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Estimation and Propagation of Parameter Uncertainty in Lumped Hydrological Models: A Case Study of HSPF Model Applied to Luxapallila Creek Watershed in Southeast USA

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Abstract

Explicit quantification of the uncertainty associated to the predictions of a hydrologic model is a necessary activity to objectively evaluate and report the limitations of the model caused by different sources of error. The current state of the practice of hydrologic modeling indicates that parametric uncertainty is considered as one of the most important sources of uncertainty. Some of the most relevant problems remaining in the practice include the identification of the principal parameters affecting model predictions and quantification of parameter ranges. This study evaluated stochastically one of the most popular deterministic watershed water quality models for decision making in USA. The lumped parameter watershed model, Hydrologic Simulation Program FORTRAN – HSPF, was used to simulate hydrologic processes in the Luxapallila Creek watershed in Mississippi and Alabama. Sensitivity and uncertainty of selected HSPF parameters were evaluated as well as a reduction of parameter range was suggested. Analysis of parameter uncertainty propagation on streamflow simulations from 12 HSPF parameters was accomplished using 5,000 Monte Carlo random samples. The model was evaluated at the outlet of the watershed using daily streamflow data. Daily observed streamflow data from 01/01/2001 to 11/30/2004 were clustered into three groups to assess the model Reliability and Sharpness by each class: below normal, normal, and above normal flows. In general, the model Reliability was better for below normal flows than normal and above normal flows. Four out of 12 parameters were found to account for the majority of parameter uncertainty propagation. The four most sensitive parameters affected the different stages of the simulated hydrograph (below normal, normal, and above normal flows). Parameter ranges of the four most sensitive parameters were reduced between 20% and 40%. Results from this study assist in improving model accuracy and improve the models ability to predict future conditions based upon landuse changes. Additionally, the HSPF stochastic framework developed in this study could be used to evaluate the impact of different rainfall datasets, digital elevation model resolutions, and sub-watershed delineations on model results.

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Keywords

Parameter sensitivity; Parameter uncertainty; Monte Carlo simulation; Hydrology modeling; Hydrologic simulation program FORTRAN–HSPF

Introduction

Hydrologic models are defined by input time series (e.g., precipitation, evaporation, etc), physical characteristics of the area (e.g., size, slope, land use, etc), and algorithms. When analyzing model results, modelers are faced with various uncertainties in input and output data, model structure, and model parameters. These uncertainties negatively affect the usefulness of hydrologic models. Error analysis propagation throughout different components of a hydrologic model is one of the major challenges when a model is evaluated [1]. Model prediction uncertainty is reported for Total Maximum Daily Load (TMDL) decision support [2]. Uncertainty in input data is due to natural variability, measurement inaccuracy, and errors in handling and processing data [3]. For example, studies in rainfall input data uncertainty use physically-based atmospheric models to propagate rainfall uncertainty into model results [4]. Model parameters and structure show uncertainty from model assumptions/approximations, scale effects, and variability of inputs and parameters in time and space [5,6]. Continuous semi-distributed hydrologic models are complex and highly parameterized. For instance, the Hydrologic Simulation Program FORTRAN (HSPF) model uses 26 parameters to simulate flow in a previous land segment without snow simulation [7]. So, more than one calibrated parameter set may be obtained with equal streamflow simulations [8,9] and high correlation between parameters would be expected. Both problems mean that the model and/or measured data may not be appropriate to represent the physical values. In addition to the non-uniqueness and correlation in model parameter sets, watershed models are simplifications of the physical world. Therefore, parameters of hydrologic models produce uncertainty. The current state of the practice of hydrologic modeling indicates that parametric uncertainty is considered as one of the most important sources of uncertainty [10-17]. Assessment of model parameter uncertainty is useful to [6,18] understand the inability of a model to accurately and precisely depict the real world; enhance the value of information reported; identify which parameters are most and least important; determine where to place more effort/resources to decrease the total uncertainty of the output; re-build a model; understand model limitations and strengths; calculate statistical properties of a model output; determine reliability analysis; and compare and choose between models. Finally, more investigation is necessary to evaluate the benefits of incorporating uncertainty analysis as a fundamental component of hydrologic studies.

Numerous watershed models that mathematically represent the real world exist (e.g., continuous or event based, distributed or lumped parameters, empirical or physical equations), [19-21]. One of the most extensively used hydrologic software is the HSPF model [22-31]. While HSPF is widely used, little work has been done to quantify the effect of parameter uncertainty and sensitivity on model simulations.

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Uncertainty analysis methods used in hydrologic simulations can be arranged in four groups: first-order methods, probabilistic point estimation methods (PPEMs), Monte Carlo (MC) and re-sampling methods, and Bayesian methods. The MC simulation is the best known uncertainty method, and simplest way of sampling the entire range of likely observations of the system being studied [32]. Monte Carlo techniques require calculating the joint probability density function (PDF) of model parameters, then a large number of model runs are made, and finally the PDF and statistical moments of outputs are calculated. The MC simulation has been applied to study the uncertainty of forcing input data and model parameters in computer models of watershed hydrology [3,14]. Melching [3] pointed out that "*for complex, nonlinear models with many uncertainty basic variables, however, the number of simulations (thus the computer time) necessary to achieve an accurate estimate may become prohibitive.*" In recent times, the increase of computer processing speeds makes computations more tractable. In other studies, Monte Carlo method results have been used as a baseline when comparisons with other uncertainty methods have been done [3,15,33-35]. Mishra [36] concluded that MC simulation is more general and requires lesser assumptions than first-order methods and PPEMs. Therefore, MC simulation is used in this study for assessment of parameter uncertainty.

