Journal of Hydrology 420–421 (2012) 216–227

Contents lists available at SciVerse ScienceDirect

Journal of Hydrology

journal homepage: www.elsevier.com/locate/jhydrol

SAC-SMA *a priori* parameter differences and their impact on distributed hydrologic model simulations

Ziya Zhang [a,*], Victor Koren [a], Seann Reed [a], Michael Smith [a], Yu Zhang [a], Fekadu Moreda [b], Brian Cosgrove [a]

[a] Office of Hydrologic Development, NOAA/NWS, Silver Spring, MD 20910, USA
[b] Water and Ecosystems Management, RTI International, 3040 Cornwallis Road, Research Triangle Park, NC 27709, USA

ARTICLE INFO

Article history:
Received 29 April 2011
Received in revised form 18 November 2011
Accepted 2 December 2011
Available online 13 December 2011
This manuscript was handled by Andras Bardossy, Editor-in-Chief, with the assistance of Vazken Andréassian, Associate Editor

Keywords:
SSURGO
STATSGO
SAC-SMA
A priori parameters
Distributed modeling

SUMMARY

Deriving *a priori* gridded parameters is an important step in the development and deployment of an operational distributed hydrologic model. Accurate *a priori* parameters can reduce the manual calibration effort and/or speed up the automatic calibration process, reduce calibration uncertainty, and provide valuable information at ungauged locations. Underpinned by reasonable parameter data sets, distributed hydrologic modeling can help improve water resource and flood and flash flood forecasting capabilities. Initial efforts at the National Weather Service Office of Hydrologic Development (NWS OHD) to derive *a priori* gridded Sacramento Soil Moisture Accounting (SAC-SMA) model parameters for the conterminous United States (CONUS) were based on a relatively coarse resolution soils property database, the State Soil Geographic Database (STATSGO) (Soil Survey Staff, 2011) and on the assumption of uniform land use and land cover. In an effort to improve the parameters, subsequent work was performed to fully incorporate spatially variable land cover information into the parameter derivation process. Following that, finer-scale soils data (the county-level Soil Survey Geographic Database (SSURGO) (Soil Survey Staff, 2011a,b), together with the use of variable land cover data, were used to derive a third set of CONUS, *a priori* gridded parameters. It is anticipated that the second and third parameter sets, which incorporate more physical data, will be more realistic and consistent. Here, we evaluate whether this is actually the case by intercomparing these three sets of *a priori* parameters along with their associated hydrologic simulations which were generated by applying the National Weather Service Hydrology Laboratory's Research Distributed Hydrologic Model (HL-RDHM) (Koren et al., 2004) in a continuous fashion with an hourly time step. This model adopts a well-tested conceptual water balance model, SAC-SMA, applied on a regular spatial grid, and links to physically-based kinematic hillslope and channel routing models. Discharge and soil moisture simulated using the different set of parameters are presented to show how the parameters affect the results and under what conditions one set of parameters works better than another. In total, 63 basins ranging in size from 30 km^2 to 5224 km^2 were selected for this study. Sixteen of them were used to study the effects of different *a priori* parameters on simulated flow. Simulated hourly flow time series from three cases were compared to hourly observed data to compute statistics. Although the overall statistics are similar for the three different sets of parameters, improvements in simulated flow are observed for small basins when SSURGO-based parameters are used. Fifty-seven basins covering different climate regimes were used to analyze differences in the modeled soil moisture. Results again showed that the use of SSURGO-based parameters generate better soil moisture results when compared to STATSGO-based results, especially for the upper soil layer of smaller basins and wet basins.

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1. Introduction

Hydrologic models typically need to be calibrated in order to achieve the simulation accuracy acceptable for operational river forecasting. Often, different calibrators may derive slightly different parameter data sets due to various factors including data sets and objective functions used in calibration, level of experience and personal approach to calibration. Furthermore, the overall simulation statistics can be similar from different parameter sets in the same basin, reflecting the equifinality concept discussed by many (e.g., Beven, 2006)—yet one set of parameters may be superior and more robust due to greater spatial consistency and more realistic representation of hydrologic processes. Lack of attention to the

* Corresponding author. Address: Office of Hydrologic Development, NOAA National Weather Service, 1325 East West Highway, Room 8376, Silver Spring, MD 20910, USA. Tel.: +1 301 713 0640x158; fax: +1 301 713 0963.
E-mail address: Ziya.Zhang@noaa.gov (Z. Zhang).

0022-1694/$ - see front matter Published by Elsevier B.V.
doi:10.1016/j.jhydrol.2011.12.004

physical properties of basins and regional variations can limit the transferability of parameters and the consistency of model performance across basins in a region. This problem is due, in part, to the high levels of uncertainty in the initial parameter values used at the start of the calibration process. Because there are dependences between parameters, if initial parameters are highly uncertain, the calibration results could vary a lot depending on who does the manual calibration. As Kuzmin et al. (2009) indicated in a study of automatic calibration algorithm, with an informative and spatial variability of priori estimated parameters, one can speed up calibration process using one of filtering, i.e., improving the *a priori* estimates based on observed data (typically precipitation and streamflow), rather than one of bounded global optimization as in traditional automatic model calibration. While problematic in a lumped modeling environment, the issue will be of even greater concern with distributed modeling where spatially varying gridded parameter sets are required. With this in mind, better initial parameter estimation for hydrological modeling is important. It can either speed up the calibration process or improve simulations for ungauged basins (Koren et al., 2000; Carpenter and Georgakakos, 2004). By reducing the subjectivity in the calibration process, the resulting model parameters will be more reliable and consistent and will exhibit a reasonable variation of value over a large region or different regions (e.g., Koren et al., 2006). Physically derived initial parameters can help constrain the calibration process and mitigate the issues of data sets and personal approach mentioned above.

With the increased availability of spatially detailed data and computer processing power, and the ever increasing demand for localized information, more and more distributed hydrological models are being developed and applied for research and operational use (Leavesley et al., 1983; Abbott et al., 1986; Wigmosta et al., 1994; Bell and Moore, 1998; Koren et al., 2004; to name a few). Such is the case in the National Weather Service (NWS), where, historically, lumped implementations of the Sacramento Soil Moisture Accounting model (SAC-SMA) have been used for river forecasting. Recently, NWS hydrologists have started using a finer scale, distributed hydrologic model for improved river and flash flood forecasting, as well as for producing prototype gridded soil moisture and temperature products. The system used is the National Weather Service Hydrology Laboratory's Research Distributed Hydrologic Model (HL-RDHM) (Koren et al., 2004). HL-RDHM in this study uses the heat transfer version of SAC-SMA (SAC-HT; Koren et al., 2006) to model rainfall-runoff processes including soil moisture, and kinematic routing for hillslope and channel routing in an hourly, continuous mode for several years.

One of the challenges facing distributed modeling efforts is to have a set of initial parameters that is based on a basin's physical properties, so that either a smaller number of parameters will require calibration, or minimum manual or automatic calibration will be required. Addressing this challenge, Koren et al. (2000) developed a systematic approach to derive eleven SAC-SMA parameters from soil and land use properties. In the initial implementation of the method, they used the State Soil Geographic Database (STATSGO) to derive the parameters for the conterminous United States (CONUS). The STATSGO data are available at a scale of 1:250,000. The soil polygons defined in the STATSGO data set typically range in the size from about 100 to 200 km^2. Although the method of Koren et al. (2000) allows one to account for different land use types, they derived initial CONUS parameters assuming that the land cover/land use across the United States is "pasture or range land use" under "fair" hydrologic conditions. The only spatially variable inputs were soil texture and hydrologic soil group. Subsequent work has shown that when spatially variable land cover data are incorporated into the process, more physically meaningful parameters can be derived (Anderson et al., 2006), although their results were based on lumped simulations on a selected few basins.

While the STATSGO-based gridded parameters provide a good estimate of initial values for distributed modeling as shown in the Distributed Model Intercomparison Project (DMIP) (Smith et al., 2004; Reed et al., 2004; Koren et al., 2004), there are a few shortcomings that limit their application. In addition to the constant land cover and land use assumption in the STATSGO based gridded parameters estimation used in the DMIP, the STATSGO data offer less detailed soil information. A map unit in STATSGO can contain a large number of components. When a distributed model is applied to basins less than 100 km^2 (the case for most flash flood scenarios), the parameters based on 100–200 km^2 soil polygon texture information may not resolve spatial variations within the basin and therefore may not accurately depict runoff process. Serving as a solution to this resolution problem, the Natural Resources Conservation Service (NRCS) also develops and maintains the Soil Survey Geographic Database (SSURGO) data in which the data resolution is approximately 10 times higher than that of STATSGO. The digitization of SSURGO data is nearly complete for most of the CONUS. By using this high-resolution soil data, a new set of gridded SAC-SMA parameters can be derived (Zhang et al., 2011). Based on STATSGO and SSURGO soil data and different land cover assumptions, we can derive three different sets of 11 of the 16 gridded SAC-SMA model parameters. The three different parameter sets are based on (1) STATSGO soil data plus "uniform land cover" assumption (STATSGO ONLY case), (2) STATSGO soil data plus use of variable land cover (STATSGO + LULC case), and (3) SSURGO soil data plus use of variable land cover (SSURGO + LULC case). Because the STATSGO ONLY and STATSGO + LULC cases differ only in their use of land cover data, it is expected that the main differences would be in those parameters associated with the upper zone. In this paper, parameter comparisons between these three sets are presented for the CONUS and selected basins. We will concentrate on the impacts of these different *a priori* parameter sets on hydrologic simulations.

