Development and preliminary evaluation of an integrated field scale model for perennial bioenergy grass ecosystems in lowland areas

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Abstract

Computer models are useful tools for evaluating environmental and economic sustainability of proposed dedicated cellulosic grass ecosystems for biofuel production. This study developed an integrated, field scale, and process-based ecosystem model (DRAINMOD-GRASS) for simulating hydrological processes, soil carbon and nitrogen cycling, and plant growth in cropping systems for producing bioenergy grasses in lowland areas. We tested the model using measurements from three replicated switchgrass (*Panicum virgatum*) plots located in eastern North Carolina, USA. Results showed that the model accurately predicted 5-year (2009-2013) biomass yield. Predicted daily water table depth closely matched field measurements with Nash-Sutcliffe coefficient of 0.86. The model also accurately predicted temporal dynamics of daily soil moisture and temperature with Nash-Sutcliffe coefficients of 0.7 and 0.9, respectively. Predicted seasonal changes in net N mineralization and nitrification rates were comparable to field measurements in 2011 and 2012.

Key words: DRAINMOD-GRASS, hydrology, biogeochemistry, grass growth, switchgrass

1. Introduction

Biofuel production is expected to play a key role for ensuring global energy security (Dale et al., 2014). Competition for global food supply from first generation biofuel crops such as maize and sorghum will eventually limit expansion of grain-based biofuel production (Schmer et al., 2008). Thus, attention has been shifted to second generation liquid biofuel made from dedicated cellulosic grasses such as switchgrass (*Panicum virgatum*) and *Miscanthus spp.* (McLaughlin and Kszos, 2005; Schmer et al., 2008; Tilman et al., 2009). Such a change would necessitate large scale planting of bioenergy crops to meet global demand of biofuel. Economic and environmental implications of potential land use changes need to be thoroughly evaluated prior to large scale implementation (Feng et al., 2015; Williams et al., 2009).

Computer models are useful for projecting long-term biomass yield under various climatic and site-specific conditions and evaluating potential environmental and ecological impacts of converting

current land uses to cellulosic biomass production (Nair et al., 2012; Taubert et al., 2012; Thomas et al., 2013). Empirical models have been developed and applied for simulating bioenergy grass development based on robust relationships between plant growth and environmental conditions by assuming no nutrient limitations (Grassini et al., 2009). Process-based crop models have also been successfully adapted or developed to simulate biomass yield for a number of proposed bioenergy crops (Nair et al., 2012). Computer models have also evaluated effects of bioenergy crops on water quality using the SWAT or APEX (Demissie et al., 2012; Feng et al., 2015) or LIXIM models (Lesur et al., 2013); on biogeochemical cycling using DNDC (Gopalakrishnan et al., 2012) and DAYCENT models (Davis et al., 2012; Davis et al., 2010); on hydrological processes using a multilayer canopy-root-soil system (Le et al., 2011) and AGRO-IBIS models (Vanloocke et al., 2010), and on soil organic matter changes using the ROTHC model (McLauchlan et al., 2006).

Although existing models provided important information for policy development and decision-making, only a few of them are suitable for comprehensive model predictions in terms of biomass yield, biogeochemistry, and hydrology (Thomas et al., 2013). This has limited a thorough evaluation of environmental (i.e. water quantity and quality) and economic (i.e. biomass) impacts of land use changes associated with bioenergy biomass production. For instance, some crop yield models focus on simulating or predicting annual biomass yield, while oversimplifying hydrological and biogeochemical cycling of the system. Many existing grass ecosystem models lack hydrological modules and/or a soil C and N cycling modules with sufficient details (Taubert et al., 2012). On the other hand, many current hydrology and biogeochemistry models do not have a detailed dynamic plant growth module (Arora, 2002). Findings from some modeling studies (Le et al., 2011) received criticism because they did not use a dynamic plant growth component under various climate and site conditions, which may constrain applicability of model simulations (Basso et al., 2012). A process-based model that represents the complete agro-ecosystem with integrated interactions between water, soil C and N, and vegetation is necessary to adequately investigate bioenergy grass systems (Thomas et al., 2013).

The Atlantic coastal plain of the southeastern USA could be an important source of cellulosic biomass for achieving the national biofuel production target because of its large area, long growing season, favorable temperature, sufficient water, and suitable soil (Wullschlegel et al., 2010). It is important to evaluate the productivity and environmental consequences (i.e. changes in water use and water quality) of potential land use changes for producing cellulosic biomass in this region. The objective of this study was to develop and test an integrated ecosystem model for simulating water,

soil carbon (C), and nitrogen (N) dynamics, and grass growth in bioenergy grass ecosystems with high water table soils. This integrated ecosystem model (DRAINMOD-GRASS) was developed primarily as a research tool to study the intrinsically interacting processes of hydrology, biogeochemistry, and plant physiology in a perennial bioenergy grass production system. Meanwhile, information obtained from model simulation can also assist resource managers and policy-makers in making scientifically based decisions.

2. Model development

2.1 Overview of the modeling framework for perennial grasslands

The model was developed by adding a perennial grass growth component to DRAINMOD and DRAINMOD-NII models. This strategy is similar to DRAINMOD-FOREST, which was developed as a field-scale, mechanistic, fully integrated ecosystem model for simulating water, soil C and N dynamics, and tree growth in artificially-drained lowland area forests under various management practices (Tian et al., 2012, 2013). Previous model evaluations and applications (Tian et al., 2012, 2012b, 2013) demonstrate that DRAINMOD-FOREST, with its three integrated components (hydrology, soil C/N, and vegetation growth) provides a valid template for developing a model for simulating hydrological and biogeochemical processes and plant growth in bioenergy grass systems with high water table soils.

DRAINMOD-GRASS was developed to predict productivity of bioenergy grasses (e.g. switchgrass, miscanthus) and other perennial grasses in lowland areas under different weather conditions and management practices, including fertilization and harvest methods, and evaluate effects of bioenergy grasses and other perennial grasses cultivation on hydrological and biogeochemical (mainly carbon and nitrogen) processes that influence water quality and carbon sequestration. To develop the desired integrated grass ecosystem model, with focus on bioenergy grasses, the tree growth module in DRAINMOD-FOREST was replaced with a grass growth module (Figure 1). The following section briefly describes the hydrological and soil C/N components, and presents detailed documentation of the newly incorporated grass growth component that is running on a daily time step. Brief literature review and key equations that were introduced for developing DRAINMOD-GRASS are listed in supplementary materials.

Figure 1: The schematic diagram of DRAINMOD-GRASS showing the grass growth module (① to ⑤) and its interactions (⑥ to ⑩) with DRAINMOD and DRAINMOD-N II. This is an adaption and modification of the detailed diagram of DRAINMOD-FOREST (Tian et al., 2012a). ①: estimate gross primary production (GPP); ②: estimate net primary production (NPP) after account plant respiration; ③: carbon allocation to different vegetation components; ④: Utilization of Nonstructural carbon (NSC) store for sprouting or combat environmental stresses; ⑤: Biomass harvest; Grass growth is affected by soil water (H₂O) availability(⑥) and soil nitrogen (N) availability (⑦); Hydrological processes is partly regulated by leaf area index (LAI) and grass root distribution(⑧), Soil C and N cycling is affected by soil water and temperature conditions and water movement (⑨), as well as grass root distribution and liter inputs(⑩).

