Parameter Sensitivity and Uncertainty in SWAT: A Comparison Across Five USDA-ARS Watersheds

T. L. Veith, M. W. Van Liew, D. D. Bosch, J. G. Arnold

Abstract. *The USDA-ARS Conservation Effects Assessment Project (CEAP) calls for improved understanding of the strengths and weaknesses of watershed-scale water quality models under a range of climatic, soil, topographic, and land use conditions. Assessing simulation model parameter sensitivity helps establish feasible parameter ranges, distinguish among parameters having regional versus universal interactions, and ensure that one model process does not compensate for another due to poor parameter settings. The Soil and Water Assessment Tool (SWAT) parameter sensitivity and autocalibration module was tested on two northern and three southern USDA-ARS experimental watersheds. These previously calibrated watersheds represent a range of climatic, physiographic, and land use conditions present in the U.S. Sixteen parameters that govern basin, snow accumulation/melt, surface, and subsurface response in the model were evaluated. Parameters governing surface runoff due to rainfall were found most sensitive overall, while parameters governing groundwater were the least sensitive. Surface runoff parameters were found most sensitive for areas with high evaporation rates and localized thunderstorms. Parameters from all categories were important in areas where precipitation includes both rainfall and snowfall. Differences in model performance were noticeable on a climatic basis; SWAT generally predicted streamflow with less uncertainty in humid climates than in arid or semi-arid climates. Study findings can be used to determine appropriate parameter ranges for ungauged watersheds of similar characteristics.*

Keywords. *CEAP, Hydrology, Parameter uncertainty, Sensitivity, Simulation.*

Recent advances in computing capability and Geographical Information Systems (GIS) have led to increasingly sophisticated watershed-scale models that are capable of addressing a host of issues related to water quality concerns: flood control, low flow management, and water availability. These physically based, distributed parameter models incorporate components for evapotranspiration, transmission losses, overland and channel flow, and surface and subsurface runoff on a watershed scale. However, because hydrologic simulation models are necessarily inexact representations of water movement in the natural system, they are often calibrated to available measured data. While this process often minimizes error between the model output and the data collected in the field, it is complicated by a large number of non-measurable parameters or coefficients that need to be estimated (Moriasi et al., 2007; Van Liew et al., 2005; White and Chaubey, 2005).

With widening applications of watershed-scale models, there is an increasing need to evaluate the accuracy of model simulations. Because calibration parameters and their feasible value ranges are sometimes selected in the exploratory modeling stage, they may not closely represent unique field conditions occurring during the study period of a particular watershed; conversely, they may be representative of only that time period and unique conditions. Moreover, certain processes that are improperly modeled may lead to situations in which other components of the model are forced to compensate for the model shortcomings (Haan, 1989).

Assessing parameter sensitivity is important in establishing feasible parameter ranges for calibration and for distinguishing parameters that have regional impacts and/or interactions from those that have a universal impact. For example, accurate estimation of lag time for surface water across a watershed is relevant to all watersheds, whereas estimation of snow melt parameters is relevant only in colder regions. Evapotranspiration parameters are relevant in both cold and warm climates, but in colder climates they may be particularly more important during some seasons than others. A good understanding of both regional and universal parameter sensitivity, as relevant to the study watershed, helps ensure that one model process does not erroneously attempt to compensate for another as a result of poor parameter settings. User interfaces for watershed models are beginning to in-

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clude autocalibration components that require little user interaction. This greatly simplifies parameter selection, but it also increases potential for erroneous parameter settings if a user selects default or example values without a clear understanding of the meanings of those values. As autocalibration techniques become more widely used and more practical due to faster computer runtimes, an adequate understanding of model parameters and adequate guidance toward appropriate parameter values and relationships become increasingly vital.

The Soil and Water Assessment Tool (SWAT) is a river basin model developed to predict the impact of land management practices on water, sediment, and agricultural chemical yields in large watersheds with varying soils, land-use, and management conditions over long periods of time (Arnold et al., 1998). The SWAT model has been applied to watersheds throughout the world. In the U.S., the model has been extensively used to develop total maximum daily loading plans and, more recently, was selected as one of the key components of the Conservation Effects Assessment Project being conducted by the USDA (USDA-NRCS, 2006). Current options in SWAT include tools for analyzing parameter sensitivity, calibrating model parameters, and assessing parameter uncertainty (Van Griensven, 2002). Besides providing a labor-saving method for model calibration, the tools for assessing parameter sensitivity and uncertainty enable practitioners to identify which parameters in the model are most important in governing hydrologic response and to determine the appropriate ranges over which parameters values are suitable for model simulations. However, these increasing levels of automation require increased awareness of the possible uncertainty and errors associated with incorrect parameter selection.

The objectives of this study were to (1) identify how sensitivity of hydrologic parameters varied among watersheds with distinctly different climatic conditions, (2) quantify the uncertainty of the calibrated parameters with respect to the calibrated solution set, and (3) evaluate the prediction uncertainty of the flow hydrograph due to parameter uncertainty. The investigation was conducted using data from five unique USDA-ARS experimental watersheds located throughout the U.S.: Mahantango Creek in Pennsylvania, Little River in Georgia, Little Washita River in Oklahoma, Walnut Gulch in Arizona, and Reynolds Creek in Idaho. Regional climatic differences among these watersheds have resulted in noticeable variations in model performance despite use of an autocalibration tool (Van Liew et al., 2007). The current study expands on the work of Van Liew et al. (2007) by evaluating the impact of these climatic differences on model parameter sensitivity and uncertainty.

