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Global sensitivity analysis of DRAINMOD-FOREST, an integrated forest ecosystem model

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Abstract:

Global sensitivity analysis is a useful tool to understand process-based ecosystem models by identifying key parameters and processes controlling model predictions. This study reported a comprehensive global sensitivity analysis for DRAINMOD-FOREST, an integrated model for simulating water, carbon (C), and nitrogen (N) cycles and plant growth in lowland forests. The analysis was carried out for multiple long-term model predictions of hydrology, biogeochemistry, and plant growth. Results showed that long-term mean hydrological predictions were highly sensitive to several key plant physiological parameters. Long-term mean annual soil organic C content and mineralization rate were mainly controlled by temperature-related parameters for soil organic matter decomposition. Mean annual forest productivity and N uptake were found to be mainly dependent upon plant production-related parameters, including canopy quantum use efficiency and carbon use efficiency. Mean annual nitrate loss was highly sensitive to parameters controlling both hydrology and plant production, while mean annual dissolved organic nitrogen loss was controlled by parameters associated with its production and physical sorption. Parameters controlling forest production, C allocation, and specific leaf area highly affected long-term mean annual leaf area. Results of this study could help minimize the efforts needed for calibrating DRAINMOD-FOREST. Meanwhile, this study demonstrates the critical role of plants in regulating water, C, and N cycles in forest ecosystems and highlights the necessity of incorporating a dynamic plant growth model for comprehensively simulating hydrological and biogeochemical processes.

KEY WORDS global sensitivity analysis; forest ecosystem model; DRAINMOD-FOREST; forest hydrology; biogeochemistry; plant growth

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INTRODUCTION

Process-based forest ecosystem models are useful research and management tools for exploring forest ecosystem dynamics and providing policymakers and forest managers with necessary information for making scientifically sound decisions (Makela *et al*., 2000; Johnsen *et al*., 2001). These models conceptualize scientific knowledge and understanding of the integrated hydrological, biogeochemical, and plant physiological processes occurring in forest ecosystems, and thus, they have certain advantages over empirical models in mechanistically simulating these coupled processes (Makela *et al*., 2000; Johnsen *et al*., 2001). However, process-based models tend to be complex and usually require a large number of input parameters (Johnsen *et al*., 2001; Van Oijen *et al*., 2005). Many parameters used in process-based models are difficult or even practically impossible to obtain from actual measurements (Makler-Pick *et al*., 2011). The uncertainty in parameter values increases the likelihood of errors and bias in model predictions (EPA, 2003; Beven, 2008). Therefore, identifying key model parameters and processes and refining model structure are important steps for developing and evaluating process-based models (Arora, 2002; EPA, 2003; Sieber and Uhlenbrook, 2005).

Sensitivity analysis has been widely used for quantifying effects of changes in model parameters on variance of model predictions (Wang *et al*., 2005; Pappenberger *et al*., 2008; Saltelli and Annoni, 2010; Dobler and Pappenberger, 2012). Results of sensitivity analysis provide insights into which parameters (or processes) are most influential on certain model outputs (Pappenberger *et al*., 2008). Such information is

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a useful guidance for model calibration and validation and can be used for refining and improving model structure to reduce model complexity (Sieber and Uhlenbrook, 2005). Generally, there are two types of methods for sensitivity analysis: local and global methods (Fieberg and Jenkins, 2005; Pappenberger *et al.*, 2008; Saltelli and Annoni, 2010). In local sensitivity analysis, only one parameter is changed at a time, while keeping all other parameters at their base values. This type of sensitivity analysis is commonly referred to as the one-at-a-time (OAT) method. It is known that the OAT method is only suitable for linear and additive models as it ignores the interaction effects among model parameters (Saltelli and Annoni, 2010). Because of its simplicity and high computation efficiency, however, this method has been widely used for sensitivity analysis of hydrological, biogeochemical, environmental, and ecological models (Haan and Skaggs, 2003; Esprey *et al.*, 2004; Xenakis *et al.*, 2008; Kim *et al.*, 2012), although most of which are nonlinear and nonadditive. In contrast to local methods, global sensitivity analysis is an advanced approach that is capable of altering values of all parameters simultaneously in each model simulation. Global sensitivity analysis methods have been strongly recommended for nonlinear and nonadditive computer models (EPA, 2003; Saltelli and Annoni, 2010). Among the methods of global sensitivity analysis, the most widely used is the variance-based global sensitivity analysis, which partitions the variance of model outputs to influence of individual parameters and their interactions (Saltelli and Annoni, 2010). Sobol's (2001) method, the Fourier amplitude sensitivity test (FAST), and extended FAST (E-FAST) (Saltelli *et al.*, 2000, 2005) are widely used methods for variance-based global sensitivity analysis.

DRAINMOD-FOREST is an integrated forest ecosystem model for simulating water, soil carbon (C), and nitrogen (N) dynamics and plant growth in natural and managed forests on shallow water table soils (Tian *et al.*, 2012a,2012b). Previous studies successfully tested DRAINMOD-FOREST for predicting hydrological processes, nitrate and dissolved organic nitrogen (DON) losses in drainage, and plant growth for three artificially drained loblolly pine (*Pinus taeda* L.) plantations under various management practices over a 21-year period (Tian *et al.*, 2012a,2012b, 2013). The model is highly nonlinear and nonadditive because of the tight interactions among its three components: hydrology, biogeochemistry, and plant growth. This integrated forest ecosystem model has a large number of input parameters with respect to plant physiological properties, soil hydraulic properties, and soil biogeochemical properties regulating C and N cycles. Some of these parameters are difficult to determine through field/laboratory measurements and are usually obtained through model calibration.

The objective of this study was to conduct a comprehensive global sensitivity analysis for DRAINMOD-FOREST to identify key model parameters controlling the long-term mean hydrological, soil C and N, and plant-related predictions. Results of this study are useful in verifying the interactions and feedbacks among the three components of DRAINMOD-FOREST. Information obtained would guide model users to efficiently calibrate the model and help forest managers understand processes controlling the long-term sustainability of forest plantations. This study could also validate the model structure and provide insights into the complex interactions among various model components. Lastly, findings of this study should be of general implications for other comparable integrated ecosystem models.

MATERIALS AND METHODS

DRAINMOD-FOREST

DRAINMOD-FOREST (Figure 1) is an integrated, process-based, and stand-level forest ecosystem model that integrates a physiology-based forest growth model with DRAINMOD (Skaggs, 1999) and DRAINMOD-N II (Youssef, 2003; Youssef *et al.*, 2005) models. The model was developed to simulate hydrological processes, soil C and N dynamics, and tree growth for natural and managed forests on naturally poorly drained shallow water table soils (Tian *et al.*, 2012a). In addition to common silvicultural practices, forest plantations in this kind of landscape are often artificially drained by open-ditch networks to reduce excess water stress and improve forest productivity.

The hydrologic component, DRAINMOD, was originally developed for evaluating the performance of drainage and associated water management systems in agricultural fields (Skaggs *et al.*, 1999, 2012). It conducts a water balance on either an hourly or daily basis for a soil column midway between two parallel drains, extending from the soil surface down to a shallow impermeable layer. After necessary modifications were incorporated, the current DRAINMOD component of DRAINMOD-FOREST is capable of simulating detailed hydrological processes in lowland forest ecosystems, including rainfall interception, throughfall, infiltration, evapotranspiration (ET), subsurface drainage, surface runoff, vertical and lateral seepage, water table fluctuation, and soil water distribution in the vadose zone (Figure 1). Infiltration is simulated using the Green–Ampt equation. Subsurface drainage is calculated using Hooghoudt's equation for water table drawdown and Kirkham's equations for ponded surface conditions. Surface runoff is estimated as the difference between rates of precipitation and infiltration, once site-specific surface depressional storage is filled (Skaggs *et al*., 1999). DRAINMOD-FOREST internally calculates daily potential ET (PET) using the Penman–Monteith method with canopy conductance estimated as a function of climatologically regulated stomatal conductance and leaf area index (LAI), which is predicted by the forest growth model. A modified version of the Gash model (Gash *et al*., 1995) is used to estimate rainfall interception.

DRAINMOD-N II was developed by adding soil C and N cycling components to the hydrologic model DRAINMOD. It simulates a detailed N cycle including atmospheric deposition, application of mineral N fertilizers and organic N sources, plant uptake, N mineralization and immobilization, nitrification, denitrification, ammonia volatilization, and N losses via surface runoff, lateral subsurface drainage, and vertical deep seepage (Figure 1). Transport of both mineral N and DON in the soil profile is simulated using a finite differential solution to a multiphase form of the one-dimensional advection–dispersion reaction equation. The nitrification and denitrification processes are simulated using the Michaelis–Menten function. The soil C submodel of DRAINMOD-N II divides organic matter into three soil organic matter (SOM) pools (active, slow, and passive), two aboveground and belowground residue pools (metabolic and structural), and a surface microbial pool (Figure 1). Each organic matter pool is characterized by a specific organic C content, potential rate of decomposition, and C : N ratio. The decomposition of each organic matter pool is simulated using first-order rate kinetics as a function of maximum decomposition rate and environmental constraints. In DRAINMOD-N II, the temperature constraint function is based on a form of the Van't Hoff equation with variable Q10. DRAINMOD-N II was recently modified to simulate biogeochemical and physical processes of DON, including production of DON from diverse SOM pools, microbial consumption, partitioning between solid and aqueous phases, and physical transport along the soil profile (Tian *et al*., 2013).

The forest growth component in DRAINMOD-FOREST was mainly adapted from the 3-PG model (Landsberg and Waring, 1997) with changes related to soil mineral N and water stresses affecting vegetation growth (Tian *et al*., 2012a). Gross primary production (GPP) is estimated using the radiation use efficiency

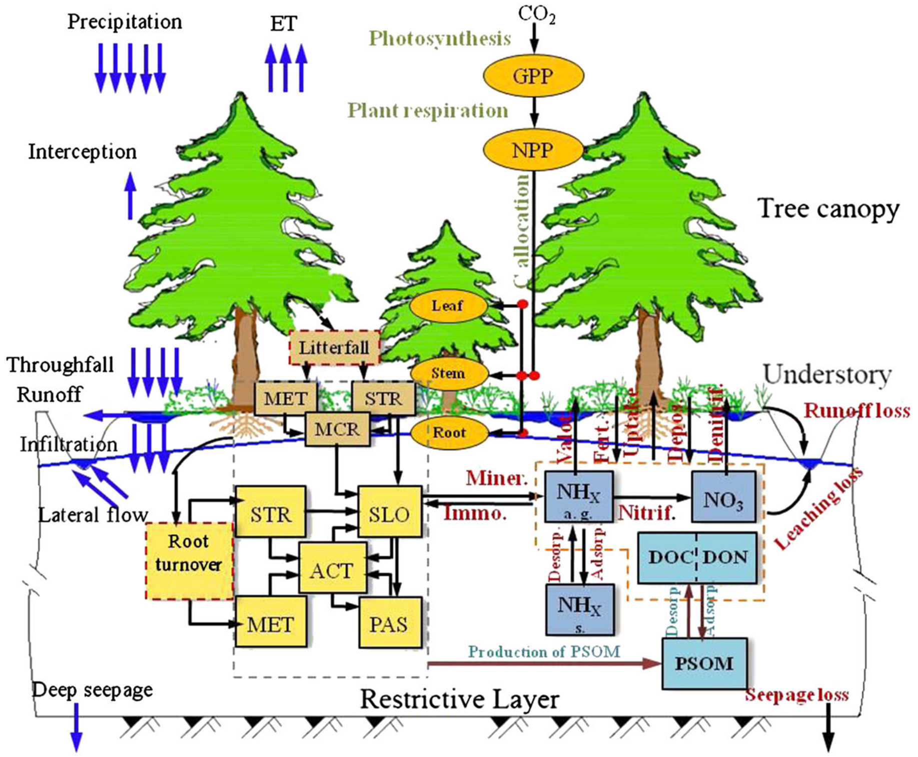

Figure 1. Schematic diagram of hydrological, biogeochemical processes and plant growth in a typical drained forest ecosystem as simulated by DRAINMOD-FOREST. Soil organic matter pools: STR = structural pool, MET = metabolic pool, MCR = microbial pool, ACT = active pool, SLO = slow pool, PAS = passive pool, PSOM = potentially soluble soil organic matter, DOC = dissolved organic carbon, DON = dissolved organic nitrogen. Nitrogen cycle: Volati = volatilization, Fertil = fertilization, Depos = air deposition, Denitrif = denitrification, Immobi = immobilization, Mineral = mineralization, Nitrif = nitrification, Adsorp = adsorption, Desorp = desorption. (Tian *et al*., 2012a)

method, which relates intercepted radiation to biomass production through quantum use efficiency (QUE). Environmental stresses considered in the model include air temperature and the availability of soil water and N. Net primary production (NPP) is estimated as a function of GPP and carbon use efficiency (CUE) in this study. The model partitions assimilated C into foliage, stem, and root biomass using species-dependent allometric functions, which are also regulated by soil water and nitrogen status. Live biomass loss through foliage litterfall is estimated as a function of leaf longevity, while fine root turnover is quantified on the basis of fine root lifespan. Several outputs, including forest productivity, LAI, tree diameter, and height, are provided by the forest growth component.

DRAINMOD-FOREST considers the internal feedbacks and interactions among hydrological, biogeochemical, and physiological processes in forest ecosystems (Figure 1). Specifically, first, ET is estimated as a function of soil water conditions and PET. PET is calculated using the Penman–Monteith equation on the basis of dynamically simulated LAI, stomatal conductance, plant height, and canopy fraction by the vegetation growth component. Second, DRAINMOD predicted hydrological variables including soil water conditions and drainage, which are used by DRAINMOD-N II to simulate the reactive transport of soil N and predict mineral N and DON leaching losses. Third, canopy photosynthesis and C allocation to different plant tissues simulated by the plant growth model are affected by water and mineral N deficit stresses predicted by DRAINMOD and DRAINMOD-N II, respectively. Fourth, litterfall and root turnover simulated by the plant growth model are sources of organic matter for the soil C and N cycles simulated by DRAINMOD-N II, which affects the availability of soil N and plant growth. A detailed model description of DRAINMOD-FOREST is given by Tian *et al.* (2012a).

