EVALUATION OF CONSERVATION TARGETING INDICES ON A CLAYPAN WATERSHED

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The undersigned, appointed by the dean of the Graduate School, have examined the thesis entitled

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LIST OF ABBREVIATIONS

Agricultural Policy Environmental eXtender (APEX)

Avoid (A)

CEAP Conservation Benefits Identifier (CCBI)

Conductivity Claypan Index (CCI)

Conservation Effects Assessment Program (CEAP)

Control (C)

Critical source area (CSA)

Depth to claypan (CD)

Geographic Information Systems (GIS)

Goodwater Creek Experimental Watershed (GCEW)

Hydrologic Unit Area (HUA)

Hydrologically sensitive area (HSA)

National Nonpoint Source Monitoring Program (NNPSMP)

Natural Resources Conservation Service (NRCS)

Nitrogen (N)

Non-point source (NPS)

Phosphorus (P)

Phosphorus index (PI)

Rural Clean Water Program (RCWP)

Saturated hydraulic conductivity (KSAT)

Slope (SL)

Soil & Water Assessment Tool (SWAT)

Soil Vulnerability Index (SVI)

Topographic Wetness Index (TWI)

Trap (T)

Upper Mississippi River Basin (UMRB)

ABSTRACT

Non-point source pollution from agricultural activity is extremely problematic in the U.S. It is responsible for damage to aquatic ecosystems, contamination of drinking water sources, and loss of farm productivity. The Goodwater Creek Experimental Watershed (GCEW) is a claypan watershed in north-central Missouri that is particularly prone to non-point source pollution because it is comprised of soils with very high runoff potentials. Targeting indices are tools that have the potential to reduce non-point source pollution by identifying potential areas in watersheds that contribute the most to overall pollutant loads, allowing such areas to be treated with conservation practices. Applying conservation practices to critical areas identified by targeting indices is predicted to greatly reduce contaminants.

The objective of this study was to evaluate three targeting indices, the Soil Vulnerability Index (SVI), Conductivity Claypan Index (CCI), and CEAP Conservation Benefits Identifier (CCBI), in terms of their classification of critical areas in the GCEW. The SVI and CCI are intended to identify critical areas most vulnerable to contaminant transport by surface runoff, while the CCBI is designed to identify critical areas that lack sufficient conservation treatment considering their vulnerability to contaminant transport by surface runoff as determined by the SVI.

The SVI and CCI were evaluated in the first study by comparing the distribution of watershed vulnerability classifications determined by each, using contingency tables to calculate agreement between critical areas determined by each index, and assessing

whether each index identified a known critical area in the watershed. Variability of input parameters in each index was analyzed as a means to explain differences in classification of watershed areas by indices. SSURGO and DEM slopes were used in each index to assess sensitivity to the slope parameter and assess effects of using different slope sources. The CCI consistently identified over twice the amount of potential critical areas identified by the SVI and also classified more of the watershed as moderately high vulnerability. Most of the potential critical areas identified by the SVI, however, were also identified as potential critical areas by the CCI. In comparison with field observations, the CCI was found to identify a known critical area that wasn't identified by the SVI. Analysis of input parameters used by each index found that slope had the most impact in the SVI, while depth to claypan (CD) as well as slope had the most impact in the CCI. The additional variability of the CD parameter used by the CCI resulted in the CCI identifying a greater amount of potential critical areas than the SVI. Planners should consider the effect this limited variability has on SVI classifications in a watershed with a restrictive layer, such as the GCEW, before using it to make decisions about conservation treatment.

The CCBI identifies critical areas based on contaminant reductions that can be achieved through additional conservation treatment. In the second study, the Soil and Water Assessment Tool (SWAT) model calibrated and validated for the GCEW was used to determine contaminant reductions that could be obtained with additional treatment. While contaminant reductions obtainable through additional treatment according to the CCBI were calculated based on soil vulnerability levels determined using the SVI, soil

vulnerability levels were determined using the CCI when the SWAT model was used to determine contaminant reductions obtainable through additional treatment in the GCEW. The CCI was used due to limited variety in watershed vulnerability classifications determined by the SVI using input parameters determined from SWAT model soils data. Contaminant reductions from additional conservation treatment determined from the SWAT model were compared with those associated with the CCBI. The SVI and CCI were used to determine vulnerability levels of cropland HRUs from the SWAT model based on soil type and hydrologic response unit (HRU) data from the model. CCI and SVI classification of HRUs was assessed by testing for correlation between vulnerability levels of cropland HRUs and contaminant loads from cropland HRUs. Significant correlation was only found for vulnerability levels determined using the CCI. Contaminant reductions possible through additional treatment determined from the SWAT model and those associated with the CCBI both increased as vulnerability level increased, and decreased as level of conservation treatment increased. This suggests that the CCBI can be used to identify critical areas in a claypan watershed similar to the GCEW. Contaminant reductions of sediment estimated by the SWAT model were lower on average than those associated with the CCBI, while contaminant reductions of nitrogen and phosphorus estimated by the SWAT model were higher on average than those associated with the CCBI. This result shows that there is uncertainty regarding the values of contaminant reductions obtainable through additional conservation treatment according to the CCBI in the GCEW. Further evaluation of the CCBI is advised before it is used in the GCEW or a similar claypan watershed.

CHAPTER 1: INTRODUCTION & LITERATURE REVIEW

BACKGROUND

Pollution associated with agriculture is recognized as a major problem in the United States (Shortle et al., 2012). Common pollutants include nutrients such as phosphorus (P) and nitrogen (N), pesticides, herbicides, and sediment. Pollutants are typically transported away from fields via surface runoff or leaching leading to downstream problems such as contamination of drinking water, damage to aquatic ecosystems, and sedimentation (Baker, 1992). The transported pollutants also affect farmers in the form of lost inputs that can affect future crop yields.

A challenging aspect of the problem is the non-point source (NPS) nature of the pollution. A defining characteristic of NPS pollution is that it cannot be traced to a single source such as a pipe. Instead, NPS pollution typically enters receiving water bodies in runoff or leachate that comes from large areas. Transported pollutants may have originated from many different locations making it very difficult to completely monitor NPS pollution (Carpenter et al., 1998; Horan and Ribaudo, 1999). Occurrence of NPS pollution is also influenced by precipitation events that can be hard to predict, another factor making it difficult to monitor and control.

Tools such as indices, hydrologic models, and geographic information systems (GIS) have been used to gain better perspective about the problem and deal with some

of the challenges in controlling and reducing NPS pollution at the watershed scale. Scaling, which involves applying information obtained at one scale to a different scale, is one challenge involved (Brezonik et al., 1999). In the case of watershed modeling, scaling from a finer scale to a watershed scale involves more complex mathematical relationships than were previously used (Brezonik et al., 1999). Current watershed models attempt to consider these complexities in their representations of hydrologic processes and determination of pollutant loads (Brezonik et al., 1999). Another challenge in reducing NPS pollution at the watershed scale is ensuring that conservation practices are applied at optimal locations in watersheds. Critical areas, which contribute the most contaminants to receiving water bodies, and undertreated areas, which have insufficient conservation treatment relative to soil vulnerability to surface runoff, are both locations where conservation practices have the potential to significantly reduce the amount of NPS pollution that occurs compared with other locations (Gale et al., 1993; USDA-NRCS, 2012). These locations, however, have been found to lack sufficient treatment in many watersheds (Gale et al., 1993; Tomer and Locke, 2011; USDA-NRCS, 2012). Models, indices, and GIS can be used to identify critical areas and undertreated ones (Meals et al., 2012; USDA-NRCS, 2012). While these tools have been used to make progress toward controlling and reducing NPS pollution (Tim and Jolly, 1994; Santhi et al., 2001; Maringanti et al., 2009), this type of pollution remains an important problem, with much room to improve existing tools and develop new ones. For example, some watersheds may need indices developed based specifically on their unique characteristics so that critical areas can be correctly identified (Chan et al., 2013).

This research discusses two studies in which several indices designed to identify the optimal location of conservation efforts in a watershed were tested in the Goodwater Creek Experimental Watershed (GCEW), a claypan watershed study area in north-central Missouri. Claypan soils, which cover about 3 million hectares in Missouri and Illinois, are particularly prone to surface runoff and resulting NPS pollution due to a shallow, low permeability clay layer that limits percolation and available water capacity. Soils with similar restrictive layers can also be found in other parts of the U.S. such as Texas (Baffaut et al., 2015). Problems such as excessive soil erosion and herbicide transported via surface runoff have been documented in the GCEW (Lerch, Donald, Li, & Alberts, 1995; Arabi et al. 2012).

In the first study, the Soil Vulnerability Index (SVI) and Conductivity Claypan Index (CCI) were evaluated. The SVI was developed by the Natural Resources Conservation Service (NRCS) to identify U.S. cropland areas most vulnerable to surface runoff and leaching based on soil properties. It categorizes areas as having high, moderately high, moderate, or low vulnerability to surface runoff or leaching (USDA – NRCS 2012). While both surface runoff and leaching are nationwide problems, analysis in this project was limited to surface runoff vulnerability classifications as leaching is a lesser problem on claypan soils. The CCI was developed by Mudgal et al. (2012) to identify the most environmentally sensitive areas in a field located in the GCEW. Areas within the field were identified as environmentally sensitive based on relative amounts of sediment, runoff, and atrazine generated according to model results (Mudgal et al., 2012). Similar to the SVI, the CCI also uses soil properties, but takes into account several

soil type-specific parameters not used in the SVI. Sensitive areas predicted by the CCI were found to match well when compared with those found to produce the most runoff and sediment yield according to the Agricultural Policy Environmental eXtender (APEX) model (Mudgal et al., 2012). In this thesis research, the methodology of the CCI was adjusted to find sensitive areas at a watershed scale.

The second study focused on the CEAP Conservation Benefits Identifier (CCBI). The CCBI goes a step further than the SVI by considering the level of conservation treatment in place in addition to soil vulnerability. It was developed by the NRCS as a tool to identify cropland areas nationwide that would benefit most from receiving additional conservation treatment. Areas are ranked into one of four priority levels (high, moderately high, moderate, or low) with higher priority levels indicating that more benefit could be obtained from treatment with additional conservation practices.

CONSERVATION PRACTICES

Implementation of conservation practices has been one attempt to control and reduce the negative effects associated with agricultural NPS pollution. For example, terraces are used to decrease erosion on sloped areas by reducing the length and steepness of hillside slopes. Use of conservation practices in the U.S. became more prevalent after the Dust Bowl crisis of the 1930's led to the government taking a more active role in soil conservation and related activities (Baveye et al., 2011). At the time, the purpose of implementing conservation practices was focused on reducing soil erosion rather than reducing agricultural pollution, which is an additional emphasis in

the current policy (USDA-NRCS, 2012). Some commonly used agricultural practices are grassed waterways, contour farming, buffer strips, conservation tillage, and nutrient management. Deciding what conservation practice should be used in a particular location is a complex process dependent upon many factors, some of which include soil characteristics, topography, and the particular pollutant of concern (Osmond et al., 2012).

Effectiveness of Conservation Practices

With a large increase in funding for conservation programs implemented in the 2002 farm bill, there has been concern about what environmental benefits are being obtained from additional money spent on conservation programs, especially at national and watershed scales (Mausbach and Dedrick, 2004). Many studies have found conservation practices to be ineffective in reducing pollution when measured at the watershed scale (Park et al., 1994; Inamdar et al., 2002; Chaubey et al., 2010; Tomer and Locke, 2011). On the other hand, studies have shown that conservation practices are effective in reducing the amount of pollutants leaving the field when measured at field scale (Jokela et al., 2004; Sharpley, 2006; Nangia et al., 2010; Douglas-Mankin et al., 2013).

Several past programs such as the Rural Clean Water Program (RCWP), hydrologic unit area (HUA), USEPA Section 319 National Nonpoint Source Monitoring Program (NNPSMP), and the more recent Conservation Effects Assessment Program (CEAP) have taken place in part to study and address these observations (Osmond et al., 2012). The RCWP found that one way to improve the effectiveness of conservation

practices at the watershed scale would be to target their placement to critical areas in watersheds (Gale et al., 1993). This finding has since been reiterated several times in some of the other aforementioned programs (Osmond et al., 2012).

CRITICAL AREAS

Definition of Critical Areas

Gale et al. (1993) defined critical areas as "sources of nonpoint source pollutants identified as having significant impacts on the impaired water resource." Nowak et al. (2006) described critical areas as those that contribute disproportionally more contaminant relative to other areas in a particular watershed. A similar term, critical management zone, was defined by Walter et al. (2000) to be an area within a watershed that is both a hydrologically sensitive area (HSA) and an area contributing pollutant loads. An HSA was defined as an area within a watershed that would be most likely to generate runoff (Walter et al., 2000). In summary, critical management zones would be areas within a watershed that have sources of contaminant and that have a high probability of generating runoff. Critical management zones were referred to as critical source areas (CSAs) by Agnew et al. (2006) and will be referred to by that name in this study.

Identification of Critical Source Areas

Locations of CSAs and pollutant sources vary from watershed to watershed based on hydrology, climate, topography, soils, land use, proximity to streams, and

management (Agnew et al., 2006; White et al., 2009). The process by which runoff occurs throughout a watershed also affects where CSAs are located (Agnew et al., 2006). Runoff can be classified into two types based on how it occurs: infiltration excess overland flow and saturation excess overland flow. Infiltration excess overland flow occurs when the rate of rainfall exceeds the infiltration rate of the soil (Agnew et al., 2006). Robert Horton did early research on this process (Horton, 1933; Beven, 2004). Factors affecting soil water drainage such as soil properties, management practices, surface sealing, and precipitation intensity can all influence the occurrence of infiltration excess overland flow (Agnew et al., 2006). Saturation excess overland flow occurs when the soil has reached its maximum capacity to store water so that water is no longer able to infiltrate (Hursh, 1944; Agnew et al., 2006). It would be most likely to occur on soils having characteristics or conditions such as a high water table, restrictive layer near the surface, and humid climate (Agnew et al., 2006).

While CSAs at the field scale can be found through visual evaluation by a conservation professional, this is not an economical option when there are many fields to consider, thus other tools that rely on numerical processing need to be used (White et al., 2009). Modeling, indices, and GIS are tools that provide an alternative means of evaluation. For example, a field scale hydrologic model, such as APEX, can simulate a variety of management operations (Gassman et al., 2010) and has been used to identify potential critical areas for contaminants of sediment, runoff, and atrazine in a field within the GCEW (Mudgal et al., 2012). The Soil and Water Assessment Tool (SWAT) is an internationally recognized watershed scale model that has been used to model

effects of climate change, land use change, and conservation practices (Arnold & Fohrer, 2005). Many examples in the literature can be found where the SWAT model has been used to identify CSAs (Busteed et al., 2009; Ghebremichael et al., 2010; Srinivasan et al., 2005; White et al., 2009). Using indices to identify CSAs instead of models can be less time consuming due to fewer parameters involved and no need for calibration to be performed.

The phosphorus index (PI) and topographic wetness index (TWI) are examples of index approaches to finding CSAs. The PI is used to assess risk of edge of field phosphorus losses (Lemunyon and Gilbert, 1993). The TWI identifies areas in a watershed where saturation excess overland flow, and thus pollutant transport, would likely occur (Beven and Kirkby, 1979). GIS can be used in conjunction with indices or modeling to identify CSAs.

GIS allows data layers containing slopes determined from DEM or soil properties downloaded from a database to be used as input sources for models or indices that identify CSAs in a watershed. CSAs for soil loss were found in the Cheney Lake Watershed in Kansas using a GIS combined with a model based on the Revised Universal Soil Loss Equation (Nelson et al., 2011). Zollweg et al. (1995) discussed a methodology involving a GIS to identify specific CSAs that would be responsible for a majority of phosphorus loss in a studied watershed.

There are advantages and limitations to each of the methods of finding CSAs. Some, such as the PI and APEX model are designed for field-scale applications. The PI can, however, be adapted to find CSAs at the watershed scale (White et al., 2009).

Models, compared with indices, provide information that is more quantitative than qualitative, such as how much contaminant a particular CSA is contributing to the overall amount of pollution. As discussed earlier, using indices can require less time and effort compared with models.

UNDERTREATED AREAS

Improving Effectiveness by Targeting Undertreated Areas

An additional finding of the CEAP in regards to future placement of additional conservation practices was that the conservation treatment status of areas should be considered along with the area vulnerability classification in order to obtain further reductions in NPS pollution (USDA-NRCS, 2012). Treatment status was assessed by classifying areas into different levels of conservation treatment based on field-level model quantifications of the extent to which conservation practices in place would reduce sediment and nutrient losses given the SVI-determined soil vulnerability classification of areas (USDA-NRCS, 2012). Information about current practices in place in the Upper Mississippi River Basin (UMRB) was determined from four sources: the NRI-CEAP Cropland Survey, NRCS field offices, the USDA Farm Service Agency, and the 2003 NRI (USDA-NRCS, 2012). The determined level of conservation treatment of areas was used to identify undertreated areas and rank them in terms of their need for additional conservation treatment.

