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. More complex vegetation dynamics can be simulated by coupling water-carbon-nitrogen cycles to identify the hydrology 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 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 GEOMON (GEOchemical MONitoring) 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 hydrogeologic 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 logging and replanting 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 Penman-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 net radiation at the vegetation surface, G is soil heat flux density, $\varepsilon_s - \varepsilon_a$ represents the air vapor pressure deficit, ρ_a is the air density, and C_p is the specific heat of the air. Δ is the slope of the saturation vapor pressure-temperature relationship, γ is the psychrometric constant, and r_s , r_a are the surface and aerodynamic resistances. The ET calculation equations are adapted from Noah_LSM (Chen & Dudhia, 2001) for computing the actual evapotranspiration:

$$e_c = \sigma_f e_p \left(\frac{W_c}{S}\right)^{0.5} \quad (2)$$

$$e_t = \sigma_f e_p B_c \left[1 - \left(\frac{W_c}{S}\right)^{0.5}\right] \quad (3)$$

$$e_s = (1 - \sigma_f) \beta e_p \quad (4)$$

where σ_f refers to vegetation fraction, W_c is the intercepted canopy water content, and S is the maximum canopy capacity. B_c is a function of canopy resistance, and β is calculated by:

$$\beta = \frac{\Theta - \Theta_w}{\Theta_{ref} - \Theta_w} \quad (5)$$

where Θ_{ref} is field capacity and Θ_w is wilting point.

2.3. Biome-BGC

The model Biome-BGC is a 1-D model describing carbon (C), nitrogen (N), and water (H_2O) states and fluxes of a plant functional type (PFT). The PFTs generally include: evergreen needle leaf forest (ENF), shrub, deciduous broad leaf forest (DNF), deciduous

broad leaf forest (DBF), C3 grass (C3G), and C4 grass (C4G). The processes simulated in Biome-BGC include photosynthesis, respiration (autotrophic and heterotrophic), evapotranspiration, decomposition, final allocation of photosynthetic assimilate, and mortality (Running and Hunt, 1993). Biome-BGC models the phenology of the systems based on local meteorological input data. The model processes are simulated at daily and summarized at annual time scales. The total ET consists of canopy evapotranspiration (e_c) and soil evaporation (e_s). In the calculation of canopy evapotranspiration, the intercepted water evaporates first, and then transpiration starts after all the intercepted water is gone. In Biome-BGC, the Penman-Monteith Equation is used to calculate the two parts within the context of dynamic vegetation. Although Biome-BGC introduces a more physical basis for integrating ecological growth into the catchment hydrology, it comes with additional costs of model complexity, computation and possibly uncertainty from the additional parameters.

The Biome-BGC uses a similar equation as Equation (1) for calculation of potential evaporation. The calculation of interception loss and transpiration is obtained by varying the surface resistance r_s . For leaf intercepted water and soil water, r_s is the boundary layer resistance. For transpiration, r_s is a function of stomatal, cuticular, and boundary layer resistance. The soil water evaporation is calculated by scaling the potential evaporation

by a quantity determined by the days since the previous rain event. $e_s = \frac{0.3}{DSR^2} e_p$, where

DSR is the days since the previous rain event. The source code is available online (<http://www.ntsg.umd.edu/project/biome-bgc>). For a detailed description of the model, the reader is referred to Thornton et al. (2002).

2.4. Hydrological indices

For interpretation of each realization, several hydrological indices were examined: total runoff, recharge, unsaturated storage, and saturated storage. The units and descriptions are summarized in Table 1. The indices were calculated from the simulation results in 1994 (before management) and 1995 (after management). Discharge was normalized by basin area and presented in units of mean depth (mm).

2.5. Uncertainty analysis

Over the last decade, a large body of literature has evolved to quantify the hydrological model uncertainty by Monte Carlo methods and generalized likelihood uncertainty estimation (Beven and Andrew, 1992). These methods select a range of possible values during the calibration processes, and then use the parameter range to create the range of model results to quantify the uncertainty. In this study, we focused on uncertainty from forest management and ET estimation methods and how they affected hydrologic performance. In general, we found that the range of vegetation parameter values is very limited. Therefore a simple method outlined in Harder and Pomeroy (2014) was applied to calculate realization for the uncertainty in management practices and spatial ET estimation:

$$uncertainty = \frac{\sum_{i=1}^n (Max_i - Min_i)}{n} \quad (1)$$

where *Min* and *Max* refer to the lowest and highest values of an output variable from all the model runs, *i* is the index (time step) of the value and *n* is the number of values (total

time steps). The units of uncertainty were the same as the hydrological variables being considered.

