Strategic targeting of cropland management using watershed modeling

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Abstract: Effective water-quality protection should target Best Management Practices (BMPs) on watershed areas that contribute most to water-quality impairment instead of the typical voluntary implementation of practices, which may not be better than a random distribution of BMPs within a watershed. This paper demonstrates a strategic approach for targeting watershed areas to maximize water-quality benefits from BMP implementation. Almost half of the Smoky Hill River Watershed, Kansas, USA is cropland, a major sediment and nutrient source. The impacts of reduced tillage, edge-of-field vegetative filter strips, and contoured-terraced practices on erosion and nutrient loads both overland and at the watershed outlet were evaluated using either random or targeted implementation, based on simulated average subbasin erosion rate. The targeted approach was more effective in reducing sediment and nutrients, both at subbasin and watershed levels. Annual average overland pollutant load reductions of 10% required BMP adoption on less than half the land area with targeted versus random placement. The benefits of targeting were greater for initial increments of BMP adoption and decreased as implementation area increased.
Keywords: targeting, conservation practices, erosion, SWAT modeling, watershed.

1. Introduction

Agricultural nonpoint sources (NPS) of sediment, nutrients, and bacteria, primarily in surface runoff, have been identified as the major causes of water-quality problems in streams and lakes (USEPA, 2000; Ice, 2004). Minimizing watershed pollutant yields requires coordinated implementation of agricultural best management practices (BMPs).

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Strategic targeting and prioritization of areas for implementation of BMPs is conceptually preferable to a "voluntary" basis, which has no guarantee of resulting in better pollution abatement than a random distribution of practices within a watershed (Diebel *et al.*, 2008). Identifying fields/areas with high pollution potential and treating these fields first would be a more efficient way to allocate financial and educational resources and control NPS pollution.

Targeting has three primary facets: (1) "practice" targeting, where management measures are prioritized based on relative effectiveness toward meeting a pollution-reduction (or other environmental) target; (2) spatial targeting, where areas within a watershed are prioritized based on relative pollution-generation potential; and (3) temporal targeting, where practices and locations within a watershed are selected based on relative potential to reduce delivery of pollutants during a critical time frame (e.g., season). Watershed models can directly address each targeting issue by assisting with prioritization of practices, spatial targeting of actions, and assessment of temporal delivery of pollutants to a water resource.

One widely used watershed model is the Soil and Water Assessment Tool (SWAT), a distributed, deterministic, continuous, watershed-scale simulation model developed by the USDA Agricultural Research Service (Arnold *et al.,* 1998; Di Luzio *et al.,* 2004). It uses spatially distributed data on topography, soils, land cover, land management, and weather to predict water, sediment, nutrient, and pesticide yields. A modeled watershed is divided spatially into subwatersheds using digital elevation data according to the threshold drainage area specified by the user. Subwatersheds are modeled as having uniform slope and climatic conditions, and they are further subdivided into lumped, nonspatial hydrologic response units (HRUs) consisting of all areas within the subwatershed having similar soil, land use, and land management characteristics. Within each HRU, SWAT simulates runoff and erosion processes, soil water movement, evapotranspiration, crop growth and yield, soil nutrient and carbon cycling, and pesticide and bacteria degradation and transport. It allows simulation of a wide array of agricultural structures and practices, including tillage, fertilizer and manure application, and edge-of-field filter strips. The channel component routes flows, settles and entrains sediment, and degrades nutrients, pesticides and bacteria during transport. SWAT simulates on a daily time-step and can be set to produce daily, monthly or annual load estimates.

Evaluation of monthly and annual streamflow and water-quality outputs indicate that SWAT functions well in a wide range of regions, conditions, practices, and time scales (Gassman *et al.,* 2007). Relatively poor results in some cases, particularly for daily flow and pollutant outputs, were attributed partly to input and calibration data uncertainty and partly to model limitations. In general, the model had more difficulty simulating wet years than dry years and tended to overestimate soil water in dry soil conditions and underestimate soil water in wet soil conditions. SWAT directly addresses practice targeting by simulating the effects of farm/plot scale BMPs, spatial targeting by its use of subwatersheds and HRUs to subdivide larger areas, and temporal targeting by its use of daily, continuous simulation.

Watershed modeling strategies for identifying and prioritizing critical areas and impacts of BMPs have been demonstrated by a number of studies, briefly reviewed below. Simulation models integrated with geographical information systems (GIS) have also been used at the watershed scale to aid in critical area selection. Mass *et al.* (1985) described critical area selection criteria from both land-resource and water-resource perspectives. Critical areas can be determined based on several factors, including the type of water-quality impairment, the dimensions and dynamics of the watershed as well as the water body, and the investment in BMP (Mass, Smolen and Dressing, 1985). Dickinson, Rudra and Wall (1990) identified areas with estimated sediment-yield rates exceeding a selected tolerable-yield rate and areas with estimated soil-loss rates exceeding a selected soil-loss tolerance value as "target zones". They then applied two levels of soil-erosion control (reduced cropping factor, 'C', and increased surface roughness factor, 'n') under four different remedial strategies, and concluded that targeting was very effective in reducing sediment loads compared with a random approach, and more so in the areas of localized high erosion and sediment yield rates. Feather, Hellerstein and Hansen (1999) assessed Conservation Reserve Program effectiveness resulting from a shift in spatial targeting from sole use of an erodible-land criteria to use of an Environmental Benefits Index (since 1990) and estimated that benefits have doubled.

