VALIDATING THE SOIL VULNERABILITY INDEX FOR A CLAYPAN WATERSHED

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ABSTRACT

Assessment studies of conservation efforts have shown that best management practices were not always implemented in the most vulnerable areas where they are most needed. While complex computer simulation models can be used to identify these areas, resources needed for using such models are beyond reach for most water resources managers. Soil and water conservationists need simple, spatially explicit tools such as the USDA-NRCS's Soil Vulnerability Index (SVI) to evaluate the inherent vulnerability of soils and the risk they pose to water quality when used for row crop agriculture. In this study, the SVI was evaluated in the Goodwater Creek Experimental Watershed (GCEW), a claypan watershed in Missouri, using three methods: professional judgement, comparison to the Conductivity Claypan Index (CCI) developed specifically for claypan soils, and comparison to model results. Factors affecting the critical

areas identified by each method were assessed and classified areas were compared. Slope and depth to claypan had the most variability in GCEW and were found to be influential in determining area classification by each index. While the original definition of SVI included the soil type representative slope from the USDA SSURGO database, slope values provided by a Digital Elevation Model (DEM) improved the index usefulness by classifying visibly degraded and non-degraded areas in different categories. High and moderately high vulnerability areas identified with SVI, CCI and model results with DEM slopes were consistent and matched professional judgement. Additional testing of SVI is recommended in areas characterized by soils of different permeability and under different climates.

¹

1. 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

¹ **Abbreviations:** CCI: Conductivity Claypan Index, CD: Depth to claypan, DEM: Digital Elevation Model, GCEW: Goodwater Creek Experimental Watershed, HRU: Hydrologic Response Unit, KSAT: hydraulic conductivity, NPS: Non-point source, NRCS: Natural Resources Conservation Service, SL: Slope, SSURGO: Soil Survey Geographic Database, SVI: Soil vulnerability Index, SWAT: Soil and Water Assessment Tool, USDA: US Department of Agriculture.

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.

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 for implementing conservation practices was more reducing soil erosion than reducing agricultural pollution, an additional focus of current policy. Since then, the goal has also included protecting streams and water bodies downstream of agricultural areas from the negative effects associated with agricultural NPS pollution through the use of grassed waterways, contour farming, buffer strips, conservation tillage, and nutrient management plans among other best management practices.

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 funding allocated to conservation programs, and especially obtained at watershed and regional 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 in larger watersheds 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 is that conservation practices have not been targeted to critical areas that contribute the most contaminants to receiving water bodies (Gale et al., 1993, Strauss et al.,

2007; Tomer and Locke, 2011). It is therefore very important that these critical areas are identified.

Modeling, indices, and geographic information systems (GIS) 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 located in Northeast Missouri (Mudgal et al., 2012). The Soil and Water Assessment Tool (SWAT) model is a watershed scale model that has also been used, sometimes in combination with APEX, to quantify contaminant delivery to a water body and identify the critical areas (Srinivasan et al., 2005; Busteed et al., 2009; White et al., 2009; Douglas-Mankin et al., 2010; Ghebremichael et al., 2010; Rabotyagov et al., 2014; White et al., 2014). These models are complex and analyses using these tools require significant resources that are beyond those of a state, county, or other local resource management authority. Thus tools that are simpler to implement within a GIS platform are being considered for local or regional analyses.

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). Methods based on GIS technology are often used in conjunction with modeling or index methods to display critical areas on watershed maps (Hamlett et al., 1992; Tim et al., 1992). Zollweg et al. (1995) demonstrated the use of a GIS-based tool to identify critical areas

responsible for a majority of phosphorus loss in a studied watershed, and Nelson et al. (2011) combined GIS technology with a model based on the Revised Universal Soil Loss Equation (Revised USLE) to identify critical areas for soil loss in a watershed in Kansas.