Several published papers, described below, feature comparisons between STATSGO- and SSURGO-based parameters and detail how use of the parameter data sets affects simulated discharge and soil moisture. In comparing outlet stream flow simulations using STATSGO-based and SSURGO-based parameters for the Little Washita watershed (600 km^2) in Oklahoma, Reed (1998) found that there was not much difference between the two cases. Using soils data, Reed (1998) estimated runoff model parameters for the Green and Ampt infiltration equation and a simple percolation model. Part of the reason for the small simulation differences was that the overall surface soil texture distribution, and hence the model parameters defined by the STATSGO and SSURGO data, were similar for this basin. In related research, Anderson et al. (2006) derived basin-averaged STATSGO-based and SSURGO-based SAC-SMA parameters for use by the lumped SAC-SMA model in simulations over several basins within the National Weather Service's (NWS) Ohio River Forecast Center and the West Gulf RFC domains. They found that use of SSURGO-based parameters improved the simulation of basin-outlet flow for basins where there was a noticeable difference in soil texture distributions between STATSGO and SSURGO data sets. The TOPMODEL has also been used to investigate the impact of parameter estimates on simulated streamflow. In particular, Williamson and Odom (2007) used the TOPMODEL for the prediction of streamflow in the South Fork of the Kentucky River near Booneville, Kentucky (area of 1938 km^2) using soil properties from STATSGO and SSURGO data sets. Results show that use of SSURGO-based data produced more accurate streamflow output as compared to the use of STATSGO-based data.

Peschel et al. (2006) applied a partially distributed SWAT model to the Upper Sabinal River Watershed (with basin area of 541 km^2) near Uvalde, Texas. They found that SSURGO-based flow simulations were more closely correlated with gauge observed flow than were their STATSGO-based counterparts. Mednick et al. (2008) examined 18 research efforts which focused mainly on applying hydrologic models using STATSGO and SSURGO soil data to conduct water quality and flow simulations. Although they confirmed the preferability of higher resolution soil data for estimating water quality variables, they concluded that the available findings are far from unanimous and reveal no clear pattern as to how STATSGO and SSURGO soil data usage affects model output. They pointed out that a likely cause for this lack of an explanatory pattern is the small sample size within and across the different studies. Therefore, larger sample sizes are needed to support a further analysis of the potential benefits of using higher resolution SSURGO data versus STATSGO soil data.

Further research guidance was produced by Moriasi and Starks (2010) who applied the 2005 Soil and Water Assessment Tool (SWAT2005) to three basins with drainage areas of 342, 154 and 75 km^2. Their study analyzed the effects of soil and precipitation dataset resolution on streamflow calibration parameters and simulation accuracy. Results were presented for different combinations of soil and precipitation data sets and showed that precipitation data resolution plays a more important role than soil data resolution. They recommended that both STATSGO and SSURGO soil datasets be used in combination with high-resolution precipitation data, and that results should be reported for a range of outputs from the simulations.

Since our study is about applications of the two soil data sources, STAGSGO and SSURGO, which are available for USA, discussions here are therefore concentrated on those applications of using STATSGO and SSURGO soil data within USA basins. There are, however, similar studies using different soil data sources. Romanowicz et al. (2005) in a case study in the Thyle catchment, Belgium, used two types of soil data with different scales (1:500,000 and 1:25,000) to test the sensitivity of the SWAT model to the soil and land use data parametrisation. Their results showed that the model is very sensitive to the quality of the soil and land use data as well as how soil and land data were pre-processed.

Levick et al. (2004) added the internationally available Food and Agriculture Organization of the United Nations (FAO) soil data (in the scale of 1:5,000,000) in addition to STATSGO and SSURGO soil data to the Automated Geospatial Watershed Assessment Tool (AGWA) to transform into input parameters for hydrologic models in their study. Their conclusion was that the integration of FAO soils into AGWA is adequate for hydrologic modeling and can produce comparable results as from STATSGO and SSURGO soils data, although their results had not been compared to observed runoff in that study.

The number of recent studies on the topic of SSURGO-based parameter estimation highlights the importance of this issue to the hydrologic modeling community. Our study adds substantially to the body of knowledge on this subject with a relatively large sample size compared to other studies, particularly with respect to the soil moisture analysis. While several studies have shown the benefits of using higher resolution SSURGO data in deriving parameters for hydrologic models, only Anderson et al. (2006) have previously published results using the SAC-SMA model, and their positive results were limited to a small number of basins. An immediate benefit of this study will be the ability to advise NWS RFCs which have performed calibration using STATSGO-based parameters as to whether it is worthwhile to repeat the work with SSURGO-based starting parameters. The results of this study will also help to validate the physical assumptions in the method used to estimate SAC-SMA parameters from soil data.

2. Methodology, study basins, and data

Koren et al.'s (2000) approach was used to produce the STATSGO-based parameters for this study and 2001 National Land Cover Data (NLCD 2001) supplied the necessary variable land cover information. The algorithms used in translating the STATSGO and SSURGO soil data into model parameters are the same as were developed by Zhang et al. (2011). Initial parameter values were calculated for each soil polygon defined in the SSURGO data set and were then transformed to gridded form at the desired resolution. A total of 63 basins within the domain of the Arkansas-Red Basin RFC (ABRFC) were selected to study the response of the modeled stream flow and soil moisture to the use of the three different *a priori* parameter data sets described above. Table 1 and Fig. 1 shows the basin information and location map.

Based on the availability of observed flow data, sixteen of these basins were selected for a streamflow modeling comparison using the HL-RDHM in distributed mode with *a priori* parameters. A second set of 57 of the 63 basins covering a range of climate regimes was selected to compare soil moisture simulations when STATSGO- and SSURGO-based parameters were used. Monthly statistics were computed. No parameter calibration was performed during the simulation runs mentioned above. The resultant analyses seek to determine whether use of finer resolution SSURGO data and variable land cover data can improve distributed modeling efforts, and under what conditions such improvements can most effectively be realized.

2.1. Discharge study

Utilizing the three sets of *a priori* parameters, HL-RDHM was executed with an hourly time step over 16 basins located in Oklahoma, Arkansas and Missouri. The basin areas range from 37 km^2 to 2484 km^2. Although some of them are nested basins, we treated each basin independently. Some of the selected basins were studied previously in the Distributed Model Intercomparison Project (DMIP) (Smith et al., 2004; Reed et al., 2004). Therefore, extensive hydrological data have been collected and are available for these basins. Precipitation and evaporation are the main forcing data needed for the model. Hourly gridded multi-sensor (NEXRAD and gauge) -based precipitation data (Fulton et al., 1998; see "About the multi-sensor data" http://www.nws.noaa.gov/oh/hrl/dmip/2/ok_precip.html) for ABRFC are available from 1993 onward and were used as model input. Gridded monthly climatology-based potential evapotranspiration (PE) data and monthly vegetation-based PE adjustment grids were used for the model runs. Hourly observed flow data at each basin's outlet were obtained from the

Table 1
Basins for discharge comparison.

