Field-Level Targeting Using SWAT: Mapping Output from HRUs to Fields and Assessing Limitations of GIS Input Data

P. Daggupati, K. R. Douglas-Mankin, A. Y. Sheshukov, P. L. Barnes, D. L. Devlin

Abstract. *Soil erosion from agricultural fields is a fundamental water quality and quantity concern throughout the U.S. Watershed models can help target general areas where soil conservation measures are needed, but they have been less effective at making field-level recommendations. The objectives of this study were to demonstrate a method of field-scale targeting using ArcSWAT and to assess the impact of topography, soil, land use, and land management source data on field-scale targeting results. The study was implemented in Black Kettle Creek watershed (7,818 ha) in south-central Kansas. An ArcGIS toolbar was developed to post-process SWAT hydrologic response unit (HRU) output to generate sediment yields for individual fields. The relative impact of each input data source on field-level targeting was assessed by comparing ranked lists of fields on the basis of modeled sediment-yield density (Mg ha^{-1}) from each data-source scenario. Baseline data of field-reconnaissance land use and management were compared to NASS and NLCD data, 10 m DEM topography were compared to 30 m, and SSURGO soil data were compared to STATSGO. Misclassification of cropland as pasture by NASS and aggregation of all cropland types to a single category by NLCD led to as much as 75% and 82% disagreement, respectively, in fields identified as having the greatest sediment-yield densities. Neither NASS nor NLCD data include land management data (such as terraces, contour farming, or no-till), but such inclusion changed targeted fields by as much as 71%. Impacts of 10 m versus 30 m DEM topographic data and STATSGO versus SSURGO soil data altered the fields targeted as having the highest sediment-yield densities to a lesser extent (about 10% to 25%). SWAT results post-processed to field boundaries were demonstrated to be useful for field-scale targeting. However, use of incorrect source data directly translated into incorrect field-level sediment-yield ranking, and thus incorrect field targeting. Sensitivity was greatest for land use data source, followed closely by inclusion of land management practices, with less sensitivity to topographic and soil data sources.*

Keywords. *BMP, Erosion, Modeling, Sediment, Watershed.*

Soil erosion and sedimentation are fundamental water quality and quantity concerns throughout the U.S. Soil erosion from agricultural fields is a major contributor of sediment yields into surface waters. Watershed models, both empirical and process-based, are used for watershed management, planning, development, and best management practice (BMP) implementation. Process-based models, such as the Soil and Water Assessment Tool (SWAT; Arnold et al., 1998), have been used widely to assess the extent of soil erosion as affected by agricultural land use and management practices at both field and watershed scales (Pandey et al., 2007).

Strategic targeting and prioritization of areas that need BMP implementation is the key to effective watershed management (Mankin et al., 2004; Diebel et al., 2008). Identifying fields or critical source areas (CSAs) with the greatest sediment-yield potential and targeting these fields or areas for educational and implementation efforts would efficiently allocate time, money, and educational resources (Pionke et al., 2000; Strauss et al., 2007; White et al., 2009; Busteed et al., 2009; Tuppad et al., 2010). Targeting can be separated into two phases: (1) an assessment phase, in which BMPs and/or source areas are identified and prioritized, and (2) a planning phase, in which a stakeholder group considers BMPs and source areas targeted by the assessment process along with other information to target actions, such as educational efforts or financial support. In Kansas, watershed modeling has been widely used in the assessment targeting phase to quantify and prioritize pollutant yields from BMPs and source areas (Devlin et al., 2005; Nejadhashemi et al., 2011). In this study, the term "targeting" generally refers to this assessment-phase targeting.

Over the past few decades, empirical-based and process-based models have been used widely to identify CSAs. Tim et al. (1992) integrated simulation modeling with a geographic information system (GIS) to identify CSAs in Nomini Creek watershed in Virginia. Sivertun et al. (1998), Sivertun and Prange (2003), and Barnes et al. (2009) used GIS and a Revised Universal Soil Loss Equation (RUSLE) (Renard et

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The authors are **Prasad Daggupati, ASABE Member,** Graduate Research Assistant, **Kyle R. Douglas-Mankin, ASABE Member Engineer,** Professor, **Aleksey Y. Sheshukov, ASABE Member Engineer,** Research Assistant Professor, **Philip L. Barnes, ASABE Member Engineer,** Associate Professor, Department of Biological and Agricultural Engineering, and **Daniel L. Devlin,** Professor, Department of Agronomy, Kansas State University, Manhattan, Kansas. **Corresponding author:** Kyle R. Douglas-Mankin, Department of Biological and Agricultural Engineering, Kansas State University, 129 Seaton Hall, Manhattan, KS 66503; phone: 785-532-2911; fax: 785-532-5825; e-mail: krdm@ksu.edu.

al., 1991) based model to identify CSAs in which to implement conservation practices. Tripathi et al. (2003), White et al. (2009), and Busteed et al. (2009) used the SWAT model to identify and prioritize CSAs.

The SWAT model can be effective for identifying CSAs because it uses a distributed hydrologic modeling approach that utilizes spatially distributed climate, topography, soils, land use, and land management practices (Gassman et al., 2007; White et al., 2009). SWAT subdivides the watershed into subwatersheds and further into hydrologic response units (HRUs), areas within a subwatershed that have unique combinations of land use, soil, and slope. The HRU-level output can be referenced to the original land areas having the specific characteristics of each HRU and thus can be used to identify CSAs that exceed a threshold pollutant yield value (Busteed et al., 2009; Ghebremichael et al., 2010). HRUs may spread across several fields, or a given field may contain several HRUs, each with different pollutant yield potential (fig. 1). However, the management unit for crop BMP implementation typically is the field, not the HRU, because the entire area within a field receives the same crop type, tillage, and management practices. Farmers or landowners typically are not willing to manage field subareas differently. Therefore, HRU-level output must be aggregated or disaggregated to produce field-level output when the intention is to use the modeled information for practical targeting of BMP implementation.

The SWAT model requires input data and parameters that describe the characteristics and distribution of topography, soils, land cover, and weather within the watershed. Watershed modelers can readily download these input data from various data sources. The SWAT model is sensitive to the quality of land use, topographic, and soil data and the preprocessing techniques used to prepare and input these data (Romanowicz et al., 2005). Inamdar and Naumov (2006) used SWAT to determine annual sediment yields and identified CSAs of erosion for the Buffalo River watershed. They used a land use/land cover (LULC) layer downloaded from the EPA BASINS website and manually updated the LULC layer by using 2002 digital ortho quarter quads. They concluded that the accuracy and resolution of the cropland areas delineated on the LULC layers are critical for reliable sediment predictions. Zhan et al. (2009) used the SWAT model to simulate runoff and sediment yield by changing LULC layers (from 1990 and 2000) in the Chao River catchment in China. Their results showed that the LULC change had little influence on runoff but had more influence on sediment yield.

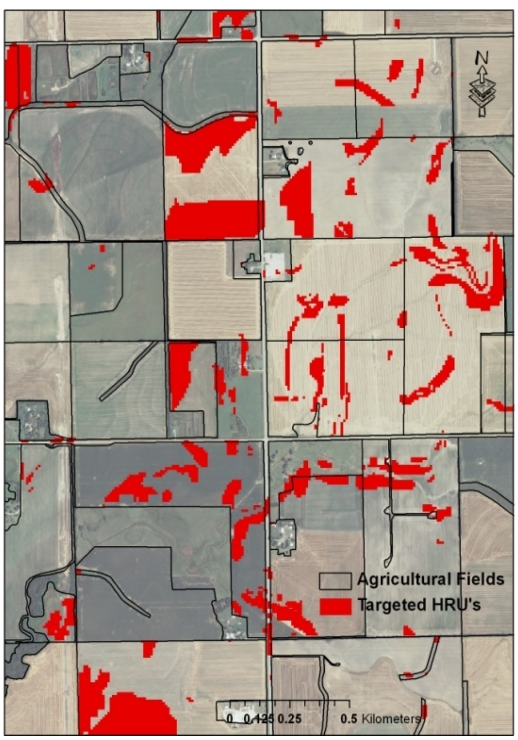

Figure 1. Locations of HRU areas (in red) with the greatest SWAT-estimated sediment yield in relation to field boundaries.

