is calculated from the days that temperature starts to increase from the coldest
 191 days in the non-growing season. The critical value of GDD that the plants require for growth
 192 (GDD_c) is defined as a function of chilling days in the non-growing season (Prentice et al.,
 193 1992):

$$GDD_c = a_0 + d \cdot e^{-b \cdot N_{CD}}, \quad (1)$$



194 where, N_{CD} is the days of the cold period in nongrowing season before bud burst, a_0 is the
 195 minimum GDD_c (50) when the cold period is sufficiently long, d is the maximum addition of
 196 GDD_c (800) when there is no cold period (i.e., $N_{CD}=0$), b is a shape coefficient (0.025). These
 197 parameters are tunable and should change with acclimate to new climates.

198 The running mean temperature that represents the mean temperatures over a short period of time
 199 is calculated as:

$$\begin{cases} T_m(i) = T_d(i), & \text{when } i = 1 \\ T_m(i) = 0.8T_m(i-1) + 0.2T_d(i), & \text{when } i \geq 2 \end{cases} \quad (2)$$

200 We used an index of cold condition (accumulative low temperature, ALT) to make sure the low
 201 temperature signal is persistent and differentiates the signal of the seasonal temperature changes
 202 and the stochastic low temperature stresses in growing seasons. The critical temperature for
 203 triggering leaf senescence (T_c) is calculated as a function of the number of growing days (N_{GD}).

$$T_c = T_{0,c} - s \cdot e^{-c \cdot (\max(0, N_{GD} - L0))}, \quad (3)$$

204 where, $T_{0,c}$ is the highest critical temperature when N_{GD} is sufficiently long, s is the range that a
 205 critical temperature can change, c is a shape parameter, $L0$ defines the lowest critical temperature
 206 ($T_{0,c} - s$) when N_{GD} is smaller than $L0$. The rationale in this equation is that when a growing
 207 period is not long enough, plants need a lower T_c to trigger leaf fall so that they can have a
 208 growing season that is not too short. This setting is based on the thermal adaptation analysis of
 209 Yuan et al. (2011).

210 For the drought deciduous PFTs (tropical drought deciduous broadleaf, arid shrub, C_4
 211 grass), we used a soil moisture index (s_D) to initiate and terminate a growing season.



$$s_D = \sum_{i=1}^n \text{Min} \left(1.0, \max \left(\frac{\theta_i - \theta_{WP,i}}{\theta_{HC,i} - \theta_{WP,i}}, 0.0 \right) \right), \quad (4)$$

where i is the soil layer in root zone, θ is soil water content (vol/vol), θ_{WP} is wilting point, and θ_{HC} is soil water holding capacity. The critical soil moisture (θ^*) that triggers leaf fall is defined as a PFT-specific parameter with evergreen PFTs having low θ^* .

Plant demography and biogeochemical cycles

Allometry and Plant architecture

The allometry of woody PFTs follows the equations used in LM3-PPA (Weng et al., 2015; Farrior et al., 2013). Plant allometry is described by the following equations:

$$\begin{cases} A_C = \alpha_C D^{\theta_C} \\ Z = \alpha_Z D^{\theta_Z} \\ S = 0.25\pi\rho\Lambda\alpha_H D^{2+\theta_H} , \\ A_L^* = l_{max} A_C \\ A_{FR}^* = \varphi_{RL} l_{max} A_C \end{cases} \quad (5)$$

where D is tree diameter; A_C is crown area; Z is tree height; S is structural biomass; α_C , α_Z , θ_C , θ_Z , are the allometry parameters for crown area and tree height, respectively; π is ratio of a circle's circumference to its diameter; ρ is wood density (kg C m^{-3}); Λ is the taper factor from a cylinder to a tree with the same D ; A_L^* and A_{FR}^* are the surface area of leaves and fine roots, respectively; φ_{RL} is the area ratio of leaves to roots. l_{max} is potential leaf area per unit crown area (i.e., potential crown LAI), defined as a function of plant height (Z):

$$l_{max}(Z) = L_{max,0}(Z + h_0)/(Z + H_0), \quad (6)$$



where $L_{\max,0}$ is the maximum crown LAI when a tree is sufficiently tall, H is tree height, h_0 is a small number that makes a minimum $l_{\max} (L_{\max,0} (h_0/H_0))$ when tree height is close to zero, and H_0 is a curvature parameter.

Plant growth and allocation of carbon and nitrogen to plant tissues

BiomeE has an optimal allocation scheme for allocating assimilated carbon to different tissues when nitrogen supply is limited (Weng et al., 2019). This allocation scheme prioritizes the allocation to leaves and fine roots, while maintaining a minimum growth rate of stems and keeping the constant area ratio of fine roots to leaves during the lifetime of a plant. According to these rules, the average allocations of carbon and nitrogen to leaves, fine roots, and wood over a growing season are governed by the targets for the leaf area per unit crown area (i.e., crown leaf area index, l^*) and fine root area per unit leaf area (ϕ_{RL}). We assume the allocation between structural (e.g., stems) and functional (e.g., leaves and fine roots) tissues is that which is optimal for a given nitrogen availability, optimizing the use of carbon gain and light competition.

Wood tissue growth (G_W) drives the growth of tree diameter, height, and crown area and thus increases the targets of leaves and fine roots. By differentiating the stem biomass allometry in Eq. 5 with respect to time, using the fact that dS/dt equals the carbon allocated for wood growth (G_W), we have the diameter growth:

$$\frac{dD}{dt} = \frac{G_W}{0.25\pi\Lambda\rho_w\alpha_z(2+\theta_z)D^{1+\theta_z}} \quad (7)$$

This equation transforms the carbon gain from photosynthesis to the diameter growth that results from wood allocation and allometry (Eq 5). With an updated tree diameter, we then calculate the new tree height and crown area using allometry equations and targets of leaf and fine root biomass (Eq. 5).



246 **Reproduction and Mortality**

247 At a yearly time-step, the cumulative carbon and nitrogen allocated for reproducing by a canopy
 248 cohort over the growing season length, T , is converted to seedlings according to the initial plant
 249 biomass (S_0) and germination and establishment probabilities (p_g and p_e , respectively).
 250 Generally, the population dynamics can be described by a variant of the von Foerster equation
 251 (von Foerster, 1959):

$$N(S_0, t) = \frac{p_g p_e}{S_0} \int_0^T N(\tau) G_F(\tau) d\tau$$

$$\frac{dN(s, t)}{dt} = -\mu(s, t) N(s, t).$$
(8)

252 where $N(S_0, t)$ is the spatial density of newly generated seedlings, $N(\tau)$ is the spatial density of
 253 this cohort of trees at time τ , G_F is the carbon allocation to seeds, and μ is PFT-specific mortality
 254 parameter. Each PFT has a canopy-layer-specific background mortality rate that is assigned from
 255 the literature. These background rates are assumed to be size-independent for the canopy layer
 256 trees, but size-dependent for understory trees. Many factors affect tree mortality, such as light,
 257 size, competition crown damage, hydraulic failure, trunk damage etc. (Zuleta et al., 2022; Lu et
 258 al., 2021). These factors result in a “U-shaped” general mortality curve. We assume the
 259 background mortality rate is represented as a function of vertical position (light fraction) and tree
 260 size

$$\mu(s, t) = \mu_0(1 + f_L f_s) f_D$$
(9)

261 where $f_L = \sqrt{L - 1}$, $f_s = A_{SD} e^{-B_{SD} \cdot D}$, and $f_D = m_s \frac{e^{A_D(D-D_0)}}{1 + e^{A_D(D-D_0)}}$. L is the layer this plant is in
 262 ($L=1$ for the canopy layer and 2 for the second, and so on), A_{SD} is the maximum multiplier of
 263 mortality rate for the seedlings in the understory layers, B_{SD} is the rate of mortality decreasing as



tree diameter (D) increases, m_s is the maximum multiplier of mortality rate for large-sized trees,
 D_0 is the diameter at which the mortality rate increases by $m_s/2$, and A_D is a shape parameter
 (i.e., the sensitivity to tree diameter).

Crown self-organization and layering

Tree crowns are arranged into different vertical canopy layers according to tree height and
 crown area if their total crown area is greater than the land area following the rules of the PPA
 model (Strigul et al., 2008). In PPA, individual tree height is defined as the height at the top of
 the crown, and all leaves of a given cohort are assumed to belong to a single canopy layer. The
 height of canopy closure for the top layer is referred to as critical height (Z^* , the height of the
 shortest tree in the layer) and is defined implicitly by the following equation:

$$k(1 - \eta) = \sum_i \int_{Z^*}^{\infty} N_i(Z, t) A_{CR,i}(Z^*, Z) dZ \quad (10)$$

where $N_i(Z, t)$ is the density of PFT i trees of height Z per unit ground area; $A_{CR,i}(Z^*, Z)$ is the
 crown area of an individual PFT i tree of height Z ; and η is the proportion of each canopy layer
 that remains open on average due to wind and imperfect spacing between individual tree crowns.

The top layer includes the tallest cohorts of trees whose collective crown area sums to $1 - \eta$
 times the ground area; lower layers are similarly defined. Trees within the same layer do not
 shade each other, but there is self-shading among the leaves within individual crowns. Cohorts in
 a sub-canopy layer are shaded by the leaves of all taller canopy layers. In each canopy layer, all
 cohorts are assumed to have the same incident radiation on the top of their crowns. Note, the gap
 fraction η is necessary to allow additional light penetration through each canopy layer for the
 persistence of understory trees in monoculture forests in which the upper layer crowns build a
 physiologically-optimal number of leaf layers (Farrior et al., 2013). The grasses only form one



285 layer. Those individuals who cannot stay in that layer because of limited space will be killed
 286 (i.e., when the total grass crown area is larger than the land area).