Tim, Mostaghimi and Shanholtz (1992) integrated simulation modeling with GIS and used soil-erosion rate, sediment yield, and phosphorus (P) loading to identify areas in 15.05 km^2 Nomini Creek Watershed in Virginia that were potentially high, medium, and low sources of NPS pollution. Tripathi, Panda and Raghuwanshi (2003) simulated the 92.46 km^2 Nagwan Watershed in Bihar, India by using the SWAT model to identify and prioritize critical areas on the basis of average annual sediment yield and nutrient losses. Using the AGNPS model, Yang *et al.* (2005) estimated that targeted retirement of cropland could have achieved 20% reductions in erosion, compared to the actual 12%, at almost 40% less total cost. BMP placement scenarios and their effectiveness at the watershed scale are reported in Secchi *et al.* (2007). Parajuli, Mankin and Barnes (2008) applied SWAT to targeting of edge-of-field vegetative filter implementation for sediment and fecal bacteria control. They reported that targeting could be used to improve reduction effectiveness for both sediment and bacteria, but had greater impact on sediment. Further, Veith, Wolfe and Heatwole (2004) applied an optimization procedure that uses a genetic algorithm to search for the combination of site-specific practices that meets pollution reduction requirements and minimizes cost.

In the state of Kansas, USA, total suspended solids are a leading cause of water-quality impairment in the impaired water bodies (KDHE, 2000). The Kanopolis Lake, which is the receiving water body of Smoky Hill River Watershed in central Kansas, has a High-Priority Total Maximum Daily Load (TMDL) designation for eutrophication (KDHE, 2005). To reduce eutrophication rates, lower pollutant-load targets have been established for contributing pollutants such as sediment, nitrogen (N), and P (Minson, 2006). Meeting TMDL targets will require coordinated implementation of multiple BMPs.

The goal of this study was to develop watershed-modeling-based information that could help local stakeholders and decision makers target BMP implementation based on water-quality benefits. Specific objectives were to (1) demonstrate a strategic approach that uses the SWAT model to identify areas within the Smoky Hill River Watershed that have the greatest potential to contribute to water-quality improvement and (2) quantify sediment, N, and P load reductions due to the targeting strategy relative to the random implementation of practices.

2. Methods and materials

2.1 Model

A complete review of SWAT including historic developments and applications can be found in Gassman *et al.* (2007). A detailed description of the components and mathematical equations representing the hydrologic processes can be found in Neitsch *et al.* (2005). A brief description of flow, sediment, and nutrients is given below.

The SWAT model uses a modification of United States Department of Agriculture – Soil Conservation Service (USDA-SCS) Curve Number (CN) method (USDA-NRCS, 2004), in which surface runoff is estimated as a function of daily CN adjusted for the moisture content of the soil on that day. SWAT uses modified Universal Soil Loss Equation (USLE) (Williams, 1975) to estimate erosion. Sediment routing equation uses modification of Bagnold's equation (Bagnold, 1977). SWAT first calculates the maximum amount of sediment that can be transported from a reach segment. Sediment deposition or degradation occurs depending on the incoming sediment concentration.

Nitrogen is modeled by SWAT in the soil profile and in the shallow aquifer. Organic-N associated with humus and mineral forms of N held by soil colloids and in dissolved form are the three major forms of N simulated. External sources of N include rain, fertilizer or manure application or residue, and bacterial fixation. Nitrogen is removed from the soil by plant uptake, leaching, volatilization, denitrification, and erosion. Amounts of nitrate transported with runoff, lateral flow, and percolation are estimated as mass of nitrate lost from the soil layer by multiplying volume of water and concentration of nitrate-N in the soil layer. The amount of organic-N transported with sediment is a function of concentration of organic-N in the top 10 mm, sediment yield on a given day (Mg), and N enrichment ratio, which is the ratio of the concentration of organic-N transported with the sediment to the concentration in the soil surface layer.

Similar to N, the three major forms of P that the model tracks include organic P associated with humus, insoluble forms of mineral P, and plant-available P in soil solution. Phosphorus may be added to the soil by fertilizer, manure or residue application and removed from the soil by plant uptake and erosion. Soluble P transported in surface runoff is estimated based on the amount of P in solution in the top 10 mm, surface runoff on a given day, soil bulk density in the top 10 mm, and the P soil partitioning coefficient (ratio of soluble-P concentration in the surface 10 mm of soil to soluble-P concentration in surface runoff). Sediment-bound-P transport is similar to organic-N transport described earlier. QUAL2E model (Brown and Barnwell, 1987) has been incorporated into SWAT to process in-stream nutrient dynamics.

2.2 The study area and model inputs

The Smoky Hill River Watershed, which drains into Kanopolis Lake (Figure 1), has an area of 6,316 km^2, including both the Big Creek Watershed (HUC 10260007) and Middle Smoky Hill River Watershed (HUC 10260006), and covers parts of 11 counties in central Kansas. Kanopolis Lake has a High-Priority TMDL designation for eutrophication (KDHE, 2005). Preliminary experimental studies indicated that sediment and, in turn, sediment-bound nutrients, from moderately erodible soils are likely the major pollutant sources contributing to the eutrophication impairment in the Kanopolis Lake (Mankin *et al.*, 2007).