The Soil Vulnerability Index (SVI) was developed by the NRCS as part of the CEAP cropland study (USDA-NRCS, 2012) to rank soils nationwide in terms of their inherent vulnerability to contaminant transport by surface runoff or by leaching when cropped. 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. No consideration is given to vegetation or management. Relevant soil properties were determined based on APEX model results for sediment and nutrient losses by surface runoff and percolation in the Upper Mississippi River Basin (USDA-NRCS, 2012). The model was run for a subset of the National Resources Inventory cropland sites throughout the Upper Mississippi River Basin, using the NRCS soil survey database, a climate database, and operator surveys about land management. Each site was ranked as having high, moderately high, moderate, or low soil erosion or nutrient loss, and nitrogen leaching potential based on its output of sediment and nutrient yield and percolation. 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 affect infiltration and contaminant leaching. Ranges of values for slope, erodibility factor, and coarse fragment content were statistically determined for each hydrologic soil group to determine criteria to

101 classify areas into different vulnerability classes. The final ranking criteria were then used to
102 classify all soils within the U.S. so that regional comparisons could be conducted (USDA-NRCS,
103 2012).

104 Compared with using models, using indices to identify critical areas can be a simpler
105 approach requiring fewer input parameters and less preparatory work such as model
106 calibration. However, indices do need to be validated before they can be used to make
107 decisions on conservation efforts. Validation of the SVI within and outside the Upper Mississippi
108 River Basin is necessary before this index is widely used to guide policy. The overall goal of this
109 study was to validate the SVI within the Goodwater Creek Experimental Watershed (GCEW), a
110 Missouri watershed where contaminant transport has been monitored and simulated in detail
111 (Blanchard and Donald, 1997; Donald et al., 1998; Lerch et al., 2011; Baffaut et al., 2015b). The
112 dominance of soils with a restrictive layer causes a high potential for surface runoff and
113 transport of sediment and nutrients to water bodies, and makes this watershed a good
114 candidate for validation of a targeting index. The specific study objectives were to 1) evaluate
115 the ability of the SVI to classify critical areas in terms of vulnerability to contaminant transport
116 by surface runoff in the GCEW, and 2) assess how input parameters used by the SVI affect
117 vulnerability classifications in this watershed. The evaluation was based on professional
118 judgement, comparison with another targeting index developed specifically for soils with a
119 restrictive layer, and comparison with the results of a hydrologic model.

2. Materials and methods

2.1. Study area

The Goodwater Creek Experimental Watershed (GCEW; Sadler et al., 2015b) is in Major Land Resource Area 113, Central Claypan Areas (Fig.1): 4 Mha of primarily agricultural land use that cover a portion of Missouri and Illinois and where claypan soils dominate (USDA-SCS, 1981). Claypan soils are characterized by a shallow, low permeability clay layer, the claypan, that limits percolation and available water capacity, resulting in a high potential for surface runoff and other surface runoff induced problems. Excessive soil erosion and herbicide transported in surface runoff are known problems throughout the region (Lerch et al., 2008). The GCEW itself covers 72 km² in Boone and Audrain County in Missouri. Long-term (1970-2010) data from a weather station and a network of rainfall gauges in the watershed show annual precipitation ranging from 569 mm to 1620 mm, averaging 981 mm per year (Sadler et al., 2015a). Average annual air temperature was 12 °C, ranging from a January average of -2.7 °C to a July average of 25.0 °C (Sadler et al., 2015a). Over the same period, average annual discharge per unit area was 310 mm, or 32% of the average annual precipitation (Baffaut et al., 2015a).

2.2. SVI Vulnerability Classification

Risk classification for the SVI was based upon criteria specified by the USDA-NRCS (2012) shown in Table 1, which are based on soil hydrologic group, USLE soil erodibility (K-factor), and slope information for each SSURGO soil polygon in the watershed. Inputs were processed using ArcMap resulting in maps showing risk classifications throughout the GCEW.

Hydrologic soil group, slope, and K-factor were determined from SSURGO data publicly available online at the Geospatial Data Gateway website, <http://datagateway.nrcs.usda.gov/> (January 2013). The hydrologic soil group status was determined from the Revised USLE, Version 2, Related Attributes report. When the hydrologic group was dependent on the drainage status, soils were assumed to be undrained based on knowledge of the watershed. As a result, all non-floodplain soils in GCEW had a hydrologic soil group D. K-factor values were determined from the surface layer Kw values in the Physical Soil Properties report. Slopes values were the representative slope value of each soil type (Lee Norfleet, USDA-NRCS, personal communication, 10 July 2012). As an alternative to representative slope values, vulnerabilities were also calculated based on slopes derived from a 10-m digital elevation model (DEM).

