

1 Technical Note: An efficient method for accelerating the spin-up
2 process for process-based biogeochemistry models

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15 **Abstract**

16 To better understand the role of terrestrial ecosystems in the global carbon cycle and their
17 feedbacks to the global climate system, process-based biogeochemistry models need to be
18 improved with respect to model parameterization and model structure. To achieve these
19 improvements, the spin-up time for those differential equation-based models needs to be
20 shortened. Here, an algorithm for a fast spin-up was developed by finding the exact solution of a
21 linearized system representing cyclo-stationary state of a model and implemented in a
22 biogeochemistry model, the Terrestrial Ecosystem Model (TEM). With the new spin-up
23 algorithm, we showed that the model reached a steady state in less than 10 years of computing
24 time, while the original method requires more than 200 years on average of model run. For the
25 test sites with five different plant function types, the new method saves over 90% of the original
26 spin-up time in site-level simulations. In North America simulations, average spin-up time
27 saving for all grid cells is 85% for either daily or monthly version of TEM. The developed spin-
28 up method shall be used for future quantification of carbon dynamics at fine spatial and temporal
29 scales.

30

31 1. Introduction

32 Biogeochemistry models contain state variables representing various pools of carbon and
33 nitrogen and a set of flux variables representing the element and material transfers between
34 different state variables. Model spin-up is a step to get biogeochemistry models to a steady state
35 for those state and flux variables (McGuire et al., 1992; King, 1995; Johns et al., 1997;
36 Dickinson et al., 1998). Spin-up normally uses cyclic forcing data to force the model run, and
37 reach a steady state, which will be used as initial conditions for model transient simulations. The
38 steady state is reached when modeled state variables show a cyclic pattern or a constant and
39 often requires a significant amount of computation time, which needs to be accelerated for
40 regional and global simulations at fine spatial and temporal scales.

41 Spin-up is normally achieved by running model repeatedly using one or several decades of
42 meteorological or climatic data, until a steady state is reached. The step could require model
43 repeatedly run for more than 2000 annual cycles in some extreme cases. Specifically, the model
44 will check the stability of the simulated carbon and nitrogen fluxes as well as state variables with
45 specified threshold values. For instance, the model will check if the simulated annual net
46 ecosystem production (NEP) is less than $1 \text{ g C m}^{-2} \text{ yr}^{-1}$ (McGuire et al., 1992). Another method
47 to reach a steady state is to obtain the analytical solutions (King et al., 1995; Comins, 1997),
48 which might also take a significantly long time.

49 For different biogeochemistry models, spin-up could take hundreds and thousands of years to
50 reach a stability, normally longer than the model projection period (Thornton et al., 2005).
51 Therefore, a more efficient method to reach the steady state will speed up the entire model
52 simulation. Recently, a semi-analytical method (Xia et al., 2012) has been adapted to a carbon-
53 nitrogen coupled model to speed up the spin-up process. The idea is to get an analytical solution

54 very close to a steady condition, then start spin-up from the solution, which could significantly
55 reduce spin-up time. This technique did not reach a cyclic pattern for state and flux variables and
56 required an additional spin-up process to achieve the steady state. However, Lardy et al (2011)
57 and Martin et al (2007) have implemented their spin-up methods for a linear problem of soil
58 carbon dynamics including their seasonal cycles.

59 Here we developed a method to accelerate the spin-up process in a non-linear model. We
60 tested the method for representative plant function types and the North America with both daily
61 and monthly versions of TEM (Zhuang et al., 2003). In addition, we compared the performance
62 of our algorithms with the semi-analytical version of Xia et al. (2012). The new algorithms shall
63 help us conduct very high spatial and temporal resolution simulations with process-based
64 biogeochemistry models in the future.