287 **Ecosystem carbon and nitrogen biogeochemical cycles**

288 Ecosystem biogeochemical cycles (carbon and nitrogen in this model) are driven by plant and
 289 microbial demographic processes. There are seven pools in each plant: leaves, fine roots,
 290 sapwood, heartwood, fecundity (seeds), and non-structural carbohydrates and nitrogen (NSC and
 291 NSN, respectively). The carbon and nitrogen in plant pools enter soil pools with the mortality of
 292 individual trees and the turnover of leaves and fine roots. Soil has a mineral nitrogen pool for
 293 mineralized nitrogen and five soil organic matter (SOM) pools for carbon and nitrogen:
 294 metabolic litter (x_1), structural litter (x_2), microbial (x_3), and fast (x_4) and slow-turnover (x_5) SOM
 295 pools.

296 The microbial pool plays a central role in the transfer and decomposition of SOM. The
 297 decomposition processes are simulated by a model modified from Manzoni et al. (2010). The
 298 technical details have been described in detail in Weng et al. (2019, 2017). The decomposition
 299 rate of a SOM pool is determined by the basal turnover rate together with soil temperature and
 300 moisture following the formulation of the CENTURY model. The microbial carbon use
 301 efficiency (transfer from litter to microbial matter) is a function of litter nitrogen content,
 302 following the model of Mazoni et al. (2010).

303 The N mineralization in decomposition is determined by microbial nitrogen demand,
 304 SOM's C:N ratio, and decomposition rate. In the high C:N ratio SOM, microbes must consume
 305 excess carbon to get enough nitrogen for growth. By contrast, in the low C:N ratio SOM,
 306 microbes must release excess nitrogen to get enough carbon for energy. Depending on the C:N
 307 ratios of SOM, soil microbes may be limited by either C or N.



308 The out-fluxes of C and N from the i^{th} pool (dC_i and dN_i , respectively) are calculated by:

$$\begin{aligned} dC_i &= \xi(T, M) \rho_i Q C_i, \\ dN_i &= \xi(T, M) \rho_i Q N_i, \end{aligned} \quad (11)$$

309 where ξ is the response function of decomposition to soil temperature (T) and moisture (M), ρ_i is
 310 the basal turnover rate of the i^{th} litter pool at reference temperature and moisture, $Q C_i$ is the C
 311 content in i^{th} pool, and $Q N_i$ is the N content in the i^{th} pool.

312 The new microbial growth (dM) is calculated as the co-limit of available carbon and
 313 nitrogen mobilized at this step:

$$dM_i = \text{Min}(\varepsilon_0 \cdot dC_i, \Lambda_{\text{microbe}} \cdot dN_i), \quad (12)$$

314 where ε_0 is default carbon-use efficiency of litter decomposition (0.4) and Λ_{microbe} is a microbe's
 315 C:N ratio, which is a fixed value (10 in this model). The soil heterotrophic respiration (R_h) is the
 316 microbial respiration (i.e., the difference between carbon consumption and new microbial
 317 growth), and the total N mineralization rate ($N_{\text{mineralized}}$) is calculated as the sum of mineralized N
 318 in the SOM pools and microbial turnover:

$$\begin{aligned} R_h &= \sum_{i=3}^5 dC_i - \sum_{i=4}^5 M_i, \\ N_{\text{mineralized}} &= \sum_{i=3}^5 dN_i - \sum_{i=3}^5 m_i / \Lambda_{\text{microbe}} \end{aligned} \quad (13)$$

319 The R_h releases to atmosphere as CO₂. Mineralized N enters the mineral N pool for plants to use.
 320 The dynamics of the mineral N pool is represented by the following equation:

$$\frac{dN_{\text{mineral}}}{dt} = N_{\text{deposition}} + N_{\text{mineralized}} - U - N_{\text{loss}}, \quad (14)$$

321 where $N_{\text{deposition}}$ is N deposition rate, assumed to be constant over the period of simulation; N_m is
 322 the N mineralization rate of the litter pools (fast and slow SOM and microbes); U is the N uptake
 323 rate (Kg N m⁻² hour⁻¹) of plant roots; and N_{loss} includes the loss of mineralized N by



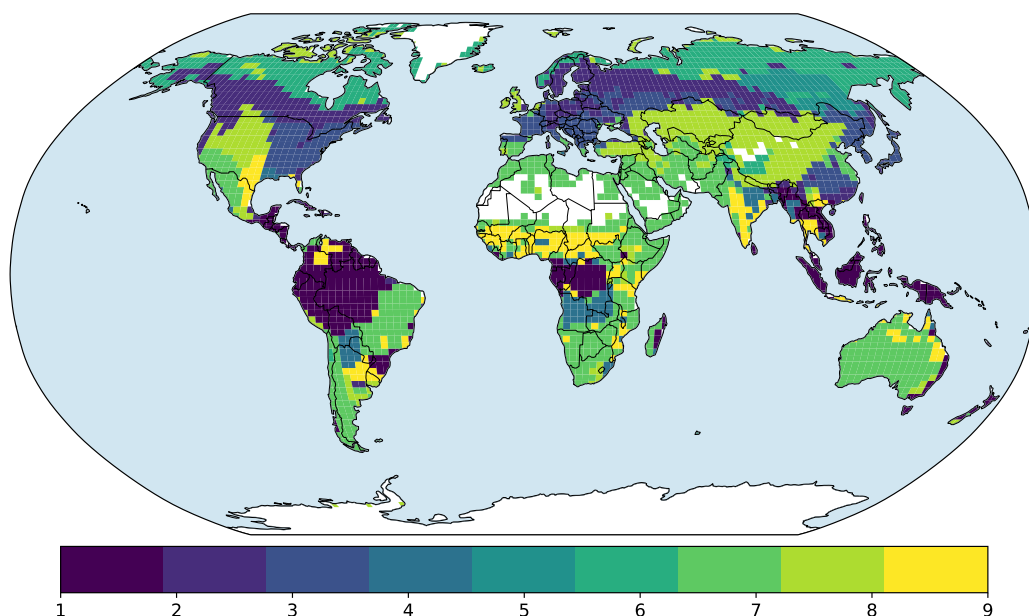
324 denitrification and runoff. The N deposition ($N_{\text{deposition}}$) is the only N input to ecosystems, and we
325 set nitrogen fixation as zero in this version of the model.

326

327 **3 Model Test runs**

328 For our comparison of model performance against observations and other models, we used
329 the full demographic version of BiomeE (described above) and also designed a “single-cohort”
330 version of the model to benchmark our demographic implementations. In the single-cohort
331 model, the mortality of trees is simulated as the turnover of woody biomass, and the fecundity
332 resources (carbon and nitrogen) are used to build the same-sized parent trees, instead of
333 seedlings growing from understory layers. If the total crown area of the trees in this cohort is
334 greater than the land area, the extra trees will be removed to make the total crown area less than
335 or equal to the land area. At equilibrium, the turnover of wood biomass is equal to the new
336 growth each year and the new trees generated from fecundity resources are to be killed by self-
337 thinning. The single-cohort model uses the mean state of the canopy layer trees to represent the
338 characteristics of the whole community. This single-cohort model performs like the traditional
339 biogeochemical models and simplifies vegetation computation.

340 In the test runs, the distribution of PFTs was from the Ent vegetation map (Ito et al., 2020),
341 which is derived from 2004 MODIS land cover and PFT data products (Friedl et al., 2010) and
342 climate data (Fig. 2). For these simulations, croplands and pastures were replaced by the
343 potential natural vegetation types.



344

345 **Figure 2 Prescribed global distribution of plant functional types.** Data is from the Ent Global
 346 Vegetation Structure map. The numbers are corresponding to the PFTs in Table 1.

347

348 Forcing data are from TRENDY project CRU-NCEP data (Sitch et al., 2015) and have a 6-
 349 hour time step at a spatial resolution of $0.5^\circ \times 0.5^\circ$. These data are available at the website
 350 <https://www.uea.ac.uk/web/groups-and-centres/climatic-research-unit/data>.

351 We aggregated these data into $2.0^\circ \times 2.5^\circ$ grid cells and used thirty years' data (1988~2017) to
 352 force the model to run for 600 years, which is long enough for the model to approach equilibrium
 353 states for both vegetation and soil carbon pools. These data include temperature, precipitation,
 354 shortwave radiation, longwave radiation, specific humidity, and wind speed (U and V
 355 directions). The interpolation of radiation (R) is based on the zenith angle (θ_s) and penetration
 356 rate calculated from the 6-hour step data.



$$R_S(t) = \left(\frac{R_{H6}}{S^* \cos \theta_s(H6)} \right) S^* \cos \theta_s(t), \quad (15)$$

where S^* is solar constant (1362 W/m^2). Other variables are linearly interpolated to the model time steps, which is half hourly in this study. CO_2 concentration is set at the model default level (350 ppm) in our model runs.