2.2. Hydrology and soil C/N simulation

The hydrological component, DRAINMOD (Skaggs et al., 2012), conducts a water balance at the soil surface and along a soil column midway between two parallel drains on a daily or hourly basis. At each time step, the model simulates key hydrological processes including infiltration, evapotranspiration (ET), subsurface drainage, surface runoff, subirrigation, deep and lateral seepage, water table fluctuation, and soil water distribution in the vadose zone. Specifically, infiltration is simulated by 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. Soil water distribution in the unsaturated zone is quantified using soil water characteristic curves under the assumption of a hydrostatic drained-to-equilibrium condition. ET is a function of potential ET (PET), soil water conditions, and predicted dynamic root depth, which regulates accessibility of vegetation to soil water. The PET is calculated by the Penman-Monteith method with dynamic stomatal conductance controlled by climate conditions and predicted leaf area index (LAI). The FAO- Penman-Monteith method is used for estimating PET during non-growing seasons. Following the method proposed by Couturier and Ripley (1973), rainfall interception by grass canopy is simulated as a function of LAI, storage capacity and rainfall amount (Eq. [S-1]). Storage capacity is separately calculated for dead and live leaf mass due to their different water holding capacities (Eq. [S-2]).

The soil C and N module was adapted from a soil C and N model, DRAINMOD-NII (Youssef et al., 2005), which simulates detailed daily N transformation processes including atmospheric deposition, application of mineral N fertilizers and organic N sources, plant uptake, N mineralization /immobilization, nitrification, denitrification, ammonia volatilization, and mineral N losses via deep seepage, subsurface drainage, and surface runoff (Youssef et al., 2005). Nitrification and denitrification processes are simulated using a Michaelis-Menten function. Mineral N reactive transport is modeled with a finite difference solution to a multiphase form of the one dimensional advection-dispersion-reaction equation. Soil C dynamics use a soil C submodel adapted from the CENTURY model (Parton et al., 1987). The soil C submodel represents three soil pools (active, slow, and passive), two above- and below-ground residue pools (metabolic and structural), and one surface microbial pool. Individual organic matter pool is characterized by specified organic C content, potential rate of decomposition, and C:N ratio. The litterfall and root turnover predicted by the grass growth model (see below) are used to update organic matter pools represented in the DRAINMOD-N II. Decomposition of each organic matter pool is simulated using first-order rate kinetics and further constrained by multiple environmental factors.

2.3 Development of the grass growth model

2.3.1 Carbon assimilation and respiration

There are three commonly used approaches to simulate carbon assimilation through photosynthesis: radiation/quantum use efficiency, photosynthesis and respiration, and biochemical (Nair et al., 2012; Taubert et al., 2012). Among these methods, radiation/quantum use

efficiency is most widely used because of its simplicity (Grassini et al., 2009; Hastings et al., 2009). In this study, we adapted a method that has been widely used for grass growth models, such as LINGRA (Schapendonk et al., 1998) and GRASSMIND (Taubert et al., 2012). The gross primary production (GPP) is estimated as a function (Eq.[S-3]) of maximum quantum use efficiency, intercepted photosynthetic available radiation (IPAR), and multiple constraints including temperature, water, and N. The IPAR is simulated using the Beer-Lambert Law as a function of predicted LAI. The stress factors pose multiplicative effects on reducing maximum quantum use efficiency. Among these stresses, temperature and water deficit modifiers were adapted from DRAINMOD-FOREST (Tian et al., 2012). A new function (Eq. [S-4]) was incorporated to represent impacts of water logging on photosynthesis processes. In addition, DRAINMOD-GRASS adapts concepts from other crop growth models (Jones et al., 2003; Shibu et al., 2010) that assume N stress occurs in grass when N concentration of above ground tissues (stem and leaf) falls below a critical value. The N stress is quantified by using a nitrogen nutrition index as a function of actual N content, critical N content, and residual N content of aboveground organs (Eq.[S-5]). The actual N content of aboveground live tissues is updated at each time step as a function of current N concentration and N uptake (Eq.[S-6]). Nitrogen uptake is simulated based on a demand-supply mechanism (Eq.[S-7]).

Net primary production (NPP) is defined as the difference of GPP and plant respiration, which includes both growth and maintenance respiration. In this model, two choices are provided for simulating NPP. In the simpler option, NPP is estimated as a fixed fraction (0.47) of GPP as in Tree-Grass model (Simioni et al., 2000), and DRAINMOD-FOREST (Tian et al., 2012). The other option directly estimates plant respiration and calculates NPP as the difference between GPP and plant respiration (Eq.[S-8]). The latter approach, adapted from GRASSMIND (Taubert et al., 2012), estimates growth respiration as a function of a constant fraction of remaining C assimilation after deducting maintenance respiration, which is estimated as a function of live biomass and mean air temperature (Eq.[S-9]).

2.3.2 Development stages

Figure 2: The proposed developmental phenology stages based on thermal degrees, and dynamic carbon allocation to roots (R), leaf (L), stem (S), and nonstructural carbon reserve at each developmental stage simulated in DRAINMOD-GRASS model.

DRAINMOD-GRASS simulates five phenological stages including: early growth (juvenile), stem elongation, reproduction, senescence, and dormancy. These stages are initiated by five sequential critical events: leaf appearance (growth initiation), stem elongation, anthesis (planting flowering), maturity, and harvest (Figure 2). These developmental stages are simulated in DRAINMOD-GRASS using a similar approach to Agro-BGC model (Di Vittorio et al., 2010) and MISCANFOR model (Hastings et al., 2009). The growing season starts whenever the 14-day moving average topsoil temperature (top 20cm) exceeds a vegetation species-specific threshold (T_{cri}). Further developmental phenology, stages are predicted by growing degree days (GDD), which is quantified as a function of daily average temperature and a species-dependent base temperature (Eq.[S-10]). Three critical cumulative thermal degrees define major developmental stages (Figure 2).

2.3.3 Dynamic Carbon Allocation

In DRAINMOD-GRASS, live biomass increment of each component at each time step is determined from carbon assimilation, allocation, retranslocation and senescence (Eq.[S-11]). Carbon allocation is defined as the process partitioning assimilated carbon (in units of dry matter) at each time step to the different functional organs of vegetation. Some grass growth models (Grassini et al., 2009; Hastings et al., 2009) consider aboveground biomass as one single carbon pool, which is directly

linked with radiation use efficiency and intercepted PAR. In contrast, other process-based models adapt dynamic carbon allometric functions for partitioning assimilated carbon to various carbon pools (Nair et al., 2012; Taubert et al., 2012). DRAINMOD-GRASS represents four carbon pools: roots (R), stem(S), leaf (L) and non-structural carbohydrate reserve (NSC) (Figure 1 and Figure 2). To simplify the model, we assume flower and seeds are parts of stem.