65

66 2. Method

67 2.1 TEM description

68 We used a process-based biogeochemistry model, the Terrestrial Ecosystem Model (TEM;
69 Zhuang et al. 2003) as testbed to demonstrate the performance of the new algorithms of spin-up.
70 TEM simulates the dynamics of ecosystem carbon and nitrogen fluxes and pools (McGuire et al.,
71 1992; Zhuang et al., 2010, 2003). It contains five state variables: carbon in living vegetation (C_v),
72 nitrogen in living vegetation (N_v), organic carbon in detritus and soils (C_s), organic nitrogen in
73 detritus and soils (N_s), and available inorganic soil nitrogen (N_{av}). Carbon and nitrogen
74 dynamics in TEM are governed by following equations:

$$\frac{dC_v}{dt} = GPP - R_A - L_C \dots \dots \dots (1)$$

$$\frac{dN_v}{dt} = NUPTAKE - L_N \dots \dots \dots (2)$$

$$\frac{dC_s}{dt} = L_c - R_H \dots \dots \dots (3)$$

$$\frac{dN_s}{dt} = L_N - NETNMIN \dots \dots \dots (4)$$

$$75 \quad \frac{dN_{av}}{dt} = NINPUT + NETNMIN - NLOST - NUPTAKE \dots \dots (5)$$

76 Where GPP is gross primary production, R_A is autotrophic respiration, L_C is carbon in
 77 litterfall, $NUPTAKE$ is nitrogen uptake by vegetation, L_N is nitrogen in litterfall, R_H is
 78 heterotrophic respiration, $NETNMIN$ is net rate of mineralization of soil nitrogen, $NINPUT$ is
 79 nitrogen input from outside ecosystem, $NLOST$ is nitrogen loss from ecosystem. Key carbon
 80 fluxes are defined as:

$$GPP = C_{max} f(PAR) f(PHENOLOGY) f(FOLIAGE) f(T) f(C_a, G_v) f(NA) f(FT) \dots \dots \dots (6)$$

$$81 \quad NPP = GPP - R_A \dots \dots \dots (7)$$

$$NEP = GPP - R_A - R_H \dots \dots \dots (8)$$

82 For detailed GPP definition, see Zhuang et al. (2003). NEP will be near zero when the
 83 ecosystem reaches a steady state. Therefore, the spin-up goal is to keep running the model
 84 driven with repeated climate forcing data until NEP is close to zero with a certain tolerance value
 85 (e.g., $0.1 \text{ g C m}^{-2} \text{ yr}^{-1}$).

86 2.2 Spin-up acceleration method

87 TEM can be re-formulated as:

88 $\frac{d\vec{x}}{dt} = g(\vec{x}, t) + \vec{h}(t)$(9)

89

90 Where \vec{x} is a vector of state variables (e.g., C_v); $\vec{h}(t)$ is the vector of carbon/nitrogen input
 91 from the atmosphere (such as nitrogen input), independent on \vec{x} ; $g(\vec{x}, t)$ is the process rate
 92 function of element pools (e.g., GPP).

93 By linearizing the model in term of pools, we could get:

94 $g(\vec{x}, t) = g(\vec{x}_0, t) + J(\vec{x} - \vec{x}_0)$(10)

95 Where \vec{x}_0 is initial pool sizes, J is the Jacobian matrix of the process rate:

96 $J = \frac{dg}{dx} = \begin{bmatrix} \frac{\partial g_1}{\partial x_1} & \cdot & \cdot & \cdot & \frac{\partial g_1}{\partial x_n} \\ \cdot & & & & \cdot \\ \cdot & & & & \cdot \\ \frac{\partial g_n}{\partial x_1} & \cdot & \cdot & \cdot & \frac{\partial g_n}{\partial x_n} \end{bmatrix}$(11)

97 where g represents $g(\vec{x}, t)$. \vec{x}_n represents each of state variables in the TEM (e.g., V_C). The
 98 numerical discretization of eq. (9) is:

99 $x_{i,k} - x_{i,k-1} = \tau \cdot J_{k-\frac{1}{2}} \cdot x_{i,k-1} + \tau \left(g(x_0, k-1) - J_{k-\frac{1}{2}} \cdot x_{0,k-1} + h_{k-1} \right)$(12)

100

101 where τ is time step (month), $x_{i,k}$ is the pool x_i size at time k , $J_{k-\frac{1}{2}}$ is a Jacobian matrix at
 102 time step $k - \frac{1}{2}$. Here $\frac{1}{2}$ refers to the half time step in the middle of a month, at which values
 103 of J are calculated as the mean value at time steps k and $k-1$. $x_{i,0}$ refers to the initial pool x_i size.