Data sources for model evaluation

Gross primary productivity (GPP) data are from a global retrieval of surface turbulent fluxes including latent heat, sensible heat, and GPP using remote sensing observations. These data are on a $1^\circ \times 1^\circ$ geographic grid at a monthly time step based on an Artificial Neural Network retrieval algorithm (Alemohammad et al., 2017). This algorithm uses six remotely sensed observations as input: Solar Induced Fluorescence (SIF), Air Temperature, Precipitation, Net Radiation, Soil Moisture, and Snow Water Equivalent. The data are available from 2007 to 2015. **The tree height data** are from spaceborne light detection and ranging (lidar) global map of canopy height at 1-km spatial resolution developed by Simard et al. (2011). These authors used the 2005 data from the Geoscience Laser Altimeter System (GLAS) aboard ICESat (Ice, Cloud, and land Elevation Satellite) to derive global forest canopy heights. **Biomass data** are from a Global 1-degree Maps of Forest Area, Carbon Stocks, and Biomass, 1950-2010 developed by Hengeveld et al. (2015). **Soil carbon data** are from Food and Agriculture Organization (FAO) Harmonized World Soil Database (version 1.2), updated by Wieder et al. (2014).

MsTMIP model simulation data

We chose six model simulations (BiomeBGC, CTEM, CLM4, LPJ, Orchidee, VEGAS) from the Multi-scale Synthesis and Terrestrial Model Intercomparison Project (MsTMIP) (Huntzinger et al., 2012) to compare against our model simulations. These models are well-developed and



378 widely used in Earth system models, representing the state-of-art of current land vegetation
 379 model development.

380 Selected Grid Cells for Comparison

381 For illustrating model behavior, we selected 8 grid cells that cover boreal forests, temperate
 382 forests, tropical forests, C₄ grass, and arid shrubs to show the simulated ecosystem development
 383 patterns across the climate zones with different dominant PFTs (Table 2). Brazil Tapajos (TPJ),
 384 Oak Ridge (OKR), Harvard Forest (HF), Manitoba old black spruce site (MNT), and Bonanza
 385 Creek (BNC) are covered by tree PFTs. Konza long-term ecological research station (LTER)
 386 (KZ) is C₄ grass. Walnut Gulch Kendall (WKG) and Sevilleta LTER (SV) are covered by arid
 387 shrubs. These sites were chosen because they have extensive data on vegetation and climate
 388 conditions for future comparisons.

389

390 **Table 2 Grids for simulated ecosystem development illustration**

Grid	Dominant PFT	Coordination	Mean Temperature (°C)	Annual Precipitation (mm)
Bonanza Creek (BNC)	Broadleaf deciduous	63.92°, -145.38°	-3.1	269
Manitoba old black spruce site (MNT)	Evergreen needleleaf	55.88°, -98.48°	-3.2	520
Harvard Forest (HF)	Broadleaf deciduous	42.54°, -72.17°	8.5	1050
Oak Ridge (OKR)	Broadleaf deciduous	35.96°, -84.29°	13.7	1372
Konza LTER (KZ)	C ₄ grass	39.08°, -96.56°	12.4	835
Sevilleta LTER (SV)	Arid shrub	34.36°, -106.88°	12.7	365
Walnut Gulch Kendall (WKG)	Arid shrub	31.74°, -109.94°	17.7	350
Brazil Tapajos (TPJ)	Broadleaf evergreen	-2.86°, -54.96°	26	1820

391



4 Results

4.1 Simulated ecosystem dynamics in different climate zones

Across all the 8 sites, GPP aligns closely with LAI in the full demographic simulations (Fig. 3), with forested sites having, overall, higher LAI, biomass, and carbon stocks per area compared to the shrub and grass sites. Vegetation biomass is lowest at the grassland site (i.e., KZ) because, within the model, grassland ecosystems cannot accumulate persistent woody biomass.

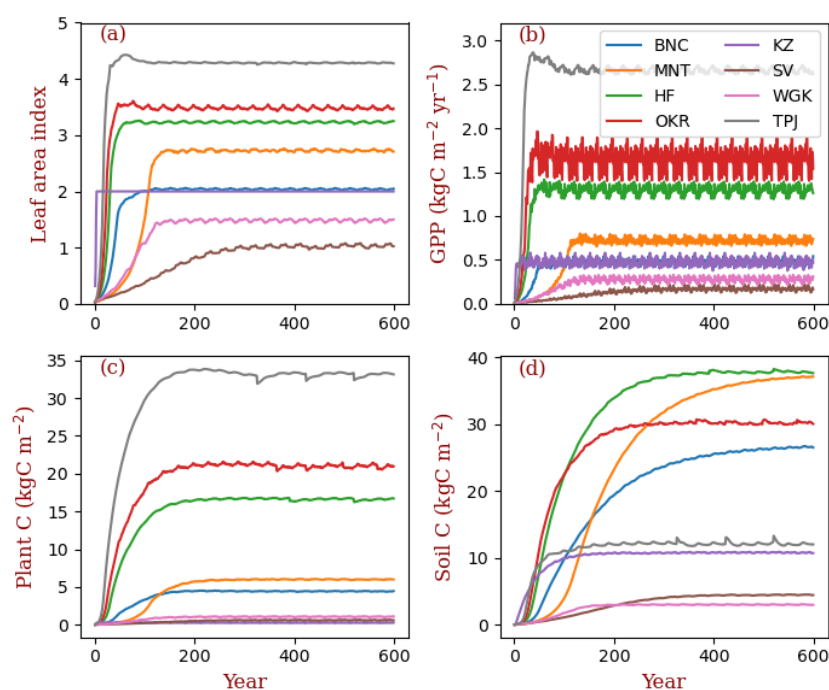
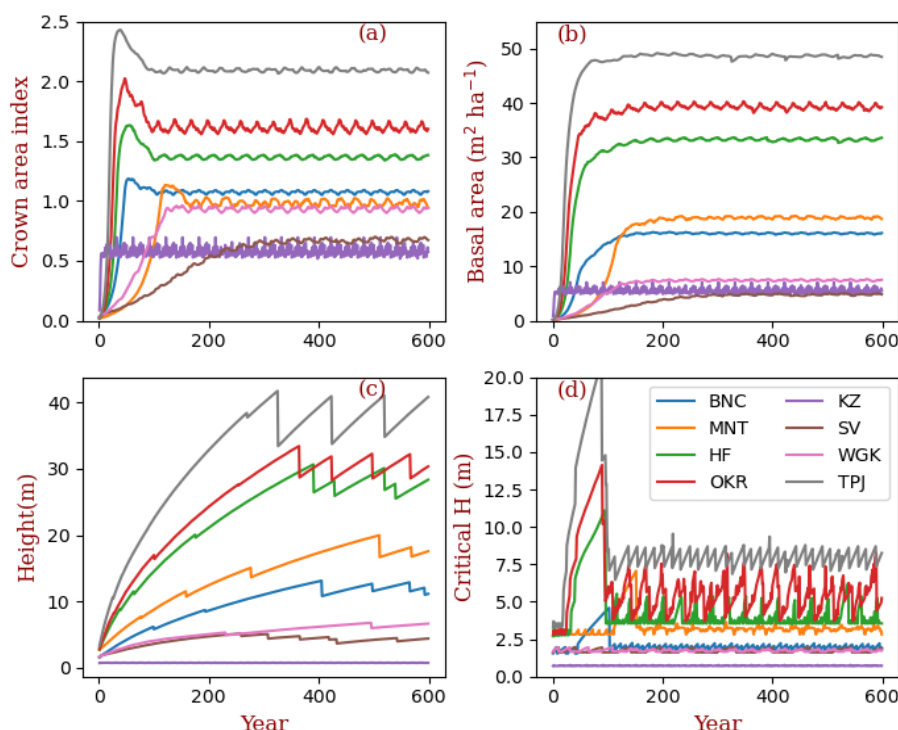


Figure 3: Site ecosystem development simulated by BiomeE with full demography.



402

403 **Figure 4. Vegetation structural dynamics.** Critical height (H) is an emergent property of the
 404 model PPA, which separates the trees that are in full sun light if taller than critical height and
 405 those that are fully shaded if shorter than critical height.

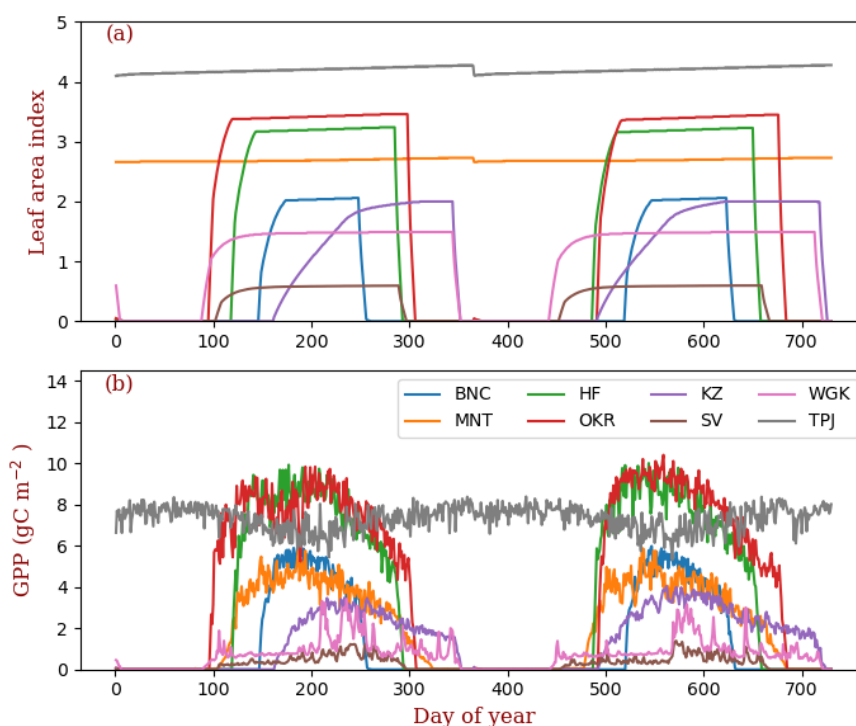
406

407 The tropical forest site (TPJ) has the highest crown area index (around 2.2), followed by
 408 warm temperate forest at OKR, mixed forest at HF, and boreal forests at BNC and MNT (Fig. 4).
 409 The shrubs and grasslands in arid regions have the lowest crown area index (CAI), with basal
 410 area following similar patterns. For forested sites, tree height is tallest at TPJ, followed by OKR,
 411 HF, MNT, and BNC. The shrubs are short according to their allometry parameters and the height
 412 of grasses during non-growing season is zero. The critical height, which separates canopy layer
 413 trees from the understory layers, follow the same order as that of tree height with high
 414 fluctuations with cohort changes. Equilibrium time scales for LAI and GPP are similar across



415 sites, but biomass accumulation is much slower in forests because of the longer time needed for
 416 forest structure (size distribution) to approach equilibrium. Soil carbon equilibration is faster in
 417 the warm regions than in cold regions because of the high turnover rate of SOM pools in warm
 418 regions.