Chaubey et al. (2005) evaluated the effect of digital elevation model (DEM) resolution (from 30 to 1000 m) on SWAT model predictions. They found that the DEM resolution affected the watershed delineation, stream network and subbasin classification, and the model predictions. Dixon and Earls (2009) used the SWAT model to test the sensitivity of DEM resolution (30, 90, and 300 m) and resampling techniques in predicting streamflow. They concluded that model predictions were sensitive to DEM resolution, and resampling may not be an adequate technique for modeling streamflow using the distributed watershed model. Chaplot (2005) determined the impact of DEM resolution (20 to 500 m) and soil map scale (1:25,000; 1:250,000; and 1:500,000 scale) by using SWAT to simulate runoff, sediment, and NO_3-N loads. They concluded that a DEM resolution of 50 m was required to simulate watershed loads, and decreasing the DEM resolution beyond 50 m affected the predictions of nitrogen and sediment yields. They also concluded that the detailed soil map needed to be considered to accurately estimate the watershed loads. Wang and Melesse (2006) and Peschel et al. (2006) evaluated the effects of soil layer (SSURGO and STATSGO) on modeling predictions and found that the SSURGO soil layer predicted streamflow better than the STATSGO soil layer.

Heathman et al. (2009) used SWAT to evaluate the impact of different combinations of GIS-based soil data (SSURGO and STATSGO) and land use data (GAP and NASS) on streamflow prediction. The two land use layers studied resulted in greater differences in predicted streamflow than the two soil layers studied. Veith et al. (2008) used SWAT to assess high and low resolution land use management data on flow, sediment concentration, and P concentration at the outlet of a small watershed (<100 ha). Their results showed that the high-resolution data can enable the model to provide valuable water quality information, while the low-resolution data can be used for initial problem-solving efforts. Research has evaluated the difference in modeled watershed-scale yields of flow, sediment, and nutrients resulting from input data having a range of spatial resolutions. In these studies, changes in spatial representation of topography, soils, and land use were assessed by comparing impacts on watershed-scale yields. However, very few studies have assessed the impact of spatial data resolution on the representation or modeling accuracy of watershed models at the individual field scale.

Therefore, objectives of this study were to (1) demonstrate the use of ArcSWAT output mapped at the field scale for conservation practice targeting, and (2) assess the impact of topography, soil, land use, and land management source data on field-scale targeting results. This study focused on evaluating

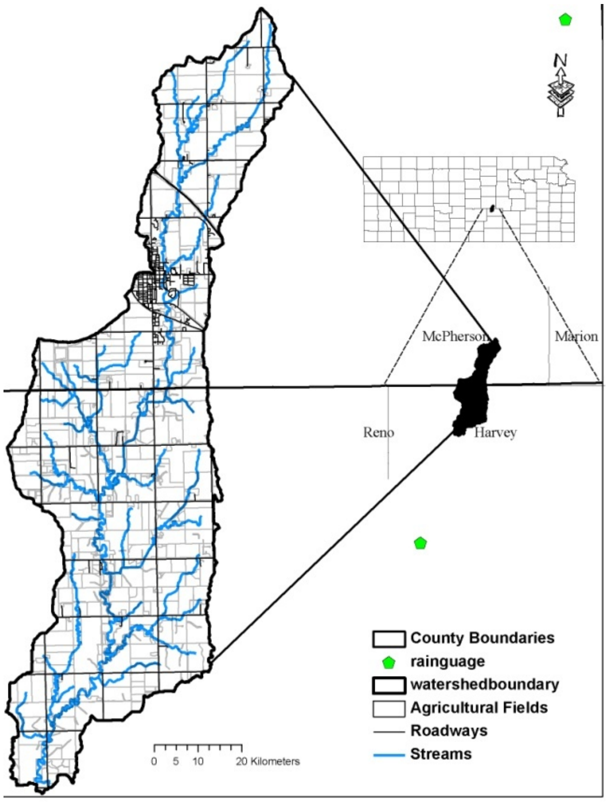

Figure 2. Field boundaries and stream network for Black Kettle Creek watershed.

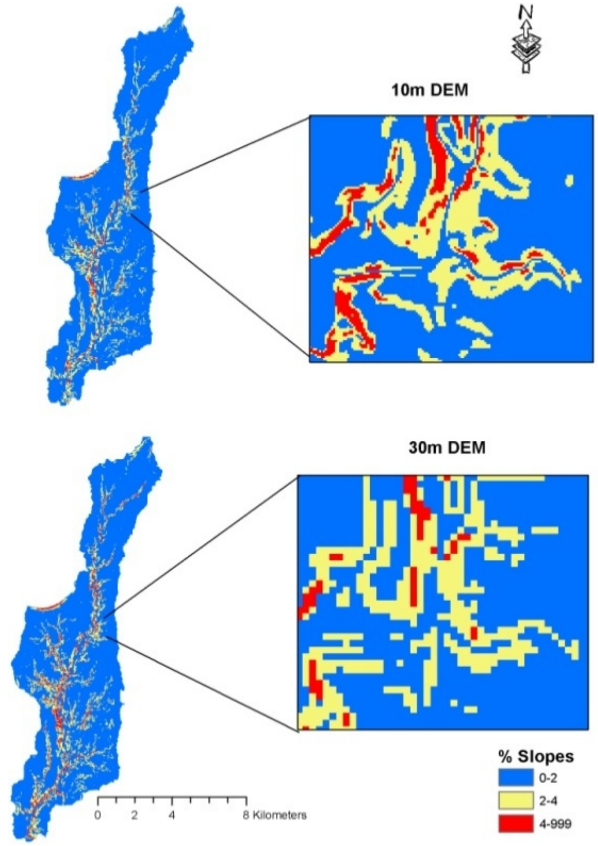

Figure 3. Slope classifications (10 m and 30 m DEM) for Black Kettle Creek watershed.

common datasets that were readily downloadable from the internet or manually prepared.

Study Area and Project Setting

The city of Wichita in south-central Kansas undertook the Equus Beds Aquifer Storage and Recovery (ASR) project, which diverted water from the Little Arkansas River watershed through bank storage (diversion) wells during high flows. In 2007, approximately 1.3 million m^3 (350 million gal) of water was injected into the Equus Beds aquifer. However, for every 3,800 m^3 (1 million gal) of water injected, an average of 6.4 Mg (7 tons) of sediment needed to be removed prior to injection (Steele, 2006), representing a substantial treatment expense. Steele (2006) conducted a water quality monitoring study and concluded that the Black Kettle Creek subwatershed of the Little Arkansas River watershed delivered the greatest sediment yields compared with other subwatersheds. This led to initiation of a project with the goal of reducing sediment yields from Black Kettle Creek watershed by cost-sharing implementation of targeted conservation practices in agricultural fields with the greatest soil erosion potential.

Black Kettle Creek watershed is a 7,818 ha (19,295 acres) subwatershed of the Little Arkansas River watershed (360,000 ha) located within McPherson and Harvey counties in south-central Kansas (fig. 2). Primary land uses in the watershed are cropland (84% of total area) followed by rangeland (12%), urban area (2%), and forests (2%). The cropland is predominantly wheat, followed by sorghum, soybeans and corn. The major pollutant concerns in this watershed are sediment and phosphorus (Steele, 2006).

Methods

The Soil and Water Assessment Tool (SWAT), a widely used, watershed-scale, process-based model developed by the USDA Agricultural Research Service (ARS) (Arnold et al., 1998; Neitsch et al., 2005; Gassman et al., 2007; Douglas-Mankin et al., 2010), was used to identify and target the specific fields with the greatest soil erosion potential.

SWAT Input Data

Watershed and subwatershed boundaries were delineated with U.S. Geological Survey 10 m × 10 m DEM (USGS, 1999) or 30 m × 30 m DEM (USGS, 1999) depending on the modeling scenario. Watershed and subwatershed boundaries for all model runs were set using a minimum stream-definition area of 500 ha, which defined nine subbasins with the 10 m DEM and seven subbasins with the 30 m DEM. Slope categories of 0% to 2%, 2% to 4%, and >4% were used for all the modeling scenarios to capture low, medium, and high slopes in the watershed (fig. 3). Relative to the 10 m DEM, the 30 m DEM overestimated the watershed area in the 0% to 2% slope class by 2.1% but underestimated the area in the 2% to 4% class by 1.9% and underestimated the area in the >4% class by 49.8%, although the total area in the >4% class was less than 5% of the watershed area in both DEM cases (table 1).

Soil data were derived from either the Soil Survey Geographic (SSURGO) database (USDA-NRCS, 2005) or the State Soil Geographic (STATSGO) database (USDA-NRCS, 1994) depending on the modeling scenario (fig. 4). The SSURGO soil layer was prepared using a SSURGO process–

Table 1. Characteristics of 10 m and 30 m DEM data for Black Kettle Creek watershed.

Slope Category (%)	10 m DEM Area (ha)	10 m DEM Mean Slope (%)	10 m DEM Overall Slope (%)	30 m DEM Area (ha)	30 m DEM Mean Slope (%)	30 m DEM Overall Slope (%)
>4	281	5.17		141	4.89	
2-4	1027	2.7	2.58	1007	2.6	2.18
0-2	6487	0.96		6620	0.97	

Table 2. Characteristics of SSURGO and STATSGO soil data for Black Kettle Creek watershed.

