Calibration Of A Semi-Distributed Hydrologic Model For Streamflow Estimation Along A River System

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Abstract. An important goal of spatially distributed hydrologic modeling is to provide estimates of streamflow (and river levels) at any point along the river system. To encourage collaborative research into appropriate levels of model complexity, value of spatially distributed data, and methods suitable for model development and calibration, the National Weather Service Hydrologic Laboratory (NWSHL) is promoting the Distributed Modeling Intercomparison Project (DMIP). In particular, the project is interested in how spatially distributed estimates of precipitation provided by the Next Generation Radar (NEXRAD) network, high resolution Digital Elevation Models (DEM), and soil, land-use and vegetation data can be integrated into an improved system for distributed hydrologic modeling that provides more accurate and informative flood forecasts.

The goal of this study is to explore the following questions: Can a semi-distributed approach improve the streamflow forecasts at the watershed outlet compared to a lumped approach? What is a suitable calibration strategy, and how much improvement can be obtained? What is the minimum level of spatial complexity required, above which the improvement in forecast accuracy is marginal? How is the required spatial complexity influenced by basin characteristics? What spatial details must be included to enable flow prediction at any point along the river network?
The study compares lumped, semi-lumped and semi-distributed versions of the SAC-SMA (Sacramento Soil Moisture Accounting system) model for the Illinois River basin at Watts (OK). A kinematic wave scheme is used to rout the flow along the river channel to the outlet. A Multistep Automatic Calibration Scheme (MACS) using the Shuffled Complex Evolution (SCE-UA) optimization algorithm is applied for model calibration.

Keywords: NEXRAD, Distributed Hydrologic Modeling, Calibration, Flow Forecasting
1 1 Introduction

The sensitivity of runoff hydrographs to the spatial and temporal variability of forcing data has been a major concern of researchers over the last two decades (e.g. Schulz, 1988, Michaud and Sorooshian, 1994, Olivera and Maidment 1999). Remotely sensed, high-resolution hydrologic data such as the Next Generation Radar (NEXRAD) rainfall data, Digital Elevation Maps (DEM), soil, land-use, and land-cover data are now becoming readily available to modelers in the U.S. The National Weather Service-Hydrologic Laboratory (NWS-HL) is promoting the Distributed Modeling Intercomparison Project (DMIP) to encourage use of this spatially distributed data to improve flow modeling and prediction along the entire river system. The main goal of DMIP is to promote the development of models and modeling systems that best utilize NEXRAD and other spatial data sets to improve River Forecast Center (RFC)-scale river simulations.

The first lumped conceptual rainfall-runoff models, developed in the 1960’s, were applied mainly to runoff forecast in small and midsized watersheds where discharge measurements were available (Koren et al., 1999). Large basin runoff prediction with these models introduced many assumptions such as uniformity of precipitation and parameters over the basin, that decreased accuracy (Koren et al., 1999). The main goal of flood prediction is to study the causes and attempt to predict the onset of flood events prior to their occurrence. The ability to predict flood events has been enhanced by the availability of new sources of high-resolution data. Hydrologic models, which can use these high-resolution data to predict the spatial distribution of the hydrologic response,
have been under study for the past several decades (e.g. Betson, 1964, Dunne and Black, 1970a, b, Schulz, 1988, Michaud and Sorooshian, 1994, Olivera and Maidment 1999).

Despite the research completed to date there is still little guidance on how to build and calibrate distributed hydrologic models. Many questions remain unanswered and need to be addressed. In this study we explore particularly the following:

• Can a semi-distributed approach improve the streamflow forecasts at the watershed outlet compared to a lumped approach?

• What is a suitable calibration strategy, and how much improvement can be obtained?

• What is the minimum level of spatial complexity required, above which the improvement in forecast accuracy is marginal?

• How is the required spatial complexity influenced by basin characteristics?

• What spatial details must be included to enable flow prediction at any point along the river network?

Several calibration scenarios and model setups are investigated here in an attempt to answer these questions. This study explores in particular the use of NEXRAD rainfall data in the context of hydrologic modeling of the Illinois River basin using distributed versions of the Sacramento Soil Moisture Accounting (SAC-SMA) model. A Multi-step Automatic Calibration Scheme (MACS) using the Shuffled Complex Evolution (SCE-UA; Duan et al., 1992) optimization algorithm is applied for calibration.
2 Distributed hydrologic modeling

Hydrologic systems often show a large degree of spatial heterogeneity with respect to many aspects (Grayson and Bloeschl, 2000). There has been significant interest in spatial patterns in hydrology, since the pioneering work on spatial heterogeneity in runoff production mechanism during the sixties and seventies (e.g. Betson, 1964, Dunne and Black, 1970a, b). The development of spatially distributed hydrologic models provide a means to interpret spatial response to the capabilities of remote sensing methods which provides information on the state variables of fundamental importance to catchment hydrology (Grayson and Bloeschl, 2000). Beven (1985) stated that the main advantages of distributed models are the spatially distributed nature of their inputs and the use of physically based parameter values, which can be used to investigate the sensitivity of the hydrological response of the catchment to these distributed inputs. The ability of distributed hydrologic models to apply parameters directly measured in the field, without the need for calibration, is unfortunately less developed than initially hoped. It is for example limited by the differences between model (parameters) scale and measurement scale. Boyle et al. (2001), meanwhile, reported that improvements in model performance can be related to the spatial distribution of the model input and streamflow routing but, surprisingly, do not seem to be related to the distribution of the surface characteristics (model parameters).

