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Hydrological model uncertainty due to spatial evapotranspiration estimation methods

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ABSTRACT

Evapotranspiration (ET) continues to be a difficult process to estimate in seasonal and long-term water balances in catchment models. Approaches to estimate ET typically use vegetation parameters (e.g., leaf area index [LAI], interception capacity) obtained from field observation, remote sensing data, national or global land cover products, and/or simulated by ecosystem models. In this study we attempt to quantify the uncertainty that spatial evapotranspiration estimation introduces into hydrological simulations when the age of the forest is not precisely known. The Penn State Integrated Hydrologic Model (PIHM) was implemented for the Lysina headwater catchment, located 50°03′N, 12°40′E in the western part of the Czech Republic. The spatial forest patterns were digitized from forest age maps made available by the Czech Forest Administration. Two ET methods were implemented in the catchment model: the Biome-BGC forest growth sub-model (1-way coupled to PIHM) and with the fixed-seasonal LAI method. From these two approaches simulation scenarios were developed. We combined the estimated spatial forest age maps and two ET estimation methods to drive PIHM. A set of spatial hydrologic regime and streamflow regime indices were calculated from the modeling results for each method. Intercomparison of the hydrological responses to the spatial vegetation patterns suggested considerable variation in soil moisture and recharge and a small uncertainty in the groundwater table elevation and streamflow. The hydrologic modeling with ET estimated by Biome-BGC generated less uncertainty due to the plant physiology-based method. The implication of this research is that overall hydrologic variability induced by uncertain management practices was reduced by implementing vegetation models in the catchment models.

1. Introduction

Evapotranspiration (ET) is important to the water balance because it represents a considerable amount of moisture lost from the Earth's land and ocean surface to the atmosphere. In a watershed, as precipitation falls, a certain amount of water is intercepted at the canopy and then evaporates into vapor. The rest precipitation infiltrates into the soil, which is absorbed by plants and then is transpired through the leaves, stem, and flowers. When they are combined with the evaporation from the soil, a significant amount of water vapor is returned to the atmosphere. There has been a long debate as to how complex the method of estimating ET should be (Andréassian et al., 2004; Oudin et al., 2005). For example, the ET processes can be treated as the surface boundary of flow processes. Integrated Hydrology Model (InHM, VanderKwaak and Loague, 2001) considers ET as the surface boundary of hydrological simulation, and uses a process-based model, Brook90 (Federer et al., 2003), to estimate throughfall and potential evapotranspiration (Carr et al., 2014). Penn State Integrated Hydrologic Model (PIHM) couples the ET in each computation grid as a sink term of the ordinary differential equation to represent the interactions between ET and soil water saturation (Qu and Duffy, 2007). Process-based Adaptive Watershed Simulator (PAWS) considers the vegetation dynamics cycle (Shen and Phanikumar, 2010) with piecewise linear parameterization to describe the daily vegetation growth. Shi et al. (2013) coupled surface energy balance scheme to estimate the land surface energy flux. More complex vegetation dynamics can be simulated by coupling water–carbon–nitrogen cycles to identify the hydrology

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and biogeochemistry interactions (Shen et al., 2013; Tague and Band, 2004). Recent studies on the influences between hydrological and ecological processes suggest the importance of physiological factors as a key driver of hydrologic processes via vegetation dynamics (Orellana et al., 2012; Witte et al., 2012). It is difficult to distinguish the most efficient ET estimation method (Andréassian et al., 2004). One major reason of the debate on ET estimation complexity is the difficulty in direct measurement of ET. In catchment models, ET is often considered a residual term and thus becomes a critical process for assessing uncertainty (Newman et al., 2006; Kay and Davies, 2008; Buttafuoco et al., 2010; Schewe et al., 2014; Bartholomeus et al., 2015).

Spatial heterogeneity is of course another issue in the estimation of ET at the catchment scale. Evapotranspiration is spatially affected by land cover (vegetation type), soil hydraulic properties, and subsurface storage of moisture (Shen et al., 2013). Distributed hydrologic models attempt to capture the impact of heterogeneity on catchment dynamics through the use of landscape mapping products. Spatial GIS information (e.g. topography, land cover, and soil hydraulic properties) provides the basic data to parameterize each distributed grid across the catchment. However, land cover spatial heterogeneity is always impacted by different natural and anthropogenic disturbances (e.g. wildfire (Beeson et al., 2001), forest management (Ebel and Mirus, 2014)). Spatial uncertainty should always be assumed and addressed as part of the modeling (Newman et al., 2006).