Parameter		Area (ha) SSURGO	Area (ha) STATSGO
Hydrologic soil group	A	2.8	0
	B	841.5	0
	C	4778.1	5265.3
	D	2186.4	2504.4
ULSE K	0.37	6965.8	7796.4
	0.32	768.8	0
	0.28	50.1	0
	0.20	22.2	0
	0.01	2.8	0

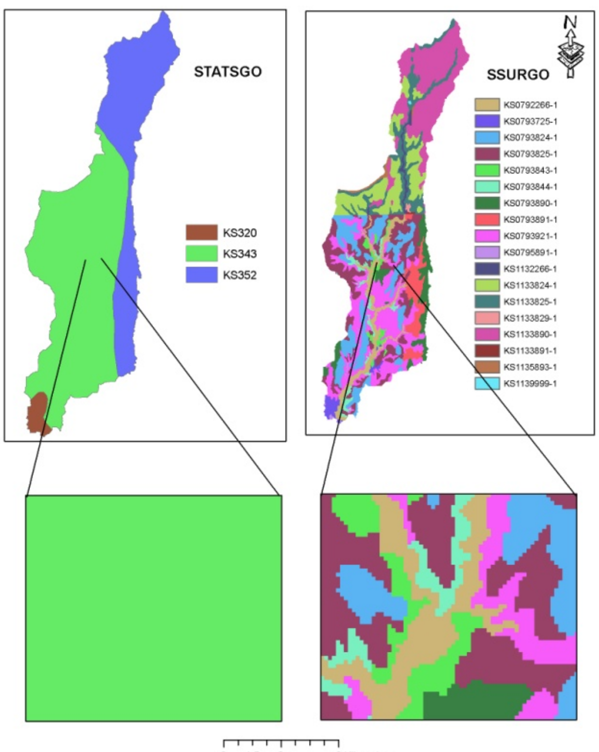

Figure 4. Soil classifications (SSURGO and STATSGO) for Black Kettle Creek watershed.

ing tool (Sheshukov et al., 2009) that converted the SSURGO data to a format compatible with ArcSWAT. The soil series in the SSURGO database for the Black Kettle Creek watershed included a broader range of hydrologic soil groups and USLE K values than the soil associations in the STATSGO database. The STATSGO soil data overestimated the watershed areas in the higher-runoff hydrologic soil groups (C and D) and in the highest erosivity class (K of 0.37) relative to the SSURGO data (table 2).

The LULC data were derived from the 2001 National Land Cover Dataset (Homer et al., 2004), the USDA National Agricultural Statistical Service (USDA-NASS, 2008), or from field reconnaissance survey data depending on the modeling scenario (fig. 5). The NLCD land cover was compiled for all 50 states utilizing Landsat 5 and Landsat 7 imagery centered on a nominal collection year of 2001 (Yang, 2008). The NASS land cover was produced for each state utilizing the Thematic Mapper (TM) instrument on Landsat 5, Landsat 7 ETM gap-filled data, and Indian Remote Sensing (IRS) Advanced Wide Field Sensor (AWiFS) on Resourcesat-1. The NASS land cover was developed based on satellite imagery taken during mid-July of each year (Mueller and Seffrin, 2006). The NASS land cover data are assessed mostly for agricultural areas, and NLCD land cover data are suggested for use in non-agricultural areas (www.nass.usda.gov/research/Cropland/metadata/metadata_ks08.htm). The metadata of the NASS land cover (USDA-NASS, 2008) used in this study reported classification errors (omission and commission errors) of 9.68% and 12.52% for sorghum, 8.74% and 6.93% for soybeans, and 4.48% and 4.48% for winter wheat. The NLCD land cover data distinguished 21 different data classes, while the NASS land cover data distinguished 84 classes; however, the non-agricultural classes (e.g., rangeland, pasture, woody wetlands) in the NASS land cover data are derived from the NLCD land cover data.

In the case of field reconnaissance survey data, the field data were developed using the common land use unit (CLU) field boundary shapefile, obtained from the USDA Natural Resource Conservation Service online geospatial data gateway (USDA-NRCS, 2004). Each field's land cover was manually edited based on a field-by-field reconnaissance survey conducted by the authors in November 2008 and October 2009. The difference in the total cropland area in the NLCD land use layer and the field layer was minimal, which indicates that there was not much of a temporal difference of cropland from 2001 to 2009 in this watershed (table 3). However, the three LULC data sources produced different estimates of total area in each land use category (table 3) as well as spatial location of land uses (fig. 5). For example, figure 5 shows that a field identified as grain sorghum (GRSG) by the field reconnaissance was identified largely as rangeland (RNGE) by NASS and general agriculture (AGRL) by NLCD. Similar disagreement was observed at numerous locations in the study watershed. As a result, over the watershed as a whole, NASS underestimated cropland by 1076 ha relative to field reconnaissance and overestimated rangeland by a similar area (1109 ha) (table 3).

SWAT parameters ALPHA_BF, EPCO, and ESCO were adjusted from the default SWAT parameters for all the scenarios in this study. ALPHA_BF was set to 0.028 based on the baseflow filter program (Arnold and Allen, 1999; Nathan and McMahon, 1990), while EPCO of 0.8 and ESCO of 0.2 were used based on experience in a nearby watershed (Gali, 2010).

Representation of Hydrologcial Response Units (HRUs)

HRUs in SWAT do not have spatial reference. However, this limitation was overcome by redefining the topographic, soil, and land use thresholds to 0%, which retained all combinations of topography, soil, and land use in the model output and allowed reconnection of HRU output back to its original position in the landscape (Gitau et al., 2006). Anoth–

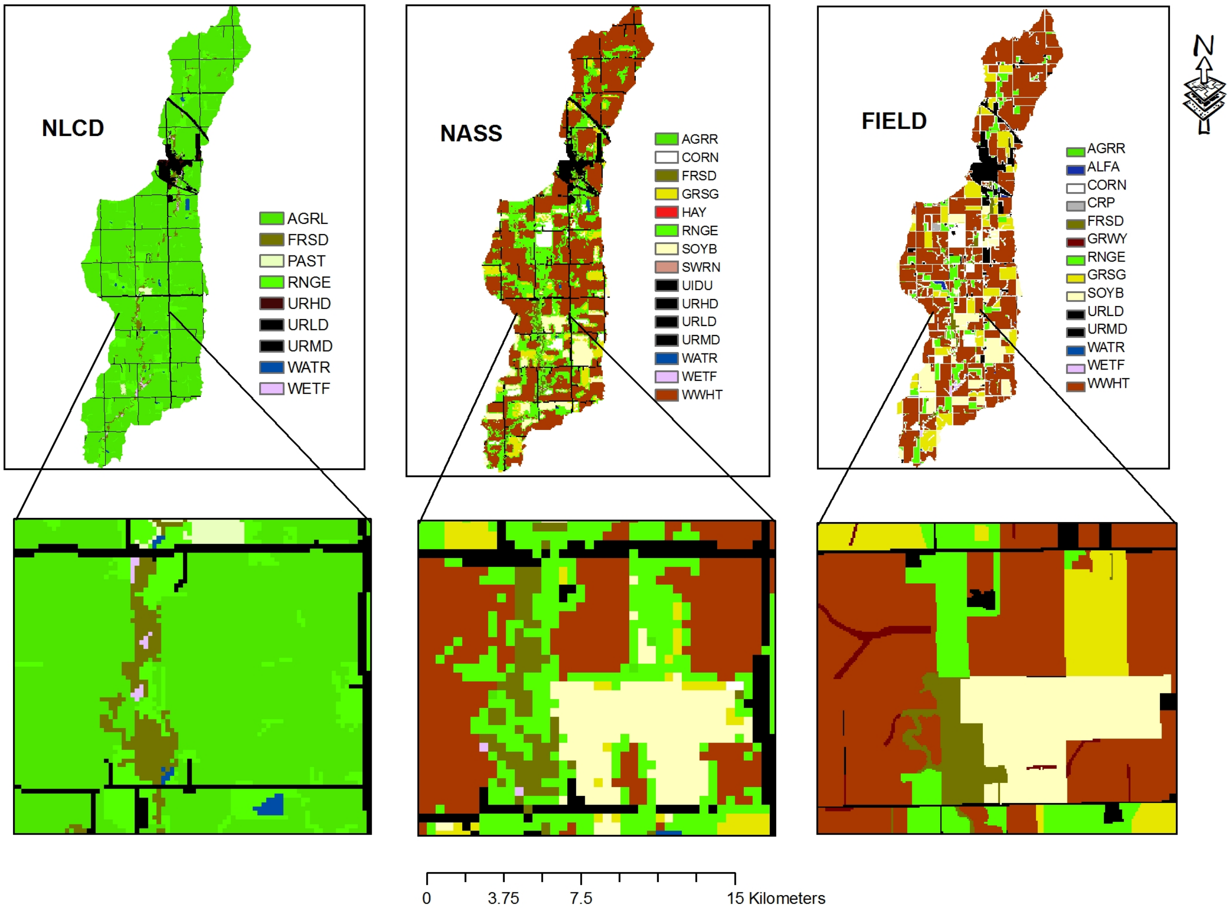

Figure 5. Land use/land cover classifications (field reconnaissance, NASS, and NLCD) for Black Kettle Creek watershed.

