doi:10.2489/jswc.75.1.12

Performance of the Soil Vulnerability Index with respect to slope, digital elevation model resolution, and hydrologic soil group

S. Lohani, C. Baffaut, A.L. Thompson, N. Aryal, R.L. Bingner, D.L. Bjorneberg, D.D. Bosch, R.B. Bryant, A. Buda, S.M. Dabney, A.R. Davis, L.F. Duriancik, D.E. James, K.W. King, P.J.A. Kleinman, M. Locke, G.W. McCarty, L.A. Pease, M.L. Reba, D.R Smith, M.D. Tomer, T.L. Veith, M.R. Williams, and L.M.W. Yasarer

Abstract: Soil erosion and nutrient loss from surface runoff and subsurface leaching are critical problems for cultivated land. Conservation initiatives show a persistent need for field-scale cropland vulnerability assessments to inform farm management options and prioritize efforts at watershed or regional scales. The Soil Vulnerability Index (SVI) was developed by USDA's Natural Resources Conservation Service (NRCS) to assess inherent vulnerability of cropland to surface runoff and leaching using readily available soil and topographic inputs: hydrologic soil group, slope, erodibility K-factor, coarse fragments, and organic carbon (C). The SVI has been evaluated in a few watersheds but requires further evaluation across a wider range of physiographic and climatic conditions. The objective of this study was to evaluate the ability of the SVI to correctly identify vulnerability class based on slope, digital elevation model (DEM) resolution, hydrologic soil group, and soil erodibility across 13 of USDA's Conservation Effects Assessment Project (CEAP) watersheds. The SVI classification was consistent with model output classification with a similarity rate of more than 70% when the SVI component corresponded to the primary route of loss for nutrients or sediment. Results showed that SVIs were consistent with local scientific expertise about the site vulnerability to runoff and leaching, and were particularly useful in areas with mixed slopes and hydrologic soil groups. In watersheds with uniform C or D hydrologic soil groups, the SVI was primarily driven by slope. In these cases, it was important to use a digital elevation map with 10 m resolution or higher to more finely distinguish vulnerability. In areas with uniform slopes and hydrologic soil group, and in areas with uniformly steep slopes, the SVI was not able to identify fields with greater or lower vulnerability than others. In these cases, vulnerability assessments required additional factors: depth of restrictive layer, clay content, slope length, and landscape position. While the SVI was able to categorize vulnerability correctly in mixed soil and slope conditions, findings from this project highlight the need for incorporating DEM-sourced slope and other factors like depth of restrictive layer, clay content, slope length, and landscape position into the SVI to ensure that the SVI is applicable to the broad range of geomorphic conditions found in the United States.

Key words: conservation practices—erodibility—erosion—hydrologic soil group—leaching—runoff

Nutrient impairment from excessive nonpoint source pollution (NPS) is a difficult challenge in modern agricultural practices due to the spatial diffusion of the sources of NPS pollution (Sharpley et al. 2011). Many studies have documented the effects of cropland conservation practices (e.g., conservation cover and grassed waterway) at reducing field-scale NPS pollution (Douglas-Mankin et al. 2013; Jokela et al. 2004; Nangia et al. 2010; Sharpley et