Dynamic carbon allocation algorithms were adapted in DRAINMOD-GRASS to accommodate various environmental conditions and different developmental stages during the growing season (Figure 2). During each phenological stage, the model partitions assimilated carbon into different pools (Eq.[S-12]). The carbon allocation to belowground and aboveground pools is mediated by an allocation ratio (Eq.[S-13]). The ratio is estimated based on the hypothesis that net acquisition of carbon by roots is determined by their functional equilibrium with shoots (Farrar and Jones, 2000) and is affected by stresses resulting from water and N deficit (Eq.[S-14]). During the stem elongation stage, carbon allocated to aboveground is further partitioned between leaf and stem. The stem-to-leaf carbon allocation ratio increases linearly from a vegetation-specific value to a maximum value at the end of stem elongation stage (Eq.[S-15]). During stages of stem elongation and senescence, roots and NSC get a constant share of assimilates allocated to belowground tissues (Eq.[S-16]). It is widely acknowledged that carbon allocation to aboveground tissues increases after grass cutting during the growing season to maintain the functional equilibrium (Bazot et al., 2005). In DRAINMOD-GRASS, leaf regrowth during the initial stage after harvesting following the same manner as spring sprouting. Meanwhile, the percentage of newly assimilated carbon allocated to aboveground tissues will be increased by 50% until the ratio of aboveground biomass to belowground biomass reaches the ratio prior to harvesting.

NSC translocation between plant organs is a dynamic process occurring when photosynthesis is limited. Typically, NSC translocates from the aboveground tissues to the rhizomes /root system at the end of each growing season (after anthesis but before full maturity) and reverse during sprouting period at the beginning of each growing season (White, 1973; Zegada-Lizarazu et al., 2012). DRAINMOD-GRASS represents the bidirectional translocation of NSC pool between above- and belowground plant organs (Eq.[S-17]). During senescence, NSC stored in stem and leaf is gradually translocated to NSC pool in the root system until no NSC reserve is left in the aboveground organs at the end of growing season. Translocation from aboveground tissues to NSC pool in rhizomes /root system is quantified as a constant fraction of senesced biomass at each time step (Eq.[S-11]). Translocation of NSC from the reserve to other vegetation tissues occurs whenever

carbon assimilation by photosynthesis is not sufficient to support the carbon requirements. For example, a maximum portion of NSC reserve can be used to support R_m of live biomass when photosynthesis is limited ($GPP < R_m$) under stressed environmental conditions (Eq.[S-17]); NSC storage in the rhizomes/root is also used for early leaf growth at the beginning of each growing season or after grass cutting as described next.

2.3.4 Leaf area index simulation

Stomata in leaves control mass (water and carbon) transfer between vegetation and the atmosphere. Quantifying temporal dynamics of growing season LAI is fundamental for accurately simulating hydrological processes and plant growth (Adam et al., 2011). Rather than arbitrarily assigning initial LAI for triggering carbon assimilation at the start of a new growing season, we adapted a detailed LAI dynamic approach used by the LINTUL (Spitters, 1990) and other models (Adam et al., 2011). During the juvenile phase, carbon for leaf emergence mainly comes from NSC storage in roots (Jing et al., 2012). Leaf growth rate is controlled by air temperature (Eq.[S-18] and Eq.[S-19]) and limited by the C supply, which is quantified as the summation of C assimilation from photosynthesis at each time step and contemporary carbohydrate storage in rhizomes/root system (Eq.[S-20]). At each time step, we assume a maximum constant fraction of total carbohydrate storage in roots can be used for foliage growth, when C assimilated through photosynthesis is not sufficient for potential leaf growth (Eq.[S-16]). When growth stage proceeds to the second critical event or LAI is greater than a threshold value (0.75 is default in the model) (Adam et al., 2011), the C supply only includes assimilated C from photosynthesis. Once the second developmental stage starts, LAI is simulated as the product of dry biomass of live leaf and specific leaf area, which is assumed to be constant through the growing season as many other models (Di Vittorio et al., 2010).

2.3.5 Simulation of root depth, root turnover and litterfall

Root depth in this study is defined as the depth that contains 95% of the total root biomass (Arora and Boer, 2003), which is assumed to be equivalent to the so-called effective root depth in DRAINMOD (Skaggs et al., 2012). To dynamically simulate temporal variations of root depth, we adapted an innovative method proposed by (Arora and Boer, 2003), which links root depth to biomass through a power-law relationship (Eq.[S-21]). The root density profile is estimated by using the commonly assumed exponential root density profile (Eq.[S-22]). DRAINMOD-GRASS assumes that the root turnover rate exponentially increases with rising temperature (Eq.[S-23]) while senescence rate of aboveground biomass exponentially increases as the temperature decreases (Eq.[S-24]). Although N translocation occurred at all stages (Fife et al., 2008),

DRAINMOD-GRASS assumes all N translocation occurs during leaf and stem senescence period. At each time step, total translocated N is estimated as a function of amount of senesced leaf and stem biomass, their N content and a user-specified translocation efficiency (Eq.[S-25]). Translocated N is stored in plant roots and is used during regrowth after mowing or spring sprouting or under conditions when soil mineral N is insufficient.

3. Field testing of the model

3.1 Study site

The study site was located in Lenoir County (Figure 3.A and B), on the Lower Coastal Plain of North Carolina, USA (35°N, 77°W). This site was established to investigate environmental and ecological impacts of cultivating switchgrass for biomass production. Soil at the site was Pantego and /or Rains soil series and was deep and poorly drained under natural conditions. Land use prior to planting switchgrass was loblolly pine (*Pinus taeda*) plantation; pine trees were planted in 1974 and harvested in 2008. While this study site was designed with multiple treatments, including pine-switchgrass intercropping and pure switchgrass, the latter treatment was the focus of this model testing. Climate conditions of the study period (Figure 3 D and E) were similar to historical average daily temperature of 16.5 °C and mean annual precipitation of 1262 mm . Switchgrass (Alamo variety) was planted in June of 2009 on three experimental plots. Each plot was 0.8 ha and drained by parallel open ditches that were 0.9-1.2 m deep and spaced 90 m apart. In the switchgrass-only treatment, site preparation was whole area V-shearing and root raking prior to planting. In June 2009, switchgrass (Cultivar Alamo) seed was machine-planted at 9 kg pure live seed ha⁻¹ in rows with 40 cm spacing. After planting, selective herbicide was applied in May 2010 for suppressing growth of other unwanted grasses. In April 2010 and April 2012, fertilizer (Arborite®CUF) was applied at rates of 65.6 kg N ha⁻¹ and 6.6 kg P ha⁻¹, respectively. Readers are referred to Albaugh et al. (2012) for a detailed description of this site and experimental plots.