Table 3. Characteristics of field reconnaissance, NASS, and NLCD land use/land cover data for Black Kettle Creek watershed.

Land Use Category	SWAT Abbreviation	Land Use Data Source: Field (ha)	NASS (ha)	NLCD (ha)
Winter wheat	WWHT	4529	3917	0
Soybean	SOYB	609	518	0
Grain sorghum	GSRG	801	424	0
Corn	CORN	210	197	0
General agriculture	AGRL, AGRR	1	18	6060
Sum of cropland	--	6149	5073	6060
Rangeland	RNGE	685	1794	912
Forest	FRSD	156	166	157
Forested wetlands	WETF	26	10	30
CRP	CRPP[a]	25	0	0
Alfalfa	ALFA	23	0	0
Grassed waterway	GRWY[a]	72	0	0
Urban	URLD, URMD, URHD	658	733	604
Water	WATR	2	18	30

[a] Created crop parameters in land cover/plant growth database.

Table 4. Source data used for each modeled scenario.

Scenario	No. of HRUs	No. of Sub-basins	Source Data Designations: Soils[a]	Topo-graphy[b]	Land Use[c]	Land Mgmt.[d]	Tillage Mgmt.[e]
0	1456	9	S	10	F	T	R
1	1112	7	S	30	F	T	R
2	1169	9	S	10	F	N	C
3	1133	9	S	10	A	N	C
4	800	9	S	10	L	N	C
5	319	9	O	10	F	N	C
6	344	9	O	10	A	N	C
7	216	9	O	10	L	N	C
8	1338	9	S	10	F	T	C
9	1292	9	S	10	F	N	R

[a] S = SSURGO, and O = STATSGO.
[b] 10 = 10 m DEM, and 30 = 30 m DEM.
[c] F = field reconnaissance of land uses/crop types, A = NASS-2008, and L = NLCD-2001.
[d] T = digitized satellite image of terraced areas, and N = assume no terraces.
[e] R = field reconnaissance of no-till or high-residue fields, contour farming, and C = assume conventional tillage only.

er method was used by Ghebremichael et al. (2010), who defined HRUs according to field boundaries to maintain the spatial location of crop fields. In contrast to the Ghebremichael et al. (2010) approach, this study set the topographic, soil, and land use thresholds to 0% so that all slope, soil, and land use combinations in the watershed were captured and then post-processed HRU results to represent field-level results, as described below. A summary of input data sources used in each modeled scenario is presented in table 4. The number of HRUs varied from 1456 to 216 depending on the scenario (table 4).

Representation of Conservation Practices in SWAT

The fields with conservation practices (e.g., terraces, contour farming, no-till) were identified from either the field reconnaissance survey or analysis of the digital ortho imagery (KGS, 2002; USDA-NRCS, 2004). Combinations of land cover, conservation structures, and tillage practices (e.g., wheat crop with terraces and conventional tillage) were created in the SWAT database by copying the data from its original land cover (e.g., wheat) and assigning a new land cover name (e.g., wheat with terrace) and crop code (CPNM) (e.g., TWHT). The terrace structural practice (12% of cropland area), assumed to be coupled with contour farming, was simulated by reducing the curve number (CN) by six units (USDA-SCS, 1972; Neitsch et al., 2005; Arabi et al., 2008) and reducing USLE practice factor values to 0.1 (Wischmeier and Smith, 1978; Arabi et al., 2008). The contour farming practice alone (0.02% of cropland area) was simulated by reducing the CN by five units and reducing USLE practice factor values to 0.5 (Arabi et al., 2008). The no-tillage or residue management practice (5% of cropland area; no overlap with terrace practice fields) was simulated by reducing the CN by two units (Arabi et al., 2008) and increasing Manning's roughness coefficient for overland flow (OV_N) to 0.14 for no residue, to 0.20 for 0.5 to 1.0 Mg ha^{-1} residue, and to 0.30 for 2 to 9 Mg ha^{-1} residue (Neitsch et al., 2005; Arabi et al., 2008). Arabi et al. (2008) used a procedure that adjusted the USLE practice factor (USLE_P) and minimum USLE cover factor (USLE_C0) to incorporate the impact of residue biomass on erosion and transport of nutrients from upland areas because the current version of SWAT does not incorporate the impact of residue biomass on erosion. The residue biomass left on the surface in all no-till fields was assumed to be 500 kg ha^{-1} (Arabi et al., 2008), based on experience by the authors in the study watershed.

The baseline scenario (scenario 0, table 4) represented the best resolution and most accurate data available from each source: HRU slopes from 10 m × 10 m DEM data, soil distribution and characteristics from the SSURGO database, land use and crop types from the field reconnaissance data, structural land management (terrace) locations by the digital ortho imagery, and tillage management practices (no-till, contour farming) from the field reconnaissance data. Other scenarios were developed by varying the input data source, as shown in table 4, and comparing the output results.

Daily precipitation data for the watershed were obtained from the Hesston weather station (Harvey County) located about 10 km northeast of the watershed and the Goessel weather station (McPherson County) located about 15 km east of the watershed. Temperature, solar radiation, wind speed, and relative humidity data were obtained from the Newton (Harvey County) weather station located about 25 km south of the watershed. Missing data were adjusted by using SWAT's weather generator. Each SWAT scenario was simulated for the period from 1992 to 2009 (18 years). Annual average precipitation and temperature over the study period were 795 mm (31.2 in.) and 13.9°C (57°F). Data from 2006 to 2009 were used for model validation, and data from 1995 to 2006 (12 years) were used for all field targeting analyses. The HRU, Subbasin, and Reach outputs files were exported and written as tables in the Access database (SWATOutput.mdb).

Model Validation

Modeled streamflow for the baseline condition and selected scenarios was evaluated using measured flow data collected from 1 January 2006 to 31 July 2009 at the outlet of Black Kettle Creek watershed. Stream stage was recorded at 15 min intervals using an automated stage recorder (6700 water sampler, 730 bubbler flow module, Isco, Inc., Lincoln, Neb.) and 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).

The statistical parameters used to evaluate the relationship between the observed and simulated streamflow were coefficient of determination (R^2), Nash-Sutcliffe model efficiency (NSE) (Nash and Sutcliffe, 1970), and percent bias (PBIAS), as recommended by Moriasi et al. (2007). The R^2 value indicates the consistency with which measured versus predicted values follow a best fit line, with 1.0 being optimal (Santhi et al., 2001). The NSE has been widely used to evaluate the performance of hydrologic models (Wilcox et al., 1990; Mankin et al., 2002; Gassman et al., 2007; Parajuli et al., 2009; Douglas-Mankin et al., 2010). The NSE value can range from 1 to $-\infty$, where a value of 1 indicates perfect model fit. PBIAS measures the average tendency of the simulated data to be larger or smaller than their observed counterparts. The optimal value of PBIAS is 0.0%, with positive values indicating model underestimation bias and negative values indicating model overestimation bias (Gupta et al., 1999).

For the baseline (scenario 0), the model agreement with observed flow data was satisfactory to good for monthly statistics of R^2 (0.75), NSE (0.66), and PBIAS (-18.1%) (table 5) using performance ratings proposed by Moriasi et al. (2007). The annual average observed and simulated flows were also in good agreement. For the other selected scenarios, the model agreement with monthly observed flow data was satisfactory based on NSE (0.50 to 0.65) but more variable based on PBIAS (very good for two scenarios $<\pm 10\%$, good for one scenario $<\pm 15\%$, satisfactory for one scenario $<\pm 25\%$, and unsatisfactory for two scenarios) depending on

Table 5. Monthly model validation statistics for selected scenarios.

