Evaluating controls on coupled hydrologic and vegetation dynamics in a humid continental climate watershed using a subsurface-land surface processes model

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[1] Understanding key controls on hydrologic dynamics is important for effectively allocating resources for data collection, reducing model dimensionality, and making modeling decisions. This work seeks to elucidate the physical factors responsible for the observed hydrologic patterns of a watershed in Michigan using an integrated hydrologic model, Process-based Adaptive Watershed Simulator and Community Land Model (PAWS+CLM). The model is tested using observed data for streamflows, soil temperature, groundwater table depths, and satellite-based observations of evapotranspiration (ET) and leaf area index (LAI). Numerical experiments are carried out to lump the effects of key controls, including land use types, nitrogen levels, groundwater redistribution, and soil texture, into different process indices. Using analysis of variance (ANOVA), we quantitatively determine the strengths of these controls on ET, net primary production (NPP), and other important variables. Groundwater flow is found to be the major control on runoff and infiltration, with soil texture ranking next, while vegetation type and nitrogen levels are found to dominate NPP, top soil temperature, and transpiration. Soil texture and groundwater are found to have comparable influence on soil moisture, which is in agreement with analysis of field data in the literature. All controls are found to colimit ET, which serves as the nexus for ecosystem-hydrology interactions. From the simulation results, we find that nitrogen significantly controls transpiration, through which it influences other hydrologic fluxes. While there is room for improving descriptions of the nitrogen cycle in the current version of CLM, these novel results call for an understanding of the interplay between hydrology and biogeochemistry. Additional analysis shows that the relative strengths of the controls examined in this work are fairly robust with respect to changes in parameters and spatial resolution.


1. Introduction

[2] Recently, there has been a surge of interest in identifying, understanding, and utilizing hydrologic and ecosystem patterns and controls in hydrologic predictions [Hwang et al., 2012; McDonnell et al., 2007; Thompson et al., 2011; Vivoni, 2012; Wagener et al., 2010]. Understanding the physical processes that control the variability of hydrologic variables is crucial for predictions and management [Joshi and Mohanty, 2010; Pan and Wang, 2009; Wilson et al., 2004]. The recognition of key patterns and controls can help reduce the dimensionality of the prediction problem [Sivapalan et al., 2011], facilitate predictions in ungauged basins [Sivapalan, 2003], and promote an in-depth understanding of the underlying principles. Topography-induced groundwater flow leads to convergence of subsurface moisture, which crafts spatial patterns in hydrologic, geomorphologic, and vegetation processes. In some systems, groundwater flow plays a vital role in ecosystem functioning. However, despite intensive recent studies [e.g., Ivanov et al., 2008; Maxwell and Kollet, 2008a, 2008b; Miguez-Macho and Fan, 2012], the relative importance of groundwater flow as compared to other controls such as soil texture, land use, and vegetation characteristics remains unclear.

[3] The coupling between hydrology and biogeochemistry has recently received growing attention [Chorover et al., 2011; Lohse et al., 2009; Manzoni and Porporato, 2011; Riveros-Iregui et al., 2012]. Strong controls and feedbacks have been identified between water, carbon, and nitrogen biogeochemistry in various environments [Burt and Pinay, 2005; D’Odorico et al., 2003; Lohse et al., 2009; Schimel et al., 1997]. The strong relationship between evapotranspiration (ET) and biological nitrogen fixation (BNF) [Cleveland et al., 1999] has long been recognized, so has the correlation between nitrogen...
availability, successional stage, soil moisture, and topography [Robertson et al., 1988]. In ecosystems where vegetation growth is limited by nutrient availability [Galloway et al., 2004; Wilson et al., 1999], higher inputs of nitrogen are expected to lead to a relatively more active ecosystem with higher productivity, thus altering ET and the hydrologic cycle. Presently, human activities are creating reactive N at unprecedented rates [Galloway et al., 2004], leading to increased nitrogen deposition [Dentener et al., 2006; Galloway et al., 2008]. The implications of this excess nitrogen and its interplay with the carbon and water cycles is worth detailed, mechanistic and integrated investigation. The relative importance of N is difficult to evaluate from field surveys alone due to the various time scales of the complex N biogeochemical reactions, its interactions with the carbon cycle, and its covariance with climatic input [e.g., see Burke et al., 1997]. On one hand, inclusion of nitrogen dynamics in global land surface simulations is relatively recent (see Bonan and Levis [2010], Reich et al. [2006], and Sokolov et al. [2008] for the effects of the C/N interactions), and the current hydrologic descriptions in these climate scale models are very crude, oversimplifying the subsurface and channel dynamics. On the other hand, with the exception of very few (TOPOG-IRM [Vertessy et al., 1996] and RHESSys [Band et al., 2001; Mackay and Band, 1997; Tague and Band, 2004]), “traditional” watershed-scale models often do not consider any carbon/nitrogen dynamics. Understanding the relative strengths of the water-carbon-nitrogen coupling helps identify unrecognized yet important linkages.

[1] Besides synthesizing and mining observed data for correlations, one may also study the influences of separate processes using the simulations of physically based hydrologic models (PBHMs), which are “derived deductively from fundamental physical laws” [Beven, 2002]. Although PBHMs may never match the full complexity of reality, they have the potential to reveal patterns and pinpoint cause-effect relations. To reconcile differences and similarities in formulations and to aid scientific understanding of the complex processes involved, new models, approaches, and model intercomparison exercises are all expected to play an important role. Recent advances in PBHMs have focused on the linkages of terrestrial fluxes, ecohydrology, and the integral role played by surface and subsurface water dynamics. For an incomplete list, see the papers by Fatichi et al. [2012], Ferguson and Maxwell [2010], Goderniaux et al. [2009], Ivanov et al. [2008], Kollet and Maxwell [2008], Mackay and Band [1997], Miguez-Macho et al. [2007], and Niu et al. [2013]. A novel hydrologic model, Process-based Adaptive Watershed Simulator (PAWS), was recently introduced by Shen [2009] and Shen and Phanikumar [2010], hereinafter SP10]. PAWS was created with intermediate complexity, Geographical Information System (GIS) data interface and parameterization functionalities, attempting to strike a balance between physics and computational tractability at large scales. The model efficiently solves the governing equations for major hydrologic processes using some of the best available algorithms. By reducing the dimensionality of the fully three-dimensional (3-D) subsurface problem using a quasi-3-D saturated groundwater domain and one-dimensional Richards’ equation to approximate soil columns in every grid cell, the model significantly reduces the computational demand with little loss of physics. The computational efficiency of the PAWS model allows for long-term, large-scale simulations and makes parameter estimation and uncertainty analysis feasible. The PAWS model was tested extensively (SP10) with laboratory “recharge” experiments, analytical solutions, idealized test cases, and numerical solutions from models that solve the full 3-D Richards equation. The model achieved good performance in simulating hydrology in a medium-sized watershed in the U.S. midwest. Descriptions of land surface processes, including energy balance and vegetation growth cycles, were nonetheless simple in the original PAWS model.

[5] The National Center for Atmospheric Research (NCAR) community land model (CLM), a process-based land surface model, was developed from grassroots collaboration among climate scientists [Collins et al., 2006; Dickinson et al., 2006; Lawrence et al., 2011; Niu and Yang, 2007; Oleson et al., 2010; Sakaguichi and Zeng, 2009; Zeng et al., 1998, 2002]. The model now encompasses a comprehensive suite of land surface processes including surface heat/momentum/vapor transfer, surface radiation balance, snow/soil heat transfer and freeze-thaw phase changes, photosynthesis and plant growth, as well as carbon and nitrogen fluxes, mostly using process-based descriptions. However, the flow modules in CLM, e.g., surface runoff and channel flow, subsurface flow, and characterization of geologic and soil properties, all tend to be overly simplified as compared to other components. CLM treats each computational element as independent columns, neglecting the lateral fluxes and hence their spatial interactions. As discussed in Anyah et al. [2008], Maxwell and Kollet [2008a], and Shen and Phanikumar [2010], the surface flow is an integral component of the hydrologic cycle that significantly influences local water fluxes and the climate through feedbacks. To further enhance the simulation capabilities of the PAWS model, we recently coupled the flow processes in PAWS to the land surface processes in CLM. This suite of modules brings together surface flow, 3-D subsurface flow, carbon/nitrogen dynamics, and land surface processes to offer a higher degree of model realism.