419



420

421 **Figure 5. Seasonal patterns of LAI and gross primary production in the sample grids.** Two
 422 years of data are shown in this figure. The key of location abbreviations is in Table 2.

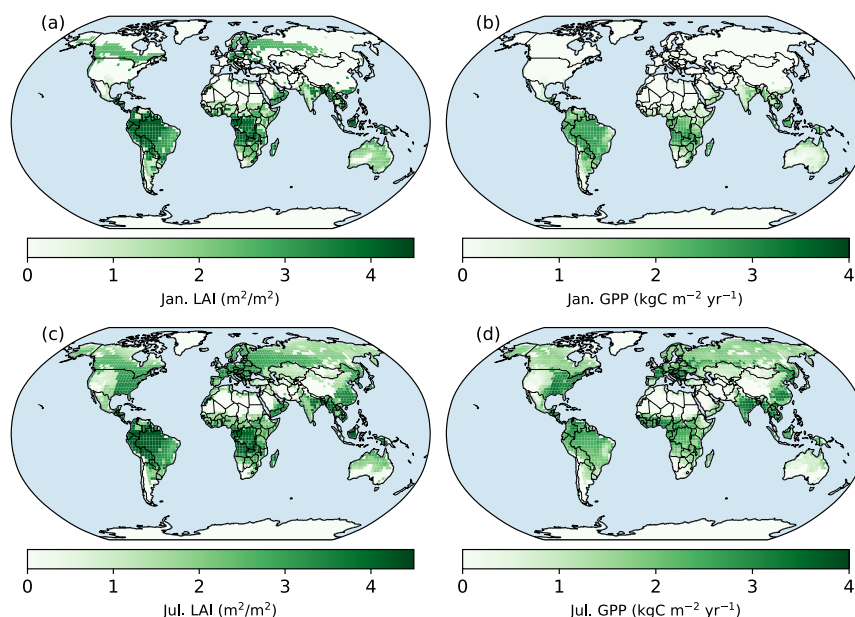
423

424 The PFTs at TPJ and MNT are evergreen forest. Their LAI does not change over the whole
 425 year (Fig. 5: a). The forest in OKR has the longest growing season in the three deciduous forest
 426 grids, followed by HF and BNC. BNC's growing season is only around 120 days, about half of
 427 OKR's growing season. The growing season of grasses in KZ starts in late May and ends in



428 September. The two arid-adapted shrub sites (SV and WKG) are controlled by water availability.
 429 In TPJ (tropical evergreen forest), the trees have photosynthesis throughout the entire year (Fig.
 430 5: b). In MNT, photosynthesis only happens in warm seasons with the leaves kept in the crowns
 431 (evergreen needleleaf). The deciduous trees in OKR and HF have high photosynthesis rates
 432 during the growing season. The photosynthesis rates in SV and WKG are generally low because
 433 of the drought environment. However, the precipitation events can drive photosynthesis rates
 434 high in these arid regions. At the global spatial scale, only evergreen needle-leaved forests keep
 435 their leaves in northern high latitude regions during January (Fig. 6). The photosynthesis of
 436 plants in this region is off because of the low temperature. In July, northern high latitude regions
 437 green up and their photosynthesis rates are high in wet regions.

438



439

440 **Figure 6. Spatial patterns of LAI and GPP in Jan and July.** Panels a and b are the LAI and
 441 photosynthesis of January in the year of 600 (the last year of model run). Panels c and d are
 442 July's in the same year.

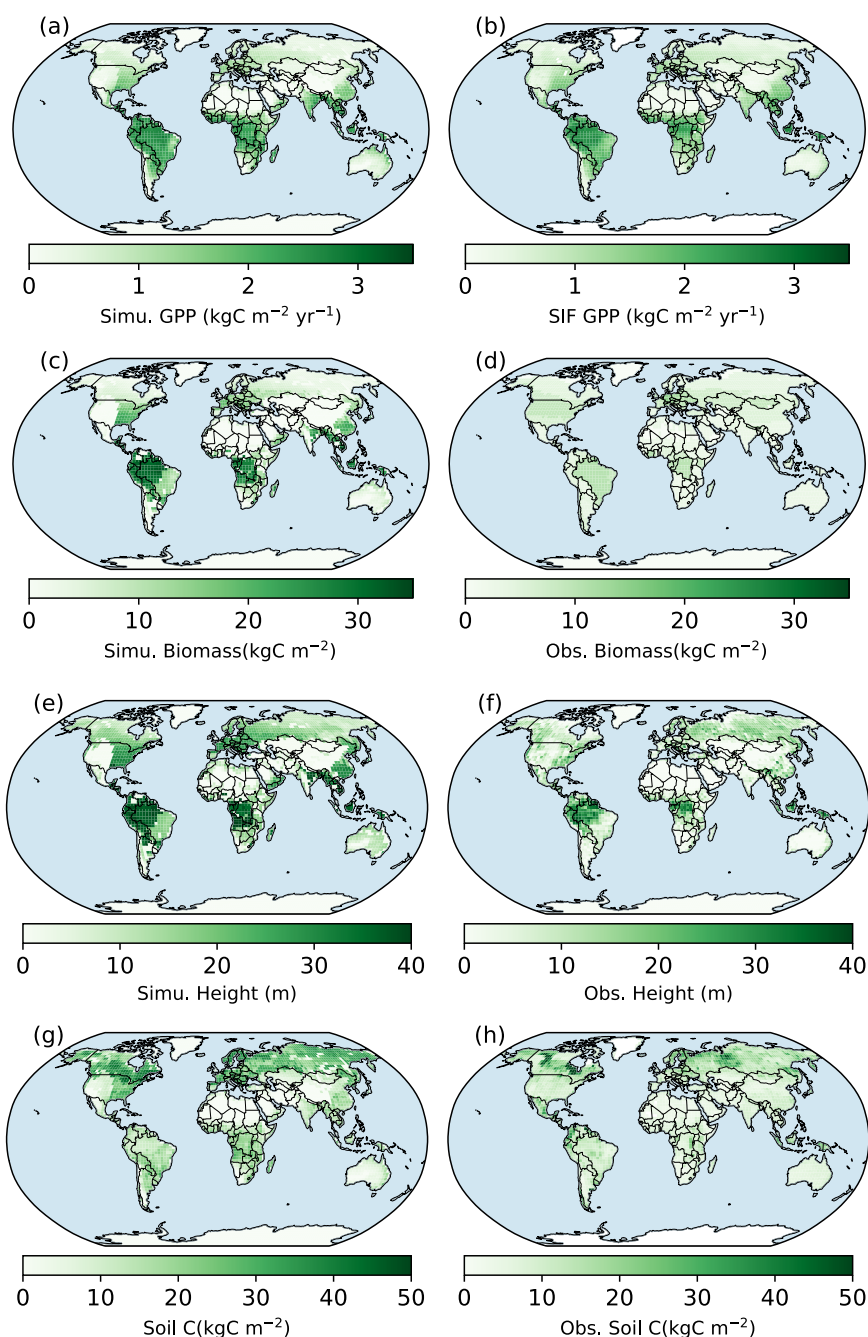


443

444 4.2 Global Comparisons with Observations

445 We tuned the parameter of maximum carboxylation rate (V_{cmax}) to fit the general pattern of
446 global GPP. Compared with SIF GPP (Alemohammad et al., 2017), simulated GPP is higher than
447 the SIF GPP generally (Figs. 7 and 8), though lower in arid regions (Fig. 7). The simulated tree
448 height is mostly taller compared to observations (Simard et al., 2011) because most forests have
449 been altered by human activities (Pan et al., 2013). However, the model and observations cover
450 approximately the same range of tree heights (up to 40 m). Simulated biomass is much higher
451 than the observations because most forest regions have been transformed to low biomass land
452 use types or represent earlier successional stages with less accumulated carbon (i.e., not
453 equilibrium states). Simulated soil carbon does track the observations better than biomass, likely
454 because soil carbon stocks are more stable compared to biomass. For areas where the model
455 underpredicts soil carbon, the difference could arise because of missing processes that may lead
456 to high accumulation in some regions (e.g., peats) or the relatively high uncertainties in the soil
457 carbon data (Tifafi et al., 2018).