Methods and Materials

The SWAT model was used to estimate hydrologic flow conditions of the five test watersheds. The impact of input parameter fluctuations on output variance was evaluated using the sensitivity analysis component within the model (Van Griensven, 2002). The simulated streamflow for each watershed was then compared to the measured flow using the autocalibration optimization routine within SWAT (Van Griensven and Bauwens, 2003). This process identified "good" parameter uncertainty ranges for 16 hydrologic parameters. The resulting "good" parameter ranges for each watershed were evaluated and compared across watersheds. Additionally, hydrographs resulting from the "good" parameter ranges were evaluated and compared. This information helps establish suggested initial parameters values for ungauged watersheds of similar characteristics.

Test Watersheds

The test watersheds were established in compliance with U.S. Senate Document 59 to depict downstream, off-site impacts of watershed practices. The test watersheds represent a range in climatic, physiographic, and land use characteristics (fig. 1, table 1). Average monthly streamflow over a three- to five-year period was previously calibrated against measured data for each watershed using mean square error, percent bias, and visual comparison, as detailed by Van Liew et al. (2007). The resulting variations in hydrologic response provide a spectrum of data for testing the robustness of SWAT in simulating hydrologic responses and of the autocalibration programs in determining parameter uncertainty.

Mahantango Creek in Pennsylvania

Located about 80 km northeast of Harrisburg, Pennsylvania, WE-38, a 7.2 km^2 experimental subwatershed of the Mahantango Creek watershed, is typical of upland agricultural watersheds within the nonglaciated, folded and faulted, Appalachian Valley and Ridge Physiographic Province (Veith et al., 2005). Mature forest covers the dominant ridge to the north, while cropland and pasture dominate the rolling hills of the watershed interior. Elevation ranges from about 490 m (msl) on the ridge top down to 160 m (msl) at the watershed outlet. Regional climate is temperate and humid, with a long-term average annual precipitation of 1100 mm based on data collected by the USDA-ARS from 1967 to the present. Upwards of 50% of annual streamflow is derived from groundwater return flow (Gburek et al., 1986), which in turn is controlled by a shallow zone of intensively fractured and weathered bedrock (Gburek and Folmar, 1999). The watershed is characterized by shallow, fragipan soils in near-stream areas, and deep, well-drained soils in the uplands. Land use types consist of pasture (38%), forest (34%), mixed croplands (26%), and farmsteads (2%).

Little River in Georgia

The 330 km^2 subwatershed B of Little River is located in south central Georgia about 1 km north of Tifton, Georgia. Climate in the region is characterized as humid subtropical with long, warm summers and short, mild winters, with an average annual precipitation of about 1215 mm based on data collected by the USDA-ARS from 1971 to 2004 (Bosch et al., 2006). The Little River watershed landscape is dominated by a dense dendritic network of stream channels bordered by riparian forest wetlands and upland areas devoted mostly to agricultural uses. The region has low topographic relief and is characterized by broad, flat alluvial floodplains, river terraces, and gently sloping uplands (Sheridan, 1997). Soils on the watershed are predominantly sands and sandy loams with high infiltration rates. Since surface soils are underlain by shallow, relatively impermeable subsurface horizons, lateral and shallow aquifer flows contribute significantly to streamflow, while deep seepage and recharge to regional groundwater systems are impeded (Sheridan, 1997). Land use types include forest (65%), cropland (30%), rangeland and pasture (2%), wetland (2%), and miscellaneous (1%).

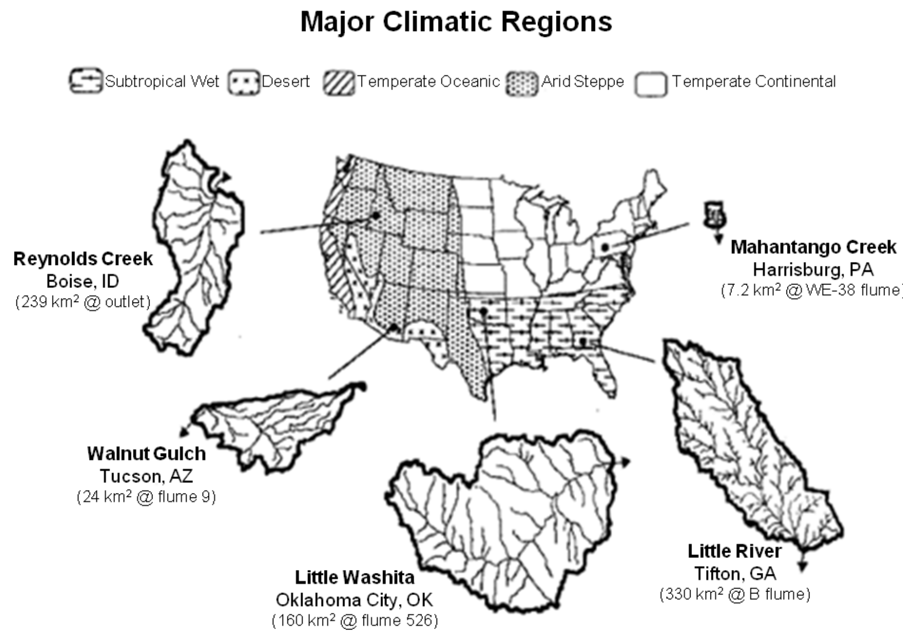

Figure 1. Locations and relative sizes of the five USDA-ARS study watersheds.

Little Washita River in Oklahoma

The 160 km^2 subwatershed 526 of the Little Washita River is located about 90 km southwest of Oklahoma City, Oklahoma. The climate in the region is sub-humid to semi-arid, with an average annual precipitation of about 795 mm, based on data collected by the USDA-ARS from 1961 to 2000. Topography of the watershed is characterized by gently to moderately rolling hills, and the soil types primarily consist of silt loams, loams, fine sandy loams, and sandy loams. Land use types include rangeland and pasture (59%), cropland (28%), forest (6%) and miscellaneous (7%, including urban, abandoned oil fields, farmsteads, ponds) (Allen and Naney, 1991). The watershed has 13 NRCS flood-retarding structures that control drainages on the Little Washita River that range in size from 249 to 1974 ha and consist of storage capacities ranging in size from 2.0×10^5 to 1.7×10^6 m^3. These structures delay and reduce peak surface flows and modify subsurface flows. They also lead to small increases in average annual evaporation due to a larger percentage of open water in the watershed.