Two-step sensitivity analysis

Because of these interactions among various processes that are simulated in the three components of DRAINMOD-FOREST, the model is highly nonlinear and nonadditive. Thus, the variance-based global sensitivity analysis approach was selected to conduct the sensitivity analysis of DRAINMOD-FOREST. The sensitivity analysis was conducted for nine model outputs: two hydrology related (mean annual drainage and ET), five soil C/N related (long-term mean of SOM content, mean annual mineralization rate, plant uptake, nitrate, and DON leaching losses), and two plant related (mean annual NPP and mean LAI). Given its large number (67) of model input parameters, computation 'cost' in terms of the total number of model simulations required for this global sensitivity analysis can be prohibitively high. Therefore, the OAT method was firstly used for initial parameter screening to select the top 20 parameters for each model prediction, which are further included in the global sensitivity analysis. A similar two-step global sensitivity analysis was also used by Wang *et al.* (2005). Results from this two-step global sensitivity analysis could partly minimize the potential bias generated from a single method, because different sensitivity analysis methods may yield different rankings with respect to the importance of model parameters (Frey and Patil, 2002; Pappenberger *et al.*, 2008).

Screening procedure. The screening procedure was carried out for 67 parameters using the Latin hypercube (LH) OAT (LH-OAT) method (van Griensven *et al.*, 2006). The LH method, used in this step, is a stratified sampling technique that divides the range of a parameter (X) value used for the OAT analysis into N intervals of equal probability. One sample is randomly generated from each interval to produce N nonoverlapping samples (X_i, $i = 1, 2, 3, \ldots, N$) of each parameter. For each model simulation, the value of only one parameter was changed while keeping the other parameters fixed at their base values.

A relative sensitivity index (Wang *et al.*, 2005), defined by Equation 1, was used to quantitatively evaluate the responses of each model output to changes in individual parameters. The relative sensitivity index (*RSI*) can be either negative or positive, indicating the two trends of change in model outputs.

$$RSI_{O,X} = \frac{\sum_{i=1}^{N-1}\left[\left(\frac{O_{i+1}-O_i}{X_{i+1}-X_i}\right)\left(\frac{X_{i+1}+X_i}{O_{i+1}+O_i}\right)\right]}{N-1} \qquad (1)$$

where $RSI_{O,X}$ is the relative sensitivity index for model output O with respect to model parameter X and O_i represents the model output corresponding to model parameter value X_i. The first term inside the summation of Equation (1) represents the change in model output O per unit change in the value of model parameter X, while the second term is used to normalize the response. The top 20 parameters with highest absolute magnitude of *RSI* were selected for carrying out the global sensitivity analysis.

Variance-based sensitivity analysis. Variance-based analysis is one of the most prevalent methods used in global sensitivity analysis (Saltelli *et al.*, 1999). This method has been widely used across various engineering disciplines such as chemical engineering (Saltelli *et al.*, 2005), water resources engineering (van Griensven *et al.*, 2006), and environmental engineering (Kioutsioukis *et al.*, 2004). It decomposes the total variance of model output into individual contributions of each input parameter and their interactions as expressed by (Saltelli *et al.*, 2005)

$$V(Y) = \sum_{i=1}^{k} V_i + \sum_{i=1}^{k}\sum_{j>i}^{k} V_{ij} + \sum_{i=1}^{k}\sum_{j>i}^{k}\sum_{m>j}^{k} V_{ijm} + \ldots + V_{1,2,\ldots,k} \tag{2}$$

where $V(Y)$ is the total unconditional variance of model output (Y) with k model parameters, V_i represents the first-order fractional variance of model outputs, V_{ij} is the second-order fractional variance of model outputs, and V_{ijm} and $\mathrm{V}_{1,2,\ldots,k}$ are higher-order variances of interactions among multiple (≥3) model parameters i, j, m, …, k. In general, only the first two terms are considered in the sensitivity analysis. These two terms are calculated by Equations 3 and 4:

$$V_i = V\left(E\left(Y|X_i = x_i^*\right)\right) \tag{3}$$

$$V_{ij} = V(E(Y|X_i = x_i^*, X_j = x_j^*)) - V\left(E\left(Y|X_i = x_i^*\right)\right) - V\left(E\left(Y|X_j = x_j^*\right)\right) \tag{4}$$

where $V\left(E\left(Y|X_i = x_i^*\right)\right)$ represents the variance of expected value of Y when X_i has a fixed value x_i^* and $V\left(E\left(Y|X_i = x_i^*, X_j = x_j^*\right)\right)$ is the variance of the expected value of Y when X_i has a fixed value x_i^* and X_j has a fixed value x_j^*.

The first-order sensitivity index S_i for parameter X_i represents the contribution of individual parameters to the variance of model outputs and can be calculated as

$$S_i = \frac{V_i}{V(Y)} \tag{5}$$

The first-order sensitivity index cannot fully address the impacts of one parameter on the model predictions if interactions among parameters exist. The S_{T_I} of parameter X_i is defined as the sum of its main sensitivity measure and its interaction effects with all other parameters and can be expressed as (Saltelli *et al.*, 2005; Pappenberger *et al.*, 2008)

$$S_{T_I} = 1 - \frac{V\left[E\left(Y|X_{\sim i} = x_{\sim i}^*\right)\right]}{V(Y)} \tag{6}$$

where $V\left[E\left(Y|X_{\sim i} = x_{\sim i}^*\right)\right]$ represents the variance of model outputs caused by changes of all model parameters other than parameter i. By definition, S_{T_I} is greater than or equal to S_i. The difference between S_{T_I} and S_i is a measure of how much X_i is involved in interactions with all other input variables. The sum of S_{T_I} or S_i is an indicator of the presence of interaction effects among parameters when the sum of S_{T_I} is great than 1 and/or the sum of S_i is less than 1.

Pappenberger *et al.* (2008) indicated that for correlated inputs the first-order effects are larger than the total effects because of the dependence structure in the inputs. However, it also depends upon the way the sensitivity method is formulated. Generally, parameters with small total sensitivity indices are of negligible effect on the model output and can be fixed at a nominal value. In contrast, parameters with high first-order indices have strong identifiable influence on the model output and need to be determined accurately. It is possible that some parameters may have small first-order indices but large total sensitivity indices, indicating large effects on the model output due to their interactions with other parameters. In this study, we selected the E-FAST method (Saltelli *et al.*, 1999) to carry out the variance-based global sensitivity analysis. This method has proven to be more reliable and computationally efficient than other variance-based techniques (Saltelli *et al.*, 1999, 2000). Saltelli *et al.* (1999) provided a detailed description of the E-FAST method. This E-FAST method was previously used to conduct sensitivity analysis for the DRAINMOD-N II model (Wang *et al.*, 2005).

Set-up of sensitivity analysis

The sensitivity analysis of DRAINMOD-FOREST was applied to a loblolly pine plantation (about 24 ha) located in Eastern North Carolina, USA, which was previously used for a field testing of DRAINMOD-FOREST (Tian *et al.*, 2012a). The site is relatively flat (less than 0.1% slope) and has hydric soil (Deloss fine sandy loam, fine-loamy, mixed, semiactive, Thermic Typic Umbraquults). It was drained by four 1.2-m-deep parallel lateral ditches dug at 100-m spacing. This type of loblolly pine plantations is typically distributed in the lowland areas of South-eastern USA. Onsite measured long-term (21-year) precipitation is 1517 mm, and ET is 1005 mm (Amatya and Skaggs, 2011). Model simulations in this study were applied for a 21-year (1988–2008) period with onsite climate measurements, including temperature, precipitation, solar radiation, wind speed, and relative humidity (Amatya and Skaggs, 2011). The simulation covered a typical mid-rotation pine plantation (14-year-old trees in 1988) until its harvest in 2009. A detailed site description including drainage system, soil properties, and vegetation can be found elsewhere (Tian *et al.*, 2012a). To eliminate effects of disturbances of management practices, the sensitivity analysis excluded commonly used silvicultural practices such as fertilization, thinning, and harvesting.

DRAINMOD-FOREST requires three types of input parameters: soil physical properties (Table A1 in Appendix), soil C and N cycle-related parameters (Table A2 in Appendix), and vegetation-related parameters (Table A3 in Appendix). Drainage system settings, including drain spacing and depth, were excluded from this sensitivity analysis because these are certain for most study sites. Parameters of soil C and N dynamics include soil physical and chemical properties, N transport and transformations parameters, and parameters quantifying decomposition of SOM. Vegetation parameters are mainly associated with NPP, C allocation, litterfall, and physiological properties. A total of 67 parameters were included in the screening procedure. Parameter distributions and ranges were carefully defined on the basis of published studies (Tables A1, A2, A3 in Appendix). In this study, ranges of plant-related parameters were selected specifically for loblolly pine, while most (when applicable) hydraulic and soil C and N related parameters were obtained from literature for South-eastern USA. Similar to other sensitivity analysis studies of forest ecosystem models (Verbeeck *et al.*, 2006; Xenakis *et al.*, 2008), most model parameters that do not have adequate published literature values were assumed to follow a uniform distribution characterized by minimum and maximum values. Other parameters that have sufficient documented values were assumed to follow a normal distribution. The base value of each parameter was set as the calibrated value obtained in a previous model testing (Tian *et al.*, 2012a). Each of the 67 parameters was arbitrarily partitioned into 10 intervals, and a total of 670 runs of DRAINMOD-FOREST were carried out for the screening procedure. In this study, the E-FAST generated 2600 samples from 20 parameters previously selected from the screening procedure. For the total nine model outputs considered in this study, a total of 23 400 model runs were carried out. The parameter sampling and post-sensitivity index (S_{T_i} or S_i) calculation were carried out using the SIMLAB software, developed by the Joint Research Centre of the European Commission (SIMLAB, 2011).

Computer models that simulate long-term SOM dynamics usually require a steady-state solution for initial SOM pools before conducting model calibrations and validations (Lardy *et al.*, 2011). The initial SOM content was determined from two field measurements conducted in 2007 (unpublished data), which is an acceptable approximation of initial conditions because changes in the SOM of forest soils usually occur over long periods (several decades to centuries) (Johnson *et al.*, 2003). The initial partitioning of SOC into active, slow, and passive pools was adjusted prior to each model execution to achieve quasi-equilibrium among the three SOC pools. An iterative procedure, requiring multiple runs (usually less than five) of the model using the measured 20-year climate record, was followed to obtain the initial partitioning of SOC (Tian *et al.*, 2012a).

RESULTS AND DISCUSSION

Parameters controlling hydrologic predictions

Figures 2 and 3 summarize the *RSI*, S_i, and S_{T_i} of the selected 20 parameters for model predictions of long-term annual mean ET and drainage (Q), respectively. According to results obtained from the LH-OAT screening, the selected 20 parameters are the same but with opposite impacts on mean annual ET and Q (Figures 2A and 3A). For instance, increasing QUE and specific leaf area (SLA) will increase ET (positive RSI in Figure 2A) and reduce drainage (negative RSI in Figure 3A). Among these selected parameters, three are related to soil hydraulic properties, five are related to soil C and N dynamics, and 12 are related to vegetation. The top five parameters ranked by the LH-OAT sensitivity analysis are all related to plant physiological properties, including canopy QUE, SLA, C allocation ratio between leaf and stem (P20), maximum stomatal water conductance (gsmax), and CUE. The S_i (Figures 2B and 3B) and S_{T_i} (Figures 2C and 3C) obtained from the E-FAST analysis suggested the same top five parameters, but with different rankings, with maximum stomatal water conductance ranked first, QUE ranked second, and SLA ranked fifth. Parameter rankings given by S_i and S_{T_i} based on the global sensitivity analysis are very similar. Nevertheless, the summation of all S_i and S_{T_i} was 0.95 and 1.4 for ET predictions and 0.91 and 1.3 for Q predictions, respectively, indicating the presence of interactions between these parameters. Among all parameters, the C allocation ratio between leaf and stem (P20) has the largest interaction effects with other parameters, with an S_i of 0.09 and an S_{T_i} of 0.18.

The top five parameters identified by the sensitivity analysis (Figures 2 and 3) are related to plant physiological processes, suggesting that vegetation is the dominant factor regulating the long-term mean hydrological predictions. The model was not found very sensitive to soil hydraulic conductivity, a commonly recognized parameter with large influence on hydrological processes (Blanco-Canqui *et al.*, 2002; Haan and Skaggs, 2003) (ranked 16th by the LH-OAT screening procedure and ninth by the global sensitivity

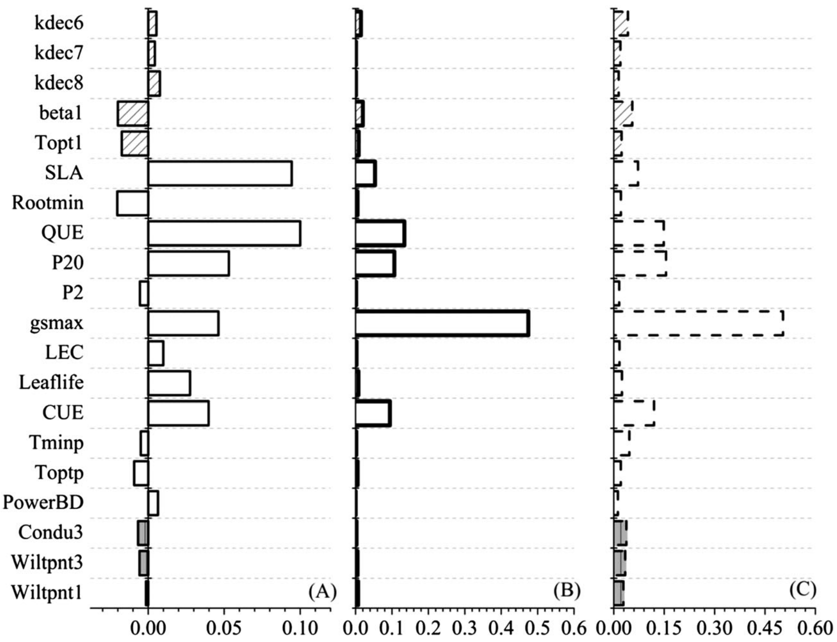

Figure 2. Results of the two-step global sensitivity analysis for long-term annual mean evapotranspiration (ET). (A) The relative sensitivity index (RSI), (B) the first-order sensitivity index (S_i), and (C) the total order index (S_{T_i}) of these identified top 20 parameters through screening procedure. Parameters associated with soil physical properties, plant, and soil carbon and nitrogen cycles are highlighted by grey-filled, blank, and dashed bars, respectively