Levels of conservation treatment of areas were assessed for the specific resource concerns of sediment loss due to water erosion, nitrogen loss transported by surface runoff, nitrogen loss transported by subsurface flows, and phosphorus lost to surface water (USDA-NRCS, 2012). The overall findings in the UMRB were that 15% (9 million acres) had a high need for additional treatment, 45% (26 million acres) had a moderate need, and 40% (23 million acres) had a low need (USDA-NRCS, 2012).

Modeling scenarios were also run to quantify potential gains in reductions of contaminants if additional conservation practices were implemented on areas found to be in need (USDA-NRCS, 2012). Several different scenarios were modeled including treating only the areas with a high need for additional treatment, treating the areas with a high and moderate need for additional treatment, and simulating different types of conservation practices on such areas. Overall, when additional erosion control and nutrient management practices were simulated with the APEX model on areas with a high and moderate need for additional treatment, it was found that 32% more reductions in sediment could be obtained, 56% more reductions in nitrogen could be obtained, and 33% more reductions in phosphorus could be obtained at the field-level (USDA-NRCS, 2012). Large potential gains in reductions from additional conservation treatment were estimated in the UMRB.

INDEX VALIDATION

Validation of targeting indices is an important step that should take place before they are used for planning, management, or other purposes. There are five basic

methods that can be used to validate targeting indices: professional judgment, comparison with aerial photos, comparison with other indices, comparison with model results, and comparison with field data (Claire Baffaut, USDA-ARS, personal communication, 5 August 2014). Dosskey et al. (2011) used the Vegetated Filter Strip Model to validate results of two indices made to identify optimal locations to place vegetated buffers in agricultural watersheds. Dosskey et al. (2013) compared optimal locations for placement of vegetated buffers determined by five targeting indices. The ability of two wetness indices to predict wetland areas was compared using a map of the spatial distribution of wetland areas in a watershed (Grabs et al., 2009).

While validation is an important part of the development of a targeting index, indices vary in terms of what methods have been used for validation and the extent of validation. The TWI, for example, has been in existence since the 1970's and has been tested and modified from how it was originally calculated (Beven and Kirkby, 1979; Sørensen et al., 2006). Other indices have not been tested as extensively and can likely be improved through further validation (Chan et al., 2013). This should be a consideration when relying on any targeting index.

OBJECTIVES

The overall research goal was to evaluate the performance of the SVI, CCI, and CCBI on a claypan watershed. Specific objectives were developed to evaluate the indices.

Study 1: This chapter was entitled: "Evaluating the Soil Vulnerability Index and Conductivity Claypan Index on a claypan watershed in Missouri". The specific objectives were to: 1) evaluate and compare the ability of the SVI and CCI to determine the most critical areas in a claypan watershed, in terms of vulnerability to pollutant transport by surface runoff and 2) assess how input parameters used by the SVI and CCI affect vulnerability classifications in a claypan watershed.

Study 2: This chapter was entitled: "Evaluating the CEAP conservation benefits identifier on a claypan watershed in Missouri". Specific objectives were to: 1) determine vulnerability of soils in GCEW using the SVI and CCI with input parameters derived from SWAT model soils data and verify that the determined vulnerability of soils correlates with amount of pollutant loadings (sediment, P, and N) from SWAT cropland HRUs, 2) determine potential gains in contaminant reductions that can be achieved in the GCEW at different levels of initial conservation treatment and soil vulnerability using a SWAT model calibrated and validated for use in a claypan watershed, and 3) compare potential gains in contaminant reductions determined in objective 2 with those determined by NRCS modeling used in support of CCBI priority rankings.

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CHAPTER 2: EVALUATING THE SOIL VULNERABILITY INDEX AND CONDUCTIVITY CLAYPAN INDEX ON A CLAYPAN WATERSHED IN MISSOURI

ABSTRACT

Research shows that conservation practices are more effective when they are applied to critical areas that generate the greatest amounts of contaminant loads in watersheds. Using targeting indices is one method to identify these areas in watersheds. The main objective of this study was to compare two targeting indices designed to identify critical areas most vulnerable to contaminant transport by surface runoff, the Soil Vulnerability Index (SVI) and Conductivity Claypan Index (CCI), using a claypan watershed in terms of areas they classified as critical and in terms of how input parameters used by each affected classification of watershed areas. Index critical area classifications were compared by comparing the distribution of vulnerability classifications determined by each index throughout the watershed, using contingency tables to measure agreement between indices, and determining whether indices were identifying known critical areas in the watershed. The effect of input parameters on index classifications was assessed by relating the variability in input parameters used by each index to differences in classification of watershed areas and by evaluating indices using SSURGO and DEM slope sources. Comparison of watershed classifications found that the CCI consistently classified a greater amount of high and moderately high

vulnerability areas compared with the SVI. It classified 20.6% more watershed area in these categories using SSURGO slopes and 28.9% more watershed area in these categories using DEM slopes. Even though the CCI classified a greater percentage of high vulnerability areas, contingency tables showed that the majority of areas classified as high vulnerability by the SVI were also classified as high vulnerability by the CCI. Comparing SVI and CCI watershed classifications with those of known critical areas in the watershed provided evidence that the CCI was able to identify critical areas not identified by the SVI. Analysis of variability in input parameters found that there was little variability in input parameters used by the SVI. Slope was the parameter with the most variability, and the SVI was the most sensitive to this parameter. The CCI had the most variability in the depth to claypan (CD) and slope parameters. Variability in the CD parameter allowed the CCI to classify critical areas not classified as critical by the SVI. The results illustrate effects of using a site-specific targeting index that is sensitive to local conditions.

INTRODUCTION

Non-point source (NPS) pollution from agricultural activity is a major problem in the United States (Shortle et al., 2012). Common pollutants include nutrients such as phosphorus (P) and nitrogen (N), pesticides and herbicides, and sediment. Pollutants are typically transported away from fields via surface runoff or leaching, leading to downstream problems such as contamination of drinking water, damage to aquatic

ecosystems, and sedimentation (Baker, 1992). The transported pollutants also affect farmers in the form of lost inputs that can affect future crop yields.

Implementation of conservation practices has been the main attempt to reduce the negative effects associated with agricultural NPS pollution. Some commonly used agricultural practices are grassed waterways, contour farming, buffer strips, conservation tillage, and nutrient management plans. Use of conservation practices in the U.S. became more prevalent after the Dust Bowl crisis of the 1930's led to the government taking a more active role in soil conservation and related activities (Baveye et al., 2011). At the time, the focus of implementing conservation practices was geared more toward reducing soil erosion rather than reducing agricultural pollution, an additional focus of current policy.

Despite billions of dollars spent on conservation programs and a large increase in funding in the 2002 farm bill, skepticism has been expressed by many about the environmental benefits obtained from additional money spent on conservation programs, especially when assessing benefits at national and watershed scales (Mausbach and Dedrick, 2004). Research has typically shown conservation practices to be effective in reducing NPS pollution at field scales (Jokela et al., 2004; Sharpley et al., 2006; Nangia et al., 2010; Douglas-Mankin et al., 2013). In contrast, effectiveness in reducing NPS pollution at the watershed scale, has been found to be minimal (Park et al., 1994; Inamdar et al., 2002; Chaubey et al., 2010; Tomer and Locke, 2011). One potential reason for this finding is that conservation practices have not been targeted to critical areas that contribute the most contaminants to receiving water bodies (Gale et

al., 1993, Tomer and Locke, 2011). It is therefore very important that locations of these areas within watersheds are identified.

Modeling, indices, and geographic information systems (GIS) are tools that can be used to identify and delineate critical areas (Meals et al., 2012). The Agricultural Policy Environmental eXtender (APEX) model is a field scale hydrologic model that can simulate a variety of management operations (Gassman et al., 2010) and has been used to identify critical areas for sediment, runoff, and atrazine in a field within a Missouri watershed (Mudgal et al., 2012). The Soil and Water Assessment Tool (SWAT) model is a watershed scale model that has also been used to identify critical areas (Srinivasan et al., 2005; Busteed et al., 2009; White et al., 2009; Douglas-Mankin et al., 2010; Ghebremichael et al., 2010;). The phosphorus index (PI) and topographic wetness index (TWI) are examples of index approaches to identifying critical areas. The PI is used to assess phosphorus losses at a field level (Lemunyon and Gilbert, 1993). The TWI identifies areas in a watershed where saturation excess overland flow is likely to occur by estimating the saturation potential of soils (Beven and Kirkby, 1979). These areas could potentially contribute large pollutant loads through generated surface runoff. GIS is often used in conjunction with modeling or index methods and allows the location of critical areas to be displayed on watershed maps (Hamlett et al., 1992; Tim et al., 1992). Zollweg et al. (1995) demonstrated an example of a GIS-based tool used to identify critical areas that would be responsible for a majority of phosphorus loss in a studied watershed, and Nelson et al. (2011) used GIS combined with a model based on the

Revised Universal Soil Loss Equation to identify critical areas for soil loss in a watershed in Kansas.

Compared with using models, using indices to identify critical areas can be a simpler approach requiring fewer input parameters and less preparatory work such as calibration. Indices do however, still need to be validated before they can be used to make decisions about watershed management. This can involve professional judgement, comparison with other indices, comparison with aerial photos, comparison with field data, or comparison with results from models (Dosskey et al., 2011; Chan et al., 2013; Dosskey et al., 2013). Regardless of what method is used to validate an index, results of the validation can give confidence in using an index and help to better understand its results about locations of critical areas (Dosskey et al, 2013).

The Soil Vulnerability Index (SVI) is an index developed by the NRCS to rank areas nationwide in terms of their vulnerability to contaminant transport by surface runoff or by leaching (USDA-NRCS, 2012). Vulnerability to contaminant transport by surface runoff was determined based on soil properties that were found to promote surface runoff and erosion, while vulnerability to contaminant transport by leaching was based on soil properties found to promote infiltration. Soil properties were determined in part using APEX model outputs of sediment yield and percolation nitrogen obtained from runs conducted for Natural Resource Inventory cropland sites throughout the United States (L. Norfleet, personal communication, July 18, 2012; USDA-NRCS, 2012). Each site was ranked as having high, moderately high, moderate, or low soil erosion and leaching potential based on its output of sediment yield and percolation. Higher values were

assigned a higher risk category. With all sites ranked, soil properties that correlated well with the risk classes were determined. Hydrologic soil group, erodibility factor, and slope were the top properties for surface runoff and soil erosion, while the same properties plus coarse fragment content were the top properties found to promote infiltration and constituent leaching. Ranges of values for slope, erodibility factor, and coarse fragment content were statistically determined for each hydrologic soil group to determine criteria to classify areas into different vulnerability classes. The final criteria determined to rank areas was used to classify all soils within the U.S. so that regional comparisons could be conducted (USDA-NRCS, 2012). While the criteria used by the SVI may work for many U.S. soils, it is possible there are some regions containing soils for which it would not work. Evaluating the SVI on such soils would help to ensure its applicability.

Claypan soils are one soil type for which the SVI might not be applicable since it wasn't developed specifically with such soils in mind. Such soils are characterized by a shallow, low permeability clay layer, called a claypan, that limits percolation and available water capacity, resulting in soils that have a high potential for surface runoff and other surface runoff induced problems. MLRA 113, Central Claypan Areas, is a 2.8 Mha primarily agricultural region that covers a portion of Missouri and Illinois and is composed primarily of claypan soils (USDA-SCS, 1981). Excessive soil erosion and herbicide transported in surface runoff are known problems throughout the region (Lerch et al., 2008).

The Goodwater Creek Experimental Watershed (GCEW) is a watershed within MLRA 113 where claypan soils and issues such as contaminant transport have been studied in detail (Blanchard and Donald, 1997; Donald et al., 1998; Lerch et al., 2011). An index called the Conductivity Claypan Index (CCI) was developed by Mudgal et al. (2012) to identify critical areas generating excessive amounts of runoff, sediment, and atrazine loads in a field of the watershed.

To develop the CCI, first subareas within a field of the GCEW were designated as environmentally sensitive if they generated a significant annual amount of surface runoff, sediment yield, or atrazine loading based on APEX modeling results (Mudgal et al. 2012). Using the properties of depth to claypan (CD), slope (SL), and surface saturated hydraulic conductivity (KSAT) for subareas, index values were calculated for every subarea using equations with different combinations of the properties. The values determined by each equation were tested for correlation with the APEX determined subarea output values of runoff, sediment yield, and atrazine loss. The final equation was found to have the strongest correlation with APEX subarea outputs of runoff and sediment yield and was used in determining risk levels for areas, with lower values of CCI implying a higher level of vulnerability to surface runoff. The CCI was further tested by comparing the critical areas with those found from APEX results. The CCI successfully matched many of the APEX determined environmentally sensitive areas in the field producing the most runoff and sediment yield (Mudgal et al., 2012). This index and the research that has already been done in the GCEW make it a good candidate to use in evaluating the SVI.

The CCI, which was developed to identify critical areas in a field with claypan soils, was used to validate the SVI in the GCEW. The specific study objectives were to 1) evaluate and compare the ability of the SVI and CCI to classify critical areas, in terms of vulnerability to contaminant transport by surface runoff, in a claypan watershed, and 2) assess how input parameters used by the SVI and CCI affect vulnerability classifications in a claypan watershed.

MATERIALS AND METHODS

SVI and CCI Vulnerability Classification

Watershed areas were classified into one of four vulnerability classes (high, moderately high, moderate, or low) based on the methodologies of the SVI and CCI. Inputs were processed using ArcMap resulting in maps showing risk classifications throughout the GCEW according to each index.

Classification using SVI

Risk classification for the SVI was based upon criteria specified by the USDA-NRCS (2012) shown in table 1. This information was determined from soil type, USLE soil erodibilility (K-factor), and slope information for areas in the watershed and used to determine vulnerability levels.

Table 1. Criteria used to classify areas using SVI (USDA-NRCS, 2012).

	Hydrologic soil group			
Soil Vulnerability	A[a]	B	C	D
Low	none	Slope < 4	Slope < 2	Slope < 2 K-factor[b] < 0.28
Moderate	none	4 ≤ Slope ≤ 6 K-factor < 0.32	2 ≤ Slope ≤ 6 K-factor < 0.28	Slope < 2 K-factor ≥ 0.28
Moderately high	none	4 ≤ Slope ≤ 6 K-factor ≥ 0.32	2 ≤ Slope ≤ 6 K-factor ≥ 0.28	2 ≤ Slope ≤4
High	none	Slope > 6	Slope > 6	Slope > 4

[a] Cells with "none" in the table, found under the hydrologic soil group A column, mean that there are no restrictions on slope and K-factor values for soils with hydrologic soil group A.

[b] K-factor refers to the soil erodibility factor (K) found in the USLE.

Classification using CCI

Classification using the CCI is based on an equation with inputs of CD, KSAT, and SL (Mudgal et al., 2012). The specific equation is written as:

$$CCI = KSAT * CD/SL$$

where

KSAT = surface layer saturated hydraulic conductivity (mm h^{-1})

CD = depth to claypan (mm)

SL = average area slope (%).

Using the CCI equation, CCI values for all watershed areas (discretized based on slope and soil type) were calculated. The natural logarithm of these values was then

taken to reduce the magnitude of values and deviation in the dataset so that it could be classified appropriately. Next, the set of ln(CCI) values was divided into four groups using the Jenks natural breaks method (Jenks, 1967). This method determines breaks by minimizing variance within groups and maximizing variance between groups (Mudgal et al., 2012). Ranges of ln(CCI) values determined for each group were used to define vulnerability levels, with higher ranges representing lower vulnerability levels. Watershed areas were assigned vulnerability levels based on the group of their ln(CCI) value.

Input Specifications

The SVI uses inputs of slope (%), hydrologic soil group (A, B, C, or D), and K-factor, while the CCI uses inputs of slope (%), depth to claypan (CD, mm), and surface layer saturated hydraulic conductivity (KSAT, mm h^{-1}). Slope values used in the SVI were the representative slope value of soil types according to SSURGO data (Lee Norfleet, USDA-NRCS, personal communication, 10 July 2012). The CCI however, was originally made using average slopes determined from a digital elevation map (DEM) that can capture more variability than SSURGO slopes (Mudgal et al., 2012). Both SSURGO slopes and slopes calculated in ArcMap from a 10m USGS DEM were used as inputs in each index in order to preserve the original state of each and to make valid comparisons.

Hydrologic soil group and K-factor were determined from SSURGO data available publicly online at the Geospatial Data Gateway website, http://datagateway.nrcs.usda.gov/ (January 2013). The hydrologic soil group status was

determined from the RUSLE 2 Related Attributes report for Boone and Audrain counties, which lists hydrologic soil group by map symbol and soil name. Some soil types had hydrologic soil groups that could vary depending on whether the soil was drained or not. In this case, soils were assumed to be undrained based on knowledge of the watershed, resulting in all soils having hydrologic soil group D. K-factor values for each soil type were determined from the surface layer Kw values found in the Physical Soil Properties report for Boone and Audrain counties. The Kw erodibility factor considers the whole soil including rock fragments.