Sapana Lohani is a postdoctoral scholar in the Department of Biology, University of Nevada-Reno, Nevada. **Claire Baffaut** is a research hydrologist at the Cropping Systems and Water Quality Research Unit, USDA Agricultural Research Service (ARS), Columbia, Missouri. **Allen L. Thompson** is a professor in the Department of Bioengineering, University of Missouri, Columbia, Missouri. **Niroj Aryal** is an assistant professor of Biological Engineering at North Carolina Agricultural and Technical State University, Greensboro, North Carolina. **Ronald L. Bingner** is an agricultural engineer at the USDA ARS National Sedimentation Laboratory, Oxford, Mississippi. **David L. Bjorneberg** is a supervisory agricultural engineer at the USDA ARS Northwest Irrigation and Soils Research Unit, Kimberly, Idaho. **David D. Bosch** is a research hydraulic engineer at the USDA ARS Southeast Watershed Research Laboratory, Tifton, Georgia. **Ray B. Bryant** is a research soil scientist and **Anthony Buda** is a research hydrologist at the USDA ARS Pasture Systems and Watershed Management Research Unit, University Park, Pennsylvania. **Seth M. Dabney** is a collaborator with the National Sedimentation Laboratory, Oxford, Mississippi. **Austin R. Davis** is a graduate student in the Department of Bioengineering, University of Missouri, Columbia, Missouri. **Lisa F. Duriancik** is the Conservation Effects Assessment Project (CEAP) watersheds leader at the Resources Inventory and Assessment Division, USDA Natural Resources Conservation Service (NRCS), Beltsville, Maryland. **David E. James** is a geographic information specialist at the USDA ARS Agroecosystems Management Research Unit, Ames, Iowa. **Kevin W. King** is research leader and agricultural engineer at the USDA ARS Soil Drainage Research Unit, Columbus, Ohio. **Peter J.A. Kleinman** is research leader and soil scientist at the USDA ARS Pasture Systems and Watershed Management Research Unit, University Park, Pennsylvania. **Martin Locke** is a research soil scientist and the laboratory director at the USDA ARS National Sedimentation Laboratory, Oxford, Mississippi. **Gregory W. McCarty** is a research soil scientist at the USDA ARS Hydrology and Remote Sensing Laboratory, Beltsville, Maryland. **Lindsay A. Pease** is an assistant professor and extension specialist at University of Minnesota-Twin Cities, Minneapolis, Minnesota. **Michele L. Reba** is a research hydrologist with USDA ARS Delta Water Management Research Unit, Jonesboro, Arkansas. **Douglas R. Smith** is a research soil scientist at the USDA ARS Grassland Soil and Research Laboratory, Temple, Texas. **Mark D. Tomer** is a soil scientist at the USDA ARS Agroecosystems Management Research Unit, Ames, Iowa. **Tamie L. Veith** is an agricultural engineer at the USDA ARS Pasture Systems and Watershed Management Research Unit, University Park, Pennsylvania. **Mark R. Williams** is a research agricultural engineer at the USDA ARS National Soil Erosion Research Unit, West Lafayette, Indiana. **Lindsey M.W. Yasarer** is a research hydrologist at the USDA ARS National Sedimentation Laboratory, Oxford, Mississippi.

al. 2006; USDA NRCS 2012, 2016). In spite of beneficial edge-of-field effects of conservation practices, watershed-scale benefits of conservation programs remain elusive and, in some cases, even undetectable (Chaubey et al. 2010; Inamdar et al. 2002; Park et al. 1994; Tomer et al. 2003, 2014; Tomer and Locke 2011). Multiple reasons contribute to this lack of observable benefit, including the legacy effect of past management practices (Sharpley et al. 2013) or the low adoption rate (Jackson-Smith et al. 2010; Ryan et al. 2003). However, research has also shown that conservation practices have often not been implemented in the most vulnerable areas (Gale et al. 1993; Nowak and Cabot 2004; Nowak et al. 2006; Strauss et al. 2007; Tomer et al. 2003; Tomer and Locke 2011; Yang et al. 2005). Where this has been done, data from appropriate monitoring designs have documented improvements at watershed level (Osmond et al. 2012). However, one prerequisite for practices to be implemented where they are most needed is to identify these high vulnerability areas, which remains technically challenging (Tomer et al. 2013). Thus, there is a need for targeting tools to define these areas. Overlaying the presence or absence of conservation management practices can then help assess where new practices are needed.

Several indices and tools can help to identify these critical source areas. For example, remote sensing, geographic information system (GIS), and the Revised Universal Soil Loss Equation (RUSLE) (Renard et al. 1991) are routinely used to map soil erosion risk (Meals et al. 2012). Watershed-scale computer simulation models like the Agricultural Policy Environmental eXtender (APEX) model (Williams and Izaurralde 2005) and the Soil and Water Assessment Tool (SWAT) model (Arnold et al. 1998) are hydrologic models extensively used to understand the linkage between land use and management, and outputs like sediment, runoff, or yield (Busteed et al. 2009; Douglas-Mankin et al. 2013; Lee et al. 2018; Gassman et al. 2007). However, these tools are complicated and require multiple data sets and modeling expertise, many of which are typically lacking at the field, county, and state levels.