104 We introduce:

105
$$f_{k-1} = g(x_0, k-1) - J_{k-\frac{1}{2}} \cdot x_{0,k-1} + h_{k-1} \dots \dots \dots (13)$$

106 The eq. (12) can then be written as:

107
$$x_{i,k} - x_{i,k-1} = \tau \cdot J_{k-\frac{1}{2}} \cdot x_{i,k-1} + \tau \cdot f_{k-1} \dots \dots \dots (14)$$

108 Where $J_{k-\frac{1}{2}}$ is a Jacobian matrix at the time step $k - \frac{1}{2}$. After running a large number of
 109 annual cycles, the model approaches a cyclo-stationary state, which can be expressed by
 110 condition $x_{T+i} = x_i$, where T is the number of time steps in one cycle. For example, when spin
 111 up is made at monthly time step using monthly climatology of temperature, precipitation and
 112 other forcing data, T equals 12, and \vec{x}_1 is the size of carbon pools on January 1st, while $J^{1.5}$ is
 113 the matrix of mean process rate constants for January.

114 By introducing:

115
$$A_k = \tau \cdot J_{k-\frac{1}{2}}, y_k = \tau f_{k-1}, B_k = I, C_k = I + A$$

116 where I is an identity matrix.

117 Eq. (12) can be further written as:

118
$$-C_k \cdot x_{i,k-1} + B_k \cdot x_{i,k} = y_k \dots \dots \dots (15)$$

119 The cyclic boundary condition is: $x_1 = x_{T+1}$

120 Then Eq. (13) will become:

121
$$-C_1 \cdot x_{i,T} + B_1 \cdot x_{i,1} = y_1 \dots \dots \dots (15a)$$

122 Thus eq. (15) and (15a) become a formulation of a linear problem with T unknown vectors
 123 \vec{x}_T , which can be solved using LU (lower and upper) decomposition or Gaussian elimination
 124 (Martin et al., 2007). Xia et al (2012, see Eq. 4) and Kwon and Primeau (2006) also had linear
 125 equations for a steady state, but conducted the model simulation at annual time step. Going for
 126 annual average form reduces the size of the problem and prevents Xia et al (2012) from
 127 obtaining the exact solution of the problem including seasonal cycle (see their Eq. 15, 15a).
 128 While our new approach runs the model at monthly time step with the cyclic boundary
 129 conditions for state variables x, it still targets a steady state for the ecosystem at annual time step
 130 instead of monthly time step.

131 2.3 Numerical implementation

132 Eq. (15a) is explicitly expressed as:

133
$$\begin{pmatrix} B & 0 & 0 & \dots & 0 & 0 & 0 & -C \\ -C & B & 0 & \dots & 0 & 0 & 0 & 0 \\ 0 & -C & B & \dots & 0 & 0 & 0 & 0 \\ \dots & \dots & \dots & \dots & \dots & \dots & \dots & \dots \\ 0 & 0 & 0 & \dots & -C & B & 0 & 0 \\ 0 & 0 & 0 & \dots & 0 & -C & B & 0 \\ 0 & 0 & 0 & \dots & 0 & 0 & -C & B \end{pmatrix} \times \begin{pmatrix} x_1 \\ x_2 \\ \cdot \\ \cdot \\ \cdot \\ \cdot \\ x_T \end{pmatrix} = \begin{pmatrix} y_1 \\ y_2 \\ \cdot \\ \cdot \\ \cdot \\ \cdot \\ y_T \end{pmatrix} \dots \dots \dots (16)$$

134 Eq. (16) can be shown in form $Mx = Y$.

135 We apply the Gaussian elimination to upper block that reduces M to a lower triangular form

136 (Figure 1). The resulting matrix is lower diagonal:

$$M' = \begin{pmatrix} B' & 0 & 0 & 0 & 0 & 0 & 0 \\ -C & B & 0 & 0 & 0 & 0 & 0 \\ 0 & -C & B & 0 & 0 & 0 & 0 \\ \dots & \dots & \dots & \dots & \dots & \dots & \dots \\ 0 & 0 & 0 & -C & B & 0 & 0 \\ 0 & 0 & 0 & 0 & -C & B & 0 \\ 0 & 0 & 0 & 0 & 0 & -C & B \end{pmatrix} \dots\dots\dots(17)$$

138 The eq. (16) is thus reduced to form $M'x = Y'$, where M' is lower diagonal, and solution of eq.
 139 (15a and 16) will be readily obtained for x.