3.2. Field measurements

An automatic weather station located in Block 2 (Figure 3.C) was used to collect weather data required by DRAINMOD-GRASS, including hourly precipitation (mm), photosynthetic active radiation (PAR) (umol m⁻² day⁻¹), air temperature (°C), relative humidity (%), and wind speed (m s⁻¹). Weather data measured approximately 11 km (Kinston7) southeast of the study site was used when on-site measurements were missing.

Soil water content and soil water temperature were measured and recorded using ECH2O Soil Moisture Sensors (EC-20) and Em50R dataloggers (Decagon Devices, Inc., Pullman, WA, USA), respectively. Measurements were made at the center of each plot (Figure 3.B) at two depths: 0-10 and 10-20 cm. Water table depth was measured in the middle of each plot midway between two ditches using U20 HOBO water loggers (Onset Computer Co., Inc., MA, U.S.A.) at a 15-minute interval. Soil N mineralization and nitrification rates were measured using sequential in-situ soil incubation method (Cacho, 2013) at the top 20 cm. Each incubation period lasted about 28 days. Readers are referred to Cacho (2013) for detailed description of measurements of water table depth and soil N transformations. Aboveground biomass was collected at the end of the growing season in November from 2009 to 2013. Biomass samples were taken by cutting switchgrass at a height of 10 cm aboveground using five randomly located quadrats in each plot. Samples were processed in a laboratory by drying at 70 °C to a constant mass. Measured weight (kg m^{-2}) of dried samples were scaled to a hectare value to estimate biomass yield on a land area basis. Results of measurements from the three plots (Figure 3-B) were averaged for model testing.

Figure 3. Location of the study site (A and B), schematic layout of three experimental plots (C), and monthly mean precipitation (P, mm mo⁻¹) (D) and temperature (T, °C) (E) during the study period.

3.3 Model initialization

The model simulation started 1 June 2009, the first day with measured weather data. Initial water table depth was determined based on field measurements. The surface litter pool, representing foliage and woody litter on the forest floor, was defined based on field measurements. The below-ground litter pool represents dead roots and any previously incorporated woody litter within the top 20 cm soil layer. Initial soil organic C (SOC) content was determined based on field measurements conducted in 2012 (Cacho, 2013). Measured SOC content (5%) in 2012 was considered as a good approximation of the initial SOC content in 2009 as changes in organic matter content of forest soils are usually slow. Initial partitioning of SOC into active, slow, and passive pools was adjusted during model calibration to achieve quasi-equilibrium among the three SOC pools. Based on records of field practice, the initial switchgrass biomass was set as 9 kg ha⁻¹ biomass of seed, 30% of which was regarded as NSC pool for sprouting.

3.4 Model parameterization and calibration

Parameterizing this integrated ecosystem model was a multi-objective task involving three iterative and sequential steps: first calibration of the hydrological module, followed by calibrating the soil C and N module, and then calibrating the grass growth module. It should be noted that the calibration presented herein was manually conducted. Initial values of most parameters were obtained from a previous model application in a nearby study site (Tian et al. 2012a), while others were obtained from the literature as described next.

Parameterization of the hydrological component was performed by comparing predicted daily water table depth and soil moisture to field measurements. Drainage system parameters including drain depth and spacing were set as physical dimensions of the onsite drainage system. Depth to restrictive layer was determined by field observations during groundwater well installation. Surface storage was calibrated to minimize surface runoff. Effective drain radius and drainage coefficient was set as in previous applications of DRAINMOD-FOREST because of their similar drainage systems (Tian et al. 2012a). The saturated hydraulic conductivity values for different soil profile layers were obtained through model calibration. These calibrated lateral soil hydraulic conductivities (Table 1) represent field effective values and were much higher than laboratory measurements of vertical hydraulic conductivities in undisturbed soil cores from nearby sites

(Cacho et al., 2015). The relationship between upward flux and water table depth was initially derived from soil water characteristics measured from adjacent fields (Cacho et al., 2015) but slightly adjusted to achieve best agreement between measured and predicted water table depth, The calibrated maximum stomatal conductance was comparable to reported values for switchgrass (Dohleman et al., 2009; Hickman et al., 2010). Water holding capacities of green and dead leaves were obtained from Couturier and Ripley (1973). Most soil temperature related parameters were adapted from Luo et al. (2000). However, soil thermal conductivity function coefficients were adjusted to achieve the best match between predicted and measured soil temperature. Calibrated soil thermal conductivity function coefficients were smaller than values for agricultural fields (Luo et al., 2000), which was reasonable since higher soil organic matter content could decrease soil thermal conductivity (Abu-Hamdeh and Reeder, 2000).

Table 1. Hydrologic input parameters for the hydrology component.

Parameter description	Value		
Drainage system design parameters			
Drain spacing (m)	90		
Drain depth (m)	1.0		
Depth to impermeable layer (m)	2.75		
Surface storage (cm)	7.5		
Kirkham's depth (cm)	3.75		
Effective drain radius (cm)	50		
Drainage coefficient (cm d ⁻¹)	5.0		
Soil hydraulic properties			
Soil layer (cm)	0-45	45-100	100-275
Effective hydraulic conductivity (m d ⁻¹)	65	9.6	4.8
Drainable porosity	0.04	0.07	0.12
Saturated water content (cm ³ cm ⁻³)	0.38	0.41	0.42
Water content at wilting point (cm ³ cm ⁻³)	0.13	0.12	0.15
Rainfall interception and stomatal conductance parameters			
Maximum stomatal conductance (mmol m ⁻² s ⁻¹)	275		
Rate of stomatal closure to VPD (mmol m ⁻² s ⁻¹ ln(kpa) ⁻¹)	24		
Radiation regulator (MJ m ⁻² day ⁻¹)	12		
Water hold capacity for green leaf (kg H ₂ O kg ⁻¹ biomass)	0.4		
Water hold capacity for dead leaf (kg H ₂ O kg ⁻¹ biomass)	3.5		
Soil temperature parameters			

Soil thermal conductivity function coefficient A ($\text{W m}^{-1}\text{°C}$)	0.21
Soil thermal conductivity function coefficient B ($\text{W m}^{-1}\text{°C}$)	0.47
Rain/snow dividing temperature (°C)	0
Air temperature phase lag (hr)	8
Temperature at the bottom of the soil profile(°C)	15.6
Snowmelt base temperature (°C)	2
Degree day coefficient (mm d^{-1})	5
Critical ice content ($\text{cm}^3 \text{cm}^{-3}$)	0.2

The soil C/N module was calibrated against field measurements of N cycling including mineralization and nitrification. Parameters needed for simulating soil C and N dynamics include soil physical and chemical properties, N transport and transformation parameters, and parameters related to decomposition and cycling of soil organic matter (Table 2). Soil physical and chemical properties including bulk density and pH were obtained from field measurements(Cacho, 2013) . Maximum nitrification rate was taken from Cacho et al. (2013), who determined soil nitrification potential based on a lab incubation study. Other N transport and transformation parameters were obtained through model calibration and were comparable to values used by Tian et al. (2012a) who applied DRAINMOD-FOREST to simulate a pine plantation in the same region. Calibrated organic matter decomposition rates were comparable to parameters obtained from an agricultural field located in the coastal area of North Carolina (Youssef et al., 2006). However, the calibrated decomposition rates were higher than values for a mid-rotation pine plantation located in the same region (Tian et al., 2012a).