Walnut Gulch in Arizona

Located about 115 km southeast of Tucson, Arizona, the Flume 9 subwatershed in Walnut Gulch comprises 24 km^2 near the historical western town of Tombstone. With a mean annual precipitation of about 325 mm, the climate of the region is considered semi-arid. Soils are generally well-drained, calcareous, gravelly loams with large percentages of rock and gravel at the surface (Gelderman, 1970). Watershed relief ranges from 1250 to 1585 m, and the topography consists of low undulating hills to mountains. Streamflow results from high-intensity rainstorms, primarily during the summer months, and is subject to substantial transmission losses in the channel beds and banks. Shrub canopy cover ranges from

Table 1. Physical and data resolution characteristics of the five USDA-ARS study watersheds.

	Mahantango Creek, Pennsylvania	Little River, Georgia	Little Washita River, Oklahoma	Walnut Gulch, Arizona	Reynolds Creek, Idaho
Topography	Rolling hills in non-glaciated ridge and valley	Flat floodplains to gently sloping uplands	Gently to moderately rolling hills	Low undulating hills to mountains	Flat valley to steep mountain slopes
Avg. annual precipitation	1100 mm	1215 mm	795 mm	325 mm	250 to 1100 mm
Avg. annual streamflow	393 mm	347 mm	130 mm	7.6 mm	223 mm
Land use	26% cropland, 38% pasture, 34% forest, 2% farmstead	30% cropland, 2% rangeland and pasture, 65% forest, 2% wetlands, 1% miscellaneous	28% cropland, 59% rangeland and pasture, 6% forest, 7% miscellaneous	83% rangeland, 12% forest, 5% urban	6% irrigated cropland, 94% rangeland and forest
Soil	Loams with near-stream fragipans; highly fractured bedrock	Fragipans underlying quick-draining sands and sandy loams	Silt loams, loams, fine sandy loams, and sandy loams	Well-drained, calcareous, gravelly loams; frequent surface rocks	Mainly steep, shallow, rocky soils; some deep, rock-free loams
Data resolution	10 m	30 m	30 m	10 m	30 m
Land use data	Aerial photograph	Landsat	Landsat	Landsat	Landsat
NRCS soil data	SSURGO	STATSGO	STATSGO	SSURGO	STATSGO

30% to 40%, and grass canopy cover ranges from 10% to 80%. Land cover on Walnut Gulch is comprised of rangeland (83%), forest (12%), and urban (5%). Land is primarily devoted to cattle grazing, with mining, limited urbanization, and recreation making up the remaining uses (Renard et al., 1993).

Reynolds Creek in Idaho

The 239 km^2 Reynolds Creek watershed is located about 80 km southwest of Boise, Idaho, and exhibits a considerable degree of spatial heterogeneity. Topography of the watershed varies from a broad, flat alluvial valley to steep, rugged mountain slopes, with a range in elevation from 1101 to 2241 m (Seyfried et al., 2000). There is more than a four-fold increase in average annual precipitation on the watershed, ranging from about 250 to more than 1100 mm. Perennial streamflow is generated at the highest elevations in the south and northwest parts of the watershed, where deep, late lying snow packs are the source for most water (Seyfried et al., 2000). Although much of the watershed has steep, shallow, rocky soils, there are areas of deep, loamy soils that are rock-free. Land cover on Reynolds Creek consists of rangeland and forest communities of sagebrush, greasewood, aspen, and conifers (94%) and irrigated cropland (6%).

Watershed Delineation

For this investigation, subbasins were delineated to account for variations in topography and precipitation based on the spatial distribution of precipitation gauges in each watershed and to account for the impact of the NRCS flood-retarding structures on hydrologic response in the Little Washita. SWAT hydrologic response units (HRUs) provide an all-inclusive division of a watershed such that watershed characteristics (soils, land use, topographic, and climatic data) within each HRU can be assumed uniform for the study purposes. Because the watersheds differ in all four of the characteristics involved in determining HRUs, HRUs were defined by a threshold of characteristic similarity instead of by equality in area or GIS cell count. Thus, the HRU threshold was based on a land use and soil type covering an area of at least 5% and 20%, respectively, within any given subbasin. As a result, the HRU sizes vary within and among watersheds (table 2). While three of the watersheds (Mahantango, Little River, and Reynolds Creek) have a similar number of GIS cells per HRU, the Mahantango data resolution was 10 m (table 1), and this is the smallest watershed. Thus, the average area per HRU for this watershed is much lower than the others. Little Washita has the most subbasins because of the flood-retarding structures and, thus, small HRUs relative to other large watersheds. Walnut Gulch, the second smallest watershed, does not have a lot of variation in land use and soils. Consequently, its HRUs are, on average, about the same size as those of the two largest watersheds. Several studies have shown that HRU size has little impact on hydrologic results (Jha et al., 2004; Arabi et al., 2006; Migliaccio and Chaubey, 2008). It should be kept in mind, however, that the same studies have shown that HRU sizes do impact water quality results.