The objective of this study was to evaluate model parameter uncertainty and sensitivity propagation on simulated flows using Monte Carlo methods. This work attempts to model daily flows and their certainty bounds for a watershed in Alabama and Mississippi. The HSPF model was selected to simulate continuous flow of the Luxapallila Creek watershed. An approach to reduce HSPF parameter ranges is presented.

The HSPF/BASINS model

The Hydrologic Simulation Program – FORTRAN (HSPF) model [7] computes the movement of water through a complete hydrologic cycle – rainfall, evapotranspiration, runoff, infiltration, and flow through the ground – and the associated transport of constituents with that flow. It represents a watershed as a collection of land segments and channels (reaches). The land segments, either pervious or impervious, are connected to other land segments or to channel reaches, which can function as either streams or reservoirs. Rainfall is computed over the entire watershed and runs off land segments and reaches. Pervious land segments also store water in the plant canopy, on the surface, and in the soil, from which it can percolate into groundwater or flow downslope as interflow. Water in the plant canopy, surface, and surface soil layers can be lost to evapotranspiration. Water in reaches can be lost to evaporation, but not to groundwater. Water can flow from a land segment to a reach or to another land segment. Water in a reach must either be stored there or flow into another reach; it cannot flow onto land except by irrigation. These hydrologic processes are coded in HSPF using mathematical equations with several conceptual and physics-based parameters. Table 1 describes HSPF parameters and their ranges related to hydrology in areas without snow. This table also shows the impact of each parameter on the model hydrograph (calibration scenarios). The most probable values showed in table 1 were found in an 18-year model evaluation in the Luxapallila Creek watershed, Alabama/Mississippi [37].

The HSPF model also computes the transport and kinetics of multiple water quality constituents, including temperature, sediment, nutrients, and pesticides. As such it presents a nearly complete package for modeling hydrology and water quality of a watershed. A more complete description of features and capabilities can be found in the HSPF user's manual [7]. Some versions of HSPF can be run in standalone mode, but the EPA-supported version is run through a BASINS interface, WinHSPF [38]. The rainfall-runoff model HSPF requires specific inputs that BASINS can generate. Watershed delineation tools within BASINS enable the user to automatically or manually generate a watershed drainage network and sub-networks, each consisting of land segments and receiving water reaches. BASINS (or its utility program, WDMUtil) creates a binary file with a ".wdm" extension to store input time-series information such as rainfall, wind speed, and temperature for stations in or near the watershed. HSPF reads these text and binary files and constructs two more files, an ASCII run control file (with a ".uci" extension) and a binary input/output file (with a ".wdm" extension). These files can be manipulated by the user and used in all subsequent simulations (Figure 1).

HSPF Parameter Sensitivity and Uncertainty

This section discusses sensitivity and uncertainty studies of the HSPF model (see Table 1 for HSPF parameter definition). While the HSPF model has been extensively and successfully tested in different countries since 1980, little work has been done to quantify the effect of parameter uncertainty and sensitivity on streamflow simulations. Garen and Burges evaluated parameter error propagation of the Stanford Watershed Model (SWM), which is the hydrology predecessor of the HSPF model [39]. They assessed error bounds of channel inflow hydrographs for several storm events using two uncertainty approaches, first-order uncertainty analysis and Monte Carlo analysis. The most sensitive parameters were the raingage scaling factor (K1) and the upper zone storage nominal capacity (UZSN). The authors pointed out that the first-order uncertainty analysis did not perform satisfactorily under extreme conditions (i.e., a highly nonlinear response of the model) or coefficients of variation greater than 0.25 for the most sensitive parameters.

Jacomino and Fields performed a sensitivity analysis of thirteen hydrologic HSPF parameters. AGWRC (ground water recession coefficient) and AGWS (initial condition for ground water storage) parameters showed the greatest sensitivity [40]. The degree of saturation in the lower zone soil moisture (LZSN, LZS), the volume of the upper soil moisture zone (UZSN, UZS) and the infiltration rate (INFILT) were less significant. The rest of the parameters had no effect on the model results. Fontaine and Jacomino [41] evaluated the sensitivity of HSPF parameters for simulating flow and sediments

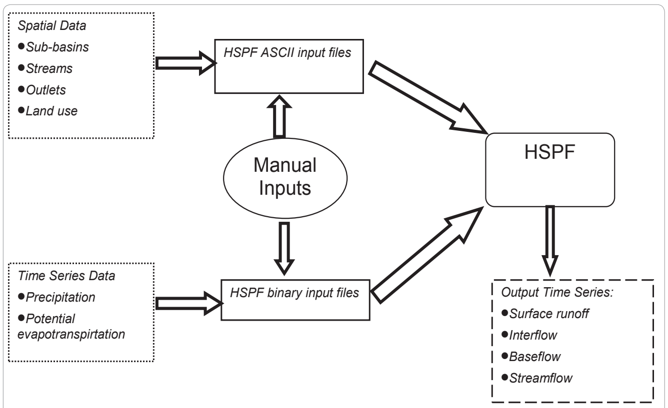

Figure 1: Input architecture and data pathways of BASINS/HSPF for hydrology simulation.