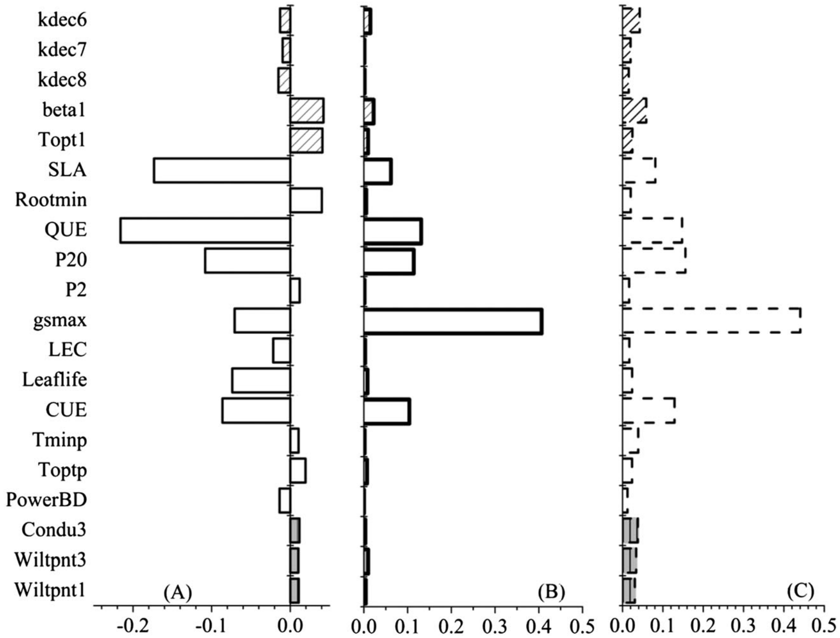

Figure 3. Results of the two-step global sensitivity analysis for long-term annual mean drainage (Q). (A) The relative sensitivity index (RSI), (B) the first-order sensitivity index (S_i), and (C) the total order index (S_{T_i}) of these identified top 20 parameters through screening procedure. Parameters associated with soil physical properties, plant, and soil carbon and nitrogen cycles are highlighted by grey-filled, blank, and dashed bars, respectively

analysis). This conclusion is different from results of an OAT sensitivity analysis of the DRAINMOD model applied for an agricultural field located in the Southeastern USA (Haan and Skaggs, 2003), in which the lateral hydraulic conductivity of the bottom soil layer was found to be the dominant parameter influencing DRAINMOD predictions of long-term mean annual drainage. However, these results are not contradictory because the previous analysis did not take into consideration the dominant role of plant canopy in regulating the water flux between canopy and air (Arora, 2002). Similar to findings from this study, recent local sensitivity analyses on DRAINMOD (Luo *et al*., 2009) and the watershed-scale version of DRAINMOD (called DRAINWAT) (Kim *et al*., 2012) also concluded that PET estimated using various methods is the most sensitive temporal parameter affecting its hydrological outputs.

We also found that a few soil C and N related parameters had minor but noticeable effects on model predictions of hydrological processes (Figures 2 and 3). For instance, the decomposition rate of active soil C pool (kdec6) was found with a sensitivity index higher than that of soil hydraulic conductivity (conduc3). This is evident because soil biogeochemical processes influence the availability of plant nutrients and thus affect vegetation growth and accordingly the long-term mean hydrological expressions of the ecosystem (Lohse *et al*., 2009).

The critical role of plants in regulating water and energy fluxes between biosphere and atmosphere is well known (Asbjornsen *et al*., 2011; Waring and Landsberg, 2011). As we identified in Figures 2 and 3, stomatal conductance (gsmax) and other plant-related parameters are the dominant factors controlling water losses through transpiration (Rodriguez-Iturbe, 2000; Arora, 2002). This is confirmed by previous model applications (Tian *et al*., 2012a,2012b). However, most hydrological models do not include a dynamic plant growth component (Arora, 2002), which may explain why previous sensitivity analysis of hydrologic models did not identify a dominant influence of plant physiological properties on hydrological predictions (van Griensven *et al*., 2006; Tang *et al*., 2007; Foglia *et al*., 2009). Results from this study verified the fact that it is essential to adequately represent the dominant role of vegetation in regulating long-term water cycle in both process-based (Arora, 2002) and empirical hydrological models (Donohue *et al*., 2007; Li *et al*., 2013).

Parameters controlling soil C and N related outputs

Soil organic matter content. Figure 4 shows *RSI*, S_i, and S_{T_i} of the selected 20 parameters for model predictions of long-term mean annual SOM content. The LH-OAT screening procedure suggests that seven of the top 20 parameters are soil C and N related, 12 parameters are plant related, and only one is soil physical property related (Figure 4A). On the basis of the LH-OAT screening procedure, there are six parameters having noticeable effects on model predictions of long-term mean SOM content: optimum temperature for SOM decomposition (Topt1), empirical shape factor for temperature function (beta1), maximum decomposition rates for slow (kdec7) and passive SOM pools (kdec8),

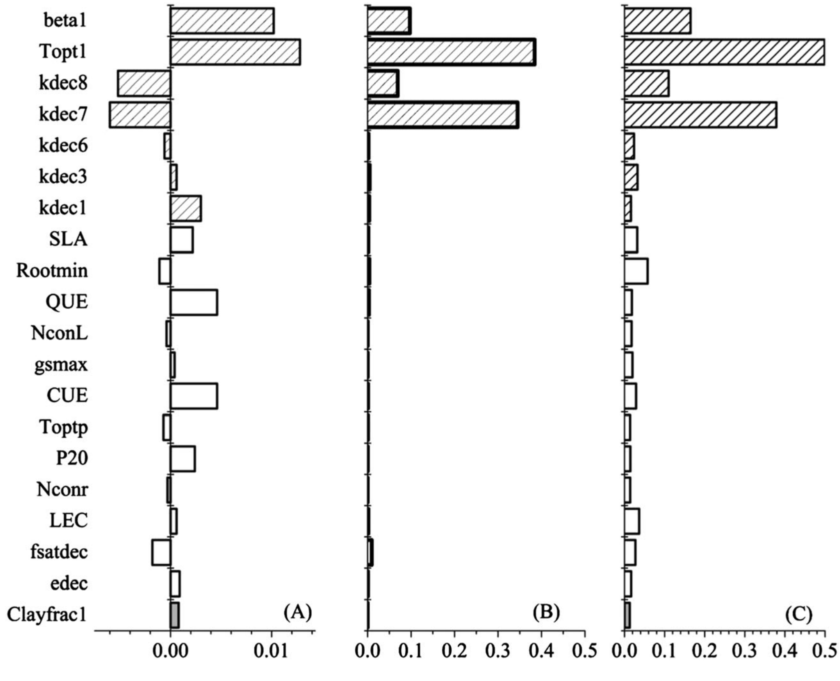

Figure 4. Results of the two-step global sensitivity analysis for long-term annual mean soil organic matter (SOM) content. (A) The relative sensitivity index (RSI), (B) the first-order sensitivity index (S_i), and (C) the total order index (S_{T_i}) of these identified top 20 parameters through screening procedure. Parameters associated with soil physical properties, plant, and soil carbon and nitrogen cycles are highlighted by grey-filled, blank, and dashed bars, respectively

canopy QUE, and CUE. The results of our LH-OAT analysis are similar to results obtained in another sensitivity analysis on a SOM model linked with the 3-PG model (Xenakis *et al.*, 2008). Rankings of top parameters identified by LH-OAT and E-FAST are similar. Nevertheless, S_i and S_{T_i} based on the E-FAST global sensitivity analysis (Figure 4B, C) demonstrated that only four parameters have a substantial influence over model predictions of long-term mean SOM content: optimum temperature for SOM decomposition (Top1), maximum decomposition rates of slow and passive pools (kdec7 and kdec8), and empirical shape factor for temperature function (beta1). As demonstrated in Figure 4B, C, S_{T_i}'s of the selected 20 parameters are generally larger than S_i. The sum of S_i is 0.93, while the sum of S_{T_i} is 1.4, indicating the presence of interaction effects among these parameters.

Theoretically, the long-term mean SOM content is influenced by the balance among the total system productivity, the delivery of new organic matter to SOM pools, and the microbial decomposition. This is clearly reflected in the results from the LH-OAT. For instance, soil clay fraction (Clayfrac1) showed a positive impact on predicted SOM content because clay physically protects SOM (Six *et al.*, 2002), slowing decomposition and reducing SOM loss. Meanwhile, parameters such as QUE and CUE have positive impacts on SOM because both parameters positively affect plant production. The *RSI*s of decomposition rates of surface litter pools (kdec1 and kdec3) and of decomposition rates of slow and passive SOM pools (kdec7 and kdec8) have opposite signs. This is because the part of the decomposed litter stored on the forest floor is recycled into SOM, and thus, the decomposition of litter is considered a source of SOM, while SOM decomposition itself is a sink (Figure 1).

Both the LH-OAT and global sensitivity analyses suggested that the temperature-mediated decomposition processes exert a dominant influence on the long-term mean SOM content. We found that the higher optimum temperature for SOM decomposition poses a positive impact on SOM content (Figure 4A). This is consistent with the common view that global warming will reduce soil C sequestration by accelerating the depletion of the soil C storage (Knorr *et al.*, 2005; Davidson and Janssens, 2006).

The maximum decomposition rates of slow and passive SOM pools were also identified as key parameters regulating model predictions of long-term mean SOM content, suggesting that stable SOM pools are the main contributor to the SOM accumulation because of their long residence time (Knorr *et al.*, 2005). The global sensitivity analysis suggests that factors related to plant growth did not obviously affect model predictions of SOM. Although root turnover is a major pathway to SOM storage (Matamala *et al.*, 2003), root turnover rate was found to be insignificant in controlling SOM content, presumably as a result of the fast decomposition rate of root litter, which usually has a low lignin-to-N ratio (Ostertag and Hobbie, 1999). The insignificant effect of plant-related parameters on model predictions of long-term mean SOM content has also been found in conclusions obtained by other similar studies (Paul *et al.*, 2008; Xenakis *et al.*, 2008).

Nitrogen mineralization. For a forest plantation without fertilization, N mineralization from SOM decomposition is the main source of mineral N or plant uptake (Vernimmen *et al.*, 2007). *RSI*, S_i, and S_{T_i} of the selected 20 parameters for model predictions of long-term mean annual mineralization rate are shown in Figure 5. Nine of the top 20 parameters identified by the LH-OAT screening procedure using the calculated indices were plant-related parameters, while seven were soil C and N cycle related and four were soil hydrologic and texture related (Figure 5A). The most sensitive parameters based on the screening procedure were mainly SOM decomposition related, such as parameters of temperature constraint function (topt1, beta1), decomposition rate of active (kdec6), slow (kdec7), and passive (kdec8) pools, and plant-related parameters, including QUE and N content in roots (NconR) and leaf (NconL). Identified parameters by the S_i (Figure 5B) and S_{T_i} (Figure 5C) are largely different from the LH-OAT results. According to the results of global sensitivity analysis, only four parameters had strong effects on model predictions of long-term annual mean net N mineralization: the optimum temperature for SOM decomposition (Topt1), maximum decomposition rates for active (kdec6) and slow (kdec7) SOM pools, and empirical shape factor for the temperature function (beta1). According to the S_i (Figure 5B), the ranking of decomposition rates of the active and slow SOM pools climbed to the second and fourth, respectively. The S_{T_i} of the E-FAST analysis (Figure 5C) suggests the same top four most sensitive parameters as did the S_i, while the fifth one was stem N content (NconS) instead of leaf N content (NconL). The presence of interactions among parameters was indicated by the sums of first-order and total sensitivity indices, which were 0.87 and 1.9, respectively. In particular, global sensitivity analysis showed the stem nitrogen content (NconS) with a low S_i value (0.08) and a high S_{T_i} value (0.63), suggesting that this parameter interacts strongly with other parameters.

The sensitivity analysis suggested that long-term mean annual N mineralization rate is dominated by

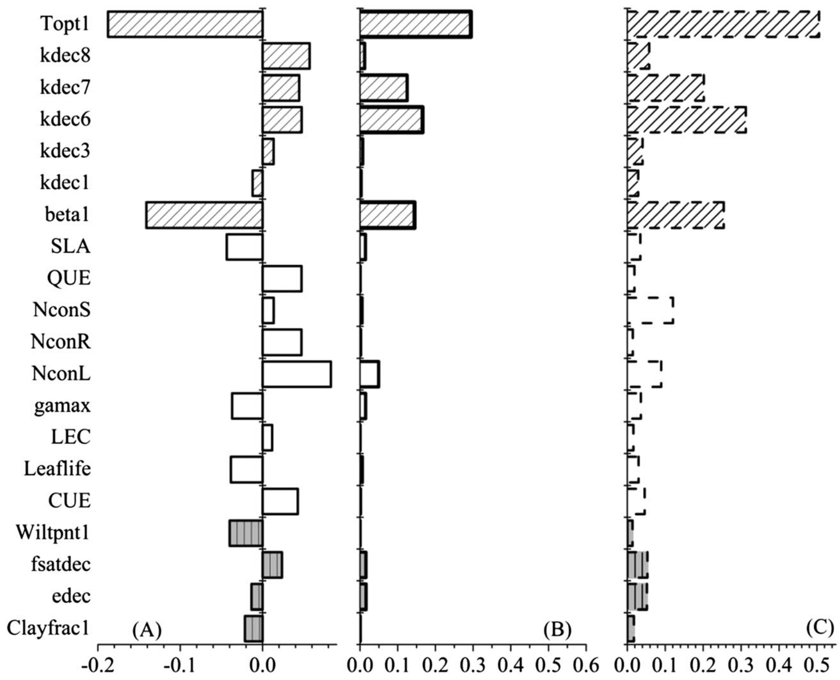

Figure 5. Results of the two-step global sensitivity analysis for long-term annual mean mineralization rate. (A) The relative sensitivity index (RSI), (B) the first-order sensitivity index (S_i), and (C) the total order index (S_{T_i}) of these identified top 20 parameters through screening procedure. Parameters associated with soil physical properties, plant, and soil carbon and nitrogen cycles are highlighted by grey-filled, blank, and dashed bars, respectively

decomposition rates of labile SOM pools and soil temperature constraint parameters. The maximum decomposition rates of active (kdec6) and slow (kdec7) SOM pools were selected as very influential parameters from the global sensitivity analysis, suggesting that the labile SOM pools exert dominant control over the net N mineralization because of their fast turnover and low C/N (Muller *et al.*, 2011). This was confirmed by another study concluding that the decomposition of labile SOM is the most important process influencing availability of soil mineral N (Xenakis *et al.*, 2008). In contrast to the results obtained from the LH-OAT analysis, those of the global sensitivity analysis suggested that the decomposition rate of the passive SOM pool (kdec8) has limited impact on mean annual N mineralization rate. Compared with SOM decomposition rates, litterfall quality and N content of tree tissues were found to be insignificant factors controlling net N mineralization, which is confirmed by a comparison across several North American forest sites (Scott and Binkley, 1997). Comparable with many other studies (Pastor and Post, 1986; Leiros *et al.*, 1999; Dalias *et al.*, 2002; Knoepp and Swank, 2002), both LH-OAT and E-FAST analyses demonstrated that parameters of temperature constraint function (topt1, beta1) have the most influential impacts on predicted mineralization rate. Although it is known that the soil moisture regime is another factor affecting N mineralization in forest soils (Pastor and Post, 1986; Leiros *et al.*, 1999; Knoepp and Swank, 2002), the effect of soil moisture was found insignificant in this study because the site is relatively wet, as indicated by the long-term mean precipitation of 1517 mm and mean water table depth of about 1 m in the study site (Amatya and Skaggs, 2011; Tian *et al.*, 2012c).