A time and cost effective, less computationally intensive approach is to use indices that rely on readily available input parameters. For example, the Phosphorus Index (PI) can rank fields based on their vulnerability to phosphorus (P) losses (Lemunyon and Gilbert 1993). The Conductivity Claypan Index (CCI), developed by Mudgal et al. (2012), classifies fields or subfield areas based on the vulnerability to surface runoff. The Water Quality Index (WQI) combines measured values of multiple water quality factors such as dissolved oxygen (O), pH, biological O demand, C-O demand, *E. coli*, temperature, and nutrients (nitrogen [N] and P) into a single value used for evaluating the quality of water in rivers, streams, and lakes (Lal 2011). The Water Quality Index for Agricultural Runoff (WQIag) is also a web-based index that uses multiple field characteristics and management factors to evaluate effectiveness of conservation practices for improving water quality of runoff water from agricultural lands (Lal and McKinney 2012). An equally simple index that does not require water quality measurements is the Soil Vulnerability Index (SVI).

The SVI was developed by USDA Natural Resources Conservation Service (USDA NRCS) as a product of the Conservation Effects Assessment Project (CEAP) to quantify cropland vulnerability to runoff and leaching. The SVI was originally developed for large-scale, regional analysis support (USDA NRCS 2012). The SVI uses publicly available data from the SSURGO database (Soil Survey Staff 2015) to categorize land into four vulnerability classes—low, moderate, moderately high, and high. The SVI runoff component defines the potential risk of sediment and sediment-bound contaminants' loss via surface runoff, whereas the SVI leaching component depicts the potential risk of nutrient loss through infiltration and subsurface flows (e.g., lateral seepage, return flow, and tile drainage). Details on the development and purpose of the SVI are discussed by Thompson et al. (2020).

An initial evaluation of the SVI was conducted by Chan et al. (2017) in the Goodwater Creek Experimental Watershed in Missouri. One finding was that, for watershed planning purposes and for individual field evaluation, the SVI produced more useful results by using slopes derived from a 10 m digital elevation model (DEM) than from the SSURGO representative slope (Chan et al. 2017). These results emphasize the importance of using 10 m DEMs, currently available for the entire United States, in addition to SSURGO polygons and soil properties. Lee et al. (2018) compared SVI sediment risk categories against SWAT-modeled total and organic N loads from cropland in two adjacent subwatersheds with contrasting soil characteristics within the Choptank River watershed in the Chesapeake Bay watershed. The paper concluded that vulnerability classification based on model outputs matched the SVI runoff classification for variables that relied on topographic characteristics for transport (e.g., organic N) and the SVI leaching classification scheme for constituents that are transported based on soil water movement characteristics (e.g., nitrates [NO_3]). Hence, the SVI has a strong potential to serve as an initial water quality vulnerability classification index without requiring water quality data inputs. Yasarer et al. (2020) compared the SVI vulnerability classification against outputs from the Annualized Agricultural Non-Point Source (AnnAGNPS) model in two watersheds in Lower Mississippi. The study concluded that the SVI is effective for identifying areas that could potentially contribute to NPS pollution.

In spite of these regionally specific evaluations, the SVI requires further validation across a range of physiographic and climatic conditions. The objective of this study was to assess the ability of the SVI to correlate with local scientific knowledge on identifying vulnerability class based on slope, DEM resolution, hydrologic soil group, and soil erodibility across 13 CEAP watersheds. This study complements SVI evaluations described in companion articles in this issue of the *Journal of Soil and Water Conservation*.

Materials and Methods

Study Area. A brief overview of the 13 sites (figure 1) can be found in table 1, and additional details are given by Thompson et al. (2020). For this study, the sites were grouped based on croplands in dominant slope: steep slopes (>6%), flat slopes (<2%), and mixed slopes.