No.	Short name	Station name	Area (km^2)
1	SPRINGT	Flint Creek at Springtown, AR	37
2	WSILO	Sager Creek near West Siloam Springs, OK	49
3	CHRISTI	Peacheater Creek at Christie, OK	65
4	CAVESP	Osage Creek near Cave Springs, AR	90
5	DUTCH	Baron Fork at Dutch Mills, AR	105
6	KNSO2	Flint Creek near Kansas, OK	285
7	ELMSP	Osage Creek near Elm Springs, AR	337
8	POWELL	Big Sugar Creek near Powell, MO	365
9	SAVOY	Illinois River at Savoy, AR	433
10	LANAG	Indian Creek near Lanagan, MO	619
11	ELDO2	Baron Fork at Eldon, OK	795
12	BLUO2	Blue River near Blue, OK	1233
13	SLOA4	Illinois River South of Siloam Springs, AR	1489
14	WTTO2	Illinois River near Watts, OK	1645
15	TIFM7	Elk River at Tiff City, MO	2258
16	TALO2	Illinois River near Tahlequah, OK	2484

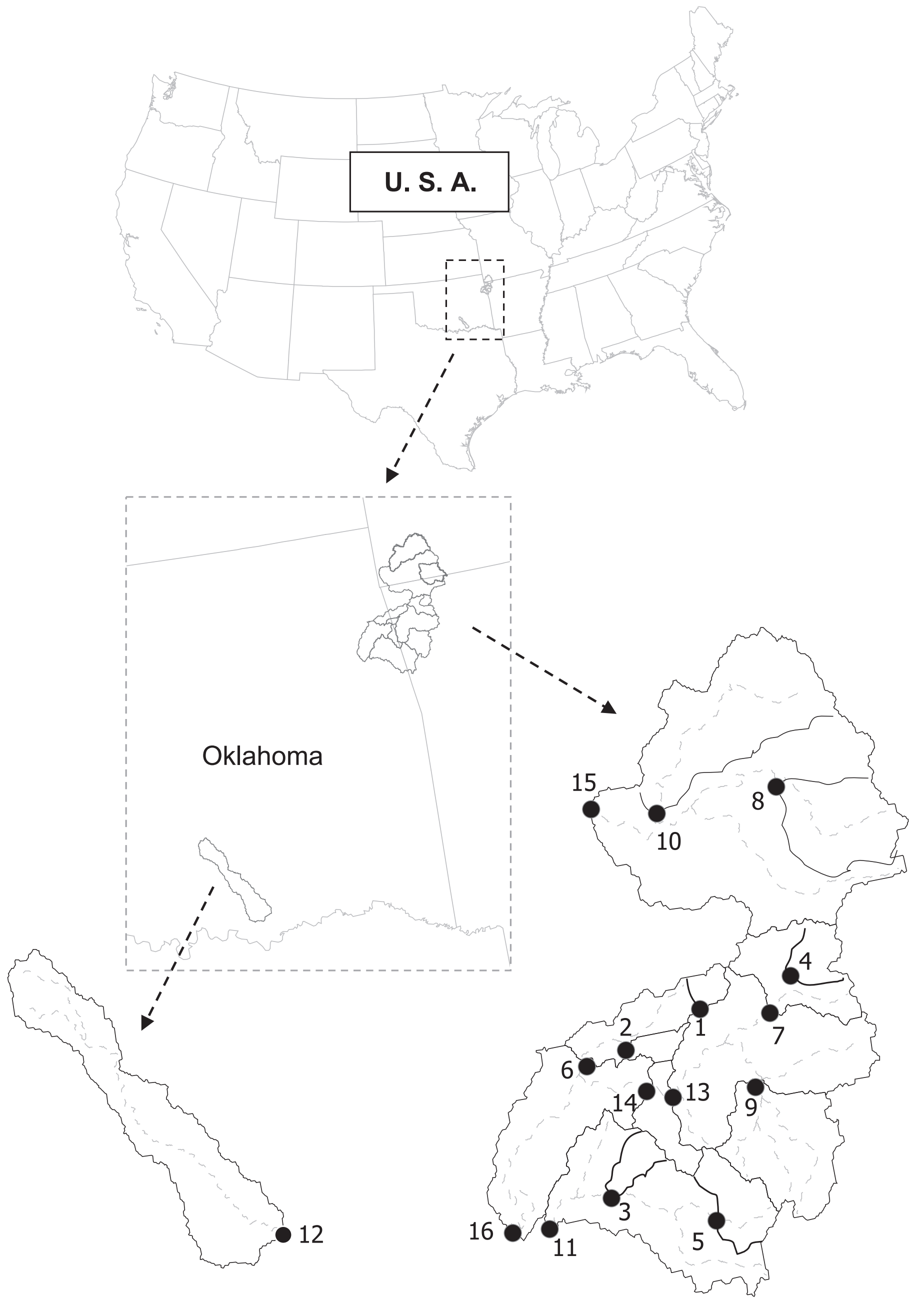

Fig. 1. Basin location map for discharge comparison. The solid dots are the outlets of basins. The dotted lines within the basins are river networks.

United States Geological Survey (USGS) and were used to compare and verify model simulations. The archived USGS hourly flow data are provisional since there was limited quality control performed by the USGS. Additional quality control was carried out on the observed hourly flow time series by comparing hourly totals to USGS daily flow data (which had already been quality controlled by USGS). If there were differences between the two, we flagged those values as missing in the hourly flow time series.

Simulations were conducted over a period of 11 years from October 1995 to September 2006. Using the same forcing data, but with different parameters, three sets of simulated flow time series were generated with HL-RDHM. Various summary statistics as suggested in Smith et al. (2004) can be calculated from the output by comparing each simulated flow time series to observed flow data. In this paper, the modified correlation coefficient R_m defined by McCuen and Snyder (1975) was calculated for each comparison. Comparisons were made over the whole simulation period, for different events, and for different basin sizes. The flow peak error was also compared among events.

2.2. Soil moisture analyses

Soil moisture simulations were carried out using SAC-HT (NOAA/NWS/OHD, 2007), a modification of SAC-SMA which introduced a heat transfer component to model frozen ground effects. As a by-product, soil temperature and soil moisture are computed for various depths over an area (Koren et al., 2008).

Fifty-seven basins (as shown in Fig. 2) within the ABRFC domain were selected to conduct soil moisture comparisons and analyses (some of which were included in the flow comparison study described above). Basin areas range from 18 km^2 to 5225 km^2. The basins span a wide range of climates as indicated in the climate

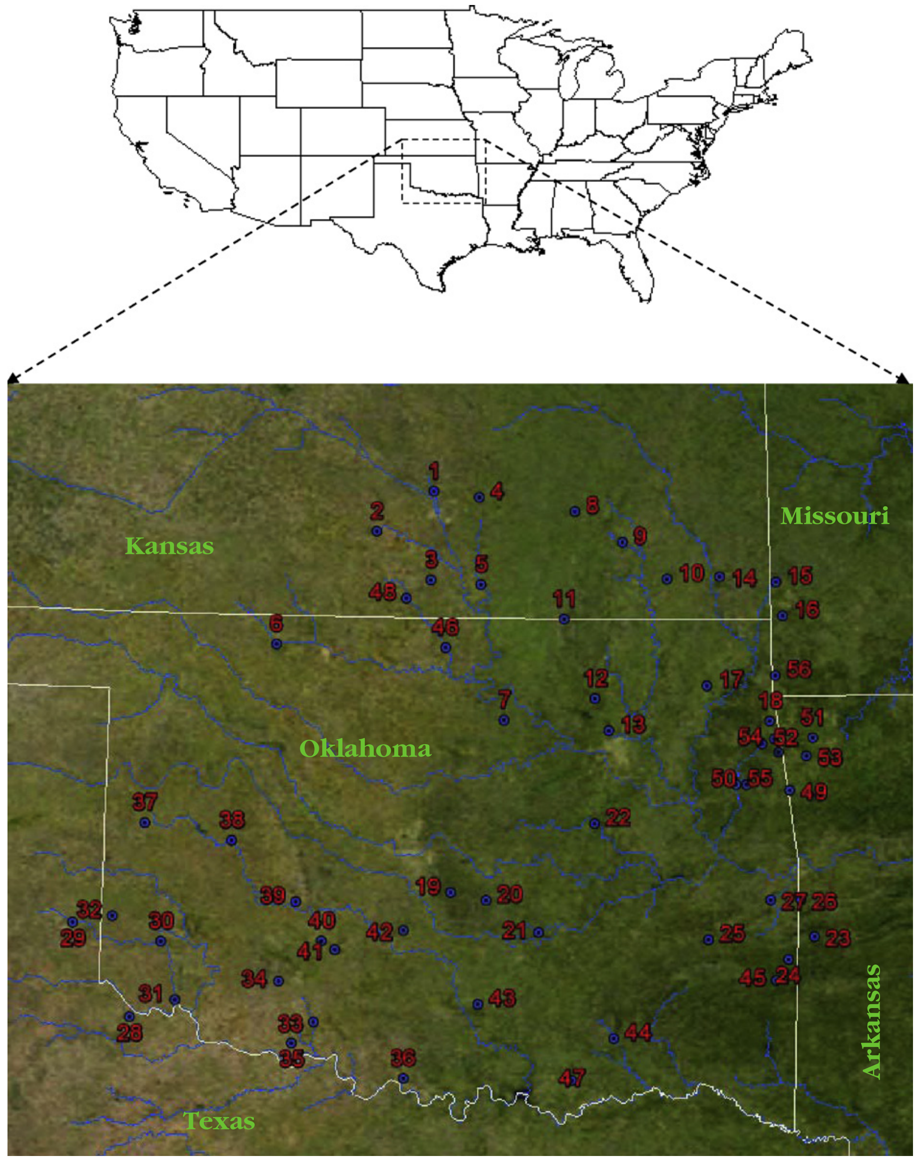

Fig. 2. Map of the outlets of 57 selected basins for soil moisture analyses with the vegetation (related to greenness) and river networks as the background.

index column in Table 2. The climate index here is defined as the ratio of annual precipitation, *P*, to annual potential evaporation demand (*PE*), and ranges from 0.60 (very dry) to 1.25 (rather wet) for the selected basins. In Table 2, the annual average vegetation greenness fraction (greenness), calculated from the National Environmental Satellite, Data, and Information Service (NESDIS) monthly data set (Gutman et al., 1995), is also included. The value for this greenness index is more consistent because it does not depend on the calibration process and does not require potential evaporation data. It also correlates well (correlation coefficient $R = 0.94$) with the *P*/*PE* index according to Koren (2008) internal report). Because of these factors, the greenness index was chosen for use in presenting soil moisture results.