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Table 1: HSPF parameter definition (BASINS web page, technical note 6).

Name	Definition	Range	Most Probable Value	Calibration Scenarios			
LZSN (mm)	Lower zone nominal soil moisture storage	50.8 -381.0	228.6	X			
INFILT (mm/hr)	Index to infiltration capacity	0.025 – 12.7	2.8	X	X	X	
KVARY (1/mm)	Variable groundwater recession	0.0 – 127.0	45.7				X
AGWRC (1/day)	Base groundwater recession	0.92 - 0.999	0.997		X		
DEEPFR	Fraction of groundwater inflow to deep recharge	0.0 - 0.5	0.2	X	X		
BASETP	Fraction of remaining evapotranspiration from baseflow	0.0 - 0.2	0.04		X		X
AGWETP	Fraction of remaining evapotranspiration from active groundwater	0.0 - 0.2	0.025				X
CEPSC (mm)	Interception storage capacity	0.0 – 10.2	3.8				X
UZSN (mm)	Upper zone nominal soil moisture storage	1.27 – 50.8	27.9				X
INTFW	Interflow inflow parameter	1.0 - 10.0	3.0			X	
IRC (1/day)	Interflow recession parameter	0.3 - 0.85	0.6			X	
LZETP	Lower zone evapotranspiration parameter	0.0 - 0.9	0.1	X			X

at the hillslope and watershed levels. In addition, HSPF parameters were evaluated for normal and flood flow scenarios. Table 2 shows the most sensitive HSPF parameters for streamflow simulation calculated by the authors.

Al-Abed and Whiteley [26] tested the HSPF model in a Canadian watershed. A sensitivity-index approach showed that by far the LZSN parameter was the most sensitive. Doherty and Johnston [8] performed an uncertainty analysis of nine HSPF parameters (LZSN, UZSN, INFILT, BASETP, AGWETP, LZETP, INTFW, IRC, and AGWRC; see parameter definitions in Table 1) using the parameter optimization software PEST. The most sensitive parameters were AGWRC and INFILT at the watershed scale. In addition, the authors found a number of different parameter sets with the same fit between simulated and observed streamflows.

Diaz-Ramirez et al. evaluated the HSPF model in a 98-km^2 tropical island watershed [31]. Based on the results of the sensitivity analysis the HSPF parameter that most affected the streamflow and suspended sediment prediction was AGWRC. Paul evaluated the effect of parameter uncertainty in the HSPF model to predict in-stream bacterial concentrations using Monte Carlo and First Order Analysis techniques [42]. He pointed out that hydrologic parameters drive most of the parameter uncertainty in simulated in-stream bacterial concentrations. In addition, he concluded that to make a reliable total maximum daily load the simulation of hydrology processes must be accurate.

Iskra and Droste evaluated the HSPF model on a watershed located in Ontario, Canada [43]. The authors evaluated parameter sensitivity of 11 hydrological parameters at daily flows and monthly volumes between 1990 and 1998. The most sensitive parameter at daily flows was the INFILT parameter. The AGWRC parameter was the most sensitive at monthly volumes. The authors did not find any sensitivity of the CEPSC parameter at both daily flows and monthly volumes. They pointed out that the CEPSC was insensitive because the low forest ratio in the study area.

Table 2: The most sensitive HSPF parameters for streamflow simulation (Fontaine and Jacomino, 1997).

Flow Scenario	Hillslope Level	Watershed Level
Normal	AGWRC	AGWRC
Flood	LZS, AGWRC, LZSN, and UZSN	LZS, AGWRC, and LZSN

Young tested the effect of rainfall spatial resolution in the HSPF model using radar and raingage data in the Little Washita River experimental watershed, Oklahoma [44]. In addition, the author evaluated the error variance in radar precipitation data finding high uncertainty for both hydrology and water quality simulations. He concluded that the hydrology simulation for this 600-km^2 watershed with a high quality, high density of raingage was insensitive to rainfall spatial resolution; however, the use of raingage data showed high uncertainty when sediments and other water quality constituents were simulated. He recommended evaluating the error propagation of rainfall through the model and the variability of other spatial properties, e.g., soils, land use.

Jia investigated parameter uncertainties in the HSPF model applying the generalized likelihood uncertainty estimation (GLUE) approach [9]. A Latin hypercube sampling technique was used to generate random multiple parameter sets. Seven hydrologic parameters were evaluated in this project (i.e., LZSN, INFILT, AGWRC, DEEPFR, UZSN, and IRC) at the watershed outlet. After 50,000 HSPF runs, many acceptable parameter sets were identified by the GLUE approach. Information on the total runoff distribution was not available, and wide variations of the total runoff (i.e., surface runoff, interflow, and baseflow) were acceptable. The author pointed out that equifinality (potential for multiple parameter sets that provides acceptable fits to field data) [45] in model parameter sets was due to the accumulative effects of model structure errors, flow measure errors, and a lack of sufficient data (e.g., runoff distribution data at hillslope level).

