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Original Article

High Spatial Resolution Soil Data for Watershed Modeling: 2. Assessing Impacts on Watershed Hydrologic Response

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Abstract

Spatial resolution of soil datasets used in watershed modeling is known to affect simulated hydrological response. Two databases, the Soil Survey Geographic (SSURGO) and the State Soil Geographic (STATSGO), provide publicly available soil datasets for hydrologic modeling of watersheds in the U.S. This study evaluated three soil representations using the Soil and Water Assessment Tool (SWAT) model to simulate hydrologic response in the Black Kettle Creek Watershed in Kansas, U.S.A.: SWAT using either 1) STATSGO data, or 2) SSURGO data, or 3) a third HYBRID model that used STATSGO soil data with the more refined SSURGO spatial distribution. The SSURGO-ArcSWAT utility was used to facilitate development of detailed soil data for SWAT modeling projects. The SWAT model with STATSGO data produced the greatest surface runoff and streamflows among the three models, especially during higher-rainfall events, in part due to overrepresentation of hydrologic group C and D soils. The SWAT model with SSURGO data produced the best calibration statistics, and exhibited the least flashy surface runoff behavior. The model with HYBRID soil data exhibited lower percentage bias and improved Nash-Sutcliffe model efficiency compared to the model with STATSGO soil data, and it was attributed to increased spatial resolution of hydrologic response units (HRUs) inherited from the SSURGO soil dataset. Calibration results and hydrologic impact may vary in other areas of the United States and in the world, but benefits of using SSURGO soil dataset are expected to come from both greater resolution of soil property data and a greater number of HRUs.

Key words: Hydrologic Modeling, SSURGO, STATSGO, SWAT

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INTRODUCTION

Soil properties directly affect hydrologic processes in a watershed, including infiltration into the soil, surface runoff, subsurface flows, percolation to shallow aquifer, and baseflow contribution to streamflow. Spatial representation of the soils, soil taxonomy, and numerous soil parameters contained in a geospatial soil database are important inputs in watershed modeling.

The State Soil Geographic (STATSGO) database and the Soil Survey Geographic (SSURGO) database have been widely used for watershed modeling in the United States (Mednick 2010). The STATSGO database (USDA-NRCS 1994) was created on the 1:250,000-scale maps and the SSURGO dataset (USDA-NRCS 2009) was structured on the 1:24,000-scale maps. The STATSGO and SSURGO databases were made from the same field soil surveys conducted by the USDA Soil Conservation Service. SSURGO soil maps were compiled using aerial photographs and field methods. Coarser STATSGO soil maps were compiled by generalizing more detailed SSURGO soil survey maps. Each SSURGO soil map unit is composed of up to three survey identified soil components. Each soil component represents a soil type that covers a certain percentage of the map unit area and consists of multiple layers with unique physical properties. STATSGO soil map unit covers larger area in the map than SSURGO soil map unit and is composed of up to 21 soil components. Because of differences in resolution, STATSGO was intended for general land-use planning and management at the larger river basin scale, while the SSURGO dataset was recommended for projects at the catchment, township, and county scale.

Watershed modeling projects benefit from SSURGO's greater spatial data resolution because it provides more detailed geospatial representation of soil properties and better recognizes dominant soil components compared to STATSGO. Using SSURGO soils is preferable for modeling small watersheds, catchments, or individual fields. For larger-scale projects, it increases the number of soil groups and improves representation of the soil spatial distribution; however, SSURGO also significantly increases the number of unique combinations of geospatial features, thus making the watershed representation more detailed and complex and increasing model computation time. One example is a soil-slope-land use combination that is used to represent hydrologic response units (HRU) in Soil and Water Assessment Tool (SWAT) model (Arnold et al. 1998).

Several watershed-modeling studies with SWAT have assessed the effectiveness of higher-resolution SSURGO soil data on hydrologic characteristics of watersheds, such as runoff, infiltration, water yield, and streamflow, as well as water-quality impacts, such as sediment and nutrient loads to streams. Kumar and Merwade (2009) found that using STATSGO soils provided better uncalibrated SWAT model performance than SSURGO soils for a 70,000-ha watershed in Michigan. Peschel et al. (2006) observed similar improved model performance using STATSGO soils, although none of the model runs produced satisfactory model simulation of USGS-observed data. Moriasi and Starks (2010) also found no significant differences between monthly model performance using SSURGO or STATSGO data in three Oklahoma watersheds (7,500 to 34,200 ha). In contrast, Daggupati et al. (2011a) found that SWAT simulations of a 7,818-ha watershed in Kansas using SSURGO data produced slightly (about 10%) greater Nash-Sutcliffe model efficiencies (NSE) and substantially (61 to 88%) lower percentage bias (PBIAS) than STATSGO data for flow simulation. These differences resulted in substantially different field-scale results, such as 10 to 40% disagreement in the top-ranked sediment-yielding fields. Geza and McCray (2008) provided a comparison of SSURGO and STATSGO datasets applied to the same watershed before and after calibration. A finer-resolution SSURGO dataset resulted in more areas with soil types having low infiltration potential resulting in greater stream discharges. The results of the SWAT study by Wang and Melesse (2006) indicated that the SSURGO dataset provided an overall better prediction of the streamflow discharges than the STATSGO dataset. Models with both datasets resulted in a comparable statistics of predicting the high streamflows, but the STATSGO model predicted the low streamflows more accurately. The discrepancies between the streamflow discharges predicted by these two SWAT models tended to be larger at upstream locations than at those farther downstream. Di Luzio et al. (2004) found greater sensitivity (and larger loads) for organic-N and organic-P loadings, and lower sensitivity for sediment and nitrates using SWAT with SSURGO soils on a small 55-ha watershed. They noted that greater soil carbon content for the two top soil layers using SSURGO might have contributed to the documented differences. Overall, these studies demonstrate that spatial misclassification of soil parameters can have a significant and pronounced effect on hydrologic and water-quality simulation accuracy.