Nitrate losses. Figure 6 shows *RSI*, S_i, and S_{T_i} for the selected top 20 parameters influencing long-term mean annual nitrate loss predictions. There were ten plant-related parameters and nine soil C and N cycle related parameters among the 20 parameters. According to results of the LH-OAT screening procedure (Figure 6A), the five most sensitive parameters were canopy QUE, optimum temperature for SOM decomposition (Topt1), CUE, SLA, and empirical shape factor for temperature function (beta1), while the maximum stomatal conductance (gsmax) was ranked sixth. The ranking of the most important factors regulating nitrate losses identified by the E-FAST global sensitivity analysis was slightly different than that identified by the LH-OAT screening. Specially, the maximum stomatal conductance (gsmax) was ranked third and second, respectively, according to the S_i and S_{T_i} of E-FAST methods. In addition, the sum of S_{T_i} and S_i for all parameters is 1.4 and 0.88, respectively, suggesting the presence of interaction effects among parameters.

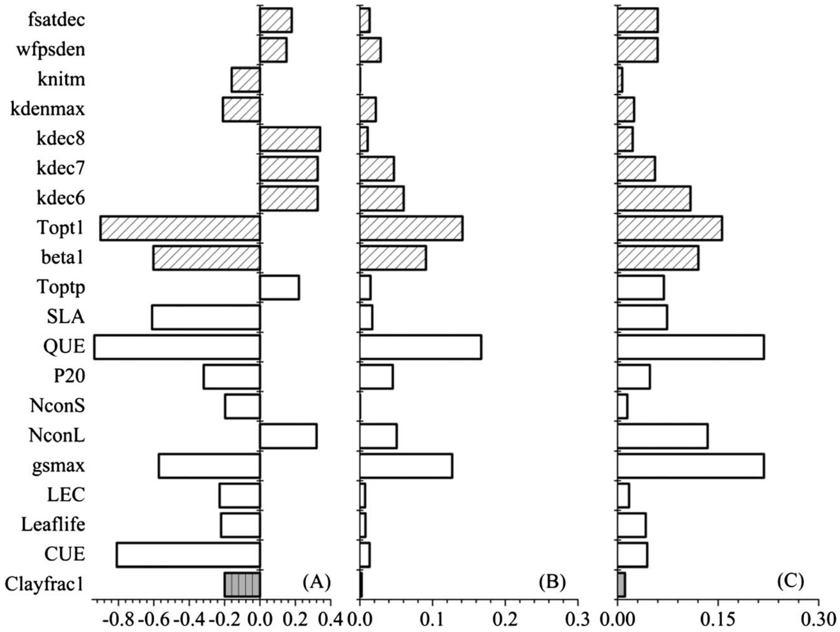

Figure 6. Results of the two-step global sensitivity analysis for long-term annual mean nitrate losses. (A) The relative sensitivity index (RSI), (B) the first-order sensitivity index (S_i), and (C) the total order index (S_{T_i}) of these identified top 20 parameters through screening procedure. Parameters associated with soil physical properties, plant, and soil carbon and nitrogen cycles are highlighted by grey-filled, blank, and dashed bars, respectively

Field studies have shown that nitrate leaching losses from forests are controlled by its availability depending on the sources and transformations and hydrological processes, which control the transport capacity of the system (Sebestyen *et al.*, 2008; Tian *et al.*, 2012c). Parameters identified as controlling long-term mean nitrate losses can be divided into three groups. The first group relates to the source of nitrate, including parameters influencing SOM decomposition, such as maximum SOM decomposition rates (kdec6, kdec7, and kdec8), optimum temperature for SOM decomposition (Topt1), and empirical shape factor for the temperature function (beta1). Parameters of the second group are associated with plant uptake, such as canopy QUE and N content of leaf (NconL). Parameters of the third group describe plant physiological properties controlling hydrological processes and C assimilation, such as SLA, C allocation ratio between leaf and stem (P20), and the maximum stomatal conductance (gsmax). Most of the identified soil C/N cycling parameters are comparable with those obtained in a previous sensitivity analysis of DRAINMOD-NII model that was conducted for agricultural field conditions (Wang *et al.*, 2005). In addition to soil temperature and active pool decomposition rate parameters, Wang *et al.* (2005) found denitrification parameters to be dominant in regulating nitrate losses from agricultural ecosystems. However, denitrification-related parameters were not among these key parameters controlling model predictions of nitrate losses from forests. This is generally evident because forest soils tend to have much lower nitrate concentration compared with the fertilized agricultural land (Tian *et al.*, 2012a). In this study, plant-related parameters were found to be the main factors controlling the long-term nitrate losses because plant uptake is the main sink of nitrate in forest ecosystems. Additionally, plant physiological parameters largely control model predictions of hydrological processes (drainage and ET), which are key factors in regulating physical losses of nitrate (Creed and Band, 1998; Tian *et al.*, 2012c). This is also supported by a previous model calibration for predicting nitrate losses from two loblolly pine plantations (Tian *et al.*, 2012a,2012b).

Nitrogen uptake. Nitrogen uptake is the largest N sink in forest ecosystems, and accurate uptake prediction is essential for quantifying soil C and N cycles. The *RSI*, S_i, and S_{T_i} of the identified top 20 parameters controlling model predictions of N uptake were summarized in Figure 7. Among these selected 20 parameters, 12 parameters were plant related, six were soil C and N related, and two parameters were soil property related (Figure 7A). Results obtained from the LH-OAT and E-FAST suggested similar rankings of these selected parameters. According to the results of the global sensitivity analysis (Figures 7B, C), most parameters affecting N uptake were also found with interaction effects, as suggested by the higher S_{T_i} compared with S_i.

DRAINMOD-FOREST simulates N uptake as a function of biomass increment and tissue N content and the available

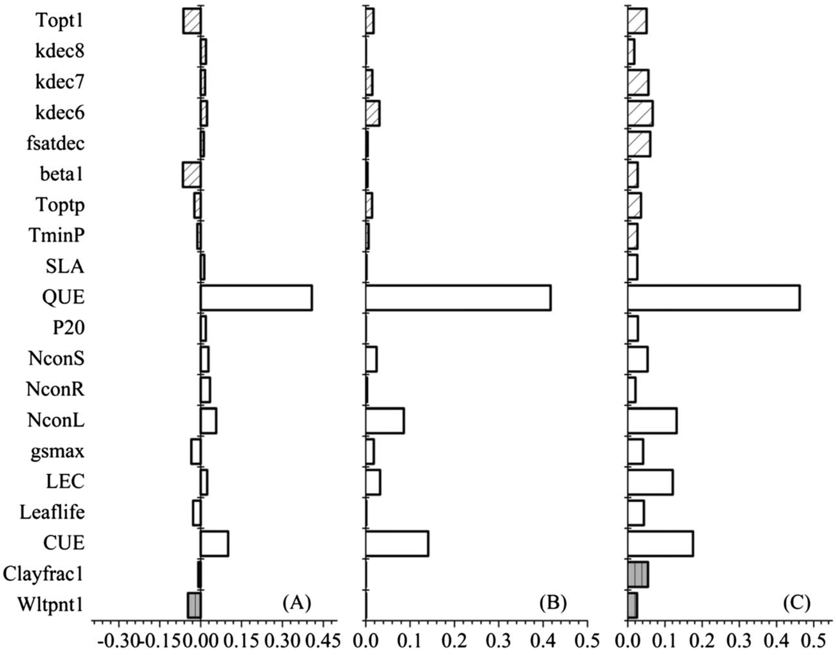

Figure 7. Results of the two-step global sensitivity analysis for long-term annual mean annual nitrogen uptake. (A) The relative sensitivity index (RSI), (B) the first-order sensitivity index (S_i), and (C) the total order index (S_{T_i}) of these identified top 20 parameters through screening procedure. Parameters associated with soil physical properties, plant, and soil carbon and nitrogen cycles are highlighted by grey filled, blank, and dashed bars, respectively

mineral N in the root zone, which is mainly controlled by the N mineralization (Tian *et al.*, 2012a). According to these sensitivity indices from both the LH-OAT and E-FAST methods, plant productivity-related parameters, including canopy QUE and CUE, are the predominant factors regulating N uptake. Given the close relationship between forest production and N uptake, we expected to find out that 16 out of the identified 20 parameters for N uptake were the same as those parameters identified for mean annual NPP (Figure 9). Leaf N content of plant (NconL) was also identified as one of the key parameters controlling N uptake because it affects both mineralization rate (Figure 5) and plant N demand by the plant. Soil C/N cycling parameters that have significant impacts on soil N mineralization rates (Figure 5), such as optimum temperature for SOM decomposition (Topt1) and maximum decomposition rates for active (kdec6) and slow (kdec7) SOM pools, also exert noticeable impacts on N uptake, although not as significant as the plant-related parameters (Figure 7).

DON losses. It has been widely recognized that DON represents a large portion of N leaching from forest ecosystems to surface waters (Perakis and Hedin, 2002; Neff *et al.*, 2003; Tian *et al.*, 2012c). Challenges still exist for accurately predicting DON losses using process-based models because of the current limited understanding of mechanisms controlling sources and sinks of DON, as well as its transport in the soil profile. DRAINMOD-FOREST was modified to simulate key processes associated with transformations and transport of DON in the soil profile (Tian *et al.*, 2013). In the modified model, DON production rates were empirically linked with organic matter pools on forest floor and in forest soil. The Langmuir isotherm was used to quantify the assumed instantaneous equilibrium between potentially soluble organic nitrogen in solid and aqueous phases. DON transport with groundwater flow was simulated using a numerical solution to the advection–dispersion reaction equation.

According to the LH-OAT analysis, there are six parameters clearly influencing model predictions of DON losses, including the maximum adsorption capacity (Maxadsorp), CUE, the fraction of soil microbial pools that is soluble (fsom), maximum decomposition rate of the surface structural litter pool (kdec1), root turnover rate (TurnoverR), and leaf longevity (Leaflife) (Figure 8A). Results of the E-FAST analysis (Figure 8B, C) suggested a different set of six most sensitive parameters: the fraction of soil microbial pool that is soluble (fsom), maximum adsorption capacity (Maxadsorp), binding affinity of the soluble SOM (Bindaff), optimum temperature for SOM decomposition (Topt1), the maximum stomatal conductance (gsmax), and empirical shape factor for temperature function (beta1).

According to the results of both the LH-OAT screening procedure and global sensitivity analysis (Figure 8), we

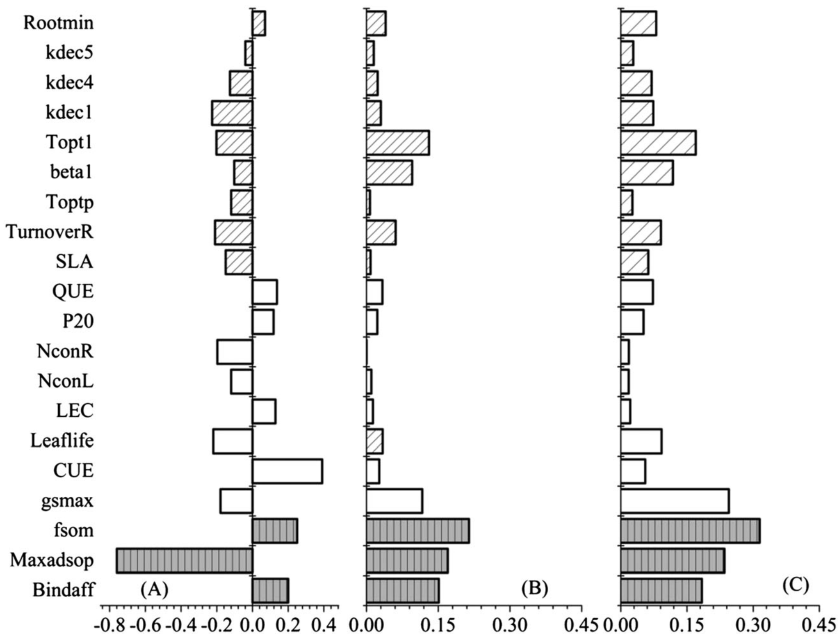

Figure 8. Results of the two-step global sensitivity analysis for long-term annual mean dissolved organic nitrogen (DON) losses. (A) The relative sensitivity index (RSI), (B) the first-order sensitivity index (S_i), and (C) the total order index (S_{T_i}) of these identified top 20 parameters through screening procedure. Parameters associated with soil physical properties, plant, and soil carbon and nitrogen cycles are highlighted by grey-filled, blank, and dashed bars, respectively

found that the most important controlling factors for DON losses are mainly associated with soil sorption, while hydrological flux moderately influences the long-term DON losses. This finding is similar to the results of sensitivity analysis of other process-based models (Neff and Asner, 2001; Yurova *et al.*, 2008), which highlight the importance of accurately parameterizing the sorption algorithm for simulating DON dynamics. This is further supported by an uncertainty analysis of DRAINMOD-FOREST in predicting long-term DON losses (Tian *et al.*, 2013). Additionally, hydrological processes (represented by the maximum stomatal conductance (gsmax)) were also important in predicting long-term annual DON losses. This is consistent with experimental findings that discharge is a key factor explaining the temporal dynamics of DON losses from forest ecosystems (Mitchell, 2001; Tian *et al.*, 2012c). We also found that leaf longevity (leaf life), root turnover rate (TurnoverR), and optimum temperature of SOM decomposition (Topt1) have a moderate effect on predicted mean annual DON losses.