Wu assessed the propagation of parameter uncertainty in both HSPF and CE-QUAL-W2 models using First-Order Error Analysis

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(FOEA) [46]. He pointed out that the uncertainty in parameters related to streamflow generation was the main source of variance in simulated nutrient loads. However, when simulated nutrient concentrations were analyzed, some parameters related to hydrology process have no significant effect. The author justified this difference by the non-linear relationship between pollutant loads and their concentrations. So, FOEA may not be an appropriate method to analyze propagation of parameter uncertainty in complex models with non-linear relationships. Wu recommends more analysis between FOEA and Monte Carlo analysis [46].

Methodology

Watershed description

This study used physical data from the Luxapallila Creek watershed (Figure 2). The watershed flows through Fayette, Lamar, Marion, and Pickens counties in Alabama and into Lowndes and Monroe counties in Mississippi. Near the outlet (USGS Station 02443500), the watershed has a drainage area of 1,801 km^2, an average basin slope of 2%, and average annual precipitation (1982 - 2004) of 1,379 mm recorded at the Millport 2E weather station (Figure 3). Seasonal fluctuations in rainfall result in maximum river discharges from January to April and minimum discharges from August to September. Elevation in the study area ranges from 45 to 274 m mean sea level. Seasonal temperatures vary widely in the basin from average daily values around 4°C in January to roughly 27°C in August. The study area is mainly sandy loam soils in hydrologic soil group B (USDA-NRCS, 2009) [47]. Diaz-Ramirez et al. [48] concluded, after an 18-year HSPF evaluation, that simulated runoff and actual evapotranspiration were the main source of water losses in the Luxapallila Creek watershed. The USGS Geographic Information Retrieval and Analysis System (GIRAS) land cover developed in the early 1980's is distributed as 73% forest land, 20% agricultural land, 6% wetlands, and 1% other land types (barren, urban, and non-urban). This watershed has not changed considerably its land cover since 1980s. Diaz-Ramirez et al. [30] assessed three different land cover maps (1980 GIRAS, 1992 National Land Cover Data - NLCD, and 2004 MODerate Resolution Imaging Spectroradiometer-MODIS) and found that GIRAS, NLCD, and MODIS datasets classified more than 73% of the watershed area as covered by forest and more than 16% covered by agricultural lands. Forest areas showed small changes among databases. Larger percent differences in agricultural areas were detected when comparing NLCD and MODIS datasets to GIRAS (-8.9% and 10% respectively). Therefore, GIRAS is used in this study for assessment of HSPF parameter uncertainty.

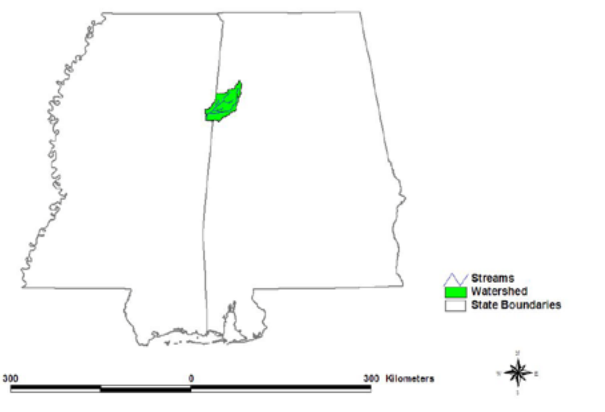

Figure 2: Location of the Luxapallila Creek watershed.

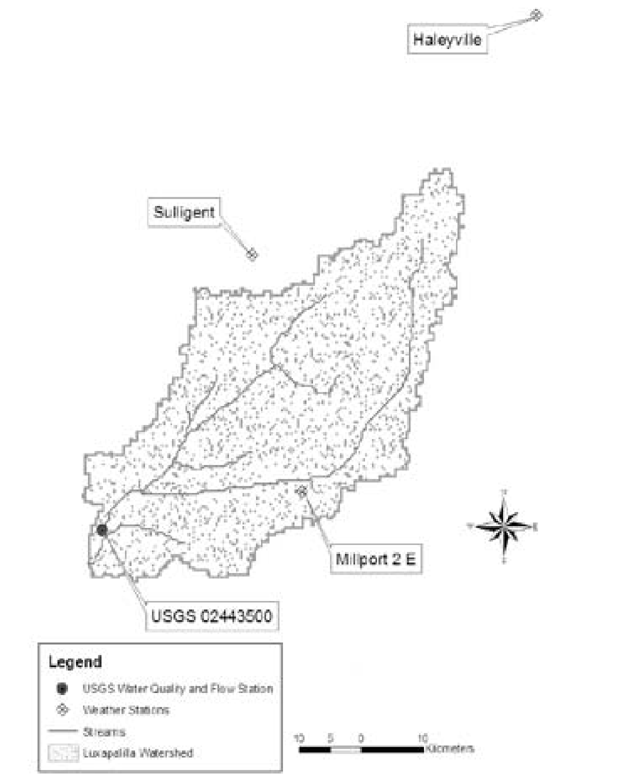

Figure 3: Location of USGS and weather stations used in this study.