458



459

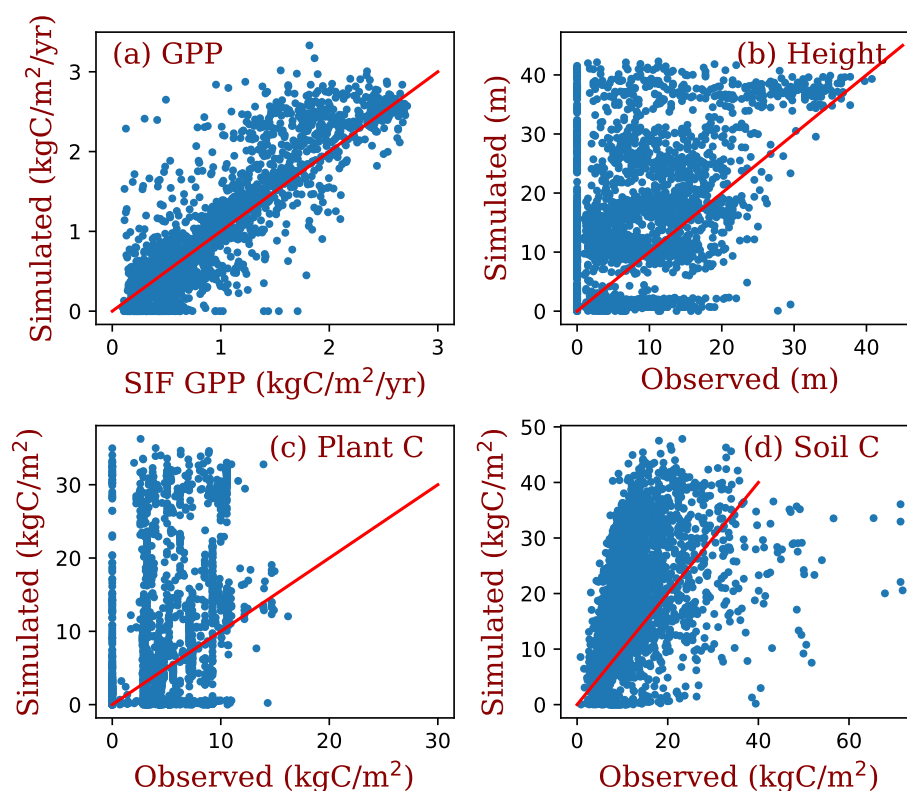
460

461 **Figure 7. Spatial patterns of BiomeE (full demography) simulations and those from data.**
 462 “Obs.” means different way retrieved from observations. Some are model-based (e.g., GPP is



463 from SIF data and tree height is from LiDAR data). Obs. **GPP** is derived from Solar Induced
 464 Fluorescence (SIF) data with a machine learning approach (Alemohammad et al., 2017). The
 465 data are available from Jan. 2007 to Dec. 2015. **The tree height data** are from spaceborne light
 466 detection and ranging (lidar) global map of canopy height at 1-km spatial resolution developed
 467 by Simard et al. (2011). **Biomass data** are from Hengeveld et al. (2015). **Soil carbon data** are
 468 from FAO Harmonized World Soil Database (version 1.2), updated by Wieder et al. (2014).

469



470

471 **Figure 8 Grid comparison of full demographic BiomeE simulations with observations**
 472 **estimates.** The red line in each panel is the 1:1 line. This figure uses the same simulated and
 473 observed data as those of Figure 7.

474

475 4.3 Comparison with MsTMIP models

476 We compared the performance of our model with MsTMIP models at the 8 locations that
 477 were used to show ecosystem development patterns (Table 2). For most of these sites, LAI in



BiomeE is lower compared the other MsTMIP models (Fig. 9: a), while the estimated GPP is centered in within the range of MsTMIP predictions (Fig. 9: b). Differences are a consequence of the formulations within BiomeE. Specifically, BiomeE simulates leaf growth by using a maximum crown LAI, which is lower than the real forest LAI. However, the low LAI does not affect crown total photosynthesis because leaves in lower canopy layers contribute little to the total carbon assimilation. BiomeE predicted biomass (Fig. 9: c) and soil carbon (Fig. 9: d) generally fall towards the higher end of the MsTMIP simulations, except for the more arid grass- and shrub-dominated sites. We note, however, that there are wide differences in estimates for vegetation and soil carbon across the models, likely because of different treatments of mortality and decomposition functions in these models.

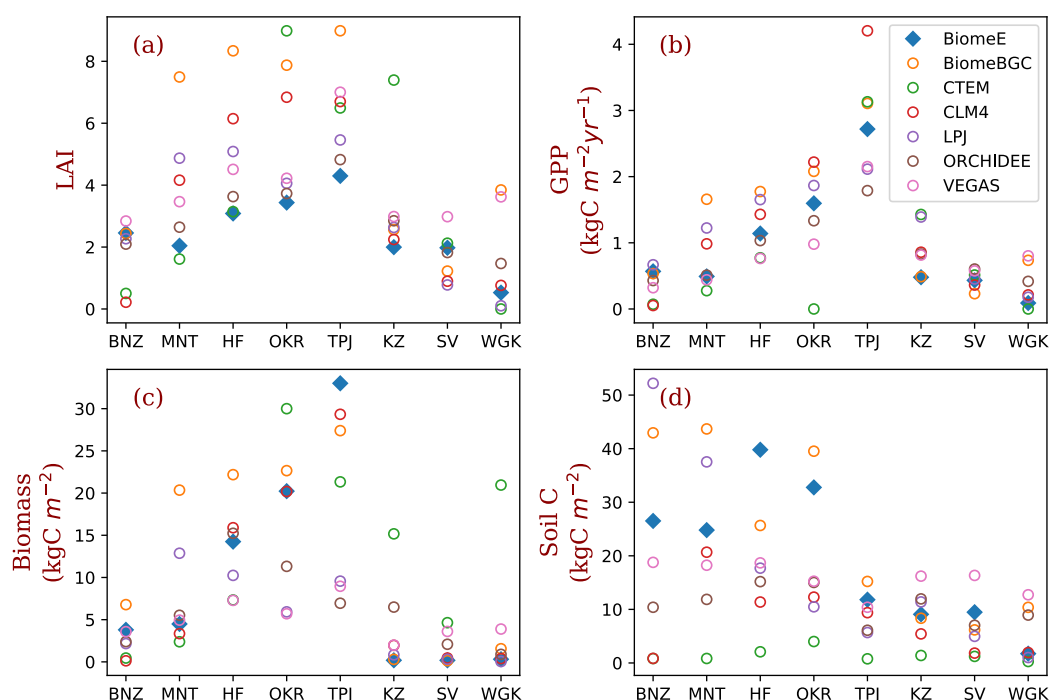
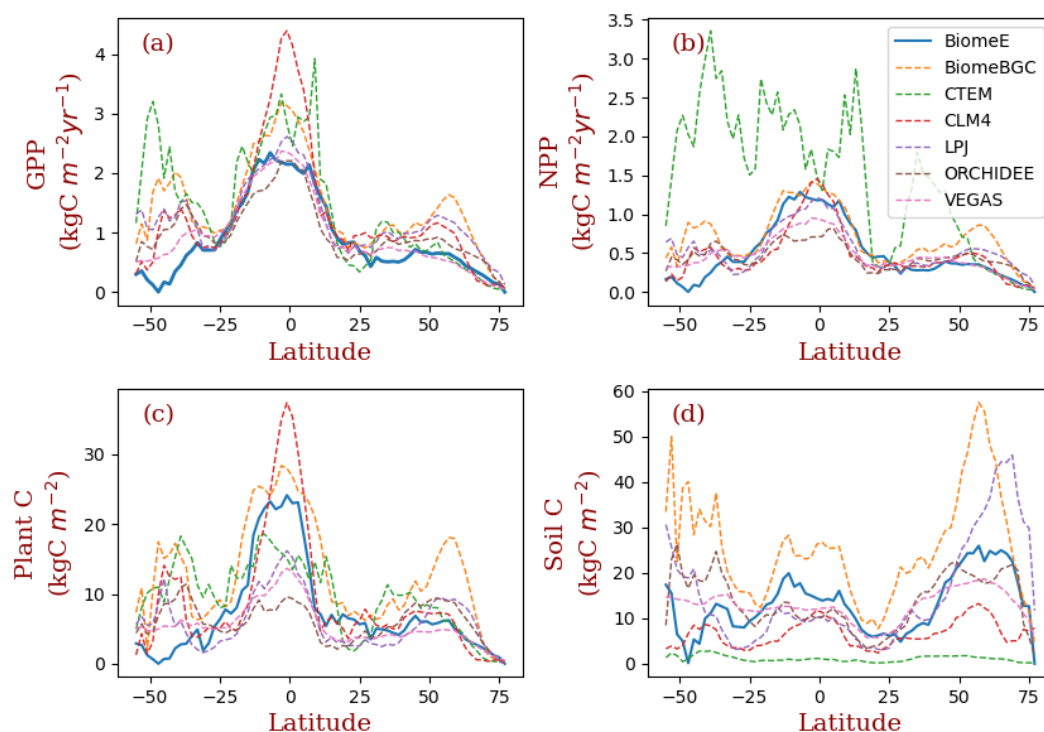


Figure 9 Site-level comparison with MsTMIP models.



490 The BiomeE predictions are from the model version with full demography. The abbreviations of
 491 the 8 sites (corresponding to model grid cells) and their coordination, dominant PFTs, and
 492 climatic conditions are in Table 2.