[6] In this paper, we employ the PAWS+CLM model to study the water-energy-nutrient controls on hydrology in a humid continental climate watershed in the Great Lakes region of North America. Although progress has recently been made in understanding the hydrology of this region with a focus on the impacts of land cover/land use changes [Mao and Cherkauer, 2009] and projected climate change on hydrology [Mishra et al., 2010], the applications of PBHMs have the potential to offer additional insights into fundamental processes. Our objectives in this paper are (a) to quantify the relative importance of physical processes including land cover, soil texture, land use and groundwater flow on water, energy, and carbon fluxes using a process-based hydrologic model and (b) to examine the coupling strengths and mutual influences between hydrology and nitrogen biogeochemistry. The paper is organized as follows. After a brief description of the PAWS+CLM model, we present the results of extensive model testing using field and satellite-based observations. Using the well-tested model, we show the rich spatiotemporal patterns of the hydrologic and vegetation dynamics in the basin. Then,
we carry out numerical experiments to analyze the relative importance of the controlling processes on various fluxes and states and how they together produce the patterns.

2. Model Description

[7] Since the mathematical and algorithmic details of the PAWS model have already been presented elsewhere (SP10), we will only provide a brief outline of the model here followed by short descriptions of the coupling with CLM. PAWS uses 3-D structured grids with the top layer representing the ground surface and the overland flow domain. Several key processes take place exclusively on the ground surface (e.g., overland flow, vegetation interception, depression storage) while others (e.g., ET) extend over the entire vertical depth of the soil column. To avoid confusion, we define our terminology as follows: the term “cell” is used to refer to the unit of the 2-D horizontal discretization of the ground surface (this corresponds to the “grid cell” concept in CLM 4.0). We use the word “column” to denote the totality of the soil matrix and pore spaces underneath a cell (under each cell, we only have one column, with a single set of moisture/thermodynamic states, as opposed to the possibility of multiple columns in CLM); the word “layer” refers to the vertical discretization of the soil column.

2.1. Flow Modules

[8] The flow domain is divided into surface overland flow, channel flow, unsaturated soil water flow, and saturated groundwater. Processes in these domains are linked by the surface-unsaturated-saturated coupling method described in SP10. The ground surface is partitioned into the flow domain and the ponding domain. The ponding domain is updated together with the soil water states. Runoff rate from the ponding domain to the flow domain is determined by the Manning’s equation. Only water in excess of the interception depth can become runoff. Under flooding conditions, water in the flow domain may also backfill into the ponding domain. For the overland flow domain, we solve the 2-D diffusive wave equation using an efficient and stable Runge-Kutta finite volume (RKFV) scheme. A similar method is used for the channel network, which exchanges flow with the overland and groundwater flow domains. The exchange between groundwater and channel flow is calculated based on the leakage concept [Gunduz and Aral, 2005], after the diffusive wave equation is solved. Wetlands are an important land cover type that modifies hydrologic responses. A new lowland-storage module is developed as part of this work and is described in Appendix A (Figure 1 illustrates the conceptual model used by the module).

[9] The subsurface is discretized into a series of 1-D soil columns connected to saturated groundwater layers at the bottom. The saturated-unsaturated soil water flow is governed by the Richards equation, which is solved using a modified Picard iteration approach [Celis et al., 1990; van Dam and Feddes, 2000]. The vadose zone module handles infiltration into the soil under normal conditions; however, under heavy rainfall conditions, we employ a modified form of the generalized Green and Ampt method [Jia, 1998]. We bring the dynamics of regional groundwater flow into the soil columns by writing a separate mass balance equation for the last grid cell, whose thickness changes as the water table fluctuates. The bottom of the last cell extends to the top of the bedrock. Lateral flow exchange calculated by the groundwater flow equation is fed into the Richards equation, and the recharge flux obtained from the solution of the Richards equation is in turn passed to the groundwater flow equation as a source term. As described in SP10, this coupling method produces physically consistent (in that the soil moisture profile is consistent with the groundwater head) and stable solutions and compares well with solutions based on the fully 3-D variably saturated Richards equation models for different conditions (e.g., conditions corresponding to infiltration excess, saturation excess, and return flow).

2.2. (PAWS+CLM): Coupled Subsurface and Land Surface Processes

[10] The processes included in CLM have been detailed in Oleson et al. [2010]. For the sake of completeness, we provide a brief overview of CLM processes incorporated in the coupled model in this section and then discuss linkages. PAWS is coupled to the latest release of CLM (version 4.0), with a prognostic crop model [Lawrence et al., 2011]. The soil hydrology and river routing routines in CLM are replaced by the corresponding procedures in the PAWS model. The coupling details are described in section 2.2.2.

2.2.1. Introduction to CLM Processes

[11] For canopy radiative fluxes, the two-stream approximation of Dickinson [1983] and Sellers [1985] is used to keep track of incoming, transmitted, reflected and absorbed direct or indirect radiation, over multiple solar wavebands. The plants are parameterized by detailed ecophysiological descriptors to capture the optical variability among plant species, especially trees. Canopy scaling/integration of sunlight penetration is based on the specific leaf area (SLA, the ratio of leaf area to leaf mass) concept [Thornton and Zimmermann, 2007], which is based on the assumption that
SLA increases linearly as a function of overlying leaf area index (LAI), and the two-big-leaf canopy model, which treats the canopy as a sun-lit leaf and a sun-shaded leaf [Dai et al., 2004]. CLM employs the resistance concept, rather than the widely used Penman-Monteith (PM) approach to calculate momentum/heat/vapor transfer. Although the PM equation assumes a wet-bulb augmentation for vegetation surface temperature, the resistance approach explicitly solves for the leaf temperature to satisfy the coupled latent and sensible heat transfer equations. Aerodynamic resistances are calculated based on the Monin-Obukov similarity theory [Kundu and Cohen, 2010; Zeng et al., 1998]. Canopy resistances are solved simultaneously with photosynthesis using the Farquhar model for C3 plants [Farquhar et al., 1980] or the model of Collatz [Collatz et al., 1992] for C4 plants. As classified in Arora [2002], this is a biochemical approach that provides a process-based description of CO2 assimilation and may be more suitable for the assessment of future climate scenarios. The water stress function couples hydrology with ecosystem dynamics and is parameterized as described in section 2.2.2.

[12] Soil and snow temperatures are updated by solving the heat conduction equation. The SNICAR (SNow, Ice, and Aerosol Radiative model) module [Toon et al., 1989] included in CLM 4.0 keeps track of the mass balance of aerosols and impurities in the snowpack. Snow aging impacts effective grain size and consequently snow albedo. Soil freezing is calculated by a freezing-point depression formulation of Niu and Yang [2006]. This formulation allows supercooled water and ice to coexist in a wide range of below-freezing temperatures. The soil hydraulic conductivities are scaled down by an impermeability factor depending on the fraction of ice in the soil water content.

[13] The carbon and nitrogen cycle on the land surfaces are fully incorporated with the biogeochemical vegetation dynamics and phenology module of Biome-BGC [Thornton and Rosenbloom, 2005; White et al., 1997]. The photosynthesized carbon is sent into a central carbon pool, which is first spent on maintenance respiration by live compartments (leaf, fine root, live coarse root, and live stem if applicable). Surplus carbon is then allocated to growth and phenological carbon pools (leaf, dead steam, root, and storage/transfer pools) depending on the allometric relationships prescribed for different plant species. This process is strongly controlled by available nitrogen. Growth respiration is consumed when allocation occurs. Offsetting, gap mortality, and fragmentation of coarse wood debris send carbon and nitrogen into the litter pools. Carbon and nitrogen (C/N) then trickle down a cascade of litter/soil organic matter (SOM) pools with varying turnover rates. The displayed structure of vegetation (LAI, tree height) is prognostically updated based on the carbon stored in different pools. Different plant species are parameterized with different phenological traits (e.g., evergreen, stress-deciduous, seasonal deciduous, etc). Nitrogen transformations are book kept in plant pools, three litter pools, four SOM pools, and a soil mineral pool. Simulated nitrogen-specific dynamics include deposition, fixation, leaching, and uptake.

[14] It is worth mentioning that although CN (Carbon and Nitrogen) module in CLM is a complex model with respect to the number of pools as compared to many other models [Manzoni and Porporato, 2009], there are still large uncertainties with the biogeochemical cycling in CLM. The CN module is a compartment model and does not track chemical species (except for the distinction between cellulose and lignin pools), microbial community, age/residence time, and vertical distribution of C/N, all of which can play important roles [e.g., see Berg and Laskowski, 2005; Fang et al., 2005; Maggi and Porporato, 2007; Maggi et al., 2008; Wutzler and Reichstein, 2008; Xu-Ri and Prentice, 2008]. The allometric coefficients, base turnover rates (base rates are then adjusted by temperature and water functions), nitrogen deposition/fixation rates, and denitrification rates all face uncertainties. There are also uncertainties associated with the appropriate spatiotemporal scales at which these rates should be applied [Manzoni and Porporato, 2009]. Data sets to validate the internal dynamics of CN cycling models are generally lacking.