Steep Slopes. WE-38 (7 km^2) was an intensively monitored and researched catchment within the Mahantango Creek watershed in central Pennsylvania and was characterized by steep slopes (>6%). Land use in WE-38 watershed included cultivated land (54.9%), woodlands (39.6%), pasture (3.2%), and developed area (2.3%). Cropping systems varied by operation, with most including corn (*Zea mays* L.) and soybeans (*Glycine max* [L.] Merr.) in rotation with other crops, including small

Figure 1
Study areas.

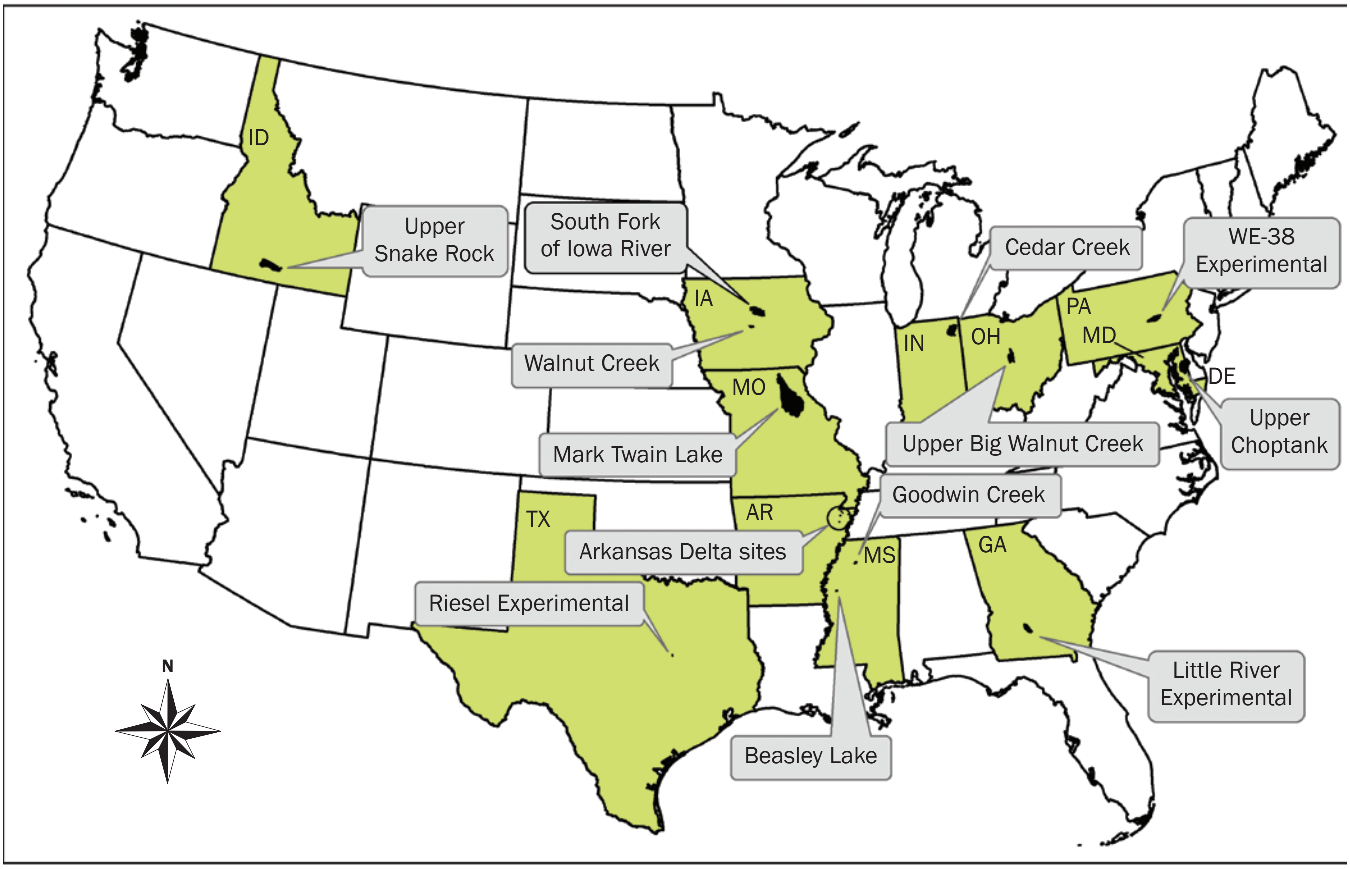


Table 1
Study sites.