Parameters controlling plant-related outputs

Net primary productivity. Figure 9 shows *RSI*, S_i, and S_{T_i} of the identified top 20 parameters controlling model predictions of mean annual NPP. Ten of the 20 parameters were plant related, eight were associated with soil C and N cycles, and only two parameters were related to soil hydraulic and texture properties (Figure 9A). According to the results of the LH-OAT screening procedure, CUE and QUE have overwhelming positive effects on model predictions of NPP, while parameters associated with temperature constraints for plant growth (Toptp) and SOM decomposition (Topt1), maximum stomatal conductance (gsmax), and leaf longevity (Leaflife) have moderately negative influences. Results of the LH-OAT and E-FAST sensitivity analyses did not show obvious difference in terms of parameter rankings, except for the empirical shape factor for temperature function (beta1). The interaction effects of these parameters were demonstrated by results from E-FAST (Figure 9B, C), as shown by the larger sum of S_{T_i} (1.23), compared with the sum of S_i (0.92).

These results were supported by the sensitivity analysis of the 3-PG model conducted by Esprey *et al.* (2004) and Xenakis *et al.* (2008) who concluded that QUE and CUE were the two key parameters controlling predicted forest NPP in the 3-PG model. The high sensitivity of photosynthesis to QUE was also reported by Verbeeck *et al.* (2006) and Song *et al.* (2012). We also found that the optimum temperature for plant growth (toptp) ranked fourth, which is comparable with results obtained by other sensitivity analysis of 3-PG-based models (Esprey *et al.*, 2004; Xenakis *et al.*, 2008). However, unlike previous sensitivity analyses on the 3-PG model (Esprey *et al.*, 2004; Xenakis *et al.*, 2008; Song *et al.*, 2012), we did not find the NPP highly sensitive to exponent power (PowerBD) in the relationship between stem mass and diameter. This difference can be primarily

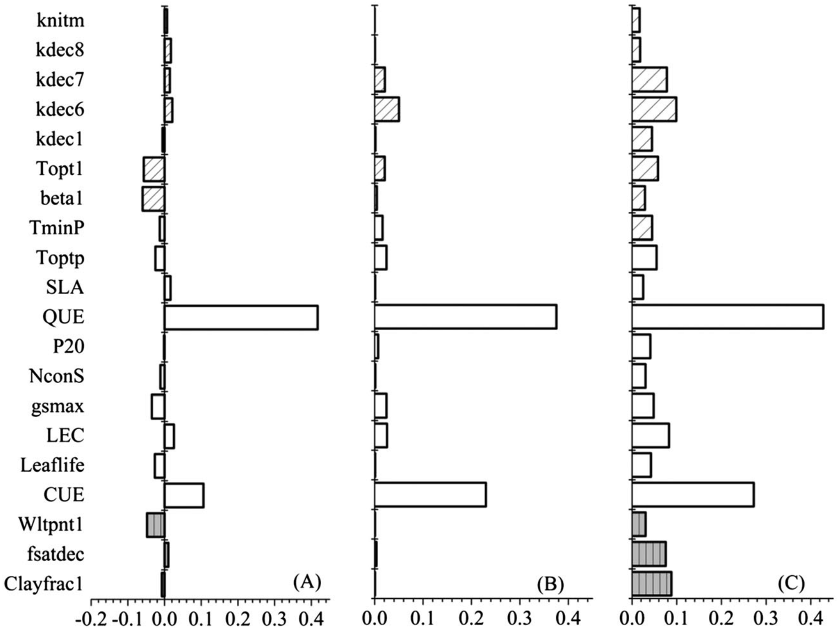

Figure 9. Results of the two-step global sensitivity analysis for long-term annual mean net primary production (NPP). (A) The relative sensitivity index (RSI), (B) the first-order sensitivity index (S_i), and (C) the total order index (S_{T_i}) of these identified top 20 parameters through screening procedure. Parameters associated with soil physical properties, plant, and soil carbon and nitrogen cycles are highlighted by grey-filled, blank, and dashed bars, respectively

attributed to the different ranges specified in this study and the other studies. The parameter range [1.5, 2.84] defined in this study is specified for loblolly pine and was based on insensitive field measurements (Jenkins, 2004), while previous studies determined the parameter range by arbitrarily increasing and decreasing the base value by 30%, resulting in an unrealistic range for loblolly pine [1.7, 3.3]. This example also suggested that researchers must carefully assign proper ranges and distributions to parameters for sensitivity analysis.

Similar to the results of Xenakis *et al.* (2008), results of LH-OAT sensitivity analysis indicated that soil C cycling parameters had little direct impact on productivity of the forest ecosystem. The optimum temperature constraint for SOM decomposition (Topt1) slightly affected model predictions of mean annual NPP, as confirmed by Esprey *et al.* (2004). However, on the basis of the first-order indices of global sensitivity analysis (Figure 9B), the maximum decomposition rate of active SOM pool (kdec6) ranked third and the decomposition rate of slow SOM pool (kdec6) ranked eighth among the 20 parameters influencing model predictions of NPP. The importance of the maximum decomposition rate of active SOM (kdec6) for predicting NPP is consistent with the importance of kdec6 for controlling net mineralization (Figure 5), which is the main source of mineral N affecting vegetation growth and forest productivity. Therefore, results of the global sensitivity analysis are more realistic than those obtained from the LH-OAT sensitivity analysis in this study and in other studies (Esprey *et al.*, 2004; Xenakis *et al.*, 2008).

Compared with other parameters, maximum stomatal conductance was found to be a much less influential parameter affecting model predictions of NPP (Figure 9), suggesting that stomatal conductance does not play a very significant role in simulated C cycle by DRAINMOD-FOREST, which is supported by another sensitivity analysis on an ecosystem model called WxBGC(Miao *et al.*, 2011). However, we think this conclusion is only valid for plant growth models using radiation use efficiency methods to simplify photosynthesis processes, in which the stomatal conductance did not directly affect the exchanges of carbon dioxide between the leaf's interior and ambient air. In reality, the stomatal conductance has been commonly found to be a critical property in regulating the C flux between plant canopy and atmosphere (Kleidon, 2004).

Leaf area index. The LAI is the key variable in regulating water, C, and energy fluxes between canopy and air (Rodriguez-Iturbe, 2000; Arora, 2002). Fourteen of the identified top 20 parameters for model predictions of LAI were plant related, five parameters were associated with soil C/N dynamics, and only one parameter was related to soil hydraulic properties (Figure 10A). According to the results obtained from the LH-OAT screening procedure, LAI was highly sensitive to canopy QUE, CUE, leaf longevity (Leaflife), foliage-to-stem partitioning ratio (P20), and SLA

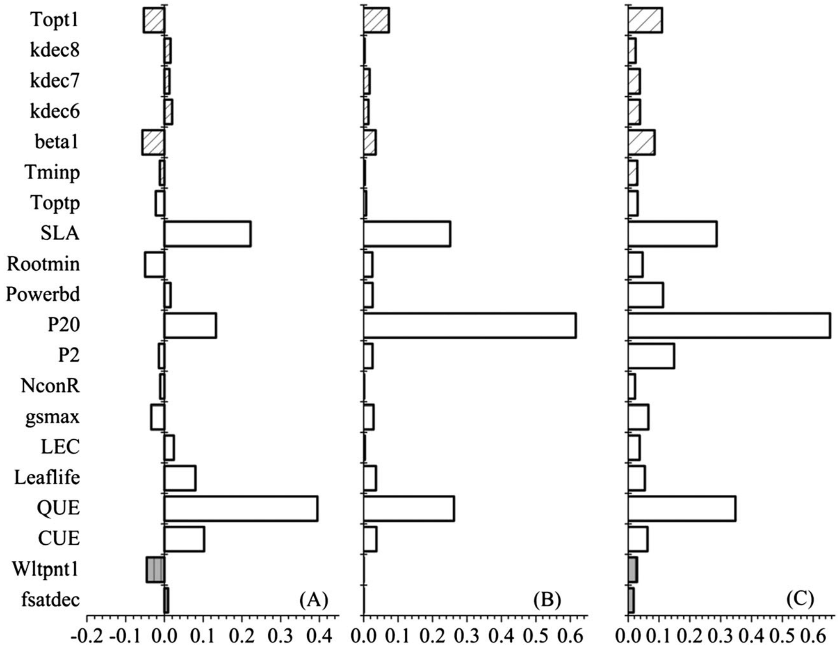

Figure 10. Results of the two-step global sensitivity analysis for long-term annual mean annual leaf area index (LAI). (A) The relative sensitivity index (RSI), (B) the first-order sensitivity index (S_i), and (C) the total order index (S_{T_I}) of these identified top 20 parameters through screening procedure. Parameters associated with soil physical properties, plant, and soil carbon and nitrogen cycles are highlighted by grey-filled, blank, and dashed bars, respectively

of mature trees. The same top four parameters were identified by the OAT analysis of this study and by previous OAT sensitivity analyses of the 3-PG model (Esprey *et al.*, 2004; Xenakis *et al.*, 2008). S_i and S_{T_I} from the E-FAST analysis also suggested similar top sensitive parameters, but with different ranking orders.

These identified top sensitive parameters represent the processes of assimilation and allocation of C and litterfall, which regulate the balance of leaf biomass. For instance, the C allocation ratio between leaf and stem (P20) determines the amount of C allocated to leaf, the canopy QUE dominantly affects the amount the NPP, and the SLA defines the size of LAI for a given unit of leaf biomass. Model predictions of NPP and LAI are noticeably sensitive to maximum decomposition rates of liable SOM pools (kdec6 and kdec7) and optimum temperature of SOM decomposition (Topt1) (Figures 9 and 10), validating the tight linkages between biogeochemical processes and plant growth. The minor negative impacts of the maximum stomatal conductance (gsmax) and wilting point (Wilpnt1) suggest that hydrological parameters only posed limited influence on plant growth in the study site.

Implications

Figure 11 summarizes the S_i indices based on E-FAST global sensitivity analysis. Of a total of 30 parameters (excluding the three parameters specified for DON simulation) selected for nine model outputs, four parameters are related to soil properties, ten are associated with soil C and N cycles, and the other 16 are plant-related parameters. For each model output, the number of parameters with S_i above 0.1 is less than four, suggesting that model performance is only controlled by a few input parameters. This finding provides model users with a useful guide to efficient model calibration by targeting the few most influential parameters for data acquisitions and value adjustments, while safely setting default values for other less influential parameters. Meanwhile, results of the E-FAST sensitivity analysis revealed that the S_{T_I} was higher than S_i across all selected parameters. This suggests that interactions among input parameters were strong and cannot be revealed by local sensitivity analysis using the OAT method. This is especially true for the parameters selected for model predictions of nitrate losses (Figure 6), which is consistent with findings of the previous sensitivity analysis of the DRAINMOD-N II model (Wang *et al.*, 2005).

Hydrological processes are known to play a key role in regulating C and N cycles in many terrestrial ecosystems (Morales *et al.*, 2005). Lack of accurate representation of hydrological processes in ecosystem models could result in large bias in model predictions of C cycle in boreal ecosystems (Govind *et al.*, 2009). Nevertheless, this comprehensive sensitivity analysis did not find a significant effect of soil hydraulic-related parameters on

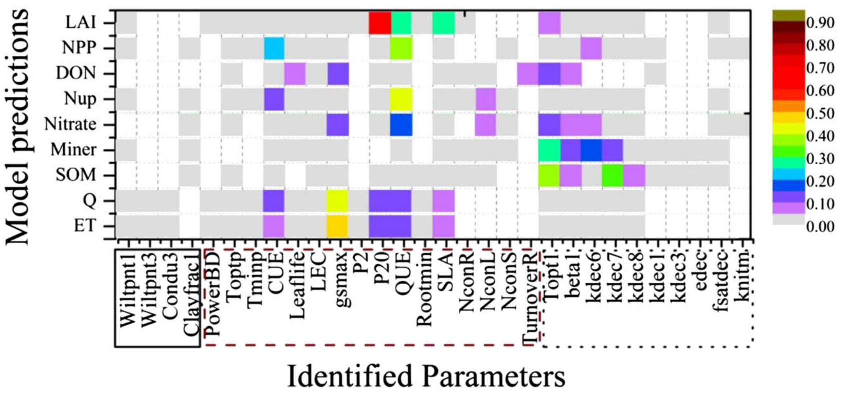

Figure 11. Summary of the first-order sensitivity index (S_i) of E-FAST analysis for each of the nine model outputs. Parameters related to the DON module were excluded from this figure. Parameters associated with soil physical properties, plant, and soil carbon and nitrogen cycles are highlighted by solid, dashed, and dotted rectangles, respectively

predicted long-term mean annual NPP. Hydrology-related parameters were also not in the list of sensitive parameters regulating long-term predicted mean SOM content, although soil moisture has been regarded as one of the key factors regulating SOM decomposition (Schimel *et al*., 1997; Six *et al*., 2002; Reichstein *et al*., 2005). This is mainly due to the site-specific climatic conditions characterized by large precipitation with long-term mean annual precipitation of around 1500 mm and shallow water table depth (about 1 m) (Amatya and Skaggs, 2011; Tian *et al*., 2012a). Because of large precipitation and high water table, soil moisture is not a key factor constraining forest productivity and long-term SOM accumulation at the study site. Similarly, field experiments have found temperature effects on SOM decomposition more pronounced than soil moisture effects in temperate and boreal regions (Davidson *et al*., 2000).