Scenario[a]	R^2	NSE	PBIAS (%)	Annual Avg. Flow ($m^3 s^{-1}$)
Observed	--	--	--	0.29
0	0.75	0.66	-18.1	0.30
2	0.68	0.64	-6.9	0.31
3	0.55	0.48	-12.4	0.34
4	0.59	0.52	-3.0	0.31
5	0.62	0.60	-24.6	0.36
6	0.53	0.45	-31.8	0.38
7	0.56	0.48	-26.1	0.39

[a] 0 = S10FTR, 1 = S30FTR, 2 = S10FNC, 3 = S10ANC, 4 = S10LNC, 5 = O10FNC, 6 = O10ANC, 7 = O10LNC, 8 = S10FTC, 9 = S10FNR, where S = SSURGO, O = STATSGO, 10 = 10 m DEM, 30 = 30 m DEM, F = field reconnaissance of land uses/crop types, A = NASS-2008, L = NLCD-2001, T = digitized satellite image of terraced areas, N = assume no terraces, R = field reconnaissance of no-till or high residue fields, and C = assume conventional tillage only.

the modeling scenario (table 5). The annual average observed and simulated flows for other scenarios were in close agreement. Further detailed calibration was not done in this study to avoid site-specific empiricism and bias of parameters, as the goal of this study was to compare different scenarios with different data sources.

Stream sediment data were not available for calibration. Model results were validated using published measurements of sediment yields from small cropland drainage areas in Kansas (Holland, 1971). According to Holland, cropland areas in the Black Kettle Creek watershed area had sediment yields ranging from 2.78 to 5.86 Mg ha^{-1} year^{-1} (1.24 to 2.48 ton acre^{-1} year^{-1}). Before 1971, typical cropland areas in this region had minimal implementation of conservation practices and few terraces. Modeling results for the top 25 fields, also with no conservation practices or terraces, ranged from 2.83 to 5.50 Mg ha^{-1} year^{-1} (1.26 to 2.45 ton acre^{-1} year^{-1}), in good agreement with measured sediment yields. Further sediment calibration was not considered to be warranted for this study.

Tool to Map HRU Output to Field Boundaries

To identify specific fields for targeting, the SWAT HRU output had to be mapped to the actual field boundaries. Converting SWAT HRU output to field-level results and identifying the fields that produced the greatest sediment yields involved several steps after running SWAT: (1) calculate average annual sediment for HRUs from SWATOutput tables, (2) join to FullHRU shapefile, (3) process FullHRU shapefile, (4) convert FullHRU shapefile to Grid, and (5) use zonal statistics to get pollutant yields for each field. These steps are time consuming and labor intensive. Therefore, an ArcGIS-based SWAT Targeting Toolbar (fig. 6) was developed with

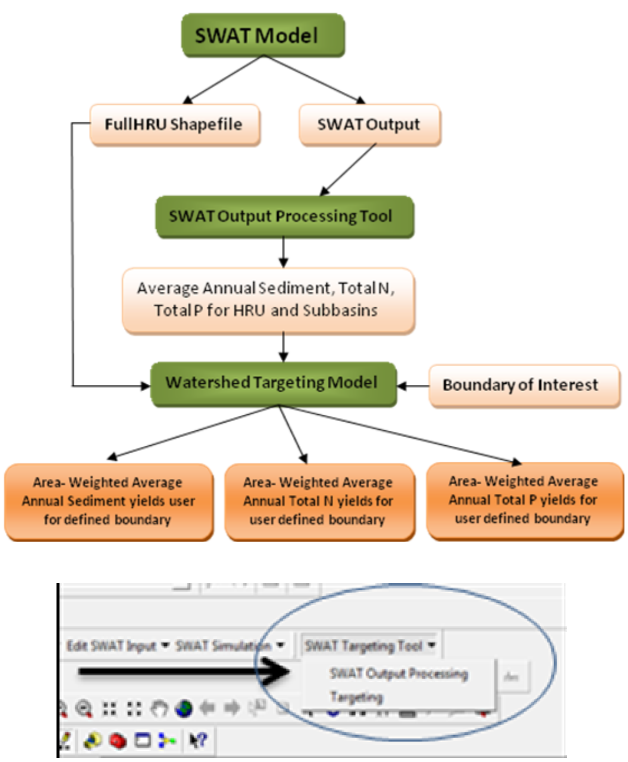

Figure 6. Overview of SWAT targeting toolbar.

ArcGIS-Visual Basic to post-process the SWAT output and prepare maps of sediment, total phosphorus, and total nitrogen yields for a user-defined land-area boundary. The toolbar was divided into two menu items: the SWAT Output Processing tool, and the Watershed Targeting tool.

The SWAT Output Processing menu opened the Excel spreadsheet-based SWAT Output Processing tool. This tool read the SWAT output tables that were stored in an Access database (SWATOutput.mdb) and exported average annual sediment, total nitrogen, and total phosphorus yields for HRUs and subbasins.

The Targeting menu opened the Watershed Targeting tool that was built with Model Builder in the ArcGIS environment. This tool needed output from the SWAT Output Processing tool, FullHRU shapefile (generated in SWAT model run), and boundary of interest (e.g., fields, subbasins, counties). Once the inputs were satisfied, the tool produced maps of area-weighted average annual pollutant yields (sediment, total phosphorus, and total nitrogen yields) for the user-defined boundary. In this study, the CLU field boundary shapefile was used. Because this project involved identifying and targeting the fields producing the greatest sediment yields, we used only the sediment-yield analyses in this study. Using these tools and procedures, area-weighted average annual sediment yields were developed for each field for each scenario.

Data Resolution Assessment

The area within each CLU field boundary was calculated using GIS. A substantial number of small parcels in the CLU field boundary represented windbreaks, field borders, grassed waterways, and other small (<1 acre) areas that were less than a typical farm field-management unit. Since the focus of this study was on field-level targeting, these sub-field units were not relevant. Therefore, a threshold of 0.4 ha (1 acre) was applied, which reduced the number of field parcels included in analyses for this study from 677 to 593.

For each modeling scenario, field-scale sediment-yield density (Mg ha^{-1}) for each of 593 fields in the watershed was ranked from high to low. We used four subsets of fields in this ranking for comparison: the top 10% of fields (60 fields), top 20% of fields (118 fields), fields that summed to equal the top 10% of total field sediment yields (Mg), and fields that summed to equal the top 20% of sediment yields. The number of fields that contributed to the top 10% or 20% of sediment yields varied by scenario. These methods were referred to as the top 10% of fields, 20% of fields, 10% of yields, and 20% of yields, respectively. The ranking thresholds selected in this study were chosen for two reasons. First, project funding was available to pay for management practices on about 10% to 20% of the watershed's land area. Second, previous studies (Parajuli et al., 2008; Tuppad et al., 2010) have shown that the benefit of targeting (relative to random placement) diminishes substantially after practices have been implemented on the "most critical" ~20% of land area.

The individual fields identified as in the top percentage of fields and top percentage of yields were compared among modeling scenarios. Scenario 0, or S10FTR (abbreviations described in table 4), was considered to be the baseline scenario because SSURGO soils data, 10 m DEM, field-by-field land use reconnaissance assessment, and inclusion of terraces and no-till practices were considered to constitute the available input data that best represented actual conditions of the watershed. Comparisons were conducted by spatially overlapping two different scenarios in the GIS framework. For example, the shapefile of scenario 1 was overlapped with the shapefile of scenario 0 to obtain a new shapefile that showed fields that were in agreement between both scenarios.

The goal in this study was to identify the specific fields that should be targeted for conservation practice implementation and cost-share funding. If a given scenario produced a ranked list with the same fields as the comparison scenario, it was considered to be in agreement. Agreement between each pair of scenarios was assessed by reporting the percentage of fields that appeared in corresponding ranked subsets for both scenarios as a percentage of the number of fields in the scenario that best represented actual conditions (as stated above).

Results and Discussion

Impact of Data Source on Characteristics of Top-Ranked Fields

Source of soil, slope, land use, and land management data impacted the field-scale sediment yields simulated by SWAT, and these changes were not uniform across fields in the study watershed. In many cases, the ranking of field-scale sediment-yield densities (Mg ha^{-1}) changed as a result.

Characteristics of the ten fields with the greatest field-scale sediment-yield density for each scenario are summarized in table 6. Modeled HRUs within a field that were not identified as cropland were labeled “noise.” Even scenarios based on field reconnaissance LULC data (scenarios 0, 1, 2, 5, 8, and 9) had 1.1% to 3.0% of field area incorrectly modeled as non-cropland (“noise”) area. The source of this noise was in the conversion of the field reconnaissance data shapefile (based on CLU field boundaries) into raster format during input to SWAT. Greater noise was observed in fields using NLCD LULC data (scenario 4 with 7.2%; scenario 7 with 7.3%) and NASS LULC data (scenario 3 with 22.3%; scenario 6 with 28.6%). The NLCD and NASS data are already in raster form when input to SWAT, so noise from these data are directly caused by inaccurate land use assignment. The NASS data included more detailed categories of LULC than NLCD (table 2) but more often incorrectly identified cropland as rangeland, which was the primary factor in causing 3 to 4 times more field area to be misclassified as cropland for NASS than NLCD on the top sediment-yielding fields (table 6).