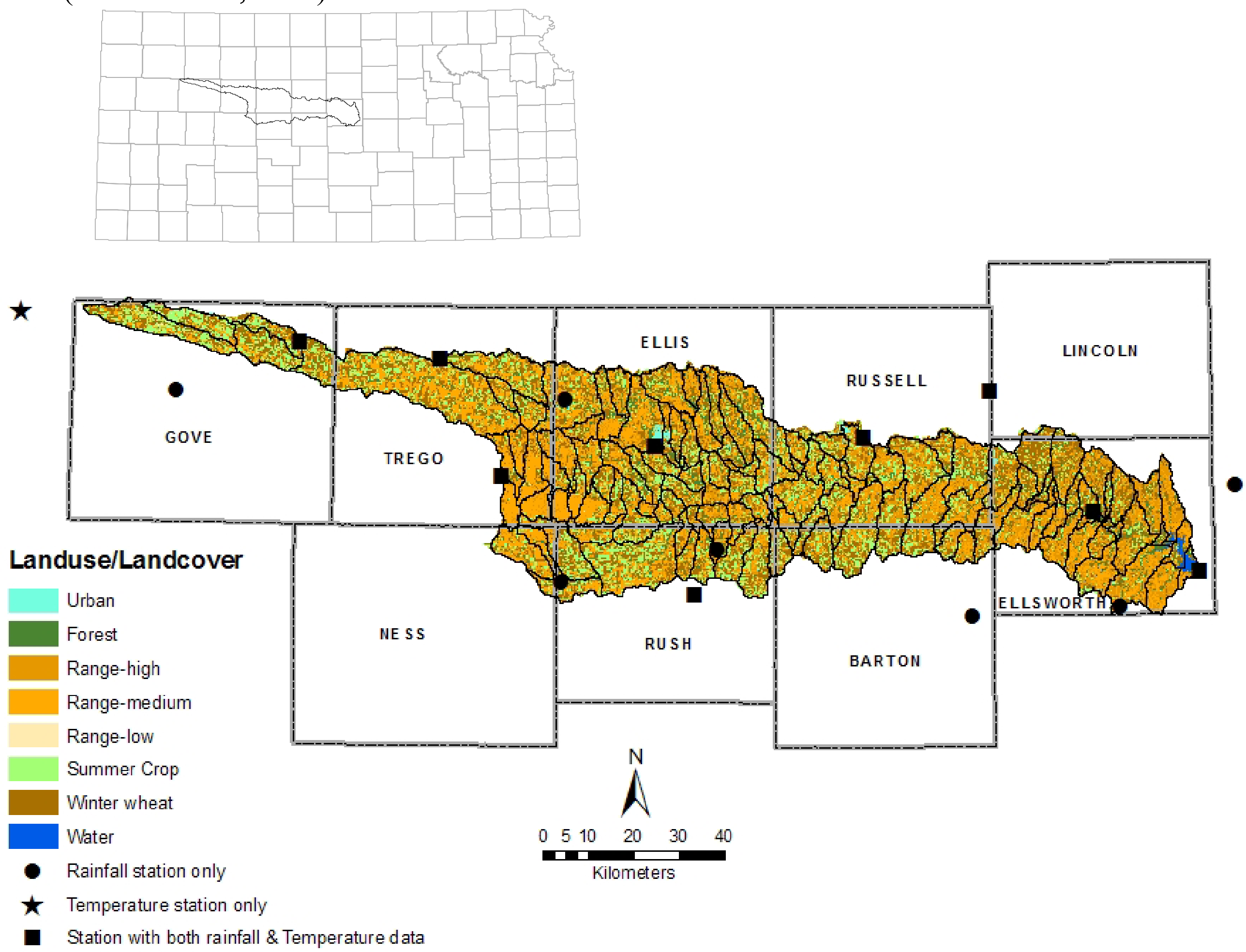

Figure 1 Smoky Hill River Watershed, Kansas, USA.

ArcView Geographical Information System interface of the SWAT 2000 version (AVSWAT-2000 Version 1.0) (Arnold *et al.*, 1998; Di Luzio *et al.*, 2002; Di Luzio *et al.*, 2004) was used in this study. A 7.5-minute (30-m interval) digital elevation model (DEM) was used to derive the geomorphological parameters of the study watershed. Elevation in the watershed ranges from 430 m to 921 m, with an average slope of 3.2%. The STATSGO soil database used to define soil properties identified 25 different soil types in the study area. Watershed soils are mostly silty loam. The landuse/landcover map used was derived from multi-temporal Landsat Thematic Mapper 5 imagery of the year 1992 (using a method described in Bhuyan *et al.*, 2002). Landuse/landcover (Table 1) is dominated by cropland (48%) and rangeland (46%) (Figure 1). The main crops grown in the watershed are winter wheat and grain sorghum. The annual average precipitation in the watershed was 691 mm/yr (from 1971-2000), ranging from 620 mm/yr in the west to 882 mm/yr in the east.

Table 1 Landuse/landcover distribution in the Kanopolis Lake watershed

Landuse/landcover	% area
Forest	4.6
Range-high	16.2
Range-low	0.2
Range-medium	29.4
Summer crop	18.6
Urban	0.5
Water	0.3
Winter wheat	30.2

Rangeland was differentiated into high, medium, and low vegetative cover classes. These classes were modeled in terms of minimum cover-factor (0.003 for high, 0.042 for medium, and 0.15 for low), leaf-area index (2.5, 1.7, and 1.0), and canopy height (1.0 m, 0.4 m, 0.2 m) (Koelliker and Bhuyan, 2000). Measured daily precipitation was obtained from sixteen raingage stations and minimum and maximum daily temperature from ten stations in and around the watershed (Figure 1). This weather data was obtained from the National Climatic Data Center. Other weather parameters such as wind speed, solar radiation, and relative humidity were generated by the SWAT model using inbuilt weather generator. A threshold area of 25 km^2 was specified in AVSWAT; this resulted in the watershed being delineated into 128 subwatersheds, with areas up to 459 km^2. These subwatersheds roughly aligned with the HUC-14 or smaller subwatersheds. A zero threshold was used for landuse and soil, which resulted in a total of 2,519 HRUs. The simulation was run for a 10-year period, from 1992 to 2001.

All cropland in the watershed was simulated in a typical cropping practice of a 3-year conventionally tilled (CT), wheat-sorghum-fallow rotation with fertilizer and pesticides applied (Table 2). All rangeland was simulated in grazing operation, with a stocking rate of 0.05 km^2/cow-calf (12 acres per cow-calf) pair as the baseline scenario. The stocking rate used in the study was suggested as typical by extension specialists and local experts. Grazing-operation parameters required by SWAT were calculated based on a report by Ohlenbusch and Watson (1994) (see Tuppad, 2006 for more details). Flows and nutrient loadings from seven municipal wastewater treatment plants were input as point sources.