140 2.4 Algorithm implementation for TEM

141 In the original TEM, carbon fluxes can be defined as:

$NPP = GPP - MR - GR$(19)

142 $MR = V_C \cdot K_T$(20)

$GR = \begin{cases} 0.25 \cdot (GPP - MR), & \text{if } GPP > MR \\ 0 & , \text{otherwise} \end{cases}$(21)

143 Where net primary production (NPP) is defined as the difference of GPP and plant maintenance
 144 respiration (MR) and growth respiration (GR). MR is assumed as a function of C_v and
 145 temperature (K_T). Here we revised MR calculation:

146 $MR = \begin{cases} V_C \cdot K_T, & \text{if } GPP > V_C \cdot K_T \\ 0.75 \cdot V_C \cdot K_T + 0.25 \cdot GPP, & \text{otherwise} \end{cases}$(21)

147 The net ecosystem production (NEP) is defined as the difference between NPP and
148 heterotrophic respiration (R_H).

149 The basic workflow to implement the method is: 1) linearizing TEM first to get a sparse
150 matrix with n-variable (for TEM, n=5) system; 2) performing Gaussian elimination for the linear
151 system; 3) solving the sparse matrix to acquire the state variable values (Figure 1). To adapt this
152 method to a daily version of TEM, we changed the cyclic condition T from 12 to 365. The other
153 steps are the same as monthly version. We tested the new method for carbon only version and
154 carbon-nitrogen coupled version of TEM for different plant functional types (PFTs) (Table 1).
155 Specifically, for the carbon only version, we only solved the differential equations that govern
156 the carbon dynamics, while for the carbon-nitrogen coupled version, we solved the differential
157 equations that govern both carbon and nitrogen dynamics in the system. For the both versions,
158 the spin-up process strives to reach a steady state for carbon pools and fluxes.

159 3. Results and Discussion

160 At Harvard Forest site, the traditional spin-up method took 564 years to get the steady state
161 for both the carbon-only and coupled carbon–nitrogen simulations with annual NEP less than 0.1
162 $\text{g C m}^{-2} \text{yr}^{-1}$ (Figure 2). In contrast, the improved method took 72 years for the carbon only and
163 122 for the coupled carbon–nitrogen simulations, respectively. For carbon and nitrogen pools, it
164 took another 45 years (equivalent cyclic time) to reach a steady state with NEP less than 0.1 g C
165 $\text{m}^{-2} \text{yr}^{-1}$. In comparison with the traditional spin-up method (Zhuang et al., 2003), the new
166 method saved 65% of computational time to get the steady state in the carbon-only simulations
167 (Table 2). The differences in steady-state carbon pools between using the new method and
168 traditional spin-up methods were small (less than 0.85%). Similarly, for the coupled carbon–
169 nitrogen simulations, the new method saves a similar amount of time to reach the steady state.

170 For all seven test sites, the original spin-up method in TEM takes 204-564 years (1.1-2.5
 171 seconds of computing time) to reach the steady state at different sites. In contrast, our new
 172 method only takes 0.3-0.6 seconds, while the semi-analytical method (Xia et al., 2012) will need
 173 0.5-0.9 seconds to reach the steady state at different sites (Table 2). Compared to the original
 174 spin-up method, the new method is not only faster, but also computationally stable.

175 The time of spin-up to reach a steady state of NEP varied for different PFT grids using the
 176 original method (Figure 2). In general, to allow 98% grid cells reach their steady states of NEP,
 177 it will take 250 annual model runs. While the new method will only need on average 0.6 seconds
 178 (equivalent to 60-year annual model runs with the original method) (Figure 3). For regional tests
 179 in North America, we found that the average saving time with the new method with monthly
 180 TEM is 25%, 32%, and 22%, for Alaska, Canada, and the conterminous US, respectively.

181 To compare the performance of the new method with other existing methods, we adapted the
 182 semi-analytical method (Xia et al., 2012) to TEM model. To do that, we first revised the TEM
 183 model structure to:

184
$$\frac{dP(t)}{dt} = \varepsilon ACP(t) \dots \dots \dots (22)$$

185 Where P(t) is a vector of pools in TEM (e.g., C_v and C_s). ε is a scalar. A is a pool transfer matrix
 186 (in which A_{ij} represents the fraction of carbon transfer from pool j to i). C is a diagonal matrix
 187 with pool components (where diagonal components quantify the fraction of carbon left from the
 188 state variables after each time step). With this method, we obtained an analytical solution for the
 189 intermediate state. We then kept running TEM with the traditional spin-up process. Specifically,
 190 we started TEM simulation to estimate the state variable values. Based on these values, the spin-
 191 up runs were conducted to reach the final steady state. We found that the semi-analytical solution

192 is better than the original spin-up method, but slower than the new method proposed in this study
193 (Table 2).