Table 2. Model parameters for simulating soil C and N cycling by using DRAINMOD-N II model

Parameter description	Value		
Soil texture, physical, and chemical properties			
	0-45cm	45-100cm	100-275cm
Clay fraction	0.27	0.19	0.18
Silt fraction	0.07	0.19	0.21
Dry soil bulk density (g cm ⁻³)	1.06	1.50	1.62
Distribution coefficient (cm ³ g ⁻¹)	3.8	3.8	3.7
Soil pH	4.2	4.3	4.7
Nitrogen transport parameters			
Longitudinal dispersivity (cm)	10		
Tortuosity	0.5		
Critical pH	7.5		

Transformation parameters			
	Urea hydrolysis	Nitrification	Denitrification
Maximum reaction rate (µg N g ⁻¹ soil day ⁻¹)	60	0.8	1.0
Half saturation constant	30 mg L ⁻¹	2.5 µg g ⁻¹	2 mg L ⁻¹
Optimum temperature (°C)	40	32	35
Threshold water-filled pore space	---	---	0.7
Optimum water-filled pore space range	0.5-0.7	0.5-0.7	---
Organic matter decomposition parameters			
Mineral [N] at which litter enters SOM pool with minimum C:N		2.0 mg L ⁻¹	
Optimum temperature (°C)		35	
Optimum water-filled pore space range		0.5-0.6	
Litter pools		K _{dec} (day ⁻¹)	C:N ratio
Surface structural		1.23×10 ⁻²	150
Surface metabolic		2.55×10 ⁻²	15
Surface microbes		1.84×10 ⁻²	8
Below ground structural		1.47×10 ⁻²	150
Below ground metabolic		4.06×10 ⁻²	15
SOM pools			
Active		3.65×10 ⁻²	8
Slow		2.08×10 ⁻⁴	24
Passive		1.23×10 ⁻⁵	20

The newly added grass growth module was calibrated by comparing predicted annual biomass yield to field measurements. Parameters describing grass growth were needed to simulate carbon assimilation and respiration, C allocation, and litterfall and root turnover (Table 3). The calibrated maximum quantum use efficiency and light extinction coefficient of switchgrass were comparable to field measurements (Albaugh et al., 2014; Dohleman et al., 2009). Temperature constraint parameters were obtained from Lee et al. (2012). Water logging and plant respiration parameters were obtained through model calibration. Specific leaf area was measured (Mitchell et al., 1997; Sanderson and Moore, 1999; Tian et al., 2015). Maximum leaf emergence rate was adapted from published studies (Adam et al., 2011). Parameters characterizing phenological stages were calibrated to match field observations (Tian et al., 2015) and other published literatures (Mitchell et al., 1997; Sanderson and Moore, 1999). Carbon allocation parameters were calibrated and were in the range of literature reports (Di Vittorio et al., 2010). Nevertheless, the calibrated C allocation

fractions to roots were in the lower range of these reported values because of relatively wet soil at the study site. Calibrated root depth parameters were in the range of reported values (Arora and Boer, 2003). Calibrated root turnover rates and temperature coefficient were also comparable to other studies (Di Vittorio et al., 2010; Gill and Jackson, 2000). Base leaf senescence rate and its temperature coefficient was calibrated to ensure that no live leaf biomass was left by the end of the growing season. Nitrogen contents of various plant tissues were obtained from literature (Dohleman et al., 2009; Johnson et al., 2007; Kering et al., 2012; Reynolds et al., 2000). NSC content of switchgrass stem and leaf was adapted from a published literature (Gesch and Johnson, 2010). Lignin content of switchgrass tissues were obtained from published studies (Johnson et al., 2007). N translocation efficiency was calibrated and was comparable to many field measurements for switchgrass (Dohleman et al., 2009; Kering et al., 2012; Reynolds et al., 2000) .

Table 3. Parameters for simulating grass growth

Carbon assimilation related parameters				
Maximum quantum use efficiency (in mol C mol ⁻¹ IPAR)			0.06	
Light extinction coefficient			0.63	
Minimum temperature for growth (°C)			0	
Optimum temperature for growth (°C)			31	
Maximum temperature for growth(°C)			46	
Maximum duration of water logging effects (days)			20	
Empirical exponent factor quantifying water logging effects			3.4	
Specific leaf area (one-sided) (m ² kg ⁻¹)			16	
Dimensionless growth respiration factor			0.22	
Maintenance respiration rate (g DM g ⁻¹ DM d ⁻¹)			0.03	
Q ₁₀ for temperature response function for respiration			2.7	
Maximum growth rate of LAI during the juvenile phase (°C ⁻¹)			0.01	
Parameters characterizing phenology stages (°C)				
Tem _{soil}	T _{base}	GDD _{stem}	GDD _{flr}	GDD _{mat}

13	10	450	1950	2600	
Carbon allocation related parameters					
Maximum root-to-shoot ratio	Minimum root-to-shoot ratio	Maximum stem-to-leaf ratio	Minimum stem-to-leaf ratio	Constant fraction to NSC	Maximum NSC depletion rate
0.77	0.35	7.0	2.5	10%`	10%
Leaf and root growth related parameters					
` Root growth direction parameter	Empirical factor affecting root depth	Base root turnover rate	Temperature coefficient for root turnover	Base leaf death rate	Temperature coefficient for leaf death
0.67	1.5	0.003 day ⁻¹	0.02	0.04	0.05
Biochemical properties of grass tissues					
	[N]max	[N]res	[NSC]	[Lignin]	N retranslocation efficiency
Leaf	2.24%	0.8%	12%	12%	62%
Stem	1.2%	0.5%	12%	22%	15%
Root	`1.8%	`0.8%	n/a	17%	n/a

3.5 Model performance evaluation

Model performance was evaluated by comparing model predictions to field measurements of biomass yield, groundwater table depth, soil moisture content, soil temperature, and periodic measurements of N cycling. Several statistical measures including Nash-Sutcliffe coefficient (NSE), mean absolute error (MAE) and normalized percent error (NPE) were used as goodness-of-fit indices to assess model performance (Bennett et al., 2013; Moriasi et al., 2007). In addition, goodness-of-fit indices were calculated for different seasons to better interpret model performance. A student t-test was used to detect significance ($\alpha=0.05$) of difference of model performance between different seasons. Other predicted key internal cycling variables (e.g. ET, denitrification, biomass pools) that do not have field measurements were compared to published values from similar landscapes.