Table 2 Wheat-sorghum-fallow rotation (3 years)*

Date	Conventional Till	Reduced Till
Year 1		
30-Jun	Harvest and kill Winter Wheat	Harvest and kill Winter Wheat
15-Jul	Tandem Disk Plow	Pesticide (Glyphosate (Roundup) at 0.56 lb ae/A (0.63 kg/ha) + 2,4-D amine at 0.5 lb ae/A (0.5616 kg/ha))
14-Aug	Chisel Plow	--
31-Aug	--	Pesticide (Glyphosate (Roundup) at 0.56 lb ae/A (0.63 kg/ha) + 2,4-D amine at 0.5 lb ae/A (0.5616 kg/ha))
13-Sep	Chisel Plow	--
Year 2		
1-May	Chisel Plow	Field Cultivator
14-May	Fertilizer (DAP#: 73 kg/ha, urea: 117 kg/ha)	Fertilizer (DAP: 73 kg/ha, urea: 117

Date	Conventional Till	Reduced Till
		kg/ha)
15-May	Field Cultivator	Field Cultivator
1-Jun	Plant/begin growing season - Grain Sorghum (GS)	Plant/begin growing season - Grain Sorghum (GS)
15-Jun	Pesticide (Atrazine 1 lb ai/A (1.0123 kg/ha) + crop oil concentrate at 1qt/A (1 qt = 946ml) 0.5 kg/ha)	Pesticide (Atrazine 1 lb ai/A (1.0123 kg/ha) + crop oil concentrate at 1qt/A (1 qt = 946ml) 0.5 kg/ha)
13-Oct	Harvest and kill GS	Harvest and kill GS
Year 3		
1-Jun	Offset Disk, Heavy duty	Pesticide (Glyphosate (Roundup) at 0.56 lb ae/A (0.63 kg/ha) + 2,4-D amine at 0.5 lb ae/A (0.5616 kg/ha))
15-Jul	Chisel Plow	--
14-Aug	Chisel Plow	Field Cultivator
20-Aug	Pesticide (Glyphosate (Roundup) at 0.56 lb ae/A (0.63 kg/ha) + 2,4-D amine at 0.5 lb ae/A (0.5616 kg/ha))	Pesticide (Glyphosate (Roundup) at 0.56 lb ae/A (0.63 kg/ha) + 2,4-D amine at 0.5 lb ae/A (0.5616 kg/ha))
14-Sep	Fertilizer (DAP: 49 kg/ha, urea: 104 kg/ha)	Fertilizer (DAP: 49 kg/ha, urea: 104 kg/ha)
15-Sep	Field Cultivator	Field Cultivator
16-Sep	Plant/begin growing season–Winter Wheat	Plant/begin growing season–Winter Wheat

#Diammonium Phosphate

*Additional details in Tuppad (2006)

2.3 Targeted versus random selection criteria

The strategic targeting method for this watershed focused on the use of BMPs to reduce overland erosion sources of sediment. Spatial targeting of potential sediment contributing areas was done at the subwatershed level. Annual average sediment-yield (Mg/ha) for each subbasinfrom SWAT model was used as the sole criterion for selecting the subbasins for targeting. Subbasins were ranked based on SWAT sediment-yield estimates from the baseline scenario (0% BMP adoption or 100% CT practice). Starting with the subbasin having the greatest sediment yield, the next highest ranked subbasin was successively added until the cumulative cropland area equaled the targeted percentage of total cropland area in the watershed (nominally, 10, 25, 50, and 100%). Cropland targeting was implemented in each subbasin on an "all-or-nothing" basis, which resulted in actual percentages of 10, 26, 52, and 100% of total cropland area for the scenarios simulated in this study.

In the absence of spatial targeting, farmers from any location in the watershed are equally likely to volunteer for BMP implementation (Diebel *et al.*, 2008; Parajuli, Mankin and Barnes, 2008). This was simulated by selecting the subbasins randomly for implementation. For the random method, subbasins were ordered randomly by SWAT subbasin number. Following the randomly ordered listing, subbasins were successively added until the cumulative cropland area equaled the percentage of total cropland area in the watershed used in the targeting scenarios (10, 26, 52, and 100%). The resulting distributions of selected subwatersheds for both targeted and random selection methods are shown in Figure 2.

