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Paying for sediment: Field-scale conservation practice targeting, funding, and assessment using the Soil and Water Assessment Tool

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Abstract: Watershed models have been widely used to estimate soil erosion and evaluate the effectiveness of conservation practices at different temporal and spatial scales; however, little progress has been made in applying these theoretical model results to the practical challenge of allocating conservation practice funding to meet specific soil loss objectives. Black Kettle Creek subwatershed (7,809 ha [19,295 ac]) of Little Arkansas River Watershed (360,000 ha [889,579 ac]) in south central Kansas was the focus of an innovative project to target conservation practice funding and pay directly for modeled sediment reduction. Detailed data (10 m [33 ft] digital elevation model topography, Soil Survey Geographic database soils, and a manually developed land use/land cover layer) were input into the Soil and Water Assessment Tool model, and the calibrated model was used to quantify soil erosion for each field. Effectiveness of locally relevant best management practices (BMPs) was simulated for each field. The simulated field-scale effectiveness for implemented BMPs ranged from 9% to 83% for single BMPs and 67% to 100% for selected combinations of BMPs. An in-field signup sheet was developed with field-specific sediment loss–based payments calculated for each BMP option. BMP implementation was 16.7% of cropland area prior (preinstalled BMPs) to the project, and 30.6% of cropland area (postinstalled BMPs) was added due to project-funded implementation. Postinstalled BMP implementation (47.3% of cropland) resulted in 35.8% sediment yield reduction compared to the no-BMPs scenario and 21.9% reduction compared to preinstalled BMP conditions, which was better than initially projected for this project. Inclusion of nontargeted fields and less-than-optimal BMPs had no influence on achieving soil loss objectives because payments were based on implemented soil loss rather than implemented area. Targeting of conservation practices based on payments scaled directly by project outcome (in this case, dollars per ton of sediment reduction) using a modeling approach allowed flexibility for both adopters (farmers) and funders (project staff) while assuring the project objective (i.e., sediment reduction) was met.

Key words: best management practices—critical source areas—sediment yields—watershed modeling

Soil erosion from cropland can be reduced by strategic selection and placement of agricultural conservation practices in the highest sediment-producing areas or critical source areas (CSAs) (Pionke et al. 2000; Strauss et al. 2007; Busteed et al. 2009; White et al. 2009; Tuppad et al. 2010a). Watershed models have been widely used to estimate soil erosion, identify CSAs, and evaluate effectiveness of best management practices (BMPs) at various temporal and spatial scales. Ability of watershed models to process spatially distributed input data (climate, topography, soils, land use, and land management practices) has led to identification of the CSAs within a watershed in many studies (Tripathi et al. 2003; Busteed et al. 2009; White et al. 2009; Daggupati et al. 2011). In Bracmout et al. (2006), Arabi et al. (2008), and Tuppad et al. (2010b), alteration of input parameters within one watershed model, the Soil and Water Assessment Tool (SWAT), allowed simulation of BMPs and evaluation of the effectiveness at different scales. Douglas-Mankin et al. (2010a) and Tuppad et al. (2010b) showed that both structural BMPs (e.g., grassed waterways, terraces, and filter strips) and nonstructural BMPs (e.g., no-till, conservation till, and strip till) could be assessed and targeted with SWAT.

Many modeling studies have quantified water quality impacts of BMP implementation, focusing on sediment, nutrient, or bacteria loads; this study focused on sediment. The water quality benefits of crop rotation, riparian buffer, and strip cropping practices in two watersheds in central Iowa resulted in a 15% to 60% decrease in median sediment loading at the watershed level (Vache et al. 2002). Benefits of using BMPs ranged from 5% to 99% sediment loss reduction at farm level (5% to 99% less sediment entering streams) and 1% to 2% reduction at the watershed level (1% to 2% less sediment exported at the watershed outlet) (Santhi et al. 2006). The lower reduction at the watershed level was due to very small implementation area compared to watershed area. Watershed level sediment loss reductions were greatest for terraces (over 60%), whereas other practices ranged from 30% to 40% (Gassman et al. 2006). Structural BMPs in good condition and in current conditions reduced average annual sediment yield by 16% to 23% and 7% to 10% at the watershed outlet (Bracmort et al. 2006). Conversions of 40%, 50%, 75%, and 100% of cropland from conventional tillage to conservation tillage resulted in sediment loss reductions of 20%, 26%, 33%, and 40%, respectively, at the watershed outlet (Dalzell et al. 2004). The implementation of individual BMPs reduced sediment loads from 3% to 37% at the watershed level with even higher reductions at the subwatershed and field levels (Tuppad et al. 2010b).

Establishing, implementing, and maintaining environmentally effective BMPs can be costly (Gitau et al. 2004). Implementation of a BMP that costs less and gives more reduction in pollution load would be desirable. BMP optimization techniques (single