3. Modeling setup

3.1. Study area

The Lysina headwater catchment is situated in the western part of the Czech Republic with a drainage area of 0.293 km² (see Figure 1). The characteristic of the climate is temperate continental, with relatively hot summers and cold, cloudy and snowy winters (Benčoková et al., 2011). The mean annual temperature of the nearest meteorological station (Mariánské Lázně) was 6.0°C from 1967 to 2012. The average daily maximum temperature was 10.8°C, and the average daily minimum temperature was 2.4°C. The annual rainfall varied between 523 and 1165 mm in this period. The topography at Lysina is low hills with an average slope of 11.5%, North-East orientation and an elevation range between 829-949 m a.s.l.

3.2. Data Compilation

The data gathered for the Lysina catchment and the pre-processing procedures for the application of PIHM were summarized in the following:

- (i) A digital elevation map (DEM) at the scale of 1:1000 was obtained from a topographic survey and a stream channel survey. The DEM was used for watershed delineation and stream definition as well as for constraining the unstructured meshed for model domain by the GIS tool PIHMgis (Bhatt et al, 2014). Due to the relatively simple topography, 455 irregular triangles and 37 linear segments of the stream channel were generated as the PIHM simulation

241 domain (Yu et al., 2015). The average area of the triangles was 648.44 m² and the
242 average length of the channels was 28.25 m (Figure 2).

243 (ii) Meteorological data, which contained hourly precipitation, air temperature, wind
244 speed, relative humidity and global radiation, were provided by the national
245 meteorological service, the Czech Hydrometeorological Institute (CHMI).
246 Hydrological observations included stream discharge data and groundwater level
247 data (Yu et al., 2015).

248 (iii) A soil map was provided by the Forest Management Institute (ÚHÚL) of the
249 Czech Republic, Brandýs nad Labem, branch Karlovy Vary. The dominant soils
250 were gleysol (52%) and podzol (41%), along with occasional peaty soil (6%),
251 ranker (1%) and non-developed soil on rock outcrops (0.3%). The soil sample was
252 composed of 60.4% sand, 26.5% silt, and 13.1% clay, and the bulk density was
253 1.32 g/cm³. Saturated hydraulic conductivity, K_s , and saturated water content, θ_s ,
254 were initially estimated using pedotransfer functions (Wösten et al., 2001).

255 (iv) The land cover was Norway spruce (*Picea abies*) monoculture stands since 1850.
256 The Czech Forest Administration produces a forest age map periodically to record
257 actual species composition, forest age and biomass stock. From the forest age map
258 in 1984 and 2004 (Figure 3), we could infer the forest management practice. Yu et
259 al. (2015) proposed one possible spatial pattern of forest logging and replanting
260 from the forest age maps. However, the precise patch cutting history is more
261 complicated due to considerable uncertainties in the forest management history,
262 e.g. the harvesting may happen due to poor health of trees, which is caused by the

wind damage, snow or ice damage, bark beetle attack, acid rain, or ozone injures.

In this study, we used a probabilistic approach to describe the land cover change due to forest management practices. We used ArcGIS to create two raster layers with the resolution of 1 by 1 meter (Figure 4a and 4b). And then we created a management layer according the age difference between Figure 3a and 3b using the following criteria:

$$management \ layer = \begin{cases} 0, & age_{2004} - age_{1984} = 20; \\ 1, & age_{2004} = 10; \\ 0.5, & other. \end{cases} \quad (2)$$

where 0 means no intervention from 1984 to 2004, and 1 means there was a logging and replanting intervention. The result of management layer is shown in Figure 4c. At last, we overlay the PIHM domain mesh with the management layer to calculate the proportion of management area in each triangle. We used the proportion as the probability of management happened in 1994 (Figure 4d).