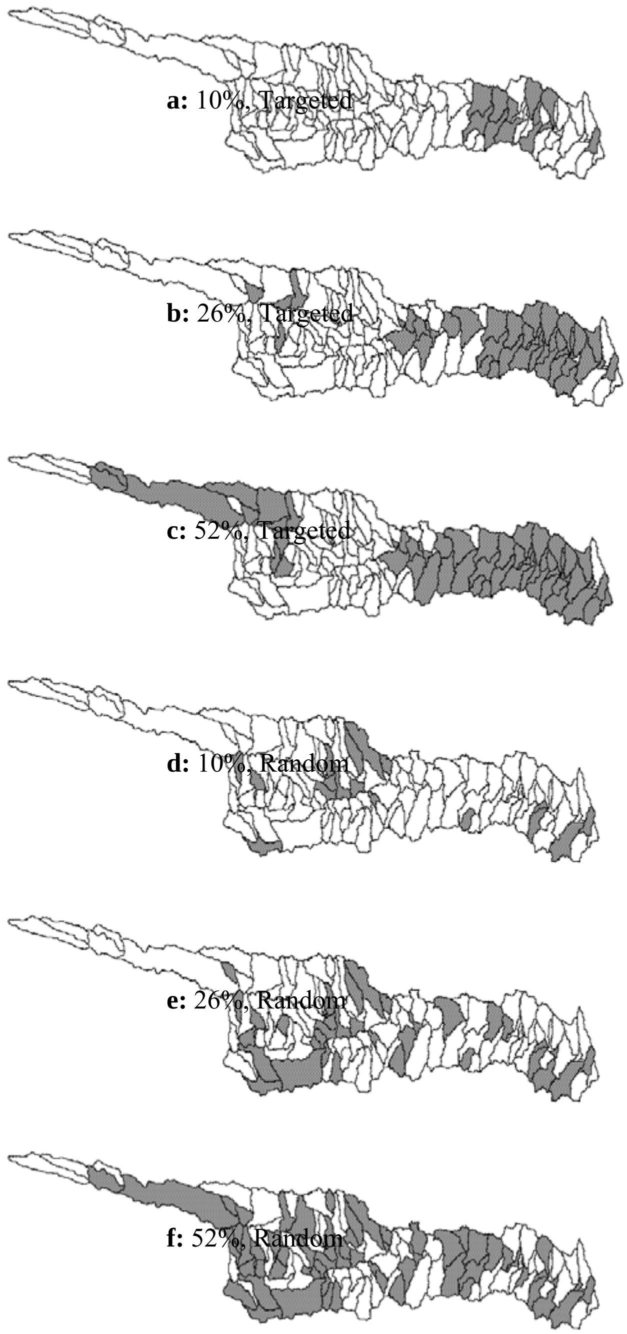

Figure 2 Subbasins selected for BMP implementation by percentage watershed-cropland area and selection method.

2.4 Best Management Practices evaluated

Three BMPs were evaluated in this study: reduced tillage (RT); edge-of-field vegetative filter strips (VFSs); and contoured-terraces with graded channels (TERR). As with the CT system, the RT practices and the fertilizers and pesticides applied were based on the most common practices carried out in the study area (Table 2). Type and dates of tillage operations, and dates and rates of fertilizers and pesticides applied, were obtained from local experts and extension specialists at Kansas State University.

Edge-of-field VFSs were modeled by using the filter-strip (FILTERW variable in *.hru file) feature in SWAT, in which sediment and nutrient trapping efficiencies were determined by the simple exponential relationship:

$$\text{Trapping efficiency} = 0.367\ (\text{filter-strip width, m})^{0.2967} \tag{1}$$

A filter-strip width of 6 m (which translates into a trapping efficiency of 62%) was used in this study (USDA-NRCS, 2003).

The contoured-terrace system was modeled by using a P-factor of 0.12 (for subbasins with overland slopes of 1 to 2% and 9 to 12%) or 0.1 (for subbasin with overland slopes of 3 to 8%) (Wischmeier and Smith, 1978). The P-factor is an HRU-level parameter, which is defined in the management (*.mgt) file in SWAT.

2.5 Targeting analysis

The impact of each BMP adoption scenario was evaluated for sediment, total-N, and total-P. Impacts were assessed at both the subbasin level and the watershed level. Subbasin-level pollutant losses (termed overland pollutant “yields” in this study) included both overland and edge-of-field processes. An area-weighted average of all subbasin yields for each scenario was used for analysis. Watershed-level pollutant losses (termed pollutant “loads” in this study) included in-stream processes and represented overall pollutant loading at the watershed outlet. This value was taken as the modeled load at the watershed outlet, without including Kanopolis Lake. Effectiveness of each BMP scenario was expressed as a percentage reduction of pollutant (sediment, total-N, or total-P) yield or load relative to the baseline (no BMP) scenario. Studies have shown that the uncertainty associated with estimated BMP effectiveness is substantially smaller than that associated with the absolute prediction (Arabi, Govindaraju and Hantush, 2007).

3. Results and discussion

3.1 Model validation

The SWAT model was run and validated based on a set of standard, default input parameters but was not calibrated. Modeled daily streamflow for the baseline scenario was compared to measured flow at USGS gaging station 06864500, upstream of Kanopolis Lake (Figure 1), resulting in modeling efficiency (Nash and Sutcliff, 1970) of 0.52 and coefficient of determination (R^2) of 0.54. This uncalibrated model efficiency was classified as “satisfactory” according to Moriasi et al. (2007). Comparing this uncalibrated result against all daily model statistics reported by Gassman et al. (2007) from a literature review of more than 250 published SWAT studies, the R^2 was better than 12 (29%) of calibration values and 10 (26%) of validation values reported, and E was better than 38 (38%) of calibration values and 40 (50%) of validation values reported. These results were considered sufficient for use in calculating relative differences between simulated scenarios for targeting purposes.

3.2 Subbasin sediment yield reductions

Reduction in annual average overland sediment yield achieved with 100% adoption of RT as a BMP (all cropland converted from CT to RT) was 29.2% (Figure 3a). The reduction in sediment loss due to RT implementation on 10% of the cropland area was 6.8% by the targeted approach, compared with 2.4% by the random approach. This difference increased at 26% RT adoption, with 14.1% reduction for targeted approach, compared with 6.2% reduction for the random approach.

These results can also be summarized as the percentage area required to achieve the same (e.g., 10%) overland sediment-yield reductions by using the two methods. The RT practice must be implemented on 36% of the watershed's cropland to achieve 10% sediment yield reduction by using random implementation, whereas the strategic targeting approach would require implementation on only 17% of the cropland in the watershed to achieve the same sediment yield reduction (Figure 3a). In this example, the random approach required BMP implementation in about 2.2 times more watershed area than the targeted approach did.

Modeled pollutant reductions using VFS were greater than the reductions for RT. Reduction in annual average overland sediment yield achieved with 100% VFS adoption (6-m VFS added to all cropland) was 80.6% (Figure 3d). The reduction in sediment loss due to VFS adoption in 10% of the cropland area was 15.4% by the targeted approach, compared with 5.4% by the random approach. This difference increased at 26% VFS adoption, with 31.2% reduction for targeting, compared with 13.1% reduction for random. To achieve 10% sediment yield reduction, VFS must be implemented on 25% of the watershed by using random implementation, whereas the strategic targeting approach would require implementation on only 8% of the cropland in the watershed.

In another Kansas watershed, Parajuli, Mankin and Barnes (2008) found implementation of VFS on 10% of watershed cropland area resulted in 46% sediment reduction using a similar targeting approach compared to 28% reductions for random implementation. Similarly, implementation of VFSs on 25% of the cropland area resulted in 63% reduction using targeting and 33% reduction using random implementation. These results showed a greater magnitude of sediment reduction, presumably due to their use of larger (15-m) VFSs, but a similar two-fold or greater improvement of targeting compared to random implementation.