493



494

495 **Figure 10 Latitudinal patterns of GPP, NPP, Biomass, and soil carbon as simulated by**
 496 **BiomeE (with full demography) and MsTMIP models**

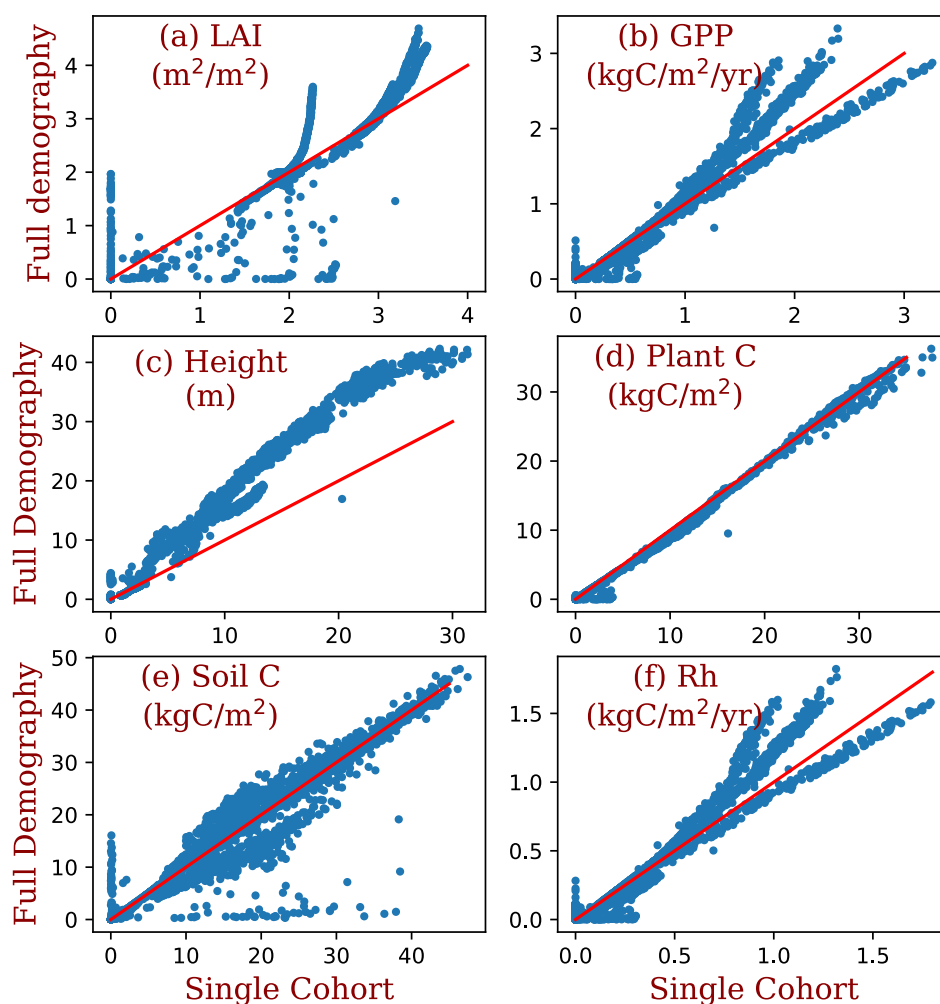
497

498 More broadly, the latitudinal mean of BiomeE simulated GPP is at the lower end of MsTMIP
 499 model predictions (Fig. 10: a). Since BiomeE's GPP was tuned to fit remote sensing data derived
 500 GPP, the MsTMIP models may over-estimate global GPP. BiomeE simulated NPP (Fig. 10: b),
 501 plant carbon (Fig. 10: c), and soil carbon (Fig. 10: d) are within the range simulated by the
 502 MsTMIP models. This indicates that BiomeE has slightly lower respiration than the MsTMIP



models. In the arid regions (e.g., around latitude 40-50° S), our model's GPP is lower than
 MsTMIP's because of sensitive drought responses in our model.

505



506

507 **Figure 11 Comparison between the simulations of the full demography and the single**
 508 **cohort settings of BiomeE.**

509

510 The demographic processes have significant impacts on the simulations of GPP, biomass, soil
 511 carbon, and vegetation structure compared to the single-cohort version of BiomeE (Fig. 11). The



512 demographic version of the model includes an understory layer of plants, resulting in higher LAI
513 in high LAI regions and also slightly higher GPP. Higher GPP in the model with full
514 demography leads to a high allocation to leaves and fine roots. However, the total biomass
515 predicted by the two model versions are similar because of the tradeoffs in allocation between
516 leaves and stem growth and tree size distribution and because most biomass is concentrated in
517 stems. In the full demography model, tree mortality removes all the biomass, including leaves,
518 fine roots, and stems, while in the single-cohort model, the mortality is represented as the
519 turnover of woody biomass. Consequently, the full demography model has higher emergent
520 turnover rate for the whole vegetation.

521 Compared to the single-cohort model, the full demography model predicts higher LAI and
522 GPP in warm and wet regions and lower values in cold and dry regions (Fig. 12: a, b). The full
523 demography model also predicts much lower biomass and soil carbon than the single-cohort
524 model in cold and dry regions (Fig. 12: c). Because the single cohort model has the same SOM
525 pools and turnover/decomposition processes, the reduced biomass input from full demography
526 alone is causing the difference in SOM dynamics. This is consistent with the functions of
527 demographic processes in these regions, which greatly reduce model stability because
528 reproduction and survival are lower in dry and cold regions. By contrast, the single-cohort model
529 does not model these processes explicitly and instead uses a simplified routine turnover of
530 materials that allows plants to stay in extremely dry or cold conditions.

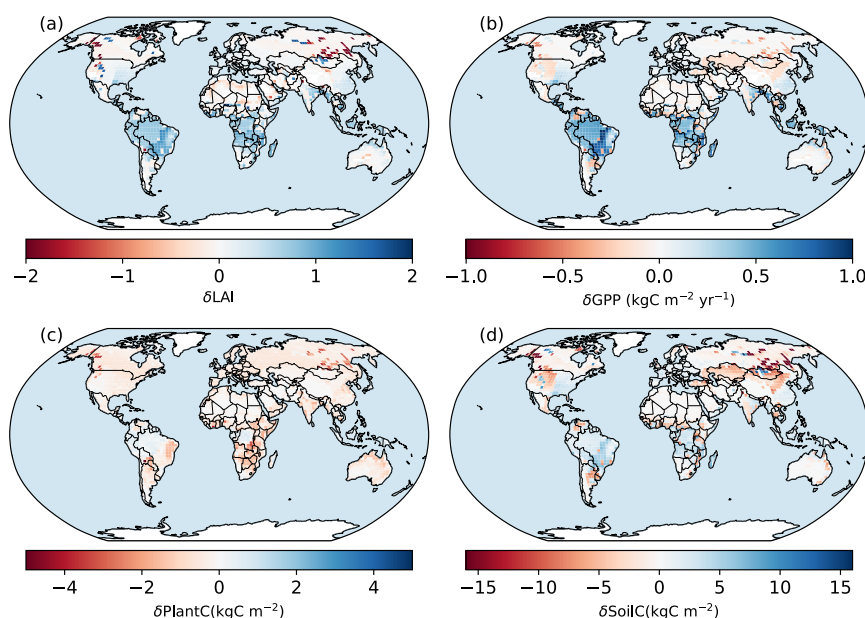


Figure 12 Spatial patterns of the differences between the simulations of the BiomeE with full demography and with the single-cohort settings.

5 Discussion

We developed BiomeE, a parsimonious terrestrial ecosystem model for ModelE, to simulate vegetation dynamics and biogeochemical cycles. This model includes a cohort-based representation of vegetation structure, a height structured light competition scheme, demographic processes, and coupled carbon-nitrogen biogeochemical cycles. This model has four major modules that organize the hierarchical processes of ecosystems together into a cohesive modeling structure: 1) plant physiology (photosynthesis, respiration), 2) plant phenology and growth, 3) vegetation structural dynamics, and 4) soil biogeochemical cycles (Fig. 1). Each module is cohesive and has a minimum set of variables as the input from other modules.



545 5.1 Model formulation

546 In designing this model, we considered the simulation of competitively optimal strategy of
547 plants in different climates based on fundamental ecological rules (Purves and Pacala, 2008;
548 Falster and Westoby, 2003; Franklin et al., 2020). These strategies are mainly related to light
549 competition, water conditions, nutrient use efficiency, and disturbances (e.g., fire), and
550 represented by the traits of wood density, height growth, leaf longevity, and photosynthesis
551 pathways. PFTs are used in this model as an integrative unit representing combinations of plant
552 traits for simulating (1) the spontaneous dynamics of carbon, water, and energy fluxes as the core
553 functions of an ESM-based land model and (2) the transient vegetation structural and
554 compositional dynamics and ecosystem biogeochemical cycles in response to climate variations.
555 We adopted a generic design for the PFTs in the standalone BiomeE (Weng et al., 2019): since
556 the PFTs are samples of plant traits in their natural ranges, the numbers of PFTs are flexible,
557 depending on what strategies users wish to test. This approach substantially simplifies the
558 parameterization of PFTs because it changes the parametrizations to the selections of strategies
559 through choosing different trait values (i.e., parameters). Thus, the PFTs are adaptive and can
560 change to each other in different climate zones, making it possible to reduce the number of PFTs
561 while representing functional diversity and the optimal adaptation to climate conditions.

562 To represent the major variations in plant functional diversity, we chose four plant traits as
563 the primary axes to define PFTs: wood density, leaf mass per unit area (LMA), height growth
564 parameter, and leaf maximum carboxylation rate (V_{cmax}). Wood density is relatively conservative
565 (Swenson and Enquist, 2007; Chave et al., 2009), mostly ranging from 200 to 500 kg C m⁻³,
566 while herbaceous stem density ranges from 400~600 kg C m⁻³ (Niklas, 1995). However,
567 herbaceous stems are usually hollow, making the ratio of total biomass to its volume low, and



568 grasses shed their stems each growing season, resulting in faster stem turnover. It is a strategic
 569 difference from woody plants, which keep the woody tissues to build up their trunks and thus
 570 display their leaves on top of trunks for light competition (Dieckmann et al., 2007; Falster and
 571 Westoby, 2003). LMA is the key leaf trait that determines leaf life longevity and leaf types (i.e.,
 572 evergreen vs. deciduous) (Osnas et al., 2013), and represents the strategy for the competition in
 573 different soil nutrient levels (Tilman, 1988; Reich, 2014; Weng et al., 2017) and resistance to
 574 stresses of water and temperature (Oliveira et al., 2021).