Model setup

Spatial and climatic data, including topography, land use, soil properties, reach characteristics, and detailed meteorological data were established using the BASINS/HSPF MapWindow interface. The topographic data used in the model setup was the United States Geological Survey (USGS) Digital Elevation Model (DEM). The DEM was used to delineate the watershed and sub-watershed boundaries and generate the associated stream network (digitized streams). All geoprocessing operations were performed using the toolkits provided by BASINS. During this process, land use areas and topographical parameters (overland plane slopes, streams slope and length, etc.) were summarized for export to HSPF's User Control Input file. HSPF also requires a tabular characterization of streams geometry (FTABLE) with relationships among area, volume, and flow in a river cross section. These relationships were calculated by BASINS using the DEM and Manning's equation for steady uniform flow.

Daily rainfall data were obtained from the National Weather Service (NWS) for the Sulligent and Millport 2E gauging stations (Figure 3). Hourly precipitation recorded at the Haleyville station was used to disaggregate the above cited stations. Hourly potential evapotranspiration values were obtained from the Haleyville station. The weather database for the Haleyville station was downloaded through the BASINS MapWindow Interface. The weather database period used in this study was between 01/01/2000 and 11/30/2004.

BASINS' automatic delineation tool sub-divided the Luxapallila

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watershed into ten sub-watersheds or hydrologic response units (HRUs). Consequently, the channel network was divided into ten reaches. After delineation, the initial (not calibrated) HSPF model for Luxapallila was generated from within BASINS. The climatological database was processed independently using the WDMUtil software (also part of the BASINS suite) and then incorporated into the watershed data management file (.wdm) specific for Luxapallila.

Parameter uncertainty analysis

To perform parameter uncertainty analysis using Monte Carlo simulation, the following steps were completed:

1. Identify the output target. Daily HSPF streamflows at the USGS 02443500 station were the output target (Figure 3).
2. Select model parameters to be evaluated. Twelve HSPF parameters were identified from previous deterministic and probabilistic research performed in the study area [16,36,48]. These parameters covered all of the hydrologic aspects simulated by HSPF in the Luxapallila Creek watershed (Table 1). HSPF initial parameters were not evaluated because the model was initialized from 01/01/2000 to 12/31/2000.
3. Develop probability distributions functions for each HSPF parameter. Triangular probability distributions were developed using the parameter ranges and most probable values (Table 1). This study used the MATLAB software to generate pseudo random parameter sets.
4. Propagate parameter uncertainty into model results. Propagation of parameter uncertainty was accomplished calculating random numbers from each HSPF parameter probability distribution developed in Step 3. Five thousand random numbers were calculated for each parameter. Then, a parameter set was developed using the 12 parameters. Each parameter set was imported and run in the HSPF model to yield a discrete simulated flow for each simulated day. Finally, after using five thousand model parameter sets, five thousand simulated flows for each day were calculated by the model.
5. Quantify the 90% of certainty in simulated flows due to 12 HSPF parameters. Using model results from Step 4, the 5^{th} and 95^{th} flow quartile for each day was calculated. The 90% of certainty was calculated by the difference between the 95^{th} and 5^{th} flow quartile.
6. Evaluate the simulated certainty bounds. Daily flows collected by the USGS at 02443500 station from 01/01/2001 to 11/30/2004 were used to evaluate the simulated 90% certainty bounds. Two criteria were used to evaluate the HSPF 90% certainty bounds:

Reliability: the number or percentage of daily observed streamflows within the HSPF 90% certainty bounds;

Sharpness: the width of the HSPF 90% certainty bounds (minimum, median, and maximum values).

Three percentile classes of observed flows developed by the USGS (http://waterwatch.usgs.gov/) were calculated to find out the effect of model *Reliability* to above normal, normal, and below normal flows (Table 3). In addition to the *Reliability* and *Sharpness* criteria, continuous hydrographs of 90% confidence bounds and observed data were plotted.

Parameter sensitivity analysis

To perform parameter sensitivity analysis using Monte Carlo simulation, the following steps were completed:

1. Identify the output target (see Step 1 from parameter uncertainty analysis section).
2. Select model parameters to be evaluated (see Step 2 from parameter uncertainty analysis section).
3. Develop probability distributions functions for each HSPF parameter (see Step 3 from parameter uncertainty analysis section).
4. Propagate parameter sensitivity into model results. Propagation of parameter sensitivity was accomplished calculating random numbers from a selected HSPF parameter probability distribution developed in Step 1 and holding the rest of parameters with the most probable value. Five thousands of random numbers were calculated for the selected parameter. Then, a parameter set was developed using the 12 parameters. Each parameter set was imported and run in the HSPF model to yield a discrete simulated flow for each simulated day. Finally, after using five thousands of model parameter sets, five thousands of simulated flows for each day were calculated by the model.
5. Quantify the 90% of certainty in simulated flows (see Step 5 from parameter uncertainty analysis section).
6. Evaluate the simulated certainty bounds (see Step 6 from parameter uncertainty analysis section).
7. Rank the parameters contributing most to uncertainty in the simulated streamflows. The importance of each parameter was measured using the model *Reliability* and *Sharpness*. If the model *Sharpness* depart from zero, the parameter was considered important, with greater uncertainty associated with greater depart. If the model *Reliability* depart from zero, the parameter was considered important, with greater performance associated with higher values.