3.3. ET estimation from prescribed LAI

The default LAI database in PIHM classifies the Norway spruce as evergreen forest, and the annual maximum LAI is $6.22 \text{ m}^2\text{m}^{-2}$. To simulate the forest management probability scenarios, we used the published data (Köstner et al., 2002; Pokorný et al., 2008; Spinnler et al., 2002) to crudely estimate the historic vegetation growth dynamics, by developing a regression equation for LAI (Leaf Area Index) and age according to field observations:

$$\max LAI = -0.0007796 \times age^2 + 0.1372 \times age + 2.329 \quad (3)$$

where $\max LAI$ is annual maximum LAI in m^2m^{-2} , and age is in years. Thus the model adjusted the seasonal LAI curves based on (2) for all forest stands. The range of LAI was

95% confidence of the regression (Figure 5). To model the logging and replanting processes, we modified the temporal variation of LAI when the management intervention happens. From the management probability map (Figure 4d), we generated 10 simulation scenarios corresponding to the realization of management on each triangle. And then, we applied the maxLAI with the upper and lower boundaries (Figure 5) for each scenario of management. In total, there were 30 simulation scenarios to quantify the uncertainty (Table 2). Notably, we were able to simulate the spatial ET pattern by this method.

3.4. ET estimation with Biome-BGC

We modified Biome-BGC to enable the simulation of forest management according to method by Tatarinov and Cienciala (2006). In the method, the forest management was simulated by modification of C and N pools. Assuming at a particular time, there was a logging and replanting intervention covering P% area of the watershed. In the model, we assumed that the P% of foliage and fine root was translocated to litter, while P% of the coarse roots was translocated into the coarse woody debris pool. Also P% of the stem wood was removed from the biome. The physiological parameters of Biome-BGC were provided for major biome types (White et al., 2000). We collected all the values of Norway spruce (*Picea abies*). We used maximum, mean, and minimum for quantification uncertainty of each parameter. Where information on some parameters was not available, we used the default values from coniferous forests (ENF) reported by White et al. (2000). The parameter sets are presented in Table 3. We used 1-way coupling between Biome-BGC and PIHM. The Biome-BGC simulated ET was input to PIHM as a negative flux uniformly across the finite volume mesh. From the 10 scenarios of management intervention on each mesh element, we calculated the corresponding total logging area,

which was then input to Biome-BGC to generate the management practice scenarios. For each Biome-BGC forest management practice scenario, we used three groups of physiological parameters of Norway spruce (Table 3). In total, 30 simulations of PIHM were conducted using the Biome-BGC estimated ET (Table 2).

4. Results

4.1. Uncertainty in streamflow

Daily streamflow variability increased after the management practice in 1994 (Figure 6, Table 4), which was due to the uncertainty in the unknown area (P%) of logging and replanting practices at the end of 1994. The uncertainty from PIHM estimated ET was greater than the uncertainty from the simulations with Biome-BGC estimated ET. Due to the plant physiology-based method in the ET estimation in Biome-BGC, the uncertainty in streamflow was reduced in the growth period of Norway spruce. Similar temporal patterns of uncertainty were found at different locations along the stream (see the upper reach in Figure 7 and the middle reach in Figure 8). The ET estimation by PIHM was spatially distributed according to the tree age pattern. While, the simulation with Biome-BGC applied the average ET uniformly throughout the catchment. However the spatial variation in ET did not affect the variability of streamflow uncertainty patterns at different locations.

4.2. Uncertainty in recharge

The average recharge was almost uniformly distributed (Figure 9d) in the simulations with Biome-BGC estimated ET, due to the uniform ET flux. While the recharge in the simulation with PIHM estimated ET demonstrated considerable heterogeneity (Figure 9a). The variability maps were quite similar in the two different methods

generated results (Figure 9b 9c 9e 9f). We interpret that the uncertainty in recharge is related to the soil hydraulic properties. In the year of 1995, the uncertainty increased (Table 4), while the spatial pattern is still similar to that of 1994, even if the spatial ET estimations were different. The reason is that the spatial pattern is determined by the spatial soil properties. The average recharge ranged from -0.005 m/day to 0.025 m/day, while the uncertainty reached as high as 0.005 m/day. It demonstrated that the simulated spatial recharge has contained considerable amount of uncertainty from different ET estimation methods.