Sites	Area (km²)	Cropland area in watershed (%)	Dominant slope	Proportion of watershed in each hydrologic soil group (A/B/C/D) (%)
WE-38, Pennsylvania	7	55	Steep slopes (>6%)	19/59/11/11
Delta Water Management Research Center, Arkansas	Range of areas (0.07 to 0.3)	100	Flat slopes (<2%)	8/4/14/74
Choptank, Maryland	1,042 (headwater)	49	Flat slopes (<2%)	18/24/16/42
Upper Snake Rock, Idaho	1,136	76	Flat slopes (<2%)	0/4/64/32
Goodwin Creek, Mississippi	16	6	Flat slopes (<2%	0/21/25/54
Beasley Lake, Mississippi	6	71	Flat slopes (<2%)	0/3/31/66
South Fork of Iowa River, Iowa	785	84	Flat slopes (<2%)	1/28/14/57
Walnut Creek, Iowa	50	79	Flat slopes (<2%)	0/34/7/59
Upper Big Walnut Creek, Ohio	491	44	Flat slopes (<2%)	0/2/14/84
Cedar Creek, Indiana	710	63	Mixed slopes	5/6/8/81
Little River Experimental Watershed, Georgia	334	55	Mixed slopes	7/57/12/24
Riesel, Texas	3.3	35	Mixed slopes (uniform hydrologic soil group)	0/0/11/89
Mark Twain Lake, Missouri	~4,100	38	Mixed slopes (uniform hydrologic soil group)	0/1/7/92

grains and, for dairy operations, alfalfa (*Medicago sativa* L.) (mixed alfalfa-grass) (Veith et al. 2015). Slopes in the cultivated portions of WE-38 ranged from 0% to 18%, with a few woodland hillslopes approaching 32% (Bryant et al. 2011). Hydrologic soil groups A through D were present, but group B was dominant. Soils having shallow restrictive layers were common in the lower portions of the landscape.

Flat Slopes. The Delta Water Management Research Unit, hereafter referred to as Delta Water, in northeast Arkansas, included the Little River Ditches basin in Mississippi County and the Lower St. Francis basin in Poinsett County. Both areas were predominantly agricultural; however, the cropping systems differed significantly as mostly rice (*Oryza sativa* L.) was grown in the Lower St. Francis and cotton (*Gossypium hirsutum* L.), corn, or soybean were grown in the Little River Ditches basin (Aryal and Reba 2017). The studied areas were part of an ongoing field-level study of the larger state-wide Mississippi River Basin Healthy Watersheds Initiative (MRBI) network (Reba et al. 2013) and included six different sites: Caraway, Leachville, Manila, Burdette Zero Grade, Burdette Precision Level, and Marked Tree, ranging in size from 0.07 to 0.3 km^2. All fields in this watershed were very flat, with slopes ranging from 0% to 1%. Each site was split into a control and a treatment field with monitoring equipment installed in each treatment to evaluate the effects of specific agricultural best management practices (BMPs) to reduce losses of nutrients (N and P) and sediment in the runoff water.

The Choptank River watershed (headwater 1,042 km^2) in Maryland was impaired by excessive nutrient and sediment loads from agricultural land (McCarty et al. 2008). Land use in the watershed was dominated by agricultural land (65%), forests (26%), and developed areas (5%) (Fisher et al. 2006). Almost 70% of the watershed had slope less than 2%. This watershed had variation in the hydrologic soil group, the dominant one being hydrologic soil group D, followed by hydrologic soil group B. Even though Lee et al. (2018) evaluated suitability of the SVI in identifying inherent vulnerability to NO_3 and organic N transport in two subwatersheds of the Choptank basin, results were included here as part of the overall synthesis across all the studied watersheds.