Reduction of parameter ranges

Reduction of HSPF parameter ranges was accomplished according to the sensitivity analysis. The most important parameters were selected to refine their parameter range. Parameter ranges were gradually increased from the Most Probable Value – MPV (Table 1) until to cover all of the spectrum values. This process stopped when we found close and/or better values of model *Reliability* and *Sharpness* between the most sensitive parameters and the 12 parameter set.

Results

Parameter uncertainty

Confidence intervals for HSPF simulated daily streamflows at the watershed outlet were generated using the 5th and 95th percentiles

Table 3: Percentile classes of flow observed data.

Percentile classes	Explanation
>75th	Above normal
25th-75th	Normal
<25th	Below normal

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after 5,000 Monte Carlo simulations. From the bounds constructed for the period 01/01/2001 to 11/30/2004, the *Reliability* and median *Sharpness* of the HSPF streamflow simulations were 69.8% and 19.8 m^3/s, respectively. Thus, 69.8% of the daily observed data were within the 90% confidence bounds (*Reliability*), and the median width (*Sharpness*) of the 90% certainty bounds was 19.8 m^3/s.

Results of the model *Reliability* by observed flow percentiles are shown in Table 4. The model had a very good performance for below normal flows (<25th percentile), but the poorest performance was for normal flows (25^{th} -75^{th} percentile). Almost 70% of the observed data of high flows were within 90% certainty bounds.

Table 5 depicts selected percentiles of the model *Sharpness* and observed flow. This table showed that the higher the observed flow, the higher the width of certainty bounds (*Sharpness*). In general, the model *Sharpness* results were in the same order of magnitude as the observed data.

Selected daily hydrographs are shown in Figures 4 and 5. Figure 4 indicates that most of the observed data for January-March of 2001 were within 90% certainty bounds. Figure 5 depicts that some recession limbs were outside the certainty bounds.

Parameter sensitivity

Table 6 depicts model *Reliability* and median model *Sharpness* results using 12 HSPF parameters and a single parameter. Of the 12 parameters evaluated, daily streamflow values were sensitive to ten. INFILT was the most important parameter. The INFILT parameter drives the infiltration-runoff process at the hillslope level. Model *Reliability* calculated using the INFILT parameter was 66.4% of total model *Reliability* (12 parameters). Additionally, median model *Sharpness* results using the INFILT parameter was 53.1% less than the median model *Sharpness* using 12 parameters. AGWRC was the second most important parameter accounting for 58.6% of total model *Reliability* and 52.6% less median model *Sharpness.* CEPSC and LZETP did not affect the daily streamflow at the watershed outlet. CEPSC and LZETP control the evapotranspiration water loss retained by vegetation and storage in the lower zone (root zone of the soil profile), respectively. LZET works like a “crop coefficient” and its value depends on simulated vegetation cover.

Table 7 shows model *Reliability* and *Sharpness* results clustered

Table 4: Results of the model *Reliability* by observed flow percentiles (01/01/2001-11/30/2004).

Observed flow percentiles	Observed flows within 90% certainty bounds (%)
<25th	89.4
25th-75th	60.1
>75th	69.5

Table 5: Selected percentiles of the model *Sharpness* and observed flows.

Percentile	Model *Sharpness* (m^3/s)	Observed flow (m^3/s)
Minimum	3.2	2.1
25th	7.0	9.5
50th	19.9	20.8
75th	58.4	45.2
Maximum	1034.1	492.7

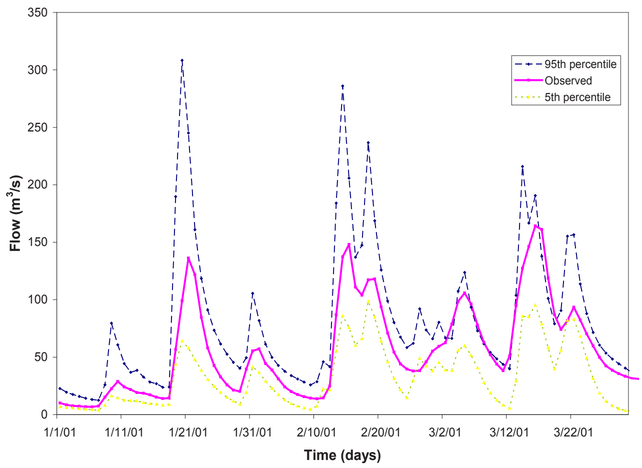

Figure 4: Daily observed hydrographs and certainty bounds estimated by the MCS for January-March/2001.