2.3. SVI evaluation

Index validation can involve professional judgement, comparison with other indices, comparison with field data, or comparison with results from well calibrated models (Tomer et al., 2003; Dosskey et al., 2011; Chan et al., 2013; Dosskey et al., 2013). In this study, the SVI was validated using professional judgement, comparison with the conductivity claypan index (CCI, a risk assessment index developed specifically for soils with a restrictive layer, Mudgal et al., 2012), and comparison with modeling results.

2.3.1. Professional judgement

Professional judgement is a subjective method. In this case, the extent of the critical areas and their characteristics were critically assessed. In addition, 2009 aerial photos (obtained from Google Earth) of an area known for its poor management at the time were overlaid with the map of critical areas determined with the SVI. Because of the poor management, soil degradation was clearly visible and the quality of the match was visually assessed.

2.3.2. Comparison with CCI

2.3.2.1. CCI vulnerability classification

An index called the Conductivity Claypan Index (CCI) was proposed by Mudgal et al. (2012) to rank areas according to their vulnerability to losses by surface runoff in regions dominated by claypan soils. It was developed based on field data obtained in the GCEW.

CCI is based on an equation [Eq. (1)] with inputs of depth to claypan (CD [mm]), saturated hydraulic conductivity of the first soil layer (KSAT [mm h^{-1}]), and slope (SL [%]) (Mudgal et al., 2012).

$$\text{CCI} = \text{KSAT} * \text{CD} / \text{SL} \quad (1)$$

The natural logarithm of CCI was then taken to reduce the magnitude of the values across the watershed and the deviations in the dataset so that it could be classified appropriately. Next, the set of $\ln(\text{CCI})$ 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 $\ln(\text{CCI})$ values determined for each group were used to define vulnerability levels, with higher values of $\ln(\text{CCI})$ representing lower vulnerability levels.

Both SSURGO slopes and slopes calculated from a 10m USGS DEM were used as inputs in order to make valid comparisons with SVI using both sources of slope values. When SSURGO slopes were used, the watershed was divided into polygons based on SSURGO soil type boundaries. 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.

Values of KSAT and CD for each soil type were determined in part from the Physical Soil Properties Report generated from the SSURGO data, 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 map unit were determined by using the lowest value within the range of saturated hydraulic conductivity values given for the surface horizon of the dominant component of that map unit. 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) found that mulch-tilled cropland under a corn-soybean rotation had lower average KSAT compared to hay crop or land in the Conservation Reserve Program. Thus, the lowest value was used for the CCI to reflect typical cropland management throughout the GCEW.

Depth to claypan is not part of any SSURGO report or data table. While soil science defines the claypan as a soil layer having close to a doubling in clay content relative to the overlaying layer (Soil Science Glossary Terms Committee, 2008), CD values for each soil type were assigned based on which soil horizons had saturated hydraulic conductivity values less

than 1 mm h⁻¹. Using this method of identifying restrictive layers instead of examining clay content of soil horizons is easier to implement for large study areas and produces results similar to those found using clay content information (not shown). 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.

2.3.2.2. Comparison of SVI with CCI: contingency tables

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.

2.3.2.3. Variability of input parameters

CCI and SVI have input parameters associated with runoff and erosion processes. The hydrologic group in SVI and the combination of KSAT and CD both quantify the potential for surface runoff. Similarly, both indices use the slope as an input parameter, which significantly affects erosion process. However, erosion processes are further considered by SVI by including the Universal Soil Loss Equation (USLE) erodibility factor while no similar parameter is considered in CCI. The variability of input parameters throughout the GCEW was represented by the fraction of the watershed having parameter values within a certain range. Regarding slopes, the percentage of watershed area having slope values in specified ranges was determined with both SSURGO and DEM slopes as information source. Similarly, the variability of CD, KSAT, and hydrologic group and the number of distinct values for these parameters in the watershed was assessed based on their area distribution. Similar analysis was performed for the USLE erodibility factor.

2.3.3. Comparison with modeling results

2.3.3.1. GCEW SWAT model

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. (2015b). 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 three weirs in the GCEW. Model performance was assessed using the percent bias, the Nash-Sutcliffe efficiency, and the coefficient of determination. Additional details about changes made to the SWAT code to improve the simulation of

percolation processes in claypan soils, about the model parameterization, and about its calibration and validation can be found in Baffaut et al. (2015b).

