Evaluating Nonpoint Source Critical Source Area Contributions at the Watershed Scale

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Areas with disproportionately high pollutant losses (i.e., critical source areas [CSAs]) have been widely recognized as priority areas for the control of nonpoint-source pollution. The identification and evaluation of CSAs at the watershed scale allows state and federal programs to implement soil and water conservation measures where they are needed most. Despite many potential advantages, many state and federal conservation programs do not actively target CSAs. There is a lack of research identifying the total CSA pollutant contribution at the watershed scale, and there is no quantitative assessment of program effectiveness if CSAs are actively targeted. The purpose of this research was to identify and quantify sediment and total phosphorus loads originating from CSAs at the watershed scale using the Soil and Water Assessment Tool. This research is a synthesis of CSA targeting studies performed in six Oklahoma priority watersheds from 2001 to 2007 to aid the Oklahoma Conservation Commission in the prioritized placement of subsidized conservation measures. Within these six watersheds, 5% of the land area yielded 50% of sediment and 34% of the phosphorus load. In watersheds dominated by agriculture, the worst 5% of agricultural land contributed, on average, 22% of the total agricultural pollutant load. Pollutant loads from these agricultural CSAs were more than four times greater than the average load from agricultural areas within the watershed. Conservation practices implemented in these areas can be more effective because they have the opportunity to treat more pollutant. The evaluation of CSAs and prioritized implementation of conservation measures at the watershed scale has the potential to significantly improve the effectiveness of state and federally sponsored water quality programs.

Water quality impairment due to sediment and nutrients is a serious problem in the USA. In 2002, 45% of streams and rivers and 47% of lakes and reservoirs were listed as impaired and unable to support their designated uses (USEPA, 2007). Agricultural production is the leading source of impairment for streams and rivers in the USA (USEPA, 2007). Conservation practices can significantly reduce nonpoint-source pollution, but to be effective, appropriate practices must be located to prevent the mobilization of pollutants or intercept them en route to streams. The placement of these practices within a watershed significantly influences their overall effectiveness (Gitau et al., 2004). Nonpoint-source pollution is diffuse in nature, but some areas contribute significantly more pollutant per unit area than others. Areas that contribute disproportionate pollutant loads are often referred to as critical source areas (CSAs) and are often optimal locations for conservation practices. The disproportionate pollutant losses from CSAs generally result from a combination of characteristics, including soil type, land use, management, slope, placement within the landscape, and/or proximity to streams or sensitive water bodies. The concept of targeting CSAs has been widely recognized as an important consideration in the placement of conservation practices within a watershed (Sivertun et al., 1998; Pionke et al., 2000; Gburek et al., 2002).

The identification of CSAs is essential to efficiently manage phosphorus (P) loss at the watershed scale (Gburek et al., 2002). The identification of CSAs at the field or farm scale is a routine practice. Tools such as the P index (Lemunyon and Gilbert, 1993) and the Universal Soil Loss Equation (USLE) (Wischmeier and Smith, 1978) are simplistic models used to assess P or sediment losses and are easily applied to a single field. Critical source areas can also be identified via qualitative evaluation by conservation planners based on professional judgment. The identification of CSAs at the farm scale is important, but the identification of CSAs over much larger areas is also needed. The manual evaluation of each individual field

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Abbreviations: CSA, critical source area; DEM, digital elevation model; GIS, geographic information system; HRU, hydrologic response unit; OCC, Oklahoma Conservation Commission; P, phosphorus; SWAT, soil and water assessment tool; USLE, Universal Soil Loss Equation.

within a large watershed is resource and cost prohibitive for state and federally funded conservation programs.

Due to their simplicity, empirically derived models, such as the USLE and the P index, are well suited for watershed scale evaluation using a Geographic Information System (GIS) (Sivertun et al., 1998; Birr and Mulla, 2001; Sivertun and Prange, 2003). Both are comprised of relatively simple factors, many of which can be derived from existing GIS data. The use of the USLE in a GIS to map erosion is relatively simple because most USLE parameters can be derived directly from widely available soils and landcover data. Other parameters, such as the slope length-gradient factor, can be estimated from elevation data (Moore and Burch, 1986). Sivertun and Prange (2003) used soils, slope, landcover, and distance to watercourse within a GIS to predict pollutant losses. Their research focused on simple methods applicable in commercial GIS products. Although this method is not quantitative (i.e., actual pollutant loads were not predicted), it is a useful tool to identify CSAs for planning purposes. Phosphorus indices are typically more complex and include data, such as soil P status and fertilizer application rates, that are not readily available at the watershed scale. Many P indices use erosion estimates from other models like the USLE to better predict particulate P loss (Sharpley et al., 2003). Birr and Mulla (2001) applied a modified version of a P index at the regional scale in Minnesota. These P index results compared favorably with measured water quality data, but the coarse discretization was ineffective for targeting CSAs.

Although the adaptation of field-scale P indices for use at the watershed scale is useful, it has limitations. The majority of P indices predict indexed risk, not quantity of P loss. These tools can be used to rank potential sites and identify areas with the highest risk for P loss. Although P indices are potentially effective at locating CSAs, they cannot predict the quantity of P loss or the effect of establishing a conservation practice within a CSA. Because water quality objectives increasingly include specific pollutant load reduction goals or numeric water quality standards, the quantity of pollutant loss and the extent of CSAs are needed to develop more efficient water quality management strategies at the watershed scale.