Values of KSAT and CD for each soil type were determined in part from the Physical Soil Properties Report generated from the SSURGO data for Boone and Audrain counties. The report and associated data can be downloaded from the Geospatial Data Gateway website, http://datagateway.nrcs.usda.gov/. Values were converted into mm (CD) and mm h^{-1} (KSAT) in order to stay consistent with units used in the original development of the CCI. KSAT values for each soil series were determined by using the lowest value within the range of saturated hydraulic conductivity values given for the surface horizon. Several factors such as land management and landscape position have been shown to significantly affect saturated hydraulic conductivity for claypan soils in central Missouri (Jiang et al., 2007). Jiang et al. (2007) found that land under management such as a tilled corn-soybean rotation had lower average KSAT compared to others such as hay crop or land in the Conservation Reserve Program. The lowest value was used for the CCI as a simplification to reflect typical management throughout the GCEW. CD values for each soil type were assigned based on which soil horizons had

saturated hydraulic conductivity values less than 1 µm h^{-1}. Using this method of identifying restrictive layers instead of one that examines clay content of soil horizons is easier to implement for larger size study areas and found similar results to those found using clay content information. Since the method doesn't rely solely on clay content information, it also has the ability to find additional restrictive layers that are not caused by high clay content. If the low saturated hydraulic conductivity value occurred at the surface horizon, a minimum depth of 50 mm was assigned. If the low saturated hydraulic conductivity value occurred at a subsequent layer, CD was set equal to the depth to reach the top of the subsequent layer. If no layer for a given soil type was found to have the low saturated hydraulic conductivity value, the depth to the bottom of the last layer was used as CD. Table 2 summarizes the inputs described above by describing the name of the source used to obtain input values, and nomenclature of inputs found in each report.

Table 2. Summary of index inputs, sources for inputs, and names of inputs in sources.

Input name	Name of source used to obtain input values	Input name used in source
Hydrologic soil group	RUSLE 2 Related Attributes	Hydrologic group
SSURGO Slope	Component Legend	Percent slope, RV
DEM Slope	USGS National Map Viewer	USGS NED
USLE K-factor	Physical Soil Properties	Erosion factors, Kw
KSAT	Physical Soil Properties	Saturated hydraulic conductivity
CD	Physical Soil Properties	Depth

Discretization of Watershed

The watershed was divided up differently depending on whether SSURGO or DEM slopes were used. When SSURGO slopes were used, the watershed was divided into polygons based on SSURGO soil type boundaries available for download from http://datagateway.nrcs.usda.gov. When DEM slopes were used, SSURGO soil type boundary polygons were combined with polygons created from the grid of DEM slopes for the watershed, creating smaller polygons within soil type boundaries containing individual DEM slope values. Two watershed polygon maps were created after dividing up the watershed as described above for SSURGO and DEM slopes. Soil vulnerability classification was then determined for each polygon based on criteria and data used by each index.

Comparison of Index Classifications

Risk classifications determined by the SVI and CCI were compared based on the watershed area classified in each vulnerability category and on the watershed area that was in agreement or disagreement between indices (contingency tables). In order to focus on comparing the high risk, critical areas, vulnerability classifications compared in contingency tables were reduced to two classes: high vulnerability areas defining one class, designated as “high”, and the remaining three categories defining another class, designated “not high”. Agreement occurred if each was classified the same (high or not high) by each index while disagreement occurred if areas were classified oppositely by each index. Index classification of critical areas was considered to be the same if the

high vulnerability areas agreed with each other according to contingency tables. Two contingency tables were made, one comparing the SVI and CCI when SSURGO slopes were used and another comparing them when DEM slopes were used.

Analysis of Variability of Input Parameters

To compare variability of SSURGO and DEM slopes, the percentage of watershed area having slope values in specified ranges was determined. The percentages in each range were compared between the slope sources. A table showing CD and KSAT values by soil type and the percentage of watershed area having each CD and KSAT value was constructed to assess the variability of CD and KSAT. The percentage of watershed area having each CD and KSAT value and the number of distinct values of CD and KSAT were considered in analyzing the variability of each parameter. Similar analyses were performed for the hydrologic soil group and K-factor parameters.

RESULTS

SVI and CCI Watershed Risk Classification

Table 3 shows the percentage of the watershed classified into each vulnerability class according to the SVI and CCI when SSURGO and DEM slopes are used. Figures 1-4 show maps of classified areas made using the SVI and CCI with SSURGO and DEM slope sources. It should be noted that no areas were classified as low vulnerability when the SVI was used with DEM slopes (figure 3). For each source of slope data, the CCI classified

about 10% more of the watershed as high vulnerability and 10-20% more as moderately high vulnerability than the SVI did (table 3). On the other hand, the CCI classified about half as much area in the moderate vulnerability class compared with the SVI. Using DEM slopes in each index resulted in 24% less moderately high vulnerability areas on average, which were often classified instead in the moderate vulnerability class (table 3). Analysis of areas classified as high or moderately high vulnerability by the CCI and some lower vulnerability category by the SVI showed that the slopes of these areas were always lower than the slope values required by the SVI to reach high or moderately high vulnerability. Variability in other parameters used by the CCI, which will be discussed later, therefore influenced the differences in the distribution of high and moderately high vulnerability areas classified by the SVI and CCI (table 3).

Table 3. Percentage of watershed area classified into each vulnerability class by the SVI and CCI.

	Vulnerability class			
Index	High	Moderately high	Moderate	Low
SVI, SSURGO slopes	4.1	51.9	44.0	0.0
CCI, SSURGO slopes	14.3	62.3	18.1	5.3
SVI, DEM slopes	6.3	23.7	70.0	0.0
CCI, DEM slopes	16.4	42.5	32.9	8.3

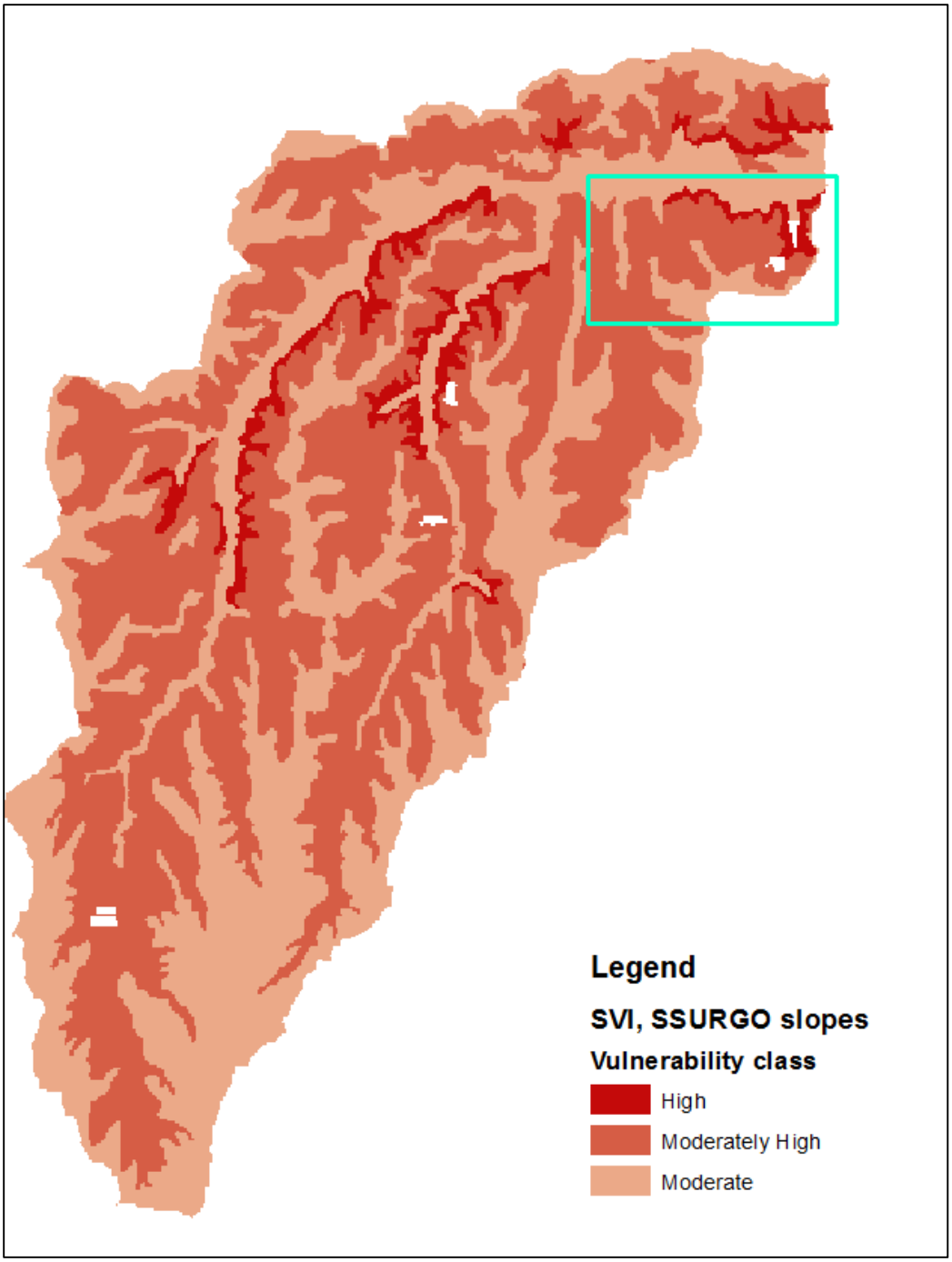

Figure 1. Map of SVI classifications in GCEW using SSURGO slopes.

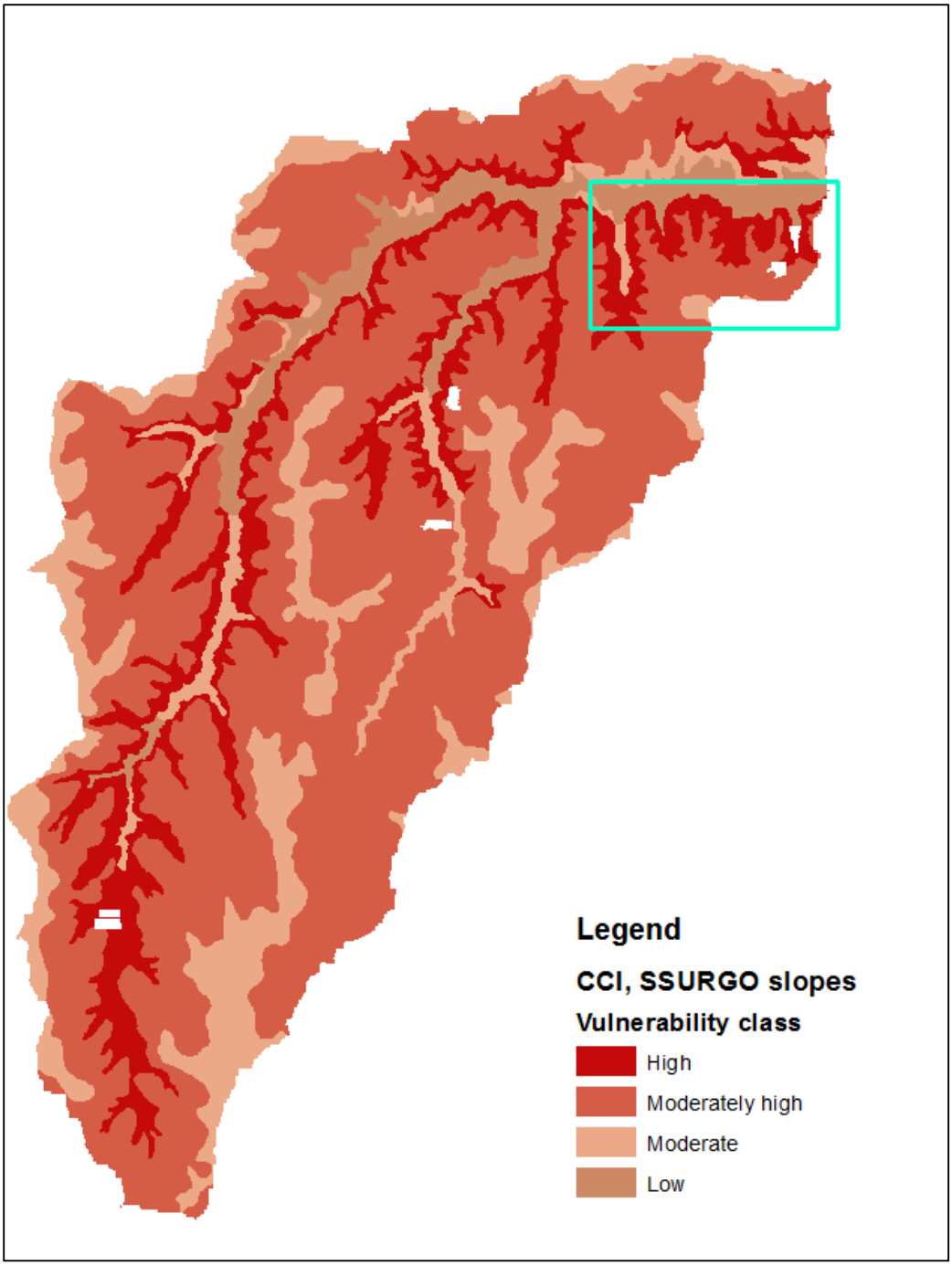

Figure 2. Map of CCI classifications in GCEW using SSURGO slopes.

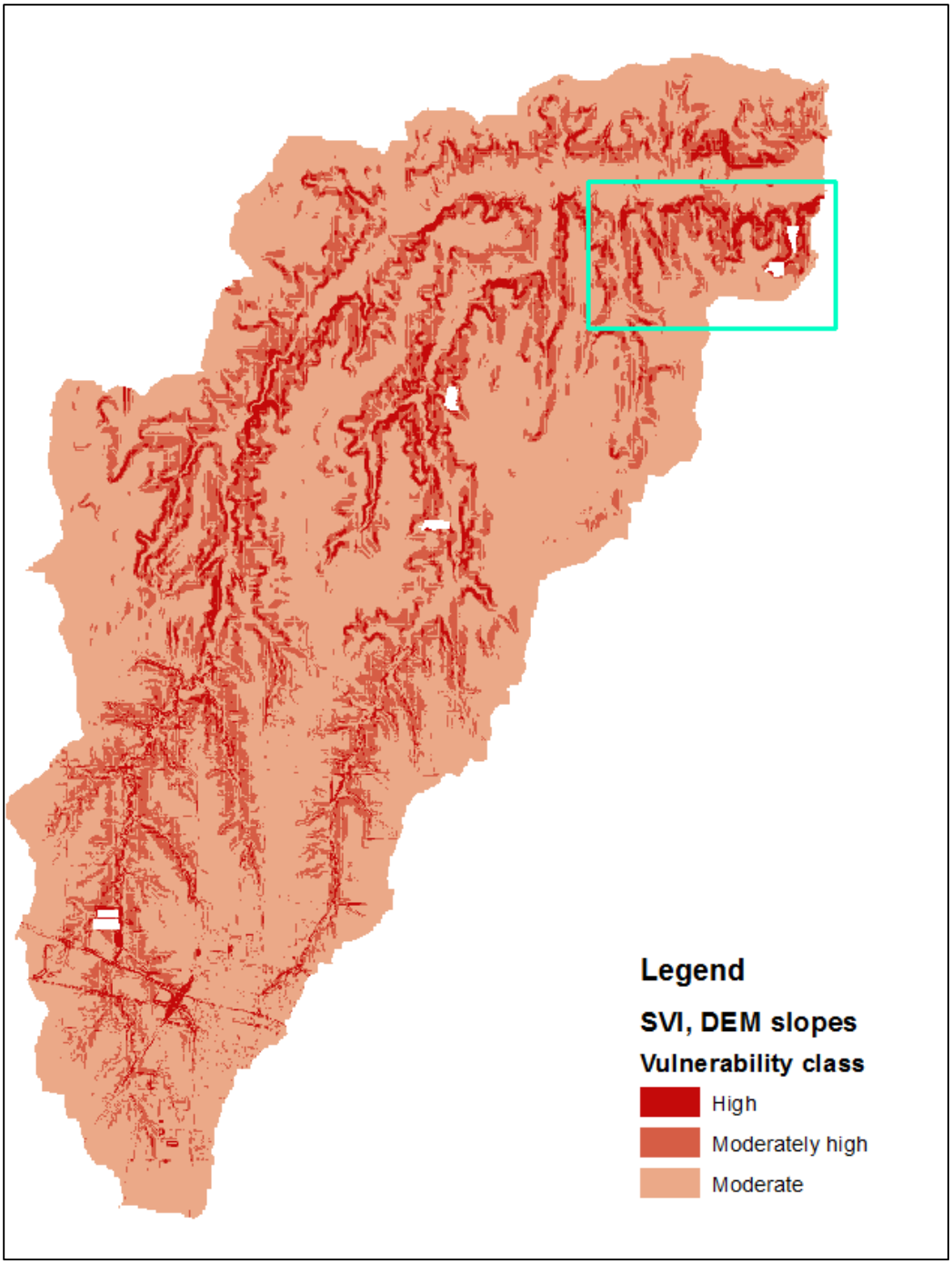

Figure 3. Map of SVI classifications in GCEW using DEM slopes.