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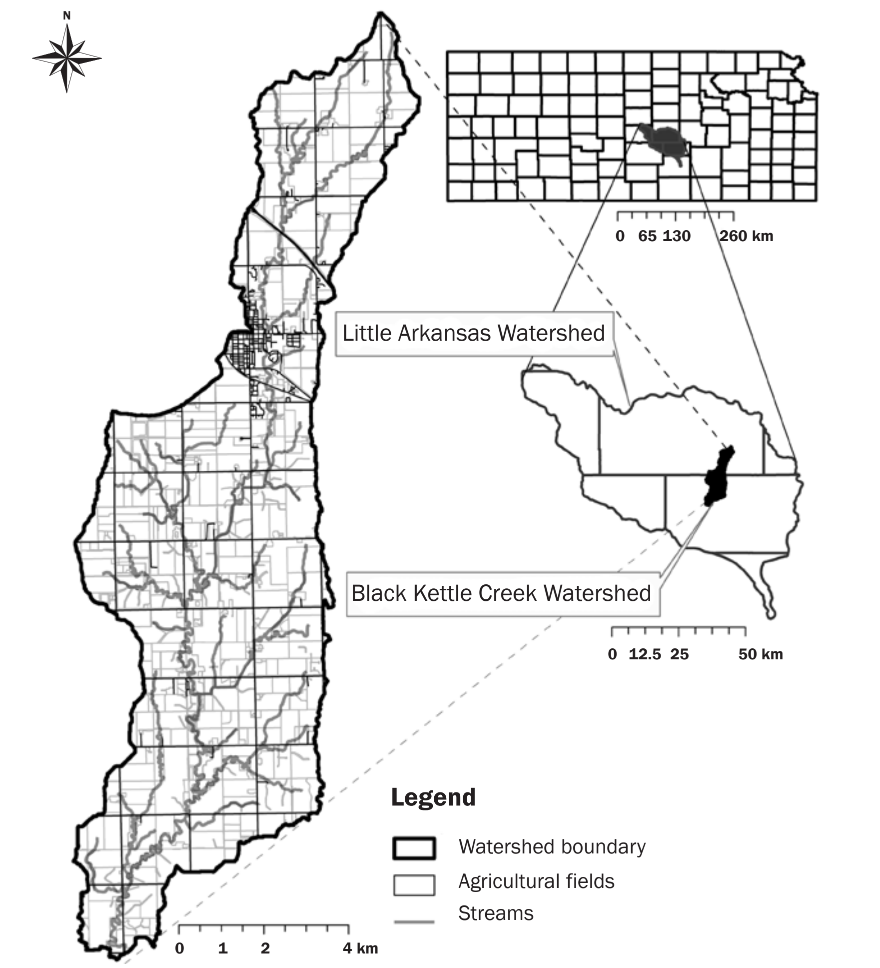
and multiple objective functions) have been used to recommend the best possible BMP(s) among various different possibilities to achieve maximum pollutant reduction with minimum increase in cost from implementation and maintenance (Maringanti et al. 2009). BMP optimization techniques use heuristic search algorithms, such as genetic algorithms, to obtain an optimal solution (Gitau et al. 2004). Various studies have used BMP optimization techniques to select and place BMPs (Gitau et al. 2004; Arabi et al. 2006; Maringanti et al. 2009; Veith et al. 2008; Chaubey et al. 2010); however, none of these studies have demonstrated how to use model results to improve farmer BMP adoption. Published studies have used watershed models to develop hypothetical scenarios or best-case scenarios to achieve a particular water quality goal for making watershed management recommendations (e.g., sediment load reduction as a result of implementing a selected BMP in 20% of the highest priority area), but little progress has been made in applying theoretical model results to the practical challenge of allocating conservation practice funding to maximize soil loss reductions.

The goal of this study was to develop a targeted, flexible method to ensure attainment of sediment reduction objectives by paying farmers explicitly for sediment yield reductions using watershed modeling. Specific objectives were to (1) identify cropland fields with the highest soil erosion potential and accurately quantify baseline sediment yields, (2) simulate and evaluate the effectiveness of various BMPs for each identified field using a calibrated SWAT model, and (3) evaluate the impacts of actual farmer-implemented BMPs compared to other potential implementation scenarios on soil loss.

Figure 1
Little Arkansas Watershed and Black Kettle Creek Watershed.



Materials and Methods

Study Area. Black Kettle Creek Watershed is a 7,809 ha (19,295 ac) subwatershed of the Little Arkansas River Watershed located within McPherson and Harvey counties in south central Kansas (figure 1). Primary land use in the watershed was cropland (84% of total area), followed by rangeland (12%), urban area (2%), and forest (2%). The cropland was predominantly wheat (*Triticum aestivum* L.), followed by sorghum (*Sorghum bicolor* [L.] Moench), soybean (*Glycine max* L.), and corn (*Zea mays* L.). A water quality monitoring study conducted by Steele (2006) found that the Black Kettle Creek Watershed delivered the greatest sediment yields in south central Kansas. This led to initiation of a project with the goal of reducing sediment yields from Black Kettle Creek Watershed through cost-sharing implementation of targeted conservation practices in agricultural fields with greatest soil erosion potential. Many people in this watershed are aware of the water quality problems and are engaged in various educational programs and demonstration projects.

The Soil and Water Assessment Tool Model. This study utilized the SWAT model, version 2005 (ArcSWAT 2.1.6), a widely used, watershed-scale, process-based model (Gassman et al. 2007; Douglas-Mankin et al. 2010b) developed by the USDA Agricultural Research Service (Arnold et al. 1998; Neitsch et al. 2005). The SWAT model divides the watershed into a number of subwatersheds based on topography. Each subwatershed is further divided into hydrologic response units (HRUs), which are the smallest landscape component of SWAT used for computing hydrologic processes. Flow, sediment, nutrients, and other constituent yields are simulated at the HRU level, summed to the subwatershed level, and then routed through the channels, ponds, reservoirs, and wetlands to the watershed outlet. The SWAT model uses the Modified Universal Soil Loss Equation (Williams 1975) to estimate sediment yield at the HRU level. In-stream sediment transport is modeled using a modified Bagnold's equation, which is a function of peak channel velocity. Sediment is either deposited or reentrained through channel erosion depending on the sediment load entering into the channel.

Extreme care needs to be taken in selecting the model input data when using SWAT for field-level studies (Daggupati et al. 2011). The topographic dataset was prepared from the US Geological Survey 10 by 10 m (33 by 33 ft) Digital Elevation Model (USGS 1999). The soil dataset was developed from the Soil Survey Geographic database (USDA NRCS 2005) with a processing utility (Sheshukov et al. 2011) that converted the Soil Survey Geographic dataset into an ArcSWAT compatible format. Land use/land cover (LULC) data were derived manually using the common land use unit field boundary shapefile. Each field land cover in the LULC data was manually edited based on a field-by-field survey conducted by the authors in November of 2008 and October of 2009. Structural and nonstructural management practices were derived from field surveys, whereas farming operations such as planting, harvesting, and manure application were derived by consulting extension specialists. Sets of unique 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 data from its original land cover dataset (e.g., wheat) and assigning a new land cover name with a crop code parameter (CPNM) in SWAT (e.g., TWHT for wheat with terrace). The final LULC dataset was extensively checked to confirm that management practices were accurately represented for every field in the watershed.

Daily precipitation data for the watershed were obtained from the Hesston weather station (Harvey County), located about 10 km (6.2 mi) northeast of the watershed, and the Goessel weather station (McPherson County), located about 15 km (9.3 mi) 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 (15.5 mi) south of the watershed. Missing daily weather data (e.g., 94 days [Hesston] and 81 days [Goessel] over the 2006 to 2009 calibration period) occurred primarily during the winter (dry) season and were adjusted for both calibration and scenario runs using a stochastic weather generator embedded in SWAT. Each SWAT scenario was simulated for the period from January 1, 1990, to July 31, 2009.

During watershed delineation, a minimum subwatershed drainage area was set at 500 ha (1,235 ac), which resulted in nine subwatersheds in the Black Kettle Creek Watershed. Three slope categories (0% to 2%, 2% to 4%, and >4%) were used to identify areas of low, medium, and high slopes. The HRUs in SWAT do not have spatial reference, but this limitation was overcome by redefining the topographic, soil, and land use thresholds to 0%, 0%, and 0% (Gitau et al. 2006; Busteed et al. 2009; Daggupati et al. 2011), which forced simulation of every combination of slope category, soil type, and land use type, resulting in 1,456 HRUs. Management practices (structural and nonstructural) and farming operations were simulated by modifying SWAT management files for each HRU that represented individual farm fields within the watershed.