Greenness values range from 0.26 to 0.67 for the selected basins. The background of Fig. 2 shows the vegetation (related to the greenness) variation across the area. Basin IDs, their location, and some basic basin properties are listed in Table 2.

The study region contains a unique soil moisture data collection network; the Oklahoma Mesonet. Since 1997, the Oklahoma Mesonet has provided real-time data including soil moisture measurements from more than 100 sites at up to four depths (5, 25, 60, and 75 cm) (Brock et al., 1995). However, only 64 sites provide measurements at all four depths. In this study, validation soil moisture grids were derived from Mesonet point estimates using Koren et al.'s (2006) method. All analyses were performed with daily soil moisture saturation values, *SR*, for the period 1 January, 1997 to 31 October, 2003. Weighted averages of observed soil moisture (in units of soil moisture saturation) over two soil layers (0–25 cm and 25–75 cm) were derived. For each layer, point-type saturation ratio values were interpolated to 4 km grid cells over Oklahoma using an inverse distance weighting method. Weights were computed on a daily basis depending on available station locations. The gridded daily maps of *SR* were then used to generate time series of basin-average soil moisture saturation. This observation-based time series was then used to validate the model-simulated time series of basin-averaged soil moisture produced using the three sets of *a priori* parameters. In this portion of the study, the user-defined SAC-HT soil moisture output layers were configured to match the observation depths of the two soil moisture measurement layers. Given that changes in soil moisture occur relatively slowly, monthly averaged values of soil moisture formed the basis for comparison.

Table 2
Properties of 57 basins for soil moisture comparison.

No.	ID	Lat	Lon	Area (km^2)	Elev. (ft)	P/PE	G
1	7144200	37.8322	−97.3881	3435	1326	0.78	0.41
2	7145200	37.5642	−97.8531	1683	1358	0.67	0.39
3	7145700	37.25	−97.4037	399	1157	0.84	0.41
4	7147070	37.7958	−97.0128	1103	1231	0.85	0.41
5	7147800	37.2242	−96.9948	4867	1083	0.85	0.42
6	7148400	36.815	−98.6481	2612	1292	0.64	0.33
7	7153000	36.3437	−96.7995	1491	803	0.84	0.44
8	7167500	37.7084	−96.2253	334	978	0.86	0.43
9	7169500	37.5084	−95.8336	2141	819	0.85	0.44
10	7170700	37.2667	−95.4683	96	796	0.98	0.48
11	7172000	37.0037	−96.3153	1152	763	0.84	0.44
12	7176500	36.4868	−96.0642	942	651	0.90	0.45
13	7177500	36.2784	−95.9542	2343	579	0.90	0.45
14	7184000	37.2817	−95.0325	510	818	1.05	0.49
15	7186000	37.2456	−94.5661	3013	833	1.04	0.56
16	7187000	37.0231	−94.5163	1105	887	0.99	0.6
17	7191000	36.5684	−95.1522	1165	622	0.99	0.52
18	7191220	36.3347	−94.6414	344	868	1.02	0.62
19	7230000	35.2217	−97.2139	665	966	0.85	0.43
20	7230500	35.1726	−96.932	1181	899	0.86	0.44
21	7231000	34.9654	−96.5125	2239	732	0.87	0.45
22	7243500	35.674	−96.0686	5224	633	0.87	0.45
23	7247000	34.919	−94.2988	526	570	1.12	0.66
24	7247250	34.7737	−94.5122	193	684	1.18	0.67
25	7247500	34.9126	−95.1558	316	541	1.01	0.6
26	7249400	35.1626	−94.4072	381	460	1.07	0.61
27	7249413	35.1657	−94.653	4575	388	1.07	0.63
28	7299670	34.3545	−99.7404	784	1426	0.65	0.28
29	7300000	34.9576	−100.221	3164	1941	0.60	0.26
30	7300500	34.8584	−99.5087	4054	1490	0.60	0.27
31	7301110	34.479	−99.3823	4862	1260	0.63	0.29
32	7303400	35.0117	−99.9037	1077	1715	0.61	0.28
33	7311000	34.3623	−98.2825	1747	938	0.77	0.39
34	7311200	34.6234	−98.5637	64	1215	0.78	0.37
35	7311500	34.2209	−98.4531	1597	924	0.77	0.35
36	7315700	34.0043	−97.567	1481	728	0.79	0.43
37	7316500	35.6264	−99.6684	2056	1901	0.59	0.3
38	7325,000	35.5309	−98.967	5118	1467	0.63	0.34
39	7326,000	35.1437	−98.4428	795	1254	0.71	0.42
40	7327,442	34.8926	−98.2331	30	1259	0.73	0.42
41	7327,447	34.8378	−98.1245	160	1184	0.74	0.42
42	7328,180	34.9715	−97.5848	19	1024	0.84	0.43
43	7329,852	34.4954	−96.9886	114	897	0.91	0.45
44	7334,000	34.2715	−95.9122	2814	440	0.94	0.51
45	7335,700	34.6384	−94.6127	104	887	1.25	0.67
46	BLKO2	36.8114	−97.2773	4813	967	0.78	0.42
47	BLUO2	33.997	−96.2411	1232	504	0.94	0.46
48	CBNK1	37.1289	−97.6014	2056	1108	0.74	0.41
49	DUTCH	35.8801	−94.4866	105	986	1.09	0.61
50	ELDO2	35.9212	−94.8386	795	701	1.05	0.59
51	ELMSP	36.222	−94.2885	337	1052	1.03	0.64
52	**KNSO2**	36.1865	−94.7069	285	855	1.02	0.62
53	**SAVOY**	36.1031	−94.3444	432	887	1.05	0.62
54	**SPRING**	36.2162	−94.6044	155	1173	1.03	0.63
55	**TALO2**	35.9229	−94.9236	2483	664	1.03	0.62
56	**TIFM7**	36.6315	−94.5869	2258	751	1.00	0.62
57	**WTTO2**	36.1301	−94.5722	1644	894	1.03	0.63

3. Results

3.1. Parameter comparison for CONUS and selected basins

Parameters were derived to cover CONUS. Although we did not run simulations over this domain, the effect of vegetation on parameters can be more easily verified when we visually examined CONUS data sets. Fig. 3 shows one of 11 derived SAC-SMA parameters, upper zone tension water capacity, UZTWM, generated using the three tested *a priori* parameter sets. Examination of Fig. 3a, b, and c reveals similar spatial patterns for all three cases. The areas that differ most between Figs. 3a–c generally correspond to dense forest cover (Fig. 3d), illustrating the impact of the LULC data. This is conceptually correct, because water losses in forest areas are usually relatively high and correspond to a higher capacity of the upper zone tension water. Comparing the forest map (Fig. 3d) and the two STATSGO-based UZTWM maps, one can see the differences over the northeastern part of the US which arise from the differing land cover assumptions. Similar differences are present in the other parameters as well (not shown). The effect of land use and land cover is reflected through the curve number, CN, and hence the upper layer thickness and other SAC-SMA parameters (Koren et al., 2000). The differences between Fig. 3b and c shows the effect of using different soil data, as both cases take the land use and land cover information into account. Comparisons shown in this figure provide a general sense of the impact of soil data source and the use of LULC data on derived parameter values.

Fig. 4 shows the percentage change among the three sets of UZTWM maps across the CONUS. Similarities between Figs. 4a and d can be noted and are due to 4a's use of variable LULC data. The variation of percentage change between SSURGO + LULC and STATSGO ONLY shown in Fig. 4b is larger than in Fig. 4a, indicating the larger effect from the combined use of soil and LULC data. Fig. 4c shows the percentage difference between STAGSGO + LULC and SSURGO + LULC highlighting the effect of using different soil data. High spatial variation exists in Fig. 4c due to the soil data differences between SSURGO and STATSGO. It also illustrates that the impact on UZTWM of using a different soil data set is greater than that of incorporating LULC data. Fig. 4c also shows that the differences between SSURGO and STATSGO are not uniform across the CONUS. Part of the reason is that soil texture variation is larger in some areas and these variations can be represented in SSURGO data, but not in the STATSGO data set. This is due to SSURGO's coarse resolution in that either one value represents otherwise quite variable values or one value is the result of aggregating soil layers and components.