The Upper Snake Rock 8-digit hydrologic unit code (HUC) was 6,300 km^2 with 60% range and forest land, and 37% irrigated cropland. This project focused on the Twin Falls irrigation project (1,136 km^2), which was 80% irrigated cropland, 10% developed (urban or subdivision), and the remainder was open water, roads, or fallow. The study area was dominated by flat slopes and hydrologic soil group C and D. Large canals were used to supply water from the Snake River to irrigate cropland and pastures. Irrigation-induced soil erosion was a common environmental concern in the Upper Snake Rock watershed (Bjorneberg et al. 2008).

The Goodwin Creek watershed was 21 km^2 in area and had mixed land use and management practices that influenced sediment loss to the streams (Alonso and Bingner 2000). There was substantial gullying, and gullied land, mostly silty, were reported for nearly a quarter of the watershed. The hydrologic soil groups ranged from A to D, with edge-of-field gauges sampling mostly areas with hydrologic soil group C soils. A key characteristic of this watershed was the large sediment loads generated by stream channel erosion. Croplands include only 6% of the watershed, and almost 80% of the croplands are in flat slopes.

The Beasley Lake watershed was a 6 km^2 oxbow lake watershed with no contributing streams in the Lower Mississippi River Basin. The cropping system has transitioned from predominantly conventionally tilled cotton to predominantly conservation tillage soybean in 2002, and approximately 14% of the watershed was subsequently converted to Conservation Reserve Program (CRP, USDA Farm Service Agency) in 2003 (Lizotte et al. 2017). The site was dominated by hydrologic soil group C and D soils in undrained conditions. Slope was flat (<2%) in most fields, and drainage ditches were used to transfer water from fields to the oxbow lake.

The South Fork of Iowa River watershed (785 km^2) and the Walnut Creek watershed (50 km^2) were poorly drained flat watersheds in Upper Mississippi River Basin in Iowa. Corn and soybean were the dominant crops in the South Fork of Iowa River watershed, grown annually in 85% of the watershed. Pasture covered 6% of the watershed. Highly erodible land covered 13% of the watershed area (Tomer and James 2004). The Walnut Creek watershed was predominantly under row crop production with corn and soybean rotation accounting for 80% of the land use (Hatfield et al. 1999). Soil wetness was a key concern for agriculture due to dominant D soils, so tile drainage was common in both watersheds.

The Upper Big Walnut Creek watershed, approximately 491 km^2, was located in central Ohio. Almost 50% of the watershed had slope less than 2%. Cropland for production agriculture was the dominant land use (73%) in the watershed, followed by urban/farmstead (21%) and woodland (6%) (Williams et al. 2015). The primary crops grown were corn, soybean, and wheat (*Triticum aestivum* L.) managed with conservation tillage, fertilizer, and pesticide applications (King et al. 2008). There was an extensive network of subsurface tile drainage in this watershed. More than 75% of agricultural cropland in the watershed was tile drained.

Mixed Slopes. The Cedar Creek watershed (710 km^2) was characterized by soils with slow permeability and small closed depressions or "potholes" that were scattered throughout the landscape. The closed depressions and poorly drained fields were often too wet to farm and required the use of artificial drainage to remove excess water during the growing season. While the extent of subsurface tile drainage and the number of surface inlets in Cedar Creek watershed were unknown, it was estimated that the vast majority (>80%) of agricultural fields with poorly drained soils had artificial drainage. Almost 40% of the watershed had <2% slope, 30% of the watershed had between 2% to 4% slope, and the remainder had >4% slope.

The Little River Experimental Watershed (334 km^2) had broad floodplains and mostly sandy soils. Most slopes were less than 5%, with some valley side slopes ranging from 5% to 15% (Bosch et al. 2007). Land use in the watershed included agriculture (31%), pasture (10%), riparian forest (28%), upland forest (22%), and urban area (7%) (Sullivan et al. 2008). The primary crops grown were row crops (cotton, corn, and peanut [*Arachis hypogea* L.]), and vegetables, typically without artificial drainage.