Flow was calibrated to daily measured streamflow recorded at the outlet of the watershed from January 1, 2006, to July 31, 2009. An automated baseflow filter program (Arnold and Allen 1999) was used to determine the baseflow recession constant. Monthly and yearly sediment calibration was performed for the period from January 1, 2006, to July 31, 2008, using measured sediment data. Daily calibration of sediment was not performed due to the lack of daily sediment data. Detailed descriptions of flow and sediment calculations were presented in Daggupati et al. (2011). During calibration, the model parameters were either increased or decreased from their respective baseline values (table 1) based on the hydrographs and model statistics. The model was evaluated statistically using coefficient of determination (r^2), Nash-Sutcliffe model efficiency (NSE) (Nash and Sutcliffe 1970), percent bias (PBIAS), root mean square error (RMSE), and RMSE to standard deviation ratio (RSR) (Moriasi et al. 2007).

Field-Level Sediment Yield and Best Management Practice Simulation. Daggupati et al. (2011) reported that SWAT HRU output must be downscaled to the field level for practical simulation of BMP implementation. A similar approach was used in this study. Average annual sediment yields over a 12-year period (1995 to 2006) were calculated for each HRU from the calibrated SWAT model for baseline conditions and each BMP scenario. A conversion utility within the SWAT HRU-to-Field Toolbar in ArcMap geographic information system (Daggupati et al. 2011) was used to convert an HRU-level output to area-weighted field-level output.

Individual BMPs and combinations of BMPs were selected *a priori* by local extension personnel together with the authors to be candidates for farmer adoption based on BMPs that were previously in the watershed and that would be effective in reducing sediment yields. Effectiveness of each BMP in the targeted fields was simulated using the calibrated SWAT model, similar to Gitau et al. (2006) and Tuppad et al. (2010a, 2010b). Baseline sediment yields were established for each common land use unit field using the SWAT HRU-to-Field Toolbar based on preinstalled field conditions. Appropriate SWAT parameters were adjusted for each BMP (table 2), and resultant field-scale sediment yields were simulated (table 3). Combinations of BMPs were represented by combining parameter adjustments from the individual BMPs shown in table 2. The effectiveness, E_{BMP}, for each BMP in every field was calculated using the following formula:

$$E_{BMP} = \frac{(\text{baseline sediment yield - new BMP sediment yield})}{\text{baseline sediment yield}} \times 100. \quad (1)$$

Sediment Payment Calculations. A fundamental goal of this project was to develop a method to pay farmers explicitly for sediment yield reductions. Therefore, payment for BMP implementation was based on simulated sediment yield reductions, which varied by field and by BMP implemented. The payment for implementing a particular BMP on a specific field was calculated based on equation 2:

$$Payment(\$) = [Yield_{Baseline}\left(\frac{tn}{ac}\right) - Yield_{BMP}\left(\frac{tn}{ac}\right)] \times Area(ac) \times 100\left(\frac{\$}{tn}\right). \quad (2)$$

For example, if field #525 (1.26 ha [3.11 ac], table 4) produced a baseline sediment yield of 6.2 Mg ha^{-1} (2.76 tn ac^{-1}), and if the farmer of that field decided to implement the no-till practice, then we would pay the farmer according to the simulated sediment yield after implementing no-till practice, in this case 2 Mg ha^{-1} (0.87 tn ac^{-1}). The payment that the farmer would receive for implementing no-till practice on that field (showing full precision values in customary US units) would be (2.7630 – 0.8694) tn ac^{-1} × US\$100 tn^{-1} × 3.1068 ac = US\$588.30.

The unit cost of US\$110 Mg^{-1} (US\$100 tn^{-1}) was the amount that the expert man-

Table 1
SWAT model calibration parameters.

Variable	Description	Model range	Value used
Hydrology			
CN2	Curve number 2	±5	−3
ESCO	Soil evaporation compensation factor	0 to 1	0.8
EPCO	Plant uptake compensation factor	0 to 1	0.2
ALFA_BF	Baseflow recession constant (d)	0 to 1	0.2
ALFA_BNK	Baseflow factor for bank storage (d)	0 to 1	0.04
Gw_Revap	Groundwater revap coefficient	0.02 to 0.2	0.04
Ch_K2	Channel hydraulic conductivity (mm h^{-1})	−0.001 to 500	2
SURLAG	Surface runoff lag coefficient (d)	1 to 24	2
SHALLST	Initial depth of shallow aquifer (mm)	0 to 1000	600
SMTMP	Snow melt base temperature (°C)	−5 to 5	−3
GWQMIN	Depth of water in shallow aquifer required for return flow (mm)	0 to 5,000	4
Sediment			
CH_EROD	Channel erodibility factor	0 to 1	0.4
CH_Cov	Channel cover factor	0 to 1	0.1
CH_N(2)	Channel Manning's roughness coefficient	0 to 1	0.014
SPEXP	Exponent factor for channel sediment routing	1 to 2	1
SPCON	Linear parameter for channel sediment routing	0.0001 to 0.001	0.0004
LAT_SED	Sediment concentration in lateral flow (mg L^{-1})	0 to 5,000	100
SLSUBBSN	Average slope length (m)	10 to 150	multiplied by 1.5 from default

agement team decided to set as payment for each ton of sediment yield reduction. The project team estimated that it would require about US$40 ha^{-1} (US$100 ac^{-1}) for farmers to convert to no-till; thus, we expected to treat about 1,093 ha (2,700 ac) with the US$270,000 project funds, which represented 16.7% of the total cropland area. With the assumption that our anticipated BMP (no-till) would achieve about 72% sediment reduction (table 3) from an initial sediment yield of 9 Mg ha^{-1} (4 tn ac^{-1}), we anticipated to achieve a total sediment yield reduction of about 12%, which exceeded our goal of achieving 10% sediment yield reduction under the USDA Conservation Innovation Grant budget. Because contracts were signed for a five-year period, the sediment reduction being purchased averaged US$22 Mg^{-1} y^{-1} (US$20 tn^{-1} yr^{-1}) for the project period.

An individual in-field signup sheet (table 4) was prepared in Microsoft Excel with the Visual Basic for Application computer language for each field. A database of baseline and BMP-simulated sediment yields for each field was created. On selecting the field number of interest, the values of field area (ac $field^{-1}$), estimated initial average annual soil loss (tn ac^{-1}), estimated new average annual soil loss (tn ac^{-1}) for each new BMP, and payment for each BMP (US$ $field^{-1}$) were generated automatically from the database. The developed in-field signup sheets were delivered to the extension specialists, who discussed them with the owners of the targeted fields. The signup sheet specified the exact payment for each BMP for each field, thus providing clear choices for the BMP selection.