4 Results and discussion

4.1 Biomass yield

The model accurately predicted annual biomass yield from 2009 to 2013 (Figure 4). Predicted 5-yr mean annual biomass yield was 4.8 Mg ha⁻¹, which was comparable to field measurement of 4.9 Mg ha⁻¹. The fifth year produced highest biomass, while the fourth year (2012) had the lowest biomass yield because of an extremely wet growing season in 2012. Studies have shown that biomass yield of switchgrass (Alamo) can be negatively affected by wet conditions (Lemus et al., 2009; Mooney et al., 2009). Annual biomass yield of switchgrass in this study was lower than the commonly reported

productivity of switchgrass in the southern USA (Fike et al., 2006; Lemus et al., 2009; Mooney et al., 2009). This might be because many of these previous studies were in small plots (tens to a few hundred m²) under optimum water and nutrient condition.

Figure 4. Comparison between predicted and measured annual yield from 2009 to 2012. The predicted annual biomass yield was approximately estimated as 95% biomass of total aboveground biomass.

Maximum aboveground biomass was typically achieved around August. Predicted stem-to-leaf ratio ranged from 0 at the beginning of growing season to around 4 by the end of the growing season, which is comparable to findings of experimental studies (Smart et al., 2004) and close to on-site measurements in 2014 (Tian et al., in review). By the end of growing season, aboveground biomass declined by about 5-10% because of the translocation of NSC from leaf and stem to roots (Parrish and Fike, 2005; White, 1973).

Figure 5. Predicted carbon pools (Dry biomass based), including stem, leaf, root and underground nonstructural carbohydrate (NSC), showing temporal changes over the simulation period from 2009 to 2013.

According to model prediction, total root biomass (the sum of root biomass and NSC) showed large inter-annual variations (Figure 5). Predicted total root biomass increased from 0 tons ha⁻¹ at the beginning of growing season to 3.6 tons ha⁻¹ in late fall during the first year after planting. During subsequent years, total root biomass depicted similar seasonal variations from around 2.1 tons ha⁻¹ in spring to around 5.3 tons ha⁻¹ in fall, except for 2012. Peak root biomass (3.1 tons ha⁻¹) was about 37% less for 2012 compared to other years, which was consistent to the reduced aboveground biomass yield in the same year (Figure 4). Shrestha (2013) reported that root biomass density of switchgrass in nearby pine-switchgrass plots was about 5.36 kg m⁻³ in the top 35cm soil. This is equivalent to 2.6 tons ha⁻¹, assuming that top 35 cm soil accounts for 60% of total root biomass (Garten et al., 2011). Predicted peak root biomass is in the lower end of reported ranges (Garten et al., 2011) because of relative wet soil conditions at the study site. Predicted root-to-shoot ratios were comparable to reported values for switchgrass growing in southern United States (Dohleman et al., 2012; Garten et al., 2010).

Nonstructural carbohydrate reserves are important in perennial plants for winter survival, growth initiation in early spring, and regrowth after disturbances (White, 1973) and it is important for a process-based model to reasonably represent this carbon pool. Predicted underground NSC showed clear seasonal and inter-annual variations (Figure 5). Predicted seasonal NSC content of switchgrass roots ranged from 13.2% during May to 22.8% during November (Figure 5). Predicted seasonal variations of NSC is comparable to measurements that NSC content typically varied over the year with a maximum in autumn and minimum in early spring (Steen and Larsson, 1986). Temporal variation of underground NSC pool resulted from the balance between photosynthesis and respiration, and carbohydrate translocation between plant tissues (White, 1973). Specifically, part of stored NSC was used for root respiration over the winter period, which resulted in NSC decline before spring. The sudden faster decline in underground NSC at the beginning of each growing season was due to mobilization of stored NSC towards new growth of leaves (Jing et al., 2012). Afterward, NSC content increased with plant maturity to flowering and seeding. NSC storage reached the lowest level in 2012 due to reduced carbon assimilation. Predicted NSC content of switchgrass roots and its seasonal variations was comparable to published (Anderson et al., 1989; George et al., 1989; Perry and Moser, 1974; Steen and Larsson, 1986).

4.2 Hydrological predictions

Due to lack of drainage outflow measurements, hydrological testing focused on water table depth, soil moisture dynamics, and water balance simulation. Visual comparison (Figure 6) and statistical measures (Table 4) showed that the model accurately predicted temporal fluctuations of water table depths on a daily basis. Predicted mean water table depth was 0.89 ± 0.34 m (STD), which closely matched measurements of 0.92 ± 0.35 m (STD). Mean absolute error of model predictions was 0.09 m. The NSE and NPE values (Table 4) suggested very good model performance in simulating water table dynamics (Moriassi et al., 2007; Skaggs et al., 2012). The difference of model performance are insignificant ($p > 0.2$) according to a student t-test, suggesting consistent model performance for predicting daily water table depth during different phenology stages. Overall, model performance in predicting these hydrological variables was consistent with previous model applications in the same region (Tian et al., 2012, 2012b).

Figure 6. Comparison between simulated and measured daily water table depth during the period from Sep 2009 to Dec 2013.

Table 4: Model performance in predicting temporal fluctuation of water table depth (WTD) during various seasons.

	Statistics	Spring	Summer	Fall	Winter	Overall
		Mar-May	Jun-Aug	Sep-Nov	Dec-Feb	
WTD	NSE	0.62	0.89	0.72	0.73	0.85
	MAE	10.6	12.1	11.7	7.3	10.2
	NPE	3.1%	2.3%	11.6%	2.7%	5.1%

In DRAINMOD-GRASS, soil moisture content is an important hydrological variable affecting ET simulation and soil C and N cycling (Youssef et al., 2005) and accordingly vegetation growth. The model accurately predicted temporal changes of soil moisture content at 10 cm deep and 30 cm deep (Figure 7). Both visual comparison and calculated goodness of fit indices (Table 5) between model predictions and field measurements suggested that the model accurately predicted temporal dynamics of soil moisture content at the top soil layer. Predicted long-term mean soil moisture contents matched field measurements very well: $0.32 \pm 0.06 \text{ cm}^3 \text{ cm}^{-3}$ vs. $0.33 \pm 0.06 \text{ cm}^3 \text{ cm}^{-3}$, and $0.29 \pm 0.04 \text{ cm}^3 \text{ cm}^{-3}$ vs. $0.28 \pm 0.04 \text{ cm}^3 \text{ cm}^{-3}$, at 10 cm and 30 cm deep, respectively. The NSE values demonstrated good agreement between model predictions and field measurements, while MAE and NPE suggested very small model error. These results validated suitability of the model for estimating temporal dynamics of soil moisture content at top soil layers, although the model simply assumes that water content distribution in wet zone is a drained-to-equilibrium profile and equals permanent wilting point if a dry zone is present (Skaggs et al., 2012). Separately calculated goodness of fit indices during different seasons suggested no significant difference of model performance among different seasons (Table 5). This was consistent with model performance for predicting WTD fluctuations (Table 4). Meanwhile, NPE suggested that the model slightly over-predicted soil moisture content at both soil layers during winter, spring and fall seasons and under-predicted during summer seasons. Discrepancies between model predictions and field measurements could be attributed to inaccurate quantification of rainfall interception by canopy and ignored interception by surface litter in grassland (Dunkerley and Booth, 1999). Potential errors in simulating ET could also be partially responsible for the slight discrepancy between measured and predicted soil moisture content of top soil. Specifically, under predictions of soil moisture during summer seasons was mainly caused by the model's "drained-to-equilibrium condition assumptions" (Skaggs et al., 2012), which are violated more frequently during summer period with larger rainfall amount (Figure 3) but deeper water table (Figure 6).