2.2.2. Coupling CLM With PAWS

[15] The coupling between PAWS and CLM is done in a mass-conservative, theoretically consistent, and tightly integrated fashion. At initialization, vertical and horizontal discretization information in PAWS, which depends on topography, soil, and geology, is ported to CLM so that both have the same definitions of computational units. At each time step, climate forcing is passed into CLM to compute interception, throughflow, surface radiation processes, surface energy balance, photosynthesis, soil temperature, and snow processes. Then, the ET demand (both transpiration and soil evaporation) as a function of depths is passed into PAWS as a source term for the unsaturated zone. Also passed along are the soil temperature, ice content, canopy storage, ground precipitation, dew, and snowmelt amounts. The soil hydrology module in CLM is replaced with its PAWS counterpart, which then solves the Richards equation together with ET, groundwater flow, and runoff based on the coupling scheme described in SP10. Overland flow and streamflow are also calculated in PAWS. The resulting soil moisture states are then converted into the soil water state variables in CLM and supplied back into CLM for ecosystem updates and calculations in the next time step.

[16] In this paper, we will focus on the results obtained by running the (PAWS+CLM) model in the “offline” mode, in which the climate forcings are based on observations from conventional land-based stations. PAWS uses a structured grid; therefore, the CLM discretization is configured such that there is a one-to-one mapping between a PAWS cell and a CLM grid cell, and there is only one column in each CLM grid cell. At the same time, subcell heterogeneity on the plant functional type (PFT) level is supported as PAWS also adopts a similar approach. In SP10, this subcell heterogeneity of land use/land cover types was called representative plant types (RPT). To conform to the CLM literature, we adopt the term PFT in this paper. In the coupled model, PAWS provides the front-end processing utilities that reclassify raw land use data sets into CLM PFTs.

[17] Some changes to the CLM processes are necessary to make the two models consistent in theory. Since the soil water flow processes are primarily computed in PAWS, the combined model uses the van Genuchten formulation for soil water retention relationships as in the original PAWS model. Field capacity, saturated water content, and wilting...
Table 1. Model Calibration Parameters

<table>
<thead>
<tr>
<th>Symbol (Unit)</th>
<th>Parameter Meaning</th>
</tr>
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<tbody>
<tr>
<td>$K$ (m/day)</td>
<td>Groundwater hydraulic conductivity</td>
</tr>
<tr>
<td>$K_s$ (m/day)</td>
<td>Soil saturated hydraulic conductivity</td>
</tr>
<tr>
<td>$N$</td>
<td>van Genuchten parameter</td>
</tr>
<tr>
<td>$A$ (1/m)</td>
<td>van Genuchten parameter</td>
</tr>
<tr>
<td>$\gamma$</td>
<td>Parameter in Lai and Katul [2000] root efficiency function</td>
</tr>
<tr>
<td>$\alpha_{iv}$</td>
<td>Scale-dependent freezing fraction parameter as $\alpha$ in equation (11) in Niu and Yang [2006]</td>
</tr>
<tr>
<td>$K_r$ (m/day)</td>
<td>River leakances</td>
</tr>
<tr>
<td>$l$ (m)</td>
<td>Length of flow path for runoff contribution to overland flow domain</td>
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3. Results

In this section, we apply the PAWS model to a medium-sized watershed located in the U.S. Laurentian Great Lakes region. The model is first tested using observations and then utilized to elucidate the essential hydrologic dynamics of this watershed. Although extensive validations are provided to demonstrate that the new model can describe key processes accurately, the focus of this paper is in evaluating the relative strengths of controls on coupled hydrologic and vegetation dynamics. After describing the background hydrology, we use the model to study the relative importance of several controlling processes for surface fluxes: land use and vegetation type, soil texture, topography-induced groundwater flow, and nitrogen levels.

3.1. Site Description and Input Data

[21] The Clinton River (CR) watershed (1837 km$^2$) is situated in the mid-southern part of the lower peninsula of Michigan, as shown in Figure 2, and drains into Lake St. Clair. Located in the humid continental climate (hot summer) region, the basin experiences large seasonal temperature variations with very warm summer (average July temperatures above 22°C) and cold winter (average January temperatures around -3°C). Precipitation is evenly distributed in the year with an annual average of approximately 900 mm, which is slightly higher compared to nearby regions due to the lake effect. Daily or subdaily weather data are obtained from the National Climatic Data Center (NCDC) [2010]. The locations of the weather stations are shown in Figure 2a.

[22] This watershed is selected because of its diversity in land use and topography. The topography of the watershed mainly consists of rugged hills on the highlands of the west and flat, low-lying plains in the east, joined by a steep east-facing slope. The southwest corner forms semiclosed subbasins with numerous small lakes. The 30 m resolution national elevation data set (NED) is preprocessed to generate average cell elevation and lowland-storage bottom elevation in the computational grid. As shown in Figure 2b, the watershed is urbanized in the southern portion with varying extent of modification. The northern half is occupied by forest in the western quarter and agriculture in the eastern quarter. The 30 m resolution IFMAP (Integrated Forest Monitoring, Assessment, and Prescription) 2001 land use land cover data [Michigan Department of Natural Resources, MNDR, 2010], which was classified from Landsat Thematic Mapper™ imagery, is used to provide land use information. Three dominant land use types (PFTs) are modeled in each horizontal cell. The soil color data are extracted from the global data set [Global Soil Data Task, 2000].

[23] The surficial aquifer systems of the watershed are mainly composed of Pleistocene glacial drift that overlies the bedrock. Due to its proximity to Lake St. Clair, the watershed is covered by less transmissive lacustrine fine-grained sediment in the nearshore plain, while the highland portion of the watershed is characterized by relatively more stratified and permeable outwash. The glacial drift is treated as the unconfined aquifer. Spatial fields of the conductivities (lateral) of glacial drift were obtained by interpolating well records from the WELLOGIC database [Groundwater Inventory and Mapping Project (GWIM), 2006; Oztan, 2011; Simard, 2007] using kriging after noise was removed. Also interpolated from the WELLOGIC database are the aquifer thicknesses and static water table heights to provide discretization information and comparison data for the model. The bedrock is mainly coldwater shale, which is composed of shale and some limestone. This is a confining unit layer with very low permeability that produces little water yield. Lithology-based estimates of bedrock conductivities (lateral) are rasterized and input into the model. Lake St. Clair has been found to influence
groundwater flow in the basin. To better approximate reality, we enforce a constant head boundary condition at the boundary face nearest to Lake St. Clair. The average lateral conductivity of the unconfined aquifer in the basin is 13 m/day.

The model was spun-up by repeatedly looping through the climatic forcing data between 2001 and 2009 over a span of 4000 years, as in Thornton and Rosenbloom [2005]. To reduce the computational time required for model spin-up, several typical sites in the watershed are chosen. The spin-up was done in a “column mode,” in which the phreatic water table depth is kept constant. It has been verified that the ecosystem has approximately reached equilibrium. The resulting carbon and nitrogen states and other ecophysiological parameters are stored to be read in at run time.

A 880 m horizontal grid is used for the computations on the landmass. Twenty vertical layers are used for the unsaturated soil zone. The vertical discretization of the soil layer at a location depends on the local

Figure 2. (a) Map of the Clinton River watershed showing its location, elevation, weather stations, USGS gages (labeled by eight digit numbers), and the hillslope transect (A-B). (b) Land use map of the watershed.
thickness of the vadose zone and uses an adaptive approach that assigns finer grid near the surface and coarser cells near the bottom. Fourteen major rivers are simulated in the model, all discretized with spatial grid sizes of approximately 1500 m (A flexible exchange scheme in PAWS allows for flexible discretization of channel and land). The land surface and subsurface processes run on a maximum time step of 1 h. Overland flow and channel flow use a maximum of 10 min time steps. All components can adaptively change step sizes as necessary. On average, a day of serial-ized simulation takes 2.5 s on an Intel 2.3 GHz i-7 CPU.