Comprehensive hydrologic and water quality models like the Soil and Water Assessment Tool (SWAT) (Arnold et al., 1998) can predict the locations and quantities of pollutant loss from CSAs within a large watershed. SWAT is effective for identifying CSAs because it incorporates landcover, topography, soil characteristics, rainfall, and land use management, all of which influence the mobilization and transport of sediment and nutrients. SWAT is a watershed scale distributed hydrologic model, but it is effective at a variety of spatial scales (Gassman et al., 2007). Distributed parameter hydrologic models allow a watershed to be broken into many smaller sub-basins to incorporate additional spatial detail. Water yield and pollutant loads are calculated for each sub-basin and routed through a stream network to the watershed outlet. The SWAT model takes this approach a step further by incorporating the concept of hydrologic response units (HRUs). A HRU is a unique combination of soil, landcover, and sometimes slope within a subbasin that is simulated as a single unit. Processes within each HRU are calculated independently, and the total nutrient load or water yield for a sub-basin is the sum of all the HRUs it contains. The current SWAT release does not consider the position of the HRU within the sub-basin; however, future versions will allow overland flow from one HRU to another. Despite this limitation, HRUs allow more spatial detail pertaining to landcover and soil combinations to be represented in a computationally efficient manner. The additional spatial detail facilitated by HRUs allows SWAT to identify relatively small CSAs. The minimum size of CSAs that can be identified is directly related to the size of the sub-basins and HRUs defined during watershed descritization. The discretization of SWAT is a key factor in the identification of CSAs.

The SWAT model has been used to target critical source areas within larger watersheds (Tripathi et al., 2003; Gitau et al., 2004; Srinivasan et al., 2005). Tripathi et al. (2003) used the SWAT model to identify and prioritize critical sub-watersheds within a larger drainage area. However, with only 12 sub-basins, the level of descritization used was coarse. Srinivasan et al. (2005) used SWAT to identify CSAs for runoff generation and compared these with CSAs predicted by the more physically based Soil Moisture Distribution and Routing model (Soil and Water Laboratory, 2003). The predicted areas of runoff generation differed between the models, but SWAT replicated measured streamflow better than SWDR. Gitau et al. (2004) used SWAT to predict the spatial distribution of P losses on a 300-ha farm for the purpose of optimizing conservation practice selection and placement by using HRUs with an average size of 1.6 ha.

It is much easier to identify CSAs than to evaluate their contribution to the total pollutant load. The collection of water quality data at a sufficient resolution and scale is problematic. Even in a small watershed, the level of instrumentation and monitoring duration necessary to quantify pollutant loads from CSAs is prohibitively expensive. Models are currently the only feasible method to quantify these contributions at the watershed scale; even these assessments are limited. Pionke et al. (2000) used the Soil Moisture-based Runoff Model (Zollweg et al., 1996) to evaluate the contribution of critical source areas in a small 26.7-ha watershed. They predicted that 98% of the total sediment loss occurred from only 6% of the watershed area and that the majority of dissolved P originated from only 11% of the area. Diebel et al. (2008) examined P loss distributions derived from a quantitative P index and watershed-level P load estimates to evaluate the impact of targeted and random implementation of conservation practices. They found that the targeted implementation of conservation measures on 10% of fields could reduce P losses by 26%. This research demonstrates that a relatively small fraction of a watershed may generate the majority of pollutant loads. Similar research applied to more and larger watersheds is needed.

The need to identify CSAs at the watershed scale has been widely recognized, yet there is a lack of research addressing the total watershed CSA pollutant contribution. Despite the potential advantages, many state and federal conservation programs do not target CSAs at the watershed level. Large-scale programs, such as the Conservation Reserve Program, Conser-

vation Reserve Enhancement Program, Environmental Quality Incentives Program, and various state cost-share programs funded by 319(h) and state funds may address CSAs identified on a cooperator's farm, but many other CSAs in the watershed are missed. All of these programs are voluntary; the cost share rate generally determines which conservation practices will be implemented and which landowners will participate. Targeting enables local program staff to actively recruit landowners with high-pollutant-loss fields into cost share programs.

Resistance to a targeted approach is due, in part, to a lack of research demonstrating the potential advantages. It is generally agreed that a relatively small fraction of a watershed can generate a disproportionate amount of the pollutant load and that the targeted establishment of conservation measures is a reasonable approach (Sharpley 1999; Pionke et al., 2000; Yang and Weersink, 2004). Unfortunately, there is little research illustrating quantitative benefits. To address this need, the objective of this research was to identify and quantify sediment and total P loads originating from CSAs at the watershed scale using SWAT.