While this SWAT application considered all the significant crops and tillage systems present in the watershed from 1993 to 2010, land management was simplified for this study. The objective here was to evaluate the vulnerability of the land to crop production from the point of view of water quality impacts. For each hydrologic response unit (HRU), the management was set to a 2-year rotation of conventionally tilled corn followed by no-till soybean with no other conservation practices simulated, no matter what the original land use was. This rotation represents the most common practices used by the producers in the GCEW for corn and soybean, which are the most common crops in the watershed. Curve numbers were set to 84 for hydrologic group D soils, and to 80 for hydrologic group C soils. Initial residue amounts were set to 2000 T/ha for all HRUs. Specific settings used in the management operations schedule can be found in supplemental material for Baffaut et al. (2015b), in a section titled “Field operation scenarios”. Other parameters of the model were left to those of the calibrated model.

Contaminant loads from HRUs were determined for nitrogen (N), phosphorus (P), and sediment. The model was run with generated weather for 3 years to initialize the state variables followed by 60 years to calculate 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 for each HRU. Total N and P contaminant loads were then calculated by summing N and P outputs, and sediment load was determined directly from the sediment yield output.

2.3.3.2. Determination of soil vulnerabilities

SVI and CCI HRU vulnerability to surface runoff were determined for each HRU using the criteria in Table 1 and Eq. 1. The SVI inputs of slope, hydrologic soil group, and USLE K-factor were determined from the model input data. The slope was the HRU slope value found in the HRU input file, which is calculated by the ArcSWAT interface based on the DEM and the level of discretization used in the model. The hydrologic soil group and USLE erodibility factors were determined from the soil inputs for each HRU and originate from SSURGO data.

The CCI inputs of slope, KSAT, and CD were also determined from SWAT input data. Slope and KSAT were taken directly from SWAT HRU and soil input data, and CD was determined using the method explained previously. With the parameters determined, a soil vulnerability level was assigned to each HRU by calculating $\ln(\text{CCI})$ values and separating them into groups using the Jenks natural breaks method as described previously.

In addition to SVI and CCI vulnerability assessment, HRU vulnerability was assessed using the model outputs. Sediment yields, total N (TN) and total P (TP) loss were classified into 4 categories (high, moderately high, moderate, and low) using the Jenks natural breaks method with higher losses indicating more vulnerability.

2.3.3.3. Evaluation of the SVI

The SVI was evaluated by two different methods:

1. Average sediment, TN and TP loss were calculated for each SVI vulnerability class. Standard deviations were calculated as well to evaluate whether these vulnerability categories coincided well with the expected loss of sediment and nutrients.

2. Contingency tables were calculated between the number of HRUs classified in each vulnerability class by the SVI and the model. In addition, contingency tables between the CCI and the model were also calculated to understand the differences between the more general SVI index, and the claypan soil specific CCI. These contingency tables were developed on the basis of HRU counts as opposed to watershed area to avoid a distortion of the comparison caused by the fact that all HRUs do not have the same size.

3. RESULTS

3.1. Professional judgement evaluation

Maps of areas classified using the SVI with SSURGO and DEM slope sources (Fig. 2) show that no areas were classified as low vulnerability with the SVI. The level of moderate vulnerability contains the floodplain and soils on the watershed divide. Floodplains in GCEW are characterized by deeper soils, no restrictive layer, and low slope, which together explain their moderate vulnerability. Some vulnerability of these soils stems from the fact that they can be flooded, which is not a consideration factor in the SVI. Currently, these soils are most often associated with grassland or woodland and are only rarely cropped. However, this was not the case in the 1970's when land was cropped all the way to the stream bank. Soils on the watershed divide do have a restrictive layer but the low slope has slowed down erosion from these soils and the claypan is located deeper than on the back slope. Thus, the slope may indirectly reflect the impact of the depth to claypan.

High vulnerability soils are those with the steepest slopes and are concentrated close to the floodplain, on either side of the channel. Calculating SVI using DEM slopes instead of

SSURGO representative slopes caused slightly more land to be categorized in this highest class of vulnerability, especially in the upstream part of the watershed. On the other hand, DEM versus SSURGO slopes had a large impact on the moderately high and moderate categories. When SSURGO slopes were used, most of the soils were given a moderately high vulnerability (Fig.2). Unfortunately, this is not very helpful as more than half of the watershed is categorized as such. When used with DEM slopes, the index becomes more powerful with reduced areas of moderately high vulnerability that are adjacent to the high vulnerability areas. These soils are currently cropped, often with significant management practices designed to reduce erosion. However, if best management practices are not implemented (Fig. 3), erosion and soil degradation occurs.