This short review analyses the literature with respect to those aspects that are important for the study at hand. It is therefore not meant to be comprehensive. The aspects considered here are forcing data, routing schemes and calibration of distributed hydrologic models.
2.1 Forcing data for distributed models

It is often assumed that error in the rainfall input is one of the main sources of error in the model predictions. Distributed models are by nature capable of accepting the rainfall in a more realistic manner than just as a basin wide average. Analyzing the importance of this fact on runoff prediction has been focus of several studies. Beven and Hornberger (1982) found that a correct assessment of the global volume of rainfall input in a variable pattern is more important than a rainfall pattern by itself for simulating streamflow hydrographs. Krajewski et al. (1991) investigated the sensitivity of the response of a physically-based distributed hydrologic model to the spatial and temporal sampling density of rainfall input on a small rural catchment. They found that the basin response is more sensitive to the temporal resolution than the spatial resolution of the rainfall. Ogden and Julien (1993) explored 2-dimensional watershed sensitivity to the spatial and temporal variability of the rainfall by using a physically-based runoff model. Defining $t_r$ and $t_e$ as rainfall duration and time to equilibrium, respectively, they found that spatial variability dominates when $t_r < t_e$, while the temporal variability dominates when $t_r > t_e$.

Michaud and Sorooshian (1994) studied the effect of rainfall-sampling errors on distributed hydrologic simulations for a mid-sized semi-arid watershed with localized thunderstorms. They found that approximately half of the difference between observed and simulated peaks was due to rainfall-sampling errors. Additionally, both spatial averaging of rainfall over 4 km by 4 km pixels and decreasing the temporal resolution of rainfall to 1 hour led to reductions in simulated runoff in semi-arid watersheds having
convective storms and large infiltration losses. Shah et al. (1996 a, b) investigated the interaction between spatial rainfall variability and runoff production by linking a stochastic rainfall field model with a physically-based distributed rainfall-runoff model. They found that under “wet” conditions, good predictions of runoff can be obtained with a spatially averaged rainfall input. However, for the “dry” catchment conditions, the runoff prediction errors are considerably higher if spatially averaged rainfall is used. Shah et al. (1996 a,b) related this to the interaction between the spatial variability in rainfall and the spatial distribution of soil moisture. They highly recommended the use of a distributed forcing data, especially for “dry” conditions.

Winchell et al. (1998) studied the effects of uncertainty in radar-estimated precipitation input on simulated runoff generation. They considered two types of uncertainties in precipitation estimates: (1) those arising from the transformation of reflectivity to rainfall rate and (2) those due to the spatial and temporal representation of the “true” rainfall field. They found that infiltration-excess runoff generation is much more sensitive than saturation-excess runoff generation to both types of precipitation uncertainty. They also claimed that a decrease of the temporal and spatial resolution of the precipitation input will cause a significant reduction in infiltration-excess runoff volume.

Koren et al. (1999) studied the scale dependencies of hydrologic models to the spatial variability of precipitation. They found that the scale dependency of various models is different and dependent on the rainfall-runoff partitioning mechanism. Their results indicated that infiltration-excess models were the most sensitive and that the saturation-excess models were less scale-dependent. They stated that probabilistic
averaging of the point processes reduces scale dependency; however, its effectiveness varies depending on the scale and spatial structure of precipitation. They found that the surface runoff and total runoff decreases with increasing scale.

Carpenter et al. (2001) worked on the parametric and NEXRAD-radar sensitivities of a distributed hydrologic model. They found that the results of the distributed model, which uses NEXRAD data, are comparable to the results of operational spatially lumped models using rain-gauge data, and that the sensitivity of flow statistics to parameters and radar-rainfall input is scale-dependent.

The results of the above mentioned studies give two different pictures depending on whether the catchments are dry and infiltration excess dominated, or wet and saturation excess dominated. Spatial variability of rainfall seams to be of particular importance for dry catchments, while the temporal variability is the significant feature of rainfall in wet catchments.

2.2 Routing in distributed models

One of the characteristics, which separates lumped and distributed models is their routing scheme. Carpenter et al. (1999) used GIS and digital terrain elevation databases to develop a national system for determining threshold runoff. They studied the importance of channel geometry in flash flood applications. Olivera and Maidment (1999) proposed a method for routing spatially distributed excess precipitation over a watershed to produce runoff at its outlet. They defined a routing function for each DEM cell to convolve the water movement from cell to cell and to produce a response function along a flow path. They summed responses from all of the cells to find an outlet
hydrograph. Woolhiser (1990) developed KINEROS (kinematic runoff and erosion) model, which estimates Hortonian runoff on an event basis. The model is structured in a way that can utilize ground and remotely sensed estimates of soil water content. The infiltration component of the model is based on the Smith and Parlange (1978) simplification of Richard’s equation, which assumes a semi-infinite, uniform soil for each model element. Runoff generated by infiltration excess is routed interactively using a kinematic wave equation on both overland flow and channel elements via a finite difference solution (Goodrich et al., 1994). Interactive routing implies that infiltration and runoff are computed at each finite difference node considering rainfall, upstream inflow, and the current degree of soil saturation (Goodrich et al., 1994).

Kinematic wave routing scheme is often adopted and successfully applied in hydrologic models due to the simplicity of implementation and their smaller need for geomorphologic information compared to some other routing schemes.

2.3 Calibration of distributed models

Moving from a lumped to a distributed model increases the number of parameters significantly. There has been very little research into calibration schemes specifically tailored to distributed models. Calibration of these parameters is time consuming and made difficult by the lack of availability of distributed observed runoff data. Andersen et al. (2001) found that calibration against one station and evaluation against eight additional stations exposed significant shortcomings for some of the upstream tributaries, especially in semi-arid zones of the river basin. They found that further calibration
against additional discharge stations improved the performance levels for different sub-
catchments.