Materials and Methods

Study Watershed Data and Model Development

This research was a synthesis of six separate studies conducted from 2001 to 2007, in which CSAs were identified in Oklahoma Conservation Commission (OCC) priority watersheds using SWAT (Fig. 1). The OCC provides federal Clean Water Act, Section 319(h) and state funds to pay a portion of the costs to establish certain soil and water conservation measures in priority watersheds across Oklahoma. To maximize potential benefits with limited funding, the OCC actively targets sediment and P CSAs for enrollment into cost-share programs. Sediment and P are among the primary pollutants of concern in most Oklahoma waters. In an effort to assist OCC, we used SWAT coupled with satellite imagery to target CSAs and quantify their relative pollutant contribution within each priority watershed. Each priority watershed was analyzed in a separate study, each with differing objectives with respect to spatial scale and pollutants of concern. There were no existing guidelines or recommendations for the use of SWAT to identify CSAs, and thus the methods varied among the studies. The methods presented here are generalized. More specific methods are available in each cited project report (Storm et al., 2003a, 2003b, 2005a, 2005b, 2006, 2007).

Model Input Data

Model prediction accuracy depends largely on data used to construct the model. Different data sets were used in each of the six studies. The use of SWAT to evaluate P and sediment CSAs required soil, topography, landcover, field management, weather, and soil P status. The characteristics of each watershed and the pollutants of concern were considered during input data selection. Generally, the highest resolution data available at the time were used. These six study areas represented a great deal of variation (Table 1). SWAT input data and model descritization details are given in Table 2. Soil Survey Geographic (USDA, 1991a) soils were preferred over Mapping Information and Display (Senay and Elliot, 1999), which was in turn preferred over State Soil Geographic (USDA 1991b). Higher-resolution soils data allows small areas of highly erosive or low infiltration to be identified. The resolution of the digital elevation models (DEMs) affects important topographic characteristics, such as slope and slope length; the most detailed DEM available was used in each model.

Accurate and up-to-date landcover data were essential to the proper identification of CSAs. Although older landcover data were publically available from several sources, these data were classified from recent satellite imagery separately for each study. Details of the landcover classification were given in each project report. The satellite sensor was selected based on the study objectives and budget. Landsat (30-m), Satellite Probatoire d'Observation de la Terre (SPOT) 5 (10-m), and Ikonos (4-m) data were used in different studies. Landcover classified from satellite imagery was specifically tailored to identify landcovers of concern in each priority watershed. For example, it was necessary to identify pastures with a high fraction of bare soil due to overgrazing in some watersheds and to differentiate between small grains and row crops in others.

Model Descritization

The SWAT model generates predictions at a variety of spatial scales. We used HRU-level predictions to identify sediment and P CSAs, although sub-basin predictions could also be used. Significantly smaller CSAs can be identified using HRU predictions. Figure 2 illustrates the Spavinaw Creek Watershed priority area SWAT sub-basin and HRU discritizations. This 24,000-ha area was discretized into 256 sub-basins and 6600 HRUs. Unlike sub-basins, HRUs do not necessarily represent specific contiguous areas, and thus topographical parameters like slope or slope length were more difficult to properly assess. The ArcView SWAT interface (Di Luzio et al., 2004) assigned the same topographical characteristics to every HRU within a sub-basin. This approach prevents the generation of multiple HRUs to represent differing slopes of a particular landcover/soils combination within each sub-basin and reduces the complexity of the resulting model. This simplification was of little concern at the watershed scale but may be significant at the HRU level. We evaluated the most important topographical characteristics at the HRU level and modified each model accordingly.

Hydrologic response units can be directly mapped if no aggregation of landcover or soils is permitted during the HRU definition process. Relatively minor landcover soil combinations may be reassigned to more dominant combinations during this process to simplify the model. Due to this reassignment, model predictions in these smaller areas are made with inaccurate soils and/or landcover, making it difficult to identify them in the original GIS data. Hydrologic response unit level predictions from each of the study watersheds were extrapolated to the resolution of the original 30-, 10-, or 4-m GIS data. Extrapolation methods differed by study and are documented in detail in each project report. A brief description of each Priority Watershed CSA targeting study is given in the next section.

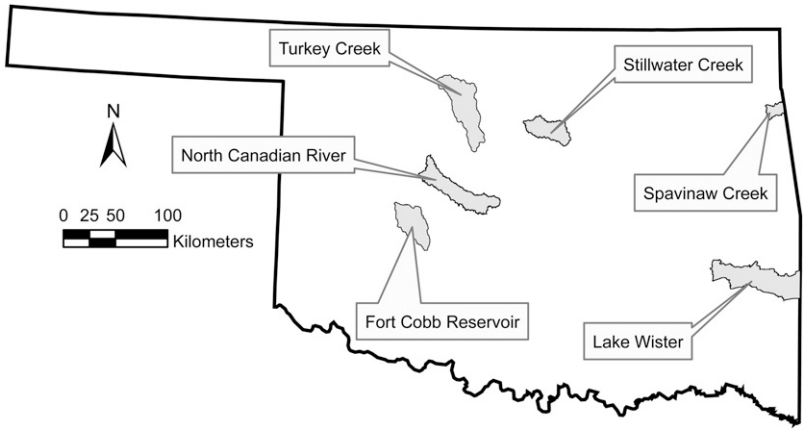

Fig. 1. Location of six priority watersheds in the State of Oklahoma.

Table 1. Study watershed characteristics.