194 The TEM model has a relatively small set of state variables for carbon and nitrogen. The
195 version we used is TEM 5.0, which has only five state variables (Zhuang et al., 2003). Thus, the
196 linearization process is relatively easy and the matrix size is relatively small, consequently, the
197 computing is not a burden. To accelerate the spin-up for multiple soil carbon pool models with
198 relatively simple and linear decomposition processes, implementing our method shall be still
199 relatively easy, but will take a great amount of computing time to equilibrate. For models such as
200 CLM, multiple methods have been tested to accelerate their spin-up process (e.g., Fang et al.,
201 2015), the direct analytical solution method introduced in this study might be time-consuming to
202 achieve.

203 4. Summary

204 We developed a new method to speed up the spin-up process in process-based
205 biogeochemistry models. We found that the new method shortened 90% of the spin-up time
206 using the traditional method. For regional simulations in North America, average spin-up time
207 saving is 85% for either daily or monthly version of TEM. We consider our method is a general
208 approach to accelerate the spin-up process for process-based biogeochemistry models. As long as
209 the governing equations of the models can be formulated as the form in eq. (9), the algorithm
210 could be adopted accordingly. Our method will significantly help future carbon dynamics
211 quantification with biogeochemistry models at fine spatial and temporal scales.

212

213 Data availability: All data used in this study are available from the authors upon request.

214 Author contributions: Qianlai Zhuang and Shamil Maksyutov designed and supervised the
215 research. Yang Qu performed model simulations and data analysis. All authors contribute the
216 paper writing.

217 Competing interests: The authors declare that they have no conflict of interest.

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222 by the Rosen Center for Advanced Computing at Purdue University.

223

224 Table 1. Test sites for new spin-up algorithms

Site Name	Location	PFT	Reference
1. Fort Peck	48.3N, 105.1W	Grassland	Gilmanov et al. [2005]
2. Bartlett Exp Forest	44.1N, 71.3W	Deciduous broadleaf	Ollinger et al. [2005]
3. UCI_1850	55.9N, 98.5W	Evergreenn needle-leaf	Goulden et al. [2006]
4. Vaira Ranch	38.4N, 121.0W	Grassland	Baldocchi et al. [2004]
5. Missouri Ozark	38.7N, 92.2	Deciduous broadleaf	Gu et al. [2007, 2012]
6. Niwot Ridge	40.0N, 105.5W	Evergreenn needle-leaf	Turnipseed et al. [2003, 2004]
7. Harvard Forest	43.5N, 72.2W	Deciduous broadleaf	Van Gorsel et al. [2009]

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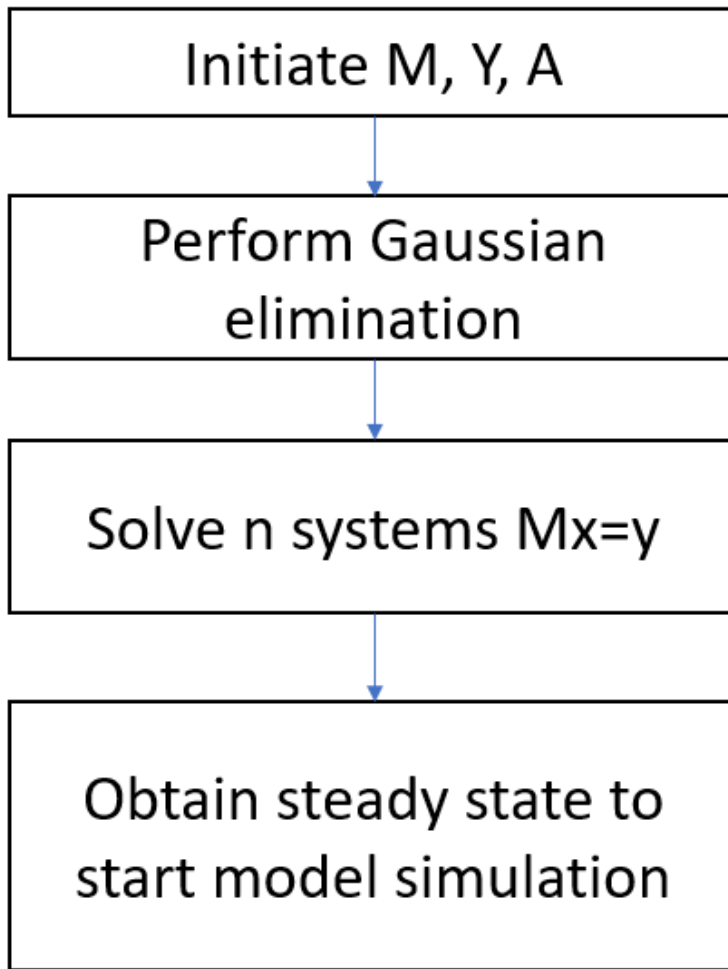
228 Table 2. Spin-up time comparison for different methods for seven study sites, seconds represent