Similar impacts are seen on the other SAC model parameters as well (readers can find the details regarding the SAC-SMA model and its parameters in Burnash et al., 1973). Using the STATSGO ONLY case as a baseline, Fig. 5a shows the percentage change of CONUS-averaged SAC-SMA parameters from the STATSGO + LULC and SSURGO + LULC cases. Parameters in the SSURGO + LULC case exhibit much larger percentage change values than those based on STATSGO + LULC data, suggesting that soil data differences have a larger effect on values of SAC-SMA parameters than does LULC data (UZFWM is an exception although the difference is small). In order to avoid the cancelling out of positive and negative values of percentage change when individual cells are averaged to form a single overall value, a second plot was created based on the absolute difference in each cell (Fig. 5b). It shows that for all of the parameters, the absolute percentage change values are much larger between the SSURGO + LULC and STATSGO ONLY cases than between the STATSGO + LULC and STATSGO-ONLY cases. While in Fig. 5a, the percentage change values for several parameters (UZTWM, UZFWM, UZK, ZPERC, REXP, LZSK, LZPK, and PFREE) are relatively small for both soil parameter cases, Fig. 5b depicts large absolute percentage change values for the SSURGO + LULC case. From this, it can be deduced that the SSURGO-based SAC-SMA parameters are more variable and therefore better reflect the scale of variation in the soil data than are the STATSGO-based ones.

Fig. 6 provides a closer look at the distribution of UZTWM within the selected basins for each of the three study cases. In general, the STATSGO ONLY-based UZTWM field (Fig. 6a) features smaller, less variable values as compared to the STATSGO + LULC and SSURGO + LULC cases (Figs. 6b and c). Note that there is higher spatial variability within the four smallest basins in the SSURGO + LULC case (Fig. 6c) and less variability over these same basins in the two STATSGO-based cases (Fig. 6a and b). From this, it can be

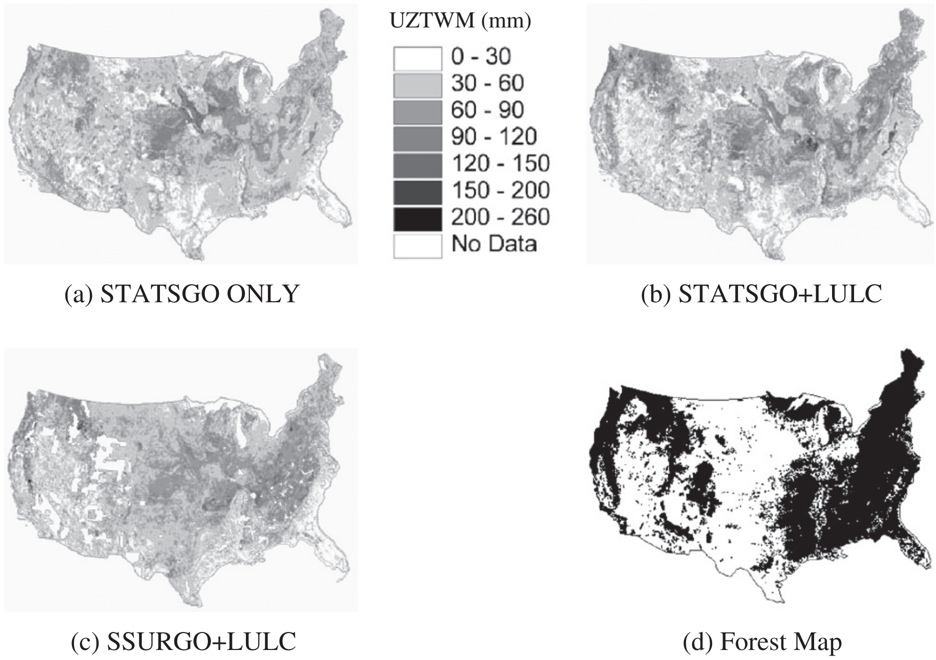

Fig. 3. (a–c) Distribution for one of the 11 derived SAC-SMA parameters, UZTWM, under different conditions and (d) forest map.

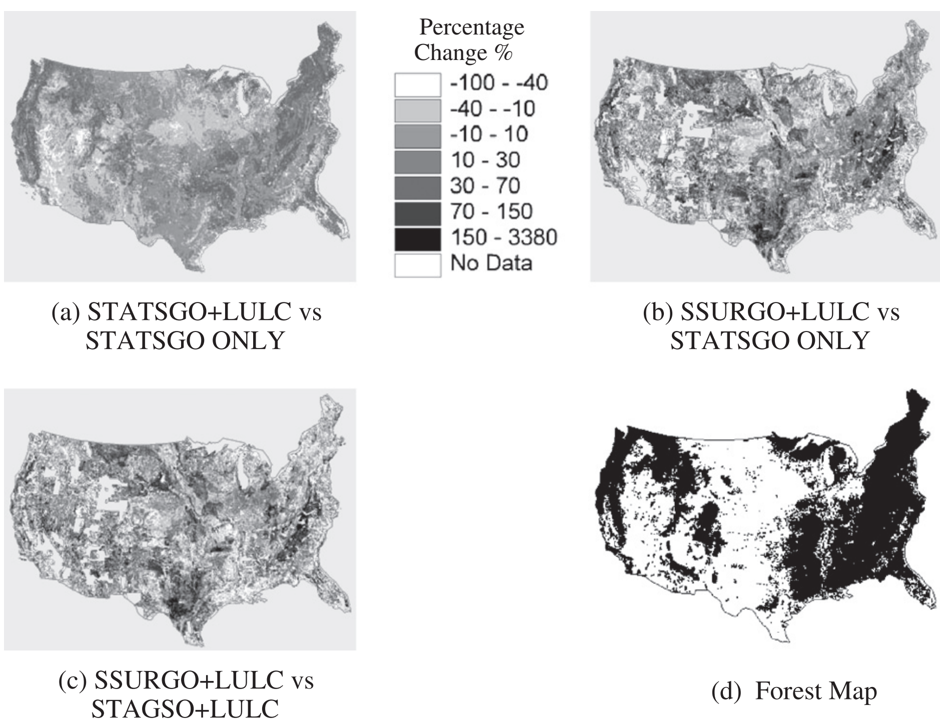

Fig. 4. Percentage change of UZTWM under different conditions.

seen that the high resolution of the SSURGO soil data leads to a better depiction of parameter variation over smaller basins.

3.2. Flow simulation results

The scatter plot of Fig. 7 shows a comparison of the modified correlation coefficient (McCuen and Snyder, 1975), R_m, between flow output from each soil parameter case and the observed flow with respect to basin areas. The modified R_m was used because it measures the goodness-of-fit in both shape and volume of hydrographs (McCuen and Snyder, 1975). In order to see the effect of parameter source on different size basins more clearly, linear trend lines are plotted for three cases as well. From these trend lines, it can be seen that the SSURGO + LULC case performs better than the other two STATSGO cases for small to mid-size basins (because the solid line is above the other two lines for basin areas of up to approximately 1000 km^2). Results for SSURGO based parameters are more consistent with a trend toward being slightly better as basin area increases. However, for large basins (areas roughly above 1000 km^2), worse results exist for SSURGO + LULC when

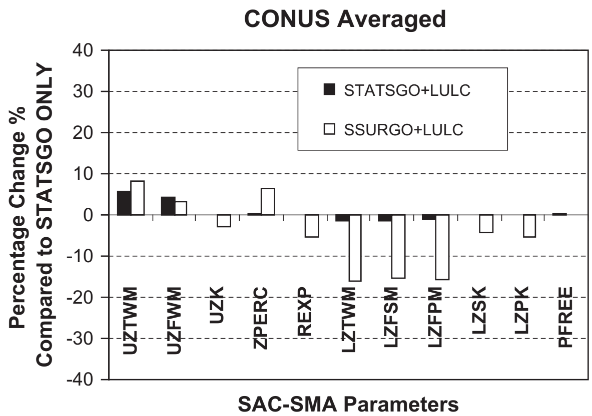

Fig. 5a. Percentage change of 11 derived SAC-SMA parameters when compared to STATSGO ONLY.