Boyle et al. (2001), investigated the improvement of the model performance
associated with various levels of spatial representation of model input (precipitation),
structural components (soil moisture and streamflow routing component), and surface
characteristics (parameters). They applied a series of lumped and semi-distributed
versions of SAC-SMA model on the Blue River Basin. Each model was designed to
separate the effects of the different levels of representation in terms of specific desirable
catchment behavior which were specified as driven flow, “peak and timing”; nondriven
quick flow, “quick recession” responses; and nondriven slow, “base flow” responses.
They used this multi criteria approach for calibration and validation of their model and
found that the semi-distributed model provided significant performance improvements
over the lumped model. However, there was a limit to the performance improvements
associated with increasing representation of spatial hydrologic variability in the model.
They showed that the main improvements were provided by spatial representation of
precipitation (inputs) and structural components (soil moisture and streamflow routing
computations). Their work did not show much improvement related to spatial
representation of soil properties (model parameters). They stated that spatial variability in
hydrologic information contributed mainly to improved simulation of the flood peaks and
the quick recessions while this modeling approach (semi-distributed modeling) did not
cause any improvements in representation of the base flow.
The very limited number of studies performed suggests that the use of “distributed” parameters does not necessarily improve the model performance at the basin outlet if no internal runoff data are available for calibration.

2.4 Consequences for this study

The general conclusions made in the above quoted studies have the following consequences for the study at hand:

1. The basin under study can be classified as humid and it is therefore likely that the temporal variability of the rainfall is of greater significance than the spatial variability.

2. The kinematic wave routing scheme seems to be suitable for the type of hydrologic model applied in here.

3. The benefit of spatially distributing the model parameters is not clear. Additionally, there is no established calibration strategy to estimate those. Development of a suitable strategy for calibration is, therefore, one of the main objectives of this study.

3 Case study

3.1 Study area and data

The study compares different lumped, semi-lumped and semi-distributed versions of the SAC-SMA model for the Illinois River basin at Watts (OK), 1645 Km². It falls under the jurisdiction of the NWS Arkansas-Red Basin River Forecast Center (ABRFC) in Tulsa (OK). The terrain of the region is moderately sloping with soils, which are
characterized by their large storage capacities and relatively deep surface horizons (NRCS, 1981; [http://esse.psu.edu/soils-info](http://esse.psu.edu/soils-info)). The vegetative cover is approximately 70% forested, with the remainder pasture and cropland (Carpenter et al., 1999). The average maximum and minimum surface air temperature in the region are approximately 22°C and 9°C, respectively. Summer maximum temperatures can get as high as 38°C, and freezing temperatures occur generally in December through February. The annual average precipitation of the region is 1200 mm/yr, and its annual average evaporation is 1050 mm/yr. The potential evapotranspiration is relatively high in June, July, and August (4.5-5 mm/day) and reaches its lowest value in January (0.81 mm/day).

To define the mean average precipitation over each sub-basin, a mesh of NEXRAD cells was created using the same coordinate system as the DEM. The Hydrologic Rainfall Analysis Project (HRAP) grid, as defined by Greene and Hudlow (1982), was used to define the location of each average precipitation value in a NEXRAD Stage III data set. To apply HRAP coordinates, the correct steps are as follows:

1. Transform the HRAP coordinates into latitude/longitude geographic coordinates.
2. Project the geographic latitude and longitude to Albers equal area coordinates.

In this study, the following steps were taken to process NEXRAD data:

1. Generate a text file within Arc/Info, which includes HRAP coordinates and related geographic and Albers coordinates as well for the study area.
2. Generate the HRAP polygon coverage.

After generating the HRAP polygon coverage (in Albers coordinates), it was intersected with watershed and sub-basins one by one. This produced cells that either fall within the watershed or sub-basin, and also the area of each cell within them. After gathering all of
this information (hrapx, hrapy, area of the cell), the next step was to assign precipitation depth to each cell from NEXRAD Stage III files and calculate the Mean Areal Precipitation (MAP) as an average of gridded precipitation values in the watershed (and its sub-basins).

\[
MAP_i = \frac{\sum_{j=1}^{N} (P_j \times A_j)}{N \times A_i}
\]  

(1)

where:

- \(MAP_i\): mean areal precipitation for the \(i^{th}\) sub-basin (in the lumped case this just represents the watershed)
- \(P_j\): gridded precipitation value for \(j^{th}\) grid cell in sub-basin \(i\)
- \(A_j\): area of the \(j^{th}\) grid cell which is within the basin
- \(A_i\): total area of the sub-basin (watershed), which is equal to:

\[
A_i = \sum_{j=1}^{N} A_j
\]  

(2)

N: number of HRAP grid points within sub-basin \(i\) (watershed)

3.2 Model description

The Sacramento Soil Moisture Accounting (SAC-SMA) model (Burnash et al., 1973; Burnash, 1995) is used by the NWS for river stage throughout the United States. The model is deterministic, continuous, and non-linear.
The SAC-SMA model has two soil layers, an upper and a lower zone. Each layer includes tension and free water storages, which interact to generate soil moisture states and five runoff components (Koren et al. 2000). Rainfall first fills the upper zone tension water storage. The rainfall above the tension water capacity, UZTWM, generates the excess rainfall. This excess rainfall goes into the free water storage tank and the water above the capacity of this storage, UZFWM, can percolate to the lower zone and generate surface runoff. The rate of this generated runoff depends on the capacity of the lower zone tension water, LZTWM, and free water, LZFSM and LZFPM storages. The surface runoff generated from each of the free water storages depends on the depletion coefficients in the upper zone, UZK and the lower zone LZSK and LZPK. The percolation rate to the lower zone is a nonlinear function of upper zone and lower zone storages and it is presented in this model by two parameters, ZPERC, which shows the maximum rate of the percolation and REXP, which is an exponent that defines the shape of the percolation curve. As it was mentioned above, the lower zone water will be divided among three tanks, consisting of free and tension components. The parameter PFREE is the fraction of the lower zone water, which will go to the free water storages.

