Examining the Robustness of the SWAT Distributed Model Using PSO and GLUE Uncertainty Frameworks

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ABSTRACT. Simulating the hydrology of a watershed system is a challenging task due to biases in input data and measurements, and mismatches in spatial and temporal scales between model representation and the physical system. Modeling difficulty increases for watershed systems with low-storage shallow soils, a large number of riparian floodplain alluvials, and non-uniform rainfall distributions. A simulation study was performed to assess feedback effects associated with uncertainty propagation in the Soil and Water Assessment Tool (SWAT) using the Generalized Likelihood Uncertainty Estimation (GLUE) and Particle Swarm Optimization (PSO) algorithms at the Waccamaw River watershed, a low-gradient forested wetland Coastal Plain watershed in the SE region.

Optimization of both algorithms indicated the evapotranspiration rate typically exceeded the combination of shallow aquifer, surface flow, and lateral flow contributions during dry periods. It was also shown that shallow aquifer contribution to the total water yield during wet spells may raise the shallow water table and increase the risk of groundwater flooding due to rapid water table responses during storm events.

INTRODUCTION

Uncertainty framework is a mathematical and computational tool used to improve understanding of the dynamics of hydrologic processes at the watershed scale with the goal to more accurately model the rainfall-runoff characteristics and system behavior. Uncertainties and associated errors are related to inconsistency among independent measurements of the hydrologic quantities as well as bias and error in the prediction process. The goal of this research wass to examine the robustness of different uncertainty algorithms in streamflow prediction at a heterogeneous watershed.

Although uncertainty quantification of complex watersheds is becoming increasingly important, it is extremely difficult to offer a coherent terminology and a significant procedure. More importantly, uncertainty estimation is a very difficult task, if not impossible, when there is variability in the forcing data, such as the hydroclimatic parameters of the southeastern landscapes.

A number of uncertainty analysis methods have been developed and successfully implemented in the hydrological forecasting, and they are voluminous both in the context of observations and projections (see Makowski et al., 2002; Wagener et al., 2003; Samadi et al., 2014; among others). Readers of uncertainty literature should be warned that there are inconsistent and varying methods to evaluate uncertainty in hydrological predictions (e.g. Wagener et al., 2003; Vrugt et al., 2008). Because estimates of flow rates are affected by uncertainties in data, modeling approaches, parameters, stochastic ambiguity, and geo-processing tools, uncertainty analysis of such models is difficult due to a large number of parameters and/or it is computationally too expensive. In this study, the soil and water assessment tool (SWAT) simulated the rainfall-runoff process in a complex hydrological system while PSO and GLUE algorithms were used to estimate accurate and efficient predictive uncertainty.

METHODS

Study Area

The Waccamaw River watershed (hydrologic unit code 03040206) is on the lower coastal plain in eastern North and South Carolina (Figure 1). The watershed has little topographic gradient (99% is < 5% slope), wide floodplains, complex ground water characteristics due to poorly drained soils, a shallow water table, and extensive wetlands (Amatya and Jha, 2011). Elevation ranges from 6m – 46 m above mean sea level. Climate in the watershed is humid subtropical with hot summers and cool winters. Precipitation in the basin occurs almost exclusively as rainfall, with an annual average of 1300 mm. Streamflow data from two US Geological Survey (USGS) gaging stations, at Freeland (34°05'42N, 78°32'54W; discontinued May 8, 2013) and Longs (33°54'45N, 78°42'55W), were used as subwatershed outlets (Figure 1). Daily precipitation, minimum and maximum temperature, wind speed, and solar radiation were obtained from climate stations at Loris, Whiteville, and Longwood, all located in North Carolina.

SWAT Model

The Soil and Water Assessment Tool (SWAT) is a watershed modeling program developed by the USDA–Agricultural Research Service to simulate hydrology and water quality at various scales (Arnold *et al*., 1998). It was developed to predict the impact of land management practices on water, sediment, and agricultural chemical yields in large complex watersheds with varying soils, land use, and management conditions (Neitsch *et al*., 2001). SWAT 2009 was used for this research. The SWAT system is embedded within a geographic information system (GIS) that can integrate various spatial environmental data including soil, land cover, climate, and topographic features. SWAT subdivided the Waccamaw River watershed into 28 sub watersheds and 2020 Hydrologic Response Units (HRUs) connected by a stream network.