4.3. Uncertainty in subsurface storage

The PIHM simplifies the subsurface domain into an unsaturated storage layer above groundwater table and saturated storage layer below (Qu and Duffy, 2007). The spatial patterns of unsaturated storage varied significantly between the different ET estimation methods (Figure 10). The differences evolve from three factors: vegetation water use, soil hydraulic properties, and topographic conditions. In the simulations with Biome-BGC estimated ET, the spatial-uniform flux of ET still resulted in spatial heterogeneity of unsaturated storage due to soil hydraulic properties and topography (slope). The uncertainty in unsaturated storage was of the same order as the average unsaturated storage values (Table 4). The saturated storage was similar in both simulations (Figure 11). There were high storage of groundwater in the relatively flat downslope area and near-channel area. The uncertainty was always below 0.2 m, except for the upslope steep areas. The differences in ET estimation did not affect the spatial pattern of saturated storage and its uncertainty.

5. Discussion

5.1. Uncertainty due to different ET estimation methods

The ET introduced uncertainty in hydrologic simulation was found to be an important driver of water budget variability (Haddeland et al., 2011). In the calibration process, both methods provided plausible water budgets and variability in the modeled fluxes and states. However, the two ET estimation methods used suggested different responses when subject to environment changes (e.g. forest management, climate change). Thompson et al. (2014) found that the potential evapotranspiration method influence projections of discharge under climate change scenarios. The ET estimation method from PIHM has fixed vegetation LAI dynamics. By default, PIHM applies the monthly average LAI values from GLDAS product (NASA, 2013), and repeats the seasonal pattern every year for long-term hydrologic modeling. In this study, we used the calibrated results from a previous study (Yu et al., 2015). The variability in the LAI-age relation and forest management uncertainty resulted in large uncertainty in streamflow, recharge, unsaturated storage and saturated storage. For Biome-BGC, combining both the meteorological forcing and physiological properties of the species to estimate the spatial averaged ET, the uncertainty in streamflow, recharge, unsaturated storage and saturated storage was reduced. The uncertainty comparison results presented here suggest that the prescribed seasonal vegetation dynamics may be inadequate for the modeling of water use of plant at Lysina. A fully coupled ecosystem model may further improve the simulation of the ET due to the forest management, and reduce the uncertainty of hydrological predictions. In the future, a dynamic view of plant water relations may be necessary in order to reduce the uncertainty in long-term catchment-scale hydrological predictions (Shen et al., 2013).

5.2. Uncertainty propagation in hydrological processes

The highest uncertainty from the simulation scenarios is unsaturated storage. This suggests the importance of reliable ET estimation for precise predictions of the surface soil moisture. However, recharge and saturated storage showed a smaller response to forcing uncertainty. Finally, the simulated streamflow dynamics was adequately captured in both ET estimation methods, which suggested that the purpose of the model might be important in choosing a more or less complex ET model. For example, lumped rainfall-runoff models have surprising adaptability of simple ET estimation methods. These models can cope numerically with imperfect ET estimation (Andréassian et al., 2004).

5.3. Coupling strategies for integrated hydrologic models

Advances in computation enable the integrated models coupling across multiple-scales of hydrological processes, which precisely reproduce benchmark problems of coupled surface subsurface flow processes (Maxwell et al., 2014). However there were not any ET benchmark problems reported. Moreover, real world studies involve complex data and processes, which may challenge the model parameterization and uncertainty quantification. In PIHM, ET calculation processes are tightly coupled with the surface subsurface flow dynamics. The ET is mainly driven by the seasonal energy processes, while, the coupled surface-subsurface processes are controlled largely by the precipitation during storm events. Therefore, the calibration strategy of PIHM (Yu et al., 2013) requires the separation between event scale processes and seasonal scale processes. This separation in time scales between energy-related and hydrologic or storm-related responses may be an important clue about the differences in the uncertainty simulations carried out here. Biome-BGC reduced the uncertainty introduced by vegetation dynamics

by the 1-way coupling as negative flux on each PIHM computational grid. This implies the advantage of simply coupling strategies across hydrological and ecological processes.