3.2. Model Testing Against Observations

[26] The majority of the parameters in PAWS are spatially distributed (e.g., hydraulic conductivity or soil properties), and their spatial heterogeneity is honored in our simulations. Modest adjustments are done to some parameters, such as the van Genuchten soil parameters, by applying a global multiplier to improve model performance. Parameters adjusted are listed in Table 1. USGS (U.S. Geological Survey) gaging station 04165500 at Mt. Clemens, which represents basin outflow, is selected to show the comparison between model simulations and observations for the watershed. A modified Nash-Sutcliffe coefficient, MNASH is used as a model performance metric:

\[ MNASH = 1 - \frac{NASH + RNASH}{2} \]

where NASH is the standard Nash-Sutcliffe coefficient, and RNASH is the Nash-Sutcliffe computed based on square-root transformed data (SP10). The rationale for using MNASH is that the NASH coefficient tends to give too much importance to the peaks (runoff) at the expense of important subsurface processes (e.g., baseflow contribution to streams). Use of the MNASH metric is expected to address this deficiency of the original NASH coefficient. Figure 3a shows the comparison between simulated and observed daily hydrographs at the outflow USGS gage, CR at Moravian Drive at Mt. Clemens, MI. Figure 3b shows a close-up of a portion of the hydrograph. In Figure 3c, we also show the hydrograph comparison at an inner gage, CR at Sterling Heights, which is not involved in calibration. The decent daily NASH values (0.61 and 0.65) at both basin outlet and inner gages are satisfactory. Qualitatively, the baseflow is captured very well. The model grossly underestimates the largest peak in May 2004, while later in June 2004 there is a separate, large simulated peak that does not correspond to any observed peaks. We suspect that some error with precipitation data has led to this temporal mismatch, which causes heavy penalty in NASH.

[27] Simulated depths to water table (averaged from 2007 to 2009) are compared with the measured values from the WELLOGIC database in Figure 4 (the model is started in 2001). As can be seen from the spatial fields and the high \( R^2 \) value (0.66), an overall good agreement is noted between simulated and observed water table depths.

[28] Figure 5 shows the simulated soil temperature at a local measurement site in Romeo, Michigan [Environ-weather, 2010]. The main deviation is in the winter of 2008, when the model predicts as low as \(-5^\circ C\) while the temperature sensor reported around 0. This is attributed to a combination of factors, including potentially imperfect soil freezing scheme, local conditions, and measurement errors. Overall, the model was able to reproduce the major dynamic cycle of soil temperature fluctuations. The formulations for soil freeze and thaw should continue to improve as this process heavily influences surface water and energy fluxes [Sinha and Cherkauer, 2008]. However, we need to keep in mind that the simulated variable represents an average over the model grid cell (880 m \( \times \) 880 m) while the
observed data are measured at a point, which can be expected to deviate from the average.

Figure 6a shows the comparison of simulated LAI with the level 4, 8-day Terra MODIS LAI product (MOD15A2) [Knyazikhin et al., 1999; NASA Land Processes Distributed Active Archive Center (LP DAAC), 2012]. In Figure 6a, the urban areas (where MOD15A2 gives NaN values) are blanked out and shown in white for easier visual comparison with the MODIS observations. Figure 6b shows the time-series comparison of simulated and observed (MODIS) LAI at two locations with relatively uniform land use type of DBF and soybean, respectively. We experience some problems when comparing with MODIS LAI: (a) MODIS products always show no LAI at all in winter while the model does predict LAI for evergreen forest (ENF), which ranges from 5.5 to 6.5 (but can be covered by snow) and (b) peak values of LAI for corn published in the literature can reach 5–6 [e.g., Howell et al., 1997; Suyker and Verma, 2009], which matches with the simulated peak corn LAI, whereas the MOD15A2 LAI for the agricultural regions in this basin never goes above 3. Both problems lead to simulated LAI being higher than MODIS observed LAI. However, the literature values seem to suggest this may be a problem of the MODIS rather than the model. We notice that the LAI of the DBF and soybean are very well simulated, especially the onset and peak periods (the MODIS product does show some temporal variation of peak LAI for the DBF, which is more likely due to cloud interferences and observational errors). The simulated offset of DBF is much more abrupt than the observed, which is due to the linear offset function used in the tree phenology in CLM, suggesting that a more smooth offset formulation should be considered in future model enhancements.

Figure 7a shows the simulated ET versus the MODIS-based ET estimates (MOD16A2 and MOD16A3 [Mu et al., 2011, 2007]). The large-scale spatial pattern is preserved, including relatively lower ET in the eastern agricultural region and higher ET in the central-western forested areas. However, some fine-scale patterns predicted by the model were not observed in the MOD16A2 data. For example, the model simulates a high ET pocket at the corner of the southwestern boundary, whereas the MODIS values there are very low. The values cannot be this low, given that the region is filled with inland lakes. The simulated agricultural ET tends to be higher than MODIS products. Considering the uncertainties and errors with the MODIS product, we argue that this level of match is quite encouraging. Figure 7b shows the temporal comparison of basin-average ET between simulated and MOD15A2. The simulated ET tends to be slightly higher than the MODIS product for most of the months. In general, the temporal dynamics agree very well.

3.3. General Background Hydrology of the Watershed

The primary purpose of this section is to use the model to elucidate the essential hydrologic dynamics in the
watershed, which serves as the context for the analysis of relative importance in section 3.4. As we will see, the spatiotemporal patterns observed in this watershed are governed by different processes with variable strengths of controls. These patterns naturally drive us to ask the questions about the relative strengths of controls.

[32] Insight into the hydrologic cycle of this watershed can be gained from Figures 8 and 9, which show, respectively, mean monthly basin-average fluxes, temporal trend of the total soil moisture content, TSMC (including water and ice), and snow water equivalent, SWE. Qgc, Ex, SatE, and InfE are the four major mechanisms of streamflow generation, namely, groundwater contribution to streamflow, lowland exfiltration, saturation excess, and infiltration excess. Their sum can be seen as approximate, but not equal, to the streamflow, because of interception and reinfiltration.

[33] Figure 8 vividly describes a system that is energy controlled most of the year and becomes moisture limited only in the hottest summer months. Precipitation increases from March until it reaches its peak in May. Streamflow normally reaches its peak in March. The first few precipitation events can be very pronounced in terms of streamflow generation. In April and May, although precipitation increases more than 80%, ET jumps even more rapidly and overcomes the added precipitation. Correspondingly, the TSMC of the basin shifts into the “net-loss” phase (Figure 9), and the soil moisture pool starts to be tapped to compensate for the increasing ET demand. There is still ample moisture in the subsurface so that streamflow does not drop noticeably. From June to August, we observe a rapid decline of soil moisture content in the basin. Soil seldom reaches saturation. ET shifts from energy-limited to moisture-limited conditions. Streamflow consequently drops to its annual minimum in August. From September to the end of the year, ET wanes quickly when TSMC steps into the “net-gain” region. ET almost vanishes in winter and the soil continues to store water until the next cycle starts.

[34] The energy-driven dynamics is also clear from the streamflow generation. The overland flow contribution to streamflow is commonly divided into saturation excess (SatE) and infiltration excess (InfE) [Dingman, 2008], which together create the peaks in the hydrograph. We define SatE as runoff that occurs when the entire soil
column underneath the surface area is saturated. Figure 8 demonstrates that streamflow generation is tightly related to the seasonal energy cycle. Saturation excess evolves in phase with TSMC in Figure 9 and is the dominant process in winter and spring. The dominance of SatE again implies that the system is energy limited in cold seasons. Infiltration excess, on the other hand, is less important than SatE in cold seasons, which is explained by the high conductivity of glacial drift soils in the region. The relative importance of InfE rises in summer, when streamflow diminishes and river stages are lowest. In August, storm events barely stimulate much streamflow, as TSMC is very low and the basin is far from saturation, and the small flashy peaks that do occur are mostly composed of infiltration excess, as shown in Figure 8b. InfE is primarily generated from the urbanized regions of the southern basin and, when SatE diminishes, its percentage in the runoff rises.

Figure 10 illustrates the spatial patterns of long-term average annual energy/water states and fluxes. The water variables seem dominated by topography, whereas the
energy variables are strongly influenced by land use/land cover types. Figure 10 shows that SatE is commonly generated from the lowland plains on the east, only sporadically on the local depressions on the high hills and around the bending corner in the southwest, which as mentioned previously is a semiclosed subbasin that hosts a chain of small lakes. The pattern of SatE is very similar to the top 10 cm soil moisture map, which shows the lowland areas being generally wetter than upland. This pattern indicates that groundwater lateral flow may have transported a large quantity of water from the western hills to the eastern low plains, over the entire spatial scale of the watershed. This hypothesis is supported by the groundwater recharge map, which shows the hills as mainly recharging areas and the low plains as discharging areas (Recharge < 0). On the other hand, sensible heat, temperature, and net primary production (NPP) maps are primarily controlled by land use types. Areas with high sensible heat correspond to the urban centers. This pattern is also obvious from the soil temperature. Ground surfaces of urban areas are, on annual average, 2° to 4° hotter than forested areas due to the “urban heat island” effect [Landsberg, 1981]. These values are similar to reported values (e.g., 4.3°C in Vukovich [1983] and 2.1°C in Turkoğlu [2010]). Unsurprisingly, the regions with the lowest annual temperature are the same areas with the highest latent heat flux. The agricultural land, dominated by soybean, has quite high soil temperature, but its sensible heat flux is not higher than the urban area. Compared to the forested areas, soybean provides less shading and dissipates less latent heat due to the rather low LAI and low canopy height of soybean (maximum LAI is around 2). Compared to the urban areas, soybean has a larger resistance to sensible heat. The highest values of latent heat are found in the forested or perennially ponded areas near streams in the high hills. These areas have ample moisture supply due to local groundwater convergence. Following the same rationale, we would expect higher latent heat to be found on the low plains. However, such an expected pattern is not visually identifiable from the latent heat flux map. The latent heat figure shows generally higher latent heat in the northern half of the basin with vegetated land covers. The southern tip of the basin is urbanized and, therefore, does not have enough vegetation to transpire water. Apparently, the influence of groundwater flow on ET is overshadowed by the land use and other spatial trends.