On this photo (Fig. 3a), the fields located in the center right are visibly degraded. However, the SVI derived with SSURGO slope classified these fields in the moderately high vulnerability category with very little indication of the highest vulnerability (Fig. 2a). When SVI was calculated with DEM slopes, these fields were clearly targeted with high and moderately high vulnerability (Fig. 3b), and differentiated from the rest, which was then categorized in the moderate vulnerability category.

3.2. Comparison of SVI and CCI

3.2.1. SVI and CCI classification

Table 2 shows the percentage of the watershed classified into each vulnerability class according to the SVI and CCI when SSURGO and DEM slopes are used. Independently of what slope values were used, the CCI classified about 10% more of the watershed in the high

vulnerability category and 10-20% more in the moderately high vulnerability category than did the SVI (Table 2). On the other hand, the CCI classified about half as much area in the moderate vulnerability category compared with the SVI.

Similarly to the SVI, the CCI classified the majority of the watershed (62%) in the moderately high vulnerability category when SSURGO slopes were used. Using DEM slopes in each index resulted in 20-25% less moderately high vulnerability areas, which were often classified instead in the moderate vulnerability category (Table 2). Using the resolution of the 10-m DEM brings additional power to these indices for targeting conservation efforts and the rest of this analysis will concentrate on only results obtained with DEM slopes.

The map of CCI categories when DEM slopes were used (Fig. 4) showed that when compared to SVI calculated with DEM slopes (Fig. 2b), CCI produced more high vulnerability land (Table 2) but that land was roughly located in the same areas. The additional land in the CCI highest vulnerability class included some of the land that was in the moderately high vulnerability category with SVI. The moderately high vulnerability category became much larger taking some of the land that was classified in the moderate vulnerability category with SVI.

Table 3 shows the contingency table resulting from comparing SVI and CCI vulnerability classifications with DEM slopes. 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.

Classifications of SVI and CCI calculated with DEM slopes agreed for 87.9% of the watershed. However, it should be remembered that the not high category includes moderately high, moderate, and low vulnerability areas and this result doesn't necessarily mean that index classifications agreed for such areas. 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 5.3% of the watershed. Comparing these numbers to the percentage of watershed area classified into the high vulnerability risk class by the SVI (Table 2) shows that the SVI and CCI 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. Most disagreement occurred between areas classified as high vulnerability by the CCI but some other vulnerability level by the SVI. Very little (1.1% of the watershed area) was put in a different category by CCI.

3.2.2. Variability of Input Parameters

Among the SVI input parameters, there was no variability in the hydrologic soil group parameter for the upland soils, and variability in the K-factor parameter didn't lead to any variation in watershed vulnerability classifications. Hydrologic soil group was D for all upland soil types in the watershed (92% of the watershed area). Among the flood plain soils, Wilbur, Twomiles, and Moniteau silt loam soil series were classified in the hydrologic group C or B when drained but in group D when undrained as is assumed in this study. Only the Belknap soil series were classified in the soil hydrologic group C. 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 (Table 2).

Table 4 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.

When comparing the percentage of watershed area classified in each vulnerability class by the same indices using different slope sources (Table 2), 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 2, increase when SSURGO slopes are used. This result reflects the larger percentage of slopes in the 2-4% range using SSURGO slopes.

Additional CCI inputs were CD and KSAT. 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 h^{-1} . In contrast, there were large differences in CD (Fig. 5). While most (68%) of the watershed had soils with a restrictive layer between 50 and 100 cm, about 14% of the watershed had a restrictive layer within the first 50 cm, and another 18% of the watershed had either no restrictive layer or it was found deeper than 1 m. This last group of soils contained the floodplain soils, characterized by poor drainage when undrained and frequent flooding

occurrences. In spite of these variations of CD, all these soils were classified as poorly drained and were in the hydrologic soil group D when undrained. Thus, the use of CD instead of soil hydrologic group provides additional opportunities to differentiate runoff potential within the soils of this watershed.