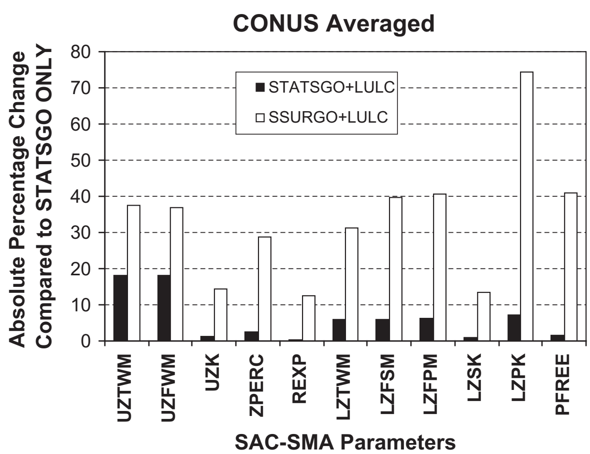

Fig. 5b. Absolute percentage change of 11 derived SAC-SMA parameters when compared to STATSGO ONLY.

compared with the two STATSGO cases. From these results, it can be seen that the use of high-resolution SSURGO soil data based parameters can improve simulations for small to mid-size basins. This observation is consistent with the fact that compared to either of the two STATSGO cases, the SSURGO + LULC parameters better reflect the natural variability in the soils data. We cannot completely explain why worse results emerge from use of the SSURGO parameters for the large basins as compared to the STATSGO cases. It is worth noting though, that relatively few large basins were analyzed. Additional studies that include more large basins are needed.

In addition to the broad overall comparison of flow simulations, event-based flow statistics were also analyzed. About 32 events per basin were selected within the analysis period. These precipitation/runoff events were the largest in each basin for which complete observations were available. Fig. 8 shows the comparison of the event-based averaged R_m for the three cases with respect to basin areas. The overall trends show little difference between the SSURGO and STATSGO + LULC cases, with the SSURGO + LULC case performing slightly better for small to mid-size basins and worse for several large basins. The trendline for the STATSGO ONLY case is above the other two, indicating better overall event-based results. Adding variable land use and land cover information may affect those parameters that are sensitive to fast overland flow values.

Complementing the R_m comparison, peak flow values and their associated timing were also compared for selected events (Fig. 9) with respect to basin areas. Looking at the trendlines in Fig. 9a, the peak errors for the three cases are similar, with the SSURGO + LULC case performing slightly better for small and mid-size basins and somewhat worse for large basins as compared to STATSGO cases (within the limited number of basins selected). The trendlines in Fig. 9b indicate that the peak time error for the three cases are similar as well, with the STATSGO ONLY case performing slightly better overall. This again confirms the observations made from Fig. 7, that using SSURGO + LULC (versus STATSGO) based *a priori* parameters can improve model simulations over the majority of basins, including small and mid-size basins.

3.3. Soil moisture simulation results

Similar to the flow analysis, basin-averaged soil moisture time series were generated for three sets of *a priori* parameters: STATSGO ONLY, STATSGO + LULC, and SSURGO + LULC. To match the soil moisture observation layers, variable depth HL-RDHM soil moisture was recalculated to fixed soil layers. For the monthly analysis, monthly soil moisture saturation values, *SR*s, were first calculated for three model cases: STATSGO ONLY ($SR_{\text{STATSGO ONLY}}$), STATSGO + LULC ($SR_{\text{STATSGO+LULC}}$) and SSURGO + LULC ($SR_{\text{SSURGO+LULC}}$). Then, the differences between simulated *SR*s and measured *SR* were evaluated for all three cases for both the upper and lower layers. The ratio of the absolute values of the differences, ($|SR_{\text{SSURGO+LULC}} - SR_{\text{MEASURED}}|/|SR_{\text{STATSGO ONLY}} - SR_{\text{MEASURED}}|$), ($|SR_{\text{SSURGO+LULC}} - SR_{\text{MEASURED}}|/|SR_{\text{STATSGO+LULC}} - \text{SR}_{\text{MEASURED}}|$), and ($|SR_{\text{STATSGO+LULC}} - SR_{\text{MEASURED}}|/|SR_{\text{STATSGO ONLY}} - SR_{\text{MEASURED}}|$) serves as an indicator as to which simulated results are closer to measured values, and therefore how soil data and land cover data impact the simulation. When the ratio is less than one, it means that the numerator is closer to the observed soil moisture than is the denominator, while the reverse is true for a ratio larger than one. When the ratio is equal to one, both cases are the same. Considering uncertainties exist in soil data, in soil moisture measurements, and in the model, cases are considered to have similar performance if the ratio differs from 1.00 by less than 15%. In other words, the case in the numerator is considered better than the case in the denominator when the ratio is less than 0.85, the case in the denominator is considered better than the case in the numerator when the ratio is larger than 1.15, and the case in the denominator is considered close to the case in the numerator when the ratio is between 0.85 and 1.15. Since we are comparing monthly values for 57 basins, there are a total of $12 * 57 = 684$ cells (values) that can be compared in the basin-month 2-D diagrams of Figs. 10–12. By looking at the number of cells which fall in three zones (better, close, or worse) for each comparison, we can determine how each set of *a priori* parameters affects the simulation results. Figs. 10–12 use three colors, grey, black, and white, to represent better, worse, or close comparisons, respectively.

Table 3 provides soil moisture comparison statistics for simulations using three pairs of *a priori* parameters. Focusing on the upper soil layer first, in the comparison of simulated soil moisture with measured data for the SSURGO + LULC and STATSGO ONLY cases, 45% of the values are better, 25% are close, and 30% are worse. Overall 70% of the SSURGO + LULC based results are either better than or close to those of the STATSGO ONLY case. Although using STATSGO soil data with consideration of variable land cover provides some improvement over using STATSGO ONLY data (26% of cases are better), the improvement is less than that provided when variable land cover is used with SSURGO-based parameters. In fact, most cases (56%) in this second comparison fall into the "close" category. In the final set of comparisons (SSURGO + LULC versus STATSGO + LULC), the difference lies only in the soil data. The improvement when using SSURGO + LULC over STATSGO + LULC of 40% is in between the other two cases mentioned.

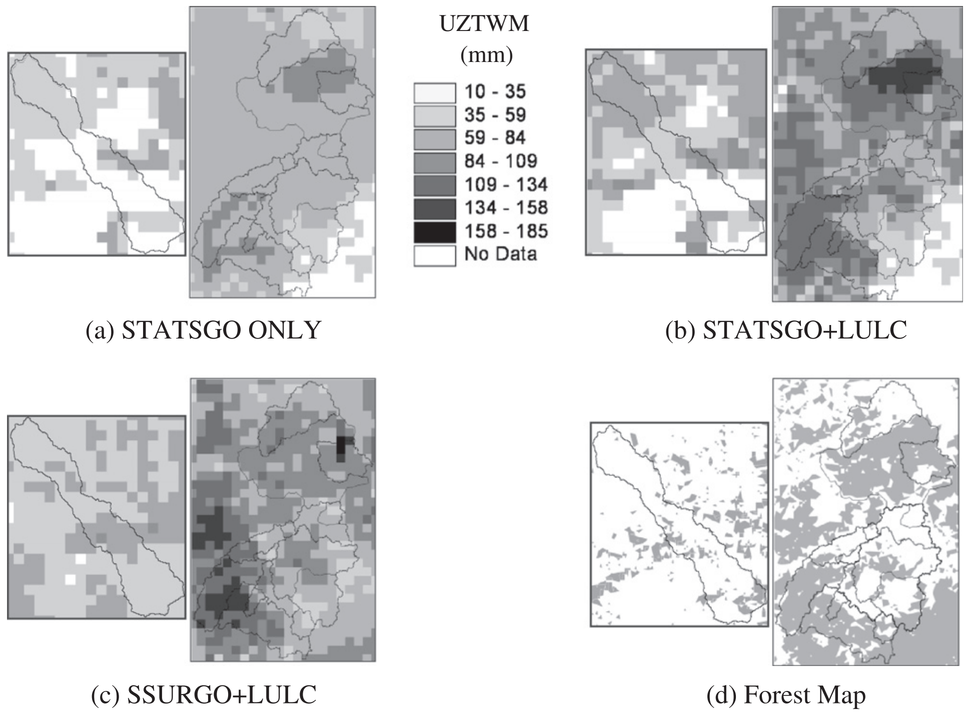

Fig. 6. Distribution for one of the 11 derived SAC-SMA parameters, UZTWM, under different conditions and forest map for selected 16 basins.