[36] Strong influences of landform and topography on runoff, energy, and vegetation processes have also been noted [Band et al., 1993; Ivanov et al., 2008; Jencso and McGlynn, 2011; Kim et al., 1999; Rihani et al., 2010] and modeled [Agnese et al., 2007; Bracken and Croke, 2007; Laio et al., 2009; Troch et al., 2003]. To get a better understanding of the spatiotemporal distribution of runoff generation and groundwater influences on vegetation in this watershed, we show in Figure 11 the fluxes and states along a hillside transect. The straight transect line begins on the central hill, nearly follows the elevation gradient and ends in the lowland plain, as highlighted by the line segment A-B in Figure 2. To reduce noise and facilitate our interpretation, the vegetation types along the profile are all set to DBF in simulation S5 (Table 2), and the soil texture is set uniformly to the most typical values. In Figure 11, time is on the x axis, and distance along the transect (abbreviated as distance) is on the y axis, such that viewing from top of a panel to the bottom corresponds to going from uphill to downhill. We show weekly averaged plots of surface runoff, top 10 cm soil moisture, groundwater head (H), and NPP. Since the runoff values vary across several orders of magnitude, we show the data after applying a cube-root transformation. As we can see, the generation of runoff is highly concentrated, both in space and in time. Unsurprisingly, the pattern of runoff correlates closely with the soil moisture pattern. There is a thin horizontal line (near distance = 4 km) of runoff generation that occurs sporadically in the year. At this location, transect A-B intersects a level 3 stream (the Stony Creek). Apart from this line, runoff occurs primarily on the lowland, which corroborates the findings from Figure 10. The divide at a distance of 15 km, where the hillslope descends to the flat plains, is clearly identifiable. As discussed by Kim et al. [1999] and Salvucci and Entekhabi [1995], this divide distinguishes two distinct zones, the upper of which is dominated by infiltration and moisture-limited evaporation while the lower is characterized by discharge and runoff production. The peaks of runoff generation occur only in two short time windows, one in early May and another in December, when there is little vegetation activity. Like in other years, several spring and winter storm events generate most of the runoff volume. Very low volumes of runoff are generated in summer even in the lowland, despite a large storm event in July, which corresponds to a relatively “quiet” summer period in the hydrograph. Compared to runoff, groundwater head (H) varies much more smoothly, demonstrating spatio-temporal continuity. In summer, the contour lines of H bend upward, corresponding to the drydown of groundwater levels. From Figure 10h, it is clear that the availability of water plays a lesser role than the seasonal energy input. NPP, both uphill and downhill, responds primarily to seasonality. The plants achieve maximum productivity in June and July, following the maturity of the LAI and the high energy input. However, during these 2 months, the influence of moisture is also visible. The lowland trees have approximately 15% higher NPP than uphill trees. Besides NPP magnitude, downhill trees also have longer period of high productivity. In June, there is a noticeable gap between the productivity peaks. Reading from the precipitation and runoff plots, we see that the timing of this gap corresponds to the hiatus between two large storm events. This period of lowered productivity is clearly due to moisture limitation. The gap is very brief and shallow for the lowland trees, owing to groundwater subsidy.

[37] The rich patterns of different fluxes and states are apparently dominated by different processes. These interesting observations force us to ask the questions: How do these processes produce, either in isolation or in concert, the observed spatiotemporal patterns? Since both groundwater and vegetation type seem to influence ET and NPP, which has a stronger influence? How relatively important is each process on different hydrologic and vegetation processes? What is the role of soil water retention and unsaturated conductivity? We use hypothetical simulations to answer these questions in the next section.

3.4. Relative Strengths of Controls

[38] In order to answer the questions raised at the end of section 3.3, we design a series of simulations to quantify
the impacts of different factors on long-term annual ET and NPP as well as other variables (infiltration, runoff, transpiration, soil temperature, and soil moisture). For simplicity, we generically refer to the outcome variable as $u$. Details of these simulations and the objectives of the numerical experiments are summarized in Table 2 and will be discussed in the following sections. In this paper, we put our focus on four factors: land use types, topography-induced groundwater flow, soil water retention, and soil nitrogen levels. Other factors such as slope aspect and micrometeorology may also be important for some sites [see Ivanov et al., 2008], but they are outside the scope of this paper. We first characterize the effect of each factor and search for an appropriate surrogate index for the factor. Realizing that each process is a complex combination of different controls (e.g., for soil properties, soil conductivity, and water retention characteristics all affect plant growth), we attempt to simplify our analysis by considering both soil characteristics and groundwater convergence as lumped “factors.” Then, we evaluate the relative strength of each control in multivariate simulations using analysis of variance (ANOVA).

Figure 11. (a) Precipitation (mm/day). (b-e) are spatiotemporal plots of fluxes and states along the hillslope transect A-B. The $x$ axis is time and the $y$ axis is distance from point A along the transect. Reading from top of the panel to the bottom is going from upland to lowland. (b) Runoff (mm/yr); (c) soil moisture content (m$^3$/m$^3$); (d) groundwater head (m); and (e) NPP (gC/m$^2$/yr). The runoff values in Figure 11b are cube-root transformed because the original values span several orders of magnitude and two peaks overwhelm all other events. Elevation plot is placed to the left of the panels to show the topographic descent of the hillslope.
Table 2. List of Hypothetical Simulations

<table>
<thead>
<tr>
<th>Simulation</th>
<th>Procedures</th>
<th>Purpose</th>
</tr>
</thead>
<tbody>
<tr>
<td>S0</td>
<td>Use the baseline parameters</td>
<td>To serve as the baseline scenario</td>
</tr>
<tr>
<td>S1</td>
<td>Based on S0, land uses are randomly distributed in the watershed</td>
<td>To show the intraclass and interclass variability of ET</td>
</tr>
<tr>
<td>S2</td>
<td>Based on S0, land use uniformly set to DBF, lateral groundwater disabled</td>
<td>To show the influence of soil characteristics on plant growth (in terms of water supply) and also to serve as a basis for comparison with S3</td>
</tr>
<tr>
<td>S3</td>
<td>Based on S0, land use uniformly set to DBF</td>
<td>Together with S2, to show the influence of lateral groundwater flow</td>
</tr>
<tr>
<td>S4</td>
<td>Based on S0, land use randomly selected from vegetated classes: temperate evergreen tree, broadleaf deciduous tree, C3 grass, and corn</td>
<td>To assess the relative significance of the controlling factors with effect of urbanization silenced</td>
</tr>
<tr>
<td>S5</td>
<td>Same simulation as S0, however, along the topographic gradient (line A-B), land use is set to DBF, and soil is set to the dominant soil type along the paths</td>
<td>To demonstrate the influence of spatiotemporal distribution of runoff, soil moisture, groundwater head, and NPP</td>
</tr>
</tbody>
</table>

3.4.1. Single Factor Analysis and Process Indices

[39] We refer to the baseline simulation as S0, which most closely represents the realistic setting of the basin and is used to generate all results in the previous sections. To evaluate the impact of land use types, we carry out a hypothetical simulation, referred to as S1, with randomly distributed land uses, while all other factors are kept identical to S0. In S1, five land use types (namely, temperate evergreen forest, temperate deciduous forest, grass, corn, and medium-intensity urban), each assigned equal areas, are randomly placed in the watershed to eliminate any spatial correlation with soil types, topography, and convergence levels. The resulting long-term annual average ET is summarized by land use types and presented in the boxplot in Figure 12. The simulated ET are in general agreement with literature reported values for DBF [e.g., Oishi et al., 2010], corn, and soybean [e.g., Suyker and Verma, 2009]. The ET for corn is somewhat in the lower range of the reported irrigated plants [e.g., Howell et al., 1997], because irrigation is not simulated. As we can see, the interspecies variation of ET can be significant. Mean forest ET is higher than that of corn, which is higher than ET of grass. However, all vegetated lands significantly have greater ET values than impervious areas, supporting the spatial pattern observed in Figure 10. The results suggest that urbanization has a significant impact on ET fluxes and explains why its spatial pattern overwhelms that of topography and groundwater convergence. To further study the impact of other factors, we carry out the ensuing analysis in this section after removing the masking effect of urbanization.