The second main component of the hydrologic model is the flow-routing model, which routes the precipitation excess through the river to the outlet. The original lumped version of the SAC-SMA, which is used by the NWS, uses a Unit Hydrograph (UH) scheme to route the generated runoff to the outlet. In this method, the UH of the watershed is used to calculate the flow at the outlet based on the generated runoff volume. In the semi-distributed version of the SAC-SMA (developed for this study), the precipitation excess component was combined with a kinematic wave flow routing model
to enable the model to simulate the streamflow along the river. The Kinematic wave approach is appropriate when inertial and pressure forces are not important. A wave is a variation in flow, such as a change in the flow rate or water surface elevation. In the kinematic wave scheme, the acceleration and pressure terms in the momentum equation are assumed to be negligible; therefore, the wave motion is described principally by the continuity equation (Chow et al., 1988).

Figure 4 shows a finite difference box for solution of the kinematic wave method. The following equation represents the general form of the kinematic wave model:

Continuity:

\[
\frac{\partial Q}{\partial x} + \frac{\partial A}{\partial t} = q
\]  

Momentum:

\[S_0 = S_f \quad \text{or} \quad Q = \alpha A^\beta\]  

where:

\(Q\): channel flow  
\(A\): channel cross-section  
\(S_0\): bed slope  
\(S_f\): friction slope  
\(\alpha, \beta\): Equation constants

By using the above definitions, the Manning equation becomes:

\[Q = \frac{1.49 \, S_0^{1/2}}{n \, P^{2/3}} \, A^{5/3}\]  

where:
\( n: \) Manning’s roughness coefficient,

\( P: \) Wetted perimeter

\[
\alpha = \frac{1.49 \, S_0^{1/2}}{nP^{2/3}}
\]  
(6)

\( \beta = 5/3 \)

Finally, by combining the continuity and momentum equations, the result is:

\[
\frac{\partial Q}{\partial x} + \alpha \beta Q^{\beta - 1} \frac{\partial Q}{\partial t} = q
\]  
(7)

These equations are solved by the nonlinear finite difference method and included in the rainfall-runoff models as a flow-routing component.

Here, the kinematic wave method was used to route the flow through the channel within each sub-basin and finally to the outlet. The main stream in each sub-basin was divided into \( n \) reaches of length \( L_i \) (\( i = 1, \ldots, 5 \)). The outflow from each reach is a monotonic function of the volume of water within the reach (kinematic assumption). The lateral flow from the contributing area of each reach was added to the routed flow at the end of the reach. Figure 3 shows a finite difference box for solution of the kinematic wave method.[add couple of sentences]

3.3 Calibration tools and Methods

The successful application of any rainfall-runoff model depends on its parameters (Koren et al., 2000). Spatially distributed models of catchment response tend to be highly complex in structure and contain numerous parameters values (Refsgaard, 2000).
The process of model calibration includes choosing the “best” set of parameter values, while model evaluation can be defined as the process that attempts to define the uncertainties in predictions or find their magnitude. In the calibration process, the goal involves adjusting a model’s parameter values to improve the fit between observed and simulated values. The closeness of fit can be checked qualitatively (e.g. plots of observed and simulated hydrographs) or quantitatively (residual statistics such as the Root Mean Square Error, Bias, etc.). In the optimization process, an “objective function” is the quantitative part of the comparison, which represents the error between observations and simulations. Minimizing or maximizing the objective function is typically achieved through an optimization procedure.

In this study, the Shuffled Complex Evolution (SCE-UA) algorithm was used as the search algorithm for calibration. The SCE-UA global search procedure (Duan et al., 1992) is based on the downhill simplex method (Nelder and Mead, 1965), combined with a random search procedure and the idea of shuffling. The algorithm takes the following steps (Duan et al., 1992):

1. Sample points from the search space, randomly.
2. Partition the population of points into groups of 2n+1 points, where n represents the number of parameters being calibrated (i.e., the dimension of the problem).
3. The downhill simplex method is applied to each group independently to evolve each group toward the global optimum.
4. At this step, all of the groups are shuffled to exchange the information and then resample and assign again to different groups.
5. The above-mentioned four steps are repeated until the entire population converges to the global or near global optimum.

The SCE-UA optimization procedure, with HRMS and LOG as objective functions was utilized in the Multi Step Calibration Scheme (MACS), developed by Hogue et al. (2000).

The following objective functions were used during the optimization process:

1. Hourly Root Mean Square Error (HRMS), which emphasizes the fitting of high flow:

   \[
   HRMS = \sqrt{\frac{1}{n} \sum_{t=1}^{n} ((Q_{\text{sim}})_t - (Q_{\text{obs}})_t)^2}
   \]  

2. LOG, which emphasizes fitting of low flows:

   \[
   LOG = \sqrt{\frac{1}{n} \sum_{t=1}^{n} (\log(Q_{\text{sim}})_t - \log(Q_{\text{obs}})_t)^2}
   \]

The goal of calibration is to estimate a parameter set for the model that brings the model as close as possible to the watershed behavior observed in reality. Calibration consists of three steps:

1. Determining approximate ranges for the parameters
2. A priori parameter estimation
3. Refining the parameter estimates by using observed data

The SAC-SMA parameter ranges for this specific basin were provided by the National Weather Service Office of Hydrology (NWS-OH) (Table 3). A method of a
priori estimation of parameters using soil texture (Koren et al., 2000) was applied. A priori estimated parameter set was used as a starting point for the calibration procedure. The parameter estimates were refined by use of the Shuffled Complex Evolution (SCE-UA) optimization procedure.