Study watershed	Area	Omernick level III ecoregion(s)	Precipitation	Landcover			
				Grassland	Forest	Cultivated	Other
	ha		mm yr^{-1}	%			
Spavinaw Creek	23,000	Ozark Highlands	1130	45	51	0.8	3.5
Stillwater Creek	72,000	Cross Timbers Central Great Plains	910	54	29	7.9	9.0
Turkey Creek	108,000	Central Great Plains	790	31	4.5	61	3.4
Fort Cobb Reservoir	81,000	Central Great Plains	860	41	6.0	50	2.1
North Canadian River	197,000	Central Great Plains	870	38	15	40	5.0
Lake Wister	174,000	Arkansas Valley Ouachita Mts.	1380	18	79	0.0	2.7

Table 2. Study watershed Soil and Water Assessment Tool input data and descritization details.

	Spavinaw Creek	Stillwater Creek	Turkey Creek	Fort Cobb Reservoir	North Canadian River	Lake Wister
Average subbasin area, ha	86	841	N/A	947	2055	2626
Average HRU† area, ha	3.5	34	N/A	65	33	44
Targeting unit	HRU	HRU	Gridcell	HRU	HRU	HRU
Landcover res., m	4	30	10	30	30	30
Satellite sensor	IKONOS	Landsat	SPOT	Landsat	Landsat	Landsat
Landcover year	2005	2001	2003	2001	2006	2004
Dem resolution, m	30	30	10	10	10	10
Soil database	SSURGO	MIADS	SSURGO	MIADS	MIADS	SSURGO
Calibration	Flow/P	None	None	Flow/Sed/P	Flow/Sed/P	Flow/P
Weather data	NEXRAD	Station‡	Station	Station	Station	NEXRAD
Simulation duration, yr	25	35	25	17	5	13

† HRU, hydrologic response unit; MIADS, mapping information and display system; NEXRAD, next generation weather radar; P, phosphorus; SSURGO, Soil Survey Geographic Database; SPOT, Système Pour Observation de la Terre.

‡ National Weather Service Cooperative Observer Station Data.

Study Watershed and Model Descriptions

Stillwater Creek

An uncalibrated SWAT model was developed for the Stillwater Creek Priority Watershed. Landcover was primarily pasture, range, and winter wheat. A database of unique soil and landcover combinations with slope and annual sediment yield was generated from HRU-level SWAT predictions. Sediment yield, at a resolution of 30 m, was interpolated by matching landcover and soils combinations between this database and individual 30-m grid cells in the original GIS data. Sediment yield was corrected for differences in slope based on USLE slope length-gradient (LS) factor relationships (Storm et al., 2003a). This method allows the topographical data provided by the DEM to be represented in the targeting map with greater fidelity. Critical source areas were identified from sediment yield extrapolated at a resolution of 30 m.

Fort Cobb Reservoir

The Fort Cobb Reservoir Priority Watershed was comprised primarily of rangeland and winter wheat (Storm et al., 2003b). Sediment yield was extrapolated at a resolution of 10 m using a methodology nearly identical to that used in the Stillwater Creek study. A sample of CSA sites identified in the watershed were visited to corroborate the model results and were found to have visual indications of high sediment loss (i.e., excessive rilling, active gullies, and/or poor cover).

Turkey Creek

Sediment and P CSAs were identified in the Turkey Creek Priority Watershed at a resolution of 10 m (Storm et al.,