Best Management Practice Implementation. Extension specialists visited on-farm with farmers of the top-ranked fields to get their commitment to implement BMPs using the in-field signup sheet (table 4). In a majority of cases, owners decided to implement and maintain no-till and intensive crop rotation (NT/R). Based on personal communication with farmers during signup, they appeared to select the NT/R practice for a combination of reasons: no-till reduced the number of tillage operations and consequently reduced time spent tilling fields and fuel usage, which was particularly important within the context of rising fuel costs, and the increased soil moisture from no-till allowed farmers to shift from continuous wheat to a more intensive crop rotation, such as a two-year rotation with three crops, including corn, sorghum, or soybean, which was anticipated by farmers to create more income, particularly within the context of strong crop prices. The NT/R BMP was not simulated when the in-field signup sheet was given to the extension specialists. Therefore, the extension specialists decided to use a BMP effectiveness of 82% for NT/R; this value was near the maximum field-level sediment yield reduction simulated for the no-till scenario (table 3). The specialists used this effectiveness and baseline sediment yield for the given field (also listed on the signup sheet) to calculate the sediment yield reduction and payment amount (equation 2) for NT/R. The extension specialists solicited BMP implementation contracts in decreasing rank order (by the field sediment yield reductions) until US$270,000 was committed. A total of 21 farmers participated in the program and contracted to implement BMPs in 124 fields (2,039 ha [5,035 ac]) in the spring of 2010. Twelve of the postinstalled BMP fields (146 ha [361 ac]) had preinstalled BMPs, including 3 fields (42 ha [104 ac]) of no-till converted to NT/R; 4 fields (33 ha [82 ac]) with terraces that added NT/R; and 5 other fields originally with either no-till or terraces that added contour farming, perennial grass, no-till, or rotational grazing.

The goal of the funded project was to achieve sediment yield reductions, so the project team decided to fund practices on 11 selected fields to address ephemeral gully erosion concerns. Although these practices were funded according to estimated sediment yield reductions, similar to the other funded practices in this study, the estimates were not based on modeled results because

Table 2

Soil and Water Assessment Tool (SWAT) model parameters changed to represent best management practices (BMPs).

BMP	SWAT variable	Initial parameter	Parameter used	Source
Riparian buffer (RB)	FILTERW	0 m	6 m	USDA NRCS (2008) recommends 6 m minimum RB width
				Bracmort et al. (2006) and Arabi et al. (2008) used FILTERW for RB
No-till (NT)	Cmin	Row crop: 0.2	Row crop: 0.1	Maski et al. (2008), NT = 0.43 TILL
		Wheat: 0.03	Wheat: 0.03	SWAT default for close grown row crops, wheat
	CN2	Varies	Reduce CN2 by 2 units	Maski et al. (2008), Δ2 to 3 for TILL vs. NT; Waidler et al. (2009), Δ3 for TILL vs. NT; and Arabi et al. (2008) reduce CN2 for NT
	Tillage	Chisel plow or tandem disc (EFFMIX: 0.3; DEPTIL: 100 mm)	Generic no-till (EFFMIX: 0.05; DEPTIL: 25 mm)	Waidler et al. (2009)
Conservation tillage (CT)	Cmin	Row crop: 0.2 (SWAT default)	Row crop: 0.15	Maski et al. (2008), NT = 0.43 TILL
		Wheat: 0.03	Wheat: 0.03	SWAT default for close grown row crops, wheat
	CN2	Varies	Reduce CN2 by 2 units	Maski et al. (2008), Δ2 to 3 for TILL vs. NT; Waidler et al. (2009), Δ2 for TILL vs. NT; and Arabi et al. (2008), reduce CN2 for NT
	Tillage	Chisel plow or Tandem disc (EFFMIX: 0.3; DEPTIL: 100 mm)	Generic conservation till (EFFMIX: 0.2; DEPTIL: 100 mm)	Waidler et al. (2009)
Terrace (T) + contour farming (CF)	P factor	1	0.1	Wischmeier and Smith (1978), P factor range 0.1 to 0.18
	CN2	Varies	Reduced by 6 units	Arabi et al. (2008) recommends 6 units for terraces
Contour farming (CF)	P factor	1	0.6	Wischmeier and Smith (1978),P factor range 0.5 to 0.6 (for 0% to 9% slope)
	CN2	Varies	Reduced by 3 units	Arabi et al. (2008) recommends 3 units for contouring
Strip cropping or contour grass strips	P factor	1	0.45	Wischmeier and Smith (1978), P factor range 0.38 to 0.45 (Type B: mostly crop/some grass strips, 0% to 9% slope)
	CN2	Varies	Reduced by 3 units	Arabi et al. (2008) recommends 3 units for contouring
Permanent grass	Cmin	Row crop: 0.2	Big bluestem: 0.003	Waidler et al. (2009)
		Wheat: 0.03		
	CN2	Varies	Reduced by 5 units	
	Management	Varies	Management operation changed to big bluestem	
No-till + intensive crop rotation (NT/R)	No-till was simulated, as described above, and intensive crop rotations (3 crops in 2 years) of wheat–soybean/sorghum–wheat in wheat fields, soybean–wheat–soybean/sorghum in soybean fields, and sorghum–wheat–sorghum/soybean in sorghum fields were simulated.			

Notes: FILTERW = width of filter strip. Cmin = minimum USLE cover and management factor. CN2 = curve number at moisture condition 2. P factor = USLE support practice factor. EFFMIX = mixing efficiency of tillage operation. DEPTIL = depth of mixing by tillage operation. TILL = conventional tillage system.

Table 3
Field-scale Soil and Water Assessment Tool-simulated sediment yield reductions for implemented best management practices (BMPs).

BMPs	Minimum	Mean ± sd	Maximum
R	9%	22% ± 3%	33%
CF	43%	52% ± 3%	67%
NT	58%	72% ± 5%	83%
NT + R	67%	77% ± 4%	87%
T + CF	67%	77% ± 2%	87%
NT + T + CF	80%	94% ± 3%	100%

Notes: R = intensive crop rotation. CF = contour farming. NT = No-till. T = terraces.

models to simulate ephemeral gully sediment yields were not available. These fields may provide substantial sediment yield reductions and will serve to demonstrate the potential effectiveness of the implemented ephemeral gully control practices. However, these practices were considered experimental and were not assessed in this study.