The TERR BMP resulted in similar pollutant reduction trends as with VFS. Reduction in annual average overland sediment yield achieved with 100% BMP implementation was 86.1% (Figure 3g). Treating 10% of the total cropland area with BMP implementation resulted in a 22.2% reduction in overland sediment yield by targeted approach and 7.8% reduction by random approach. BMP adoption on 26% of cropland area achieved a reduction of 44.9% by the targeted approach, compared with 18.8% by random approach. To achieve 10% sediment yield reduction, TERR BMP must be implemented on 14% of the watershed cropland by using random implementation, whereas the strategic targeting approach would require implementation on only 5% of the cropland in the watershed.

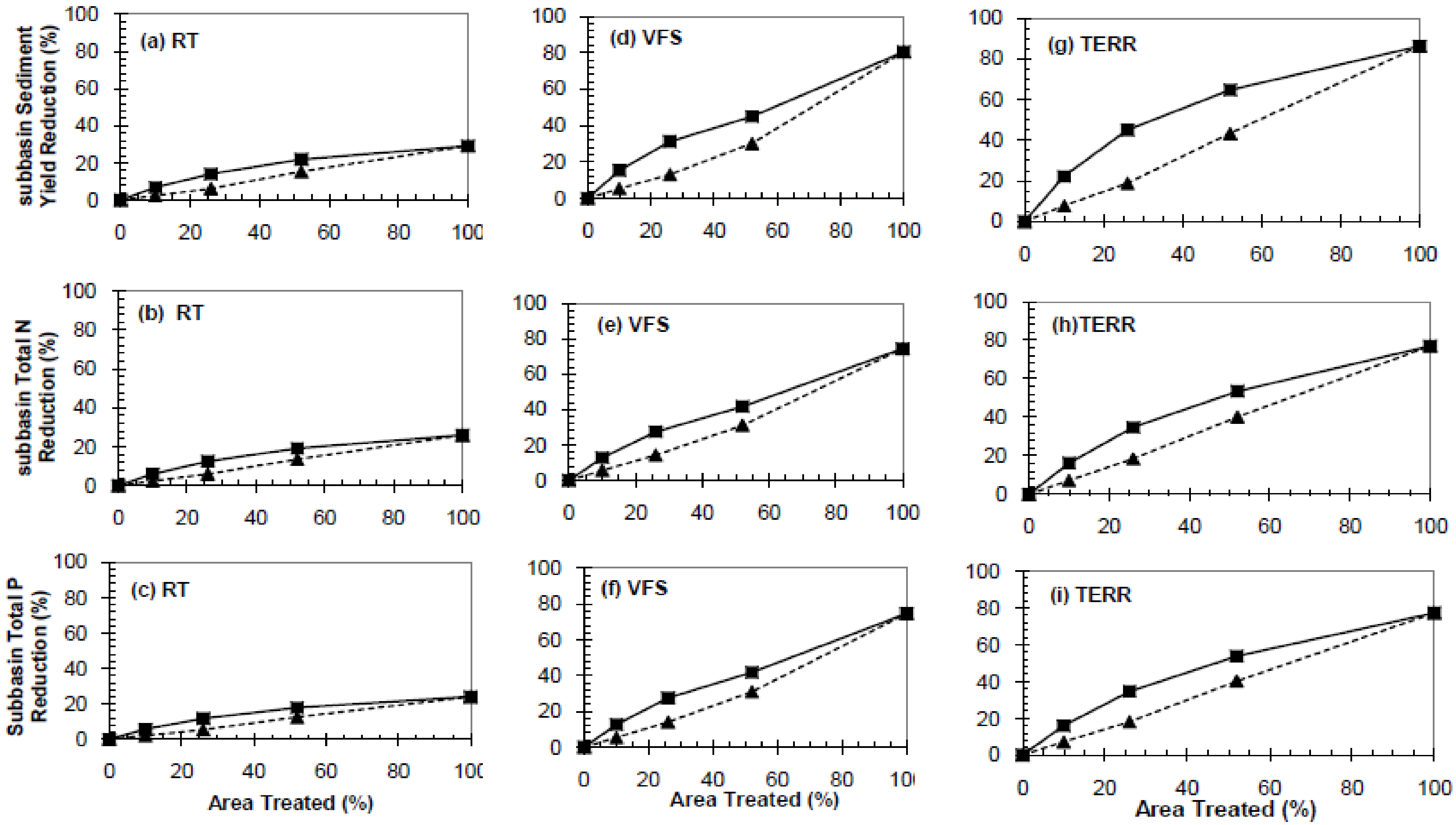

Figure 3 Effect on subbasin pollutant yields of implementing cropland BMPs (Reduced Tillage (RT), Vegetative Filter Strip (VFS), Contoured-terraced (TERR)) using the targeted (■, solid line) and random method (▲, dotted line)

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3.3 Subbasin nutrient yield reductions

Overall, reductions of nutrients were slightly less than that of sediments for 100% RT adoption: 25.9% for total-N (Figure 3b) and 23.9% for total-P (Figure 3c). Strategic targeting, however, showed relatively greater improvements than with sediments for the first increment of cropland treated. At 10% RT implementation, targeting reduced total-N yields by 6.0% compared to 2.3% for random and total-P yields by 5.6%, compared with 2.0% for random. Similar to sediment, more than double the land area was required to achieve 10% reduction in total-N and total-P yields for the random approach, compared with the targeted approach.

Overall, reductions of nutrients were slightly less than with sediments for 100% VFS adoption: 74.5% for total-N (Figure 3e) and 74.7% for total-P (Figure 3f). Strategic targeting, however, showed relatively greater improvements than with sediments for the first increment of cropland treated. At 10% VFS implementation, targeting reduced total-N yields by 12.9%, compared with 5.6% for random, and reduced total-P yields by 12.6%, compared with 5.4% for random.