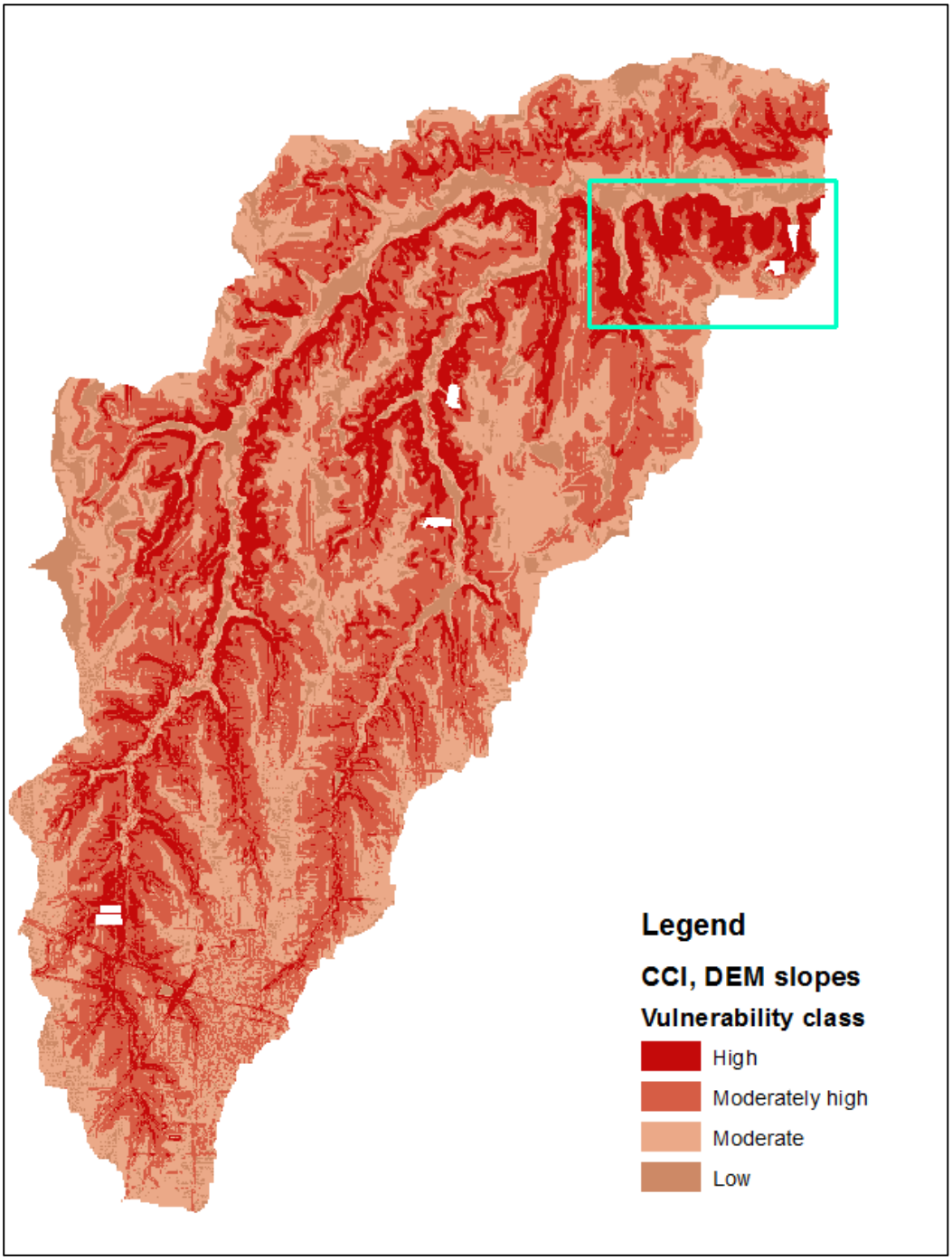

Figure 4. Map of CCI classifications in GCEW using DEM slopes.

Contingency Tables

Tables 4 and 5 show the contingency tables resulting from comparing SVI and CCI vulnerability classifications with each slope source. Low, moderate, and moderately high vulnerability areas were merged into a single class referred to as not high, while the "high" class contains high vulnerability areas. Reading diagonally from the top left to the bottom right shows the percentage of watershed area with map classifications that agreed while the other diagonal shows the percentage of classifications that disagreed.

Table 4. Contingency table showing percentage of watershed area in agreement and disagreement between indices using SSURGO slopes.

	High CCI, SSURGO slopes	Not high CCI, SSURGO slopes
High SVI, SSURGO slopes	3.8	0.3
Not high SVI, SSURGO slopes	10.5	85.4

Table 5. Contingency table showing percentage of watershed area in agreement and disagreement between indices using DEM slopes.

	High CCI, DEM slopes	Not high CCI, DEM slopes
High SVI, DEM slopes	5.3	1.1
Not high SVI, DEM slopes	11.1	82.6

Indices agreed about classifications of areas for 89.2% of the watershed using SSURGO slopes and for 87.9% the watershed using DEM slopes. The amount of areas in agreement is a majority (over 50%) in both cases, however, it should be remembered that the not high category includes moderately high, moderate, and low vulnerability areas so this result doesn't necessarily mean that index classifications agreed for such areas since they were merged into one class for the analysis. According to the NRCS,

areas classified as moderately high vulnerability in addition to high vulnerability could be considered for conservation treatment (Lisa Duriancik, USDA-NRCS, personal communication, 9 January 2014). Isolating high vulnerability areas in this analysis allowed index classifications of these areas to be compared. Indices agreed about classification of high vulnerability areas for 3.8% and 5.3% of the watershed, respectively, when SSURGO and DEM slopes were used. Comparing these numbers to the percentage of watershed area classified into the high vulnerability risk class by the SVI using SSURGO and DEM slopes (table 3) shows that the indices agreed for the majority of these areas. Even though the SVI didn't classify as many areas in the high vulnerability category as the CCI did, this gives confidence about the ones it did. Examining the lower left value of each table, it can be seen that the most disagreement occurred between areas classified as high vulnerability by the CCI but some other vulnerability level by the SVI. This is consistent with the greater percentage of areas classified as high vulnerability by the CCI as seen in table 3.

Variability of Input Parameters

There was no variability in the hydrologic soil group parameter, and variability in the K-factor parameter didn't lead to any variation in watershed vulnerability classifications. Hydrologic soil group was D for all soil types in the watershed. All values of K-factor were greater than or equal to 0.32, and combined with all soil types having hydrologic soil group D, did not cause any areas to be classified differently by the SVI (refer to table 1).

Slope

Table 6 shows the distribution of SSURGO and DEM slopes found in the GCEW. DEM slopes had a larger percentage of slopes in the 0-1% and >4% ranges than did SSURGO slopes, while SSURGO slopes had a greater percentage of slopes in 1-2% and 2-4% ranges.

Table 6. Distribution of slope classes determined from SSURGO and DEM in Goodwater Creek Experimental Watershed

	Slope source	
	SSURGO	DEM
Slope range	%	%
0-1	14.6	42.0
1-2	29.4	27.9
2-4	51.9	23.7
>4	4.1	6.3

When comparing the percentage of watershed area classified in each vulnerability class by the same indices using different slope sources (table 3), the differences between the distribution of SSURGO and DEM slopes in different slope ranges reflects how percentages of vulnerability classifications change as different slope sources are used in the SVI and CCI. When DEM slopes were used, each index found a larger percentage of high vulnerability areas and a larger percentage of moderate and low vulnerability areas reflecting the greater percentage of slopes in the 0-1% and >4% ranges for DEM slopes. Percentages of watershed area in the moderately high vulnerability class, as seen in table 3, increase when SSURGO slopes are used. This result reflects the larger percentage of slopes in the 2-4% range using SSURGO slopes.

CD and KSAT

Table 7 shows the variation in values of CD and KSAT in the GCEW. There was little variation in KSAT values with all soils having a KSAT of 14.4 mm h^{-1} except for Leonard silty clay loam, which had a KSAT of 5.04 mm hr^{-1}. It represented only a small portion of the watershed. In contrast, there was a lot of variation in the CD parameter. There were 11 distinct values throughout the watershed ranging from 330 mm to 5156 mm.

Table 7. CD (mm) and KSAT (mm h^{-1}) values for soil types represented in the Goodwater Creek Experimental Watershed and the percent of watershed area represented by each soil type.

Soil type	CD	KSAT	% Area
Mexico silt loam, 1-4% slopes, eroded	762	14.4	41.8
Putnam silt loam, 0-1% slopes	914	14.4	14.6
Mexico silt loam, 0-2% slopes	965	14.4	11.0
Adco silt loam, 0-2% slopes	1041	14.4	9.0
Belknap silt loam, 0-2% slopes, frequently flooded	5156	14.4	5.1
Leonard silt loam, 2-6% slopes, erdoded	508	14.4	4.8
Leonard silty clay loam, 2-4% slopes, eroded	457	5.04	4.7
Armstrong loam, 5-9% slopes, eroded	330	14.4	4.2
Belknap silt loam, 0-2% slopes, frequently flooded	5156	14.4	2.1
Twomile silt loam, 0-2% slopes, occasionally flooded	1549	14.4	1.3
Gifford silt loam, 1-4% slopes	457	14.4	0.6
Chariton silt loam, 0-2% slopes, rarely flooded	762	14.4	0.5
Wilbur silt loam, 0-2% slopes, frequently flooded	4267	14.4	0.1
Moniteau silt loam, 1-3% slopes, rarely flooded	4191	14.4	0.1
Wilbur silt loam, 1-3% slopes, frequently flooded	4267	14.4	0.1

DISCUSSION

One of the primary ways indices such as the SVI and CCI can be used is to determine which areas within a watershed should be given the most consideration for

receiving treatment through conservation practices and cost share dollars. As mentioned earlier, high and moderately high vulnerability areas can be considered for conservation treatment and cost share dollars. Two additional contingency tables were made considering high and moderately high vulnerability areas merged into a single class to compare index classifications of high and moderately high vulnerability areas. Tables 8 and 9 show the results.

Table 8. Contingency table showing percentage of watershed area in agreement and disagreement between indices using SSURGO slopes, high and moderately high vulnerability classes merged together.

	Merged high CCI, SSURGO slopes	Not high CCI, SSURGO slopes
Merged high SVI, SSURGO slopes	55.3	0.7
Not high SVI, SSURGO slopes	21.3	22.7

Table 9. Contingency table showing percentage of watershed area in agreement and disagreement between indices using DEM slopes, high and moderately high vulnerability classes merged together.

	Merged high CCI, DEM slopes	Not high CCI, DEM slopes
Merged high SVI, DEM slopes	28.1	1.9
Not high SVI, DEM slopes	30.7	39.2

When high and moderately high vulnerability areas were merged into a single vulnerability class, the total agreement between CCI and SVI classifications was 78.0% of areas using SSURGO slopes and 67.3% of areas using DEM slopes. A majority of areas were classified the same. Considering only agreement of merged high vulnerability areas, the indices agreed about 55.3% of areas using SSURGO slopes and 28.1% of areas using DEM slopes, representing a majority of the high and moderately high vulnerability

areas classified by the SVI using each slope source. That the majority of areas classified as high and moderately high vulnerability by the SVI were classified the same by the CCI gives confidence in the classifications determined for these areas. In contrast, 21.3% and 30.7% of merged high vulnerability areas classified by the CCI showed disagreement with classifications determined by the SVI using SSURGO and DEM slopes, respectively. On average, such areas represented about 25% of the watershed. While the CCI agreed with most of the areas classified as high or moderately high vulnerability by the SVI, the CCI classified many areas as high and moderately high vulnerability that the SVI classified in lower vulnerability categories. It should be noted that these areas would be considered for conservation treatment only if the CCI was used to classify areas in the GCEW.

Classifications determined by the SVI and CCI in a region of the GCEW with known critical areas were compared with an aerial photo of a known vulnerable area in the region to assess the ability of each index to classify the vulnerable area. Figures 5 and 6 show maps of SVI and CCI vulnerability classifications in the region that was examined, and figure 7 shows the aerial photo of the field. Degradation in the form of gullies can be clearly seen in the photo. In comparing figures 5 (SVI classifications) and 6 (CCI classifications), it can be seen that the CCI does classify a greater amount of areas in the high vulnerability category compared with the SVI. The extent of dark red, high vulnerability areas classified by the CCI in figure 6 is larger than the extent classified by the SVI in figure 5, and many high vulnerability areas seen in figure 6 are not present at all in figure 5. The high vulnerability areas classified by the CCI however, are classified

mostly as moderately high vulnerability areas by the SVI. The particular field shown in figure 7 was classified as moderately high vulnerability by the SVI and high vulnerability by the CI. Considering that high and moderately high vulnerability areas could be considered for conservation treatment, both indices would be able to identify vulnerable areas like the field that was examined in figure 7. The CCI, however, shows more discrimination between areas in the region as seen by the larger amount of high vulnerability area in figure 6. While the accuracy of this discrimination is difficult to verify without ground truthing, the CCI does show more distinction between potential critical areas according to figures 5 and 6. This distinction could be useful to planners assessing conservation needs at a local scale.

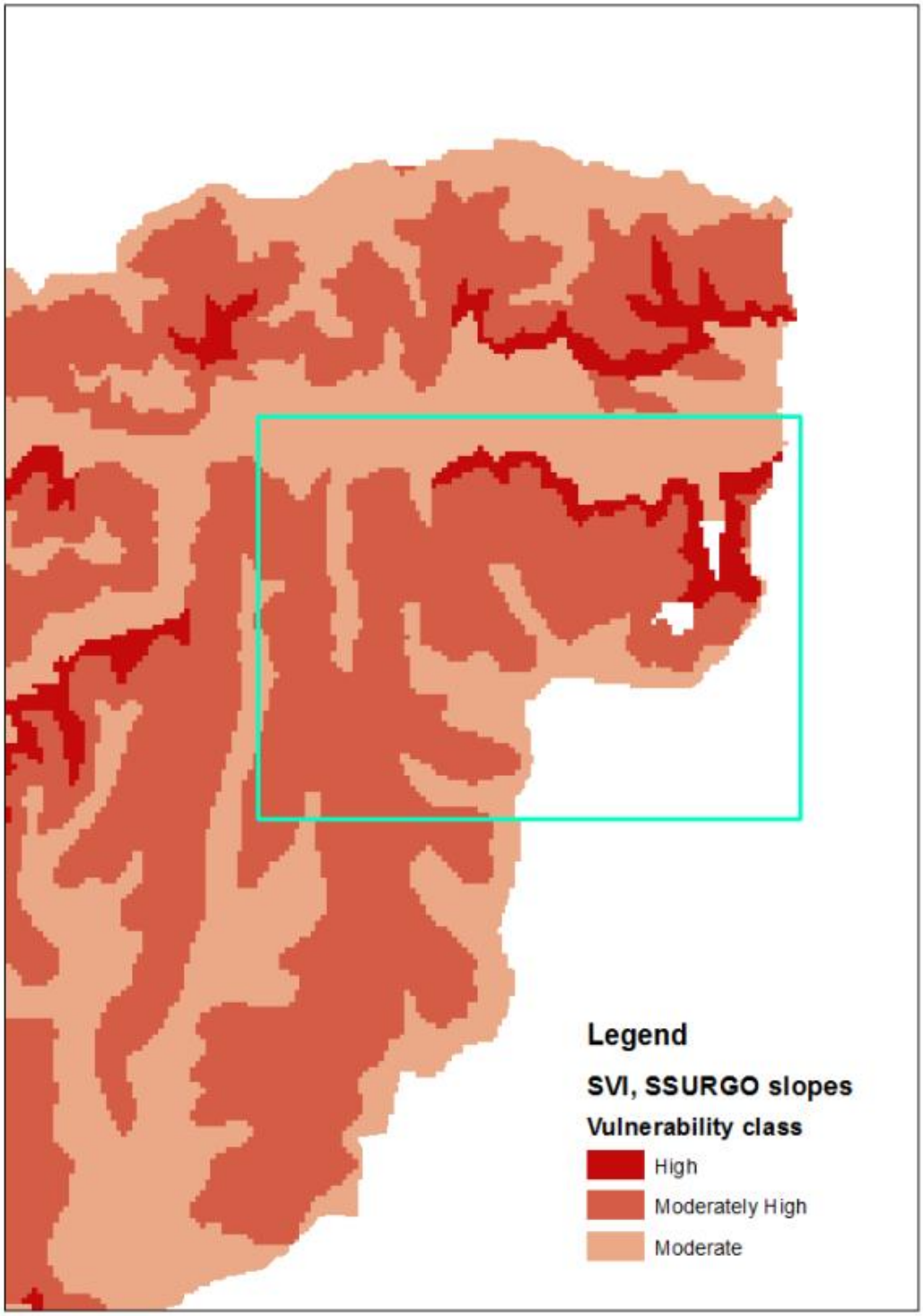

Figure 5. Map of SVI classifications highlighting a region in the GCEW with known critical areas, SSURGO slopes used as inputs.