[40] In simulation S2, the land use types are uniformly set to deciduous broadleaf forest (DBF). We disable groundwater lateral flow by setting the lateral conductivity of the aquifers to $10^{-14}$ (m/day). As a result, the cells are almost isolated from each other, as in the original CLM model. Because other variables, including vegetation type and lateral flow, are homogenized, we argue that the NPP obtained from S2 also measures the overall ability of soil (including the effect of soil water retention and thickness) to retain and supply water for tree growth. This effect is influenced not only by soil water retention characteristics but also by conductive properties and thickness. Since both soil retention and conductivities are heavily dependent on texture, we may roughly refer to this physical factor as soil texture. Therefore, the NPP values obtained from S2 can be viewed as a “soil water supply index” for NPP, or SWSI(NPP). More generally, we define $SWSI(u,x)$ as the long-term annual average values of variables $u$ from S2 at spatial location $x$ in the basin. For simplicity, $x$ is omitted in the ensuing notations. $u$ can be either ET, NPP, runoff, infiltration, or any other variable we choose. In the present simulation, $SWSI(u)$ then represents how spatial variability of soil texture impact $u$. SWSI(NPP) are shown as a spatial map in Figure 13a.

[41] An index for the groundwater flow process can be extracted from simulation S3, which has all settings identical to S2 except that lateral groundwater flow is enabled. Therefore, the difference $u_{S3} - u_{S2}$ represents the net effect of lateral groundwater flow on variable $u$. We therefore define a “lateral flow index” for the variable $u$, or $LatI(u)$, as the difference of long-term (5 years, 2005–2009) annual average $u$ between S3 and S2. ($NPP_{S3} - NPP_{S2})/NPP_{S2} \times 100\%$ is shown in the map in Figure 13b. As we can see, lateral groundwater flow subsidizes vegetation in the lowland plains under drought conditions and increases their annual productivity by $\sim 5\%$. However, this subsidy comes at the cost of a 10–15%, even up to 30% in some cases, reduction of NPP on the highland hill areas. Earlier studies
Ivanov et al. [2008, 2010] that focused on arid, moisture-limited environments showed stronger influence of lateral groundwater redistribution on vegetation growth. Our results indicate that, even for an energy-limited region as the present watershed, groundwater may still play a noticeable role in regulating plant growth, by subsidizing lowland plants while sacrificing upland productivity. The groundwater influence, in our case, also seems to impact plants on the highland much more significantly than those on the lowland plains. Interestingly, the subsidy seems higher immediately adjacent to the foot of the hills and reduces as we go deeper into the plains. This is because, on the flat plains, the trees at the foot of the hill have the best access to the lateral groundwater discharge that comes from uphill. On a side note, one would expect LatI to be correlated to topographic index (TopoI) [Beven and Kirkby, 1979], a “wetness” index that aims to provide a simple metric to estimate the likelihood of saturation. However, as shown in the (LatI-TopoI) plot in Figure 14b, such a correlation is not obvious (plotting TopoI against ET yields a similar plot). Roughly, a rectangle could be drawn to enclose the scattered dots. However, TopoI is unable to explain a large portion of the variability, which might include the heterogeneity of aquifer properties, foothill dynamics, and the particular topographic and watershed construct (concave or diverging, etc.), among other factors. It is known that the topographic index may not work well in flat terrains.

Figure 13. Spatial distributions of (a) NPP from S2, representing the soil’s ability to provide water to plants and (b) NPP percentage change from S2 to S3 (the difference is termed LatI), showing the net effect of lateral groundwater flow in subsidizing lowland trees while reducing available moisture for upland trees. [Ivanov et al., 2008, 2010] that focused on arid, moisture-limited environments showed stronger influence of lateral groundwater redistribution on vegetation growth. Our results indicate that, even for an energy-limited region as the present watershed, groundwater may still play a noticeable role in regulating plant growth, by subsidizing lowland plants while sacrificing upland productivity. The groundwater influence, in our case, also seems to impact plants on the highland much more significantly than those on the lowland plains. Interestingly, the subsidy seems higher immediately adjacent to the foot of the hills and reduces as we go deeper into the plains. This is because, on the flat plains, the trees at the foot of the hill have the best access to the lateral groundwater discharge that comes from uphill. On a side note, one would expect LatI to be correlated to topographic index (TopoI) [Beven and Kirkby, 1979], a “wetness” index that aims to provide a simple metric to estimate the likelihood of saturation. However, as shown in the (LatI-TopoI) plot in Figure 14b, such a correlation is not obvious (plotting TopoI against ET yields a similar plot). Roughly, a rectangle could be drawn to enclose the scattered dots. However, TopoI is unable to explain a large portion of the variability, which might include the heterogeneity of aquifer properties, foothill dynamics, and the particular topographic and watershed construct (concave or diverging, etc.), among other factors. It is known that the topographic index may not work well in flat terrains. Therefore, for the purpose of comparing their relative influences, we choose SWSI and LatI to represent, respectively, soil properties and groundwater flow dynamics. [c] Although the representation of the N cycle in CLM is still too crude compared to reality, it does allow us to make some initial assessment of the order of magnitude of the influence as compared to other factors. Over a long term, a dynamic balance is established between nitrogen in the plant, litter, SOM and mineral pools, BNF, deposition, leaching, and denitrification. Random perturbation of the N pools will lead to a rebalancing of the system and a gradual regression to the equilibrium. In order to express the N variability while approximately maintaining such a balance, we set the BNF rates using equation (1) [Cleveland et al., 1999; Luo et al., 2006; Oleson et al., 2010]:

\[
\text{BNF} = \alpha \times 1.8 \left(1 - e^{-0.003\text{NPP}}\right),
\]

where BNF is in gN/m^2/yr, NPP is the annual net primary production, and \(\alpha\) is an adjustment factor whose values are kept at these hypothetical levels: \(\alpha \in \{0.2, 0.6, 0.8, 1, 1.2, 1.4, 1.8\}\). We choose this range as it resembles the range of the uncertainty with natural BNF rate estimates [Galloway et al., 2004]. In the original CLM, \(\alpha\) is always equal to 1.0. In our relative control analysis, the model is spun up over 4000 years by looping through the climatic forcing data between 2001 and 2009, as in Thornton and Rosenbloom [2005], but with different \(\alpha\) values as given above. The final C and N states at steady state differ greatly between different assumed BNF rates. Table 3 shows some typical maximum LAI values, end-of-year total SOM carbon/nitrogen states as a result of the different BNF rates. While the alteration of the BNF rates changes not only N pools but also C pools, we refer to this factor as nitrogen levels, to reflect the fact that nitrogen is the limiting factor. We note that although we perturbed the BNF rates function, we do not posit any causal or ordinal relationship between BNF and NPP change. This is just a way for us to express the variability of nitrogen availability and propagate it through the ecosystem, while maintaining the balance between different N pools. Of course, we may also choose

![Figure 14. LatI(NPP) (which is NPP of S3 minus NPP of S2) as a function of topographic index. As we can see, the topographic index is not a very good predictor for NPP in this watershed.](image-url)
nitrogen deposition rates as the knob to perturb, which would generate similar effects. The C/N pools at the equilibrium corresponding to different $a$ values are recorded to be used as initial states in the following combined simulations.

3.4.2. Combined Analysis Using ANOVA

[45] Using ANOVA, we can quantitatively assess the relative strengths of the controlling processes by approximately estimating the variance of vegetation growth attributable to each one of the factors. In simulation S4, baseline soil water retention properties and aquifer conductivities are used. To mask the dominant role of urbanization, the land cover in S4 are limited to evergreen forest (ENF), DBF, C3 grass, and soybean, and these classes are randomly placed in the watershed. The nitrogen level of each cell is randomly coded between 1 and 7. For each coded level, the initial C/N states are looked up from the long term spin-up results with the corresponding BNF rate described in the last paragraph.

[44] A four-way ANOVA test (assessed at the 1% confidence level) with interactions is used to partition the total variance of $N$ in S4 into the individual contributions. The four predictors are land use types (PFT), soil (SWSI($u$)), lateral GW flow (LatI($u$)), and nitrogen levels (N level). The ANOVA results are presented in Tables 4 and 5 and graphically in Figure 15 for different $u$. We examine seven different $u$'s, which are the long-term annual averages of ET, NPP, runoff (Rf), infiltration (Inf), top 10 cm soil temperature ($t_{10cm}$), and top 10 cm soil moisture ($\theta_{10cm}$). The cross terms are generally small compared to the main factors. For simpler presentation, they are combined as an "interactions" term in Figure 15. The "error" term, which represents the variance that cannot be explained by the main factors and their interactions, is also shown. The partitioned variances sum up to 1 for all $u$'s.