Similar overland nutrient yield reduction potential was found for the TERR BMP scenario. Overall, total-N yield was reduced by 77.0% (Figure 3h), and total-P yield was reduced by 77.3% (Figure 3i), due to 100% BMP adoption. At 10% BMP implementation, targeting reduced total-N yields by 16.2%, compared with 7.2% for random, and reduced total-P yields by 16.0%, compared with 7.1% for random.

The random approach demonstrated a nearly linear reduction in overland yields of all pollutants with increasing BMP implementation area (Figure 3). In contrast, the targeted approach resulted in greater improvements (steeper slopes in the pollutant-yield curves) for the initial areas of cropland BMP implementation. Targeting provides greater benefits relative to the random approach for the first increments of BMP implemented than for later increments of implementation; the relative benefits of targeting decrease as the area of targeted implementation increases.

3.4 Watershed-outlet sediment load reductions

Annual average sediment load delivered to the watershed outlet was reduced by 7.0% with all cropland in RT, compared with having all cropland in CT (Figure 4a). With 10% BMP adoption, the reduction achieved was 2.2% by the targeted approach, compared with 0.7% by the random approach. This difference increased at 26% BMP adoption, with 5.3% reduction for the targeted approach, compared with no change (0.6% reduction) for the random approach. For sediment, a 10% reduction at the watershed outlet was not achievable. However, the targeted approach was found to achieve a 5% reduction in outlet sediment load by implementing BMPs on about 25% of the cropland area, which was less than one-third the cropland area required by the random approach (84%) (Figure 4a).

Annual average outlet sediment load was reduced by 51.1% with VFS implemented in all cropland (Figure 4d). With 10% BMP implementation, the reduction achieved was 5.3% by the targeted approach, compared with 3.2% by the random approach. Parajuli, Mankin and Barnes (2008) reported 10% VFS implementation had a slightly greater

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impact at the watershed outlet, resulting in 12% reductions for targeting compared to 2% reductions for random implementation. These differences between watersheds indicate the importance of watershed-specific analyses of the impacts of targeting. At 26% BMP implementation, the differences in our study increased, with 14.0% reduction for the targeted approach compared with 4.7% reduction for random approach. The targeted approach was found to achieve a 10% reduction in outlet sediment load by implementing BMPs on about 17% of the cropland, which was less than one-third the cropland area required by the random approach (55%) (Figure 4d).

In the TERR BMP, annual average outlet sediment load was reduced by 60.1% with 100% BMP implementation (Figure 4g). With 10% BMP implementation, the reduction achieved was 9.7% by the targeted approach, compared with 5.6% by the random approach. For 26% BMP adoption, the load reduction achieved was 31.8% through targeted approach and 8.3% through the random approach. The targeted approach was found to achieve a 10% reduction in outlet sediment load by implementing BMPs on about 9% of the cropland, which was about one-fourth the cropland area required by the random approach (33%) (Figure 4g).