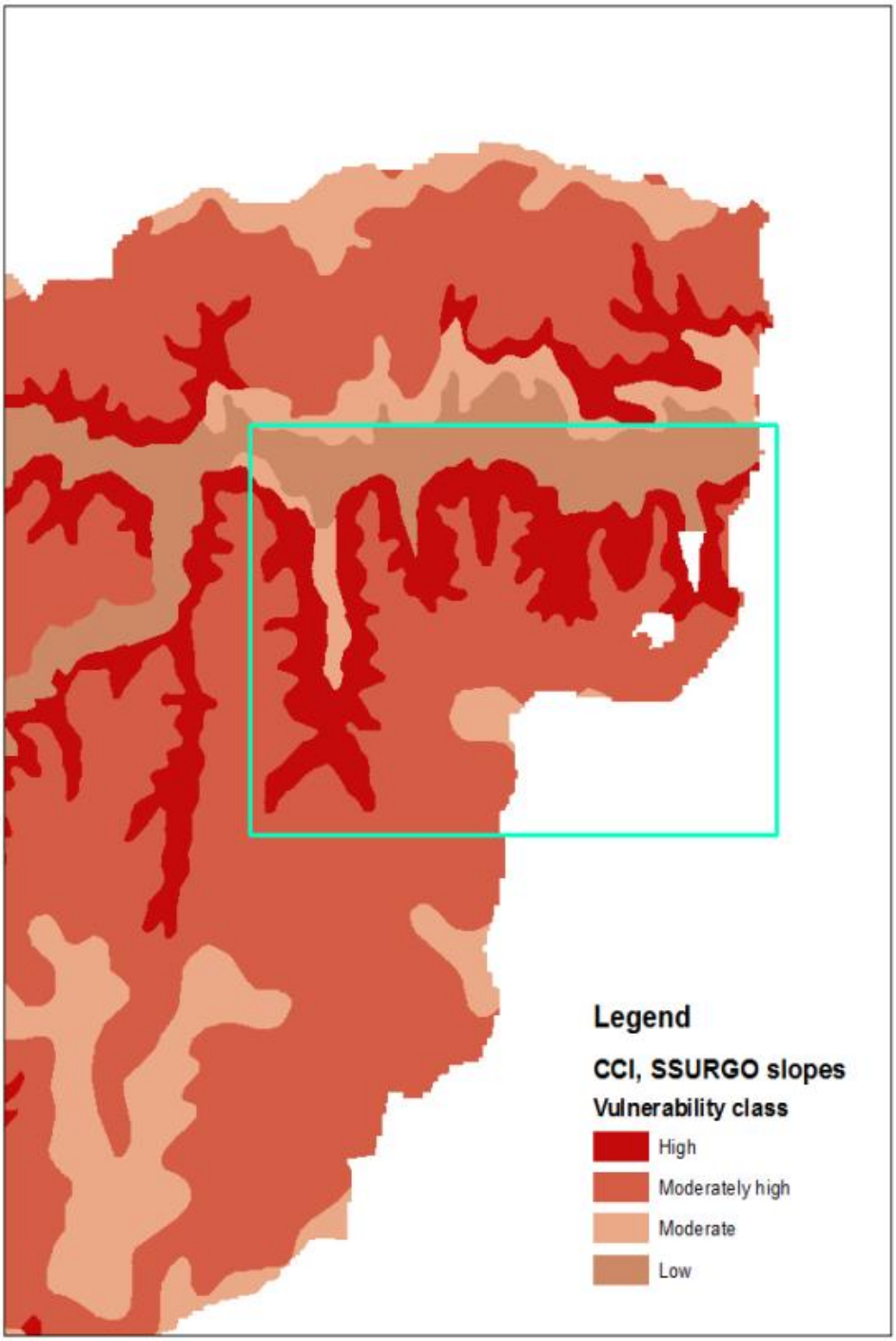

Figure 6. Map of CCI classifications highlighting a region with known critical areas in the GCEW, SSURGO slopes used as inputs.

Figure 7. Aerial photo of field found within the region highlighted in figures 5 and 6. Source: Google Earth.

Switching from SSURGO to DEM slopes while using the same index resulted in increases in the percentage of watershed area classified in the high and moderate vulnerability classes and a decrease in the moderately high vulnerability class. There was an increase in the percentage of watershed classified in the low vulnerability class by the CCI but no change for the SVI. Table 10 shows the difference in percentage of watershed area for each vulnerability class using DEM slopes instead of SSURGO slopes in each index. Positive values in the table indicate that the percentage of watershed area increased when DEM slopes were used instead of SSURGO slopes, while negative values indicate that it decreased.

Table 10. Difference in percentage of watershed area in each vulnerability class between index classifications determined using DEM slopes and those determined using SSURGO slopes.

	Vulnerability class			
Index	High	Moderately high	Moderate	Low
SVI	2.2	-28.2	26.0	0.0
CCI	2.1	-19.8	14.8	3.0

The data show that switching from SSURGO slopes to DEM slopes resulted in a decrease in moderately high vulnerability areas compensated by an increase in lower vulnerability areas and a small increase in high vulnerability areas. Considering that moderately high vulnerability areas could be considered as candidates for conservation treatment, using DEM slopes would take many areas out of consideration, and additional work would be useful to validate whether such areas should be considered or not. Despite this result, using DEM slopes did result in the classification of additional high vulnerability areas that weren't classified as high vulnerability using SSURGO slopes. These high vulnerability areas could be critical areas that would benefit from conservation treatment.

Results in table 10 can be explained by examining differences in distribution of slope classes between SSURGO and DEM slopes as seen in table 6 and considering how slope values would affect SVI vulnerability classifications according to the criteria specified in table 1. When using the criteria in table 1, it should be remembered that all soils in this watershed had hydrologic soil group D and K-factor greater than or equal to 0.32. DEM slopes had a greater percentage of slopes in the >4% range, a lower percentage of slopes in the 2-4% range, a comparable percentage of slopes in the 1-2%

range, and a greater percentage of slopes in the 0-1%. Slopes in the >4% range would lead to high vulnerability, slopes in the 2-4% range would lead to moderately high vulnerability, and slopes in the <2% range would lead to moderate vulnerability. These differences between SSURGO and DEM slope distributions are reflected in an increase in high vulnerability areas, a decrease in moderately high vulnerability areas, and an increase in moderate vulnerability areas.

When considering the benefit of using DEM slopes instead of SSURGO slopes as inputs in these indices, how each slope is determined should be considered. DEM slopes used in these indices were calculated from 10m digital elevation maps using a GIS procedure. A slope value was calculated for each 10m by 10m cell within the watershed. SSURGO slope values were the representative value given in the SSURGO database for each soil series. The representative slope is calculated as the average of the slopes of all soil type polygons found within a map unit (Jorge Lugo-Camacho, USDA-NRCS, personal communication, 8 August 2014). For example, if there were 5 polygons corresponding to a Mexico silt loam soil type within a particular map unit, the representative value slope would be calculated as the average of the 5 polygon slopes. There are several implications to calculating the slope this way. One is that the representative value slope cannot be easily associated with a particular area on a map since polygon locations vary. Another is that the area represented by each polygon is variable and likely to be larger than that of a 10m by 10m DEM cell. These implications mean that using DEM slopes provides information that is more spatially accurate and that applies to a finer scale. On the other hand, using DEM slopes requires more time and computing power than

SSURGO slopes. When it is necessary to classify a very large area such as an entire state, the time required in using DEM slopes in an index may not be reasonable and SSURGO slopes could be a better fit. For smaller scales, such as classification of a watershed, the time required wouldn't be as big of an issue and using DEM slopes could receive greater consideration. The scale of analysis, time required, and computing power that is available should all be considered when deciding what slope source is used. In future work using DEM slopes, methods to filter the data removing areas such as roads and determine average field slopes could be examined.

Changing to DEM slopes affected SVI classification more than CCI classification as seen by larger changes in the amount of moderately high and moderate vulnerability areas. Using DEM slopes did not affect the amount of low vulnerability area determined by the SVI, but this result is actually due to no soil types within the watershed having K-factor values that would lead to low vulnerability classification rather than slopes not having any effect (table 1). When comparing the amount of moderate vulnerability area classified by the SVI using DEM slopes with the amount classified using SSURGO slopes, the increase in the amount of area classified is almost equal to the difference between the amount of watershed area with DEM slopes in the 0-2% range and the amount with SSURGO slopes in the same range. This can be confirmed from tables 3 and 6. The 0 to 2% range is important because this is the range of slopes that would lead to classification in the moderate vulnerability class with the SVI (table 1). If slope values were greater than 2% in this watershed, the SVI classified areas in the moderately high or high vulnerability class. The difference between percentage of watershed areas

having DEM slopes in this range and those having SSURGO slopes in this range is almost equal to the total change in percentage of watershed area classified in the moderately high and high vulnerability classes when DEM slopes are used in the SVI instead of SSURGO slopes.

The SVI is, therefore, very sensitive to the slope parameter in this watershed. In this case, due to there being no variability in hydrologic soil group and variability in K-factor not affecting vulnerability classifications, it is the only parameter responsible for changes in the SVI. The CCI was not as sensitive to the slope parameter, and it is likely that the greater amount of variability observed for the CD input parameter affected its sensitivity to the slope parameter. The greater variability found in the CD parameter used by the CCI also shows that the parameters used by the SVI don't reflect variability in characteristics of claypan soils in the same way as the parameters of the CCI. The CCI may therefore be a more suitable choice of index for watersheds that are dominated by claypan soils.

CONCLUSIONS

In this study the SVI and CCI were used with SSURGO and DEM slope sources to classify areas for vulnerability to contaminant transport by surface runoff in a Missouri claypan watershed. Watershed vulnerability classifications determined by the indices were compared and the variability of input parameters used in each was assessed to see how it affected index classifications. While the CCI agreed with the majority of areas

classified as high vulnerability by the SVI, the CCI also consistently classified additional high vulnerability areas that weren't classified as high vulnerability by the SVI. Compared with the CCI, the SVI determined lower vulnerability classifications for many areas the CCI classified in the high or moderately high categories, areas that conservation planners might consider for conservation treatment. When DEM slopes replaced SSURGO slopes, indices classified more high vulnerability areas and fewer moderately high vulnerability areas. SVI classifications changed more in response to using a different slope source, and the SVI was found to be more sensitive to the slope parameter than the CCI in this watershed. Besides the slope parameter, there was little variability in SVI parameters. There was no variability in hydrologic soil group, and variability in K-factor did not affect index classifications. Both slope and CD had variability that was sufficient to affect watershed vulnerability classifications using the CCI. This shows that the parameters used in the CCI reflect characteristics of this particular watershed differently than the parameters of the SVI.

The CCI identified potential critical areas not identified by the SVI in this watershed, and may be a better choice to use for watersheds with claypan soils or similar restrictive layers close to the surface. Alternatively, future versions of the SVI could be modified by including parameters such as CD that can account for watersheds with restrictive layers near the surface. Additional potential critical areas were also identified when DEM slopes were used; however, using DEM slopes also resulted in a lower percentage of moderately high vulnerability areas, a result that should be investigated further to assess the conservation treatment needs of such areas. While

using DEM slopes requires more time and computing power, it also allows the location of potential critical areas to be more precisely identified due to the finer spatial resolution of the data. This may be desirable when making decisions at a local scale.

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CHAPTER 3: EVALUATING THE CEAP CONSERVATION BENEFITS IDENTIFIER ON A CLAYPAN WATERSHED IN MISSOURI

ABSTRACT

Targeting indices are tools that can be used to identify potential critical areas that generate the greatest amounts of pollutant loads in watersheds. Conservation practices applied to such areas are predicted to obtain some of the greatest reductions in contaminant loads. Before indices can be fully utilized, it is necessary to verify the accuracy of their classifications. The Soil Vulnerability Index (SVI), Conductivity Claypan Index (CCI), and CEAP Conservation Benefits Identifier (CCBI) were evaluated in this study to assess their accuracy in identifying critical areas in a claypan watershed. The SVI and CCI identify potential critical areas where contaminant transport by surface runoff could occur, while the CCBI identifies potential critical areas that are undertreated relative to their vulnerability to contaminant transport by surface runoff. Performance of indices was assessed through comparison with results determined from a SWAT model calibrated and validated for use in the Goodwater Creek Experimental Watershed (GCEW), a claypan watershed. Significant correlation was found between cropland HRU vulnerability levels determined using the CCI and SWAT outputs of contaminant loads from cropland HRUs, while no such correlation could be found based on vulnerability levels determined using the SVI. SWAT estimates of contaminant reductions obtained

with conservation practices were consistent with CCBI classification, vulnerability level, and conservation treatment level. The SWAT model estimated lower average contaminant reductions of sediment and higher average contaminant reductions of nitrogen and phosphorus compared with the CCBI.

Similar responses to changes in vulnerability level and conservation treatment level gave confidence about using the CCBI in the GCEW or a similar watershed, but showed that there is some uncertainty about the values of contaminant reductions estimated at specific levels of initial treatment and soil vulnerability.

INTRODUCTION

Nonpoint source (NPS) pollution stemming from agricultural land is the leading cause of impairment to surface waters in the United States and is therefore recognized as an important issue to address in US environmental policy (Baker, 1992). Common pollutants resulting from agricultural NPS pollution include phosphorus (P), nitrogen (N), sediment, and chemical fertilizers and pesticides. This pollution is a problem for both wildlife and humans as evidenced by damage to aquatic ecosystems, contamination of drinking water sources, and loss of soil and nutrients needed for farming (Baker, 1992).

Conservation practices such as grassed waterways, buffer strips, and nutrient management plans have been applied to agricultural areas in order to reduce NPS pollution and mitigate its effects. Practices, however, have not always been as effective as desired in reducing NPS pollution, and this has led to a search for ways in which their

effectiveness can be improved (Heathcote et al., 2013; Tomer and Locke, 2011). Targeting placement of conservation practices to critical areas that generate the greatest amounts of pollutants relative to other areas and are therefore most in need of conservation treatment has been one proposed solution (Gale et al., 1993; Tomer and Locke, 2011). For example, Strauss et al. (2007) found that targeting conservation practices to such areas can obtain significant reductions in pollution compared with other methods.

Targeting indices such as the phosphorus index (PI) and topographic wetness index (TWI) can be used to determine watershed locations of critical areas where conservation practices should be applied. The PI can identify fields where excessive phosphorus loss is more likely to occur (Lemunyon and Gilbert, 1993). The TWI estimates the saturation potential of soils, and thus identifies areas in a watershed where pollutants are likely to be transported due to saturation excess overland flow occurring (Beven and Kirkby, 1979). While it is important to identify and treat critical areas, different targeting indices, even if designed and used to find critical areas that correspond to the same contaminant, can point to different locations of critical areas in a watershed (Chan et al., 2013). This result might occur because indices use different parameters that represent different processes involved in the transport of contaminants (Dosskey et al., 2013). Such a result doesn't necessarily indicate that either index is incorrect. It does, however, illustrate the importance of validating indices and testing their results.

Validation of indices gives confidence in index results and can help planners to decide which index to use if multiple indices are available (Dosskey and Qiu, 2011). Index results can be validated through means such as professional judgment, comparison with aerial photos, comparison with other indices, comparison with model results, and comparison with field data. Dosskey et al. (2011) used the Vegetated Filter Strip Model to validate results of two indices designed to identify optimal locations for vegetated buffers in agricultural watersheds. In evaluating the SVI and CCI in Chapter 2, the distribution of vulnerability classifications determined by each index was compared to determine whether the indices were classifying the watershed similarly. Dosskey et al. (2013) compared optimal watershed locations for placement of vegetated buffers determined by five targeting indices. Wetland areas predicted by two wetness indices were compared to a map showing the actual spatial distribution of wetland areas in a watershed (Grabs et al. 2009).

The extent of validation that has been done for different indices varies. The TWI, for example, has been in existence since the 1970's and has been tested and modified from its original form (Beven and Kirkby, 1979; Sørensen et al., 2006). Sorenson et al. (2006) experimented with different methods of calculating the TWI to see how these methods affected correlation between the TWI and different measured variables. They found that different calculation methods did affect correlations.

The Soil Vulnerability Index (SVI), Conductivity Claypan Index (CCI), and CEAP Conservation Benefits Identifier (CCBI) are targeting indices that have had only limited or no validation performed. In Chapter 2, vulnerability classifications determined by the

SVI and CCI were assessed using an aerial photograph of a field with known high vulnerability to contaminant transport by surface runoff. The SVI was developed by the Natural Resources Conservation Service (NRCS) as a way to differentiate U.S. cropland areas on the basis of vulnerability to surface runoff and leaching (USDA – NRCS, 2012). Areas with higher vulnerability are ones where additional conservation treatment could be beneficial. It categorizes areas as having high, moderately high, moderate, or low vulnerability to surface runoff or leaching based on soil properties of slope, USLE soil erodibility factor (K-factor), hydrologic group, and coarse fragment content.