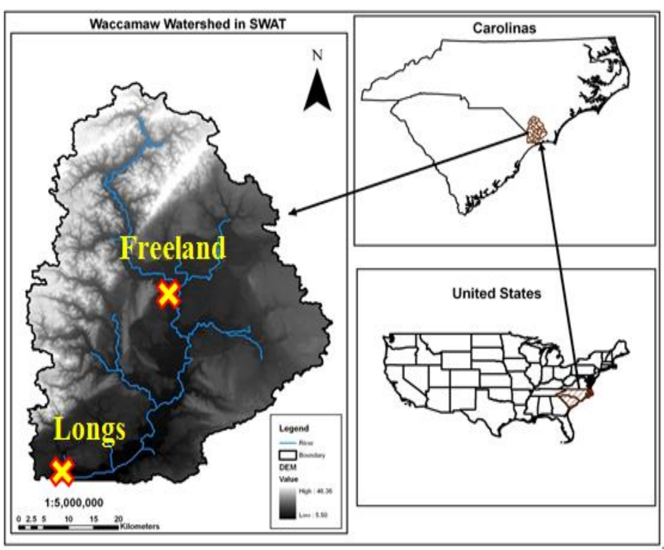

Figure 1 Location map of the study area. The delineated Waccamaw River watershed was 311,685 ha.

Generalized Likelihood Uncertainty Estimation (GLUE):

This technique is based on the estimation of the weights or probabilities associated with different parameter sets, based on the use of a subjective likelihood measure to derive a posterior probability function, which is subsequently used to derive the predictive probability of the output variables (Abbaspour, 2013). GLUE (proposed by Beven and Binley (1992)) randomly samples a large number of parameter sets from the prior distribution and each set is classified as either “behavioral” or “non-behavioral” through a comparison of the “likelihood measure” with the given threshold value. GLUE is a formal Bayesian algorithm.

PSO Particle Swarm Optimization (PSO):

Particle swarm optimization (PSO) is a population-based stochastic optimization technique proposed by Eberhart and Kennedy (1995). It shares many similarities with evolutionary computation techniques such as Genetic Algorithms (GA). Each particle is updated by following two "best" values (Abbaspour, 2013). The first one is the best solution (fitness); another "best" value that is tracked by the particle swarm optimizer is the best value, obtained so far by any particle in the population (Eberhart and Kennedy, 1995).

RESULTS

In this research, 19 flow parameters were identified as important ones to be ranked based on their sensitivity (P-factor (the percentage of observations covered by the 95PPU) and t-state (a measure of sensitivity, larger in absolute values are more sensitive)). PSO sensitivity analysis indicated that Manning's "n" value for the main channel is the most sensitive parameter.

The calibration period was conducted in 1994-1998 across the dry to wet interval by considering 1992-1993 as a warmup period. In this project, both the performance values and 95PPU (95% predictive uncertainty) bounds of the GLUE (Figure 2 and Figure 3) and PSO (Figure 4 and Figure 5) methods were extremely small, and the corresponding parameter ranges were very narrow which led to a very narrow 95PPU while bracketing most of measured and modeled flows, respectively. The best parameter values were updated in both models and SWAT was optimized using final values and the water budgets were performed (only PSO result is presented here). The results were categorized as good to very good according using the Moriasi et al., (2007) qualitative rank by presenting NSE (Nash and Sutcliffe, 1970) values of 0.77-0.80 in both uncertainty algorithms.

Water budget analysis in 1994 as dry year indicated that ground water contribution was large through the entire period and it was the major contributor in June. Wet year (1996) water balance also indicated that during wet spells (winter and early spring) groundwater contribution increases and that may increase the risk of temporary groundwater flooding due to rapid water table responses during storm events. In addition, SWAT optimization results indicated more than 70% of flow was lost through active evapotranspiration during the entire calibration interval. The contributions of ground water flow was high during dry period while lateral flow was equal to 1% in both dry and wet years. Figures 6 and 7 exhibit PSO water balance quantifications during wet and dry years respectively.

Overall two different algorithms results revealed a good ability of a physically based SWAT rainfall-runoff model to simulate streamflow and water balance components in a southeastern landscape.

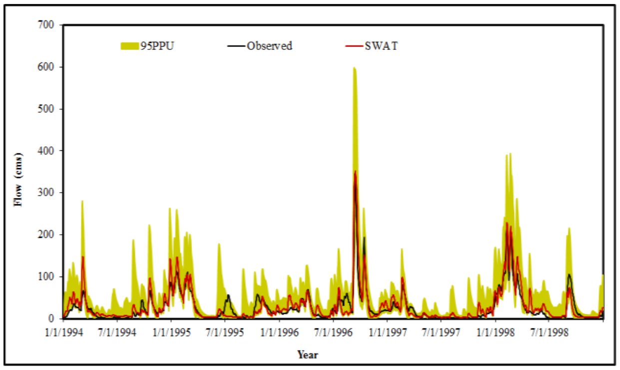

Figure 2. GLUE calibrated flow at the Freeland station.