Calibration of model parameters typically improves model accuracy (Moriasi et al. 2007) but also alters model response to input data. As demonstrated by Kumar and Merwade (2009), independent calibration of a hydrologic model for two different soil datasets (e.g., STATSGO and SSURGO) may improve model performance in each case but also may amplify or attenuate effects from soil data spatial resolution and analytical spatial resolution (e.g., sub-basin size). In the studies cited above, model calibration ranged from use of unadjusted default values of model parameters to full parameter calibration, which may have contributed to the inconsistency in results.

Although a number of studies were conducted to analyze impacts of soil datasets of different spatial resolution on hydrologic and water-quality conditions in the watersheds, the results appeared to be mixed. A combination of spatial resolution of the soil datasets with spatial resolution of the watershed models was not clearly investigated. The objective of this study was to assess modeled hydrologic response to the interactive effects of two soil datasets (STATSGO and SSURGO) and spatial scale of soil representation within the model (in this study, the distribution of HRUs in SWAT).

MATERIALS AND METHODS

Soil and Water Assessment Tool (SWAT)

The SWAT model is a continuous, physically based hydrologic and water-quality model developed for water resource managers to assess the impacts of land practice management and climate variations on non-point source pollution in complex watersheds, from catchment to river basin scale (Arnold et al. 1998; Santhi et al. 2001). SWAT model components include climate generation, hydrologic processes, sediment and nutrient routing, crop growth, and other modules. An overview of SWAT historical development, model components, and the current state of research was presented in Gassman et al. (2007), Douglas-Mankin et al. (2010), and Tuppad et al. (2011).

In SWAT, a watershed is divided into subwatersheds according to flow accumulation and stream network delineation procedures. Within each subwatershed, geo-referenced homogeneous units with uniform average slope, land use, and soil type are further identified and aggregated into HRUs. Map units of the same soil type can be constrained within the same HRU if overlaid with the same land use and average slope range. Each HRU represents a collection of spatially disaggregated areas in which hydrologic balance, crop yields, biomass production, and pollutant losses are continuously simulated. Different soil coverage would result in a different collection of HRUs.

Outputs from all HRUs within a subwatershed are summed and routed through the stream network to the watershed outlet. HRU-level processes depend on landscape characteristics, including soil properties. Daily surface runoff and amount of infiltrated water resulting from (sub) daily rainfall amounts falling onto the HRU area are simulated using either a modified NRCS curve number method (USDA-NRCS 2004) or a Green-Ampt method (Green and Ampt 1911). Soil properties are major characteristics used in both methods.

Study area

The Black Kettle Creek Watershed, a 7,818-ha (19,295-ac) sub-watershed (HUC 110300120302) of the Little Arkansas River located within McPherson and Harvey Counties in south-central Kansas, was used as a study area (Figure 1). Land use in the watershed was predominantly cropland (84% of total area) followed by rangeland (12%), urban area (2%), and forest (2%). The cropland consisted mainly of wheat followed by sorghum, soybean, and corn. Soil was predominately silty clay loam (mean permeability 0.5 cm/h), with an area along the mainstem of sandy silt. The relief generally consisted of gently sloping topography with a median slope of 1.5%. A detailed list of cropland management operations for 90% of the fields in the watershed was collected in 2009 (Daggupati et al. 2011a).

A stream-monitoring station was established at coordinates 38°04’20”N latitude and 97°33’18” W longitude, about 8.5 km upstream of the Black Kettle Creek and Little Arkansas River confluence (Figure 1). Stream stage was recorded at 15-min. intervals from January 2007 to December 2008 using an automated stage recorder (Model 6700 water sampler, Model 730 bubbler flow module, Isco, Inc., Lincoln, Neb.) and was averaged for each 24-h period (midnight to midnight). Average daily water depth was used with surveyed stream cross-sectional area, surveyed longitudinal channel slope, and estimated channel roughness coefficient (Cowan 1956) to estimate average daily streamflow using Manning's equation (Grant and Dawson 2001).

Soil datasets

Two soil databases (STATSGO and SSURGO) were used for preparing soil datasets in this study. In these datasets, spatial soil variability is represented by map units that have an assigned identifier to an area of a certain soil type. For the same area the SSURGO dataset normally contains 10 to 20 times more map units than the STATSGO dataset (Sheshukov et al. 2011).