Although there have been minor changes in land use over time on the Little River and Little Washita River watersheds, records are not available for either of these watersheds to accurately denote the actual year-to-year changes that have occurred. Moreover, testing conducted with SWAT on the Little Washita River watershed showed that changes in land use as indicated by available records resulted in only very minor changes in streamflow (Van Liew et al., 2007). Bosch et al. (2006) examined the impact of changes in land use on hydrologic patterns across the Little River watershed and found no significant relationship between the two. Similarly, long-term stream water quality trends within the Little River watershed reflected no significant relationship between changes in land use and trends in streamflow P and chloride concentrations (Feyereisen et al., 2008). Few changes in land use types have occurred on the other three ARS watersheds during the past few decades. For this study it was therefore assumed that the respective land use types on each of the watersheds remained constant for the period of record simulated. Investigating the year-to-year variations was beyond the scope of this work.

Table 2. Size and subdivision characteristics for the studied subwatershed of the five USDA-ARS watersheds.

			Mahantango, Pennsylvania	Little River, Georgia	Little Washita, Oklahoma	Walnut Gulch, Arizona	Reynolds Creek, Idaho
Subwatershed			WE-38	B	526	Flume 9	Outlet
Area (km^2)			7.2	329.9	159.9	23.7	239.0
GIS cells			72,023	366,605	177,643	237,430	265,503
Subbasins	Count		7	40	70	10	60
	Cells/subbasin		10,289	9,165	2,538	23,743	4,425
	Area (ha/subbasin)						
		Mean	103	825	228	237	398
		Median	107	793	195	236	382
		Range	128	1320	614	132	875
		Minimum	41	135	22	166	79
		Maximum	168	1456	636	298	953
HRUs[a]	Count		44	227	353	17	162
	Cells/HRU		1,637	1,615	503	13,966	1,639
	Area (ha/HRU)						
		Mean	16	145	45	140	148
		Median	11	97	30	130	108
		Range	59	659	243	249	848
		Minimum	2	9	3	43	2
		Maximum	61	669	245	292	850

[a] HRU = SWAT hydrologic response unit.

Evaluated Parameters

Sixteen calibration parameters that govern precipitation runoff processes in SWAT were selected for sensitivity and uncertainty analyses. These were the same parameters that were calibrated in an earlier study to investigate SWAT's performance on the five watersheds (Van Liew et al., 2007). Model parameters were grouped into four categories: (1) basin, (2) snow accumulation/melt, (3) surface, and (4) subsurface responses:

Basin Response Parameters. Channel hydraulic conductivity (CH_K2) governs movement of water from streambed to subsurface for ephemeral or transient streams. Surface runoff lag time (SURLAG) provides a storage factor in the model for watersheds in which runoff generally takes longer than one day to reach a subbasin outlet.

Snow Accumulation and Melt Parameters. Snowfall temperature (SFTMP) is the mean air temperature at which precipitation is equally likely to be rain, snow, or freezing rain. Snowmelt base temperature (SMTMP) defines the snow pack temperature above which snowmelt will occur. SMFMX and SMFMN are melt factors for snow on June 21 and December 21 in the Northern Hemisphere, respectively. These two factors allow the rate of snowmelt to vary through the year as a function of snow pack density. The snow pack temperature lag factor (TIMP) controls the impact of the current day's air temperature on snow pack temperature.

Surface Response Parameters. The runoff curve number (CN2) is used to compute runoff depth from total rainfall depth. It is a function of watershed properties that include soil type, land use and treatment, ground surface condition, and antecedent moisture condition. The soil evaporation compensation factor (ESCO) adjusts the depth distribution of evaporation from soil to account for the effects of capillary action, crusting, and cracking. The available soil water capacity (SOL_AWC) is the volume of water that is available for plant uptake when the soil is at field capacity. It is estimated by determining the amount of water released between *in situ* field capacity and the permanent wilting point.

Subsurface Response Parameters. The groundwater "revap" coefficient (GW_REVAP) controls the amount of water moving from the shallow aquifer to the root zone as a result of soil moisture depletion and the amount of direct groundwater uptake from deep-rooted trees and shrubs. The threshold depth of water required in the shallow aquifer for "revap," i.e., water movement to the root zone or plant, to occur is represented by REVAPMN. Likewise, GWQMN is the threshold depth of water in the shallow aquifer required for return flow to occur to the stream. The baseflow alpha factor (ALPHA_BF), or recession constant, characterizes the groundwater recession curve. This factor approaches one for flat recessions and approaches zero for steep recessions. The groundwater delay (GW_DELAY) is the time required for water leaving the bottom of the root zone to reach the shallow aquifer. The deep aquifer percolation parameter governs the fraction of percolation from the root zone to the deep aquifer (RCHRG_DP).

This study maintained a range in the calibrated values of the curve number similar to those reported in the literature (USDA-SCS, 1986) by restricting the initial lower and upper values for this parameter to ±5%. To properly account for the release of surface runoff from a subbasin to the main channel, the range in values of the surface runoff lag time was restricted from 0.5 to 10.0. Drawing from expert opinion, the initial lower and upper values for available soil water capacity were restricted to ±20%, and the upper bound on groundwater delay time was lowered to 300. All other parameter bounds were set as suggested by Van Griensven (2002) and van Liew et al. (2007). These ranges are used in the sensitivity analysis, the calibration process, and in the evaluation of parameter uncertainty.

SWAT Parameter Sensitivity and Uncertainty Modules

The SWAT2005 sensitivity analysis component determines the relative sensitivities of parameter changes to changes in the objective function by using the OAT (one factor at a time) design with Latin hypercube (LH) sampling (Van Griensven, 2002). Latin hypercube sampling is based on Monte Carlo simulation but uses a stratified sampling approach to ensure that user-specified ranges of the selected parameters are fully and efficiently sampled. The OAT design varies each parameter individually within the LH sampling stratification. Because only one parameter varies during each model run, changes in model output can be unambiguously attributed to the input parameter changed. In this study, parameters were varied ±5% across their feasible value range. Traditionally, researchers tend to estimate model sensitivity by evaluating the impact of parameter change on model output. However, as the ultimate goal of this study is to look at sensitivity on model performance, sensitivity was evaluated by the change in the objective function, which is a measure of how well the model reflects the natural system.