In contrast, this study revealed the critical importance of plant physiological properties in regulating long-term hydrological predictions and suggested that it is essential to quantify the critical role of vegetation for accurate hydrological modelling of the forest ecosystems. Previous studies showed that different dynamic plant growth models used in hydrological simulation models could result in contradictory conclusions. For example, recent global hydrological simulations suggested that the rising atmospheric CO_2 concentration increased continental runoff (Gedney *et al*., 2006; Betts *et al*., 2007), while another simulation study reported opposite conclusions (Piao *et al*., 2007). Results from the comprehensive sensitivity analysis of DRAINMOD-FOREST also demonstrated strong influences of plant physiology-related parameters on model predictions of biogeochemical predictions (Figure 11). In the future, refining the structure, framework, and parameters of the dynamic plant growth model should be of critical importance for investigating hydrological and biogeochemical changes caused by climate and land use changes.

CONCLUSIONS

This study identified key model parameters affecting model predictions of DRAINMOD-FOREST through a simple LH-OAT procedure followed by a two-step global sensitivity analysis. Results showed that long-term hydrological predictions were highly sensitive to plant-related physiological parameters such as maximum stomatal conductance, parameters regulating productivity, C allocation to leaf, and SLA index. Long-term SOM content and mineralization rate were highly sensitive to temperature-related parameters regulating microbial decomposition processes. Mean annual NPP and nitrogen uptake were highly sensitive to plant production-related parameters, including canopy QUE and CUE. Nitrogen uptake was also moderately sensitive to nitrogen content of tree components and SOM decomposition parameters. Mean annual nitrate losses were highly sensitive to parameters controlling plant production, including canopy QUE, CUE, and SOM decomposition parameters. Model predictions of DON losses were predominately controlled by parameters of the adsorption algorithm. LAI was highly sensitive to canopy QUE, CUE, leaf longevity, C allocation coefficient, and SLA of mature trees. Results of this study verified the critical role of plant physiological processes in regulating hydrological and biogeochemical processes in forest ecosystems and demonstrated that it is essential to incorporate a dynamic plant growth model in integrated forest ecosystem models.

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REFERENCES

Albaugh TJ, Allen HL, Dougherty PM, Johnsen KH. 2004. Long term growth responses of loblolly pine to optimal nutrient and water resource availability. *Forest Ecology and Management* **192**: 3–19. DOI: 10.1016/j.foreco.2004.01.002

Amatya DM, Skaggs RW. 2001. Hydrologic modeling of a drained pine plantation on poorly drained soils. *Forest Science* **47**: 103–114.

Amatya DM, Skaggs RW. 2011. Long-term hydrology and water quality of a drained pine plantation in North Carolina. *Transactions of the ASABE* **54**: 2087–2098.

Arora V. 2002. Modeling vegetation as a dynamic component in soil–vegetation–atmosphere transfer schemes and hydrological models. *Reviews of Geophysics* **40**. DOI: 10.1029/2001rg000103

Asbjornsen H, Goldsmith GR, Alvarado-Barrientos MS, Rebel K, Van Osch FP, Rietkerk M, Chen J, Gotsch S, Tobon C, Geissert DR, Gomez-Tagle A, Vache K, Dawson TE. 2011. Ecohydrological advances and applications in plant–water relations research: a review. *Journal of Plant Ecology* **4**: 3–22. DOI: 10.1093/Jpe/Rtr026

Aspinwall MJ, King JS, McKeand SE, Domec JC. 2011. Leaf-level gas-exchange uniformity and photosynthetic capacity among loblolly pine (*Pinus taeda* L.) genotypes of contrasting inherent genetic variation. *Tree Physiology* **31**: 78–91. DOI: 10.1093/treephys/tpq107

Baldwin VC, Peterson KD, Burkhart HE, Amateis RL, Dougherty PM. 1997. Equations for estimating loblolly pine branch and foliage weight and surface area distributions. *Canadian Journal of Forest Research-Revue Canadienne De Recherche Forestiere* **27**: 918–927.

Barton L, McLay CDA, Schipper LA, Smith CT. 1999. Annual denitrification rates in agricultural and forest soils: a review. *Australian Journal of Soil Research* **37**: 1073–1093.

Betts RA, Boucher O, Collins M, Cox PM, Falloon PD, Gedney N, Hemming DL, Huntingford C, Jones CD, Sexton DMH, Webb MJ. 2007. Projected increase in continental runoff due to plant responses to increasing carbon dioxide. *Nature* **448**: 1037–U1035. DOI: 10.1038/Nature06045

Beven KJ. 2008. Environmental Modelling: An Uncertain Future? Routledge: London. UK.

Blanco-Canqui H, Gantzer CJ, Anderson SH, Alberts EE, Ghidey F. 2002. Saturated hydraulic conductivity and its impact on simulated runoff for claypan soils. *Soil Science Society of America Journal* **66**: 1596–1602.

Booker FL, Anttonen S, Heagle AS. 1996. Catechin, proanthocyanidin and lignin contents of loblolly pine (*Pinus taeda*) needles after chronic exposure to ozone. *New Phytologist* **132**: 483–492.

Burton AJ, Pregitzer KS, Ruess RW, Hendrik RL, Allen MF. 2002. Root respiration in North American forests: effects of nitrogen concentration and temperature across biomes. *Oecologia* **131**: 559–568. DOI: 10.1007/s00442-002-0931-7

Creed IF, Band LE. 1998. Export of nitrogen from catchments within a temperate forest: evidence for a unifying mechanism regulated by variable source area dynamics. *Water Resources Research* **34**: 3105–3120.

Dalias P, Anderson JM, Bottner P, Couteaux MM. 2002. Temperature responses of net nitrogen mineralization and nitrification in conifer forest soils incubated under standard laboratory conditions. *Soil Biology & Biochemistry* **34**: 691–701. DOI: 10.1016/S0038-0717(01)00234-6.

Dallatea F, Jokela EJ. 1991. Needlefall, canopy light interception, and productivity of young intensively managed slash and loblolly-pine stands. *Forest Science* **37**: 1298–1313.

Davidson EA, Janssens IA. 2006. Temperature sensitivity of soil carbon decomposition and feedbacks to climate change. *Nature* **440**: 165–173. DOI: 10.1038/Nature04514

Davidson EA, Verchot LV, Cattanio JH, Ackerman IL, Carvalho JEM. 2000. Effects of soil water content on soil respiration in forests and cattle pastures of eastern Amazonia. *Biogeochemistry* **48**: 53–69.

DeLucia EH, George K, Hamilton JG. 2002. Radiation-use efficiency of a forest exposed to elevated concentrations of atmospheric carbon dioxide. *Tree Physiology* **22**: 1003–1010.

Diggs JA. 2004. Simulation of Nitrogen and Hydrology Loading of Forested Fields in Eastern North Carolina using DRAINMOD-N II. North Carolina State University: Raleigh, NC, USA.

Dobler C, Pappenberger F. 2012. Global sensitivity analysis for a complex hydrological model applied in an Alpine watershed. *Hydrological Processes*. DOI: 10.1002/hyp.9520

Domec JC, Palmroth S, Ward E, Maier CA, Therezien M, Oren R. 2009. Acclimation of leaf hydraulic conductance and stomatal conductance of *Pinus taeda* (loblolly pine) to long-term growth in elevated CO_2 (free-air CO_2 enrichment) and N-fertilization. *Plant, Cell & Environment* **32**: 1500–1512. DOI: 10.1111/j.1365-3040.2009.02014.x

Donohue RJ, Roderick ML, McVicar TR. 2007. On the importance of including vegetation dynamics in Budyko's hydrological model. *Hydrology and Earth System Sciences* **11**: 983–995.

EPA. 2003. Draft guidance on the development, evaluation, and application of regulatory environmental models. The Council for Regulatory Environmental Modeling.

Esprey LJ, Sands PJ, Smith CW. 2004. Understanding 3-PG using a sensitivity analysis. *Forest Ecology and Management* **193**: 235–250. DOI: 10.1016/j.foreco.2004.01.032

Ewers BE, Oren R, Kim HS, Bohrer G, Lai CT. 2007. Effects of hydraulic architecture and spatial variation in light on mean stomatal conductance of tree branches and crowns. *Plant, Cell & Environment* **30**: 483–496. DOI: 10.1111/j.1365-3040.2007.01636.x

Fieberg J, Jenkins KJ. 2005. Assessing uncertainty in ecological systems using global sensitivity analyses: a case example of simulated wolf reintroduction effects on elk. *Ecological Modelling*, **187**: 259–280. DOI: 10.1016/j.ecolmodel.2005.01.042

Finzi AC, Schlesinger AH. 2002. Species control variation in litter decomposition in a pine forest exposed to elevated CO_2. *Global Change Biology* **8**: 1217–1229.

Finzi AC, Allen AS, DeLucia EH, Ellsworth DS, Schlesinger WH. 2001. Forest litter production, chemistry, and decomposition following two years of free-air CO_2 enrichment. *Ecology* **82**: 470–484.

Foglia L, Hill MC, Mehl SW, Burlando P. 2009. Sensitivity analysis, calibration, and testing of a distributed hydrological model using error-based weighting and one objective function. *Water Resources Research* **45**: W06427. DOI: 10.1029/2008wr007255

Frey HC, Patil SR. 2002. Identification and review of sensitivity analysis methods. *Risk Analysis* **22**: 553–578.

Gash JHC, Lloyd CR, Lachaud G. 1995. Estimating sparse forest rainfall interception with an analytical model. *Journal of Hydrology* **170**: 79–86. DOI: 10.1016/0022-1694(95)02697-N

Gedney N, Cox PM, Betts RA, Boucher O, Huntingford C, Stott PA. 2006. Detection of a direct carbon dioxide effect in continental river runoff records. *Nature* **439**: 835–838. DOI: 10.1038/Nature04504

Gonzalez-Benecke CA, Martin TA, Clark A, Peter GF. 2010. Water availability and genetic effects on wood properties of loblolly pine (*Pinus taeda*). *Canadian Journal of Forest Research-Revue Canadienne De Recherche Forestiere* **40**: 2265–2277. DOI: 10.1139/X10-162

Govind A, Chen JM, Ju WM. 2009. Spatially explicit simulation of hydrologically controlled carbon and nitrogen cycles and associated feedback mechanisms in a boreal ecosystem. *Journal of Geophysical Research-Biogeosciences* **114**: G02006. DOI: 10.1029/2008jg000728

Green TH, Mitchell RJ, Gjerstad DH. 1994. Effects of nitrogen on the response of loblolly-pine to drought. 2. Biomass allocation and C–N balance. *New Phytologist* **128**: 145–152.

van Griensven A, Meixner T, Grunwald S, Bishop T, Diluzio A, Srinivasan R. 2006. A global sensitivity analysis tool for the parameters of multi-variable catchment models. *Journal of Hydrology* **324**: 10–23. DOI: 10.1016/j.jhydrol.2005.09.008

Haan PK, Skaggs RW. 2003. Effect of parameter uncertainty on DRAINMOD predictions: I. Hydrology and yield. *Transactions of the ASAE* **46**: 1061–1067.

Jenkins JC. 2004. Comprehensive database of diameter-based biomass regressions for North American tree species. USDA Forest Service, General Technical Report NE-319 Newtown Square: PA. USA.

Johnsen K, Samuelson L, Teskey R, McNulty S, Fox T. 2001. Process models as tools in forestry research and management. *Forest Science* **47**: 2–8.

Johnson DW, Todd DE, Tolbert VR. 2003. Changes in ecosystem carbon and nitrogen in a loblolly pine plantation over the first 18 years. *Soil Science Society of America Journal* **67**: 1594–1601.

Jokela EJ, Martin TA. 2000. Effects of ontogeny and soil nutrient supply on production, allocation, and leaf area efficiency in loblolly and slash pine stands. *Canadian Journal of Forest Research-Revue Canadienne De Recherche Forestiere* **30**: 1511–1524.

Jones DL, Healey JR, Willett VB, Farrar JF, Hodge A. 2005. Dissolved organic nitrogen uptake by plants – an important N uptake pathway? *Soil Biology and Biochemistry* **37**: 413–423. DOI: 10.1016/j.soilbio.2004.08.008

Kelly RH, Parton WJ, Crocker GJ, Grace PR, Klir J, Korschens M, Poulton PR, Richter DD. 1997. Simulating trends in soil organic carbon in long-term experiments using the century model. *Geoderma* **81**: 75–90.

Kim H, Amatya DM, Broome SW, Hesterberg DL, Choi M. 2012. Sensitivity analysis of the DRAINWAT model applied to an agricultural watershed in the lower coastal plain, North Carolina, USA. *Water and Environment Journal* **26**: 130–145. DOI: 10.1111/j.1747-6593.2011.00283.x

Kinerson RS, Ralston CW, Wells CG. 1977. Carbon cycling in a loblolly-pine plantation. *Oecologia* **29**: 1–10.

King JS, Thomas RB, Strain BR. 1997. Morphology and tissue quality of seedling root systems of *Pinus taeda* and *Pinus ponderosa* as affected by varying CO_2, temperature, and nitrogen. *Plant and Soil* **195**: 107–119.

King JS, Albaugh TJ, Allen HL, Kress LW. 1999. Stand-level allometry in *Pinus taeda* as affected by irrigation and fertilization. *Tree Physiology* **19**: 769–778.

King JS, Albaugh TJ, Allen HL, Buford M, Strain BR, Dougherty P. 2002. Below-ground carbon input to soil is controlled by nutrient availability and fine root dynamics in loblolly pine. *New Phytologist* **154**: 389–398.

Kioutsioukis I, Tarantola S, Saltelli A, Gatelli D. 2004. Uncertainty and global sensitivity analysis of road transport emission estimates. *Atmospheric Environment* **38**: 6609–6620. DOI: 10.1016/j.atmosenv.2004.08.006

Kirschbaum MUF, Paul KI. 2002. Modelling C and N dynamics in forest soils with a modified version of the CENTURY model. *Soil Biology and Biochemistry* **34**: 341–354.

