Strategic targeting of watershed management using water quality modelling

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Abstract

The key to achieving the most cost effective water-quality protection on a watershed scale is to identify and implement practices on areas that contribute most to water-quality impairment. This stands in contrast to the typical approach, where implementation depends on volunteer adoption by landowners and managers. The goal of this paper is to present a strategic approach that identifies areas that have the greatest potential to contribute to water-quality improvement and helps focus the watershed management efforts that will produce maximum water-quality benefits on these areas. The study watershed, Smoky Hill River/Kanopolis Lake watershed in Kansas, USA, consists of almost 50% cropland, considered a major source of pollutants. The impacts of reduced tillage (RT) and edge-of-field vegetative buffers (VBS) on sediment and nutrients were evaluated using either random implementation or strategic targeting based on ranked subbasin overland sediment yield. The targeted watershed modelling approach was found to be more effective in reducing pollutant load both overland and at the watershed outlet with less area than randomly selecting areas for BMP adoption. Annual average, watershed-scale, overland pollutant yield reductions of 10% 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 are greater for initial increments of BMP adoption and decrease as the proportion of BMP adoption on targeted land areas increases.
Keywords: watershed restoration, basin, SWAT, conservation practices.

1 Introduction

Nonpoint sources of sediment, nutrients, and bacteria, primarily in surface water runoff have been identified as major causes of water quality problems in streams and lakes. Minimizing watershed pollutant yields requires coordinated implementation of agricultural best management practices (BMPs). Strategic targeting and prioritization of areas for BMP implementation, rather than random or “first-come, first serve” selection of areas, is the key to cost-effective water quality improvement. Identifying fields/areas with high pollution potential and then treating these fields first would be a more efficient way to allocate financial and educational resources and control nonpoint source pollution.

Land use and land cover have a tremendous effect on water and sediment budget of watersheds (Kunhle *et al.*, [8]; Tong and Chen, [12]). Managing the land wisely can improve the downstream water quality substantially. Watershed modeling strategies for identifying and prioritizing critical areas and impacts of best management practices have been demonstrated by a number of studies. 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.* [9] described critical area selection criteria from both land-resource and the water-resource perspectives. Dickinson *et al.* [3] 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 four different remedial strategies and concluded that targeting is more effective in reducing sediment loads compared to random approach. Tim *et al.* [11] integrated simulation modeling with GIS and used soil erosion rate, sediment yield, and phosphorus loading to identify watershed areas that are potentially high, medium, and low sources of nonpoint source pollution. Tripathi *et al.* [13] identified and prioritized critical areas on the basis of average annual sediment yield and nutrient losses using SWAT.

In the state of Kansas, USA, total suspended solids (TSS) are a leading cause of water-quality impairment, behind only fecal coliform bacteria and Atrazine (KDHE, [7]) in the number of water bodies affected. Based on the Kansas Department of Health and Environment (KDHE) Watershed Assessment Report (http://www.kdhe.state.ks.us/tmdl/sstmdl.htm#Table%202), the study area, Kanopolis Lake Watershed, has a High-Priority Total Maximum Daily Load (TMDL) designation for eutrophication. To reduce eutrophication rates, lower pollutant-load targets must be established for contributing pollutants such as sediment, nitrogen (N), and phosphorus (P). The TMDL determination process estimates the maximum pollutant load a water body can receive and still meet water-quality standards for its designated uses. Possible remedial measures (such as BMPs) also are identified to reduce excess load from contributing sources. Meeting TMDL targets will require coordinated implementation of many BMPs.

The objective of this study was to demonstrate a strategic approach that identifies areas with the greatest potential to contribute to water-quality improvement and to help focus watershed management efforts that produce maximum water-quality benefits on these areas. In this study, the Soil and Water

Assessment Tool (SWAT) watershed model will be applied to target areas for effective adoption of BMPs, although the concept can be applied to many models or selection criteria.