SWAT2005 also includes "ParaSol with Uncertainty Analysis," a multi-objective, automated calibration procedure that estimates parameter uncertainty (Van Griensven and Bauwens, 2003). The calibration procedure is based on the shuffled complex evolution algorithm (SCE) developed by Duan et al. (1993) to address major characteristics of hydrologic model calibration projects. The SCE has been widely used in watershed model calibration and other areas of hydrology and has been generally found to be robust, effective, and efficient (Cooper et al., 1997; Duan, 2003). The objective function used in the procedure is an indicator of the deviation between a measured and a simulated series (Van Griensven and Bauwens, 2003).

Following from the work of the previous watershed study (Van Liew et al., 2007), this study employed the sum of squares of residuals (simulation output minus observed flow) method to minimize streamflow. Van Liew et al. (2007) showed that the SCE optimization procedure did a fairly good job in matching measured and simulated streamflow. For four out of the five watersheds, percent bias (PBIAS) was estimated to within +15%. Model performance was 0.8 or above at the monthly time scale based on the Nash-Sutcliffe coefficient of efficiency (NSE; Nash and Sutcliffe, 1970).

The analysis for describing parameter uncertainty in SWAT2005 divides model simulations that have been performed by the SCE optimization into "good" and "not good" simulations (Van Griensven, 2002). Two separation techniques are available for grouping model simulations. Both techniques are based on a threshold value for the objective function to select "good" simulations by considering all the simulations that give an objective function below this threshold. The threshold can be defined by chi-squared statistics where the selected simulations correspond to the confidence region, or by Bayesian statistics that are able to point out the high probability density region for the parameters or model outputs.

Results of the parameter uncertainty analysis process were then used to tabulate those parameter value ranges associated with "good simulations," i.e., simulations with modeled streamflow values within the confidence region defined by chi-squared statistics at the 97.5% probability level. To facilitate comparisons of parameter uncertainty by categories and watershed, each final parameter range was normalized by its initial range to create a percentage. The size of the normalized parameter range indicates the ability for fluctuation in that parameter value while still achieving a "good" simulation, with a wider range corresponding to more flexibility. On a graph, the location of the normalized range within the 0 to 1 range indicates the location of the initial parameter range in which the ideal values lie. A parameter value at either edge of the range may indicate that the initial user-selected range could be improved.

The optimal simulation run and confidence interval due to parameter uncertainty were then graphed on a monthly basis with the measured data for visual comparison. As the confidence interval is defined by the threshold statistic on the objective function, it is important to also evaluate representation of the system over time.

Results and Discussion

Parameter Sensitivity

Considering the sensitivity data in terms of the mean change in the objective function provides a relatively easy comparison to the parameter change. For example, when SURLAG is changed by 5%, it yields a 2.37% change in the objective function, or a 0.5 to 1 ratio (table 3). Evaluated in this way, changing SURLAG caused the most change to the objective function across all watersheds (table 3). Little River, which is humid with substantial lateral flow just below the surface, was largely influenced by SURLAG. The other basin parameter, CH_K2, also had a measurable impact for the larger watersheds. Surface parameters were also sensitive across all watersheds, particularly in the more arid watersheds (Little Washita and Walnut Gulch). Snow-based processes were most affected by the mean air temperature driving accumulation (SFTMP) in Reynolds Creek, perhaps due to the wide range of elevation across the watershed. Mahantango, with more rolling hills and less climatic extremes in the winter, exhibited sensitivity to the snow melt parameters. Among the six groundwater parameters investigated in this study, ALPHA_BF and GWQMN were somewhat sensitive, particularly for Reynolds Creek.

Parameter Uncertainty

The ranges of parameter values present in "good" solutions, normalized by the user-input ranges, were ordered according to the four categories described earlier in this article (fig. 2). A parameter covering the full range from 0 to 1.0 implies that the value of that variable, within the input ranges, has little impact on the model performance. In contrast, a very short range suggests the values of the variable necessary to achieve "good" model performance. The range of SURLAG was the narrowest among all parameters for all watersheds except Walnut Gulch, which has a flashy storm response and large transmission losses. Accordingly, CH_K2 has a narrower range for Walnut Gulch than for the other watersheds. The narrower the range, the closer the parameter value must be to that of the optimal run in order to maintain a good objective function value. In general, parameter ranges seem to be relatively small when it is reasonable that a watershed would be sensitive to a particular parameter; otherwise, the range is essentially the entire input range. For example, the southern watersheds are not sensitive to snow process parameters, as expected, so the range of those parameters is 100% of the input range.

Although a parameter may be sensitive for numerous watersheds, the optimal value of the parameter may vary considerably among watersheds. For example, the stream flow objective function for all five watersheds is sensitive to the curve number (CN2), as shown in table 3 and by the relatively short bars in figure 2. But the optimal value for CN2 is near the lower bound of the user-defined range for the eastern two watersheds and near the upper bound for the western three watersheds, as shown by the location of the bars in figure 2 in this article and by table 4 in Van Liew et al. (2007). Reynolds Creek watershed is not nearly as sensitive to surface runoff lag time (SURLAG) as are the other four watersheds,

Table 3. Mean change in objective function due to 5% change in parameter value (standard deviation in parentheses; values <0.1 not shown).