The extension specialists met again with a few active farmers to discuss model-simulated baseline and postBMP sediment yields for each field. The group decided to use the model-simulated baseline yields, but to use average sediment yield reduction percentages for each BMP as the basis for payments. Since this project paid explicitly for sediment yield reduction (US\$ tn^{-1}), this modification did not affect the overall sediment reduction being purchased. However, payment of an average amount per ton of sediment reduction ignored model-simulated differences in BMP effectiveness among fields and meant that some farmers were slightly overpaid or underpaid relative to the simulated sediment reduction produced by implementation of a given BMP on their field.

Assessment of Implemented Best Management Practice Scenarios. Ten scenarios, of which three were based on preproject and postproject conditions existing in the watershed and seven were based on other alternatives or potential best cases, were developed and assessed using the SWAT model. All scenarios were developed by either editing the LULC layer or management operations, depending on the scenario. Soil, slope, weather datasets, and calibrated model parameters were held constant for all scenarios. A comprehensive verification procedure was developed to verify that every field had proper management practices spatially represented in the model for each scenario. All BMP scenarios (described below) were run for 15 years (1992 to 2006). The first three years were used for model initialization, and the remaining 12 years (1995 to 2006) were analyzed for each scenario.

Main Scenarios. Scenario 1-No represented a condition with no BMPs in the watershed and was used for comparison. Scenario 2-Pre (preinstalled BMPs) repre-

Table 4
Best management practice (BMP) options as listed on the field-specific sign-up sheet developed using Soil and Water Assessment Tool output.

New best management practice(s) to be established	Estimated new soil loss (tn ac^{-1})	Soil loss payment for this BMP (US\$)
Single new BMPs		
No-till	0.87	588.29
Conservation till	1.50	392.97
Contour farming	1.31	452.71
Terraces (+ contour farming)	0.59	673.90
Contour grass strips	1.06	529.32
Riparian vegetative buffer strip (on contour)	1.04	536.31
Permanent grass	0.08	834.84
Other*: ________________		
Combinations of new BMPs		
No-till + contour farming	0.25	781.89
No-till + terraces (+ contour farming)	0.09	830.50
No-till + contour grass strips	0.18	801.03
No-till + riparian vegetative buffer	0.37	744.01
Conservation till + contour farming	0.48	708.30
Conservation till + terraces (+ contour farming)	0.34	752.44
Conservation till + contour grass strips	0.37	744.85
Conservation till + riparian vegetative buffer	0.42	728.55
Contour grass strips + riparian vegetative buffer strip	0.37	744.01
Other*: ________________		
New ephemeral gully BMP (alone or added to any BMP above, except terraces)		
Grassed waterways (to repair ephemeral gullies)*	Field assessment	

* Soil loss reductions and payments for other BMPs or combinations of BMPs must be approved by the project team.

sented the conditions in which BMPs were used on 56 fields (1,040 ha [2,571 ac]) prior to implementing new BMPs. Scenario 2-Pre was used to prepare initial targeting maps, to assess impacts of preinstalled BMPs in the watershed, and to serve as a baseline to assess impacts of BMPs implemented during this project (postinstalled BMPs).

Scenario Δ3-I_M represented practices implemented during the study that were modeled, which included all BMPs except sedimentation ponds and grass waterways installed for ephemeral gully control and riparian buffers. This scenario allowed direct comparison of changes to model results for several alternative scenarios, described below. Scenario 3-I_T represented total installed BMPs, including both preinstalled (2-Pre) and postinstalled (Δ3-I_M) BMPs, in 180 fields (2,949 ha [7,288 ac]). There were 2 fields (11 ha) that had both modeled (intensive crop rotation) and nonmodeled (riparian buffer) practices; for these fields, the portion of sediment reduction that was associated with the intensive crop rotation was included in Δ3-I_M, and the remainder was not included.

Alternative Scenarios. Alternative scenarios were developed to model the sediment reduction effects of other BMP implementation scenarios of interest. Not all BMPs implemented during the project were installed on the top-ranked fields due to realities of a voluntary farmer sign-up process (such as unwillingness of a farmer on one of the top-ranked fields to adopt). Scenario 3-NT/R_A was developed to test the sediment yield reductions that could have been achieved if the most popular BMP (NT/R) was adopted on the same total area as Δ3-I_M (1,909 ha [4,717 ac]) but only on the model-simulated highest priority areas. Scenario 3-NT/T_A was developed by changing fields with NT/R BMP in 3-NT/R_A to no-till and terraces (NT/T), which was one of the most effective BMPs simulated in this study (table 3) that could also reduce ephemeral gully erosion (not simulated in this study), based on previous research and expert opinion.

Scenarios also were developed to test the impact of allowing nontop-ranked fields to implement BMPs in this project. Both 3-NT/R_S and 3-NT/T_S simulated the same total sediment reduction (and thus the same total project cost) as the modeled portion of 3-I_T (i.e., 2-Pre plus Δ3-I_M) applied only to top-ranked fields. The number of postinstalled BMP fields to achieve sediment load reduction equivalence with Δ3-I_M (124 fields) was 70 fields in 3-NT/R_S and 58.1 fields in 3-NT/T_S.

Best-Case Scenarios. Scenarios 4-NT/R and 4-NT/T, with all cropland (412 fields, 6,234 ha [15,399 ac]) converted to NT/R and NT/T, were the final cases tested.

Table 5
Calibrated model performance in simulating measured flow and suspended sediment at the outlet of the Black Kettle Creek Watershed.

Constituent	Period	r^2	NSE	PBIAS	RMSE	RSR
Flow	Daily	0.46	0.45	4.6%	0.94	0.64
	Monthly	0.70	0.69	4.4%	0.32	0.55
	Yearly	0.96	0.89	7.5%	0.07	0.29
Sediment	Monthly	0.55	0.51	16.8%	1.44	0.53
	Yearly	0.88	0.85	17.4%	1.16	0.32

Notes: NSE = Nash-Sutcliffe model efficiency. PBIAS = percent bias. RMSE = root mean square error. RSR = RMSE to standard deviation ratio.

Results and Discussion

Model Evaluation. Results of the calibration runs conducted for daily, monthly, and annual measured and simulated streamflows at the watershed outlet are presented in table 5. Based on the ratings proposed by Moriasi et al. (2007), the model performance was considered good for monthly streamflows when evaluation was based on NSE (>0.65), very good when based on RSR (≤0.60), and excellent when based on PBIAS (<±10%). According to these values, the SWAT model was found acceptable for streamflow simulations. The model was also calibrated at the watershed outlet for monthly and yearly average sediment yields (table 5). According to Moriasi et al. (2007), the monthly performance was found satisfactory when based on NSE (>0.50) and good when based on RSR (≤0.60) and PBIAS (<±30%). The model performance of sediment was inferior to flow but was considered sufficient for estimating sediment yields in this project.