2 Methods

2.1 SWAT (Soil and Water Assessment Tool) simulation model

ArcView GIS interface of AVSWAT-2000 version 1.0 (Arnold *et al*., [1]; Di Luzio *et al*., [5]; Di Luzio *et al*., [4]) was used. SWAT is a physically based, river-basin scale, deterministic, continuous simulation model that operates on a daily time step. SWAT can predict the impact of land-management practices on water, sediment, nutrient and pesticide yields from large ungaged watersheds. The model has the capability for adding flows and measured water quality data from point sources such as municipal wastewater treatment plants.

The SWAT interface delineates watershed subbasins based on topography and specified threshold drainage area. Soils and landuse maps are overlaid to result in hydrologic response units with unique soil/landuse combinations.

2.2 The study area

The Smoky Hill River/Kanopolis Lake Watershed (fig. 1) covers 6316 km^2 in parts of 11 counties and drains into Kanopolis Lake in central Kansas. Kanopolis Lake is the drinking water source for Post Rock Rural Water District, which provides safe drinking water to residents of Osborne, Russell, Lincoln, Ellsworth, Ottawa, Saline, and McPherson counties. The watershed includes 6540 km of intermittent streams and 844 km of perennial streams.

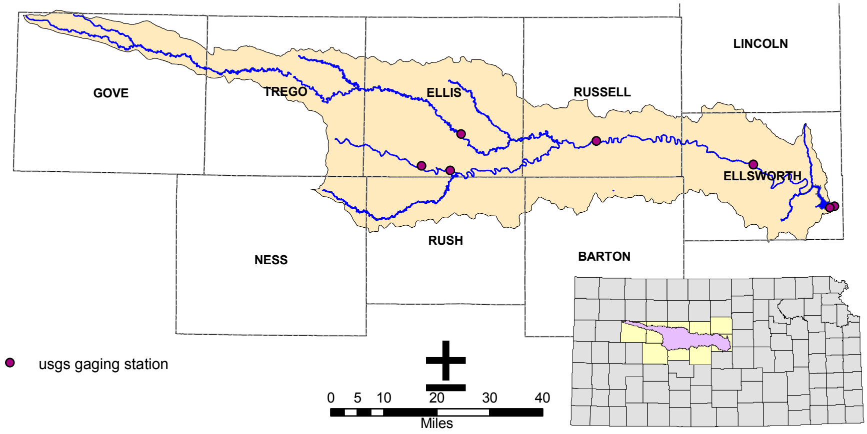


Figure 1: Smoky Hill River/ Kanopolis Lake Watershed, Kansas, USA.

Watershed soils are mostly silty loam and land-cover is dominated by cropland (48%) and rangeland (46%). Elevation in the study area ranges from 430.0 m to 921.1 m with an average slope of 3.2%. Kanopolis Lake has a High-Priority TMDL designation for eutrophication and Low-Priority TMDL designations for chloride and sulfate. Preliminary studies indicated that sediment and, in turn, sediment-bound nutrients from moderately erodible soils, is likely the major pollutant contributing to the eutrophication impairment in the Lake.

2.3 Model inputs

A 7.5-minute (30-m interval) Digital Elevation Model (DEM) was used in AVSWAT to derive the geomorphological parameters of the study watershed. STATSGO soil database was used, and according to this database, there are 25 different soil types in the study area. A land use/land cover map used was derived from multi-temporal Landsat Thematic Mapper (TM) 5 imagery of the year 1992 (using a method described in Bhuyan *et al.,* [2]). Table 1 lists the percentage area of different landcover types.

Table 1: Landcover in Kanopolis watershed.

Landcover type	Area (% of total watershed)
Winter Wheat	30.18
Grain Sorghum	18.68
Forest	4.55
Urban	0.47
Rangleland-High	16.21
Rangeland-Medium	29.45
Rangeland-Low	0.18
Water	0.34

Rangeland was differentiated into high, medium, and low vegetative cover classes. These classes were modelled in terms of cover-factor (0.15 for high, 0.042 for medium, and 0.003 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). Daily precipitation and temperature data for the period from 1970-2001 from over twenty weather stations distributed across and around the watershed, obtained from the National Climatic Data Center (NCDC), was used. A threshold area of 2500 ha was specified in AVSWAT; this resulted in the watershed being delineated into 128 subbasins with areas ranging from 0.18 ha to 45856 ha.