	Parameter	Mahantango, Pennsylvania	Little River, Georgia	Little Washita, Oklahoma	Walnut Gulch, Arizona	Reynolds Creek, Idaho
Basin	SURLAG	2.37 (2.9)	6.48 (3.0)	2.50 (2.6)	2.90 (1.3)	2.71 (2.9)
	CH_K2	--	0.30	0.16	0.66	0.64
Snow	SMFMX	1.60 (0.4)	--	0.17	--	0.72
	SMFMN	0.21	--	--	--	0.44
	SFTMP	0.52 (0.4)	--	--	--	1.71 (1.3)
	SMTMP	1.03	--	--	--	0.48
	TIMP	1.08 (0.3)	--	0.11	--	0.43
Surface	ESCO	1.43	1.54 (0.4)	6.32 (3.6)	6.80 (2.1)	0.22
	CN2	2.34	1.33	1.14	4.84 (0.9)	0.42
	SOL_AWC	0.35	0.83	1.39 (0.3)	2.96 (0.5)	0.55
Subsurface	ALPHA_BF	--	0.12	0.22	0.46	2.14 (1.2)
	GWQMN	--	0.33 (0.3)	--	0.75 (0.8)	0.57 (0.7)
	GW_REVAP	--	--	--	--	--
	REVAMPN	--	--	--	--	--
	GW_DELAY	--	--	--	--	--
	RCHRG_DP	--	--	--	--	--

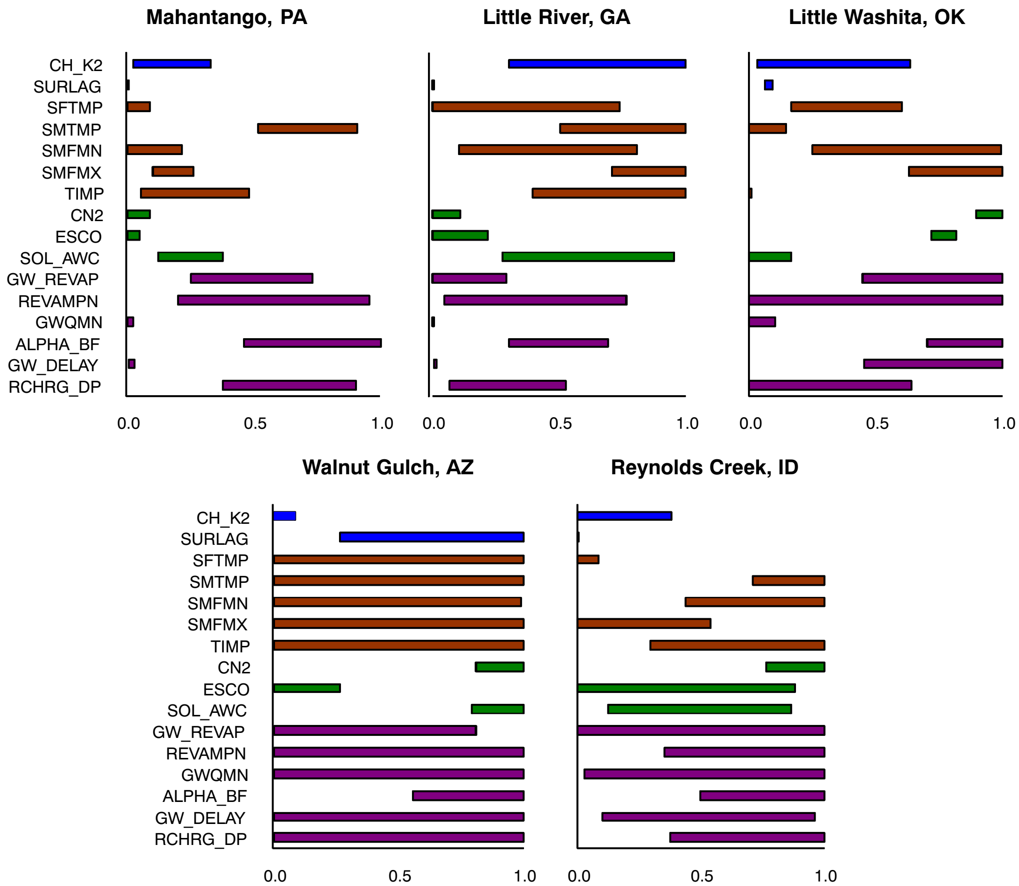

Figure 2. Size and location of the normalized, user-defined range for each parameter of all simulations falling within the confidence interval of the optimal (best calibrated) simulation.

but its optimal value and "good" parameter range for SURLAG are on the high side of the user-defined bounds instead of the low side. The evaporation coefficient factor (ESCO) varies widely among all five watersheds in both location and size of the optimal value range. Based on "good" simulations performed by watershed, Mahantango exhibited the narrowest percent of range in parameter uncertainty across the eleven non-snow parameters, while Walnut Gulch and Reynolds Creek produced the widest (fig. 2). These examples highlight the importance of considering regional characteristics in calibrating a watershed.

When percent of range in parameter uncertainty was averaged by parameter grouping (basin, snow, surface, and subsurface) within each watershed, the basin, snow (for watersheds with snow), and surface groups appeared to be independent of average annual long-term precipitation values (fig. 3). However, a strong inverse relationship ($r^2 = 0.94$) across watersheds between average annual precipitation and average percent of range for the subsurface parameters suggests a linear increase in the importance of subsurface parameters for wetter climatic regimes. As the annual precipitation value increases across the watersheds (fig. 3), the monthly precipitation values tend to become more uniform and the evapotranspiration-to-precipitation ratio becomes less extreme (fig. 4). The wetter watersheds experience groundwater recharge and subsurface water movement more constantly throughout the year than the drier watersheds. Thus, both above ground and subsurface parameters must be within appropriate ranges for "good" model performance. In contrast, the above ground processes of the drier watersheds, driven by intense, less consistent precipitation and high ratios of evapotranspiration to precipitation, likely overwhelm the subsurface processes of SWAT, a model that is driven by precipitation and infiltration excess as opposed to saturation excess.