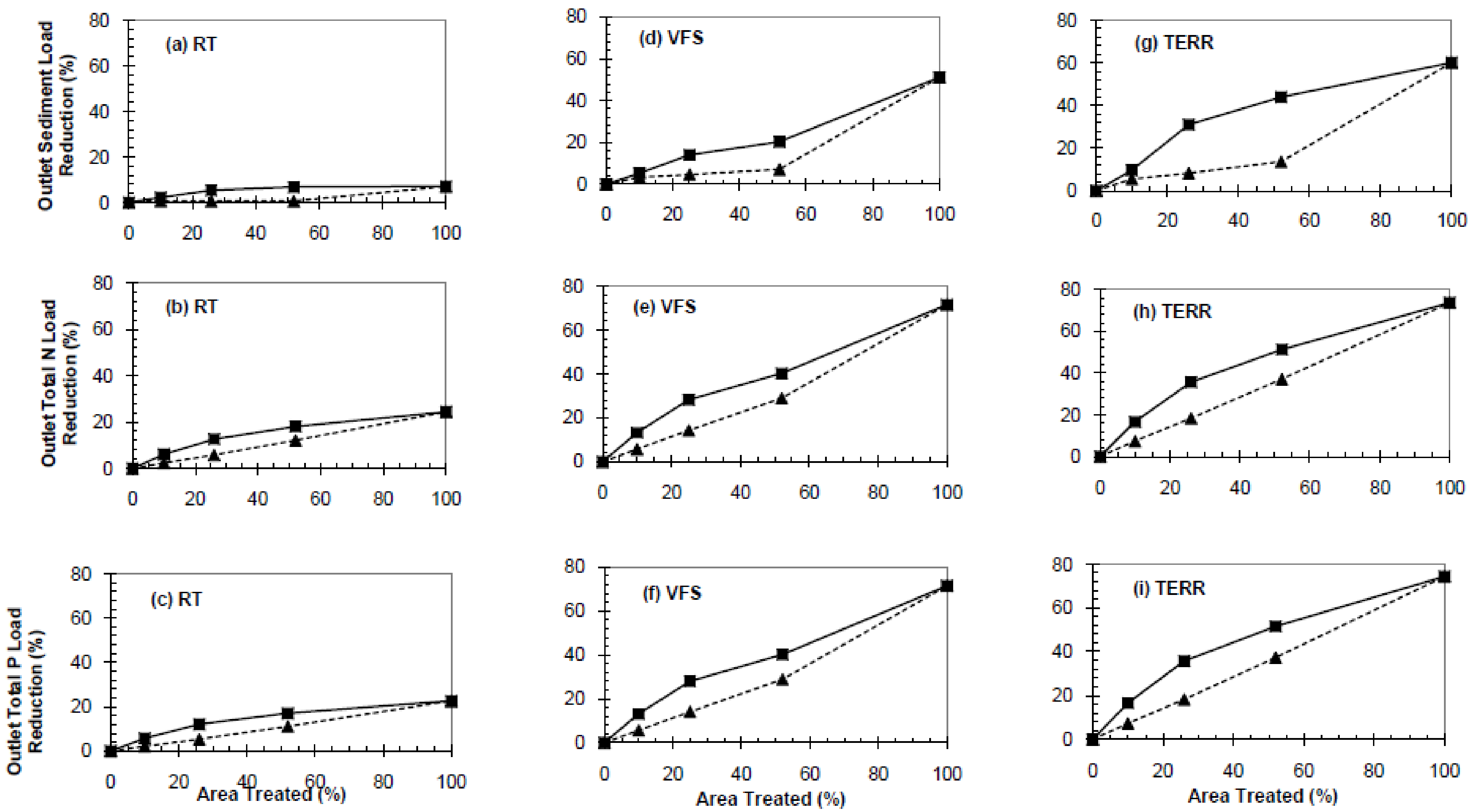

Figure 4. Effect on watershed-outlet pollutant loads of implementing cropland BMPs (Reduced Tillage (RT), Vegetative Filter Strip (VFS), Contoured-terraced (TERR)) using the targeted (■, solid line) and random method (▲, dotted line)

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3.5 Watershed-outlet nutrient load reductions

In contrast to results for sediments, watershed-outlet loads of nutrients were similar to overland yields. Implementation of RT in 100% of the watershed resulted in outlet load reductions of 24.4% for total-N (Figure 4b) and 22.6% (Figure 5c) for total-P. These reductions were 5.8% less than overland-N reduction and 5.3% less than overland-P reduction. Both total-N and total-P were 4% less for 100% VFS implementation or 100% contoured-terraced BMP compared to overland yields.

Adoption of RT BMP on all cropland resulted in a 29.2% reduction in overland sediment yield (Figure 3a) but only 6.8% reduction in the sediment load at the watershed outlet (Figure 4a). Similarly, 100% VFS adoption reduced overland yields by 80.6% (Figure 3d), but reduced watershed-outlet loads by only 51.1% (Figure 4d), and 100% contoured-terraced BMP adoption resulted in overland yield reduction of 86.1% (Figure 3g), but watershed-outlet load reduction of only 60.1% (Figure 4g). These results indicate the importance of stream sediment routing to simulate watershed-scale sediment loads. The SWAT model first estimates the maximum amount of sediment that can be transported from a reach. Then, based on the initial concentration of sediment in the reach at the beginning of the time step, deposition or degradation dominance is estimated and, accordingly, the amount of sediment that could settle or re-entrain is estimated. In-stream dynamics play an important role in transporting the pollutants downstream, and simulating these processes requires careful consideration.

3.6 Discussion of targeting method application

These results suggest that targeting can increase effectiveness of BMP implementation for water-quality improvement, particularly at the initiation of a watershed restoration effort. However, the targeting approach demonstrated in this study may have several important limitations or challenges that must be considered.

Targeted BMP implementation might be more expensive (in terms of money and effort) than random implementation. Once fields are targeted for implementation, the corresponding land-owner must be identified, located, approached, and sold on implementation. The cost savings from achieving greater pollutant-yield reductions per unit area implemented must offset any greater cost per unit area incurred to implement targeting. In this study, total implementation costs per unit area up to two times greater for targeted fields would result in the same cost per unit load reduction and would likely be justified as cost effective. If implementation costs exceeded this level, random implementation would likely be the more cost-effective option.

The results demonstrated that the water-quality reduction per unit area converted to a BMP decreased with each successive subbasin area converted to a BMP in the watershed (Figures 3 and 4). As such, the water-quality return per unit money or effort invested in targeting would also diminish as implementation progressed. This implies that the most cost-effective strategy might be to transition from targeting during the early phase of implementation efforts when returns (pollutant-yield reductions per unit monetary investment in implementation, for example) are still high, to random (first-come, first-served) implementation when returns are lower. Early, targeted implementation program

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success could be followed by more widespread adoption across all remaining fields and landowners in the watershed.

The baseline conditions for this study assumed the watershed started with no BMPs. But BMPs typically have been implemented on some portion of a watershed before targeting begins. Overcoming this limitation of this study requires additional data about specific locations of existing BMPs and additional modeling effort to exclude these areas from the pool of cropland areas eligible for implementation. The process of comparing results of BMP implementation scenarios to baseline results, however, would remain the same. If information is available about the overall extent of existing BMPs but not their specific locations, then the starting point for targeting efforts will likely fall somewhere between the random and targeted reduction levels for the given percentage of BMP implementation. If the starting point is at or below the level achieved by random implementation, targeting would likely still be effective. If the starting point is closer to the level achieved by targeting, then benefits of early-program targeting would already have been achieved and use of targeting from that point forward may not be cost effective.

4. Summary and conclusions

The concept of identifying, selecting, and targeting critical areas of point-and nonpoint-source pollution has been widely recognized for pollution control. A watershed modeling approach was used to quantify the impacts of implementing three different BMPs on incremental increases in cropland area to evaluate the effectiveness of a targeted approach versus a random approach in reducing the estimated overland pollutant yields and watershed-outlet pollutant loads. Priority areas for the targeted approach were selected on the basis of the erosion rates as estimated by the SWAT hydrologic/water-quality model.

The targeted watershed modeling approach using SWAT was more effective in reducing both overland and watershed outlet pollutant loads, with less area, than randomly selecting areas for BMP adoption. Annual average, watershed-scale, overland pollutant yield reductions of 10% generally required BMP adoption on less than half the land area when targeting was used rather than random placement of BMPs. Targeting produced even greater benefits when watershed-outlet loads were considered.

The benefits of targeting were greater for the initial increments of BMP adoption, and decreased as the proportion of BMP adoption on targeted land areas increased. Although simulated subbasin sediment yield was the sole criteria used for identifying target subwatersheds, this strategy could be extended to other selection criteria, landuse types, soil types, and other BMPs. For example, there is a substantial acreage of rangeland in these subbasins that also should be assessed for targeting.

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