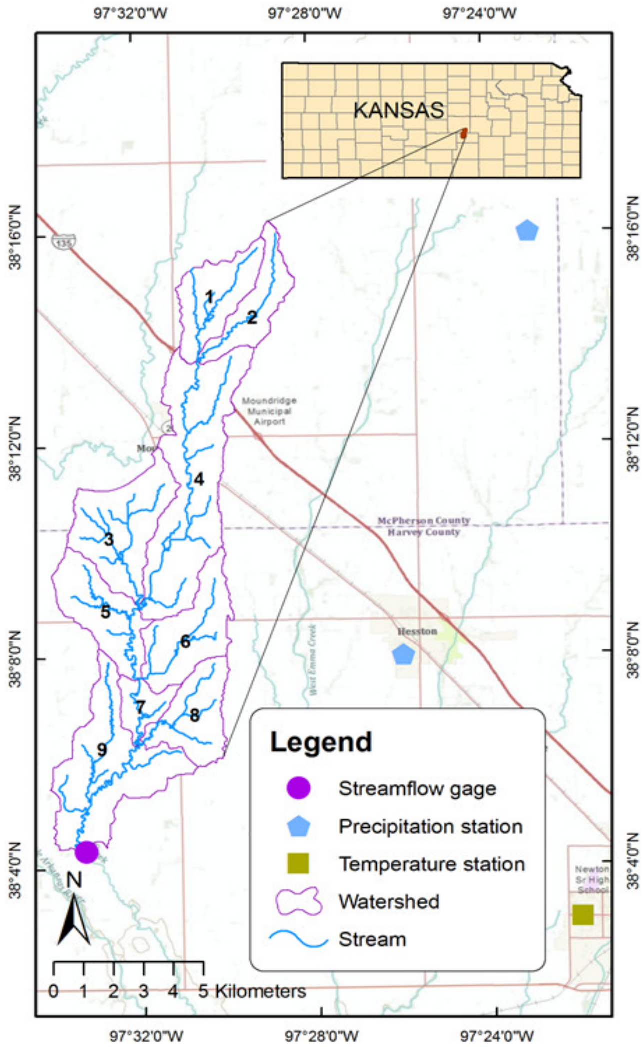

Figure 1 Map of Black Kettle Creek Watershed in south-central Kansas

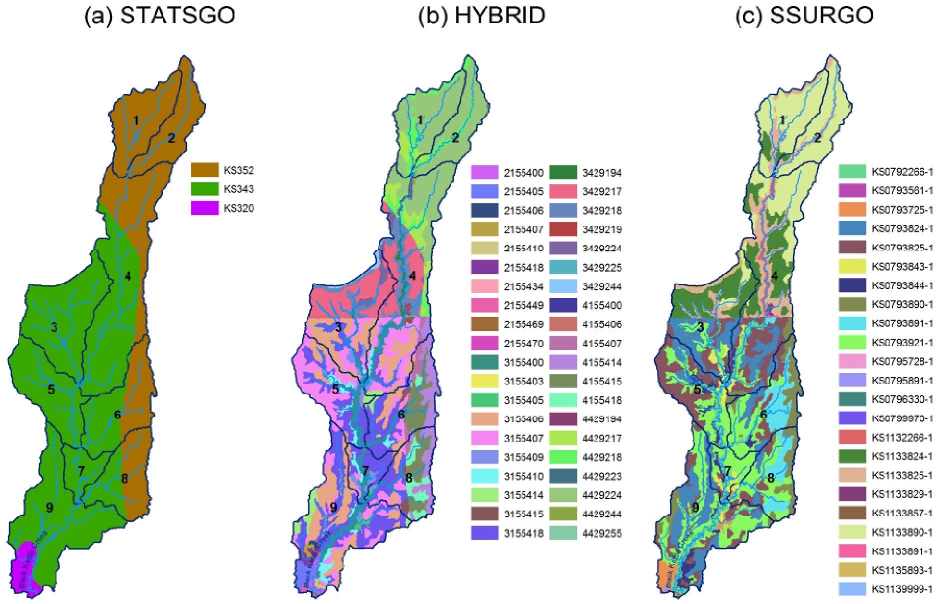

Figure 2 Three soil coverages for Black Kettle Creek Watershed: (a) STATSGO dataset with 3 soil types and 3 map units, (b) HYBRID dataset with 3 soil types taken from STATSGO and 40 map units derived from SSURGO, and (c) SSURGO soil coverage with 18 soil types and 23 map units.

Three soil datasets were prepared for this study:

1. The first dataset was developed from a STATSGO soil dataset and contained three map units representing three soil types that covered the entire watershed (Figure 2a). The dataset was independent of county lines.

2. The second dataset was developed from two county-based SSURGO soil datasets downloaded for two counties and contained 23 map units of 23 soil types (USDA-NRCS, 2009). Ten map units, five from each county, located adjacent to the county line between McPherson and Harvey Counties appeared to represent the same five soil types (Figure 2c); therefore, the total number of soil types for the watershed was reduced to 18.