Table 3. Different Ecosystem States (Maximum Value in a 9 Year Period) for DBF at Steady State as a Result of Different BNF Rates$^{a}$

<table>
<thead>
<tr>
<th>Source</th>
<th>Sum of Squares</th>
<th>Percent of Variance Explained (%)</th>
<th>Explained (%)</th>
<th>F</th>
<th>Prob &gt; F</th>
</tr>
</thead>
<tbody>
<tr>
<td>N level</td>
<td>4,835,447</td>
<td>23.53</td>
<td>1,783</td>
<td>0</td>
<td></td>
</tr>
<tr>
<td>PFT</td>
<td>7,831,229</td>
<td>38.11</td>
<td>5,775</td>
<td>0</td>
<td></td>
</tr>
<tr>
<td>SWSI</td>
<td>1,988,126</td>
<td>9.67</td>
<td>4,398</td>
<td>0</td>
<td></td>
</tr>
<tr>
<td>LatI</td>
<td>3,242,024</td>
<td>15.78</td>
<td>5,772</td>
<td>0</td>
<td></td>
</tr>
<tr>
<td>N level × PFT</td>
<td>1,100,465</td>
<td>5.35</td>
<td>150</td>
<td>0</td>
<td></td>
</tr>
<tr>
<td>N level × SWSI</td>
<td>131,682</td>
<td>0.64</td>
<td>49</td>
<td>0</td>
<td></td>
</tr>
<tr>
<td>N level × LatI</td>
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</tr>
<tr>
<td>PFT × SWSI</td>
<td>95,569</td>
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<td>70</td>
<td>0</td>
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</tr>
<tr>
<td>PFT × LatI</td>
<td>158,611</td>
<td>0.87</td>
<td>117</td>
<td>0</td>
<td></td>
</tr>
<tr>
<td>SWSI × LatI</td>
<td>10,687</td>
<td>0.05</td>
<td>24</td>
<td>1.30E-06</td>
<td></td>
</tr>
<tr>
<td>Error</td>
<td>1,056,450</td>
<td>5.14</td>
<td>100.00</td>
<td>0</td>
<td></td>
</tr>
<tr>
<td>Total</td>
<td>20,550,664</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

$^{a}$BNF = $1.8u(1 - e^{-0.003NPP/u})$ where NPP$_{a}$ is the annual NPP and $a$ is the adjustment factor.

Table 4. Four-Way ANOVA of N Level/Land Use Type/Soil Texture/Groundwater Flow on $u$ = ET

<table>
<thead>
<tr>
<th>Source</th>
<th>Sum of Squares</th>
<th>Percent of Variance Explained (%)</th>
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<tr>
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<td>100.00</td>
<td>0</td>
</tr>
<tr>
<td>Total</td>
<td>20,550,664</td>
<td></td>
<td></td>
<td></td>
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</tbody>
</table>

Table 5. Four-Way ANOVA of N Level/Land Use Type/Soil Texture/Groundwater Flow on $u$ = NPP

<table>
<thead>
<tr>
<th>Source</th>
<th>Sum of Squares</th>
<th>Percent of Variance Explained (%)</th>
<th>F</th>
<th>Prob &gt; F</th>
</tr>
</thead>
<tbody>
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<td>LatI</td>
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</tr>
<tr>
<td>N level × PFT</td>
<td>1,100,465</td>
<td>5.35</td>
<td>150</td>
<td>0</td>
</tr>
<tr>
<td>N level × SWSI</td>
<td>131,682</td>
<td>0.64</td>
<td>49</td>
<td>0</td>
</tr>
<tr>
<td>N level × LatI</td>
<td>100,415</td>
<td>0.47</td>
<td>37</td>
<td>0</td>
</tr>
<tr>
<td>PFT × SWSI</td>
<td>95,569</td>
<td>0.47</td>
<td>70</td>
<td>0</td>
</tr>
<tr>
<td>PFT × LatI</td>
<td>158,611</td>
<td>0.87</td>
<td>117</td>
<td>0</td>
</tr>
<tr>
<td>SWSI × LatI</td>
<td>10,687</td>
<td>0.05</td>
<td>24</td>
<td>1.30E-06</td>
</tr>
<tr>
<td>Error</td>
<td>1,056,450</td>
<td>5.14</td>
<td>100.00</td>
<td>0</td>
</tr>
<tr>
<td>Total</td>
<td>20,550,664</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

$^{a}$BNF = $1.8u(1 - e^{-0.003NPP/u})$ where NPP$_{a}$ is the annual NPP and $a$ is the adjustment factor.
10% and LatI: 15%). Soil nitrogen level (as a result of ecosystem spin-up to equilibrium using different BNF rates) plays an important role in ET, confirming previous observations of positive correlation between BNF and ET. As is clear from Figure 15, this influence is mainly exerted through its control on transpiration (Tp). It can then be inferred that groundwater and soil texture are much more dominant controls on soil evaporation. The influence of N levels also propagates to hydrologic fluxes and temperature, although not in a strong fashion. The findings suggest that in order to accurately predict spatiotemporal distributions of ET (or latent heat flux), the ecosystem dynamics including nitrogen availability must be carefully considered.

In contrast, LatI and SWSI have comparable significance for $\theta_{10cm}$, and each explain about 40% of the variance. As a central variable for hydrologic and biogeochemical processes, soil moisture has been the most intensively studied in the literature among the variables analyzed in this paper. Interestingly, our results have been corroborated by analysis of field data [Famiglietti et al., 1998; Joshi and Mohanty, 2010; Pan and Wang, 2009; Wilson et al., 2004], where soil and topography are found to be of similar importance (although soil/vegetation impacts are lumped in Wilson et al. [2004], and it is not clear how much variance they each explain). Therefore, for hydrologic and biogeochemical processes, which depend on soil moisture in a strongly nonlinear fashion, it is important to consider both local soil textural properties and regional groundwater flow. Qiu et al. [2001] report a larger control of mean soil moisture by land use. The actual controls of vegetation on soil moisture are expected to be higher than explained in the model. Further study should consider more diversified vegetation and the effects of hydraulic lift by vegetation or macropores created by vegetation roots. Our study intentionally breaks the correlation that naturally exists between topography and vegetation types [e.g., Brown, 1994]. We also note a large error for $\theta_{10cm}$, indicating that the complex dynamics of moisture cannot be explained by simple linear models of the variables. The complex controls of soil moisture have been reported by Zhu and Lin [2011], who conclude that terrain attributes are more important in wetter places among other dynamics.

It must be noted that, for NPP, although LatI and SWSI appear unimportant compared to vegetation types and soil nitrogen content, both have significant influence once we hold PFT and N levels constant across the basin, as we have shown in S3.

3.4.3. Robustness of the Analysis

A reasonable question to ask is whether the relative importance of different processes will stay the same when we perform the same exercise with a different model, a different spatial resolution or in another region where climatic input and physical parameters (e.g., aquifer transmissivities) are different. Intuitively, the results should change when physical parameters are altered since, if we imagine a basin with very low aquifer transmissivities, the influence of groundwater flow dynamics should be very low. Although the effect of different model formulations should also be examined in the future, in this paper, we assess the effect of the parameters and spatial resolution. To quantitatively assess this impact, we redo the ANOVA analysis in section 3.4.2 with exactly one of the following changes applied: (a) the conductivity of the unconfined aquifer

Figure 15. ANOVA analysis results show the relative strengths controls of physical processes on hydrologic and vegetation dynamics (Rf, runoff; Inf, infiltration; ET, evapotranspiration; Tp, transpiration; NPP, net primary productivity; $\theta_{10cm}$, top 10 cm soil temperature; $\theta_{10cm}$, top 10 cm soil moisture; Interactions, for simplicity, the cross terms between different factors are combined into one interaction term). “Original” stands for ANOVA test carried out without global parameter changes described in section 3.4.3. In “$K \times 0.1$” ANOVA test, all simulations (S2, S3, and S4) have their $K$ scaled by 0.1. Similarly, 0.1 is added to N in all simulations in “$N + 0.1$” ANOVA test. “Double resolution” means the spatial step size is halved (number of cells quadrupled). (a) Original, (b) $K \times 0.1$, (c) double resolution, (d) $N + 0.1$. 

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everywhere in the basin is reduced by a factor of 10. Therefore, the basin average unconfined aquifer $K$ becomes 1.3 m/day; (b) the van Genuchten parameter $n$ is increased by 0.1, thereby increasing the nonlinearity of the soil water retention and unsaturated conductivities; (c) the horizontal cell size is reduced in half (resolution is doubled), thereby quadrupling the number of cells in the basin.