The Lysina catchment is part of the GEochemical MONitoring (GEOMON) network of Czech catchments (Lamačová et al., 2014). Lysina is also involved in international networks of sites comprising the International Cooperative Program-Integrated Monitoring (Holmberg et al., 2013) and Waters (Garmo et al., 2014). Recently, Lysina joined the European Critical Zone Observatories (CZOs) through the project of Soil Transformations in European Catchments (SoilTrEC). A key research objective of SoilTrEC is to develop an integrated mathematical model of hydropedologic and ecohydrologic processes and functions (Banwart et al., 2011, 2012). Yu et al. (2015) implemented PIHM at Lysina to examine the hydrological processes during managed forest land use for intensive silviculture. The modeling results qualitatively evaluated the impacts of different forest management scenarios on the hydrological regime at Lysina. Unfortunately, the study did not address the substantial uncertainty involved in the modeling of spatial ET. Critical unknown quantities included the forest management practices and the integration such practices in PIHM simulation.

Our goal here is to quantify the uncertainty that spatial ET estimation methods introduce into coupled surface–subsurface catchment simulations. Due to the intensive forest management including selective cutting practices over the catchment, an age-related spatial tree pattern is observed at Lysina watershed. Although tree age maps are produced periodically, there is considerable uncertainty in the actual cutting history, and it is only possible to extract approximate cutting histories. In this case, the uncertainty is the result of not knowing the precise timing of patch-cutting history across the forest. Therefore, based on the forest age maps, we inferred the possible forest management practices to quantify the uncertainty in spatial ET estimation. Ten simulation scenarios with different loggings and replantings were generated according to the possible forest management practice. And then, we ran simulations with two ET estimation methods: a seasonally-fixed LAI but with age-adjusted maximum LAI and Biome-BGC simulation with forest management. The uncertainty was calculated from multiple model runs and compared at each hydrological process. The results from this study provide some insight into the importance of ecological and hydrological interactions and implications for the modeling of managed forests.

2. Methods

2.1. Penn State Integrated Hydrologic Model

The Penn State Integrated Hydrologic Model is a physics-based, fully coupled, and spatially distributed hydrologic model (available online at http://www.pihm.psu.edu/). It simulates the terrestrial water cycle including interception, throughfall, infiltration, recharge, evapotranspiration, overland flow, unsaturated soil water, groundwater flow, and channel routing in a fully coupled scheme (Qu and Duffy, 2007). Evapotranspiration is calculated using the Penman–Monteith approach (Chen and Dudhia, 2001). Overland flow is described in 2-D estimation of St. Venant equations. Movement of moisture in unsaturated zones is assumed to be vertical, which is modeled using Richards' equation. The model assumes that each subsurface layer can have both unsaturated and saturated storage components. The recharge to and from the water table couples the unsaturated and saturated zones. The channel routing is modeled using 1-D estimation of St. Venant equations. PIHM uses diffusive wave approximation for channel routing and overland flow. For saturated groundwater flow, the 2-D Dupuit approximation is applied. Spatially, the modeling domain is decomposed into Delaunay triangles. The unstructured mesh allows users to resolve spatial data over the watershed. The triangular mesh can be constrained by point or vector data (e.g., stream gauge, wells, soil maps, and land cover), and the watershed boundary conditions (Kumar, 2009). The model resolves hydrological processes for land surface energy, overland flow, channel routing, and subsurface flow, governed by partial differential equations (PDEs). The PDE system is discretized on the triangular mesh and projected prism from canopy to bedrock. PIHM uses a semi-discrete finite-volume formulation for solving the system of coupled PDEs, resulting in a system of ordinary differential equations (ODE) representing all processes within the prismatic control volume. On each prismatic control volume, the original hydrological processes can be easily modified, and new processes can be also added. The flexible approach of coupling multi-scale hydrological processes makes it adaptable for integrated hydrological simulation of diversity interests, enables the comparison and assessment of the adequacy and uncertainty of each hydrological process within the integrated framework.

2.2. ET calculation in PIHM

There are generally three major components for ET estimation in distributed catchment models (Chen and Dudhia, 2001): (1) direct evaporation from the top shallow soil layer e_s; (2) evaporation of precipitation intercepted by the canopy, e_c; (3) transpiration via canopy and roots, e_t. The meteorological forcing for the potential evaporation is first calculated by a Pennman-based energy balance approach with ground evaporation e_s scaled by normalized soil water content, e_c calculated from the intercepted canopy water content, and e_t scaled by the canopy resistance. The temporal variation of ET is handled using a seasonal leaf area index (LAI) routine. In practice, PIHM uses prescribed seasonal LAI as input for each type of vegetation, and then the scaling factors are calibrated to obtain an appropriate estimation of ET. Here we provide the key equations of the ET calculation.

The Penman–Monteith approach is used for the calculation of the potential evaporation:

$$ET_0 = \frac{\Delta(R_n - G) + \rho_a C_p \frac{(\varepsilon_s - \varepsilon_a)}{r_a}}{\Delta + \gamma(1 + \frac{r_s}{r_a})} \quad (1)$$

Here e_p refers to potential evapotranspiration, R_n is the net radiation at the vegetation surface, G is the soil heat flux density,

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