3. The third dataset was a combination of the previous two datasets. It was derived with STATSGO soils and the geospatial coverage shown in Figure 2a but contained map units identified from the SSURGO dataset. Soils from the SSURGO dataset were not utilized in this dataset. The number of soil types remained at three, the same as in the STATSGO dataset. The number of map units exceeded the number from SSURGO dataset, reaching 40 instead of the original SSURGO's 23 (Figure 2c), due to additional division of SSURGO map units into the smaller units by the STATSGO soil separation boundaries (Figure 2b). The separation lines are clearly seen in subbasins 4, 6, and 8 in Figures 2a and 2b. This dataset is called HYBRID.

STATSGO soils were of groups C and D only, whereas the SSURGO dataset also contained 0.03% of group A and 10.40% of group B areas (Table 1). This difference would result in greater overall infiltration and less overall runoff for the SSURGO setup. The HYBRID dataset used the same soils as STATSGO. The average erodibility factor (USLE_K) was similar for all datasets (0.37 for STATSGO, 0.364 for SSURGO), with lower erodibility classes represented only in the SSURGO dataset (Table 1).

Model setup

The Black Kettle Creek Watershed was delineated using a 10 m × 10 m digital elevation model for McPherson and Harvey Counties (Gesch et al. 2002) into 9 sub-basins with the GIS module in SWAT (Figure 1). The watershed outlet was set at the streamflow gaging station location. The stream network was created during the delineation process. The watershed was divided into two subarea groups using a 2% slope threshold. Areas of high slope (>2%) occupy 17% of the watershed. The land-use layer was created based on field reconnaissance survey and used as the input land-use coverage for the SWAT model (Daggupati et al. 2011a). The watershed land-use types were mainly row crop agriculture (80.4% of watershed area), with 58.1% in winter wheat. Based on the field reconnaissance survey and analysis of digital ortho imagery, the following conservation practices were applied to crop lands: 12% of row-crop lands had terraces coupled with contour farming, 5% was in no-tillage or residue management practice, and dominant management practices were traditional tillage and no-tillage (Daggupati et al. 2011a, b).

Table 1 Delineation, HRU, and soil properties of three SWAT models developed for Black Kettle Creek Watershed

		STATSGO	HYBRID	SSURGO
		Delineation properties		
General (number)	Soils	3	3	18
	Map units	3	40	23
Sub-basin (Number of HRUs)	1	14	32	32
	2	10	28	28
	3	20	148	148
	4	35	237	186
	5	19	97	97
	6	35	122	90
	7	19	80	80
	8	31	117	91
	9	41	190	141
	Total	224	1051	893
		HRU properties		
Slope (%), length (m), Manning's n	HRU_SLP	1.98	1.95	2.00
	SLSUBBASIN	107.25	107.82	107.30
	OV_N	0.121	0.125	0.125
		Soil properties		
Hydrologic soil group (% area)	A	0	0	0.03
	B	0	0	10.40
	C	66.15	66.15	62.02
	D	33.85	33.85	27.57
USLE K –erodibility (% area)	0.37	100.00	100.00	89.19
	0.32	0	0	9.84
	0.28	0	0	0.64
	0.20	0	0	0.28
	0.01	0	0	0.04

Daily precipitation and maximum and minimum temperature data were acquired from three National Climatic Data Center (NCDC 2009) weather stations (COOP ID# 143134, 143620, and 145744) located 5 to 15 km east of the watershed for the years of 1992 through 2008 (Figure 1). Daily values for other weather variables (solar radiation, relative humidity, and wind speed) were simulated with the weather generator embedded in SWAT.

As described above, three geospatial soil data layers were prepared as inputs for the three SWAT models. The number of HRUs generated for the three model setups corresponded to the respective number of map units: 224 HRUs for the STATSGO dataset, 893 for SSURGO, and 1051 for HYBRID (Table 1). The number of HRUs in HYBRID setup exceeded the number of HRUs in SSURGO setup only in the sub-basins (4, 6, 8, and 9) where SSURGO map units were split due to the county boundary, the subbsains 1, 2, 3, 5, and 7 contained the same number of HRUs.

Calibration

The SWAT model was run from 1992 to 2008 with a three-year (1992-1994) warm-up period. Daily simulated streamflows from January 2007 to December 2008 were collected at the watershed outlet to compare with the stream-monitoring station data available for this period only. The results from 1995 to 2006 were collected to analyze the watershed hydrologic response but not used for model calibration.

Monthly model performance was assessed using coefficient of determination (R^2), NSE, and PBIAS (Moriasi et al. 2007). A set of 14 model parameters were selected for model calibration (Table 2). The parameters were selected from SWAT modules on surface flow, baseflow, evapotranspiration, and weather (snowmelt and freezing). Parameters related to soil properties, such as available water capacity (SOIL_AWC) and saturated hydraulic conductivity (SOIL_K) in individual soil layers, which can also be used for calibration, remained unchanged from the original values stored in STATSGO and SSURGO databases. While these parameters may be sensitive to calibration results they were not adjusted to avoid introducing model bias to the soil datasets. Therefore, the calibration is determined to be limited and prevented reaching statistical characteristics higher than in the good to very good range, as proposed by Moriasi et al. (2007).