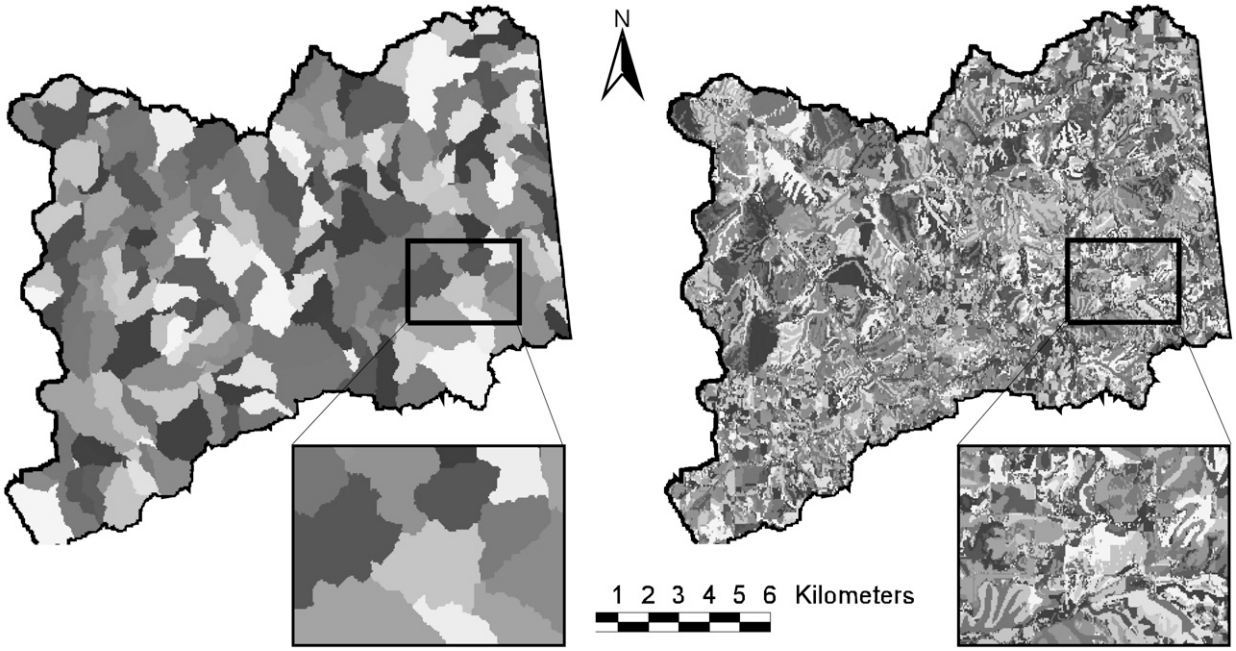

Fig. 2. Discretization level comparison between subbasins (left) and hydrologic response Units (HRUs) (right) in the Spavinaw Creek Priority Watershed.

2005a). The watershed was dominated by cultivated land, primarily winter wheat. Every unique combination of soils, slope, and landcover in the original GIS data was simulated as an individual HRU in SWAT using custom software.

Spavinaw Creek

The Spavinaw Creek Priority Area was dominated by poultry production and cow calf operations (Storm et al., 2005b). A SWAT model of the Spavinaw Creek Priority Watershed was generated with a very fine discretization; the average HRU size was 3.5 ha. Additional spatial data for poultry litter application and soil P levels were included in the SWAT model.

Lake Wister

Sediment and P CSAs were identified and evaluated in the Lake Wister Priority Watershed (Storm et al., 2006). The Lake Wister basin was similar to the Spavinaw Creek area but had less poultry production. A portion of the Lake Wister Priority Watershed lies within the Ouachita Mountains. This watershed had more topographical relief and rainfall than the other priority watersheds. To better account for topographical rainfall effects, weather data were derived from Next Generation Radar Weather Surveillance Radar 88D precipitation estimates at a resolution of 4 km.

Northern Canadian River

The North Canadian River Priority Watershed was the largest area studied (Storm et al., 2007). Wheat and range grazing were the primary agricultural activities. The SWAT model was calibrated for streamflow, P, and nitrogen. Like Spavinaw Creek and Lake Wister, CSAs were derived by mapping actual HRUs using the original GIS data.

Results and Discussion

Critical Sources in Study Watersheds

To identify CSA, some definition of what is considered an excessive pollutant load was necessary. The definition and subsequent spatial assessment of CSAs required a threshold unit area load. The threshold unit area load at which a discrete unit (HRU or gridcell) was categorized as a CSA depended on the characteristics of the watershed. For example, an HRU with a 1 Mg ha^{-1} yr^{-1} sediment yield would likely be considered a CSA if located in a forested watershed but if located in a cultivated watershed. An appropriate threshold was defined by ranking each discrete unit within a watershed by the predicted sediment or P yield and then defining the highest ranking fraction (generally 2.5 or 5.0%) as CSAs. This fraction defined CSAs in terms of extent and load threshold. This analysis also provided the total load originating from all CSAs within a watershed. In addition, multiple threshold values (i.e., 2.5 and 5.0%) for a given watershed were used to define CSA severity levels. An example of CSAs identified in the Turkey Creek Priority Watershed is given in Fig. 3.

The discretization of each watershed and ranking of individual units in terms of pollutant load was used to generate curves that illustrate the contribution of CSAs at the watershed scale. Cumulative pollutant curves for each priority watershed were developed to define CSAs (Fig. 4). Table 3 contains the contribution of CSAs for sediment and P at thresholds based on 2.5 and 5.0% of the watershed area. Critical source areas based on 2.5% of the watershed area contributed on average 36% of sediment and 21% of the P lost from the entire watershed. Critical source areas based on 5.0% of the watershed area contributed on average 50 and 34% of the entire sediment and P losses, respectively.

The shape of cumulative pollutant load curves in Fig. 4 differed by watershed. The shape appears to be dependent on the

Fig. 3. Soil and water assessment tool–predicted phosphorus critical source areas on aerial photography. Cultivated areas with high slopes and erosive soils were primarily targeted.

landcover distribution within each watershed. Primarily forested and primarily cultivated watersheds generated different shaped curves. All watersheds studied had very different landcover profiles (Table 1). Sediment and nutrient losses were highly dependent on landcover (Harmel et al., 2006). The relative abundance of high-loss landcover types had a significant influence on the cumulative pollutant load curve. Watersheds with relatively few high-loss areas had steeper curves and derived a larger fraction of their total load from a smaller contributing area. This landcover dependency made it difficult to combine predictions from different watersheds for a generalized assessment of the contribution of CSAs at the watershed scale.