MACS

The Multistep Automatic Calibration Scheme (MACS) emulates the progression of steps followed by NWS hydrologist during manual calibration of the SAC-SMA (Hogue et al., 2000). The MACS procedure works in three stages (Table 2):

1. Calibrating all parameters and initial states using the LOG objective function (Equation 4.2). As mentioned earlier, the LOG criterion places large weights on the low flow parts of the hydrograph. Hogue et al. (2000) suggested that using the LOG criterion at the first step, besides providing a good estimate for lower zone parameters, helps to limit the remaining model parameters (upper zone) loosely into the region that provides coarse fitting of the peaks.

2. Calibrate the upper zone model parameters (high flows) by using HRMS objective functions. HRMS objective functions place strong emphases on high flow (peak flow).

3. Calibrating the lower zone parameters (low flows) by using the LOG objective function in order to re-adjust them.

The MACS approach is a time-saving and reliable approach that can provide calibrations which are of comparable quality to the NWS manual calibration methods (Hogue et al., 2000).
A priori parameter estimation

Koren et al. (2000) developed a set of physically-based relationships between soil properties and SAC-SMA parameters, assuming that tension water storages are related to the available soil water and that the free water storages are related to the gravitational soil water. They suggested that the soil properties, such as the saturated moisture content, $\theta_s$, field capacity, $\theta_{fld}$, and wilting point, $\theta_{wlt}$, can be used to estimate available soil water and gravitational soil water. These soil properties can be estimated from STATSGO soil-texture grids for 11 soil layers (from ground surface to 2.5 m depth) (Miller and White, 1999). The soil-profile depth, $Z_{max}$, is assumed equal to the combined depth of the upper and lower layers. In order to split the soil profile into upper and lower zones, an initial rain abstraction concept is used (McCuen, 1982). The depletion coefficient of the lower layer primary free water storage was calculated from Darcy’s equation for an unconfined homogeneous aquifer, which requires estimation of the hydraulic conductivity, $K_s$, and the specific yield of soil, $\mu$ (Dingman, 1993).

Koren et al. (2000) developed these relationships for a priori estimation of parameters to improve calibration/estimation procedures. They suggest that the use of soil-derived parameters can improve the spatial and physical consistency of estimated model parameters while maintaining hydrological performance. These relationships were used in this study along with state soil geographic (from STATSGO) and 1-km gridded soil data for a priori estimation of the SAC-SMA parameters.
3.4 Calibration Scenarios

In this study the basin was divided into 9 sub-basins, and the river reach within each sub-basin was divided into different numbers of reaches (1-5) based on the river length. To assign the precipitation to each sub-basin, the HRAP coverage was created, and the sub-basin coverage was subsequently intersected by this coverage to define the cells, which are within each sub-basin. Next, the sub-basin mean areal precipitation was computed as an average of gridded precipitation values in the sub-basin. After running the rainfall-runoff model, the computed runoff was assigned to each river reach based on its contributing area. Figure 2 shows a schematic representation of the modeling strategy.

In this distributed modeling approach, the input data for the precipitation-excess calculation model was averaged over each sub-basin and then assigned to each river reach based on the contributing area to that reach. The flow was routed from reach to reach along the river to the sub-basin outlet, and finally combined and routed to the basin main outlet.

The Koren et al. (2000) a priori parameter estimation strategy was used to estimate starting points for the parameters. Three different scenarios were considered for calibration, lumped, semi-lumped and distributed. These strategies can be described as follows (Fig. 4):

1. Lumped: In this strategy, the SCE-UA was hooked up with the lumped version of the SAC-SMA in order to find the optimal parameter set. Then, the estimated optimal parameter set was used in the semi-distributed version of the model for flow simulation.
2. Semi-lumped: The distributed model was hooked up with the SCE-UA using identical values for the parameters of all sub-basins, while using distributed forcing data. The new optimum parameter set was used uniformly for each sub-basin again, and the procedure was continued until the SCE-UA converged.

3. Semi-distributed: In this strategy, a priori estimates of the parameters for each sub-basin were assigned based on their soil characteristics. The sub-basins were calibrated using flow at the outlet one at a time from upstream to downstream. At the end each sub-basin had separate parameters based on their soil characteristic and their contribution to the streamflow at the outlet.

The three calibration strategies were compared based on their effectiveness. Figure 5 shows the flow chart of two of the calibration scenarios (lumped and semi-lumped).

3.5 Results and discussion

A 7-year period of hourly data, 1993-99, was selected to calibrate the model. Simulations provided by the NWS manual calibration, UA (University of Arizona) lumped, UA semi-lumped, UA semi-distributed calibration strategies were compared and evaluated over the entire available historical record (1993-2000). Performance was evaluated as follows:
1. Qualitatively, using visual inspection of the observed and simulated hydrographs, the observed versus simulated graphs, and the flow duration curve. The following transformation of flows was used:

\[ Q_t = [(Q+1)^{\lambda} - 1]/\lambda, \quad \lambda = 0.3 \]  

(10)

This transformation expands the lower end of the flow scale, which provide a better view of recessions and low flows while still keeping a reasonable visual perspective of the high flows. The value of \( \lambda = 0.3 \) was chosen based on the study of Hogue et al. (2000).