The CCI was developed by Mudgal et al. (2012) to identify the most environmentally sensitive areas in a field located in a claypan watershed. Areas within the field were first identified as environmentally sensitive based on relative amounts of sediment, runoff, and atrazine generated from each according to Agricultural Policy Environmental eXtender (APEX) model results (Mudgal et al., 2012). APEX is a field scale, hydrologic model with the ability to simulate management such as drainage, buffer strips, terraces, and grassed waterways (Gassman et al., 2010). An equation using inputs of slope, surface layer saturated hydraulic conductivity (KSAT), and depth to claypan (CD) for each area was determined whose calculated values were found to correlate well with APEX output values of runoff and sediment generated from each area (Mudgal et al., 2012). Specifically, the equation was CCI = CD * KSAT / Slope. The CCI was adapted in later research to find critical areas at a watershed scale by taking the natural logarithm of CCI values determined for areas of different soil types and classifying them into four groups using the Jenks natural breaks method (Mudgal, 2010; Chan et al.,

2013). Areas were designated as having high, moderately high, moderate, or low vulnerability to surface runoff based on the range of values within each Jenks determined group with lower ranges of values corresponding to higher vulnerability classifications.

The CCBI is a tool developed by the NRCS to identify cropland areas nationwide where the greatest additional contaminant reductions can be obtained from applying additional conservation practices (K. Ingram, USDA-NRCS Resource Assessment Division GIS Lab Coordinator, personal communication, October 10, 2013). It assesses the soil vulnerability of areas determined from the SVI and an additional factor called conservation treatment level to rank areas in terms of priority to receive additional conservation treatment. The conservation treatment level used by the CCBI is a measure of how many types of conservation practice strategies are represented by practices applied to a given area. Practices have been categorized by the NRCS in terms of the conservation practice strategy they exhibit as either avoid (A), trap (T), or control (C) (USDA-NRCS, N.D.). Practices in the A category reduce contamination through avoiding pollutants (e.g. nutrient management), practices in the T category reduce contamination by trapping pollutants (e.g. filter strips), and practices in the C category reduce contamination by controlling pollutants (e.g. grassed waterways). The NRCS has found that contaminant reductions obtained from conservation treatment are greater when multiple conservation practice strategies are represented by the practices implemented (USDA-NRCS, 2012). The CCBI defined areas with a low level of conservation treatment as having one type of conservation practice strategy in place, a moderate level of

treatment as having two types of conservation strategies in place, and a high level of conservation treatment as having all three types of conservation strategies in place. A high level of treatment was considered to represent a full level of treatment where maximum reductions would be obtained. Based on CEAP cropland study model results about contaminant reductions that can be obtained at a full level of treatment compared with a given initial level of treatment and soil vulnerability class, the CCBI assigns areas a priority level between one and four with lower priority levels indicating that greater contaminant reductions are possible if a full level of conservation treatment is applied (K. Ingram, personal communication, September 14, 2014). The priority levels were defined in terms of the initial conservation treatment level and soil vulnerability level since contaminant reductions were predicted on that basis. Priority levels assigned by the CCBI can be used by planners to target areas where conservation treatment should be applied.

Another means of identifying critical areas and assessing benefits from conservation practices is by simulating these practices with a hydrologic or water quality model that has enough flexibility to represent agricultural practices as well as the variety of soils, land uses, and topographies that are present in a watershed. The Soil and Water Assessment Tool (SWAT) is a hydrologic, watershed-scale model that has been commonly used to identify critical areas in watersheds (Busteed et al., 2009; Ghebremichael et al., 2010; Srinivasan et al., 2005; White et al., 2009). SWAT can determine pollutant outputs at various scales and simulate effects of conservation practices on pollutant loads (Douglas-Mankin et al., 2010). A watershed simulated with

SWAT is divided into sub-basins and Hydrologic Response Units (HRUs). HRUs are lumped, non-spatial areas within sub-basins having the same land use, management, and soil type, which are important factors that affect hydrology and generation of NPS pollution (Gassman et al., 2007). Critical areas can be identified at a sub-basin or HRU scale by comparing estimated pollutant loads contributed by areas at each scale and choosing the ones with the greatest loads (Singh et al., 2010). While using a model such as SWAT is an effective way to identify critical areas, it is a time-consuming process involving parameterization, calibration, and validation of numerous parameters. Targeting indices require less time and fewer parameters to be determined. A SWAT or similar hydrologic model that has already been calibrated and validated for a watershed can be useful, however, in the validation of a targeting index.

In this study, a SWAT model previously calibrated and validated for the Goodwater Creek Experimental Watershed (GCEW) was used to validate the CCI, SVI, and CCBI. The GCEW is a watershed with extremely high surface runoff where previous research has already been conducted. The specific objectives of the study were to 1) test for correlation between SWAT estimated contaminant loads from cropland HRUs and their vulnerability to surface runoff determined using the SVI and CCI, 2) use a SWAT model calibrated and validated specifically for the GCEW to predict contaminant reductions that can be obtained at a full level of conservation treatment given different initial conservation treatment and soil vulnerability levels, and 3) compare predictions about contaminant reductions determined from objective 2 with those predicted by the modeling used in the development of the CCBI.

MATERIALS AND METHODS

Study Area

The study area was the Goodwater Creek Experimental Watershed (GCEW), a 72.52 km^2 area located in Boone and Audrain counties, north central Missouri. One distinguishing feature of the watershed is that it is part of the Central Claypan Areas, an approximately 3 million ha area that covers parts of Missouri and Illinois (Mudgal et al., 2012). Such areas are particularly prone to surface runoff and resulting NPS pollution due to a shallow, low permeability clay layer called a claypan that limits percolation and available water capacity (Mudgal et al., 2012). Excessive soil erosion and herbicide transported in surface runoff have been documented in the GCEW as well as in other claypan areas (Lerch et al., 2011).

Land use in the watershed is primarily agricultural but there are also some forest, water, and urban areas with the town of Centralia overlapping part of the south headwaters section of the watershed. Slopes in the watershed were determined from a 30 m DEM that was processed using ArcSWAT version 2012.10.1.15. HRUs were delineated in the watershed using thresholds of 5% for landuse, 20% for soil type, and 20% for slope. This resulted in 25% of the watershed area having slopes from 0–1%, 59% having slopes from 1-2%, 14% having slopes from 2-3%, and the remaining 2% having slopes greater than 3%. After HRU delineation, there were five soil types represented in the watershed: Mexico silt loam, Adco silt loam, Belknap silt loam, Putnam silt loam and

Leonard silt loam. The majority of the watershed area (75%) was Mexico silt loam with the remaining area evenly split among the other soil types. According to their soil series, all the soils ranged from deep to very deep and somewhat poorly drained to poorly drained but varied in terms of geographic setting. The Adco and Belknap soil types, representing 13% of the watershed area, were the soils with the lowest runoff potential and were somewhat poorly drained soils. The Belknap soil type was hydrologic soil group C, while all other soil types had hydrologic soil group D.

Swat Model Background

The SWAT model used in this study was the model application parameterized, calibrated, and validated specifically for the GCEW and claypan soil characteristics by Baffaut et al. (2015). Major changes incorporated by Baffaut et al. (2015) into the model were that the percolation algorithm used by SWAT was modified to more accurately simulate effects of a claypan, and planting progress reports and heat units were used to schedule field operations. The model was calibrated and validated for flow at a daily time step and loads of atrazine, sediment, and dissolved P at a monthly time step for the years from 1993 – 2010. Measured data were obtained from several weirs throughout the GCEW. Model performance was assessed using several criteria. One was that the percent difference between measured and simulated values had to be within a tolerance of 15% for flow, 40% for sediments, and 30% for atrazine and dissolved nutrients. Additionally, the Nash-Sutcliffe efficiency had to be greater than 0.5 and the coefficient of determination had to be greater than 0.6. These performance criteria

were met for calibration and validation with the exception of sediment during the validation period. Additional details about specific changes, parameterization, calibration and validation can be found in Baffaut et al. (2015).

Baseline Scenario

The baseline scenario consisted of a 2-year rotation of conventionally tilled corn followed by no-till soybean with no other conservation practices simulated. It represents the most common practices used by the producers in the GCEW. Specific settings used in the management operations schedule can be found in supplemental material for Baffaut et al. (2015), in a section titled “Field operation scenarios”.

Test for Correlation between HRU Vulnerability Levels and Contaminant Loads from HRUs

Determination of HRU Soil Vulnerabilities

Before a test for correlation could be performed, HRU vulnerability levels to surface runoff and contaminant loads from HRUs under baseline conditions needed to be determined. Only cropland HRUs were assessed since both indices were designed with cropland in mind. First, vulnerability levels of HRUs were determined using the SVI and CCI. The SVI inputs of slope, hydrologic soil group, and USLE K-factor were determined for each HRU from the model input data and used to assign vulnerabilities based on the methodology of the SVI (table 1). The slope used was the HRU slope value

found in the HRU input file, and the hydrologic soil group and K-factor were determined from the soil type of each HRU.

The CCI inputs of slope, KSAT, and CD were also determined from SWAT soil type data. Slope and KSAT were taken directly from SWAT HRU and soil type data, but CD was determined indirectly using a method similar to that used by Chan et al. (2013). CD used was the depth to the first soil layer having at least 40% clay content and a close to 100% increase in clay content relative to the surface layer. If these conditions weren't met, the depth of the deepest soil layer was specified. With the parameters determined, a soil vulnerability level was assigned to each cropland HRU by calculating ln(CCI) values and breaking them into groups using the Jenks natural breaks method as described previously and used by Mudgal et al. (2012).

Calculation of Contaminant Loads from Baseline Scenario HRUs

Contaminant loads from HRUs under baseline scenario conditions were determined for nitrogen, phosphorus, and sediment. The model was run using 60 years of generated weather data, and the average annual amounts of organic N, N in surface runoff, N in lateral flow, organic P, soluble P in surface runoff, mineral P attached to sediment, and sediment yield were obtained for each cropland HRU. Using these outputs, N and P contaminant loads were calculated by summing N and P outputs from each HRU, and sediment load was determined directly from the sediment yield output.

Test for Correlation

Determination of cropland HRU soil vulnerability levels and total contaminant loads resulted in an SVI and CCI vulnerability ranking for each cropland HRU and an amount of N, P, and sediment on a pollutant/ha basis contributed by each one. With these data, a test for correlation between HRU vulnerability levels determined using each index and contaminant loads of N, P, and sediment calculated by SWAT for each HRU could be performed.

Spearman's rank correlation coefficient, which can be used to test for correlation between ordinal variables (Wong and Lee, 2005), was calculated to test for correlation between HRU vulnerability levels and total contaminant loads. It is a measure of the extent that one ordinal variable increases or decreases as another ordinal variable is increased. Contaminant load values and HRU vulnerability levels were converted into rank form in order to perform the calculation. For the CCI, values calculated from the equation used by the CCI to determine vulnerability level were also ranked so that the Spearman's coefficient could be calculated. SVI vulnerability levels were converted into rank form by assigning a value from one to four based on the assigned vulnerability level. Higher vulnerability levels were assigned lower rank values (1 = high vulnerability, 2 = moderately high vulnerability, etc.). Once the correlation coefficient was calculated, a test for significance was performed by comparing the calculated coefficient to a critical coefficient value determined using a two-tailed t-test table with $\alpha = 0.05$.

Derivation of Conservation Treatment Scenarios

Conservation treatment scenarios consisting of different practices or combinations of practices were determined and defined in terms of the practice or practices to be simulated, the slope range and soil type that would be targeted, the model settings and parameters used to simulate practices, the conservation practice strategy or strategies involved, and the conservation treatment level, determined based on the definition used by the CCBI as described earlier. The conservation practice or combination of practices simulated in each scenario were chosen based on an analysis of practices that have been used historically in the watershed from 2005-2012 according to the NRCS NRI database. Findings from a survey of farm operators in the GCEW conducted by Murphy et al. (2010) were used to determine practices and management used in these treatment scenarios. Slope ranges and soil types associated with each practice were chosen by analyzing data on the historical location of the practices in the watershed, consulting NRCS standards for practices, and considering the typical landscape position on which practices might be found. Typical landscape positions of soil types were also considered when deciding to which soil types practices should be applied. Table 11 shows the conservation treatment level of each scenario, specific practice or practices that were simulated in each scenario, conservation practice strategies involved in each scenario, and the slope ranges and soil types associated with each scenario. It should be noted that treatment level is only based on how many practice strategies are represented by practices applied. For example at low treatment level, several scenarios involve more than one conservation practice being

implemented, but the treatment is still considered low because only one practice strategy is represented. Contour farming and terrace is one low conservation treatment scenario that involves two practices but has only one practice strategy represented. When terraces are implemented, contour farming is a practice that naturally follows since terraces are constructed perpendicular to slope direction, and it makes sense to farm parallel to terrace ridges.

Table 11. Characteristics of each conservation treatment scenario.

Treatment level	Practice(s)	Practice strategies	Slope range	Soil type(s)
Low	Conservation crop rotation	Avoid	All slopes	All
	CRP	Avoid	All slopes	Mexico, Leonard
	Residue & tillage management	Control	All slopes	All
	Grassed waterway	Control	All slopes	Mexico
	Contour farming	Control	All slopes	Mexico, Leonard
	Contour farming and Terrace	Control	> 2	Mexico, Leonard
	Contour farming and Grassed waterway	Control	All slopes	Mexico
	Contour farming and Residue & tillage management	Control	All slopes	Mexico, Leonard
	Contour farming, Terrace, and Grassed waterway	Control	> 2	Mexico, Leonard
	Biomass	Control	All slopes	Mexico, Leonard
	Filter strip	Trap	All slopes	Leonard
Moderate	Conservation crop rotation and Residue & tillage management	Avoid, Control	All slopes	All
	Conservation crop rotation and Grassed waterway	Avoid, Control	All slopes	Mexico
	Conservation crop rotation and Contour farming	Avoid, Control	All slopes	Mexico, Leonard
	Conservation crop rotation and Filter strip	Avoid, Trap	All slopes	Leonard
	Filter strip and Residue & tillage management	Trap, Control	All slopes	Leonard
	Filter strip and Contour farming	Trap, Control	All slopes	Leonard
High	Conservation crop rotation, Filter strip, and Residue & tillage management	Avoid, Control, Trap	All slopes	Leonard
	Conservation crop rotation, Filter strip, and Contour farming	Avoid, Control, Trap	All slopes	Leonard

Model settings and Parameters

SWAT settings and parameters used to model conservation treatment scenarios were determined primarily using the Conservation Practice Modeling Guide for SWAT and APEX (Waidler et al., 2009) and the SWAT Input/Output Documentation Version 2012 (Arnold et al., 2012). However, settings and parameters for some practices however, could not be determined using these sources. This occurred either because the sources did not have instructions about how to model certain practices or because it was not appropriate to use the parameters and settings recommended by the sources. For scenarios where these situations occurred, table 12 lists the settings and parameters used to model practices and describes how they were determined. Additional explanation is provided for some of these practices in the paragraphs that follow.

Table 12. Settings and parameters used to model specific conservation treatment scenarios.

Practice(s)	Settings/Parameters used	Notes about settings/parameters used
Residue & tillage management	CN2 not changed	Research has shown that CN2 isn't affected by this practice in the GCEW
Grassed waterway	GWATn = 0.06, GWATW = 18.3 m, GWATD = 0.6 m	Settings chosen based on knowledge of typical Missouri waterways
Conservation crop rotation	Rotation changed to a 3 year conventional corn, no-till soybean, winter wheat rotation	Chosen based on research about typical conservation crop rotation used in the GCEW
Biomass	Custom parameters for Kanlow switchgrass used, LAI_INIT = 0.75, BIO_INIT = 500 kg/ha, PHU_PLT = 1100 heat units	Kanlow switchgrass crop parameters used from ALMANAC model, other settings chosen based on study by Baskaran et al. (2010) where switchgrass was modeled
CRP	Little bluestem plant type parameters used	Reflects possible scenario for Missouri CRP
Contour farming and terrace	SLSUBBSN = 36.6 m	Reflects Missouri conditions

Several studies have found that under no-till management on claypan soils or soils with a restrictive layer, higher than recommended baseline curve numbers need to be used in order to get accurate runoff predictions using the SWAT model (Anand et al., 2007; Maski et al., 2008). Therefore curve number values calibrated for the GCEW by Baffaut et al. (2015) were used in this model when the residue & tillage management practice was modeled instead of values recommended in the SWAT user manual. The conservation crop rotation practice used a 3-year rotation based on management in the GCEW described by Baffaut et al. (2015) from surveys of farm operators. Specific details

about the operations schedule are described in the supplemental document accompanying their study, which was also used to determine the baseline rotation settings. Several changes were made when modeling the biomass practice. Crop growth parameters for Kanlow switchgrass taken from the ALMANAC model (Kiniry et al., 1992) were entered into a new entry in the SWAT crop database. Initial plant growth parameters for biomass were those used by Baskaran et al. (2010). They set the initial land cover to have mature switchgrass stands in place. The CRP practice was modeled by selecting the little bluestem crop parameters from the SWAT crop database. The management operations schedule for CRP was changed so that it was harvested once every 3 years to be in compliance with CRP management requirements.