229 real computation time, years refer to the spin-up annual cycles

Site No.	Original Spin-up Year	Spin-up computation time (Seconds)	New method computation time (Seconds)	Semi-analytical method (equivalent annual cycles)
1	231	1.3	0.5	0.7s (+76)
2	305	1.7	0.3	0.8s (+101)
3	245	1.5	0.4	0.9s (+52)
4	443	2.2	0.4	0.5s (+118)
5	304	1.8	0.4	0.8s (+86)
6	204	1.1	0.3	0.7s (+43)
7	564	2.5	0.6	0.9s (+45)

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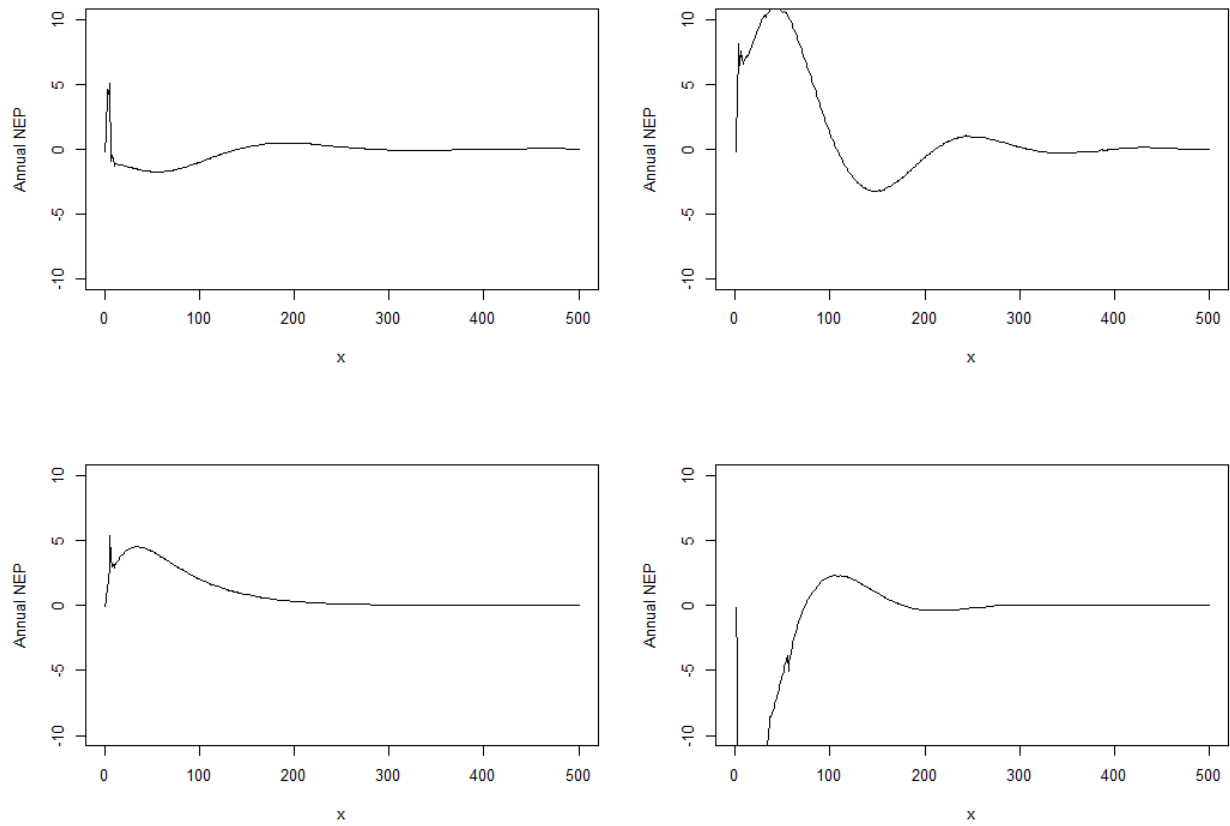