3.3. Comparison to SWAT model results

3.3.1. Contaminant loss by SVI vulnerability class

Table 5 shows the average values and standard deviations of sediment, TN, and TP loss by SVI vulnerability level. These classes were very well defined by the loss values, with low variability within each class, as indicated by the standard deviation. Mean sediment loss decreased by half for each vulnerability class. N and P losses for each class were about 70% and 60%, respectively, of those from the class directly above. SVI vulnerability categories corresponded to significant differences in sediment and nutrient loss, as predicted by this SWAT model.

3.3.2. Contingency tables between SVI, model results, and CCI

Table 6 shows the contingency table between the HRUs classified in each vulnerability class by the SVI and using model results. Tables for sediment, TN, and TP are very similar. Overall, results indicate 75% agreement between the SVI and the SWAT model results in terms of number of HRUs, which translates into 73% agreement in terms of watershed area for sediment and TP, and 86% for TN. There was especially good agreement of classification for

those HRUs given a high or moderately high vulnerability with SVI. The largest source of disagreement was found among HRUs classified in the moderate vulnerability class by SVI: almost a third of those had low sediment, TN, and TP loss according to SWAT results. Those correspond to Putnam and Adco soils (hydrologic soil group D) on land with a slope less than 1%. The vulnerability level given by SVI to these soils is moderate because their soil erodibility is greater than 0.28. However, the low slope caused lower simulated sediment and nutrient yields, which caused these HRUs to be classified in the lowest category by the model results. This problem does not occur with the classification made using CCI: these 40 HRUs end up in the lowest category of vulnerability both with CCI and using SWAT simulated sediment yields (Table 7).

There was some discrepancy between CCI and SWAT sediment yields in the highest categories of vulnerability. The five high sediment and nutrient producing HRUs, according to SWAT simulated results and to SVI, are given only a moderate vulnerability level by CCI. These HRUs all have a high slope and correspond to Leonard soils, soils that are classified in the soil hydrologic group D because of the low saturated conductivity of the least transmissive layer and the shallow depth of this least transmissive layer. This poor drainage and the high slope produce a high vulnerability level as shown by SVI and by the simulated sediment and nutrient losses. However, these characteristics do not meet the definition of a claypan soil and the high vulnerability is not picked up by CCI because the depth to claypan is set to the profile depth.

4. DISCUSSION

4.1. Discrepancies caused by the resolution of the slope map

Switching from SSURGO to DEM slopes resulted in a 28 percentage point decrease in moderately high vulnerability areas (from 52 to 24) compensated by an increase in lower vulnerability areas and a small increase in high vulnerability areas. This is an important consideration as moderately high vulnerability areas are likely to be considered as candidates for conservation treatment. In addition, the initial result using SSURGO slopes gave more than half of the watershed a moderately high vulnerability, which is again too large of an area to target for potential conservation efforts.

These results were directly related to the distribution of slope classes between SSURGO and DEM slopes. Given that all soils in GCEW were in the hydrologic soil group D and that USLE erodibilities were all greater than or equal to 0.32, the distribution of SVI categories were really equal to the distribution of slopes in the >4%, 2-4%, 1-2%, and 0-1% ranges. Slopes in the >4% range led to high vulnerability, the 2-4% range led to moderately high vulnerability, and slopes <2% led to moderate vulnerability. The 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 10-m digital elevation maps. SSURGO slope values were the

representative value given in the SSURGO database for each soil map unit. The representative slope is calculated as the average of the slopes of all soil polygons found within a map unit (Jorge Lugo-Camacho, USDA-NRCS, personal communication, 8 August 2014). As a result, the SSURGO representative slope values cannot be associated with a particular area or even with a particular size area since the size of each soil map unit varies. However, SSURGO maps were developed at scales ranging from 1:12,000 to 1:63,000, with most of it being at the 1:12,000 scale, which corresponds to a smallest delineation of 1.5 ha (USDA-NRCS, 2016). Thus the area represented by each polygon is variable and larger than a 10m by 10m DEM cell by several orders of magnitude. On the other hand, DEM slopes provide information that is more spatially accurate and that applies to a finer scale. However, 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 isn't as long and DEM slopes could receive greater consideration. In future work using DEM slopes, methods to filter the data removing areas such as roads and determine average field slopes could be examined.