Accuracy of the modeled field-level predictions was validated using published measurements of sediment yields from small cropland drainage areas in Kansas (Holland 1971). According to Holland, cropland areas in Black Kettle Creek Watershed produced sediment yields from 2.8 to 5.5 Mg ha^{-1} y^{-1} (1.24 to 2.45 tn ac^{-1} yr^{-1}). Prior to 1971, typical cropland areas in this region had minimal implementation of conservation practices and few terraces. Calibrated modeling results for the top 25 fields, with no conservation practices or terraces implemented, ranged from 3.1 to 5.8 Mg ha^{-1} y^{-1} (1.38 to 2.58 tn ac^{-1} yr^{-1}), which were in good agreement with measured sediment yields. These results confirmed that the use of field-level simulation in this study provided a realistic representation of sediment yields, thus supporting the use of the SWAT model for targeting and assessing individual fields.

Best Management Practice Simulation. A database was created that included simulated baseline sediment yield (from 2-Pre) and sediment yield for each BMP on every field. The effectiveness of each BMP compared to the baseline was calculated. Simulated mean BMP effectiveness of single BMPs implemented in this study ranged from 9% to 83%, whereas mean BMP effectiveness for combinations of BMPs ranged from 67% to 100% (table 3). The no-till BMP scenario produced the maximum mean BMP effectiveness among all implemented individual BMPs, whereas the no-till plus terraces (plus contour farming) combination had the greatest reductions among implemented combined BMPs.

The effectiveness of each BMP varied spatially by field. For example, the no-till BMP had a mean effectiveness of 72% with a range of 58% to 83% (table 3). Similar variability was observed for all implemented BMPs simulated in this study. Model predictions captured the unique and variable soil, slope, and land use conditions present on each field that interacted with each BMP to produce a given sediment reduction result. This result demonstrated the importance of using field-specific modeling results for field targeting instead of generalized percentage reductions for given practices.

Standard deviations of BMP effectiveness were 5% or less for all BMPs simulated (table 3). This shows that a majority of fields performed within a reasonably small range of sediment yield reductions. However, field targeting attempts to identify the fields with the greatest benefits from implementation, not the average benefits. The differences between mean and maximum reductions for

Table 6
Actual conservation practice implementation data in Black Kettle Creek Watershed.

Scenario	Number of fields	Area (ha)	Area of watershed (%)	Area of cropland (%)	Area of cropland in BMPs (%) NT	CF	R	NT/R	T	O
2-Pre	56	1,040	13.3	16.7	3.0	1.0	—	—	12.4	0.2
Δ3-I_M	124	1,909	24.4	30.6	6.0	0.6	4.3	18.7	1.3	0.1
3-I_T	180	2,949	37.8	47.3	9.0	1.6	4.3	18.7	13.7	0.3

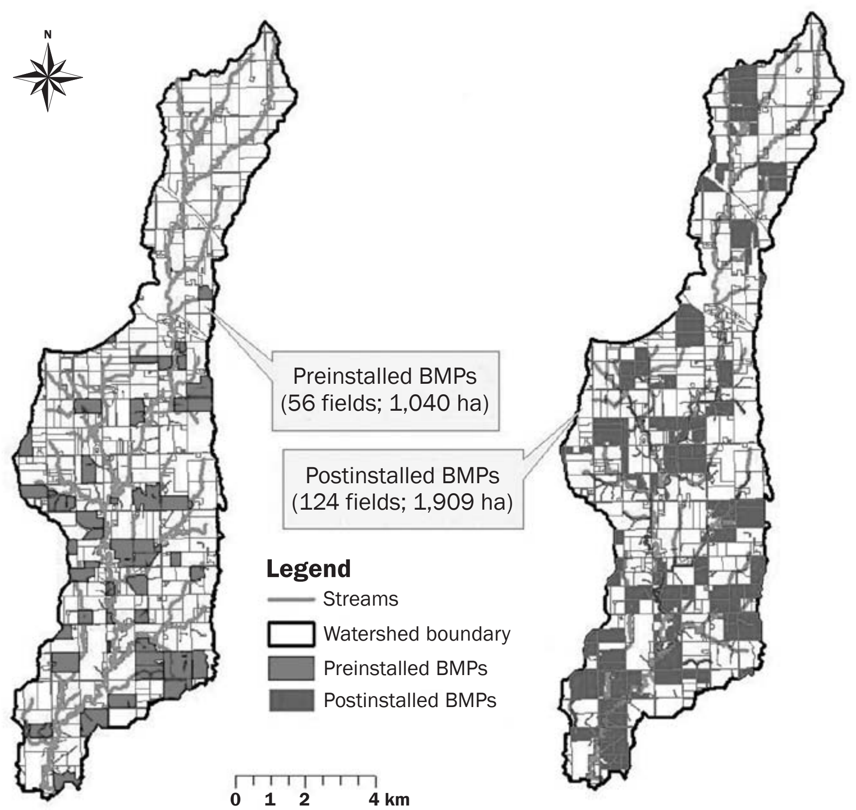
Notes: 2-Pre = practices in place at the beginning of the study. Δ3-I_M = practices implemented during the study that were modeled. 3-I_T = total practices in place at the end of the study, including 2-Pre. NT = no-till. CF = contour farming. R = intensive crop rotation. NT/R = no-till, intensive crop rotation. T = terraces. O (Other) = riparian buffers, ponds, grass waterways, and permanent grass.

a given BMP were 1.9 (NT/T) to 4.9 (contour farming) times greater than the standard deviation. Again, this demonstrates the value of using modeling results to identify these fields with the greatest potential for impact.

The modeled BMP effectiveness for the implemented BMPs was compared to the effectiveness values reported in Devlin et al. (2003) and Merriman et al. (2009) to provide general comparisons. The mean effectiveness of the selected BMPs was within 10% of the mean effectiveness reported in published studies. These comparison results verified that sediment-yield reductions for BMPs simulated in this study were represented reasonably well.