Calculation of Contaminant Reductions

Simulation of Conservation Treatment Scenarios

Conservation treatment scenarios (table 11) were simulated with SWAT in order to determine scenario-specific contaminant load outputs that could later be used to calculate contaminant reductions possible at different initial levels of conservation treatment. A separate model run was conducted for each treatment scenario, specifying cropland HRUs that each treatment scenario would be applied to based on the slope and soil type criteria specified in table 11. Each run used 60 years of generated weather data, and average annual outputs of organic N, N in surface runoff, N in lateral flow, organic P, soluble P in surface runoff, mineral P attached to sediment, and sediment

yield were obtained from cropland HRUs. These outputs were saved for use in later calculations.

Contaminant Reductions from Conservation Treatment Scenarios

Reductions in N, P, and sediment obtained by each conservation treatment scenario relative to the baseline scenario were calculated at each soil vulnerability level using contaminant loads from cropland HRUs to which practices were applied in each treatment scenario and baseline contaminant loads from cropland HRUs. First, the total contaminant load of each pollutant from each cropland HRU was calculated using the same process described in the baseline scenario. Contaminant reductions in each cropland HRU relative to the baseline were then calculated by subtracting baseline cropland HRU contaminant loads from cropland HRU contaminant loads obtained in each treatment scenario. With contaminant reductions for each cropland HRU determined, cropland HRUs were divided into groups by soil vulnerability level. Finally, the average contaminant reduction for cropland HRUs of the same soil vulnerability level was calculated for each contaminant in each scenario to determine average contaminant reductions relative to the baseline scenario obtained at different vulnerability levels. Because treatment scenarios were applied to specific cropland HRUs based on soil type and slope range, and these HRUs did not always represent the full range of soil vulnerability levels, some scenarios were not applied to HRUs of all vulnerability levels. In these cases, it was not possible to calculate a relative contaminant reduction for every soil vulnerability level as described.

Contaminant Reductions at Full Treatment

Contaminant reductions that could be obtained if a full level of conservation treatment was put in place, given an initial treatment level and soil vulnerability level, were calculated for all possible combinations of initial treatment and soil vulnerability. To calculate these final contaminant reductions, contaminant reductions obtained from conservation treatment scenarios of specified initial treatment level and soil vulnerability level were subtracted from contaminant reductions obtained by high conservation treatment scenarios at the same soil vulnerability level. Contaminant reductions obtained by conservation treatment scenarios were calculated based on reductions in contaminant loads from individual cropland HRUs as described in the previous paragraph. These contaminant reductions from cropland HRUs were used in the calculation of contaminant reductions that could be obtained if a full level of conservation treatment was put in place.

High treatment level scenarios were only applied to cropland HRUs having Leonard soil type (table 11). There were eight of these HRUs in total. Four of them were moderately high vulnerability, and the other four were moderate vulnerability. Because the high treatment scenarios were only applied to these HRUs, contaminant reductions obtained from applying full conservation treatment were calculated only using contaminant loads from these HRUs. Separate calculations were performed for HRUs of each vulnerability level. The first step in the calculation was to subtract the contaminant reductions obtained by the initial treatment level scenario from the contaminant reductions obtained by the high treatment level scenario. This resulted in a new

contaminant reduction value for each HRU. For some initial treatment scenarios, there were two possible high treatment scenarios that could be applied. Calculations were performed using both high treatment scenarios in such cases. Next, the average of the contaminant reduction values was taken to determine the average contaminant reduction obtained going from a specified initial treatment level scenario to a specified high treatment level scenario. If there were two possible high treatment scenarios, the average of the average contaminant reductions was taken to obtain an overall average contaminant reduction for the given initial treatment scenario. After average contaminant reductions were calculated for all possible initial treatment scenarios, contaminant reductions obtainable based on initial treatment level and vulnerability were calculated by averaging the average contaminant reductions obtained from initial conservation treatment scenarios of the same treatment level. The final result of this process of calculations was an estimated contaminant reduction value for each combination of initial treatment level and soil vulnerability. Values were not calculated for the low and high soil vulnerability levels since no high treatment scenario HRUs had those vulnerability levels.

Comparison of Full Treatment Contaminant Reductions

The contaminant reductions possible at full treatment determined in this study using the SWAT model were compared with those determined from CEAP cropland study results that were used to support the CCBI's prioritization hierarchy for ranking areas in terms of their need for conservation treatment. The final values of contaminant

reductions determined in each study were compared in terms of the magnitude of their values and in terms of how the values changed with vulnerability level and treatment level.

RESULTS AND DISCUSSION

HRU Vulnerabilities

Table 13 shows the number of cropland HRUs in each vulnerability level based on classifying the watershed using the SVI and CCI. Table 14 shows the percent of cropland watershed area in each vulnerability level based on classifying cropland HRUs using the SVI and CCI. There were 84 total cropland HRUs in the watershed.

Table 13. Number of cropland HRUs in each vulnerability class determined using the SVI and CCI.

Index	Vulnerability level			
	High	Moderately high	Moderate	Low
SVI	0	18	66	0
CCI	14	32	29	9

Table 14. SVI and CCI determined percent of cropland watershed area in each soil vulnerability level.

Index	Vulnerability level			
	High	Moderately high	Moderate	Low
SVI	0.0	14.3	85.7	0.0
CCI	12.6	62.3	16.7	8.4

Tables 13 and 14 show that the SVI classified a majority of cropland HRUs in the moderate vulnerability level. On the other hand, the CCI classified a majority of the cropland HRUs in the moderately high and moderate vulnerability categories. The CCI classified HRUs in all vulnerability levels, while the SVI classified HRUs only in the

moderately high and moderate vulnerability levels. The reason why the SVI classified no high vulnerability areas can be explained by reviewing the criteria it uses to classify areas. It considers information about the parameters of hydrologic soil group, K-factor, and slope to determine vulnerability levels for areas using the criteria specified in table 1. Cropland HRUs discussed above ranged in slope from 0-3% and were therefore never classified in the high vulnerability category using the SVI classification criteria.

The difference in classification of cropland HRUs by the SVI and CCI was important in this study. Because the CCBI considers areas of all vulnerability levels, it was desirable to have cropland HRUs of all vulnerability levels to conduct a thorough evaluation. For these reasons, HRU vulnerability levels were determined using the CCI in this study, and SVI results about HRU vulnerability levels were not used.

The CEAP cropland study results about contaminant reductions at each vulnerability level and initial treatment level were determined using the SVI to classify areas. In this study however, contaminant reductions were determined using the CCI. Comparing the contaminant reductions determined in the CEAP cropland study and in this one can assess the applicability of the CCBI to the GCEW or a similar watershed having a restrictive layer near the surface. If results are comparable, it gives evidence that the CCBI can be used to target areas in such watersheds. This isn't to say that the method used to determine the vulnerability of watershed areas is the only factor that should be considered when assessing the applicability of using the CCBI for a given watershed. The way treatment levels are defined and the scale of the area that is

assessed also matter, and will be discussed later. Nevertheless, the way vulnerability is determined is an important consideration.

From a conservation treatment standpoint, the CCI identified more potential critical areas that might need treatment than the SVI. This result can be partly attributed to the different parameters used by the SVI and CCI. Both indices use slope as a parameter, but the SVI uses hydrologic soil group, and the CCI uses CD and KSAT, which refer to the depth to claypan and surface layer saturated hydraulic conductivity, respectively. Hydrologic soil group is determined from the depth to reach a restrictive layer or high water table and the saturated hydraulic conductivity of the least transmissive soil layer within the depth encompassed by the restrictive layer or high water table (USDA-NRCS, 2009). The characteristics used to determine hydrologic soil group are similar to the CD and KSAT parameters. The depth to reach a restrictive layer is equal to CD in the GCEW, and the saturated hydraulic conductivity of the least transmissive soil layer above the claypan is sometimes equal to KSAT in the GCEW. However, while the soil characteristics used to determine hydrologic soil group are similar to the CD and KSAT parameters used by the CCI, hydrologic soil group doesn't reflect the variability in these characteristics as much as CD and KSAT can. The difference in variability between hydrologic soil group and the parameters of CD and KSAT can be evidenced in this watershed by the fact that all soil types except for Belknap had hydrologic soil group D but varied in terms of CD and KSAT. Table 15 shows values of CD, KSAT, and the product of CD by KSAT for each soil type represented in the SWAT model used in this study. KSAT*CD is part of the equation used to determine

vulnerability levels using the CCI and is shown because it illustrates variability seen by the CCI equation more accurately than values of CD and KSAT alone can.

Table 15. Values of CD, KSAT, and CD*KSAT for soil types represented in the SWAT model used in this study.

	Parameter		
Soil type	CD (mm)	KSAT (mm h^{-1})	CD*KSAT (mm^2 h^{-1})
Mexico	406	10	4060
Belknap	1651	10	16510
Leonard	1524	10	15240
Putnam	356	32	11392
Adco	406	32.4	13154

CD values ranged from 356 mm to 1651 mm, while KSAT values ranged from 2.4 mm h^{-1} to 32.4 mm h^{-1}. The combined CD*KSAT values ranged from 4,060 mm^2 h^{-1} to 16,510 mm^2 h^{-1}. The variation in these values is one reason why the CCI classified HRUs of all vulnerability levels. On the other hand, hydrologic soil group used by the SVI did not allow for such variation in CD and KSAT to be reflected in vulnerability classifications. The discrepancy between critical areas identified using the hydrologic soil group parameter and those identified using CD and KSAT as parameters suggests that there is benefit to using CD and KSAT parameters to identify critical areas in this watershed and that using the hydrologic soil group parameter is not sufficient to identify all critical areas.

Differences in classification by the SVI and CCI are also caused by the method each uses to classify areas. The SVI uses criteria that will always lead to certain vulnerability classifications once parameters are known for a soil. The parameter values are assessed and a soil is classified using the criteria shown in table 1. Classifications

assigned by the CCI, on the other hand, can vary even if soil parameters are known. This is because the CCI uses the Jenks natural breaks method to divide areas into different vulnerability categories. Soil parameters are used to calculate a value for each soil, and soil vulnerabilities are determined by using the Jenks method to break the values into groups. The Jenks method could determine different breaks between groups (and thus different soil vulnerability classifications) based on the sample size and the values of the numbers analyzed.

This means that the CCI and the vulnerability levels it determines can be influenced by the scale of the analysis. When the scale of analysis is changed, variability in soil properties often changes. At a larger scale of analysis, there is usually more variability than is found at a smaller scale. CCI classifications could be affected by such an increase in variability, but it can't be known specifically how classifications would be affected without further study. The CCI would have to be tested on different size study areas that share some areas in common in order to assess how classifications would change in response to different scales of analysis. So far the CCI has only been evaluated on a small scale area, the GCEW. Recommendations for using it at larger scales therefore cannot be made at this point. That the CCI can classify areas differently based on the scale of analysis used and the amount of variability in input parameters within a study area should be considered when using it to classify areas. On the other hand, classifications determined by the SVI will not change based on the scale of analysis or amount of variability in input parameters. However, the scale of analysis does need to have enough variability in soil properties so that areas of different vulnerability levels

can be identified. Otherwise, there is the possibility that no critical areas will be found in an area analyzed by the SVI or it will determine all areas to be of the same vulnerability level. In the GCEW, variability in input parameters was found to be influential on classifications determined by both the SVI and CCI. Greater variability resulted in more variety in vulnerability classifications determined by the CCI, while the opposite was true for the SVI. Based on these findings, caution is recommended when using the SVI in the GCEW or a similar watershed with a restrictive layer near the surface. In terms of the CCI, additional testing is recommended on other claypan watersheds of similar and different sizes to confirm its usefulness and to study the effects of using different scales of analysis.

Correlation Results

Table 16 shows the calculated Spearman's correlation coefficient values for each contaminant based on output loads from cropland HRUs and CCI-determined vulnerability levels of cropland HRUs. The average contaminant load by vulnerability level is also shown. Because SVI classification of cropland HRU resulted in only two classes, a test for correlation between SVI-determined vulnerability levels and contaminant loads from cropland HRUs was not applicable. Therefore no results are shown for SVI-determined vulnerability levels.

Table 16. Mean baseline contaminant loads from cropland HRUs by vulnerability class and Spearman's correlation coefficient calculated from cropland HRU contaminant loads and cropland HRU vulnerability levels determined by the CCI.

	Mean contaminant load by vulnerability level				
Contaminant	High	Moderately high	Moderate	Low	Spearman's coefficient[a]
Sediment (metric tons/ha)	3.2	2.1	1.7	1.1	-0.7
Nitrogen (kg/ha)	17.3	13.7	12.4	10.3	-0.9
Phosphorus (kg/ha)	2.0	1.4	1.2	0.8	-0.7

[a] A test for significance was performed on calculated Spearman coefficient values by comparing them with a critical value of 0.18. The critical value was calculated from a critical t-value that was determined from a t-table using n-1 degrees of freedom and $\alpha = .05$. The sample size was n = 84, equal to the number of cropland HRUs.

Strong negative correlation was found between contaminant loads of each pollutant and CCI vulnerability levels of cropland HRUs. Negative correlation was expected due to the fact that in the equation used by the CCI, lower calculated values correspond to a higher level of vulnerability, which could also be represented as a greater amount of contaminant transported via surface runoff. The correlation was found to be significant based on comparing the absolute value of all correlation coefficient values with the critical significant value of 0.18. The strong correlation between contaminant loads and CCI vulnerability levels adds confidence about the ability of the CCI to identify critical areas in the GCEW. Mean contaminant loads increased as vulnerability level increased, which was also expected, since higher

vulnerability level implies that there is a higher potential for contaminant transport by surface runoff to occur. It gives further confidence in using the CCI in this watershed.

Contaminant Reductions from Conservation Treatment Scenarios

Contaminant reductions relative to the baseline scenario at different vulnerability levels were calculated for all conservation treatment scenarios. Tables 17-19 show sediment reductions obtained by low, moderate, and high conservation treatment scenarios. Reductions increase as vulnerability level increases for each scenario. Reductions at some vulnerability levels for certain scenarios are recorded in the table as “n/a” because the scenario was not simulated in any HRUs of the specified vulnerability level. This was possible since scenarios were simulated only in HRUs with specified slope ranges and soil types.

Table 17. Average reductions in sediment (metric tons/ha) obtained from low conservation treatment scenarios relative to the baseline scenario.

	Vulnerability level			
Conservation treatment scenario	Low	Moderate	Moderately high	High
Conservation crop rotation	0.4	0.5	0.7	1.1
CRP	n/a	1.8	2.0	3.0
Residue & tillage management	0.3	0.5	0.7	1.0
Grassed waterway	n/a	0.5	0.8	1.5
Contour farming	n/a	0.2	0.3	0.5
Contour farming and Terrace	n/a	n/a	2.6	2.5
Contour farming and Grassed waterway	n/a	0.6	1.1	3.0
Contour farming and Residue & tillage management	n/a	0.7	0.9	1.3
Contour farming, Terrace, and Grassed waterway	n/a	n/a	3.8	3.4
Biomass	n/a	1.8	2.1	3.1
Filter strip	n/a	2.3	3.3	n/a

Table 18. Average reductions in sediment (metric tons/ha) obtained from moderate conservation treatment scenarios relative to the baseline scenario.

	Vulnerability level			
Conservation treatment scenario	Low	Moderate	Moderately high	High
Conservation crop rotation and Residue & tillage management	0.5	0.7	0.9	1.4
Conservation crop rotation and Grassed waterway	n/a	0.6	1.0	2.0
Conservation crop rotation and Contour farming	n/a	0.7	0.9	1.4
Conservation crop rotation and Filter strip	n/a	2.5	3.9	n/a
Filter strip and Residue & tillage management	n/a	2.5	3.8	n/a
Filter strip and Contour farming	n/a	2.4	3.7	n/a

Table 19. Average reductions in sediment (metric tons/ha) obtained from high conservation treatment scenarios relative to the baseline scenario.

	Vulnerability level			
Conservation treatment scenario	Low	Moderate	Moderately high	High
Conservation crop rotation, Filter strip, and Residue & tillage management	n/a	2.6	4.0	n/a
Conservation crop rotation, Filter strip, and Contour farming	n/a	2.6	4.1	n/a

Contaminant reductions obtained by different scenarios varied greatly, even at the same vulnerability level. For example with a low level of conservation treatment and a moderately high vulnerability level, reductions ranged from 0.7 metric tons/ha in the conservation crop rotation scenario to 3.3 metric tons/ha in the filter strip scenario. This result can also be seen for scenarios of other treatment and vulnerability levels.