4.2. Discrepancies caused by the variability of input parameters

Because there was no variability in hydrologic soil group across the soils of GCEW and variability in K-factor was not affecting vulnerability classifications, slope was the only parameter responsible for changes in the SVI. CCI used the slope, as the SVI did, but instead of the hydrologic soil group, it used CD and KSAT. 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). These characteristics 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, hydrologic soil group doesn't reflect the variability that exists between the different soil map units as much as CD and KSAT can. Among the GCEW soil map units, CD values ranged from 356 mm to 1651 mm, KSAT values ranged from 2.4 mm hr⁻¹ to 32.4 mm hr⁻¹ and the combined CD*KSAT values ranged from 4,060 mm² hr⁻¹ to 16,510 mm² hr⁻¹.

4.3. Discrepancies caused by the classification method

Differences in classification by the SVI and CCI were also caused by the method each uses to classify areas. The SVI uses criteria that always lead to the same vulnerability classification using the criteria shown in Table 1 once parameters are known for a soil. They do not change as a function of the soils present in the study area or of the study area size. This is an advantage when there is a need to be consistent across different areas. Classifications assigned by the CCI, on the other hand, can vary depending on the study area because the CCI uses the Jenks natural breaks method to define the different vulnerability categories across the range of CCI values calculated for each grid cell. Thus different thresholds between the soil vulnerability categories can occur, based on the sample size and the values of the numbers analyzed. This can be advantageous when there is a need to identify the most vulnerable areas

no matter what the overall vulnerability level is, for example when a given amount of cost share dollars is available and needs to be allocated to the most vulnerable land in a watershed or administrative district.

However, the vulnerability levels determined by CCI can be influenced by the scale of the analysis. When the scale of analysis is changed, variability in soil properties often changes as there is usually more variability for larger areas than for smaller ones. 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 study area does need to include enough variability in soil properties so that different vulnerability levels can be identified. Otherwise, there is the possibility that SVI would determine all areas to be of the same vulnerability level.

5. CONCLUSIONS

In this study the SVI was used with SSURGO and DEM slope sources to classify areas for their inherent vulnerability to contaminant transport by surface runoff in a Missouri claypan watershed. Watershed vulnerability classification was compared to the classification produced by the CCI, an alternative index designed specifically for claypan soils, and to a classification produced by a SWAT model. The variability of input parameters and its impact on index classification were assessed.

Results showed that DEM slopes gave more targeting power to the SVI than SSURGO representative slopes. When used with DEM slopes, the SVI, CCI, and the SWAT model gave similar results. Compared to the SWAT model results, CCI gave more consistent results for areas of low vulnerability. However, there were inconsistencies between the model results and CCI

for high vulnerability areas due to our criterion defining the depth to claypan. A less
constraining criterion may improve results for restrictive layers that are not claypans.

Because the SVI category thresholds do not depend on the study area, the SVI is more
useful for regional analyses or when consistency of vulnerability categories is needed across
several watersheds. The CCI may be more useful to target conservation efforts in smaller areas
where there is less variability of SVI input parameters.

In this study, the SVI was evaluated based on the conditions that exist in the GCEW, a
fairly homogeneous watershed characterized by claypan soils that were all in the soil hydrologic
group D. Because of this characteristic, the primary pollutant transport mechanism was surface
runoff. For a complete evaluation and before transfer of these results to other, more complex
watersheds, additional testing needs to be considered in areas characterized by soils of varying
permeability, which may trigger different hydrologic processes. These evaluations have been
initiated for seven additional watersheds throughout the United States. Located in different
physiographic regions, these watersheds will also provide opportunities to evaluate the impact
of precipitation regimes.

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

Soil Vulnerability	Hydrologic soil group			
	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

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

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

668

669 Table 2. Watershed area classified into each vulnerability class by the SVI and CCI.

Watershed area in each vulnerability class (%)				
Index	High	Moderately high	Moderate	Low
SVI, SSURGO slopes	4.1	51.9	44.0	0.0
SVI, DEM slopes	6.3	23.7	70.0	0.0
CCI, SSURGO slopes	14.3	62.3	18.1	5.3
CCI, DEM slopes	16.3	42.5	32.9	8.3

670

671

672 Table 3. Contingency table showing percentage of watershed area in agreement and
673 disagreement between SVI and CCI using DEM slopes.