Critical Sources in Agricultural Areas

One goal of this study was to quantify differences in pollutant losses from targeted CSAs over randomly selected sites. Within a mixed landcover watershed, conservation measure site selection would not be truly random. Some landcover types, such as forest, would not be considered as candidates for conservation practices because these areas generally contribute only small amounts of pollutants. To truly assess the potential of targeting CSAs at the watershed scale, non-agricultural landcovers were excluded from this portion of the analysis. Model predictions from each study were isolated by the two primary landcovers of interest: cultivated crops (including small grains and row crops) and pasture/rangeland (used for grazing cattle and/or hay production). Cultivated crops and pasture/rangeland were the primary landcovers in Turkey Creek, North Canadian River, Fort Cobb Reservoir, and Stillwater Creek (Table 1). Pasture and forest were the primary landcovers in Spavinaw Creek and Lake Wister, where little land was suitable for cultivation.

Each landcover/watershed combination was analyzed separately. A cumulative pollutant load distribution curve for sediment and/or P was developed by isolating cultivated or pasture units within each watershed. A total of 18 watershed/landcover pollutant distribution curves were isolated. Eleven were isolated for sediment, seven for P, eight for cultivated, and 10 for pasture (Table 3). A full factorial of combinations was not possible due to the differing constituents of interest, landcovers, and objectives for each original watershed study. These curves are given

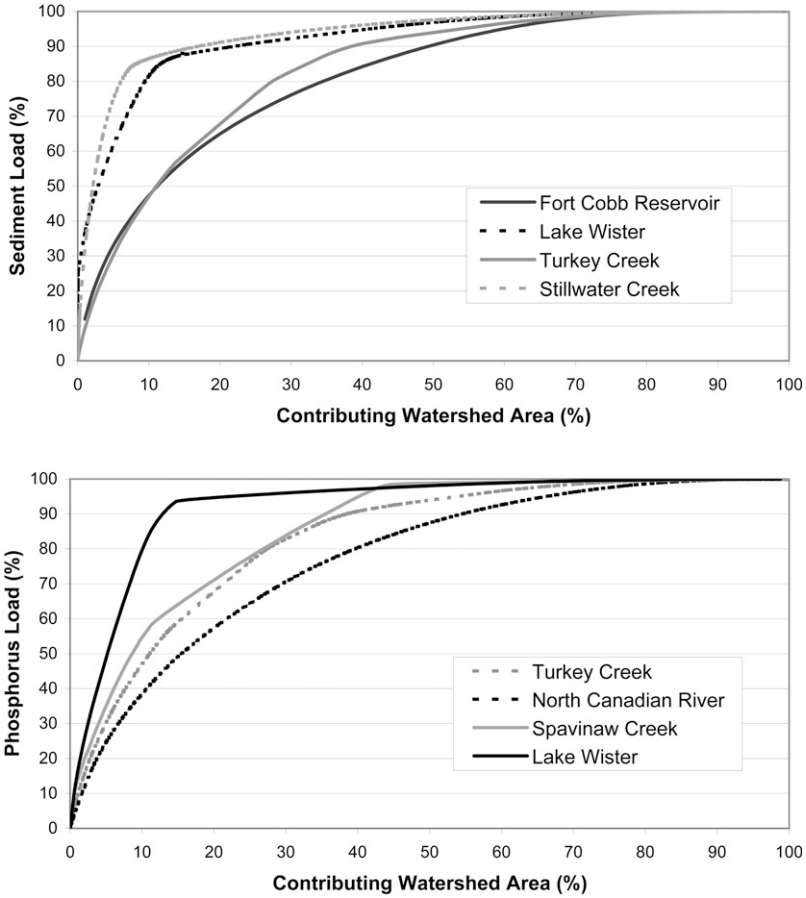

Fig. 4. Cumulative sediment yield (top) and total phosphorus load (bottom) load by percent of contributing watershed area.

Table 3. Soil and Water Assessment Tool–predicted fraction of total watershed sediment and phosphorus load originating from critical source areas defined as the highest 2.5 and 5% loss of the total watershed area.

	Contributing watershed area threshold	Pollutant load					
		Spavinaw Creek	Stillwater Creek	Turkey Creek	Fort Cobb Reservoir	North Canadian River	Lake Wister
	%						
Sediment	2.5	–	55	18	22	–	48
	5.0	–	75	29	33	–	62
Phosphorus	2.5	23	–	18	–	15	30
	5.0	35	–	30	–	24	49

in Fig. 5, subdivided by landcover (pasture or cultivated) and pollutant (sediment or P). The degree of overlap between the curves in Fig. 5 was greater than expected given the differences in primary transport mechanisms between sediment and P. To evaluate significant differences among these subdivided groups, a nonparametric Mann–Whitney test (Mann and Whitney, 1947) was applied at selected intervals of landcover contributing area. The Mann–Whitney test is a two-sample ranked sum test that evaluates the equality of population medians based on independent random samples. This nonparametric approach makes no assumption of population distribution. This analysis yielded probability values at increments across the entire cumulative pollutant load distribution curves; none of the curves was significantly different ($\alpha = 0.05$).