2. Quantitatively, using the error between observations and simulations aggregated the Hourly Root Mean Square error (HRMS), %Bias, Nash-Sutcliffe (NS), and Pearson Correlation Coefficient (R), which are defined as follows:

\[ \text{HRMS} = \sqrt{\frac{1}{n} \sum_{t=1}^{n} (Q_{sim} - Q_{obs})^{2}} \]  

(11)

\[ \% \text{Bias} = \frac{\sum_{t=1}^{n} (Q_{sim} - Q_{obs})}{\sum_{t=1}^{n} Q_{obs}} * 100 \]  

(12)
For the analysis and discussion of results we return to the questions, which this analysis set out to answer.

1. Can a semi-distributed approach improve the streamflow forecasts at the watershed outlet compared to a lumped approach?

In this section, the main focus was to compare the results of the lumped and semi-distributed version of SAC-SMA model without concentrating on calibration strategies. Figure 6 shows one year of simulation results at the outlet for the Illinois River Basin at Watts. Figure 6(b) presents the results of lumped SAC-SMA model calibrated manually by the NWS experts and Figures 6(c), 6(e), 6(g) shows the results of semi-distributed version of the SAC-SMA developed at UA at the outlet of Illinois River Basin at Watts using three different automatic calibration strategies. As one can see in these figures, applying the semi-distributed version of the SAC-SMA does not lead to a significant improvement or deterioration of the performance.
Figure 7 shows parts of the time series from Figure 6 in greater detail. In each graph the first simulation result presents the predictions of NWS lumped version of the SAC-SMA and the other three simulations are the results of the semi-distributed version of the SAC-SMA with three different calibration strategies. Looking more precisely at these figures reveals that the semi-distributed structure matches the recessions more accurate than lumped structure. Some of the small peaks during recessions are missing in the lumped simulation (at hour 2080 and 2320) while the semi-distributed structure captures the peaks though the magnitude is not correct for all the calibration scenarios.

2. What is a suitable calibration strategy, and how much improvement can be obtained?

In this part we compared the results of three different calibration approaches (lumped, semi-lumped, and semi-distributed) among themselves and with the NWS manual calibration.

Figure 6 illustrates the results of the four different calibration strategies and the generated residuals of the Illinois River Basin at Watts for the year 1998. Visual inspection shows that all the automatic calibrations are comparable to the manual calibration during recessions and both high and low flows. Among the automatic calibration strategies, the second strategy (semi-lumped) shows a better fit. Visual comparison of the semi-lumped calibration and NWS manual calibration hydrograph illustrates that the semi-lumped automatic calibration strategy gave as good a result as the NWS manual calibration while the effort time is significantly less (Figure 6). Looking at Figure 7 provides greater details. In Figure 7(a), the NWS manual calibration captures the
peaks in a similar fashion to the automatic calibration strategies. Some of the small peaks during the recessions are missing in the resulting simulations from the NWS manual calibration (lowflow events at hour 2080 and 2320) while all the automatic calibrations capture these events even though the magnitude is not always exact. During some of the events, simulation results from the NWS manual calibration and the semi-lumped calibration strategy overestimate the lowflow events (Figure 7(b), lowflow events at 3100 and 3500, the NWS manual calibration overestimated the events compared to the semi-lumped calibration strategy). In some parts of the hydrograph (Figure 7(c)), all the strategies (manual and automatics) show an overestimation. Here one can see that the simulation results from the semi-lumped calibration strategies fit the recession with slightly lower magnitudes than other strategies.

Looking at Table 4 leads to the same conclusion. As can be seen in the table, moving from UA lumped calibration to UA semi-lumped calibration improved the statistics by 10% on average for the calibration period. Also % Bias improves significantly (almost 17%). Going from a semi-lumped approach to a semi-distributed approach marginally improved the results while the computational time increased significantly (Figure 11 and Table 4).

As an additional test, flow duration curves and observed versus simulated plots were constructed for the simulation results at the outlet of the Illinois River Basin. The observed flow and simulation results for the NWS manual and automatic calibrations are presented (Figures 8 and 9). Automatic calibration strategies tend to match the observed flow as well or sometimes (mid flows and high flows) better than the NWS manual calibration. A careful examination of these figures (8 and 9) reveals that the semi-lumped
calibration is almost on top of the observed line in the flow duration curve. In the observed versus simulated curves it is following the 1:1 line except for the high flows which where it shows some underestimation (NWS manual calibration shows overestimation for high flows). It can also be seen that semi-distributed approach gives none or only marginal improvement in both flow duration curve and observed versus simulation graph.

As a final test, the monthly % Biases were calculated. The summary of statistics (Table 4) shows that the overall %Biases for both lumped and distributed automatic calibration are higher compared to the NWS manual calibration and semi-lumped automatic calibration. These results can be derived from the monthly %Bias graph (Figure 10), particularly for the UA lumped calibration during winter and spring.

Monthly %Biases for the results of the semi-lumped calibration strategy are comparable or even significantly better (during the summer and fall season) for most of the months except during spring.

Figure 11 compares the effort and computational time among the different calibration strategies. As one can see, the move from manual calibration (NWS) to UA automatic calibration decreases the effort time significantly (from 20 hours to 0.5 hour), while the computational time has not increased that much. But going from semi-lumped to semi-distributed, effects the computational time significantly (depends on the number of sub-basins with the watershed).
3. What is the minimum level of spatial complexity required, above which the improvement in forecast accuracy is marginal?