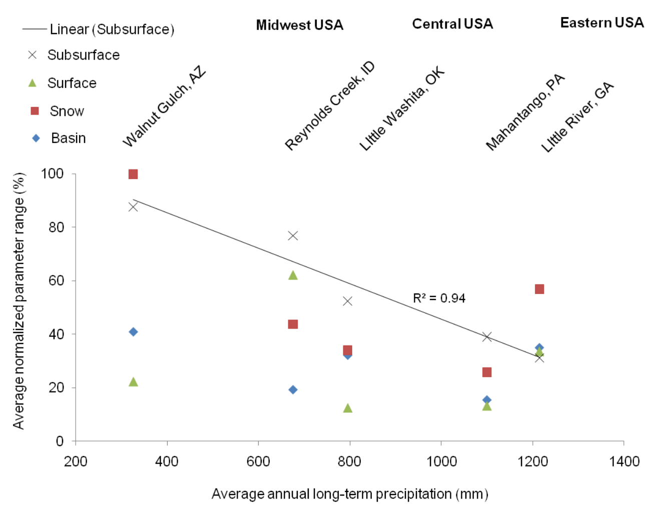

Figure 3. Relationship between precipitation and average sensitivity of the four parameter groupings for the five USDA-ARS watersheds.

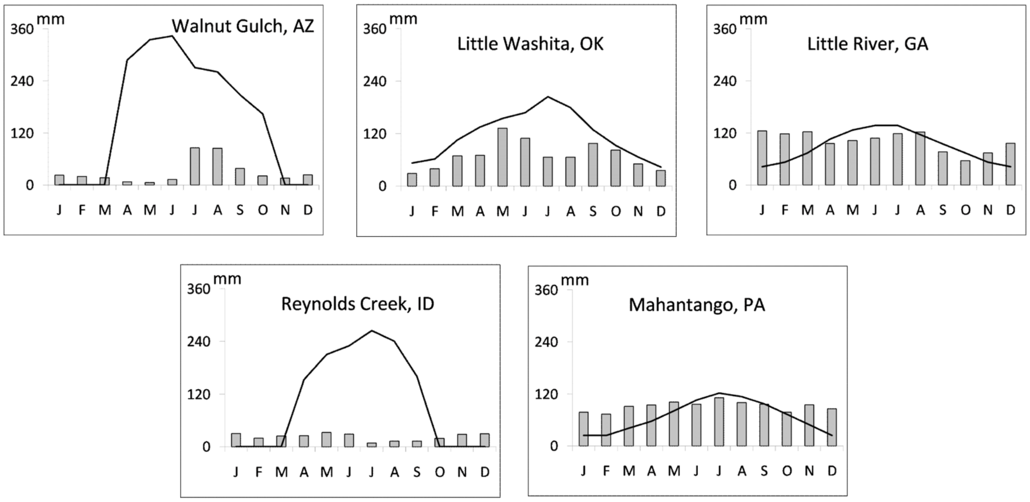

Figure 4. Long-term average monthly precipitation (bars) and evapotranspiration (lines) for the five USDA-ARS watersheds (USDA-NRCS, 1999; USDA-NRCS, 2000a, 2000b; WRCC, 2006a, 2006b, 2006c, 2006d; Basara, 2009).

Hydrograph Prediction Uncertainty

Figure 5 shows monthly measured streamflow, "best parameter" simulated streamflow, and hydrograph prediction uncertainty associated with the simulations for which the objective function values were within the confidence interval of the watershed optimum objective function value. This prediction uncertainty reflects only variation due to changes in parameter value, propagated through the model. However, the "good" simulations reasonably capture the mid-range to high-flow regions of the hydrograph, as indicated by narrow hydrograph bounds in these regions. Model simulations performed with the Sacramento soil moisture accounting model (SAC-SMA) also showed similar results (Gupta et al., 1999). Less satisfactory simulations were obtained for recession portions of the hydrograph (primarily governed by subsurface parameters), as indicated by the relatively wider bracket bounds for each of the watersheds. Wider bounds around the recession portions of the hydrograph seem to be consistent with results previously described that show narrower percent ranges for model parameters in the surface runoff and basin categories than in the subsurface runoff category.

Average monthly lower and upper bounds on streamflow associated with parameter uncertainty confidence interval are presented in table 4. When expressed as a percent departure from the average monthly discharge simulated with the "best parameter" set, the range is narrowest for Mahantango (-11.4% to +14.5%), which is the smallest subwatershed with the overall second to lowest monthly average discharge rate. However, Mahantango streamflow varies seasonally with snowmelt and regular precipitation. Walnut Gulch, the second smallest watershed, has the lowest monthly average flow rate by an order of magnitude and the widest range of variation in hydrograph uncertainty, particularly for high flows (-18.2% to +86.7%). This is further demonstration of the need for careful consideration, and perhaps model adjustments, when evaluating a watershed with long-term low flows and flashy storm responses. For the remaining three watersheds, the average percent departure in hydrograph uncertainty from the "best parameter" average monthly streamflow was within ±25%.

Summary and Conclusions

This study evaluated parameter sensitivity and uncertainty, as calculated in the 2005 version of the Soil and Water Assessment Tool, on five USDA-ARS experimental watersheds. These watersheds, three southern and two northern, represent a range in climatic, physiographic, and land use conditions present in the U.S. Sixteen parameters that govern basin, snow accumulation/melt, surface, and subsurface response in the model were evaluated. Latin hypercube one-factor-at-a-time analysis was employed to evaluate parameter sensitivity in the model. The mean square error method that matches a simulated time series to a measured series was used as the optimization scheme for model calibrations. The shuffled complex evolution algorithm was employed in SWAT to calibrate each watershed, and a 97.5% threshold value defined by chi-squared statistics was used to determine parameter uncertainty estimates from "good" and "bad" simulations.