Best Management Practice Implementation. A total of 21 farmers in this watershed participated in the project and implemented numerous BMPs (postinstalled BMPs) (table 6; figure 2, shown in green). In many cases, fields that were not listed in the top-ranked fields were nearby and owned or operated by a farmer with highly ranked fields, so they were also given contracts to implement BMPs. Fields with postinstalled BMPs were distributed across the entire range of sediment yield rankings (figure 3). Allowing contracts for these nontop-ranked fields had no impact on sediment reduction efficiency per dollar invested, since we still paid the same amount per unit of sediment reduction (US\$ tn^{-1}), although it did reduce the resulting farmer payment amount per acre to implement a given BMP relative to top-ranked fields. This is demonstrated by comparison of 3-I_T to 3-NT/R_S and 3-NT/T_S (figure 4). The sediment reduction achieved by 3-I_T relative to 2-Pre (2,008 Mg [2,213 tn] or 35.8%) was achieved at a cost of US$221,352. For each scenario, payment of the same total dollar amount (US$221,352) results in the same sediment reduction (35.8%), due to the project structure of paying per unit of sediment reduction, but on less area (3-NT/T_S < 3-NT/R_S < 3-I_T), primarily due to the improved sediment reductions achieved using these BMPs on only the top-ranked fields. Because negotiations to receive payment on nontop-ranked fields were initiated by the farmer, they were welcomed and likely improved farmer willingness to participate, improved rate of adoption, and increased efficiency of our field personnel in obtaining contracts.

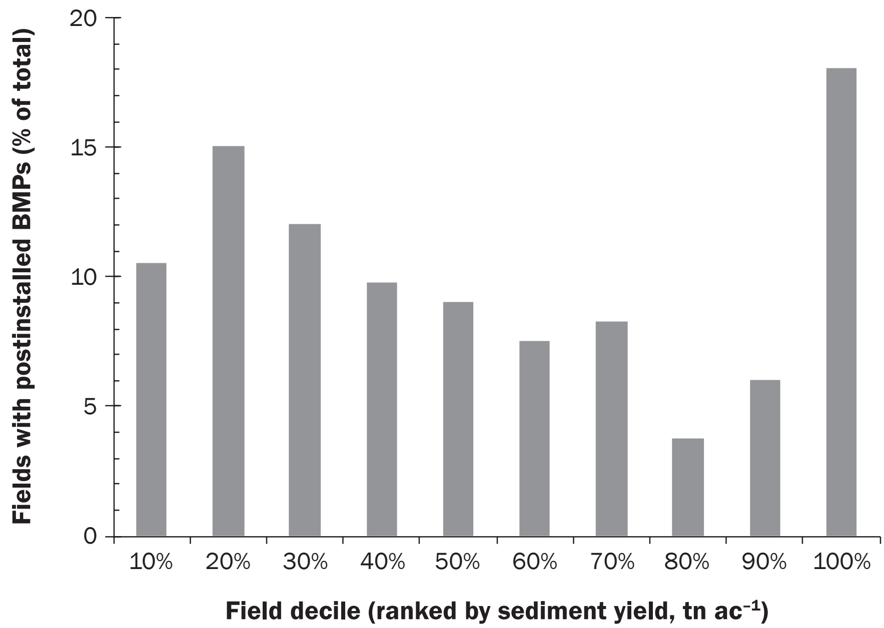
Figure 2
Map of Black Kettle Creek Watershed showing preinstalled and postinstalled best management practice (BMP) fields.



Some BMPs were already installed in this watershed prior to this project (preinstalled BMPs). Before this project, BMPs were installed in 56 fields (1,040 ha [2,571 ac]) (table 6, 2-Pre; figure 2, shown in red). Summary of BMP implementation data is provided in table 6. Terraces (13.7% of cropland) and NT/R (18.7% of cropland) were the dominant BMPs among preinstalled and postinstalled BMPs, with most of the terrace structures (12.4%) installed previously and all of the NT/R practices installed as a result of this study. At the end of this project (3-I_T), a total of 180 fields (2,949 ha [7,288 ac]), almost half of the cropland area (47.3%) in this watershed, had implemented BMPs.

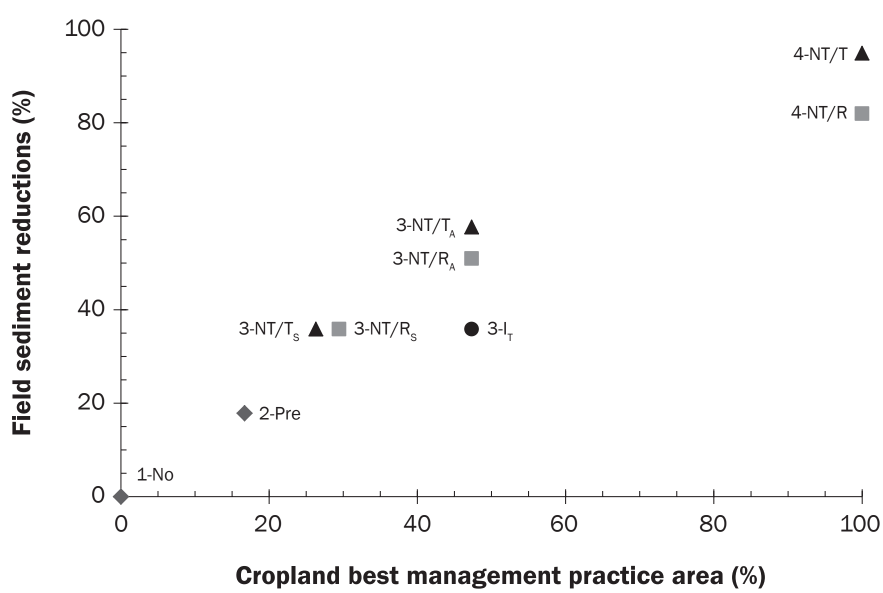
Implemented Best Management Practices and Scenario Assessment. Sediment load reductions at the field scale were analyzed for

Figure 3
Distribution of cropland fields (total = 133) with postinstalled best management practices (BMPs) by decile sediment yield ranking.



each scenario. In 2-Pre, farmers previously implemented BMPs in 16.7% of cropland area (13.3% of watershed area), reducing sediment yields by 17.8% at the field level compared to 1-No. In 3-I_T, project-funded BMPs were added, bringing the total fields with BMPs to 47.3% of cropland area (37.8% of watershed area), which reduced sediment yields by 35.8% compared to 1-No and 21.9% compared to 2-Pre. Although not all model-recommended fields had BMPs implemented, better sediment yield reduction (21.9%) was achieved by 3-I_T relative to 2-Pre than the original project target of 10% sediment yield reduction.

Figure 4
Soil and Water Assessment Tool–simulated field-scale sediment yield reductions for several scenarios in the Black Kettle Creek Watershed.