575 In this model, the phenological type is simulated as an emergent property of plant
 576 physiological processes and its strategy to deal with seasonal variations of temperature and water
 577 availability. We used three parameters – growing degree days (GDD), running mean daily
 578 temperature, and critical soil moisture – to define all possible phenological types. These three
 579 parameters are widely used in a variety of phenology models (Sitch et al., 2003; Prentice et al.,
 580 1992; Arora and Boer, 2005). As for soil organic matter decomposition, the CASA model is
 581 currently used in ModelE; it has 13 pools with different transfer coefficients and turnover rates
 582 (Randerson et al., 1997; Potter et al., 1993, 2003). The models developed thereafter have more
 583 sophisticated processes, especially those of microbial activities and carbon use efficiency
 584 (Manzoni et al., 2010; Wieder et al., 2014; Wang and Goll, 2021). We chose an intermediate
 585 complexity scheme that has only two SOM pools but a functional microbial pool for
 586 decomposing SOM so that the dynamics of SOM's C/N ratio, carbon use efficiency, and nitrogen
 587 mineralization can be reasonably simulated while keeping the model structure parsimonious.

588

589 **5.2 Model predictions and performance**



590 This model has four relatively distinctive sets of simulated variables that are critical for model
591 performance and calibration: 1) Stomatal conductance, photosynthesis, and respiration; 2)
592 demographic rates (i.e., allocation, structural growth, mortality, and reproduction); 3) LAI, tree
593 size, crown self-organization, and vegetation structure; 4) Soil carbon and nitrogen storage. In
594 this paper, we only evaluated the carbon cycle in the model simulations, though the nitrogen
595 cycle is also simulated in tandem with the carbon cycle in the model. We did not extensively
596 tune model parameters to fit observations because the purpose of this paper is to describe the
597 formulation of the model. The core processes of this model, e.g., photosynthesis, respiration,
598 phenology, growth, allocation, demography, soil biogeochemical cycles, are from well-
599 developed models and have been shown able to capture observational patterns. Data assimilation
600 approaches can be implemented when parameter tuning becomes essential.

601 The simulations demonstrate that this model can capture global patterns of GPP, LAI, tree
602 height, biomass, and soil carbon, even though the parameters are not extensively tuned. For
603 example, global GPP patterns are consistent with those derived from SIF data (Fig.7: a, b and
604 Fig. 8: a), and simulated tree heights span the same ranges of those derived from data. The
605 simulated biomass and soil carbon is generally higher than in observations, though simulated soil
606 carbon is lower in some cold regions. Several factors likely explain the apparent overestimates of
607 GPP, biomass, and soil carbon in the model. First, the model uses a potential PFT distribution
608 and does not account for land cover change and land use history. For example, carbon dense
609 ecosystems (e.g., forests) have been extensively replaced by croplands and pastures. Second,
610 while vegetation in the real world reflects a variety of successional stages and the effect of
611 various disturbance events, our model analyses are based on equilibrium simulations without
612 explicit disturbances, such as fire, deforestation and regrowth. Third, the model assumes mineral



613 nitrogen is saturated and can consistently meet demands for plant growth. We did not fix the land
614 cover mismatches by compromising ecosystem physiological processes because we cannot put
615 all these effects into current model structure (i.e., mortality) when many processes are missing.

616 LAI is an illustrative variable for understanding why compromises are necessary when
617 integrating ecologically based vegetation models into ESMs. LAI, as a critical prognostic
618 variable in vegetation models, links both plant physiology and biogeophysical interactions with
619 climate systems. While LAI is usually simulated by a fixed allocation scheme, even if the
620 allocation ratios are dynamic with vegetation productivity (Montané et al., 2017), the prediction
621 of LAI in models is often simplified as the balance between growth and turnover. Modelers tend
622 to tune LAI to fit observations and get the required albedo and water fluxes whatever their
623 parameters of photosynthesis and respirations are. This LAI usually makes the lower layer
624 leaves carbon negative. However, a first principle is that a tree should have an optimal LAI to
625 maximize its carbon gain as a result of crown structure, light interception, and community-level
626 competition (Anten, 2002; Hikosaka and Anten, 2012; Niinemets and Anten, 2009). Thus, in our
627 model, we defined a much lower target LAI due to the assumption of the uniform the leaves
628 within a crown to avoid carbon negative leaves.

629 The leaf traits in the crown profile should, in reality, be a function of light, water and
630 nitrogen (Niinemets et al., 2015). This “uniform leaf” assumption makes the lower layer leaves
631 carbon negative when LAI is tuned close to that observed in tropical and boreal evergreen forests
632 (where LAI is around 5~7). Thus, the photosynthesis rate must be tuned to fit the canopy
633 photosynthesis by keeping the carbon negative leaves. However, the carbon negative leaves do
634 not affect ecosystem dynamics in the “single-cohort” models because the whole canopy net
635 carbon gain is still reasonable and can be fitted to the observed dynamics. This contrasts with the



636 demographic version of the model, which represents trees with different sizes and in different
637 layers and creates conditions where seedlings in the understory cannot survive because of light
638 limitation and negative carbon balances in some dry and cold regions.

639 The leaf maximum carboxylation rate (V_{cmax}) used in this model is also much lower than
640 measured in young leaves (Bonan et al., 2011) because the aging of leaves is considered in the
641 mean value of V_{cmax} of all leaves with different ages. The mean V_{cmax} of the whole canopy leaves
642 is much lower than the new leaves that are usually used to measure V_{cmax} . If the leaves were not
643 specifically chosen, the mean of measured V_{cmax} is much lower than those used in models as
644 shown in Verryckt et al. (2022). This also indicates that V_{cmax} in current vegetation models is
645 over-estimated.

646 The allometry of plant architecture, rules for plant growth, and reproduction and mortality
647 processes form the basis of vegetation structural dynamics. The formulation of allometry makes
648 the whole-tree's photosynthesis and respiration proportional to crown area, and thus the growth
649 rate of tree diameter independent of crown area. These vital rates drive vegetation structural
650 changes and biogeochemical cycles (Purves et al., 2008). Our model makes it possible to
651 simulate vegetation composition and structural dynamics based on the fundamental principles of
652 ecology, and the transient changes in terrestrial ecosystem in response to climate change. This
653 model therefore has the potential to predict competitively dominant strategies represented by
654 plastic plant traits (e.g., leaf traits, allocation etc.), resulting in simulated vegetation structure and
655 composition that will be eco-evolutionarily optimized. PPA defines the height-structured
656 competition for light. The allocation scheme between the growth of stems and functional tissues
657 (i.e., leaves and fine roots) is the strategy of resources foraging for light and soil resources.

658



5.3 Major uncertainties in this model

We used many simplifying assumptions to organize ecosystem processes at different scales into a cohesive model structure that balances the complexity of different processes and our knowledge. For example, some processes are based on well-understood physical processes and mathematical derivation, including, the photosynthesis model (FVC) (Farquhar et al., 1980), respiration responses to temperature (Arrhenius equation), and height-structured light competition (i.e., PPA) (Strigul et al., 2008). Many other processes, such as phenology, drought effects, however, are phenomenological equations representing the poorly understood links between processes needed to allow the model to simulate the entire system. In the following sections, we highlight these assumptions and evaluate their relative benefits and costs. Transparency in the description of a community model such as this one will help future developers understand compromises and areas that can be improved with new information or approaches. The following phenomenological relationships represent the major sources of uncertainty in this model.

Water limitation of photosynthesis is calculated as a function of relative soil moisture following the water stress function from Rodriguez-Iturbe et al. (1999):

$$\beta_D = \text{Min} \left(1.0, \max \left(\frac{s_D - s_{\min}}{s^* - s_{\min}}, 0.0 \right) \right), \quad (16)$$

The parameters s^* and s_{\min} are PFT-specific, representing different responses of PFTs to soil water conditions, and s_D is the relative soil moisture ranging from 0 (soil water content at wilting point) to 1 (at field capacity). This formulation that scales soil moisture to a scalar between zero to 1 is repeatedly used in both physiological responses of photosynthesis and phenology in ecosystem models as a simplistic treatment of the central role of water limitation on plant



680 physiology (Harper et al., 2021; De Kauwe et al., 2015; Powell et al., 2013). This equation does
 681 not include the detailed processes of plant hydraulics and its adaptation to arid environments.

682 Plants have multiple tradeoffs and strategies to improve their competitiveness under water
 683 stress, such as regulating stomata conductance, shedding leaves, producing more roots, etc.
 684 (Oliveira et al., 2021; Volaire, 2018). At the ecosystem level, competition and evolutionary
 685 processes filter community emergent properties (Franklin et al., 2020; van der Molen et al.,
 686 2011). For example, trees in different climate regions have similar hydraulic safety margin
 687 (Choat et al., 2012), partly due to the intense competition for light (height growth) and water
 688 (root allocation) that require optimal use of available resources at any climate conditions
 689 (Gleason et al., 2017; Liu et al., 2019). However, in this model, the drought responses are only
 690 delineated by the Eq. 16. The parameter choices for s^* and s_{\min} likely explain the amplified water
 691 stresses and low productivity in arid regions within our model.