Table 4. Average monthly flow rates for runs in which the modeled objective function values were within the confidence interval of the optimal (best calibrated) simulation.

	Area (km^2)	Time Series	Average Discharge (m^3 s^{-1}) Measured	Modeled Optimum	Modeled Min.	Modeled Max.	Departure from Optimum (%) Min.	Max.	% Bias[a]	Monthly Nash-Sutcliffe Coefficient[a]
Mahantango (WE-38)	7	1/97 to 12/00	0.0827	0.0828	0.0733	0.0948	-11.4	14.5	0.07	0.84
Little River (B)	330	1/97 to 12/02	2.854	2.457	1.934	3.018	-21.3	22.8	-13.92	0.90
Little Washita (526)	160	1/80 to 12/85	0.610	0.523	0.396	0.652	-24.2	24.9	-14.36	0.90
Walnut Gulch (Flume 9)	24	1/68 to 12/72	0.0072	0.0087	0.0071	0.0162	-18.2	86.7	24.14	0.83
Reynolds Creek (outlet)	239	1/68 to 12/72	0.677	0.709	0.538	0.859	-24.0	21.2	4.75	0.80

[a] Between measured and modeled values.

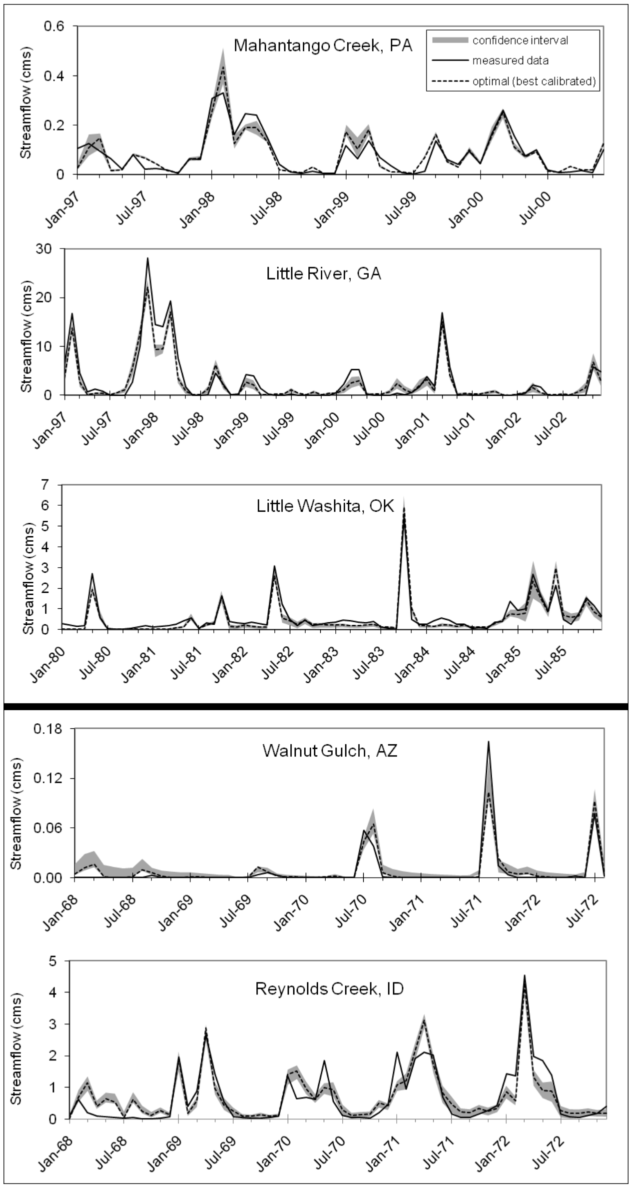

Figure 5. Time series of the parameter uncertainty around the optimal solution and the measured data for the five USDA-ARS watersheds.

All watersheds were particularly sensitive to response surface lag time, while the two southwestern watersheds were sensitive to the soil evaporation factor and the available water capacity of the soil. The northern, mountainous watershed on the arid steppe was more sensitive to snowfall temperature and the baseflow recession constant but less sensitive to snow melt parameters than the northern, rolling watershed in the temperate continental region.

Results of the parameter uncertainty analysis followed a pattern similar to that obtained for the sensitivity analysis. Of the 16 parameters investigated, the "good" parameter ranges for curve number and surface runoff lag time were the narrowest, on average. The location of the ranges for sensitive parameters, such as the curve number and soil evaporation coefficient, varied widely among the watersheds; in some cases the optimal solution value for the parameter was on the upper end of the user-defined range, and in other cases it was in the middle or on the lower end. The threshold depth of water in the shallow aquifer for "revap" to occur, the groundwater "revap" coefficient, and the groundwater delay factor, on the other hand, exhibited the widest percent of range solution space. The "good" ranges for parameters governing basin and surface responses were generally about one-half as wide as for those parameters governing snow accumulation/melt or subsurface runoff.

Maximum widths of the hydrograph uncertainty bounds resulting from the confidence interval around the objective function varied among watersheds, dependent, perhaps, on watershed size and stream discharge rate as well as regional conditions. However, widths were often widest during event recessions or low flows when measured values may also have had sizable variation. While this study has shown the impact of regional characteristics on parameter calibration and uncertainty when using SWAT, modelers should also be aware of other types of variability, such as temporal fluctuations in climate, measurement frequency and technique, spatial variability within a region, and model process uncertainty, which may play key roles for the region or question of interest.

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