The alternative 3-NT/R_A, in which the most commonly implemented BMP (NT/R) was implemented in the same area as Δ3-I_M but only in model-recommended top-ranked fields, produced sediment yield reductions of 50.9% relative to 1-No and 40.3% relative to 2-Pre (figure 4). Similarly, 3-NT/T_A, which represented implementation of the most efficient implemented BMP (NT/T) in the same area as Δ3-I_M but only in top-ranked fields, resulted in greater sediment yield reductions of 57.7% relative to 1-No and 48.5% relative to 2-Pre. An upper-bound scenario, full implementation of these two BMPs, resulted in sediment yield reductions of 82% for 4-NT/R and 94.9% for 4-NT/T relative to 1-No (figure 4). The greater sediment yield reductions simulated for 3-NT/R_A and 3-NT/T_A compared to Δ3-I_M confirms the expected result that implementing more effective BMPs on higher priority targeted areas leads to greater sediment yield reductions per unit area (figure 4). However, these greater efficiencies were not achieved in this study, nor likely in any real-life farmer-adoption setting, since adoption of only those practices with the greatest sediment yield reductions and only on the highest priority targeted fields is not likely.

Discussion. The process of paying for practice implementation per unit outcome, in this case sediment reduction (US\$ tn^{-1}), not per unit area (US\$ ac^{-1}), demonstrated by this study, provides flexibility in selecting both BMPs and implementation fields while maintaining a fixed sediment yield reduction efficiency per dollar spent. With the pay-for-outcome approach, farmers/landowners, rather than project managers, decide which conservation practices will be best within the context of their overall operations. As long as pollutant reductions for the given practice can be adequately simulated, outcome-based payments guarantee a given objective will be achieved.

Although this project focused on a single outcome (sediment reduction), the outcome-based payment approach can be used to pay independently for several outcomes resulting from a given practice. In this way, farmers/landowners can combine payments for several outcomes (e.g., reductions of sediment, nitrogen [N], and phosphorus [P] or increased soil carbon [C]) resulting from a given practice to improve the economics of implementing that practice. A similar approach could be used to set payment rates for quantifiable unit improvements in a variety of ecosystem services (Logsdon 2011).

Future Research. The use of an outcome-based payment strategy makes selection of the price paid per unit outcome critical. In this study, the payment amount per unit sediment reduction (US\$ tn^{-1}) governed the overall efficiency of the sediment reduction achieved by the project. We did not attempt to optimize the payment, but rather used the judgment of the project team to set the payment rate at US\$100 tn^{-1} (or US\$20 tn^{-1} yr^{-1} for 5 years). A more rigorous method to establish an optimal payment rate, such as based on analysis of farmer willingness to pay, actual cost of implementation, or actual benefits received, would ensure that outcomes are achieved at minimal cost. This study did not attempt to optimize this payment amount, but this is a critical area for future research.

This study developed and implemented an approach to distribute conservation funding assistance according to model-estimated sediment yield reductions. However, convenient models are not available to estimate sediment yields from all sources, most notably those sources associated with concentrated flows, such as ephemeral gully erosion, stream channel erosion, and stream bank erosion. Future research is needed to develop modeling approaches that quantify these sources so that watershed planners can adequately consider, and allow outcome-based funding of, all sediment sources.

Finally, the outcome-based approach gave farmers flexibility to accept lower per acre payments to extend implementation of given practices to nontargeted fields. We hypothesize that encouraging farmers to adopt a new conservation practice on a larger portion of their operation will enhance their continued maintenance of the adopted practice. In this way, a given payment may have conservation benefits that outlive the project period. Testing of this hypothesis is left for future study.

Summary and Conclusions

Cropland fields with the greatest sediment yield potential were identified with a SWAT model built for Black Kettle Creek Watershed. The model was calibrated using flow and suspended sediment data at the watershed outlet and validated for historical field-level sediment yields.

Single and combined BMPs were selected for each field, and BMP effectiveness was simulated using results from the calibrated SWAT model. Sediment yield reduction effectiveness of a specific BMP varied by field due to each field's unique combination of slope, soil type, and existing land use. Including both preinstalled and postinstalled BMPs, 47.3% of all cropland area (180 fields; 2,949 ha [7,288 ac]) have BMPs implemented. The postinstalled level of BMPs (3-I_T) resulted in 35.8% sediment yield reduction compared to 1-No (no BMPs installed) and 21.9% reduction when compared to prior existing conditions represented by 2-Pre (preinstalled BMPs); this reduction was better than initially projected for this project.

An in-field sign-up sheet was prepared to facilitate voluntary farmer sign-up for BMP implementation. Key elements of the sign-up sheet were field-specific simulated sediment yield values, field-specific simulated BMP effectiveness values, and sediment yield reduction–based payment calculations for each BMP on each field. Creation of the sign-up sheet was simplified using a database of model-simulation outputs for each BMP organized by common land unit. However, two important changes were made in the actual application of the sign-up sheet.

First, the decision was made to use model-simulated baseline sediment yields (tn ac^{-1}) but average BMP reduction percentages to determine fundable sediment reduction amounts. Since this project paid explicitly for sediment yield reduction (US\$ tn^{-1}), this modification did not affect the overall sediment reduction being purchased. However, payment of an average amount per unit sediment reduction ignored model-simulated differences in BMP effectiveness among fields and meant that some farmers were slightly overpaid or underpaid relative to the simulated sediment reduction produced by implementation of a given BMP on their field. This highlights a fundamental difference between traditional cost-sharing approaches that pay per acre for BMP implementation and this project, which paid directly for a pollutant reduction outcome (in this case, per ton of sediment yield reduction). This paying for sediment approach also deemphasizes the need for CSA targeting. Payment efficiency is not sacrificed if farmers choose to implement a given practice on a nontargeted field; they simply receive the same per ton payment but a lower per acre payment, due to the smaller reductions possible on the nontargeted field. This allows farmers to receive funding to convert their entire operation to a given conservation practice, which may improve long-term practice adoption. It also allows project administrators more flexibility in disbursing cost-share funds while maintaining project pollutant reduction outcomes.

Second, a BMP that had not been simulated by the model (NT/R) was added as an option for farmer implementation. An approximate sediment reduction percentage was loosely based on available model results (near-maximum sediment yield reduction for no-till BMP: 82%), although subsequent model simulations indicated somewhat lower average potential sediment yield reductions (77%). This overestimation reduced the amount of sediment yield reduction purchased with the fixed project funds. This result demonstrates the importance of accurate modeling results in establishing payment amounts in a pay for pollutant reduction program. Other agronomic, economic, and sociologic factors, such as interactive effects of practices on crop yields, profit margins, and farmer willingness to adopt specific practices, must be further investigated to determine optimal payment amounts per unit pollutant reduction. This study provided preliminary evidence that changing conservation funding from a pay per acre (of practice adoption) to a pay per pound (of pollutant reduction) mindset will enhance program flexibility, farmer adoption rates, and accountability toward achieving pollutant reduction targets.

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