692 Phenology represents the seasonal rhythms of plant physiological activities as adapted to
 693 periodic changes in temperature, precipitation, and light availability (Abramoff and Finzi, 2015;
 694 Caldararu et al., 2014; Chuine, 2010). DGVMs normally simulate leaf onset and senescence
 695 based on temperature conditions for cold deciduous plants and soil water conditions for drought
 696 deciduous plants (Arora and Boer, 2005; Caldararu et al., 2014). Phenology modeling is still
 697 highly empirical, although new models and approaches for cold deciduous and drought
 698 deciduous strategies have been proposed recently (e.g., Caldararu et al., 2014; Chen et al., 2016;
 699 Dahlin et al., 2015; Manzoni et al., 2015). We used a simple formulation of temperature (Eqs 1
 700 and 3) and drought responses. For the cold-deciduous strategies, the phenology model balances
 701 growing season length and frost risks by adjusting critical GDD0 and T0 according to chilling
 702 days and growing days to reduce frost risk in warm regions and increase growing season length



703 in cold regions. In this way, leaf senescence also considers growing season length and leaf aging.
704 For example, in areas with longer growing seasons, plants will have a higher T₀ and initiate
705 senescence at higher temperatures. For the drought phenology, we set different critical soil
706 moisture indexes to initiate and terminate a growing season (Table 1). However, these
707 relationships are phenomenological, and ecological rules will benefit future model development.

708 Mortality is an integrative result of accumulative physiological stresses, structural
709 damages, and disturbances during a tree's lifetime. The direct reasons can be starvation,
710 structural failure, hydraulic failure, etc. (McDowell, 2011; Aakala et al., 2012; Aleixo et al.,
711 2019). In this model, we only consider the background mortality and define its rate as a function
712 of tree diameter and light environment (Eq. 10). Hydraulic failure-induced mortality is required
713 for studying plant responses to climate changes.

714 We employed these general phenomenological equations primarily because more
715 mechanistic equations are not currently known. In addition, our interest is to keep this model as
716 simple as possible to improve interpretability and transparency and to reduce the computational
717 burden when it is integrated into the ModelE. In these places where the tradeoff between model
718 complexity and process accuracy is necessary, we highlight the underlying assumptions clearly,
719 rather than applying temporary fixes not based on solid ecological modeling approaches.

720 Generally, we are using the key variables that characterize ecosystem properties to define
721 the basic model structure but have to use less-than-solid information to link them together by
722 phenomenological relationships, as all the models do. The enduring issues in vegetation
723 modeling as pointed by Harrison et al. (2021), such as increasing magnitude of atmospheric CO₂
724 fluctuations, responses to warming, responses to atmospheric CO₂, drought stress effects, etc.,
725 represent our knowledge gaps in ecosystem ecology. Experiments (Ainsworth and Long, 2004;



726 Crowther et al., 2016), observatory networks (Baldocchi et al., 2001), and remote sensing
727 (Duncanson et al., 2020), provide means to improve the modeling of terrestrial ecosystems.

728

729 **5.4 Model stability and complexity**

730 Ecosystem demographic processes (e.g., reproduction and mortality) are a source of high
731 sensitivity and uncertainty in BiomeE. In some environmental conditions, especially dry or cold
732 regions, the uniform parameters lead to high mortality or failure of reproduction, leading to high
733 instability of vegetation. To understand these issues, we developed a “single-cohort” version of
734 the model to aid in the diagnosis of issues in the full demographic version of the model. The
735 major issue we identified is the fact that the model formulation is based on functional processes
736 in highly-productive regions, whereas the model is applied globally and across much more
737 diverse environmental conditions (e.g., arid environments). The variables and parameters that
738 work well in highly-productive regions (e.g., initial seedling sizes, default leaf growth, minimum
739 allocation ratios, etc.) are often unsuitable in regions with higher environmental stress. And
740 although plants have evolved special features to deal with more extreme conditions (Lloret et al.,
741 2012; Reyer et al., 2013; Singh et al., 2020), these features have not yet been integrated into the
742 model.

743 There is a tendency in current DGVMs to use individual plant physiological trait changes
744 to represent community shifts. This approach is usually characterized as “parameter dynamics”
745 or “response functions” (Fisher and Koven, 2020) for reducing model processes and complexity.
746 Adding new processes to work around existing problems, instead of redesigning the fundamental
747 model processes, is common in model development. The approach is helpful for tracking model
748 development, undoing wrong additions, and improving model performance. However, work-



749 rounds often increase model complexity without concomitant improvements in model
750 predictions.

751 Generally, a model's usefulness is improved by transparent assumptions, a well-defined
752 model structure, and output that is testable against data (Famiglietti et al., 2021; Forster, 2017;
753 Hourdin et al., 2017). Data assimilation approaches improve model parameterization more
754 efficiently and effectively than manually tuning individual parameters (Williams et al., 2009;
755 MacBean et al., 2016; Wang et al., 2009) and allow for more detailed uncertainty analysis (Luo
756 et al., 2009; Weng et al., 2011; Weng and Luo, 2011; Xu et al., 2006; Dietze, 2014). It is
757 important to only include necessary assumptions in a model and to include them in ways that do
758 not compromise other processes or parameters. Modelers should try their best not to add poor-
759 understood processes if not necessary. Additionally, many specifications of model formulation
760 are based on the questions that a user is trying to answer in their research. We should not expect
761 to develop an all-encompassing model that fits all application scenarios. On the contrary,
762 maintaining model flexibility and transparency is critical for using this model as a tool to explore
763 specific science questions. In BiomeE, we have opted for what we consider the most
764 parsimonious and at the same time theoretically sound formulations of allometry, phenology, and
765 allocation dynamics to allow for computational efficiency in capturing vegetation growth and
766 ecological dynamics in the context of an ESM.

767

768 **5.5 Legacy limitations of code and model development conventions**

769 ModelE is a general circulation model, and vegetation in the model to date has been represented
770 with a simple set of static biophysics parameterizations to regulate exchanges of energy and
771 moisture between the land surface and the atmosphere (i.e., a big leaf model) (Hansen et al.,



2007; Schmidt et al., 2014; Kelley et al., 2020). To advance the functionality of the vegetation and the land surface model within ModelE, increases in complexity must therefore be balanced with the computational demands of the fully-coupled model. Time-consuming computations in vegetation model can substantially reduce the speed of the whole model. In ModelE, the land model, TerraE, is used to calculate land surface (including vegetation) water and energy fluxes and soil water dynamics based on the characteristics of vegetation derived from the vegetation model (e.g., canopy conductance, wetness, etc.) at the grid scale. It does not calculate each cohort's transpiration and water uptake.

In our vegetation model, the water limitation of stomatal conductance is calculated as a function of soil water stress index and root vertical distribution, instead of the direct plant root water supply (plant hydraulics). This setting works well for the big leaf model (one canopy at one grid). However, when multiple cohorts of plants are represented in the model, it is unable to represent water competition and differentiate the contribution of each single cohort's contribution to the total transpiration. A structural change is required to solve this problem by calculating transpiration from the bottom up (i.e., from cohort up to grid cell).

The legacy of model coding structure and the history of model development can greatly affect the functions and the selection of model formulations (Alexander and Easterbrook, 2015). When incorporating new processes, especially a new vegetation dynamic model, we must balance the stability requirement of the parent model and the risks of the model crashing. As shown in the comparison with the single cohort model (Fig. 11), the full demography setting has many potential failing points in regeneration in more extreme environmental conditions.

6 Conclusions



795 We developed a new demographic vegetation model to improve the representation of terrestrial
796 vegetation dynamics and ecosystem biogeochemical cycles in the NASA Goddard Institute of
797 Space Studies' coupled Earth system model, ModelE. This model includes the processes of plant
798 growth, mortality, reproduction, vegetation structural dynamics, and soil carbon and nitrogen
799 cycling. To scale this model globally, we added a new set of plant functional types to represent
800 global vegetation functional diversity and introduced new phenology algorithms to deal with the
801 seasonality of temperature and soil water availability. Competition for light and soil resources is
802 individual-based, which makes the modeling of eco-evolutionary optimality possible. This model
803 predicts the dynamics of vegetation and soil biogeochemistry including leaf area index,
804 vegetation structure (e.g., height, tree density, size distribution, crown organization), and
805 ecosystem carbon and nitrogen storage and fluxes. This model will enable ModelE to simulate
806 long-term biogeophysical and biogeochemical feedbacks between the climate system and land
807 ecosystems at decadal to century temporal scales. It will also allow for the prediction of transient
808 vegetation dynamics and eco-evolutionary community assemblage in response to future climate
809 changes based on the fundamental ecological principles.

810

811

812 **Code and data availability**

813 The model codes have been coupled with NASA GISS ModelE and will be released with
814 ModelE codes (<https://www.giss.nasa.gov/tools/modelE/>). We put the relevant code files at
815 GitHub for review proposes (<https://github.com/wengensheng/ModelE-BiomeE>). The simulated
816 data are stored at NASA supercomputer discover. We will make them publicly available at the
817 acceptance of this paper.



818

819 **Author contributions**

820 EW coded the model and performed test runs and data analysis. EW and BIC wrote the first draft
821 of the manuscript. BIC, MJP, SSM, NYK, and EW designed the functional coupling with
822 ModelE and the land module. NYK, IA, RS, and MK contributed to input data, the IO structure
823 and the coupling between BiomeE and Ent. KW, RD, CE, and SWP contributed to conceptual
824 model development and PFT design. All co-authors contributed to writing or improving the
825 manuscript.

826

827 **Competing interests**

828 The authors declare that they have no conflict of interest.

829

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