A 3-year conventionally tilled (CT) wheat-sorghum-fallow rotation with fertilizer and pesticides applied was the baseline cropping practice on cropland across the entire watershed. Rangeland grazing operations were simulated with a stocking rate of 4.9 ha per cow-calf pair. Stocking rate was provided by extension specialists and local experts. Grazing operation parameters required by SWAT were calculated based on report by Ohlenbusch and Watson [10]. Flows and nutrient loadings from seven municipal wastewater treatment plants were input into the SWAT-GIS interface as point sources.

Two BMPs were evaluated: reduced tillage (RT) and edge-of-field vegetative buffer strips (VBS). As with the CT system, RT practices, fertilizers and pesticides applied were based on the most common practices in the study area. 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 VBS were modelled using the filter-strip feature in SWAT. Sediment and nutrient trapping efficiencies are determined using the simple exponential relationship: *trapping efficiency* = 0.367 (*filter-strip width*, m)$^{0.2967}$. A *filter-strip width* of 5 m (*trapping efficiency* = 59%) was used.

2.4 Selection criteria

The impact of implementing BMPs on 0, 10, 26, 52, and 100% of total cropland area within the watershed was estimated using two selection methods: random and targeted. The resulting distribution of selected subwatersheds is shown in Figure 2. For the random method, subbasins were selected randomly for BMP adoption until the cumulative area of cropland within each subbasin reached the target percentage of total cropland area in the watershed. The random selection could represent percentage of the area in each county that could potentially receive funds to implement BMPs, farmers' willingness and support to implement BMPs, etc. For the targeted method, annual average sediment-yield estimates from SWAT modelling were used as the sole criteria for selecting the subbasins for BMP implementation. Subbasins were ranked based on SWAT sediment-yield estimates from the baseline scenario (0% BMP adoption, 100% CT practice). Again, the number of subbasins corresponding to 10, 26, 52, and 100% of cropland were selected for BMP implementation.

2.5 Model response

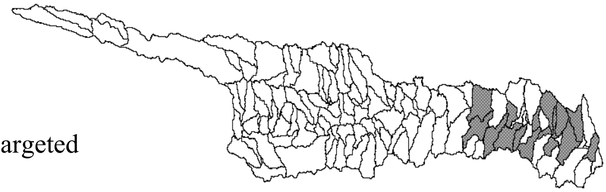
The impact of BMP adoption was evaluated for total sediment, total N, and total P. Impacts were assessed on overland pollutant losses (referred to as overland pollutant "yields"), which included both overland and edge-of-field processes, and total transported pollutants to the watershed outlet (referred to as total pollutant "loads"), which included in-stream processes and represented overall pollutant loading to the Kanopolis Lake.

3 Results and discussion

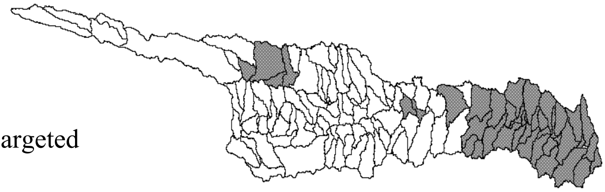
3.1 Overland pollutant yields

3.1.1 Sediment yield reductions

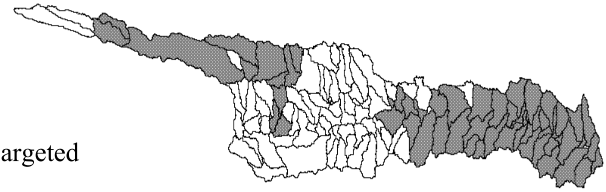
Reduction in annual average overland sediment yield achieved with 100% adoption of RT as a BMP (all cropland converted from CT to RT) was 30.2% (fig. 3a). The reduction in sediment loss due to RT adoption in 10% of cropland area was 8.0% by the targeted approach compared to 3.8% by the random approach. This difference increased at 26% RT adoption, with 15.3% reduction for targeted approach compared to 7.1% reduction for random approach.