Kleidon A. 2004. Optimized stomatal conductance of vegetated land surfaces and its effects on simulated productivity and climate. *Geophysical Research Letters* **31**: L21203. DOI: 10.1029/2004gl020769

Knoepp JD, Swank WT. 2002. Using soil temperature and moisture to predict forest soil nitrogen mineralization. *Biology and Fertility of Soils* **36**: 177–182. DOI: 10.1007/s00374-002-0536-7

Knorr W, Prentice IC, House JI, Holland EA. 2005. Long-term sensitivity of soil carbon turnover to warming. *Nature* **433**: 298–301. DOI: 10.1038/Nature03226

Kothawala DN, Moore TR. 2009. Adsorption of dissolved nitrogen by forest mineral soils. *Canadian Journal of Forest Research-Revue Canadienne De Recherche Forestiere* **39**: 2381–2390. DOI: 10.1139/X09-147

Kothawala DN, Moore TR, Hendershot WH. 2008. Adsorption of dissolved organic carbon to mineral soils: a comparison of four isotherm approaches. *Geoderma* **148**: 43–50. DOI: 10.1016/j.geoderma.2008.09.004

Landsberg JJ, Waring RH. 1997. A generalised model of forest productivity using simplified concepts of radiation-use efficiency, carbon balance and partitioning. *Forest Ecology and Management* **95**: 209–228. DOI: 10.1016/S0378-1127(97)00026-1

Lardy R, Bellocchi G, Soussana JF. 2011. A new method to determine soil organic carbon equilibrium. *Environmental Modelling & Software* **26**: 1759–1763. DOI: 10.1016/j.envsoft.2011.05.016

Lehuger S, Gabrielle B, van Oijen M, Makowski D, Germon JC, Morvan T, Henault C. 2009. Bayesian calibration of the nitrous oxide emission module of an agro-ecosystem model. *Agriculture, Ecosystems & Environment* **133**: 208–222. DOI: 10.1016/j.agee.2009.04.022

Leiros MC, Trasar-Cepeda C, Seoane S, Gil-Sotres F. 1999. Dependence of mineralization of soil organic matter on temperature and moisture. *Soil Biology and Biochemistry* **31**: 327–335. DOI: 10.1016/S0038-0717(98)00129-1

Li D, Pan M, Cong Z, Zhang L, Wood E. 2013. Vegetation control on water and energy balance within the Budyko framework. *Water Resources Research* **49**. DOI: 10.1002/wrcr.20107

Lohse KA, Brooks PD, McIntosh JC, Meixner T, Huxman TE. 2009. Interactions between biogeochemistry and hydrologic systems. *Annual Review of Environment and Resources* **34**: 65–96. DOI: 10.1146/annurev.environ.33.031207.111141

Luo W, Jing WH, Jia ZH, Li J, Pan YX. 2009. The effect of PET calculations in DRAINMOD on drainage and crop yields predictions in a subhumid vertisol soil district. *Science in China Series E-Technological Sciences* **52**: 3315–3319. DOI: 10.1007/s11431-009-0349-0

Maier CA, Albaugh TJ, Allen HL, Dougherty PM. 2004. Respiratory carbon use and carbon storage in mid-rotation loblolly pine (*Pinus taeda* L.) plantations: the effect of site resources on the stand carbon balance. *Global Change Biology* **10**: 1335–1350. DOI: 10.1111/j.1529-8817.2003.00809.x

Makela A, Landsberg J, Ek AR, Burk TE, Ter-Mikaelian M, Agren GI, Oliver CD, Puttonen P. 2000. Process-based models for forest ecosystem management: current state of the art and challenges for practical implementation. *Tree Physiology* **20**: 289–298.

Makler-Pick V, Gal G, Gorfine M, Hipsey MR, Carmel Y. 2011. Sensitivity analysis for complex ecological models – a new approach. *Environmental Modelling & Software* **26**: 124–134. DOI: 10.1016/j.envsoft.2010.06.010

Malhi SS, Mcgill WB. 1982. Nitrification in 3 Alberta soils – effect of temperature, moisture and substrate concentration. *Soil Biology and Biochemistry* **14**: 393–399.

Martin TA, Jokela EJ. 2004. Developmental patterns and nutrition impact radiation use efficiency components in southern pine stands. *Ecological Applications* **14**: 1839–1854.

Matamala R, Gonzalez-Meler MA, Jastrow JD, Norby RJ, Schlesinger WH. 2003. Impacts of fine root turnover on forest NPP and soil C sequestration potential. *Science* **302**: 1385–1387.

McCrady RL, Jokela EJ. 1998. Canopy dynamics, light interception, and radiation use efficiency of selected loblolly pine families. *Forest Science* **44**: 64–72.

McNulty SG, Vose JM, Swank WT. 1996. Loblolly pine hydrology and productivity across the southern United States. *Forest Ecology and Management* **86**: 241–251.

Miao ZW, Lathrop RG, Xu M, La Puma IP, Clark KL, Hom J, Skowronski N, Van Tuyl S. 2011. Simulation and sensitivity analysis of carbon storage and fluxes in the New Jersey Pine lands. *Environmental Modelling & Software* **26**: 1112–1122. DOI: 10.1016/j.envsoft.2011.03.004

Mitchell MJ. 2001. Linkages of nitrate losses in watersheds to hydrological processes. *Hydrological Processes* **15**: 3305–3307.

Morales P, Sykes MT, Prentice IC, Smith P, Smith B, Bugmann H, Zierl B, Friedlingstein P, Viovy N, Sabate S, Sanchez A, Pla E, Gracia CA, Sitch S, Arneth A, Ogee J. 2005. Comparing and evaluating process-based ecosystem model predictions of carbon and water fluxes in major European forest biomes. *Global Change Biology* **11**: 2211–2233. DOI: 10.1111/j.1365-2486.2005.01036.x

Mosier AR, Doran JW, Freney JR. 2002. Managing soil denitrification. *Journal of Soil and Water Conservation* **57**: 505–513.

Muller C, Laughlin RJ, Christie P, Watson CJ. 2011. Effects of repeated fertilizer and cattle slurry applications over 38 years on N dynamics in a temperate grassland soil. *Soil Biology and Biochemistry* **43**: 1362–1371. DOI: 10.1016/j.soilbio.2011.03.014

Murthy R, Zarnoch SJ, Dougherty PM. 1997. Seasonal trends of light-saturated net photosynthesis and stomatal conductance of loblolly pine trees grown in contrasting environments of nutrition, water and carbon dioxide. *Plant, Cell & Environment* **20**: 558–568.

Neff JC, Asner GP. 2001. Dissolved organic carbon in terrestrial ecosystems: synthesis and a model. *Ecosystems* **4**: 29–48.

Neff JC, Chapin FS, Vitousek PM. 2003. Breaks in the cycle: dissolved organic nitrogen in terrestrial ecosystems. *Frontiers in Ecology and the Environment* **1**: 205–211.

Nishio T, Fujimoto T. 1990. Kinetics of nitrification of various amounts of ammonium added to soils. *Soil Biology and Biochemistry* **22**: 51–55.

NRCS. 2011. Web Soil Survey. USDA Natural Resources Conservation Service.

Ostertag R, Hobbie SE. 1999. Early stages of root and leaf decomposition in Hawaiian forests: effects of nutrient availability. *Oecologia* **121**: 564–573.

Pappenberger F, Beven KJ, Ratto M, Matgen P. 2008. Multi-method global sensitivity analysis of flood inundation models. *Advances in Water Resources* **31**: 1–14. DOI: 10.1016/j.advwatres.2007.04.009

Parton WJ, Scurlock JMO, Ojima DS, Gilmanov TG, Scholes RJ, Schimel DS, Kirchner T, Menaut JC, Seastedt T, Moya EG, Kamnalrut A, Kinyamario JI. 1993. Observations and modeling of biomass and soil organic-matter dynamics for the grassland biome worldwide. *Global Biogeochemical Cycles* **7**: 785–809.

Pastor J, Post WM. 1986. Influence of climate, soil-moisture, and succession on forest carbon and nitrogen cycles. *Biogeochemistry* **2**: 3–27. DOI: 10.1007/Bf02186962

Paul KL, Jacobsen K, Koul V, Leppert P, Smith J. 2008. Predicting growth and sequestration of carbon by plantations growing in regions of low-rainfall in southern Australia. *Forest Ecology and Management* **254**: 205–216. DOI: 10.1016/j.foreco.2007.08.003

1Perakis SS, Hedin LO. 2002. Nitrogen loss from unpolluted South American forests mainly via dissolved organic compounds. *Nature* **415**: 416–419.

Piao SL, Friedlingstein P, Ciais P, de Noblet-Ducoudre N, Labat D, Zaehle S. 2007. Changes in climate and land use have a larger direct impact than rising CO2 on global river runoff trends. *Proceedings of the National Academy of Sciences of the United States of America* **104**: 15242–15247. DOI: 10.1073/pnas.0707213104

Pritchard SG, Strand AE, McCormack ML, Davis MA, Finzi AC, Jackson RB, Matamala R, Rogers HH, Oren R. 2008. Fine root dynamics in a loblolly pine forest are influenced by free-air-CO_2-enrichment: a six-year-mini rhizotron study. *Global Change Biology* **14**: 588–602. DOI: 10.1111/j.1365-2486.2007.01523.x

Reichstein M, Subke JA, Angeli AC, Tenhunen JD. 2005. Does the temperature sensitivity of decomposition of soil organic matter depend upon water content, soil horizon, or incubation time? *Global Change Biology* **11**: 1754–1767. DOI: 10.1111/j.1365-2486.2005.001010.x

Rodriguez-Iturbe I. 2000. Ecohydrology: a hydrologic perspective of climate-soil-vegetation dynamics. *Water Resources Research* **36**: 3–9.

Saad OALO, Conrad R. 1993. Temperature-dependence of nitrification, denitrification, and turnover of nitric-oxide in different soils. *Biology and Fertility of Soils* **15**: 21–27.

Saltelli A, Annoni P. 2010. How to avoid a perfunctory sensitivity analysis. *Environmental Modelling & Software* **25**: 1508–1517. DOI: 10.1016/j.envsoft.2010.04.012

Saltelli A, Tarantola S, Chan KPS. 1999. A quantitative model-independent method for global sensitivity analysis of model output. *Technometrics* **41**: 39–56.

Saltelli A, Tarantola S, Campolongo F. 2000. Sensitivity analysis as an ingredient of modeling. *Statistical Science* **15**: 377–395.

Saltelli A, Ratto M, Tarantola S, Campolongo F. 2005. Sensitivity analysis for chemical models. *Chemical Reviews* **105**: 2811–2827. DOI: 10.1021/Cr040659d

Sampson DA, Allen HL. 1998. Light attenuation in a 14-year-old loblolly pine stand as influenced by fertilization and irrigation. *Trees-Structure and Function* **13**: 80–87.

Samuelson LJ, Johnsen K, Stokes T. 2004. Production, allocation, and stemwood growth efficiency of *Pinus taeda* L. stands in response to 6 years of intensive management. *Forest Ecology and Management* **192**: 59–70. DOI: 10.1016/j.foreco.2004.01.005

Schimel DS, Braswell BH, Parton WJ. 1997. Equilibration of the terrestrial water, nitrogen, and carbon cycles. *Proceedings of the National Academy of Sciences of the United States of America* **94**: 8280–8283.

Scott NA, Binkley D. 1997. Foliage litter quality and annual net N mineralization: comparison across North American forest sites. *Oecologia* **111**: 151–159.

Sebestyen SD, Boyer EW, Shanley JB, Kendall C, Doctor DH, Aiken GR, Ohte N. 2008. Sources, transformations, and hydrological processes that control stream nitrate and dissolved organic matter concentrations during snowmelt in an upland forest. *Water Resources Research* **44**: W12410. DOI: 10.1029/2008wr006983

Shi KJ, Cao QV. 1997. Predicted leaf area growth and foliage efficiency of loblolly pine plantations. *Forest Ecology and Management* **95**: 109–115.

Sieber A, Uhlenbrook S. 2005. Sensitivity analyses of a distributed catchment model to verify the model structure. *Journal of Hydrology* **310**: 216–235. DOI: 10.1016/j.jhydrol.2005.01.004

Simek M, Jisova L, Hopkins DW. 2002. What is the so-called optimum pH for denitrification in soil? *Soil Biology and Biochemistry* **34**: 1227–1234.

Simlab. 2011. Software package for uncertainty and sensitivity analysis. Joint Research Centre of the European Commission.

Six J, Conant RT, Paul EA, Paustian K. 2002. Stabilization mechanisms of soil organic matter: implications for C-saturation of soils. *Plant and Soil* **241**: 155–176.

Skaggs RW. 1999. Drainage simulation models. In: RW Skaggs and J Van Schilfgaarde, editors, Agricultural drainage. Agron. Monogr. 38. ASA, CSSA, SSSA, Madison, WI. p. 469–500.

Skaggs RW, Youssef MA, Chescheir GM. 2012. DRAINMOD: model use, calibration, and validation. *Transactions of the ASABE* **55**: 1509–1522.

Smethurst PJ, Matschonat G, Ballard LM, Dingle JK. 1999. Phase partitioning of ammonium in Australian and European forest soils. *Communications in Soil Science and Plant Analysis* **30**: 2023–2034.

Sobol IM. 2001. Global sensitivity indices for nonlinear mathematical models and their Monte Carlo estimates. *Mathematics and Computers in Simulation* **55**: 271–280.

Song XD, Bryan BA, Paul KI, Zhao G. 2012. Variance-based sensitivity analysis of a forest growth model. *Ecological Modelling* **247**: 135–143. DOI: 10.1016/j.ecolmodel.2012.08.005

Stark JM, Firestone MK. 1996. Kinetic characteristics of ammonium-oxidizer communities in a California oak woodland-annual grassland. *Soil Biology and Biochemistry* **28**: 1307–1317.

Strain BR, Higginbotham KO, Mulroy JC. 1976. Temperature preconditioning and photosynthetic capacity of *Pinus-taeda* L. *Photosynthetica* **10**: 47–53.