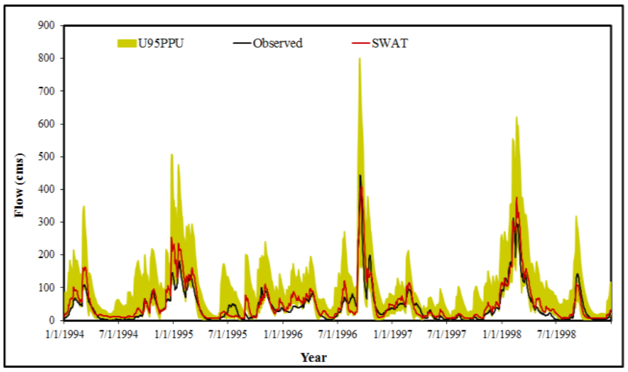

Figure 3. GLUE calibrated flow at the Longs station.

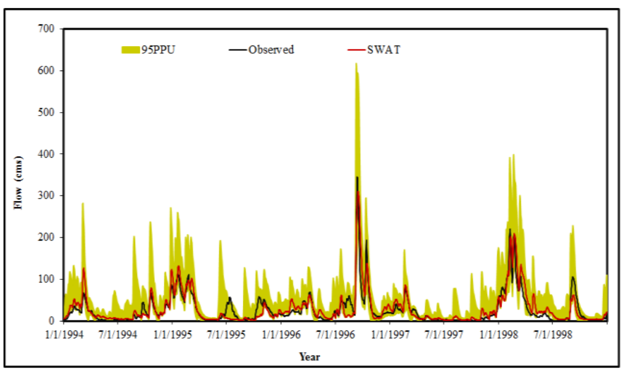

Figure 4. PSO calibrated flow at the Freeland station.

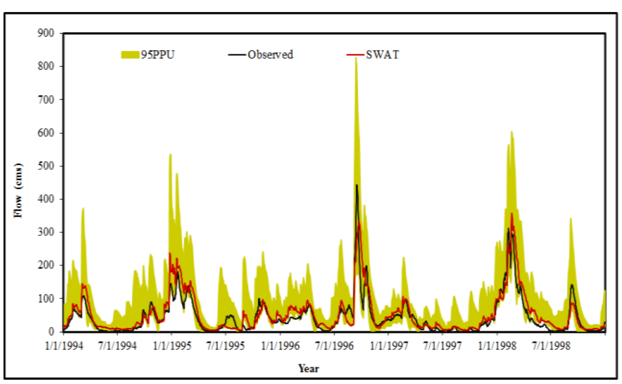

Figure 5. PSO calibrated flow at the Longs station.

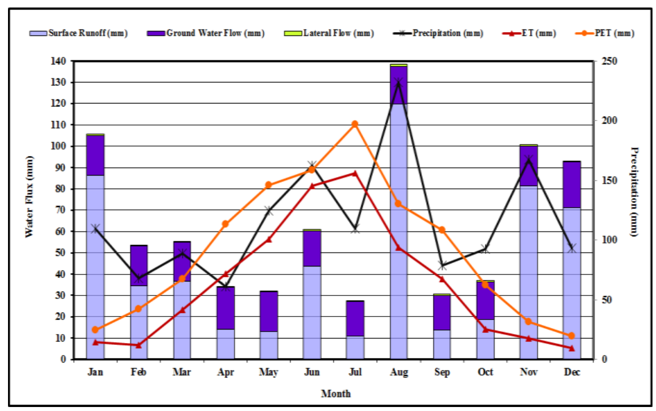

Figure 6. PSO monthly water component values in 1996 (wet year).

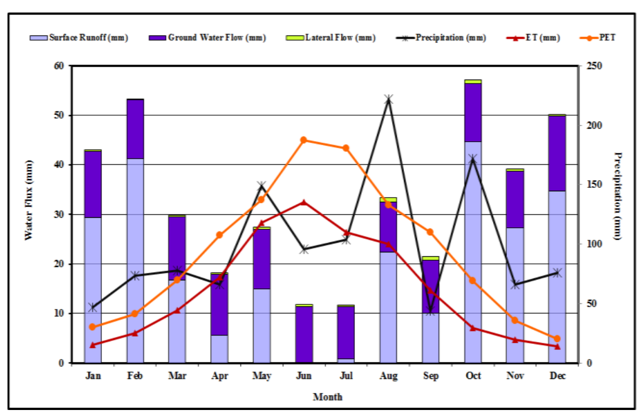

Figure 7. PSO monthly water component values in 1994 (dry year).

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