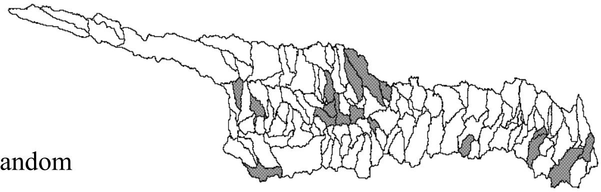
a: 10%, Targeted



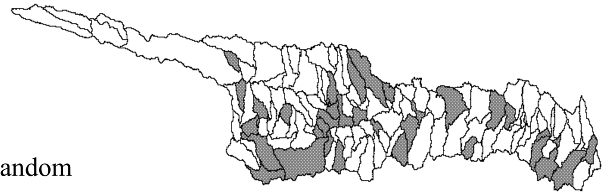
b: 26%, Targeted



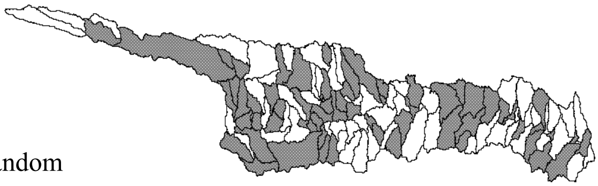
c: 52%, Targeted



d: 10%, Random



e: 26%, Random



f: 52%, Random

Figure 2: Subbasins selected for BMP adoption by percent watershed area and selection method.

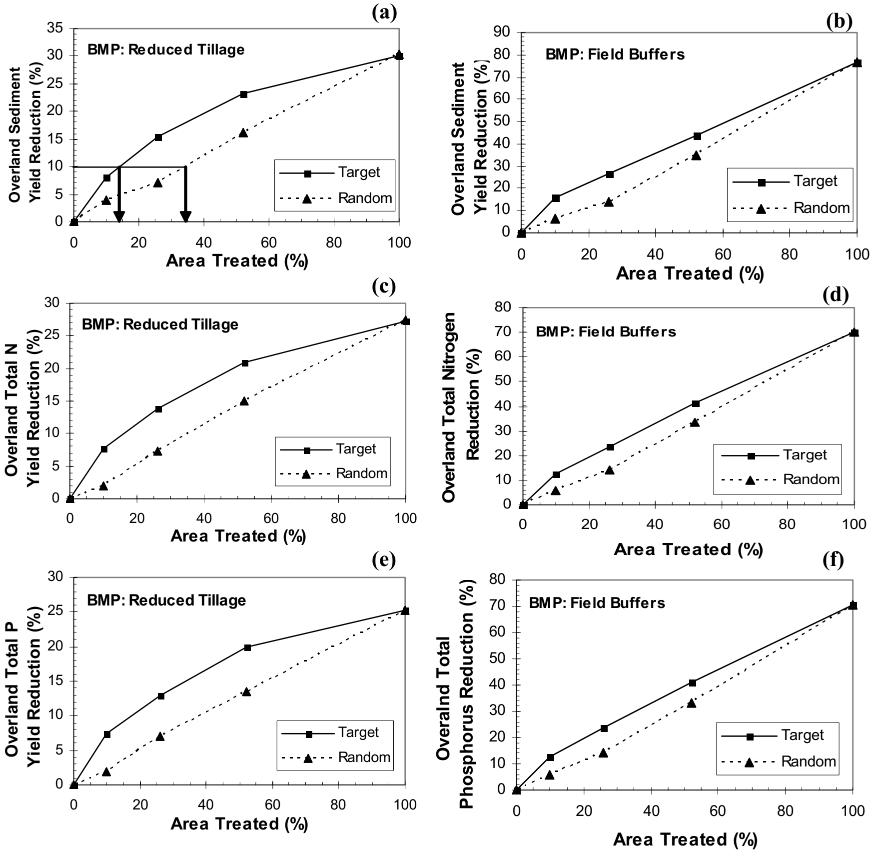


Figure 3: Effect of cropland BMP implementation method on overland pollutant yields.

Figure 3a also shows (arrows) the percentage area required to achieve the same (10%) overland sediment yield reductions using the two methods. Whereas RT must be implemented on 35% of the watershed to achieve 10% sediment yield reduction using random implementation, the strategic targeting approach would require implementation on only 14% of the cropland in the watershed. In this example, the random approach requires BMP implementation in 2.5 times more watershed area than the targeted approach.