Tang Y, Reed P, van Werkhoven K, Wagener T. 2007. Advancing the identification and evaluation of distributed rainfall-runoff models using global sensitivity analysis. *Water Resources Research* **43**: W06415. DOI: 10.1029/2006wr005813.

Teskey RO, Bongarten BC, Cregg BM, Dougherty PM, Hennessey TC. 1987. Physiology and genetics of tree growth response to moisture and temperature stress: an examination of the characteristics of loblolly pine (*Pinus taeda* L.). *Tree Physiology* **3**: 41–61.

Tian S, Youssef MA, Skaggs RW, Amatya DM, Chescheir GM. 2012a. DRAINMOD-FOREST: integrated modeling of hydrology, soil carbon and nitrogen dynamics, and plant growth for drained forests. *Journal of Environmental Quality* **41**: 764–782. DOI: 10.2134/Jeq2011.0388

Tian S, Youssef MA, Skaggs RW, Amatya DM, Chescheir GM. 2012b. Modeling water, carbon, and nitrogen dynamics for two drained pine plantations under intensive management practices. *Forest Ecology and Management* **264**: 20–36. DOI: 10.1016/j.foreco.2011.09.041

Tian S, Youssef MA, Skaggs RW, Amatya DM, Chescheir GM. 2012c. Temporal variations and controlling factors of nitrogen export from an artificially drained coastal forest. *Environmental Science & Technology* **46**: 9956–9963. DOI: 10.1021/Es3011783

Tian S, Youssef MA, Skaggs RW, Amatya DM, Chescheir GM. 2013. Predicting dissolved organic nitrogen export from an drained pine plantation. *Water Resources Research* **49**: 1952–1967. DOI: 10.1002/wrcr.20157

Valentine HT, Gregoire TG, Burkhart HE, Hollinger DY. 1997. A stand-level modes of carbon allocation and growth, calibrated for loblolly pine. *Canadian Journal of Forest Research-Revue Canadienne De Recherche Forestiere* **27**: 817–830.

Van Oijen M, Rougier J, Smith R. 2005. Bayesian calibration of process-based forest models: bridging the gap between models and data. *Tree Physiology* **25**: 915–927.

Vandenbruwane J, De Neve S, Qualls RG, Sleutel S, Hofman G. 2007. Comparison of different isotherm models for dissolved organic carbon (DOC) and nitrogen (DON) sorption to mineral soil. *Geoderma* **139**: 144–153. DOI: 10.1016/j.geoderma.2007.01.012

Verbeeck H, Samson R, Verdonck F, Lemeur R. 2006. Parameter sensitivity and uncertainty of the forest carbon flux model FORUG: a Monte Carlo analysis. *Tree Physiology* **26**: 807–817.

Vernimmen RRE, Verhoet HA, Verstraten JM, Bruijnzeel LA, Kiomp NS, Zoomer HR, Wartenbergh PE. 2007. Nitrogen mineralization, nitrification and denitrification potential in contrasting lowland rain forest types in Central Kalimantan, Indonesia. *Soil Biology and Biochemistry* **39**: 2992–3003. DOI: 10.1016/j.soilbio.2007.06-005

Wang X, Youssef MA, Skaggs RW, Atwood JD, Frankenberger JR. 2005. Sensitivity analyses of the nitrogen simulation model, DRAINMOD-N II. *Transactions of ASAE* **48**: 2205–2212.

Waring RH, Landsberg JJ. 2011. Generalizing plant–water relations to landscapes. *Journal of Plant Ecology* **4**: 101–113. DOI: 10.1093/Jpe/Rtq041

Will RE, Markewitz D, Hendrick RL, Meason DF, Crocker TR, Borders BE. 2006. Nitrogen and phosphorus dynamics for 13-year-old loblolly pine stands receiving complete competition control and annual N fertilizer. *Forest Ecology and Management* **227**: 155–168. DOI: 10.1016/j.foreco.2006.02.027

Xenakis G, Ray D, Mencuccini M. 2008. Sensitivity and uncertainty analysis from a coupled 3-PG and soil organic matter decomposition model. *Ecological Modelling* **219**: 1–16. DOI: 10.1016/j.ecolmodel.2008.07.020

Youssef MA. 2003. Modeling Nitrogen Transport and Transformations in High Water Table Soils. North Carolina State University: Raleigh, NC, USA.

Youssef MA, Skaggs RW, Chescheir GM, Gilliam JW. 2005. The nitrogen simulation model, DRAINMOD-N II. *Transactions of ASAE* **48**: 611–626.

Yurova A, Sirin A, Buffam I, Bishop K, Laudon H. 2008. Modeling the dissolved organic carbon output from a boreal mire using the convection-dispersion equation: importance of representing sorption. *Water Resources Research* **44**. W07411. DOI: 10.1029/2007wr006523

Zhang SS, Allen HL. 1996. Foliar nutrient dynamics of 11-year-old loblolly pine (Pinus taeda) following nitrogen fertilization. *Canadian Journal of Forest Research-Revue Canadienne De Recherche Forestiere* **26**: 1426–1439.

Zhou X, Hemstrom MA, Pacific Northwest Research Station (Portland Or.). 2009. Estimating Aboveground Tree Biomass on Forest Land in the Pacific Northwest: A Comparison of Approaches. United States Dept. of Agriculture, Forest Service: Pacific Northwest Research Station.

APPENDIX: RANGES AND DISTRIBUTIONS OF INPUT PARAMETERS

Table A1. Hydrologic and soil parameters for different soil layers

Parameters	Abbreviations	Soil layers (cm) 0–40	40–100	100–200	Sources
Soil conductivity (mm s^{-1})	Cond*ui*	U(14–42)	U(4–14)	U(4–24)	(NRCS, 2011)
Wilting point ($\text{cm}^3\,\text{cm}^{-3}$)	Wltpnt*i*	U(0.04–0.14)	U(0.04–0.27)	U(0.04–0.34)	
Drainable porosity	Drainθ*i*	U(0.05–0.15)	U(0.05–0.15)	U(0.05–0.15)	
Bulk density (g cm^{-3})	$\rho_b i$	U(0.8–1.2)	U(1.0–1.4)	U(1.0–1.6)	
Clay fraction (%)	Clayfrac*i*	U(5–20)	U(18–35)	U(0–40)	
Distribution coefficient	m*i*	U(0.37–26.2)	U(0.17–8)	U(0.07–8)	(Smethurst *et al*., 1999)

Note: U(Min, Max) = uniform distribution with the minimum (Min) and maximum (Max) values, *i* = 1, 2, 3, representing the three soil layers, respectively.

Table A2. Parameters for simulating soil C and N cycles

Parameters	Abbreviations		Sources
Transport			
Longitudinal dispersivity (cm)	Londis	U(0.2–29.8)	
Tortuosity	τ	U(0.3–0.7)	(Wang *et al*., 2005)
Nitrification			
Maximum rate ($\mu\text{g g}^{-1}\,\text{day}^{-1}$)	knitmax	U(0.4–33.5)	(Nishio and Fujimoto, 1990; Stark and Firestone, 1996; Diggs, 2004; Vernimmen *et al*., 2007)
Half saturation constant ($\mu\text{g g}^{-1}$)	knitm	U(0.3–0.7)	(Nishio and Fujimoto, 1990)
Optimum temperature (°C)	Toptnit	U(0.3–0.7)	(Malhi and Mcgill, 1982; Saad and Conrad, 1993)
Empirical shape factor	betanit	U(0.3–0.7)	(Saad and Conrad, 1993; Wang *et al*., 2005)
Upper pH limits	pHup	U(7–9)	(Mosier *et al*., 2002; Simek *et al*., 2002; Wang *et al*., 2005)
Lower pH limits	pHlow	U(5–7)	
Value of pH function for low	fpHlow	U(0–0.2)	(Wang *et al*., 2005)
Value of pH function for high	fpHup	U(0–0.4)	
Empirical exponent for pH	pHexp	U(0.5–2)	
Upper soil moisture (θ) limits	θup	U(0.6–0.8)	(Wang *et al*., 2005; Lehuger *et al*., 2009)
Lower θ limits	θlow	U(0.3–0.6)	
Value of θ function at θlow	fwp-nit	U(0.1–0.4)	(Wang *et al*., 2005)
Value of θ function at θup	fsat-nit	U(0–0.2)	

(Continues)

Table A2. Continued

Parameters	Abbreviations		Sources
Exponent for θ function	enit	U(0.5–2)	
Denitrification			
Maximum rate (μg g^{-1} day^{-1})	kdenmax	U(1.0–7.0)	(Barton *et al.*, 1999; Wang *et al.*, 2005)
Half saturation constant (μg g^{-1})	kdenm	U(5.0–120)	(Wang *et al.*, 2005; Lehuger *et al.*, 2009)
Optimum temperature (°C)	Toptden	U(18.5–35)	(Saad and Conrad, 1993)
Empirical shape factor	betaden	U(0.09–0.37)	(Wang *et al.*, 2005)
Threshold of relative saturation	wfpsden	U(0.5–0.9)	
Empirical exponent for θ	eden	U(1.5–2.5)	
Maximum decomposition rates of each SOM pool			
Surface structural litter pool	Kdec1	U(0.00055–0.022)	(Parton *et al.*, 1993; Kelly *et al.*, 1997; Kirschbaum and Paul, 2002; Diggs, 2004)
Surface metabolic litter pool	Kdec2	U(0.003–0.05)	
Surface microbial pool	Kdec3	U(0.006–0.06)	
Belowground metabolic pool	Kdec4	U(0.004–0.09)	
Belowground structural pool	Kdec5	U(0.0006–0.027)	
Active SOM pool	Kdec6	U(0.00055–0.04)	
Slow SOM pool	Kdec7	U(0.00007–0.001)	
Passive SOM pool	Kdec8	U(0.000001–0.00004)	
Environmental factors regulates SOM decomposition			
Optimum temperature(°C)	Topt1	U(18.5–35)	(Saad and Conrad, 1993)
Empirical shape factor	Beta1	U(0.093–0.372)	(Wang *et al.*, 2005)
Value of θ function at wf	fwp-dec	U(0.1–0.4)	
Value of θ function at ws	fsat-dec	U(0.4–0.7)	
Empirical exponent for θ	edec	U(0.5–2.0)	
DON-related parameters			
Dissolvable fraction of microbial and metabolic pool	fsom	U(0.3–0.6)	(Neff and Asner, 2001)
Maximum adsorption capacity (mg g^{-1})	Adsorpmax	U(0.2–30)	(Vandenbruwane *et al.*, 2007; Kothawala *et al.*, 2008; Kothawala and Moore, 2009)
Binding affinity (10^{-3} cm^{3} mg^{-1})	Bindaff	U(0.2–50)	
Diffusion coefficient (cm^{2} day^{-1})	Diffcoeff	U(0.3–5)	(Jones *et al.*, 2005)

Table A3. Vegetation input parameters

Parameters	Abbreviations		Sources
Foliage: stem partitioning coefficients	P2	U(0.5–1.1)	(Valentine *et al.*, 1997; King *et al.*, 1999; King *et al.*, 2002; Maier *et al.*, 2004; Samuelson *et al.*, 2004)
	P20	U(0.4–0.9)	
Maximum fraction of NPP to roots	Rootmax	U(0.35–0.6)	
Minimum fraction of NPP to roots	Rootmin	U(0.2–0.35)	
Constant in the stem mass *versus* diameter relationship	ConsBD	U(0.06–0.13)	(Jenkins, 2004; Samuelson *et al.*, 2004; Zhou *et al.*, 2009)
Power in the stem mass *versus* diameter relationship	PowerBD	U(1.5–2.84)	
Minimum temperature for growth (°C)	Tminp	U(−2–2)	(Strain *et al.*, 1976; Teskey *et al.*, 1987; McNulty *et al.*, 1996)
Optimum temperature for growth (°C)	Toptp	U(17–25)	
Maximum temperature for growth (°C)	Tmaxp	U(35–45)	
Leaf longevity (months)	Leaflife	U(18–22)	(Zhang and Allen, 1996; Finzi *et al.*, 2001; Will *et al.*, 2006)
Average root turnover rate (10^{-2} day^{-1})	TurnoverR	U(0.17–0.8)	(King *et al.*, 2002; Pritchard *et al.*, 2008)
Specific leaf area (all sided) (m^{2} kg^{-1})	SLA	N(10.8, 3.9)	(Baldwin *et al.*, 1997; Shi and Cao, 1997; Jokela and Martin, 2000; Ewers *et al.*, 2007)
Extinction coefficient of PAR by canopy	LEC	U(0.42–0.76)	(McCrady and Jokela, 1998; Sampson and Allen, 1998; DeLucia *et al.*, 2002)

(Continues)

Table A3. Continued

Parameters	Abbreviations		Sources
Canopy quantum efficiency (g MJ^{-1})	QUE	U(0.4–0.83)	(Dallatea and Jokela, 1991; DeLucia *et al*., 2002; Martin and Jokela, 2004)
Carbon use efficiency	CUE	U(0.35-0.69)	(Kinerson *et al*., 1977; Maier *et al*., 2004)
Maximum stomatal conductance (mmol H_2O m^{-2} s^{-1})	gsmax	U(85–212)	(Green *et al*., 1994; Murthy *et al*., 1997; Amatya and Skaggs, 2001; Domec *et al*., 2009; Gonzalez-Benecke *et al*., 2010; Aspinwall *et al*., 2011)
Nitrogen content of leaf (%)	NconL	N(1, 0.3)	(Green *et al*., 1994; King *et al*., 1997; Murthy *et al*., 1997; Burton *et al*., 2002; Albaugh *et al*., 2004; Will *et al*., 2006; Gonzalez-Benecke *et al*., 2010)
Nitrogen content of stem (%)	NconS	N(0.14, 0.06)	
Nitrogen content of fine root (%)	NconR	N(0.74, 0.34)	
Lignin content of leaf (%)	LconL	U(22–25)	(Booker *et al*., 1996; Finzi and Schlesinger, 2002)
Lignin content of stem (%)	LconS	U(25-30)	
Lignin content of fine root (%)	LconR	U(23-26)	

Note: U(Min, Max) = uniform distribution, N(mean, SD) = normal distribution. The mean and standard deviation for Gaussian distribution and minimum and maximum for uniform distribution were derived from published references.