The limited calibration was conducted on all three models by running the models many times (>30) until acceptable statistics were reached. The calibration parameters were iteratively adjusted in each run over allowable ranges. Range and final values of calibrated parameters are listed in Table 2. It was found that the values used to calibrate the SSURGO model provided the same degree of calibration accuracy if used in the other two models: STATSGO and HYBRID. A slight deviation from the SSURGO values did not lead to substantial improvement of either STATSGO or HYBRID models. Although, it is believed that adjustments to soil parameters could have improved the final statistics. Therefore, the values from the calibrated SSURGO model were used in final runs of the STATSGO and HYBRID models. In the discussion below the term calibration will refer to limited calibration and will be applied to the all three models. The final calibration statistics for daily, monthly, and annual streamflow are listed in Table 3; daily results rated good (R^2, NSE) to very good (PBIAS) for the SSURGO model according to the criteria proposed by Moriasi et al. (2007). Higher values of individual statistical parameters could have been reached for individual calibration runs by sacrificing the values of other parameters, using values outside recommended ranges, or adjusting soil-related parameters. This was considered unacceptable, and such model adjustments were not used. This approach helped focus attention on the effects of different soils without modifying the soil datasets.

Statistics also were calculated for uncalibrated models using model default parameters. None of the uncalibrated models produced acceptable daily, monthly, or yearly statistics (Table 3). Daily and monthly statistics were slightly lower in STATSGO and HYBRID models compared to the SSURGO model, but were still within the acceptable limits, whereas the yearly statistics became substantially lower (due to the use of only two years in calibration). The greater negative PBIAS in the uncalibrated models indicates consistent overestimation of runoff events using the STATSGO dataset. We note that bias introduced by limited calibration to the STATSGO and HYBRID models was small comparing to the differences in soil properties between SSURGO and STATSGO soil datasets. Interestingly, the HYBRID model exhibited lower PBIAS and slightly improved NSE compared to the STATSGO model. This impact was attributed mainly to increased spatial resolution inherited from the SSURGO soil dataset, as discussed below.

A scatter plot of monthly calibrated and uncalibrated streamflow data for three SWAT models compared with mean monthly observed flow data in 2007 and 2008 (Figure 3) shows that all models, calibrated and uncalibrated, simulated low-flow conditions consistently higher than observed data. This overestimation is also verified by linear regression fits presented in Figure 3 for the SSURGO model. Regression fits for all calibrated models had values of R^2 higher than those for uncalibrated models. For the SSURGO model, the value of monthly R^2 increased from 0.82 for the uncalibrated model to 0.96 for the calibrated model. The calibrated SSURGO model tended to underestimate the observed values for high-flow months, whereas the uncalibrated model consistently overestimated stream discharge. For flow values greater than 0.3 m^3/s simulated results tended to cluster closer to observed results than for lesser values. The limited calibration improved performance for all models, with the SSURGO model producing better overall performance and statistics among both uncalibrated and calibrated models.

Table 2 SWAT parameters, module, range, and final values used in model calibration

Parameter	Module	Description	Model range	Value used
ESCO	Evapotranspiration	Soil evaporation compensation factor	0 to 1	0.9
EPCO	Evapotranspiration	Plant uptake compensation factor	0 to 1	0.1
ALFA_BF	Baseflow	Baseflow recession constant (days)	0 to 1	0.2
ALFA_BNK	Baseflow	Baseflow factor for bank storage (days)	0 to 1	0.04
SHALLST	Baseflow	Initial depth of shallow aquifer (mm)	0 to 1000	600
GWQMIN	Baseflow	Depth of water in shallow aquifer required for return flow (mm)	0 to 5000	40
GW_DELAY	Baseflow	Groundwater delay (days)	0 to 500	15
GW_REVAP	Baseflow	Groundwater revap coefficient	0.02 to 0.2	0.04
RCHRG_DP	Baseflow	Deep aquifer percolation factor	0 to 1	0.5
REVAPMN	Baseflow	Threshold depth of water in shallow aquifer for revap to occur (mm)	0 to 500	2
SMTMP	Snowmelt/Freezing	Snow melt base temperature (°C)	-5 to 5	-3
SFTMP	Snowmelt/Freezing	Snowfall temperature (°C)	-5 to 5	3
SURLAG	Surface flow	Surface runoff lag coefficient	1 to 24	0.7
CN2	Surface flow	SCS runoff curve number	Δ -10 to 10%	Δ -5%

Table 3 Daily, monthly, and annual statistics of calibrated and non-calibrated model (N/A refers to the statistics not defined due to too few [n=2] observations)