Figure 7. Comparison between simulated and measured soil moisture content (θ) of soil at 10 cm deep and 30 cm deep during the period from July 2010 to Dec 2012.

Table 5: Model performance in predicting temporal dynamics of soil moisture content at 10 cm ($\theta_{10\text{cm}}$) and 30 cm ($\theta_{30\text{cm}}$) during various seasons.

Statistics		Spring	Summer	Fall	Winter	Overall
		Mar-May	Jun-Aug	Sep-Nov	Dec-Feb	
$\theta_{10\text{cm}}$	NSE	0.71	0.86	0.65	0.71	0.72
	MAE	0.03	0.02	0.03	0.03	0.03
	NPE	0.1%	-5.9%	0.5%	1.0%	-1.2%
$\theta_{30\text{cm}}$	NSE	0.70	0.83	0.72	0.48	0.68
	MAE	0.02	0.01	0.02	0.02	0.02
	NPE	1.8%	-5.2%	4.3%	5.2%	1.6%

According to model predictions of water balance components on an annual basis (Table 6), annual ET (transpiration and soil evaporation) accounted for 45 % of total annual precipitation, rainfall interception accounted for 9.5%, subsurface drainage 44.5%, and surface runoff 2%. Predicted annual total ET including transpiration, soil evaporation and canopy interception ranged from 630 mm in 2010 to 750 mm in 2012 and 2013, which was higher than Soil-Plant-Atmosphere (SPA) model estimation for the same site (Albaugh et al., 2014). The difference between ET predictions by the two models could be attributed to their different structure and methods for calculating water balance components. Nevertheless, DRAINMOD-GRASS predictions were comparable to field measurements in several studies, although the studies were in drier or cooler climates. For instance, one study observed 493 to 781 mm annual ET of switchgrass located in Oklahoma, USA

with long-term mean annual precipitation of 850 mm (Yimam et al., 2014). Another study in the southwestern U.S. reported 450 mm ET from May to Mid-November (Wagle and Kakani, 2014). Typically, lower annual ET was reported for grasses growing in regions with shorter growing season and less annual precipitation. For example, one study reported annual ET of switchgrass ranged from 492 to 570 mm, which was about 57% of total annual precipitation for a study site located in southwestern Michigan (Abraha et al., 2015).

Table 6. Predicted Water balance component of the Switch Grass stand from 2010 to 2012

Year	Precipitation	Interception	ET [†]	Subsurface Drainage	Surface runoff
mm yr ⁻¹					
2010	1225	103	527	624	35
2011	1271	104	544	579	56
2012	1356	146	609	566	17
2013	1229	127	626	482	0
Mean	1270	120	577	563	27
STD	53	18	42	51	21

[†]Note; ET represents water losses from transpiration and soil evaporation.

4.3 Soil temperature predictions

Although the algorithm used in DRAINMOD-FOREST for simulating soil temperature dynamics was developed for agricultural fields (Luo et al., 2000), it successfully captured temporal variation in soil temperature at depths of 10 cm and 30 cm (Figure 8). Predicted long-term mean soil temperature was 17.6 ± 7.0 °C and 18.0 ± 6.5 °C for 10 cm and 30 cm deep, respectively, which was comparable to field measurements of 17.2 ± 7.3 °C and 17.7 ± 6.1 °C. The model reasonably captured the higher temperature and greater variability of soil temperature in the upper soil layer. Excellent model performance was also supported by goodness of fit indices: NSE= 0.96, MAE=1.1°C, and NPE=-2.7% for soil at 10 cm deep and NSE= 0.97, MAE=0.9°C, and NPE=-2.5% for soil at 30 cm deep. Nevertheless, negative NPE values suggested that the model tended to under-predict soil temperature for both layers. Separately calculated goodness of fit indices suggested different model performance at different seasons (Table 7). Specifically, NSE values demonstrated that the model performed best for predicting soil temperature during fall and worst during summer for both soil layers. Discrepancies between predicted and measured soil temperatures were mainly attributed to these simple algorithms, developed for agricultural fields (Luo et al., 2000). Accuracy of model predictions could be improved by taking into account influence of LAI and litter cover on soil temperature as do other forest soil temperature models (Katterer and Andren, 2009; Paul et al.,

2004; Wilson et al., 2012). However, such modification necessitates more input parameters, which will potentially increase complexity of the model and uncertainties of model predictions.

Figure 8. Comparison between simulated and measured soil temperature of soil at 10 cm deep and 30 cm deep during the period from July 2010 to Dec 2012.

Table 7: Model performance in predicting temporal dynamics of soil temperature at 10 cm (Tem_{10cm}) and 30 cm (Tem_{30cm}) during various seasons.

	Statistics	Spring	Summer	Fall	Winter	Overall
		Mar-May	Jun-Aug	Sep-Nov	Dec-Feb	
Tem_{10cm}	NSE	0.87	0.67	0.92	0.71	0.96
	MAE	1.2	0.7	1.2	1.3	1.1
	NPE	-4.7%	-0.1%	-4.1%	-2.0%	-2.7%
Tem_{30cm}	NSE	0.85	0.58	0.96	0.83	0.97
	MAE	1.1	0.9	0.7	0.9	0.9
	NPE	-6.4%	-3.7%	-2.6%	2.5%	-2.5%

4.4. Nitrogen Cycling

Net N mineralization results from mineralization of organic N and immobilization of mineral N occurring during decomposition of soil organic matter and fresh plant residue. This process primarily determines soil N availability in most natural ecosystems. Predicted net mineralization rates ranged from $0.003 \text{ g N m}^{-2} \text{ day}^{-1}$ during the incubation period from May to June in 2011 to $0.03 \text{ g N m}^{-2} \text{ day}^{-1}$ during the incubation period from July to August in 2012 (Figure 9-A). The 2-

year mean net mineralization rate was $0.017 \pm 0.008 \text{ g N m}^{-2} \text{ day}^{-1}$. Model predictions were about 40% lower than field measurements with a 2-year mean rate of $0.028 \pm 0.02 \text{ g N m}^{-2} \text{ day}^{-1}$. Disagreements between model predictions and field measurements were mainly caused by under-predictions of net mineralization from May to August in 2012, which was possibly due to fertilization at the end of April. DRAINMOD-GRASS regards fertilizer application as an additional source of mineral N inputs, while the onsite soil incubation study cannot separate release of ammonium from coated urea fertilizer from the microbial-mediated mineralization processes. Overall, the model captured seasonal variations of net mineralization rates with peak net mineralization rate generally occur during summer and early fall season (Figure 9-A).