It might be expected that higher treatment level scenarios would obtain greater contaminant reductions than lower treatment level scenarios. While the NRCS did find on average that higher treatment level scenarios obtained greater contaminant reductions (USDA-NRCS, 2012), results from tables 17 and 18 show that this isn't always the case. At a low level of treatment and moderately high vulnerability level, the biomass, filter strip, and CRP scenarios obtained greater contaminant reductions than the moderate treatment level scenarios of conservation crop rotation with residue & tillage management, conservation crop rotation with grassed waterway, and conservation crop rotation with contour farming. While some low conservation treatment scenarios obtained greater contaminant reductions than moderate

conservation treatment scenarios, no lower treatment scenarios were found to obtain higher contaminant reductions at any vulnerability level than obtained by scenarios with a high level of conservation treatment. One explanation for this, however, is that all of the high conservation treatment scenarios included the filter strip practice, which was found to obtain some of the highest contaminant reductions. If other high conservation treatment scenarios were simulated that didn't include this practice or one that obtained similarly high contaminant reductions, the result might be different, and contaminant reductions obtained at a full level of treatment might not always be greater than those obtained at lower levels of treatment.

Some of the scenarios that obtained the highest contaminant reductions were CRP, biomass, filter strip, contour farming with terrace and grassed waterway, conservation crop rotation with filter strip, and filter strip with residue and tillage management. Some of these scenarios are the same as the ones discussed earlier, in which low treatment scenarios were found to obtain greater contaminant reductions than moderate treatment ones. What these scenarios have in common is that they all involve conservation practices where grass is planted. Such practices involving the planting of grass were very effective at reducing sediment and other contaminants in this watershed. These findings illustrate that the type of conservation practice used, in addition to the level of treatment, affects the contaminant reductions that are obtained.

Comparison of Contaminant Reductions

Tables 20–22 show a side by side comparison of contaminant reductions obtainable through applying additional conservation treatment at different levels of soil vulnerability and initial conservation treatment determined from CEAP cropland study results with those determined in this study using the SWAT model. Mean baseline contaminant loads from the HRUs to which high conservation treatment scenarios were applied are also shown in the tables for each contaminant. CEAP cropland study results were determined using the Upper Mississippi River Basin (UMRB) as the study area. The values of contaminant reductions were used to define CCBI priority levels in terms of initial conservation treatment levels and soil vulnerability levels.

For the none/unknown conservation treatment level, there were no reductions from treatment scenarios since there was no or unknown treatment applied, and the contaminant reductions were equal to the average contaminant reduction obtained from high conservation treatment scenarios. Values of contaminant reductions in this study could not be obtained for low and high soil vulnerability levels and are denoted by "n/a" in those rows of the tables. This occurred because there were no cropland HRUs with those vulnerability levels to which high treatment scenarios were applied. Comparison of the results was limited to the moderate and moderately high soil vulnerability levels since contaminant reductions determined from SWAT results could only be calculated for those vulnerability levels.

Table 20. Side by side comparison of contaminant reductions of sediment (metric tons/ha) obtained from CEAP cropland study results with those obtained in this study using the SWAT model. Mean baseline contaminant load from high treatment scenario HRUs also shown.

	CEAP Cropland Results				SWAT Results				
	Conservation treatment level								
Soil Vulnerability	None/ unknown	Low	Moderate	High	None/ unknown	Low	Moderate	High	Mean baseline load of HRUs to which a high treatment scenario could be applied
Low	3.4	2.3	0.6	0.0	n/a	n/a	n/a	0.0	n/a
Moderate	8.1	6.0	2.5	0.0	2.6	1.3	0.6	0.0	3.0
Mod. high	11.9	7.8	3.2	0.0	4.0	1.9	1.0	0.0	4.6
High	23.3	11.8	5.9	0.0	n/a	n/a	n/a	0.0	n/a

Table 21. Side by side comparison of contaminant reductions of nitrogen (kg/ha) obtained from CEAP cropland study results with those obtained in this study using the SWAT model. Mean baseline contaminant load from high treatment scenario HRUs also shown.

	CEAP Cropland Results				SWAT Results				
	Conservation treatment level								
Soil Vulnerability	None/ unknown	Low	Moderate	High	None/ unknown	Low	Moderate	High	Mean baseline load of HRUs to which a high treatment scenario could be applied
Low	5.3	0.3	-0.4	0.0	n/a	n/a	n/a	0.0	n/a
Moderate	11.2	4.0	1.7	0.0	11.9	7.3	3.7	0.0	16.1
Mod. high	19.1	7.8	2.4	0.0	15.0	8.6	4.5	0.0	20.3
High	39.8	23.0	11.0	0.0	n/a	n/a	n/a	0.0	n/a

Table 22. Side by side comparison of contaminant reductions of phosphorus (kg/ha) obtained from CEAP cropland study results with those obtained in this study using the SWAT model. Mean baseline contaminant load from high treatment scenario HRUs also shown.

	CEAP Cropland Results				**SWAT Results**				
	Conservation treatment level								
Soil Vulnerability	None/ unknown	Low	Moderate	High	None/ unknown	Low	Moderate	High	Mean baseline load of HRUs to which a high treatment scenario could be applied
Low	1.4	0.1	0.0	0.0	n/a	n/a	n/a	0.0	n/a
Moderate	2.5	0.3	0.2	0.0	1.5	0.9	0.4	0.0	1.9
Mod. high	3.6	0.6	0.3	0.0	2.1	1.1	0.6	0.0	2.6
High	7.2	2.5	0.7	0.0	n/a	n/a	n/a	0.0	n/a

Contaminant reductions based on CEAP cropland study results and SWAT results both increase as vulnerability level increases. This similar response occurred even though soil vulnerability levels were determined differently in each study. When examining how contaminant reductions change as the level of conservation treatment changes, CEAP cropland study results and SWAT results also show a similar trend: contaminant reductions decrease as treatment level increases. These similar results about how contaminant reductions change as soil vulnerability and conservation treatment level change give confidence that the CCBI can be used to assess conservation treatment needs in a watershed similar to the GCEW. While contaminant reductions predicted from CEAP cropland study results and SWAT results changed similarly as soil vulnerability level and conservation treatment level changed, the values estimated at specific levels of soil vulnerability and conservation treatment varied widely for each contaminant.

The results for sediment show that contaminant reductions predicted from the CEAP cropland study were considerably higher than those predicted by the SWAT model in this study. At the moderate soil vulnerability level, contaminant reductions from the CEAP cropland study were on average, about 3.5 times higher. Similarly, contaminant reductions at the moderately high vulnerability level were also about 3.5 times greater on average than those predicted by SWAT simulations. The large contaminant reductions estimated according to the CEAP cropland study results suggest that more sediment yield is occurring throughout the UMRB compared with the GCEW. This is not

expected based on the high potential for surface runoff and consequently erosion for the soils in the GCEW. This unexpected result is one that should be looked into further.

Comparing contaminant reductions for the nitrogen contaminant showed different results. At the moderate soil vulnerability level, contaminant reductions estimated using the SWAT model were on average about 1.5 times those estimated from CEAP cropland study results. At moderately high soil vulnerability level, the SWAT model estimated greater contaminant reductions were possible at low and moderate conservation treatment levels but estimated lower reductions at the none/unknown treatment level. It is not known why greater reductions were predicted from CEAP cropland results only for the none/unknown treatment level at moderately high vulnerability. The overall higher contaminant reductions estimated by the SWAT model for nitrogen may be due to greater average surface runoff generated in the GCEW compared with the amount generated throughout the UMRB.

Contaminant reductions of phosphorus estimated from CEAP cropland study results were only greater than those estimated in this study for the none/unknown category of conservation treatment level at moderately high and moderate vulnerability. In all other cases, the SWAT model predicted greater contaminant reductions than were estimated from CEAP cropland study results, ranging from 1.8 to 3 times greater than those predicted from CEAP cropland study results. It is puzzling why contaminant reductions predicted from the CEAP cropland study results were greater than those predicted from SWAT results only for the none/unknown level of conservation treatment. This also occurred for the nitrogen contaminant at moderately

high vulnerability. The overall greater contaminant reductions predicted from SWAT results may again be caused by a larger average amount of surface runoff generated in the GCEW compared with the UMRB.

There are several factors that may be behind the differences in contaminant reductions predicted by the SWAT model and from CEAP cropland study results, especially the unexpected differences seen for the sediment contaminant. Modeling related differences are one possible factor. CEAP cropland study results were determined using the APEX model (USDA-NRCS, 2012), while the SWAT model was used in this study. The conservation treatment scenarios that were simulated in each study are another possible difference. Scenarios simulated in this study were chosen to reflect actual practices used in the GCEW, while it is unknown how and what specific scenarios were chosen to model scenarios in the CEAP cropland study. Comparing contaminant reductions estimated in each study is also difficult to assess because mean baseline contaminant loads, which can be used to assess how effective conservation treatment is at reducing contaminants, are not known for the CEAP cropland study. These values are shown in tables 20-22 for the reductions determined using the SWAT model, but could not be determined for the CEAP cropland study results from which CCBI contaminant reductions were estimated.

CONCLUSIONS

This study used a SWAT model that was calibrated and validated specifically for conditions found in the GCEW to evaluate the SVI, CCI, and CCBI. The SVI and CCI were evaluated by performing a test for correlation between vulnerability levels of cropland HRUs and outputs of contaminant loads from cropland HRUs. Input parameters for the SVI and CCI were determined from SWAT model soil type and HRU data. The CCBI was evaluated by comparing contaminant reductions determined from CEAP cropland study results with those calculated using SWAT model results from this study. Contaminant reductions obtained through various conservation treatment scenarios determined from SWAT model results in this study were also used to evaluate the CCBI.

The CCI was used to determine vulnerability levels of cropland HRUs in this study since its results reflected the full range of soil vulnerability categories. The test for correlation between contaminant loads from cropland HRUs and vulnerability levels of cropland HRUs found strong negative correlation when the CCI was used but no correlation when the SVI was used. This gave confidence in the CCI's ability to classify areas in the GCEW and showed that the SVI parameters didn't reflect variability in watershed characteristics in the same way that the CCI parameters did.

When contaminant reductions obtained from different conservation treatment scenarios were compared with each other, it was found that scenarios involving conservation practices where grass was planted obtained some of the highest reductions. This occurred regardless of the level of conservation treatment that was

used, and shows that the type of conservation practice is another factor that is very influential in determining the effectiveness of treatment that is applied.

The comparison of contaminant reductions possible through additional conservation treatment determined in this study and those determined from CEAP cropland study results showed that contaminant reductions increased with vulnerability level and decreased as the level of initial conservation treatment increased. These similarities gave confidence that the CCBI could be used to target areas in the GCEW or similar claypan watersheds. A comparison of the specific contaminant reductions that could be obtained at certain levels of soil vulnerability and initial conservation treatment revealed different results depending on the contaminant analyzed. Contaminant reductions of sediment estimated from CEAP cropland study results were consistently over 3 times greater than those estimated in this study. This was an unexpected result, and it is recommended that it be examined further. Contaminant reductions of nitrogen estimated in this study were greater than those estimated from CEAP cropland study results in most cases. This result could be caused by soils in the GCEW having a higher potential for surface runoff to occur, on average, than soils found throughout the UMRB. Contaminant reductions of phosphorus estimated in this study were also greater than those estimated from CEAP cropland study results in most cases. However, contaminant reductions based on CEAP cropland study results were greater at the unknown/none level of conservation treatment. Disregarding this result, it is again proposed that the higher surface runoff potential of soils in the GCEW could explain the greater contaminant reductions predicted in this study. The results show that the CCBI

was able to identify critical, undertreated areas in the GCEW and has promise to be used in similar claypan watersheds. There is uncertainty, on the other hand, about the contaminant reductions obtainable at specific levels of conservation treatment and soil vulnerability estimated by the CCBI.

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CHAPTER 4: CONCLUSIONS

Two studies were conducted in which the Soil Vulnerability Index (SVI), Conductivity Claypan Index (CCI), and CEAP Conservation Benefits Identifier (CCBI) targeting indices were evaluated for use in the Goodwater Creek Experimental Watershed (GCEW). The SVI and CCI were evaluated for their ability to determine critical areas vulnerable to contaminant transport by surface runoff, and input parameters used by each index were assessed to determine how they affected index classifications. The CCBI was evaluated for its ability to determine critical areas that are undertreated relative to their vulnerability to contaminant transport by surface runoff. Contaminant reductions obtained by various conservation treatment scenarios determined based on SWAT results were compared to further evaluate the CCBI.

Evaluation of the SVI and CCI

The SVI and CCI were used to classify the watershed using SSURGO and DEM slope sources. Regardless of the whether SSURGO or DEM slopes were used, the CCI classified more high vulnerability areas than the SVI. The CCI classified 14.3% and 16.4% of watershed areas as high vulnerability using SSURGO and DEM slopes, respectively, while the SVI classified 4.1% and 6.3% of watershed areas as high vulnerability using SSURGO and DEM slopes. A similar result was also found for areas classified as

moderately high vulnerability by indices. These results illustrated that the CCI was able to identify potential critical areas in the GCEW that weren't identified by the SVI.

Results from contingency tables showed that the SVI and CCI agreed on 3.8% and 5.3% of high vulnerability areas when SSURGO and DEM slopes were used, respectively. Considering that the SVI classified 4.1% and 6.3% of the watershed as high vulnerability when SSURGO and DEM slopes were used, respectively, the agreement found shows that most of the high vulnerability areas classified by the SVI were also classified as high vulnerability areas by the CCI. This result gives confidence that the areas in the GCEW classified as high vulnerability by the SVI are indeed critical areas.

The CCI also classified a large amount of the watershed as moderately high vulnerability compared with the SVI. When SSURGO slopes were used, the CCI classified 62.3% of the watershed as moderately high vulnerability, while the SVI classified 51.9% as moderately high vulnerability. Using DEM slopes, the CCI classified 42.5% of the watershed as moderately high vulnerability, while the SVI classified 23.7% of the watershed as moderately high vulnerability. Further analysis with contingency tables showed that regardless of the slope source used, a majority of the additional areas classified as moderately high vulnerability by the CCI were classified into lower vulnerability categories by the SVI. Because moderately high vulnerability areas in addition to high vulnerability areas can be considered for conservation treatment, this result shows that many areas that might need conservation treatment would not be considered using the SVI to classify areas in the GCEW.

Analysis of variability in input parameters used by the SVI and CCI found that slope was the SVI parameter with the most variability, and depth to claypan (CD) and slope were the CCI parameters with the most variability. Slope was the only parameter with variability that affected vulnerability classifications determined by the SVI, while variability in the CD and slope parameter affected classifications determined by the CCI. The greater variability found in input parameters used by the CCI explained why the CCI was able to identify critical areas not identified by the SVI. This result showed that the parameters used by the SVI did not represent variability in soil characteristics of the GCEW in the same way that the parameters used by the CCI did.

To assess sensitivity of each index to the slope parameter, percentages of watershed vulnerability classifications determined by the same index using different slope sources were compared with each other. Results of this comparison found that vulnerability classifications determined by the SVI were affected more by using a different slope source than those of the CCI. This showed that the SVI was more sensitive to the slope parameter in the GCEW, compared with the CCI.

Evaluation of the CCBI

Contaminant reductions possible at given levels of initial conservation treatment and soil vulnerability according to the CCBI were compared to those determined using a SWAT model calibrated and validated for use in the GCEW. Contaminant reductions of sediment determined from the SWAT model were consistently lower compared with those used by the CCBI. Contaminant reductions of nitrogen and phosphorus determined from the SWAT model, on the other hand, were higher, on average,

compared with those used by the CCBI. These results showed that the values of contaminant reductions estimated by the CCBI for specific combinations of initial treatment and soil vulnerability may not be applicable in the GCEW.

Contaminant reductions obtainable through additional treatment according to the CCBI and those determined from the SWAT model both increased as soil vulnerability level increased, and decreased as level of conservation treatment increased. This result suggests that the CCBI can be used to identify critical areas in the GCEW. Further testing would be useful, however, to further confirm that the CCBI can be used in the GCEW or a similar watershed.

Summary

When analyzing the GCEW, the CCI identified many potential critical areas or areas in possible need of conservation treatment that weren't identified by the SVI. Based on this result, the SVI is not recommended as the best targeting index to use in the GCEW or a similar watershed. Planners may want to consider modifying future versions of the SVI so it can be used for such areas.

Comparison of contaminant reductions possible through additional treatment estimated by the CCBI with those determined for the GCEW using a site-specific SWAT model show promise that the CCBI can be used to identify critical areas in the GCEW or a similar watershed. There were, however, uncertainties about the specific values of contaminant reductions estimated by the CCBI at given levels of initial conservation treatment and soil vulnerability. Therefore, further testing of the CCBI in the GCEW and similar watersheds is recommended.