		Calibrated			Uncalibrated		
		R^2	NSE	PBIAS	R^2	NSE	PBIAS
SSURGO	**Daily**	0.53	0.53	-1.3%	0.18	-3.26	-53.2%
	Monthly	0.96	0.92	-1.6%	0.82	0.59	-53.3%
	Yearly	N/A	0.99	-1.3%	N/A	-6.71	-53.2%
HYBRID	**Daily**	0.56	0.49	-16.9%	0.17	-4.26	-63.3%
	Monthly	0.97	0.95	-17.2%	0.86	0.46	-63.2%
	Yearly	N/A	0.43	-16.9%	N/A	-9.31	-63.3%
STATSGO	**Daily**	0.58	0.48	-40.4%	0.17	-2.8	-50.9%
	Monthly	0.94	0.85	-40.7%	0.84	0.63	-50.8%
	Yearly	N/A	-2.22	-40.4%	N/A	-5.53	-50.9%

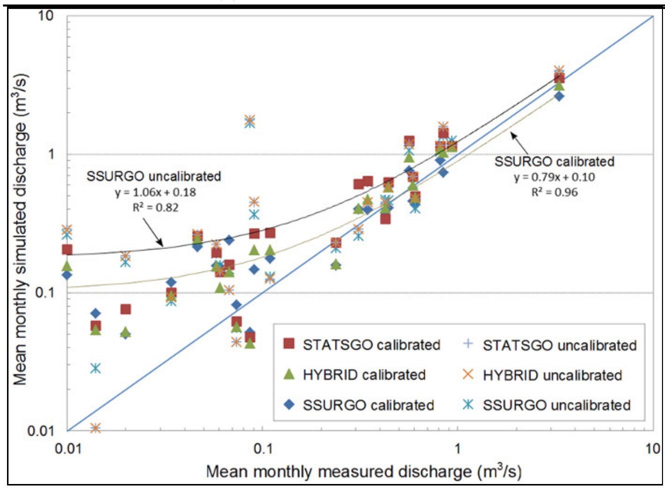

Figure 3 Mean monthly simulated discharge against mean monthly measured discharge (m^3/s) for three sets of calibrated and uncalibrated SWAT models

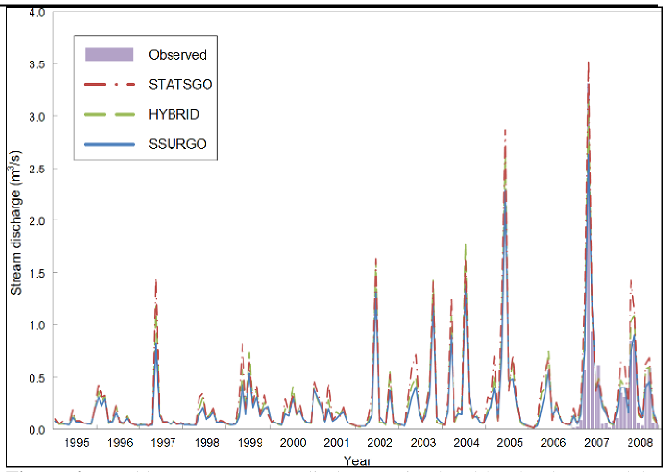

Figure 4 Monthly average stream discharges simulated by the three models (STATSGO, HYBRID, and SSURGO). Time series of observed stream discharges are plotted for 2007 and 2008 years

RESULTS

Calibrated versus uncalibrated streamflow

Mean monthly streamflow values are plotted for the three calibrated SWAT models in Figure 4. The two years used for calibration (January 2007 through December 2008) were wet years, with annual precipitation 39% (2007) and 17% (2008) higher than annual mean precipitation for the watershed in the past 14 years (1995-2008). During these years, annual mean streamflows were 135% (2007) and 60% (2008) higher than annual mean streamflows averaged over the same 14-year period generated by the calibrated SSURGO model. During the calibration period, the STATSGO model continuously produced higher monthly values among the models, whereas the SSURGO model generated the lowest values. The HYBRID model generally produced results between the other two models. During the wet months of April, May, and June, the STATSGO model produced streamflows with values up to 40% greater than those from the SSURGO model. For dry months, low streamflow exhibited a similar pattern in all models. During years prior to the calibration period (1995 to 2006), the pattern of streamflows in the three models was similar to the pattern observed in the calibration period (2007-2008).

Hydrologic balance

The impact of two soil datasets built into three SWAT models can be seen on individual components of the hydrologic balance, not only in the watershed but also in individual HRUs. This impact can be described using the hydrologic balance equation implemented in SWAT (Neitsch et al. 2005). The balance on a given day *j* is simulated based on a daily water balance equation within each HRU (all balance variables have units of mm H_2O):

$$SW_j = SW_0 + \sum_{i=1}^{j}(PR - RO - ET - DP - BF)$$

where *SW* is the soil water content, *PR* is the amount of precipitation, *RO* is the amount of surface runoff, *ET* is the amount of evapotranspiration, *DP* is the amount of water exiting the root zone (to the vadose zone), and *BF* is the amount of baseflow (to the stream). The subscript 0 indicates the initial water content at the beginning of the simulations. All SWAT models built for this study used the NRCS runoff curve number method with daily adjustment using SW_j to estimate *RO*, the Penman-Monteith method to estimate *ET*, the simplified transport decay method for groundwater, and the Muskingum method for channel routing. Annual total amounts of *PR*, *RO*, *ET*, *BF*, and outlet streamflow for both sets of three SWAT models, non-calibrated and calibrated, are presented in Figure 5.