Nitrification is affected by multiple factors such as substrate availability, soil pH, temperature, and moisture conditions. Due to high mobility of nitrate, accurate predictions of nitrification have important implications for N-use efficiency and ecosystem and environmental quality. Predicted net nitrification rates ranged from $0.002 \text{ g N m}^{-2} \text{ day}^{-1}$ during the incubation period from Jan to Feb in 2012, to $0.008 \text{ g N m}^{-2} \text{ day}^{-1}$ during the incubation period from Sep to Oct in 2012 (Figure 9-B). According to model predictions, the 2-year mean nitrification rate was $0.006 \pm 0.001 \text{ g N m}^{-2} \text{ day}^{-1}$. Model predictions were comparable to field measurements with 2-year mean rate of $0.006 \pm 0.003 \text{ g N m}^{-2} \text{ day}^{-1}$.

Figure 9. Comparison between predicted and measured net mineralization and nitrification rates during 2011 and 2012.

The overall good model performance in predicting net mineralization and nitrification was partially attributed to good model predictions of soil moisture (Figure 7) and soil temperature (Figure 8). Discrepancies between model-predicted and measured N transformations could be partially caused by bias in on-site incubation technique used in the field study, which maintained soil moisture content at initial condition. For instance, under-prediction of mineralization and nitrification rates during May to June in 2012 (Figure 9-B) was partially caused by abrupt change in soil moisture content during the incubation period (Figure 7), which started at 0.40 cm³ cm⁻³ and continuously declined to 0.26 cm³ cm⁻³. However, the soil incubation technique prevented this rapid soil moisture change and maintained the initial high soil moisture content, leading to higher measured N transformation rates (Hanselman et al., 2004; Khanna and Raison, 2013; Noe, 2011). On the contrary, the model over-predicted N transformation rates during September to October in 2011 because incubation started in a dry condition (0.30 cm³ cm⁻³) followed by several rainfall events with total rainfall of 9.9 cm.

Table 8. Summary of predicted annual rates (kg ha⁻¹ yr⁻¹) of N inputs and N transformation from 2010 and 2013.

	Fertilizer	Net mineralization	Net Nitrification	Total N uptake	Denitrification	Leaching losses
2010	65	65.9	14.4	54.9	16.7	3.8
2011		62.3	21.2	57.8	11.8	5.9
2012	65	57.4	25.9	33.5	18.5	6.8
2013		35.2	24.3	57.4	17.2	7.1

Table 8 summarized predicted N inputs and transformations rates on an annual basis. Predicted annual net mineralization from 35.2 kg N ha⁻¹ yr⁻¹ to 65.9 kg N ha⁻¹ yr⁻¹. Estimated annual net mineralization based on sequential in-situ technique were 69.7 kg N ha⁻¹ yr⁻¹ and 125.1 kg N ha⁻¹ yr⁻¹ in 2011 and 2012, respectively (Cacho, 2013). In addition to potential model errors in simulating net mineralization rates, differences could be partially attributed to inaccurate measurements of nitrogen cycling under during dramatic changes of soil moisture in the incubation period (Hanselman et al., 2004; Khanna and Raison, 2013; Noe, 2011). In addition, under prediction of net mineralization in 2012 was mainly caused by fertilizer application, which was regarded as extra N inputs from modeling perspectives, while release of mineral N from the fertilizer was measured as mineralization during the field experimental study. Model predicted annual net nitrification rates were very comparable to estimations from field experiments. Estimated annual net nitrification rate in 2011 and 2012 based on soil incubation study were 18 kg N ha⁻¹ yr⁻¹ and 25.2 kg N ha⁻¹ yr⁻¹, respectively (Cacho, 2013).

Predicted annual denitrification rate varied from 11.8 kg ha⁻¹ in 2011 to 18.5 kg ha⁻¹ in 2013 (Table 6). It is well known that denitrification rates are relatively small in forest soils (Barton et al., 1999). Predicted annual denitrification was much higher than typical findings in pine forest in the southeastern US (Robertson et al., 1987). This is because of higher substrate (nitrate) availability in switchgrass stands due to higher frequency of fertilizer application and lower N uptake compared to pine plantations. Predicted annual rates of denitrification are comparable to field measurements in many grasslands (Hofstra and Bouwman, 2005). Specifically, predicted annual N uptake changed from 32.4 kg ha⁻¹ in 2012 to 61.2 kg ha⁻¹ in 2013 (Table 5), while annual N uptake for a mid-rotation loblolly pine plantation in the southeastern US typically ranged from 50 to 100 kg ha⁻¹ (Albaugh et al., 2008; Ducey and Allen, 2001). Leaching losses of mineral N was less than 3 kg ha⁻¹ during the study period, which was minimal compared to typical agricultural fields in the same

region (Youssef et al., 2006). This model simulation supported the general acknowledgment that cellulosic grasses with low inputs have environmental advantages, in terms of possible N pollution, over conventional biofuel feedstock from cultivated crops (McIsaac et al., 2010; Schmer et al., 2008; Williams et al., 2009).

5 Summary and future work

DRAINMOD-GRASS was developed as an integrated, field scale, and process-based model for simulating hydrological, biogeochemical, and plant growth processes for perennial grass systems on high water table soils. The model links a grass growth module to DRAINMOD and DRAINMOD-NII models. The newly added grass growth module physiologically simulates daily gross and net primary production, carbon allocation to plant tissues, litter fall, and root turnover under various environmental conditions and management practices. These three components are inherently coupled and capture interactions among hydrology, biogeochemistry, and physiology in bioenergy grass systems. A preliminary field test using data from a switchgrass field study demonstrated that the model was able to accurately predict biomass yield, ground water table fluctuations, soil moisture, and soil temperature variations. In addition, the model also reasonably predicted key N transformations including net N mineralization and nitrification. This model testing demonstrated that the model can be a useful tool for investigating the productivity and environmental impacts of growing switchgrass in lowland areas. The model can be used as a tool for developing best management practices for cultivating specific grasses in these lowland areas (e.g. drainage system design, optimum fertilization timing and amount, etc).

More work is necessary to apply the model under different environmental settings (e.g. soil, weather, vegetation, etc.) to validate the general applicability of a new model and improve the model if necessary. Due to limited availability of field measurements, we did not robustly validate the model after carrying out model calibration. We are currently validating the model's performance by applying parameters obtained from this study to an adjacent pine-switchgrass intercropping system. In addition, future work is necessary to incorporate an auto-calibration tool for this integrated model with large numbers of model parameters. A global sensitivity analysis (Butler et al., 2014; Nossent et al., 2011) is also needed to identify sensitive parameters and verify the inherent linkages between plant, water and soil C/N. While this study only presented a field test for switchgrass plantations, the model should be capable of simulating ecosystems of other perennial grasses such as *Miscanthus*, and Giant reed, though more field testing for other perennial grass species is needed in the future.

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