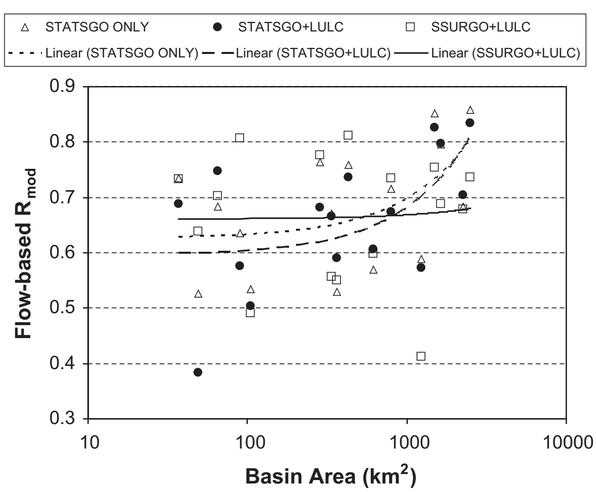

Fig. 7. Comparison of R_m of outlet flow of the three cases (using high resolution SSURGO + LULC, low resolution STATGSO + LULC and STATSGO ONLY SAC-SMA *a priori* parameters) for all 16 study basins with respect to basin area. Linear trendline for each case is plotted as well. The modified correlation coefficient, R_m, is calculated by reducing the normal correlation coefficient by the ratio of the standard deviations of the observed and simulated hydrographs (McCuen and Snyder, 1975).

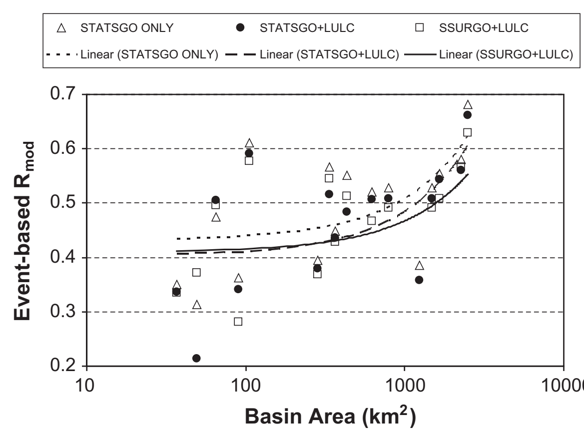

Fig. 8. Comparison of event-based modified correlation coefficient, R_m, of the three cases (using high resolution SSURGO + LULC, low resolution STATGSO + LULC and STATSGO ONLY SAC-SMA *a priori* parameters) for all 16 studied basins with respect to basin area. Linear trendline for each case is plotted as well.

It can be seen from the preceding upper soil layer comparison that simulated soil moisture can be improved through use of both SSURGO soil data and variable LULC information; however, inspection of Table 3 reveals that the benefit is greater from the SSURGO data. This suggests that soil data play a bigger role than land cover data in deriving accurate *a priori* parameters for the SAC-SMA model, and therefore in the model simulations. Table 3 also shows that the results across the three comparison cases are similar for the lower soil layer. The effects of soil and land cover data on soil moisture values in this layer are more muted. This could indicate that the effect of using different soil data and land cover on soil moisture simulations may be related to the more dynamic processes of the upper soil layer. Another possible reason is the inadequate modeling of water balance partitioning in the lower zone of the SAC-SMA model as described by Koren et al. (2008).

To determine if the soil moisture comparison results are related to basin size (19–5225 km^2) and greenness (range from 0.26 to 0.67) among the 57 basins, results were sorted and are plotted in Figs. 10–12 for the different simulation pairs listed Table 3. Figs. 10a and b are for the upper soil layer and feature the same number of black, white, and grey cells. Fig. 10a is sorted by area and Fig. 10b is sorted by greenness. From Fig. 10a, it can be seen that the SSURGO + LULC based soil moisture estimation is better than STATSGO ONLY based for most of the smaller basins (dotted line box). The SSURGO + LULC based soil moisture simulations are also better for most of large basins as compared to the STATSGO ONLY based simulations (as indicated by the right dotted line box),

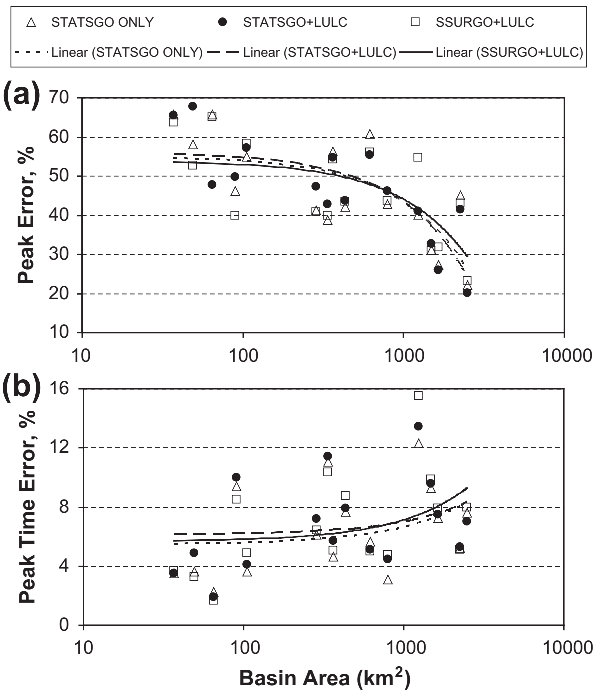

Fig. 9. Comparison of peak flow error and peak time error of the three cases (using high resolution SSURGO + LULC, low resolution STATGSO + LULC and STATSGO ONLY SAC-SMA *a priori* parameters) against observed results of 16 selected basins with respect to basin area. Linear trendline for each case is plotted as well.

although the distribution is not as clear as for smaller basins. Focusing on Fig. 10b, it is more evident that SSURGO + LULC based soil moisture simulations are better during all months for basins that have relatively high greenness values as indicated in the dotted box on the right. SSURGO + LULC based simulations are also generally better than STATSGO ONLY based simulations for basins with smaller greenness values as shown in the left dotted box. From Fig. 10, we can see the improvement from using SSURGO soil data and variable land cover data. The soil moisture comparison is consistent with the earlier flow comparison in that using higher resolution soil data can improve simulations, especially for smaller basins. Sorted plots for the lower layer (not included) do not show as clear of a pattern as those for upper soil layer.

Fig. 11 shows the sorted plot comparing the STATSGO + LULC and STATSGO ONLY simulations. The sole difference between the two is whether variable land cover data were used instead of a uniform land cover assumption. There is no obvious tread in the area-sorted plot (Fig. 11a). Although we can see improved results for small and large greenness areas as indicated by two dotted boxes (Fig. 11b), the majority of cases (56%) are close. In summary, the improvement seen by explicitly using variable land cover data is not as large as that gained by using both soil data and variable land-cover data as shown in Fig. 10. Part of the reason for this is that the land cover and land use information was already indirectly included in the STATSGO ONLY case. In this case, the NRCS hydrologic soil group information was used in deriving the CN, which in turn was used in the upper zone thickness estimation and the estimation of the rest of SAC-SMA parameters. Because the hydrologic soil group is directly related to soil properties, which is in turn linked to the land cover and land use, the STATSGO ONLY case includes indirect land cover information. This acts to lessen the difference with respect to the STATSGO + LULC case.

Fig. 12 shows the sorted plot for comparison of the SSURGO + LULC and STATSGO + LULC based simulations. Since the difference between the two is the type of soil data used, the results show the gain from using SSURGO soil data as opposed to STATSGO data. Forty percentage of the cases show better results for SSURGO + LULC while 31% of the cases show worse performance. About 69% of the using SSURGO + LULC are better or close to STATSGO + LULC. Recall that in the results shown in Fig. 10 where the difference between the two cases are the type of soil data and use of land cover data, 45% of the cases showed better results for SSURGO + LULC. Comparing the results in Fig. 10 and Fig. 12, we can see that the majority of the gain comes from using SSURGO soil data as opposed to using land cover data. From the area sorted plot (Fig. 12a), it can be seen that the better results are concentrated over the smaller basins while the results are mixed for mid-size to large basins. This is consistent with the findings in the previous flow simulation comparisons. In the greenness sorted plot (Fig. 12b), better results are mostly concentrated inside the dotted line box where greenness values are higher.