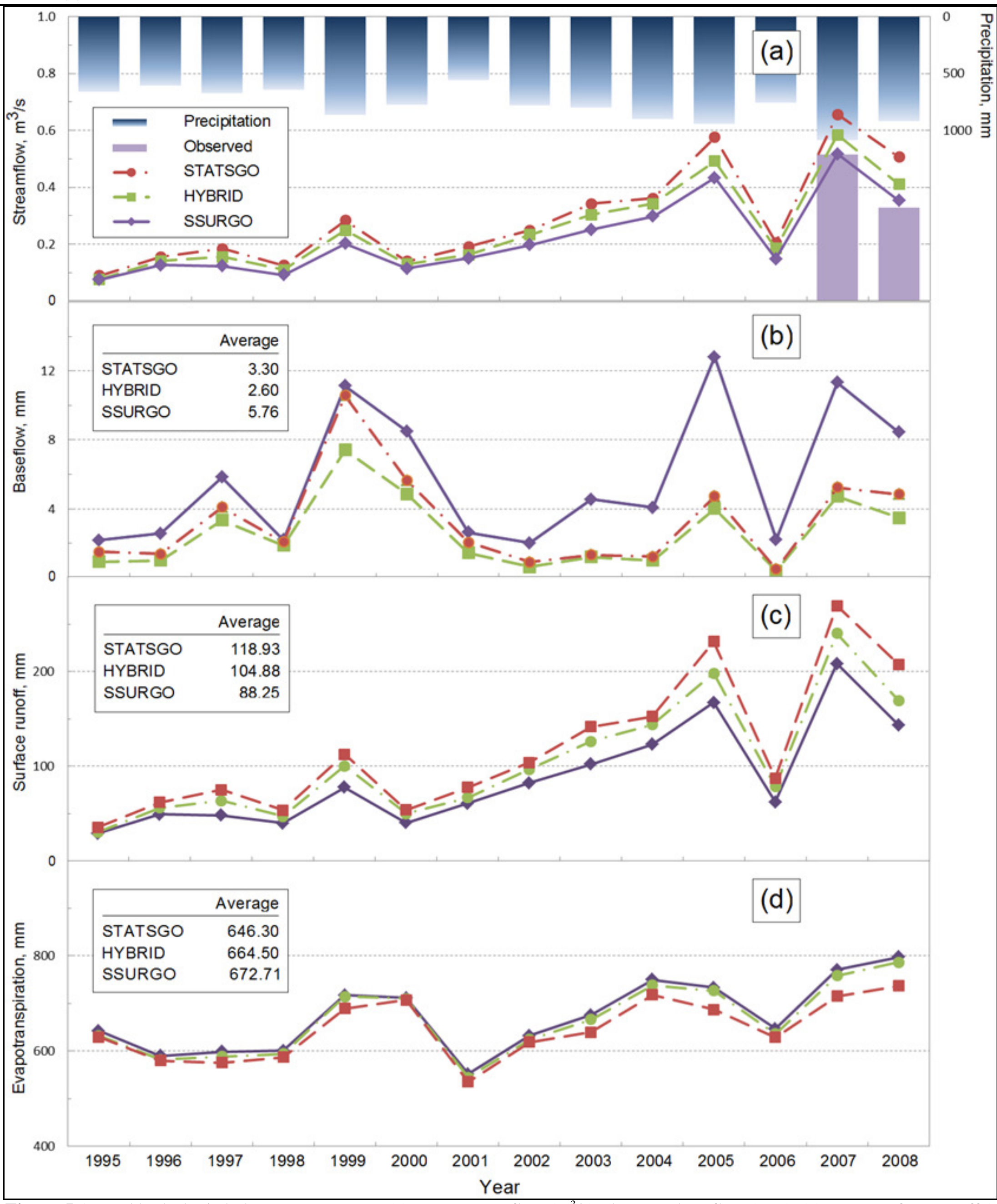

Figure 5 Annual hydrologic balance components: (a) mean streamflow (m^3/s), (b) mean baseflow (mm), (c) mean surface runoff (mm), and (d) mean actual evapotranspiration (mm). Mean annual observed streamflow is shown in (a) for 2007 and 2008. Total annual precipitation is shown as bars in (a)

Within the 14-year period of SWAT simulations (1995-2008), years 1996, 1998, 2001, and 2006 were considered dry years (annual precipitation less than 70% of average annual), whereas 1999, 2005, 2007, and 2008 were wet years (annual precipitation above 115% of average). Annual average streamflow for dry years fell below 0.2 m^3/s. For wet years, *RO*, *BF*, and streamflow exhibited higher values. *ET* also increased during wet years. Among the models, *BF* is higher for the SSURGO model, which correlates to stronger infiltration compared to other models. Although *BF* plots show a larger range of changes between the models in 2005 and 2007, for example, the differences in actual values were much smaller compared to differences in *RO*. Interestingly, *BF* for the HYBRID model was lower than for the STATSGO model, which contradicted the trend observed for other hydrologic components. Higher *ET* for the SSURGO model indicated longer water storage time within HRU than storage time for the STATSGO model.