	High CCI	Not high CCI
High SVI	5.3	1.0
Not high SVI	11.0	82.7

674

675

676 Table 4. Distribution of slope classes determined from SSURGO and DEM in Goodwater Creek
 677 Experimental Watershed

Slope range	Slope source	
	SSURGO	DEM
	% watershed area	% watershed area
0-1	14.6	42.0
1-2	29.4	28.0
2-4	51.9	23.7
>4	4.1	6.3

678

679

680 Table 5. Contaminant loads from HRUs by vulnerability class

Contaminant	Mean and standard deviation* of contaminant load			
	High	Moderately high	Moderate	Low
Sediment (metric tons/ha)	5.1 (0.6)	2.2 (0.2)	1.2 (0.6)	0.7 (0.4)
Total Nitrogen (kg/ha)	22 (1.3)	15 (0.5)	11 (2.2)	9 (1.7)
Total Phosphorus (kg/ha)	2.9 (0.2)	1.7 (0.1)	1.1 (0.3)	0.7 (0.2)

681 * The mean value is the first number and the standard deviation is in parentheses

682

683 Table 6. Contingency tables between SVI and model results for sediment, nitrogen, and
684 phosphorus.

SVI class	Number of HRUs in each SWAT simulated sediment loss class			
	High	Moderately high	Moderate	Low
High	5			
Moderately high		36		
Moderate	2	3	93	40
Low			1	3
SVI class	Number of HRUs in each SWAT simulated TN loss class			
	High	Moderately high	Moderate	Low
High	5			
Moderately high		36		
Moderate	2		96	40
Low			2	2
SVI class	Number of HRUs in each SWAT simulated TP loss class			
	High	Moderately high	Moderate	Low
High	5			
Moderately high		36		
Moderate	2	3	93	40
Low			2	2

685

686

687 Table 7. Contingency table between CCI and model results for sediment, nitrogen, and
688 phosphorus

CCI class	Number of HRUs in each SWAT simulated sediment loss class			
	High	Moderately high	Moderate	Low
High	0			
Moderately high		31		
Moderate	7	8	95	
Low				42
CCI class	Number of HRUs in each SWAT simulated TN loss class			
	High	Moderately high	Moderate	Low
High	0			
Moderately high		31		
Moderate	7	5	98	
Low				42
CCI class	Number of HRUs in each SWAT simulated TP loss class			
	High	Moderately high	Moderate	Low
High	0			
Moderately high		31		
Moderate	7	8	95	
Low				42

689

Figure1

Figure2a

Figure2a_BW

Figure2b_BW

Figure3a

Figure3b

Figure4_color

Figure4_BW

Figure 5

Figures captions

Fig. 1. Location of Goodwater Creek Experimental Watershed and Central Claypan Areas. The Central Claypan Areas are separated into two sections: one in Missouri and one in Illinois. The Goodwater Creek Experimental Watershed is located in the center of the Missouri section of the Central Claypan Areas. The soil map provides information about the diversity of soils as well as slopes in the watershed.

Fig. 2. Maps of SVI classifications in GCEW using (a) SSURGO and (b) DEM slopes. No area was classified as low vulnerability. When SSURGO slopes are used, the area of moderately high vulnerability was very large. The rectangle and the oval correspond to the photo shown in Fig.3.

Fig. 3. Aerial photo of a fraction of Goodwater Creek Experimental Watershed in 2009 (courtesy of the USDA Farm Service Agency and Google Earth), (a) without, and (b) with areas of high (in red) and moderately high (in yellow) vulnerability derived with DEM slopes. In the middle right of the photo (oval), soils are highly vulnerable and insufficient conservation efforts resulted in visible degradation. Fields on the left of the photo are on equally highly vulnerable soils but terraces have been installed.

Fig. 4. Map of CCI classifications in GCEW using DEM slopes. CCI produced more high vulnerability areas than SVI, all located in the footslope landscape position.

Fig. 5. Cumulative distribution of depth to claypan values in Goodwater Creek Experimental Watershed.

Notes

1. Figures 2 and 3 are in two different parts. The two parts are in different files.
2. We are considering having Figures 2 and 4 in black and white or in color in the print version of the article. This will depend on the cost. Different files are provided for the black and white and the color versions.