Modelled pollutant reductions using VBS were greater than for RT. Reduction in annual average overland sediment yield achieved with 100% VBS adoption (5-m vegetative buffer added to all cropland) was 76.5% (fig. 3b). The reduction in sediment loss due to VBS adoption in 10% of the cropland area was 15.6% by the targeted approach compared to 6.3% by the random approach. This difference increased at 26% VBS adoption, with 26.4% reduction for targeting compared to 13.8% reduction for random. To achieve 10% sediment yield reduction, VBS must be implemented on 17% of the watershed using random implementation, whereas the strategic targeting approach would require implementation on only 7% of the cropland in the watershed.

3.1.2 Nutrient yield reductions

Overall reductions of nutrients were slightly less than with sediments for 100% RT adoption: 27.3% for TN (fig. 3c) and 25.3% for TP (fig. 3e). Strategic targeting, however, showed relatively greater improvements than with sediments for the first increment of cropland treated. At 10% RT implementation, targeting reduced TN yields by 7.7% compared to 2.0% for random and TP yields by 7.3% compared to 2.0% for random. Similar to sediment, more than double the land area was required to achieve 10% reduction in TN and TP yields for the random approach compared to the targeted approach.

Overall reductions of nutrients were slightly less than with sediments for 100% VBS adoption: 70.2% for TN (fig. 3d) and 70.3% for TP (fig. 3f). Strategic targeting, however, showed relatively greater improvements than with sediments for the first increment of cropland treated. At 10% VBS implementation, targeting reduced TN yields by 12.6% compared to 5.9% for random and TP yields by 12.9% compared to 5.9% for random. Similar to sediment, more than double the land area was required to achieve 10% reduction in TN and TP yields for the random approach compared to the targeted approach.

3.1.3 Discussion: overland pollutant yields

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

These results suggest that targeting may be an excellent method to improve water quality by implementing BMPs, particularly at the initiation of a watershed restoration effort. However, if targeting efforts are more costly (in terms of time, money, effort, etc.) than the random implementation approach, returns on those investments in targeting decrease with time. In this case, early implementation efforts could incorporate targeting to maximize implementation efficiency (pollutant yield reductions per unit monetary investment in implementation, for example). Following this early program success, efforts may be allowed to shift to random, more widespread adoption across the entire watershed.

3.2 Watershed outlet pollutant loads

3.2.1 Sediment load reductions

Annual average sediment load delivered to the watershed outlet was reduced by 8.1% with all cropland in RT compared to all cropland in CT (fig. 4a). With 10% BMP adoption, the reduction achieved was 3.5% by the targeted approach compared to 1.1% by the random approach. This difference increased at 26% BMP adoption, with 8.5% reduction for the targeted approach compared to 1.1%

reduction for the random approach. For sediment, a 10% reduction at the watershed outlet was not achievable. A 5% reduction in outlet sediment load could be achieved with about one-fifth the cropland area by the targeted approach (15%) compared to the random approach (78%).

Annual average outlet sediment load was reduced by 45.4% with VBS implemented in all cropland (fig. 4b). With 10% BMP adoption, the reduction achieved was 6.8% by the targeted approach compared to 4.7% by the random approach. This difference increased at 26% BMP adoption, with 16.0% reduction for targeted compared to 6.4% reduction for random approach. A 10% reduction in outlet sediment load could be achieved with about one-third the cropland area by the targeted approach (16%) compared to the random approach (52%).