The results are shown in Figure 15. Indeed, the variances attributed to each factor do shift after making the changes (Figure 15a). The influence of LatI reduces for all variables, implying a less dominant groundwater system. The relative roles of other factors, especially SWSI, increased accordingly to make up for the drop in LatI. This means the relative importance of groundwater dynamics will shift when we move to a geologic configuration that extends beyond the current range of variability. With change (b), however, the changes are relatively minor, with SWSI explaining slightly more variance in Rf and Inf. The shifts in the relative importance due to a change in the range of variability have also been previously noted by field data analysis [Zhu and Lin, 2011]. With the help of a numerical model, however, the relative importance of controls at each site can be analyzed prior to extensive data collection.

The spatial resolution has a relatively weak influence on the results of the analysis. For ET, Rf, and Inf, LatI now plays a more important role when resolution is doubled, scoring 20%, 74%, and 87%, respectively. This is due to the better resolution of the effects of topography relative to the original simulation. For $t_{0\text{cm}}$ and $\theta_{0\text{cm}}$, however, SWSI increased slightly, presumably due to a larger range of SWSI as higher resolution allows more distinct soil classes to be simulated. However, the general trend stays the same as in the lower resolution simulations.

### 4. Discussion and Conclusions

The knowledge and the mechanistic understanding obtained in this study may help guide future modeling and data-gathering decisions. For example, many previous efforts focused on downscaling satellite soil moisture observations [e.g., Busch et al., 2012; Mascaro et al., 2010; Pelleng et al., 2003], and our results indicate that both topography and soil texture should be environmental predictors in such downscaling methods as they are important controls for soil moisture. For another example, for gross primary production (GPP/NPP) estimation, at least for the humid continental climatic region examined here, plant type and nutrient availability far outweigh groundwater dynamics and soil supply properties in terms of their relative importance. It is therefore important to obtain soils data sets with better carbon/nitrogen storage estimations. For quantification of terrestrial-atmospheric vapor/heat exchange, groundwater dynamics, soil properties, and ecosystem processes are all important. Because both short- and long-ranged patterns of groundwater flow exist, it is important to consider regional groundwater dynamics and subsurface processes in land surface models. This means that for large-scale simulations that aim at studying terrestrial-atmospheric vapor/energy exchange, many simplified cell-based hydrologic formulations (such as the TOPMODEL-based formulations in original CLM and Noah LSM) are likely to produce unreliable estimates. Although similar conclusions have been drawn in the literature [Anyah et al., 2008; Fan et al., 2007; Maxwell and Kollet, 2008a], our study is unique in this climatic region.

In spite of the limitations of the current nitrogen cycling schemes in CLM4.0, the results clearly indicate that the nitrogen availability heavily influences not only vegetation growth but also ET, through which other hydrologic fluxes are affected. Conventional hydrologic models often do not consider the nutrient dynamics mechanistically. For assessment of climate change on regional hydrology and vegetation, nitrogen dynamics should be considered. The results in this paper suggest that we need to take an integrative view of the ecosystem-hydrology interactions in order to make better predictions. It is important for hydrologists to continue expanding the domain of sciences in hydrologic simulations to identify previously undiscovered but potentially important linkages, echoing the call for more cross-disciplinary integration [Wagener et al., 2010] and encouraging grass-roots community collaborations.

For many variables studied in Figure 15 (e.g., ET, Tp, NPP, and $t_{0\text{cm}}$), the error terms account for less than 10% of the total variance. Consequently, it is possible to predict these variables (at least their annual averages) with a fair degree of accuracy by just using simple linear models of the main processes (land use, nitrogen, groundwater flow, and soil water retention) and their interactions. However, the variables with higher percentage of error (e.g., $\theta_{0\text{cm}}$) will need to be addressed by more complex models detailing the space-time interactions of factors.

As with other similar studies, the conclusions in the paper are somewhat tied to the model employed. The ability of a numerical model to represent linkages and interactions depends on its formulations. Considering the large uncertainties associated with descriptions of the nitrogen cycle in CLM, the numerical value of its relative importance will likely shift when improved N cycling schemes are employed. Given that a large range of BNF rates (altered by $a$) are used to get carbon nitrogen states, the true influence of nitrogen is likely smaller than estimated. Future simulations supported by novel observations will be crucial for confirming the results. PAWS+CLM considers water to move only vertically in the unsaturated zone. As a result, the model does not produce accurate results when significant interflow exists. The model currently does not track nutrient transport within groundwater and surface water. Also, the analysis in the paper does not include the effects of microtopography, micrometeorological conditions, and aspect of the slope. In the future, it would be interesting to compare results from other models using the approach described here. The effect of very deep soils on the coupling algorithm in PAWS seems to be mild given the good match with observed groundwater heads and well-captured baseflow in the hydrograph. In the future, very high resolution simulations will likely provide more insight on the effect of spatial resolution. Scale-aware or multiscale simulation approaches are called for to help with the issue of spatial scaling.

To summarize, we have described the application of a novel process-based hydrologic model PAWS+CLM to a watershed in the humid continental climate region of the U.S. Midwest to understand the relative importance of
vegetation type, nitrogen availability, groundwater dynamics, and soil texture. The model shows good comparison with various observation data sets. The background hydrology of the basin is revealed as one limited by energy and water at different times during the annual cycle, with saturation excess being the dominant runoff generating mechanism. Groundwater plays an important role in the watershed, controlling saturation excess and lowland exfiltration. Through a series of hypothetical simulations based on the model, we use ANOVA to quantify the influence and relative importance of the controlling processes. The results confirm the basin, which has an average unconfined aquifer conductivity of 13 m/day, as a groundwater-dominated system.

Groundwater flow has been found to be the major control on runoff and infiltration, explaining more than 70% of the variance. Soil texture ranks next. Vegetation type and nitrogen levels are found to determine NPP, top 10 cm soil temperature, and transpiration. Interestingly, all factors are found to significantly control ET, which serves as the nexus for ecosystem-hydrology interactions. Nitrogen is shown to be a major control of ecosystem variables, but it also significantly controls transpiration, through which it influences other hydrologic fluxes. While keeping in mind the limitations with the CN cycling in CLM, the results indicate that hydrologists need to continue expanding the domains of sciences in hydrologic simulations to discover important linkages. The analysis method used in the paper is shown to be relatively robust with respect to changes in parameter values and spatial resolution, but when we move to a region whose parameters extend beyond the current range of variability, the results are expected to shift.

Appendix A: Lowland-Storage Module

[57] Here we describe a new enhancement to the model. Wetlands are an important land cover type that exerts strong influence on hydrology, ecosystem functioning, and water quality. A flexible lowland-storage module is added to the original PAWS model to keep track of the exchanges between wetlands, overland flow, and groundwater. The wetland is conceptualized as a lowland-storage compartment of the overland flow domain, as shown in Figure 1. To accommodate the wetland compartment, the mass balance equation for the flow domain is modified as follows:

\[
\frac{\partial h_t}{\partial t} = f_0 K_{w} \left( z_w + h_t - f_s \right) \Delta z_w + E_w + F_g - \nabla (h_{of} \mathbf{u}).
\]  

(A1)

in which \(h_t\) is the flow depth in the domain, \(H\) is the groundwater head, \(E_w\) is the evaporation from lowland storage, \(f_s\) is the areal fraction of lowland storage, \(F_g\) is runoff from the ponding domain, \(u\) is overland flow velocity, \(K_w\) is the bottom conductivity, \(z_w\) is the bottom elevation of the lowland storage, \(\Delta z_w\) is the maximum of \(z_w - H\) or thickness of bed material layer, and \(h_{of}\) is the overland flow depth in excess of the lowland-storage capacity. Unit of the equation is m/day. We solve equation (A1) in two fractional steps. The first one is an implicit step that calculates the groundwater exchange and obtains intermediate states \(h^*_t\). The second step takes \(h_{of} = \max(0, h^*_t - d_w)\), where \(d_w\) is the bucket depth of the depression storage, and sends result to

the 2-D diffusive wave overland flow solver as described in SP10 to solve for the convective term, \(\nabla h_{of} \mathbf{u}\). The exchange between groundwater and lowland storage becomes either exfiltration (Ex) or infiltration (Inf), depending on the direction. Equation (A1) can also be applied to describe transient shallow concentrated flows, paddy fields, or potholes. In addition, the lowland storages in different locations are connected via overland flow paths. When flooding occurs, river water may flood the overland flow domain, and in turn, fill the lowland-storage compartments. The threshold for backfill to happen is termed as \(h_{back} \simeq f_s\) and \(d_w\), all of which can be inferred from analyzing land cover maps and fine-resolution digital elevation model (DEM).

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References


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