DISCUSSION

Simulation runs for all SWAT models, uncalibrated and calibrated, exhibited similar trends in hydrologic components. On the daily, monthly, and yearly scales, the smallest streamflows were produced by the SSURGO model, whereas the STATSGO model consistently generated the largest values. The lower streamflow values by the SSURGO dataset were related to a 10.4% greater area of soils classified in hydrologic soil group B in the SSURGO soil dataset (Table 1), which generate less surface runoff (and streamflow) than soils in groups C and D. This inconsistent soil classification is prevalent in Kansas (Sheshukov et al. 2011). The higher values of hydraulic conductivity and infiltration rates in such soils provide additional near-surface conduction and storage of water during rainfall events and greater water percolation and recharge of groundwater. HRUs with less conductive soils of groups C and D generated greater runoff than HRUs with soils of group B, therefore contributing more water flow into the stream. Because the Black Kettle Creek streamflow is predominately from surface runoff, the daily streamflow exhibited a pattern similar to the daily surface runoff.

The HYBRID model results fell between those from SSURGO and STATSGO models, demonstrating an interaction between soil parameters (defined by the soil database) and other watershed characteristics (defined by HRUs, which represent combinations of soil, land cover, and topography). The number of soil types and the spatial representation of soil map units were identical for HYBRID and STATSGO models; however, the HRU boundaries were identical for HYBRID and SSURGO models (except for several sub-watersheds along county boundaries). Thus, the HYBRID model represented STATSGO soil data (redefined at SSURGO spatial resolution) combined with greater-resolution topographic and land-cover data, resulting in hydrologic results closer to those of the higher-resolution SSURGO model. Even though the soil parameter values did not change, the refined spatial resolution improved model performance in this watershed.

Water storage time within the HRU is described by the time of concentration (Neitsch et al. 2005). Time of concentration is the duration from rainfall initiation until the entire drainage area contributes to flow, and is a sum of times for overland and channelized flows. For the same rainfall amount, greater time of concentration leads to less surface runoff and streamflow. Time of concentration depends on HRU properties, such as area, slope steepness, average slope length, channel flow length, and Manning's roughness coefficient. By the semi-empirical Rational approach implemented in SWAT, time of concentration is increased by increasing channel length, slope length, HRU area, and Manning's coefficient and decreasing slope steepness.

The average HRU area is 34.9 ha for the STATSGO model, while it is substantially smaller for SSURGO (8.8 ha) and HYBRID (7.4 ha) models. The larger average HRU area of the STATSGO model should have increased the time of concentration and decreased surface runoff comparing to SSURGO and HYBRID models. However, even small changes (within several percent) in other factors, such as the decreased slope steepness and higher Manning's coefficient for the HYBRID model and better inifiltrating soils in the SSURGO model (Table 1), offset the impact of larger HRU area in STATSGO on the time of concentration distribution within each subbasin, especially during high flow events. All of these factors combined, and not an individual model parameter, contributed to decreased surface runoff and lower streamflow.

CONCLUSIONS

The SSURGO-ArcSWAT soil conversion tool (Sheshukov et al. 2011) was utilized to analyze impact of soil spatial resolution on hydrologic response of Black Kettle Creek Watershed in south-central Kansas using three model setups built within the ArcSWAT model. STATSGO and SSURGO soil datasets were utilized in model development. An additional soil dataset (HYBRID), with STATSGO soils but SSURGO spatial distribution, was developed to analyze the interactive impacts of spatial soil resolution on watershed hydrologic response.

For the predominantly agricultural watershed, the STATSGO model produced the greatest surface runoff and streamflows among the three models, especially during higher-rainfall events, and exhibited the least flashy surface runoff behavior. The HYBRID model exhibited lower PBIAS and improved NSE compared to the STATSGO model, which was attributed to increased spatial resolution of HRUs inherited from the SSURGO soil dataset. The SSURGO model produced the best PBIAS and NSE indices. Model performance of uncalibrated models was substantially worse than that of calibrated models. Additional adjustment of soil parameters in STATSGO and SSURGO datasets that were left unchanged in this study could improve the model performance but introduce model bias to the soil datasets.

Analysis of impact of HRU properties on hydrologic equations conducted by SWAT revealed model bias of larger time of concentration and smaller surface runoff toward smaller HRUs. The benefit of using SSURGO soil dataset was demonstrated to come from greater resolution of soil property data. The results generated were based on the SWAT model applied to an agricultural watershed in the Central Great Plains of the United States. In other areas with different soil, topography and climate conditions, hydrologic differences between STATSGO and SSURGO datasets may be different from the ones simulated in this study and the resulting changes in hydrologic regimes may vary, however the trend of model improvement with either higher soil resolution or smaller map units is expected to be preserved.

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