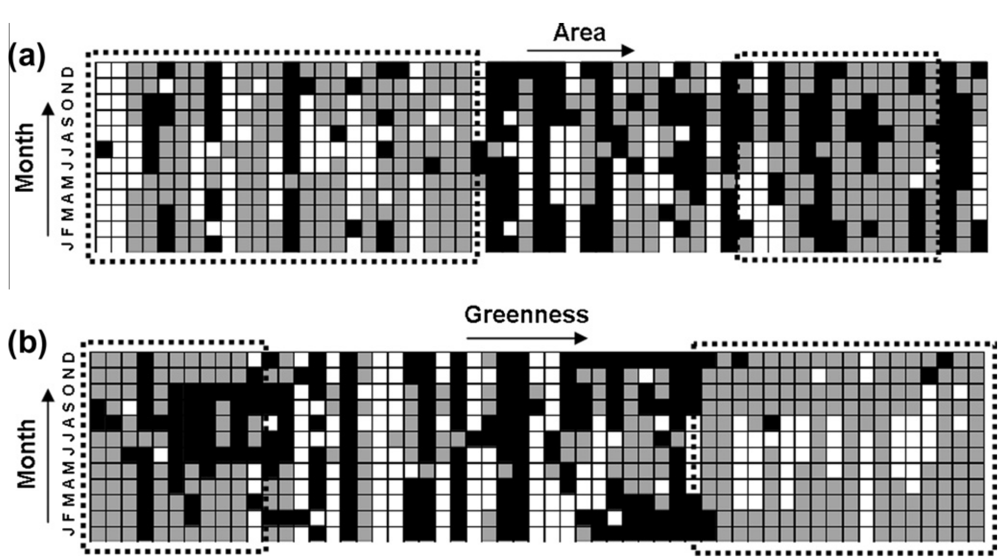

Fig. 10. Monthly soil moisture comparison results of 57 basins for upper soil layer sorted by area (Fig. 10a) and greenness (Fig. 10b) respectively. Black cells (204) indicate STATSGO ONLY performs better, grey cells (308) indicate better performance from SSURGO + LULC, and white cells (in number of 172) are results that are inside the margin of error. Dotted boxes highlight the zones that better performance from high resolution data of SSURGO + LULC than from low resolution data of STATSGO ONLY.

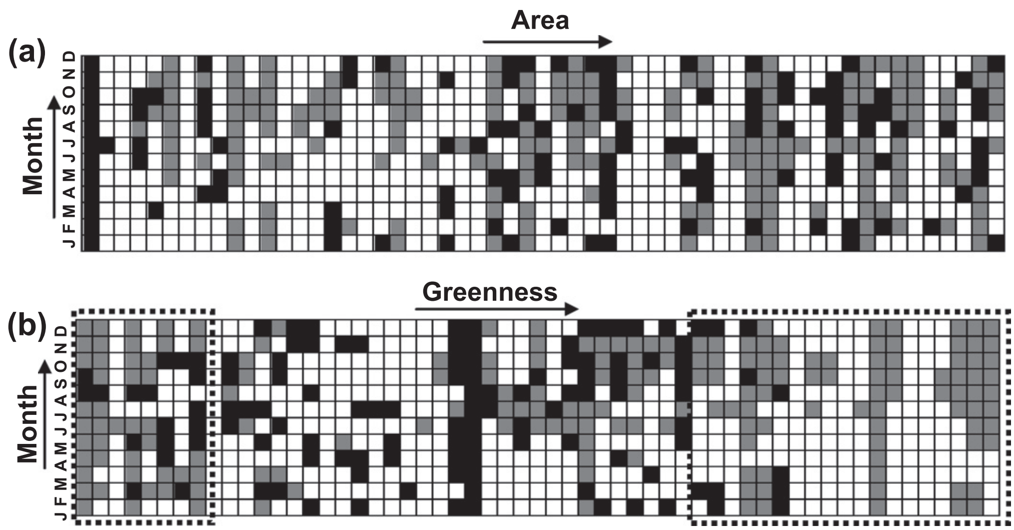

Fig. 11. Monthly soil moisture comparison results of 57 basins for upper soil layer sorted by area (Fig. 11a) and greenness (Fig. 11b) respectively. Black cells (118) indicate better performance from STATSGO ONLY, grey cells (180) indicate better performance from STATSGO + LULC, and white cells (total 386) are results that are inside the margin of error. Dotted boxes highlight the zones that better or close performance from SSURGO + LULC to the STATSGO ONLY.

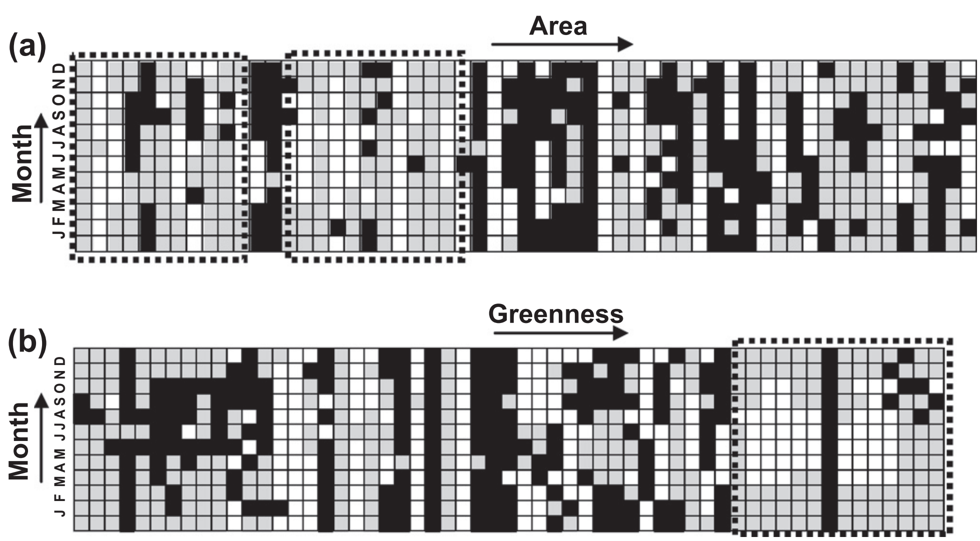

Fig. 12. Monthly soil moisture comparison results of 57 basins for upper soil layer sorted by area (Fig. 12a) and greenness (Fig. 12b). Black cells (215) are indicate better STATSGO + LULC performance, grey cells (273) indicate better SSURGO + LULC performance, and white cells (196) are results that are inside the margin of error. Dotted boxes highlight the zones that better performance from high resolution data of SSURGO + LULC than from low resolution data of STATSGO + LULC.

Table 3
Summary of simulated monthly soil moisture comparisons for different cases for 57 basins.

Cases	Soil layer	Better (grey) # and %	Close (white) # and %	Worse (black) # and %	% of Close or better
SSURGO + LULC vs. STATSGO ONLY	**Upper**	**380–45%**	**172–25%**	**204–30%**	**70%**
	Lower	217–32%	215–31%	252–37%	63%
STATSGO + LULC vs. STATSGO ONLY	**Upper**	**180–26%**	**386–56%**	**118–17%**	**83%**
	Lower	117–17%	467–68%	100–15%	85%
SSURGO + LULC vs. STATSGO + LULC	**Upper**	**273–40%**	**196–29%**	215–31%	69%
	Lower	225–33%	199–29%	260–38%	62%

4. Conclusions

The advantages of distributed modeling are more fully realized when variable gridded parameters are used. Good estimation of *a priori* gridded parameters is important for implementing a distributed model, and is critical for meaningful and efficient calibration of the model. The NWS Office of Hydrologic Development has developed a research distributed hydrologic model (HL-RDHM) that uses SAC-SMA as its rainfall/runoff component. Coarse STATSGO soil data and a uniform land use/land cover assumptions were initially used to derive *a priori* parameters for the SAC-SMA model. Another set of parameters was subsequently derived with a combination of coarse STATSGO soil data and gridded land cover data. While the spatially variable STATSGO data enabled development of distributed parameters, its coarse resolution did not allow for realistic representation of parameter variation at the fine spatial scale important for hydrologic events such as flash floods. With this in mind, finer-scale SSURGO soil data were used to derive a new set of parameters. To guide this development and the use of such parameters, a study was made of the impacts of such data on HL-RDHM streamflow and soil moisture simulations to determine if improvements anticipated in theory are confirmed in practice. In this paper, comparisons were made and the impacts on model simulations were presented using discharge of 16 selected basins, and soil moisture from 57 basins. Based on these results we can conclude that:

(1) Use of land cover data and higher resolution soil data results in different *a priori* SAC-SMA parameters.
(2) Overall discharge simulations for three sets of *a priori* parameters are similar, but improvement can be observed for smaller basins when SSURGO-based *a priori* parameters are used.
(3) Use of SSURGO based *a priori* parameters can improve soil moisture simulations over the use of either STATSGO ONLY or STATSGO + LULC based *a priori* parameters.
(4) Use of variable land cover based *a priori* parameters can improve soil moisture simulations.
(5) The incremental improvement in soil moisture simulation performance from using detailed SSURGO soil data is greater than from using variable land cover data.

In conclusion, use of SSURGO + LULC-based SAC-SMA parameters is preferable for HL-RDHM distributed modeling. The advantages of using SSURGO-based parameters can be further realized in applications such as the estimation of soil moisture over large areas and more importantly, for flash flood studies focusing on small basins or areas. The results presented in this paper are based on non-calibrated distributed modeling. Calibration may reduce the differences between *a priori* parameterization schemes; however, the amount of reduction will likely dependent on the scale and type of application. Interior points with no calibration could still benefit. Even if the parameters and results converged or narrowed from calibration we believe that the finer scale data provide the modeler with more confidence that the model is getting the right answer for the right reason.

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