In this study different combination of spatial complexity of input, model structure and parameters were explored. Three different strategies, varying from no spatial distribution (Lumped inputs, lumped model structure, lumped parameters) to medium spatial distribution (distributed input, distributed model structure, and lumped parameters) and finally higher spatial distribution (distributed input, distributed model structure and distributed parameters) were tested. Results reveal that going from a lumped calibration strategy to a semi-lumped improves the results significantly (Figures 6 and Table 4), while the effort and computational time increase are not that significant. Nevertheless going from semi-lumped calibration strategy (medium spatial distribution) to distributed calibration strategy (higher distributed resolution) shows none or marginal improvement (Figures 6, 7 and 8, Table 4). We should mention that as discussed earlier in the paper the Illinois River Basin is a flat and homogeneous basin with respect to soil, vegetation and land use which means that assuming uniform parameter sets for different sub-basins is not a bad assumption. However moving to a more heterogeneous basin may change this result.

4. How is the required spatial complexity influenced by basin characteristics?

As mentioned earlier, three levels of spatial complexity were studied in this work. Figure 4 illustrates the three different levels of complexity, in the first one inputs (precipitation) and parameter sets (soil texture of the basin) are considered lumped while in the second, input (precipitation) to the model applied is distributed while the model
parameters sets are treated lumped. In the third level, we entered the spatial distribution of soil and precipitation at the same time therefore both input and parameter sets were distributed. Applying spatially distributed precipitation, input, (semi-lumped strategy) instead of lumping the precipitation improved the simulations at the outlet almost 10% on average (Table 4). Also visual inspection of the results (Figure 6 and 7) reveals that distributing the precipitation improves the simulation especially for the peak flow simulation. As it can be concluded from Figure 6, 8 and 9, increasing the spatial complexity by distributing the parameters along with precipitation and going from the semi-lumped to semi-distributed calibration strategy, had marginal effects on the results. Statistical summary in Table 4 reveals that distributing the parameters does not lead to an improvement in model performance. Applying the semi-distributed SAC-SMA to a more heterogeneous basin may generate different results when distributed parameters are used. The required spatial complexity mainly depends on the level heterogeneity of the basin. The more heterogeneous a basin the more spatial complexity may be required.

5. What spatial details must be included to enable flow prediction at any point along the river network?

In this study one of the main challenges was to simulate the watershed response at an interior point. The only gauged point with available observed streamflow data within the Illinois River basin at Watts is Savoy with a drainage area of 433 Km² (Figure 1). However, while observed flow data were available, no calibration was done at this point. The goal of this part of the study was to see how accurately one could estimate the flow within the basin by only calibrating to the flow at the outlet. The simulated interior point
flow was compared with the observed data. Figure 12 illustrates the observed versus simulated results. As can be seen in this figure that the model did not perform very well at the interior point for both semi-lumped and semi-distributed calibration strategies and overestimated the low flows while underestimating the mid flows and high flows. Table 5 shows the summary of the statistics for the interior point at Savoy for both calibration strategies. The statistics reveal that going from semi-lumped to the semi-distributed calibration strategy and considering the spatial distribution of parameters has improved the statistics slightly, but not significantly. The statistics are generally poor for both strategies. Figure 13 confirms this statement. Both simulations curves in this figure are fairly close to each other and not following the observed curve closely. One of the main causes of this poor performance of the model could be the base flow initialization. Most humid basins have continuous baseflow component. For the initial segments of the river we need to estimate this baseflow due to the absence of measurements. Part of our continuing work is the search for an appropriate approach to estimate the initial baseflow. One of the most common methods to estimate base flow is to breakout the hydrograph which we can use it now to find some initial estimates of the base flow. In the second step we use a factor to adjust this baseflow values. This factor will be considered as an additional parameter during the calibration process.

4 Conclusions

A semi–distributed version of the SAC-SMA was developed. This structure was calibrated for the outlet of Illinois River Basin at Watts based on three different automatic calibration strategies, lumped, semi-lumped and semi distributed.
The results obtained from semi-distributed structures of SAC-SMA model using three different calibration strategy (lumped, semi-lumped, and semi-distributed) with the results of lumped structured of the model manually calibrated (NWS), shows that for such a homogeneous basin like Illinois River Basin at Watts, results improved with increased spatial complexity, but not significantly. Moving from the lumped structure to the semi-distributed and using spatially distributed inputs enable us to forecast the streamflow at any point along the river, which is one of the main goals of this study. Applying these structures in a more heterogeneous basin may improve the results more significantly at the outlet.

The results were compared among these three calibration strategies and with the NWS manually calibrated model. The results show that the automatic calibration works as well as the manual calibration. Estimated parameters from the semi-lumped calibration strategy generated the best simulation at the outlet and even the interior point. The semi-distributed model simulation and calibration time increase significantly compared to the semi-lumped and lumped models with marginal improvements. Assuming more spatial complexity in the model and calibration strategy (going from semi-lumped to semi-distributed) showed none or marginal improvements.

There is still some concerns about how to improve the model simulation results at the interior point. Part of this deals with finding the best strategy for baseflow initialization, which is being addressed in ongoing work.
Acknowledgements

This research has been made possible through the support of the World Laboratory Harshbarger Fellowship and a number of projects, among them the National Weather Service Cooperative Research Grants (87WH0582 and NA07WH0144) and the National Science Foundation Science and Technology Center on “Sustainability of semi-Arid Hydrology and Riparian Areas” (SAHRA) (EAR-9876800). Their support is greatly appreciated. Thorsten Wagener acknowledges support from German Academic Exchange Service (DAAD) through its post doctorate fellowship program.