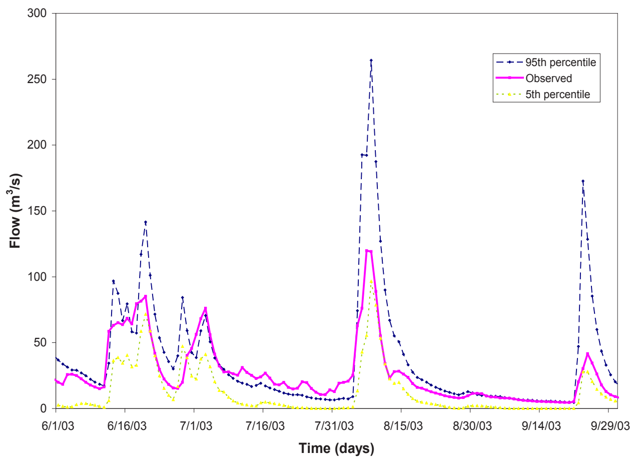

Figure 5: Daily observed hydrographs and certainty bounds estimated by the MCS for June- September/2003.

Table 6: *Reliability* and median model *Sharpness* results using 12 HSPF parameters and a single parameter.

Parameters	Model *Reliability* (%)	Median model *Sharpness* (m^3/s)
12	69.8	19.8
INFILT	46.4	9.3
AGWRC	40.9	9.4
DEEPFR	35.6	7.8
KVARY	25.7	4.4
IRC	20.1	3.1
BASETP	17.8	3.1
UZSN	16.6	3.2
LZSN	12.9	1.6
AGWETP	12.0	1.3
INTFW	5.2	0.4
CEPSC	0.0	0.0
LZETP	0.0	0.0

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into three flow groups. Parameter uncertainty propagation into model results clustered into below normal, normal, and above normal flows was done according to the parameter definition/function (Table 1 calibration scenarios). For example, AGWRC significantly controlled below normal flows (groundwater recession) in the simulation because its model *Reliability* performance was better for below normal flows (71.2%) than for above normal flows (26.3%). HSPF parameters most important for normal flow simulations were: INFILT and DEEPFR. For above normal flows, model parameters most important were: INFILT and IRC. These analyses mean that only four out of 12 parameters control the majority of uncertainty in the Luxapallila model results.

Reduction of parameter ranges

Table 8 depicts model *Reliability* and *Sharpness* results due uncertainty propagation of AGWRC, INFILT, DEEPFR, and IRC parameters. This optimization process was performed looking for decreasing parameter ranges; it started by using the four most important parameters (AGWRC, INFILT, DEEPFR, and IRC) with almost the same model *Reliability* (0.5%) and a lower median model *Sharpness* (8.1%) than the model results using 12 parameters. Parameter ranges were gradually increased from the Most Probable Value – MPV (Table 1) until all of the spectrum values were represented. Relative errors shown in table 8 were compared against model results using 12 parameters. A relative error of model *Reliability* of 9.6% was yielded when AGWRC-DEEPFR and INFILT-IRC parameter ranges were 60% and 70% of the entire spectrum values, respectively (trial 8 in Table 8). Additionally, the median width of certainty bounds (*Sharpness*) decreased 28.8%. Trial 8 yielded very low relative errors of model *Reliability* (lower than 6%) for below normal and normal flows; however, model *Reliability* results for above normal flows were as poor as 21.8%. Seeking a better balance in the different flow stages, the IRC parameter range was increased to 90% of the entire spectrum value because it is related to above normal flows. Using this new parameter set (trial 9) a slightly better performance was found. Two more trials were performed (10 and 11) but median model *Sharpness* of below normal flows were higher than those results using 12 parameters (-4.3 and -7.8%). In conclusion, the trial 9 was selected as the best set for reduction of selected parameter ranges. Table 9 shows the original and optimized parameter ranges of AGWRC, DEEPFR, INFILT, and IRC. Parameter ranges were reduced between 20% and 40%.

Conclusions

This study evaluated parameter sensitivity and uncertainty through streamflow simulations of the HSPF model. Twelve hydrology model parameters were evaluated using data from the Luxapallila Creek watershed, Alabama/Mississippi. Based on the results of the sensitivity analysis the HSPF parameters that did not affect the daily streamflow predictions were CEPSC and LZETP. Parameter sensitivity evaluation showed that only four (INFILT, AGWRC, DEEPFR, and IRC) out of 12 HSPF parameters controlled the majority of uncertainty in the Luxapallila Creek model results. The most sensitive parameter was INFILT (66.4% of total model *Reliability*) which drives the infiltration-runoff process at the hillslope level with AGWRC being the second most important parameter (58.6% of total model *Reliability*).

During the four-year model simulation, the HSPF program had a good performance for below normal flows (<25th percentile), but the poorest performance was for normal flows (25^{th} -75^{th} percentile). Almost 70% of the observed high flows were within 90% certainty bounds. It was observed that model parameters work according with the definition/function developed by the authors. For example, INTFW was more sensitive to above normal flows than normal and below normal flows due to its division role between interflow and overlandflow on storm events.

Additionally, it was found that narrow parameter ranges of

Table 7: Model *Reliability* and *Sharpness* results clustered into three flow groups.