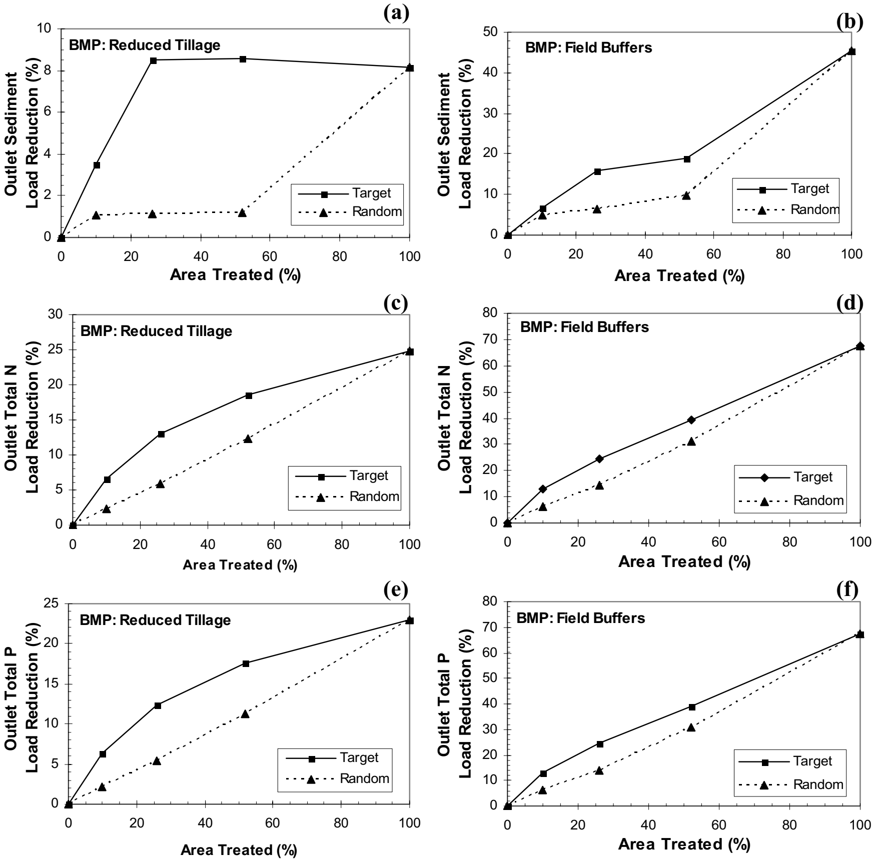


Figure 4: Effect of cropland BMP implementation method on watershed-outlet pollutant loads.

3.2.2 Nutrient load reductions

In contrast to results for sediments, overland yields and watershed-outlet loads of nutrients were similar. Outlet load reductions for both TN and TP were 9% less than overland yield reductions for 100% RT implementation and 4% less for 100% VBS implementation.

3.2.3 Discussion: Watershed-outlet pollutant loads

Adoption of RT BMP on all cropland resulted in a 30.2% reduction in overland sediment yield (fig. 3a) but only 8.1% reduction in the sediment load at the watershed outlet (fig. 4a). Similarly, 100% VBS adoption reduced overland yields by 76.5% (fig. 3b) but watershed-outlet loads by only 45.4% (fig. 4b). These results indicates the importance in understanding the model sediment routing equations and the suitability of model parameters for the stream reach being studied when evaluating BMP implementation. SWAT 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 plays an important role in transporting the pollutants downstream, and simulating these processes requires careful consideration.

Distance to the nearest water course and/or impaired water resource can serve as important criteria in targeting and evaluating the impacts of BMPs. As expected, the highest potential for soil loss was noticed on highly and moderately erodible soils, which happen to be nearer to the lake. Using more detailed soil data, such as SSURGO, may help in refining potential localized sediment pollution source areas. Future work is planned to evaluate the effectiveness of the targeted approach using other management scenarios, including no-till, terrace farming, contouring, residue management, grass waterways, etc. Economic analysis will also be important to assess the actual costs and benefits from targeted BMP implementation.

4 Conclusion

A watershed modelling approach was used to quantify impacts of implementing two BMPs on incremental increases in cropland area to evaluate effectiveness of the targeted approach vs. the random approach in reducing estimated overland pollutant yields and watershed-outlet pollutant loads. Priority areas for the targeted approach were selected based on erosion rate.

The targeted watershed modelling approach using SWAT was found to be more effective in reducing the pollutant load both overland and at watershed outlet 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 with targeted rather than random BMP placement. Targeting produced greater benefits when considering watershed-outlet loads. Benefits of targeting are greater for the initial increments of BMP adoption and decrease as the proportion of BMP adoption on targeted land areas increases. This strategy could be extended to other selection criteria, landuse types, and BMPs. For example, there is a substantial acreage of rangeland in these subbasins that should be assessed for targeting.

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