5.4 Uncertainty as a criterion in model intercomparison

As integrated hydrological modeling becomes increasingly complex, it is also important to examine the model prediction confidence when comparing against the observed hydrological variables. In terms of the observation, McMillan et al. (2012) initiated the benchmarking data uncertainties for hydrology. The results demonstrated the wide spread of uncertainty in observed hydrologic variables and implication of data uncertainty in model regionalization and evaluation. Maxwell et al. (2014) compared seven integrated hydrologic models by a standard set of test problems, and found model uncertainty increase as the complexity of domain rises. In the operational purpose of integration models at a real watershed, the complex topography and spatial heterogeneity will inevitably increase the uncertainty. Based on the uncertainty assessment presented in this study, we provided an argument for taking into account uncertainty comparison between integrated hydrological models. An intercomparison of uncertainty has the potential to lead to clearer mechanism for model applications.

6. Conclusions

With this study, we aimed to understand how the uncertainty is propagated through integrated hydrological modeling, and to make an initial evaluation of the importance of vegetation growth to long term water balances at the watershed scale. We showed that plant physiology-based coupling between ET and subsurface process reduced the uncertainty in hydrological modeling comparing to the fixed seasonal vegetation method.

Through the fully-coupled distributed hydrologic modeling, the following conclusions are reached:

- (i) PIHM estimated ET produces greater uncertainty in soil moisture, recharge, groundwater table and streamflow than the results from Biome-BGC estimated ET simulations.
- (ii) Uncertainty of soil moisture and recharge is significantly greater than that of groundwater table and streamflow with both ET estimation methods.
- (iii) As uncertainty propagating in PIHM, ET estimation has significant impacts on spatial uncertainty of soil moisture and recharge, negligible impacts on the spatial uncertainty of groundwater table and streamflow.

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597 Table 1. Hydrological variables considered in uncertainty quantification

Variable	Units	Description
Daily discharge	mm/day	Daily discharge as depth of flow rate
Recharge	mm/day	Daily recharge as depth of water to/from water table
Unsaturated Storage	m	Volume averages per unit projected horizontal area
Saturated Storage	m	

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599

600 Table 2. Uncertainty modeling scenarios for two ET estimation methods. The scenarios
 601 were determined by the sources of uncertainty: physiology and forest management.

ET estimation method	Source of uncertainty	Representation of uncertainty	Range	Number of Realizations	Total number of scenarios
PIHM	Physiology	LAI-age relation (95% confidence)	Lower limit, mean, upper limit	3	30
	Unsure cutting area	Spatial mapping of forest age	Cutting area ranges from 0 to100%	10	
Biome-BGC	Physiology	Physiological parameter of Norway spruce	Lower limit, mean, upper limit	3	30
	Unsure cutting area	Estimated harvest biomass	Cutting biomass ranges from 0 to100%	10	

602

603 Table 3. Eco-physiological parameters at Lysina used in the Biome-BGC model

Parameter	Mean	Min	Max	Unit
transfer growth period as fraction of growing season	0.3			—
litter-fall as fraction of growing season	0.3			—
annual leaf and fine root turnover fraction	0.23	0.13	0.4	year ⁻¹
annual live wood turnover fraction	0.7			year ⁻¹
annual whole-plant mortality fraction	0.005			year ⁻¹
annual fire mortality fraction	0.0025			year ⁻¹
new fine root C:new leaf C	0.662			—
new stem C:new leaf C	2.29	1.43	4.7	—
new live wood C:new total wood C	0.1			—
new coarse root C:new stem C	0.194	0.159	0.23	—
current growth proportion	0.5			—
C:N of leaves	43.45	28.1	58.8	kg C kg N ⁻¹
C:N of leaf litter	83.25	50.5	116	kg C kg N ⁻¹
C:N of fine roots	37	27.6	46.7	kg C kg N ⁻¹
C:N of live wood	116			—
C:N of dead wood	729			—
leaf litter labile proportion	0.32			—
leaf litter cellulose proportion	0.34			—
leaf litter lignin proportion	0.34			—
fine root labile proportion	0.3			—
fine root cellulose proportion	0.45			—
fine root lignin proportion	0.25			—
dead wood cellulose proportion	0.7			—
dead wood lignin proportion	0.3			—
canopy water interception coefficient	0.041			LAI ⁻¹ d ⁻¹
canopy light extinction coefficient	0.5			—
all-sided to projected leaf area ratio	2.6			—
canopy average specific leaf area	7.68	6.4	9.4	m ² kg C ⁻¹
ratio of shaded SLA: sunlit SLA	2			—
fraction of leaf N in Rubisco	0.04			—
maximum stomatal conductance	0.003			m s ⁻¹
cuticular conductance	0.00001			m s ⁻¹
boundary layer conductance	0.08			m s ⁻¹
leaf water potential: start of conductance reduction	-0.6			MPa
leaf water potential: complete conductance reduction	-2.3			MPa
VPD: start of conductance reduction	930			Pa
VPD: complete conductance reduction	4100			Pa