Parameters	*Reliability* (%)<25th	*Reliability* (%) 25-50th	*Reliability* (%) >75th	RE* *Reliability* (%)<25th	RE *Reliability* (%) 25-50th	RE *Reliability* (%) >75th
12	89.4	60.1	69.5			
INFILT	36.9	51.7	45.1	58.8	13.9	35.1
AGWRC	71.2	33.0	26.3	20.3	45.1	62.1
DEEPFR	30.7	44.9	21.8	65.6	25.3	68.5
KVARY	38.0	25.5	13.7	57.5	57.7	80.2
IRC	2.0	23.5	31.4	97.8	61.0	54.8
BASETP	29.9	18.8	3.9	66.6	68.8	94.4
UZSN	5.9	22.0	16.8	93.4	63.5	75.8
LZSN	6.4	13.3	18.5	92.8	77.9	73.4
AGWETP	33.2	6.7	1.4	62.8	88.8	98.0
INTFW	0.6	3.8	12.9	99.4	93.7	81.5

*relative error

Table 8: Model *Reliability* and *Sharpness* results due uncertainty propagation of AGWRC, INFILT, DEEPFR, and IRC parameters.

Parameter set	Evaluated range from MPV* (%)	Trial	*Reliability* (%)	Median *Sharpness* (m^3/s)	RE** *Reliability* (%)	RE median *Sharpness* (%)	*Reliability* (%)<25th	*Reliability* (%) 25-75th	*Reliability* (%) >75th	RE *Reliability* (%)<25th	RE *Reliability* (%) 25-75th	RE *Reliability* (%) >75th	Median *Sharpness* (m3/s) <25th	Median *Sharpness* (m3/s) 25th-75th	Median *Sharpness* (m3/s) >75th	RE Median *Sharpness* (%) <25th	RE Median *Sharpness* (%) 25-75th	RE Median *Sharpness* (%) >75th
INFILT-AGWRC-DEEPFR-IRC	100	1	69.4	18.2	0.5	8.1	88.8	62.1	64.7	0.6	-3.3	6.9	7.6	18.3	48.6	-7.7	8.1	16.9
INFILT-AGWRC-DEEPFR-IRC	10	2	19.0	3.2	72.8	84.0	25.4	18.7	12.9	71.6	68.8	81.5	1.9	3.2	9.9	72.7	84.0	83.0
INFILT-AGWRC-DEEPFR-IRC	20	3	34.8	6.1	50.1	69.3	53.9	31.2	23.0	39.7	48.1	66.9	3.2	6.1	18.4	54.1	69.3	68.5
INFILT-AGWRC-DEEPFR-IRC	30	4	45.5	8.4	34.9	57.6	67.0	39.6	35.6	25.0	34.2	48.8	4.1	8.4	25.3	41.5	57.6	56.6
INFILT-AGWRC-DEEPFR-IRC	40	5	53.4	10.9	23.4	45.1	77.9	46.0	43.7	12.8	23.5	37.1	4.9	10.9	34.0	30.4	45.2	41.9
INFILT-AGWRC-DEEPFR-IRC	50	6	57.2	12.3	18.0	37.9	81.8	49.7	47.6	8.4	17.4	31.5	5.6	12.3	38.8	20.2	37.9	33.6
INFILT-AGWRC-DEEPFR-IRC	60	7	61.0	13.5	12.5	31.7	83.0	54.1	52.9	7.2	10.0	23.8	6.4	13.5	40.9	8.8	31.8	30.0
AGWRC-DEEPFR	60	8	63.1	14.1	9.6	28.8	84.6	56.6	54.3	5.3	5.8	21.8	6.8	14.1	41.2	3.1	28.8	29.5
INFILT-IRC	70																	
AGWRC-DEEPFR	60	9	63.6	14.3	8.8	28.1	84.6	57.5	54.9	5.3	4.4	21.0	6.9	14.3	42.0	2.8	28.2	28.2
INFILT	70																	
IRC																		
AGWRC-DEEPFR		10	66.4	15.0	4.9	24.4	85.8	60.4	58.8	4.1	-0.5	15.3	7.4	15.0	43.5	-4.3	24.5	25.6
INFILT-IRC																		
AGWRC-DEEPFR		11	67.8	15.5	2.9	22.1	85.8	62.7	59.9	4.1	-4.2	13.7	7.6	15.5	45.0	-7.8	22.2	23.0
INFILT-IRC																		

*most probable value; **relative error

Table 9: Original and optimized parameter range.

Parameter	Original range	Optimized range	Percentage of Reduction
INFILT (mm/hr)	0.025 – 12.7	0.025 – 8.9	30
AGWRC (1/day)	0.92 - 0.999	0.952 – 0.999	40
DEEPFR	0.0 - 0.5	0.05 – 0.35	40
IRC (1/day)	0.3 - 0.85	0.38- 0.82	20

AGWRC, DEEPFR, INFILT, and IRC yielded close model *Reliability* and *Sharpness* values compared to the original parameter ranges. These parameter ranges were reduced between 20% and 40% for the Luxapallila Creek model.

This study has demonstrated a method for determining those parameters that are most sensitive to predicting observed flows in addition to narrowing the parameter range based upon multiple studies. These findings assist in improving model accuracy and improve the models ability to predict future conditions based upon landuse changes. We suggest that the parameter uncertainty methodology conducted in the Luxapallila Creek watershed could be used to assess the impact on rainfall time series (gauge, radar, and satellite), topographic map resolutions (10 m, 30 m, 300 m, etc), and sub-watershed delineations (1, 2, 3, etc) in the future, since an HSPF probabilistic framework was developed.

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