A more traditional parametric statistical approach including transformation and comparisons using linear regression was attempted but was found to be highly dependent on how individual curves were discretized into samples for analysis. This parametric procedure was not designed for continuous curves, which must be sampled frequently to provide discrete points for analysis. The frequency of sampling was highly influential in comparisons between pasture and cultivated or sediment and P groups because it determined the total number of samples. Because the sampling frequency was arbitrary, the approach was abandoned in favor of the Mann–Whitney test. This was applied at discrete intervals across the cumulative pollutant load distribution curve because the test was not sensitive to sampling frequency. Cumulative pollutant load distribution curves segregated by landcover and pollutant (Fig. 5) were intermingled, further supporting the conclusion that none of these groups was significantly different.

The median of all cumulative pollutant load distribution curves is given in Fig. 6. A nonparametric, one-sample, Wil-

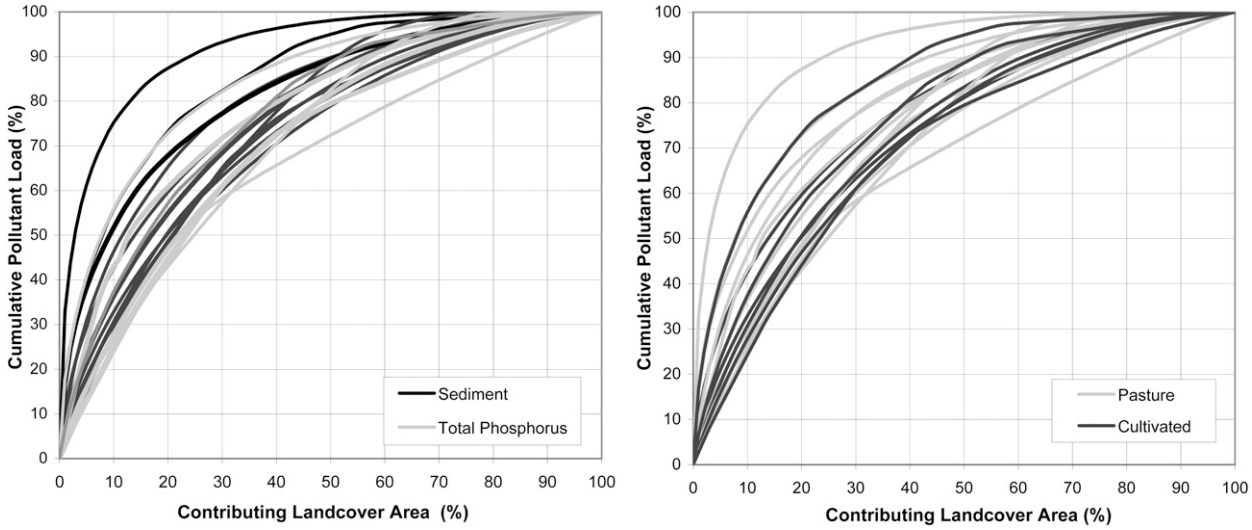

Fig. 5. Cumulative pollutant load distribution curves by landcover and pollutant identified by pollutant (left) and landcover (right).

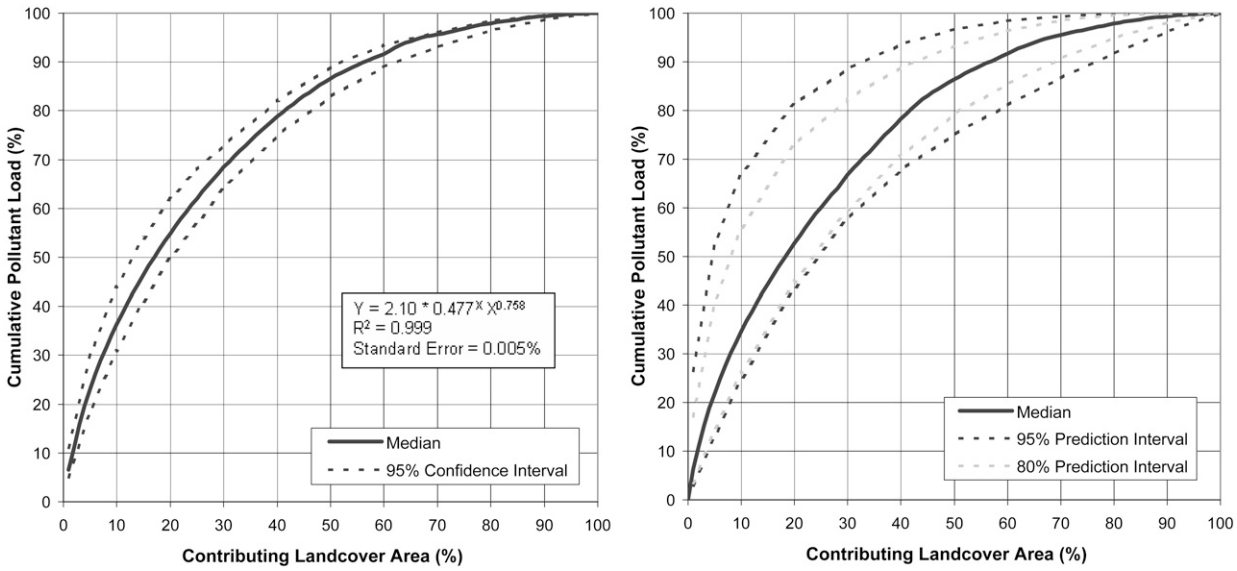

Fig. 6. Median cumulative pollutant load distribution curves with confidence intervals (left) and prediction intervals (right).