Parameters were chosen for Norway spruce (*Picea abies*) from White et al. (2000).

604
605

606 Table 4. Uncertainty caused by the ET estimation methods in hydrological process
607 simulations

ET estimation method	Year		Daily discharge mm/day	Recharge mm/day	Unsaturated storage m	Saturated storage m
PIHM	1994	mean	1.39	1.70	1.28	3.70
		uncertainty	0.17	1.60	0.43	0.06
		SD	0.20	1.25	0.66	0.05
	1995	mean	1.52	1.66	1.33	3.74
		uncertainty	0.54	4.26	0.67	0.14
		SD	0.69	3.48	0.63	0.12
Biome- BGC	1994	mean	1.54	1.70	0.95	3.76
		uncertainty	0.18	1.56	0.41	0.05
		SD	0.20	1.29	0.50	0.05
	1995	mean	1.98	1.82	1.02	3.78
		uncertainty	0.51	3.92	0.61	0.11
		SD	0.36	3.29	0.50	0.11

608 SD means standard deviation

Figure 1. Location of the Lysina catchment. Topographic contours are shown at 2 meters intervals.

Figure 2. Finite-volume mesh and boundary of Lysina Catchment. The impermeable bedrock depth was uniform 4 meters below the surface. The stream channels are represented by lines, and the computation grids are represented by the triangle mesh.

Figure 3. Forest age maps in 1984 and 2004. The stand age of forest is distinguished in color. Note the legend of the two maps are similar except for the age group 80-100, which is orange in 1984 and gray in 2004. Please refer to Figure 4 as a graphically improved version.

a) Forest age map in 1984

b) Forest age map in 2004

Figure 4. Probability of forest management in 1994. a) and b) is the digitalized forest age maps. c) is the inferred forest management. d) is the management probability of PIHM triangular mesh.

Figure 5. Leaf area index and tree age regression with uncertainty bounds. “+” represents data from (Spinnler et al., 2002), “x” represents data from (Köstner et al., 2002), and “o” represents data from (Pokorný et al., 2008).

Figure 6. Simulated streamflow at the outlet in 1994 (before management) and 1995 (after management). Uncertainty from the ET estimation methods is plotted as a grey area. The x label is the days after 1994-1-1.

Figure 7 Simulated streamflow in the upper reach in 1994 (before management) and 1995 (after management). Uncertainty from the ET estimation methods is plotted as a grey area. The x label is the days after 1994-1-1.

Figure 8 Simulated streamflow in the middle reach in 1994 (before management) and 1995 (after management). Uncertainty from the ET estimation methods is plotted as a grey area. The x label is the days after 1994-1-1.

Figure 9 Uncertainty in recharge. a) and d) are spatial pattern of average recharge. b) and e) are uncertainty in 1994. c) and f) are uncertainty in 1995. M1: the ET estimation is from PIHM originally, M2: the ET estimation is from Biome-BGC.

Figure 10 Uncertainty in unsaturated storage. a) and d) are spatial pattern of average unsaturated storage. b) and e) are uncertainty in 1994. c) and f) are uncertainty in 1995. M1: the ET estimation is from PIHM originally, M2: the ET estimation is from Biome-BGC.

Figure 11 Uncertainty in saturated storage. a) and d) are spatial pattern of average saturated storage. b) and e) are uncertainty in 1994. c) and f) are uncertainty in 1995. M1: the ET estimation is from PIHM originally, M2: the ET estimation is from Biome-BGC.