Use of STATSGO data (scenarios 5, 6, and 7) forced all soils to have a K factor of 0.37 (table 2), so obviously the same shift was observed in the top ten fields (table 6). Similarly, STATSGO data only contained hydrologic soil groups C and D (table 2), so these soil groups also would be expected to be more heavily represented in STATSGO scenarios. As a result, hydrologic soil groups for the top ten fields consistently shifted toward greater percentage of group C soils for the STATSGO scenarios (5, 6, and 7), with 90% or more of the targeted fields having group C soils compared to 80% in scenario 0 and 61% in the overall watershed (table 2).

Compared to corresponding scenarios based on field LULC data (scenario 0) (table 6), use of NLCD LULC data (scenario 4) had little influence on the percentage of field area having a given K factor (e.g., area with K = 0.37 changed from 85% to 84%), a small reduction in field area having hydrologic soil groups C and D (e.g., area with group D changed from 5% to 0%), and a large increase in the field area with 2% to 4% and >4% slope classes (e.g., area with slope >4% changed from 9% to 37%). The NLCD data resulted in 29% (scenario 7: STATSGO) and 37% (scenario 4: SSURGO) of the area of the top ten fields falling within the >4% slope class, compared to 3.6% of the total watershed (table 3, 10 m DEM), which was much greater than any other scenario (table 6). We conclude that the net result of the use of NLCD data was the increasing importance of non-land-use factors for field selection.

Use of NASS LULC data (scenario 3) had almost the opposite effect of NLCD data (scenario 4). These data increased the K factor to 0.37 for almost all targeted field areas, shifted about 5% of both B and C group soils to hydrologic soil group D, and decreased the field areas with >4% slope classes compared to corresponding scenarios based on field LULC data (scenario 0) (table 6). From a process perspective, the impact of the incorrect classifications of cropland as pasture decreased the influence of LULC on the highest ranked sediment-yielding fields and led to greater influence of soil factors (greater area of high K factor and hydrologic soil

Table 6. Average characteristics for top 10 sediment-yielding fields from each scenario. HRUs within a field that were not identified as cropland were labeled “noise.”

Scenario[a]	Avg. No. of HRUs per field	Total Ten-Field Area (m^2)	Noise Area (m^2)	Noise (%)	Average Slope (%)	Slope[b] (%)			Hydrologic Soil Group[b]			USLE K Factor[b]	
						0-2	2-4	4-10	B	C	D	0.32	0.37
0	13	236,116	2,652	1.1	2.5	66	25	9	15	80	5	15	85
1	11	117,009	3,542	3.0	2.2	65	30	4	17	78	6	15	85
2	17	101,172	1,735	1.7	2.5	58	35	7	19	72	9	15	85
3	15	175,215	39,076	22.3	2.4	75	24	2	11	75	14	1	99
4	12	47,711	3,455	7.2	3.0	23	43	37	24	76	0	16	84
5	12	134,224	2,326	1.7	2.7	48	38	14	0	90	10	0	100
6	12	202,800	57,932	28.6	2.4	69	28	3	0	97	3	0	100
7	8	66,337	4,825	7.3	3.2	26	45	29	0	100	0	0	100
8	16	123,559	2,167	1.8	2.3	89	33	5	15	45	40	15	85
9	18	181,652	3,308	1.8	2.7	55	38	7	25	52	24	25	76

[a] 0 = S10FTR, 1 = S30FTR, 2 = S10FNC, 3 = S10ANC, 4 = S10LNC, 5 = O10FNC, 6 = O10ANC, 7 = O10LNC, 8 = S10FTC, and 9 = S10FNR, where S = SSURGO, O = STATSGO, 10 = 10 m DEM, 30 = 30 m DEM, F = field reconnaissance of land uses/crop types, A = NASS-2008, L = NLCD-2001, T = digitized satellite image of terraced areas, N = assume no terraces, R = field reconnaissance of no-till or high residue fields, and C = assume conventional tillage only.

[b] Percent of total ten-field area in slope, hydrologic soil group, or K-factor category for a given scenario.

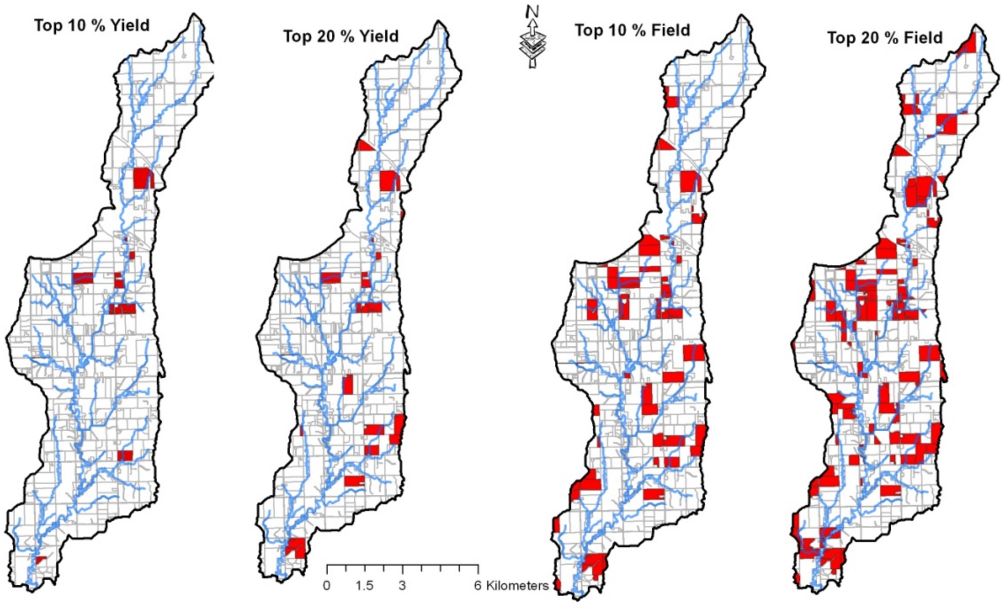

Figure 7. Top 10% and 20% of watershed fields and sediment yield for the baseline scenario 0.