coxon signed rank test (Wilcoxon, 1947) was used to calculate 95% confidence intervals on the median at selected intervals of contributing landcover area (Fig. 6). Nonlinear regression was used to develop a model of the median such that the CSA contribution at any given percent of contributing landcover area could be estimated without interpolation from Fig. 6. This model fit the median curve well, with a coefficient of determination of 0.99. This statistic did not consider the variability in the original 18 cumulative pollutant load distribution curves. To better address the uncertainty in the application of the median curve, prediction intervals were also developed (Fig. 6). Prediction intervals predict the distribution of a future single observation; in this case, confidence intervals bound the position of the median curve. To extrapolate these findings to other watersheds, the prediction interval would be the appropriate statistic. Prediction intervals are always larger than confidence intervals because they also consider variability collapsed by measures of central tendency, such as the median. Prediction intervals were calculated using nonparametric methods presented by Helsel and Hirsch (2002) at selected intervals of contributing landcover area across the entire cumulative pollutant load distribution curves. Prediction intervals in Fig. 6 can be used to estimate the range in pollutant contribution from agricultural CSAs relative to the total agricultural contribution at any fraction of contributing area.

Critical source areas contributed disproportionately high sediment and P loads in the mixed landcover watersheds studied. On average, 5% of the watershed area contributed 50 and 34% of the entire sediment and P load, respectively. Within the agricultural portions of these watersheds, 5% of the area generated between 13 and 52% (based on 95% prediction interval) of the total load due to agriculture. On average, the 5% of agriculture defined as CSAs generated 22% of the total agricultural sediment and phosphorus loads. Loads from CSAs were between 3 and 10 times higher than the average loads for agricultural areas.

Conservation measures implemented in CSAs have the potential to be several times more effective than nondirected placement because they have the opportunity to treat a much larger quantity of pollutant. These large contributions from a relatively small fraction of the watershed illustrate why the CSA concept is an effective management tool. This research found highly disproportionate contributions of CSAs at the watershed scale and illustrates the potential advantages of the targeted placement of conservation measures.

Study Limitations

The use of SWAT to target CSAs can be a powerful tool for the management of P and sediment at the watershed scale, but there are several possible limitations. First, SWAT was designed to make predictions at the watershed scale, not to predict pollutant loading at the scale of CSAs. Although SWAT has components derived from true field-scale models like the Erosion-Productivity Impact Calculator (Williams, 1990), it was optimized to function over a much larger spatial extent. Second, the HRU concept was developed to include as much spatial detail as possible without excessive computational requirements, but the position of HRUs within each sub-basin was not considered. The HRU concept disregards pollutant and water routing within individual sub-basins because loads generated at any point within the sub-basin are treated identically regardless of position (Gassman et al., 2007). Similarly, the use of HRU-level data to extrapolate gridcell-level pollutant load does not account for the position of the gridcell relative to the nearest water body in terms of sediment delivery ratio or nutrient attenuation. Third, SWAT considers primarily infiltration excess runoff mechanisms. Other mechanisms, such as saturation excess, may also be important (Garen and Moore, 2005) and a contributing factor in CSAs. Fourth, the process of calibrating a model at discrete locations, such as stream gages or water quality sample sites, does not necessarily improve the spatial accuracy of the model. Generally, data collected at a water quality sample site contain no information concerning the source of the pollutant, only that it must have originated from somewhere upstream. The evaluation of CSAs depends heavily on the spatial distribution of pollutant loads, which cannot be easily calibrated and validated with available data. Multiple sets of model parameters exist that may yield an adequate calibration using available sample sites yet may yield differing CSAs. Finally, all of the watersheds in this study were in Oklahoma; the results may not be applicable to other regions with significantly different climate, soils, or agricultural practices.

These limitations arise from the data used in the model, inadequacies in the model, or using the model to simulate situations for which it was not designed. Hydrologic models have limitations because the science behind the model is neither perfect nor complete. These limitations may influence which areas are designated as CSA and their relative contributions. The use of relative scenario comparisons (i.e., percent difference as opposed to absolute predictions [kg ha^{-1} yr^{-1}]) provides higher accuracy results, but prediction uncertainty remains. Despite these limitations, there are no other practical tools to quantitatively define the contribution of CSAs at the watershed scale.

Conclusions

The identification and evaluation of CSAs at the watershed scale is a valuable tool to effectively allocate state and federal funding for the establishment of conservation practices where they are needed. The lack of research to document the relative contribution of CSAs at the watershed scale has potentially hindered the adoption of targeting CSAs within these programs. From this study, we found that on average 22% of the sediment and P loads from agriculture originated from only 5% of the area. Practices implemented in these targeted areas have the opportunity to treat a much larger quantity of pollutant and thus have the potential to be more effective. It is difficult to evaluate how much more effective the targeted implementation of practices would be in the context of a water quality program. More research is needed because conservation practice implementation costs and effectiveness likely differ between targeted and nontarget areas. Nevertheless, the identification of CSAs and targeted implementation of conservation measures at the watershed scale has the potential to significantly improve the effectiveness of existing water quality programs.

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