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233 Fig. 1. Algorithms and procedures of the new spin-up method

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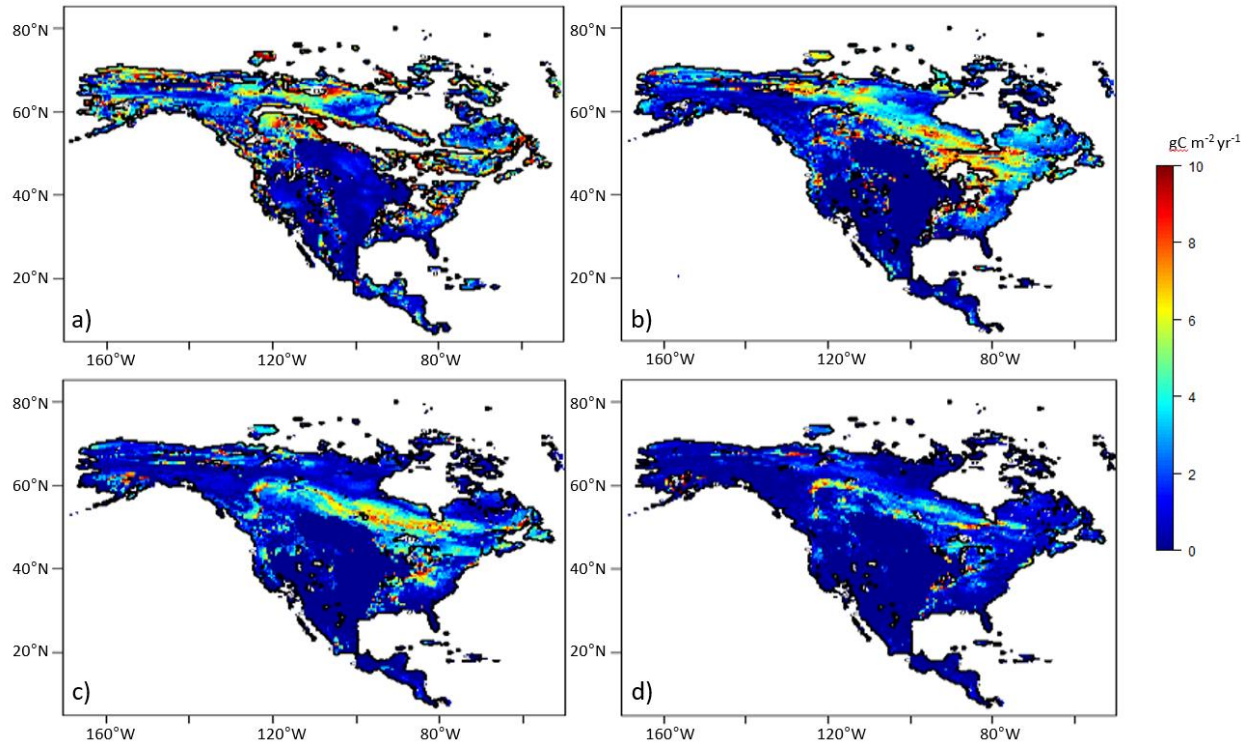
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237 Fig. 2. The time for NEP ($\text{g C yr}^{-1}\text{m}^{-2}$) reached a steady state with the original spin-up method at
 238 Harvard forest site. x represents model simulation years.

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243 Fig. 3. Simulated NEP ($\text{g C m}^{-2} \text{yr}^{-1}$) with the original spin-method after different spin-up years
 244 of (a) 50, (b) 100, (c) 150, and (d) 200 years, respectively. After these spin-up years, 63%, 89%,
 245 93%, and 98% grids will reach their steady states, respectively.

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