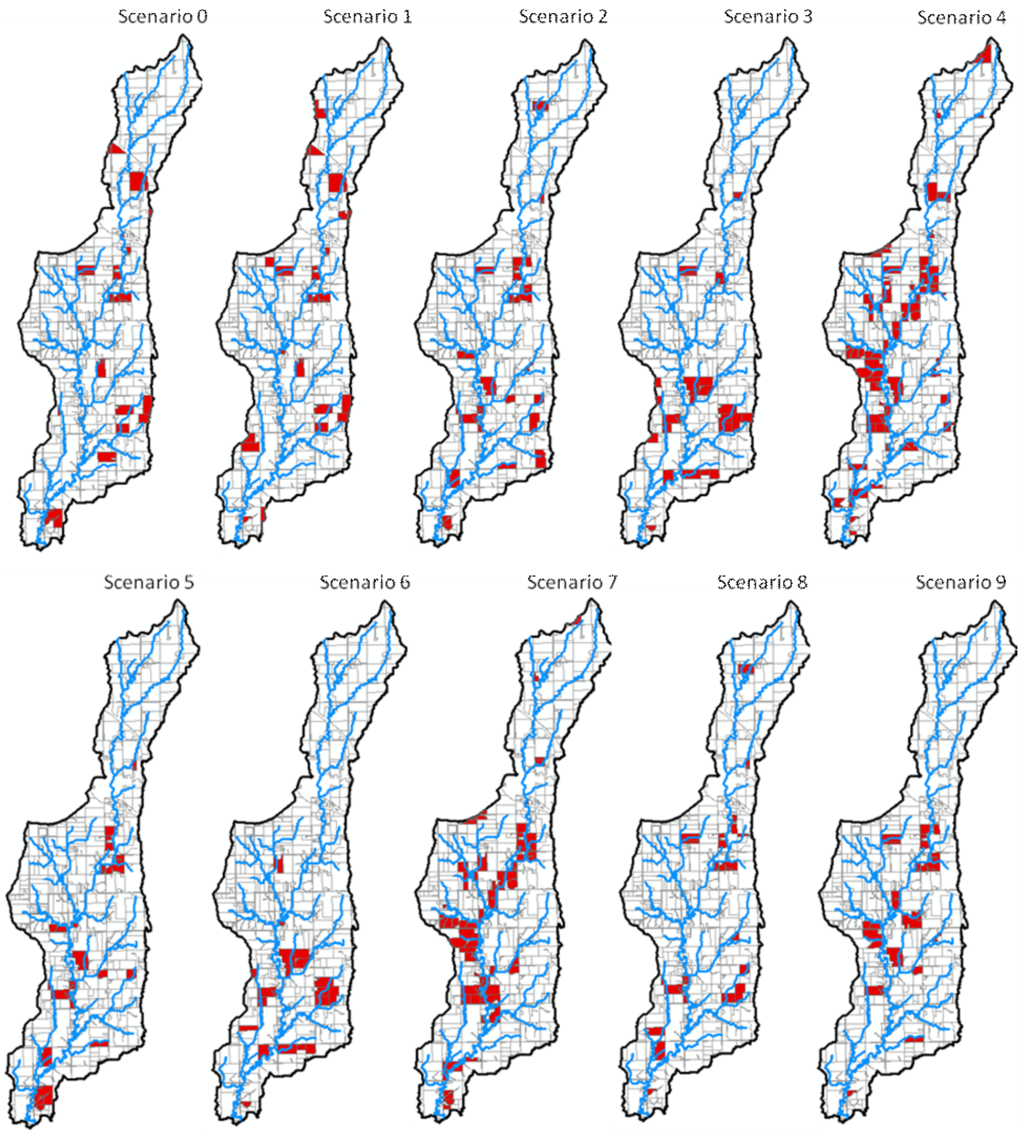

Figure 8. Fields identified as contributing to the top 20% of watershed sediment yields for the scenarios 0 through 9.

Table 7. Number, percentage of watershed area, and percentage of sediment yields of fields included in each ranking method for each modeled scenario.

	Scenario[a]	Ranking Method[b] 10%Y	20%Y	10%F	20%F
Number of fields	0	14	25	60	118
	1	16	26	60	118
	2	17	29	60	118
	3	11	25	60	118
	4 (AGRR)	45	82	60	118
	4 (WWHT)	46	81	60	118
	5	15	27	60	118
	6	10	20	60	118
	7 (AGRR)	37	75	60	118
	7 (WWHT)	39	79	60	118
	8	15	27	60	118
	9	12	22	60	118
Area (% of watershed)	0	2.5	5.4	12.3	20.0
	1	3.1	5.8	12.4	22.0
	2	2.6	6.0	13.5	23.6
	3	2.6	6.4	13.6	25.7
	4 (AGRR)	5.2	11.9	7.2	19.8
	4 (WWHT)	5.2	11.9	8.2	18.3
	5	2.2	4.9	13.2	23.4
	6	2.6	5.5	14.5	24.9
	7 (AGRR)	4.2	10.0	7.2	17.6
	7 (WWHT)	4.4	10.7	7.1	16.9
	8	2.0	4.7	12.5	21.0
	9	3.0	5.2	14.8	23.5
Sediment yield (% of total)	0	10	20	40.5	50.0
	1	10	20	38.4	52.4
	2	10	20	38.9	58.0
	3	10	20	33.7	48.2
	4 (AGRR)	10	20	13.3	31.3
	4 (WWHT)	10	20	13.7	28.5
	5	10	20	42.0	61.9
	6	10	20	39.1	52.9
	7 (AGRR)	10	20	15.2	30.0
	7 (WWHT)	10	20	15.6	31.2
	8	10	20	42.0	56.5
	9	10	20	41.5	57.9

[a] 0 = S10FTR, 1 = S30FTR, 2 = S10FNC, 3 = S10ANC, 4 = S10LNC, 5 = O10FNC, 6 = O10ANC, 7 = O10LNC, 8 = S10FTC, 9 = S10FNR, where S = SSURGO, O = STATSGO, 10 = 10 m DEM, 30 = 30 m DEM, F = field reconnaissance of land uses/crop types, A = NASS-2008, L = NLCD-2001, T = digitized satellite image of terraced areas, N = assume no terraces, R = field reconnaissance of no-till or high-residue fields, and C = assume conventional tillage only; AGRR = general row crop for all cropland, and WWHT = winter wheat for all cropland.

[b] 10%Y (20%Y) = fields with top 10% (20%) of watershed sediment yield (Mg) ranked by field sediment-yield density (Mg ha-1), and 10%F (20%F) = top 10% (20%) of fields ranked by field sediment-yield density.

group D) on the ranking. For example, the top ten sediment-yielding fields in scenario 0, none of which contained pasture, were found to average 30.7% pasture area (range of 25 to 36%) based on NASS data used in scenario 3. By comparison, the top ten sediment-yielding fields in scenario 3, again based on NASS data, averaged 12.5% pasture area, but ranged from 0% to 31%. The reduced percentage of cropland area in scenario 3 fields led to the greater importance of soil factors in contributing to simulated sediment yield in the top-ranked fields.

Impact of Data Source on Field Sediment-Yield Rank

Output maps showing the top 10% and 20% of fields and the top 10% and 20% of yields were prepared with GIS for all modeling scenarios. Examples in figure 7 show maps of the top 10% and 20% of fields and yields for scenario 0 (baseline). The number of fields, percentage of total area, and spatial location of fields in the watershed varied between scenarios and methods (by field and by yield) (table 7). Depending upon the data source scenario, different fields were identified as the greatest sediment yielders, as demonstrated in figure 8 for the top 20% of sediment yields for all scenarios.

Depending upon the scenario, the top 10% of ranked fields (10%F; 60 fields) represented 7.2% to 14.8% of the total watershed area, and the top 20% of fields (20%F; 118 fields) represented 17.6% to 25.7% of the total watershed area (table 7). Comparing the different scenarios for the same number of fields revealed that more area was accumulated for the top 60 or 118 fields when the highest-ranked fields were larger, as would be expected.

The number of fields required to accumulate a given threshold of the total sediment yield for all fields in the watershed varied by scenario (table 7). The top 10% of sediment yield (10%Y) was simulated to come from as few as ten fields (scenario 6, O10ANC) and as many as 45 fields (scenario 4, S10LNC) and from as little as 2.0% of the watershed area (scenario 8, S10FTC) to as much as 5.2% (scenario 4). Estimates for the top 20% of yields ranged from 20 fields (scenario 6) to 82 fields (scenario 4) and from 4.7% of the watershed area (scenario 8) to 11.9% (scenario 4). The percentage of total watershed sediment yield from the top-ranked fields also varied among scenarios (table 7). For example, the top 10% of sediment-yielding fields generated as little as 13.3% (scenario 4, S10LNC) to as much as 42.0% (scenario 5, O10FNC; and scenario 8, S10FTC) of the total field-scale sediment yield in the watershed.

The two scenarios using the NLCD LULC data (scenarios 4 and 7) required more fields to accumulate the 10% and 20% yield thresholds and accumulated a smaller percentage of the watershed area in the top 10% and 20% of fields compared to other scenarios (table 7). The NLCD coverage assigned all cropland to a single land use category, in this case general agriculture (AGRR; table 3), which assigned parameters according to a typical summer crop (Neitsch et al., 2005). This forced the NLCD scenarios (4 and 7) to model the fields that actually grew winter wheat (WWHT) as AGRR, which has a greater USLE C_{min} factor (0.2 for AGRR vs. 0.02 for WWHT) and a different crop phenological cycle (summer vs. winter growing season). In this watershed, winter wheat fields were smaller (mean area 13 ha) than other crop fields (mean area 20 ha). Even though winter wheat land would have been expected to have less contribution to erosion than summer cropland, the small winter wheat fields were modeled to have a greater C_{min} factor and thus greater sediment yields. Greater inclusion of these fields increased the number of smaller fields included in the top-ranked sediment-yielding fields.

To test the impact of the default crop assignment by NLCD, we ran additional scenarios identical to scenarios 4 and 7 except that all NLCD cropland was assigned parameters consistent with WWHT. The number of fields in each ranking method changed only minimally (table 7), and the specific fields identified between the two methods were largely in agreement (e.g., 78% agreement in fields identified in the top 20% of sediment yields).

The results summarized in table 7 demonstrate a fairly consistent relationship among the top-ranked fields (with the greatest sediment-yield densities) between the number of fields and the percentage of watershed area covered by those fields. For the top 118 sediment-yielding fields analyzed in this study (table 7), the relationship was linear, with a slope (expressed as fields per percentage of total watershed area) ranging from 4.6 to 6.9 and averaging 5.6 fields per percentage for eight of the ten scenarios. For model results using the NLCD data, however, slopes were much greater for both scenario 4 (9.3 fields per percentage) and scenario 7 (10.4 fields per percentage), because of the greater inclusion of WWHT fields, as discussed above. This indicates that all data sources, except NLCD, were fairly consistent in describing the relative distribution of sediment yields within the watershed.