References


### Table 1. Parameters of the SAC-SMA model

<table>
<thead>
<tr>
<th>Parameters</th>
<th>Description</th>
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<tbody>
<tr>
<td>UZTWM</td>
<td>Upper zone tension-water capacity (mm)</td>
</tr>
<tr>
<td>UZFWM</td>
<td>Upper zone free-water capacity (mm)</td>
</tr>
<tr>
<td>UZK</td>
<td>Upper zone recession coefficient</td>
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<tr>
<td>PCTIM</td>
<td>Percent of impervious area</td>
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<td>ADIMP</td>
<td>Percent additional impervious area</td>
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### State Variables

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<td>UZFWC</td>
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<td>LZFSC</td>
<td>Lower zone supplementary free-water content (mm)</td>
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<tr>
<td>LZFPC</td>
<td>Lower zone primary free-water content (mm)</td>
</tr>
<tr>
<td>ADIMC</td>
<td>Tension-water content of additional impervious area (mm)</td>
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Table 2. Parameters optimized during the MACS (Hogue et al., 2000).

<table>
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Table 3. SAC-SMA model Parameter Ranges and Optimal Values.

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<tr>
<th>Parameters</th>
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<th>Research Ranges</th>
<th>Optimal Values</th>
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<td>UZTWM</td>
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Table 4: Summary of Statistics for calibration and evaluation period of manual and Automatic calibration strategies, Illinois River Basin at Watts.

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<tr>
<th>Calibration</th>
<th>NWS Lumped</th>
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<td>0.63</td>
<td>0.68</td>
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<tr>
<td>R</td>
<td>0.89</td>
<td>0.84</td>
<td>0.83</td>
<td>0.81</td>
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</table>

<table>
<thead>
<tr>
<th>Evaluation</th>
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<th>UA Lumped</th>
<th>UA Semi-Lumped</th>
<th>UA Semi-Distributed</th>
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<td>NS</td>
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<tr>
<td>R</td>
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<td>0.88</td>
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</table>

**Automatic Calibration**

Table 5: Summary of statistics for the Interior Point, Illinois River Basin.

<table>
<thead>
<tr>
<th></th>
<th>Semi-Lumped</th>
<th>Semi-Distributed</th>
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<tbody>
<tr>
<td>HRMS</td>
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<td>R</td>
<td>0.71</td>
<td>0.73</td>
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Figure 1. DMIP Test Basins and the Illinois River Basins watersheds.

Figure 2. (a) HRAP coverage over the basin (b) Delineated river and sub-basins (c) Delineated sub-sub-basins. Colored areas show the contributing area for each river reach.
Figure 3: Finite Difference Box for Solution of the Kinematic Wave Method (Chow et al., 1988).

\[ \frac{\partial Q}{\partial x} = \frac{Q_{i+1}^{j+1} - Q_{i+1}^j}{\Delta x} \]

\[ \frac{\partial Q}{\partial t} = \frac{Q_{i+1}^{j+1} - Q_{i+1}^j}{\Delta t} \]

\[ Q = \frac{Q_{i+1}^{j+1} + Q_{i+1}^j}{2} \]

- Known Value of $Q$
- Unknown Value of $Q$

\[ \theta : \text{Parameter set} \]

- Lumped
- Semi-Lumped
- Semi-Distributed

\[ \theta_1, \theta_2, \theta_3, \theta_4 \]

\[ \theta_1 = \theta_2 = \theta_3 = \theta_4 \]

\[ \theta_1 \neq \theta_2 \neq \theta_3 \neq \theta_4 \]

Figure 4: Schematics of three different calibration strategies, lumped, semi-lumped and semi-distributed
Figure 5: Flow Chart of Lumped and Semi-Lumped Calibration Scenarios.

Lumped

- Spatially averaged rainfall over the basin
  - Lumped conceptual R-R model
    - Calibration (SCE-UA algorithm)
      - Are termination criteria satisfied?
        - No
          - Spatially averaged rainfall over each sub-basin
            - Semi-distributed conceptual R-R model with uniform parameter set for all the sub-basins
              - Semi-distributed conceptual R-R model with uniform optimal parameter set for all the sub-basins
                - Simulated runoff
                  - End
        - Yes
          - Semi-distributed conceptual R-R model with uniform optimal parameter set for all the sub-basins
            - Simulated runoff
              - End

Semi-Lumped

- Spatially averaged rainfall over each sub-basin
  - Initial parameter set
    - Semi-distributed conceptual R-R model with uniform parameter set for all the sub-basins
Figure 6: One year of hourly calibration results at the outlet for the Illinois River Basin at Watts, 1998, a) Precipitation, b) NWS manual calibration, simulation results, c) NWS manual calibration, residuals, d) Lumped automatic calibration, simulation results, e) Lumped automatic calibration, residuals, f) Semi-lumped automatic calibration, simulation results, g) Semi-lumped automatic calibration, residuals, h) Semi-distributed automatic calibration, simulation results, i) Semi-distributed automatic calibration, residuals.
Figure 8: Observed versus Simulated Graph for Illinois River Basin at Watts.

Figure 9: Flow Duration Curve for the Illinois River Basin at Watts.
Figure 10: Monthly %Bias for all the calibration strategies.

Figure 11: Effort and computational time for all the calibration strategies.
Figure 12: Observed versus Simulated Graph for Interior point at Savoy, Illinois River Basin at Watts.
Figure 13: Flow Duration Curve for Interior point at Savoy, Illinois River Basin at Watts.