The spatial distribution of top sediment-yielding fields was variable among the scenarios (fig. 8). Targeted fields for the baseline (scenario 0) were distributed throughout the watershed. This suggests that a dispersed targeted approach (Diebel et al., 2008), in which fields are targeted by specific characteristics but may be dispersed throughout the watershed, would be most effective for targeting fields for BMP implementation. This is contrary to the conclusions of Diebel et al. (2008), who suggested greater efficiency from an aggregated targeted approach, in which fields are targeted by specific characteristics but may be aggregated only from within a specific subwatershed. Although the aggregated approach might lead to more dramatic, localized impact from a given BMP implementation effort, results of this study show that it would miss fields in other subwatersheds with greater sediment-yield reduction potential.

Impact of Data Source on Spatial Field Targeting

Some of the fields targeted by the baseline (scenario 0) also appeared in many of the other scenarios (fig. 8), but many did not. This study evaluated the importance of each data source in determining the spatial location of fields with the greatest sediment-yield densities by determining the percentage of agreement between paired scenarios in terms of fields above a given threshold ranked by sediment-yield density.

Topography

Varying DEM data resolution from 10 m (scenario 0, S10FTR) to 30 m (scenario 1, S30FTR) changed the top-ranked fields included in each analyzed subset (table 8). Agreement ranged from 76% (for 20%Y) to 93% (for 10%F). However, differences in identified fields were greater for the top 14 to 25 fields (79% to 76%) than for the top 60 to 118 fields (93% to 90%). The relative lack of agreement for the highest-ranked fields probably related to the relative underestimation of fields in the highest slope class (>4%), which have the greatest potential for erosion (table 1). Agreement between the 10 m and 30 m DEM scenarios was better than for other input data categories tested (table 7), indicating that 30 m resolution was adequate to capture the gently rolling topography of this watershed.

Soils

Changing the input soil dataset from SSURGO (scenarios 2, 3, or 4) to STATSGO (scenarios 5, 6, or 7) changed the top-ranked fields included in each analyzed subset (table 8).

Table 8. Targeting comparison: agreement of fields included in targeted lists between rankings by four methods. Paired scenario comparisons have different source data for only one category.

Test Category	Scenario[a] From	Scenario[a] To	Agreement in Ranked Fields (%)[b] 10% Y	20% Y	10% F	20% F
Topography	0 (10)	1 (30)	79	76	93	90
Soils	2 (S)	5 (O)	71	79	80	90
	3 (S)	6 (O)	89	72	82	85
	4 (S)	7 (O)	60	73	73	81
Land use	2 (F)	3 (A)	35	31	25	43
	2 (F)	4 (L, AGRR)	60	59	40	58
	2 (F)	4 (L, WWHT)	35	34	18	45
Crop type	4 (AGRR)	4 (WWHT)	72	78	72	82
Land management	0 (TR)	8 (TC)	36	48	66	76
	0 (TR)	9 (NR)	36	48	61	76
	0 (TR)	2 (NC)	29	32	48	68

[a] 0 = S10FTR, 1 = S30FTR, 2 = S10FNC, 3 = S10ANC, 4 = S10LNC, 5 = O10FNC, 6 = O10ANC, 7 = O10LNC, 8 = S10FTC, 9 = S10FNR, where S = SSURGO, O = STATSGO, 10 = 10 m DEM, 30 = 30 m DEM, F = field reconnaissance of land uses/crop types, A = NASS-2008, L = NLCD-2001, T = digitized satellite image of terraced areas, N = assume no terraces, R = field reconnaissance of no-till or high residue fields, and C = assume conventional tillage only; AGRR = general row crop for all cropland, WWHT = winter wheat for all cropland.

[b] 10%Y (20%Y) = fields with top 10% (20%) of watershed sediment yield (Mg) ranked by field sediment-yield density (Mg ha-1), and 10%F (20%F) = top 10% (20%) of fields ranked by field sediment-yield density.

Agreement in field selection ranged from 60% (NLCD for 10%Y) to 90% (field for 20%F). Agreement tended to increase as the number of fields and targeted area included in the subset being compared increased. Simulations using the NLCD source data generally resulted in less agreement than using NASS or field data because the greater uniformity of LULC for the NLCD data reduced the influence of non-soil-related factors and increased the influence of soil-related factors on the field rankings. This result implies an interactive effect between soils and LULC in ranking fields by sediment-yield density.

In some scenarios, there was slightly less agreement between results from different soil data sources than between results from different topographic data sources. Generally, however, the agreement was similar, ranging from about 75% to 90% within the top 20% of ranked fields.

Land Use

Changing land use data source from field (scenario 2, S10FNC) to NASS (scenario 3, S10ANC) or NLCD (scenario 4, S10LNC) had a major impact on field rankings (table 8). Agreement with field scenario 2 was similar for NASS scenario 3 (25% to 43%) and NLCD scenario 4-WWHT (18% to 45%), and both were lower than NLCD scenario 4-AGRR (40% to 60%). In the case of NASS, the lower agreement was influenced by fact that the NASS land cover data often classified parcels of rangeland in the middle of agricultural fields and also occasionally had rangeland in place of agricultural crops. Greater agreement between scenario 2 (field) and scenario 4-AGRR (NLCD) than for scenario 4-WWHT (NLCD) indicated that many of the targeted fields actually grew summer crops, and imposing the WWHT crop type, with lower C_{min}, removed these fields from the top rankings and reduced agreement. This can be observed more directly with the comparison of scenario 4-AGRR and scenario 4-WWHT, which showed that 18% to 28% of the fields from one ranking did not agree with the other due to the change in crop designation from summer row crop to winter wheat.

Agreement between the pairs of land use data source comparisons ranged from 18% to 45% between scenario 2 (field) and scenario 3 (NASS) or scenario 4-WWHT (NLCD) and from 40% to 60% between scenario 2 and scenario 4-AGRR (NLCD). For these land use cases, agreements were less than for the topography and soil data source comparisons (ranging from 60% to 93%), indicating that having accurate land use designations was more critical than topography or soils in targeting the highest sediment-yielding fields in this watershed.

Terraces and Tillage Management

Changing the land management data from inclusion of terraces, contour farming, and tillage management (scenario 0, S10FTR) to inclusion of only terraces (scenario 8, S10FTC), only contour farming and tillage management (scenario 9, S10FNR), or neither (scenario 2, S10FNC) had a major effect on the top-ranked fields included in each analyzed subset (table 8). Agreement ranged from 29% (scenario 2 for 10%Y) to 76% (either scenario 8 or 9 for 20%F).

These results confirmed the importance of including not only land use but also current practice in identifying fields for targeting. In this case, it is likely that inclusion in the model of management practices that had already been implemented on the fields with the greatest potential sediment-yield densities reduced sediment yields enough to remove many of those fields from the highest ranked (i.e., targeted) subsets. For many fields with the highest rankings in scenarios 2 though 7, modeling the implementation of terraces and/or contour farming and no-till resulted in sediment-yield density reductions adequate to remove those fields from the targeted list. This provides support that these practices (identified by field reconnaissance) appear to have been correctly placed in areas that otherwise would have been high-loss areas. Shifting from baseline (scenario 0) to the combination of terraces, contour farming, and no-till (scenario 2) resulted in less agreement in field selection than shifting to either terraces (scenario 8) or contour farming and no-till (scenario 9) alone. This modeling result indicated that, in some cases, multiple practices are needed to reduce sediment-yield potential enough to remove a field from the targeted list.

Conclusions

Agricultural fields with the greatest soil erosion potential were identified using ArcSWAT. An ArcGIS toolbar was developed to aggregate SWAT HRU output by field and prepare maps of high-priority fields by sediment, total nitrogen, and total phosphorus yields, although only sediment-yield rankings were assessed in this study.

The fields ranked by SWAT as having the greatest sediment-yield densities (Mg ha^{-1}) changed with resolution in topographic and soil data sources. Changing from 10 m to 30 m DEM topographic data and from STATSGO to SSURGO soil data altered the fields identified as yielding the most sediment by about 10% to 25%, depending upon the areas of the included fields as well as interactive effects with other input data sources.

Land use and management data source had the greatest influence on fields identified as having the greatest sediment-yield densities. Changing from field reconnaissance to NASS or NLCD land use data altered the fields selected as yielding the most sediment by 40% to 70%. Changing just the management data by including terraces and/or contour farming and no-till independently altered the selected fields by 25% to 70%.

Results of this study clearly demonstrate that use of incorrect or improper resolution source data can directly translate into incorrect field-level sediment-yield ranking, and thus incorrect field targeting, when using SWAT. Fields with high sediment-yield density in this study appeared to be most sensitive to land use data source (field reconnaissance, NASS, or NLCD), followed closely by inclusion of land management practices (terraces, contour farming, and no-till). Both DEM (10 m or 30 m) and soil (SSURGO or STATSGO) data source also were very important, although to a lesser extent than other inputs.

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