The Riesel USDA Agricultural Research Service (ARS) (3.3 km^2) site in Texas, originally known as the Blackland Experimental Watershed, was dominated by poorly drained soils (hydrologic soil group D), and >70% of the watershed had slope <3%. It included multiple cultivated watersheds and pasture watersheds. Major land use in the watershed included pasture and rangeland, and cropland producing corn, grain sorghum (*Sorghum bicolor* L. Moench), and oat (*Avena sativa* L.) (Harmel et al. 2000).

The Mark Twain Lake/Salt River basin watershed was located in northeast Missouri and included 10 subwatersheds (North Fork, Middle Fork, Elk Fork, Long Branch, South Fork, Lick Creek, Black Creek, Crooked Creek, Otter Creek, and Ely Creek) ranging in size from 271 to 1,579 km^2. The basin had predominantly poorly drained claypan soils (hydrologic soil group D), which had characteristically high soil runoff potential. Dominant land use type included cropland (44%), pasture (33%), and forest (18%) (Lerch et al. 2008). While the watershed had a range of slopes, the cropland was mostly located on land with <4% slope. The Mark Twain Lake watershed and Riesel ARS sites were dominated by poorly drained D soils.

SVI Calculation and Evaluation. Thompson et al. (2020) describe the goals of the SVI, as well as the assumptions made and the methods employed to develop vulnerability classes and characterize them in terms of SSURGO parameters (tables 2 and 3). The runoff component of the SVI indirectly addresses the vulnerability of cropland to soil degradation and transport of nutrients via surface runoff. The leaching component of the SVI addresses the vulnerability of cropland to leaching. For this study, the SVI was calculated using ArcGIS software (version 10.3) using easily available input parameters from the SSURGO database and a DEM, and was applicable at scales ranging from a single field to a watershed. The SVI runoff component considers the hydrologic soil group, slope, and soil erodibility K-factor; while the SVI leaching component considers the same three properties plus the coarse fragment content of the soil and the presence of organic soils. A SSURGO soil layer was downloaded from the web soil survey (WSS) website (http://websoilsurvey.nrcs.usda.gov/app/HomePage.htm), and DEMs were obtained from the US Geological Survey (USGS) website (https://viewer.nationalmap.gov/launch/). Locally surveyed soil maps or properties or high resolution DEMs (10 m) were used when available. The soil layer was used to extract separate raster layers (10 m resolution) for organic soil, hydrologic soil group, and USLE soil erodibility K-factor. Slope was computed from DEMs by calculating the rate of maximum change in elevation across the eight adjacent neighbors in a 3-by-3 window (Gesch et al. 2002). The raster layers (organic soil, hydrologic soil, and soil erodibility K-factor) were then combined cell-by-cell with the DEM-derived slope layer in the raster calculator to derive both runoff and leaching components of the SVI based on the criteria for the four vulnerability classes. The SVI was calculated for every cell of the highest resolution input raster to create maps and summary tables, which were then discussed with scientists, hydrologists, and engineers from each study watershed via conference calls (included as coauthors in this article).

For soils that had a dual hydrologic soil group classification, the hydrologic soil group for undrained conditions was used per the SVI definition. In the Little River watershed, several soils were ambiguously classified within SSURGO reports, and in Goodwin Creek watershed, large gullied areas had no designated hydrologic soil group. Local scientists defined missing parameters for these soils and gullied areas. The leaching component of the SVI determined whether a soil is organic or not based on description for the Histosols and Histic epipedons (typically in the A horizon) in the SSURGO/gSSURGO soil taxonomy.

The original method for SVI calculation was to use the SSURGO soil map unit representative slope. Chan et al. (2017) showed that this method resulted in an underestimation of the erosion vulnerability estimated by the SVI in Goodwater Creek Experimental Watershed. Analysis of aerial imagery showed that some of the areas not identified as having a high vulnerability when using the SSURGO slope were showing signs of severe soil degradation (presence of rills). In this study, DEM rather than SSURGO was used to determine slopes.

In watersheds with artificial drainage (tile or ditch), the SVI calls for increasing the leaching vulnerability by two classes (moderate and moderately high increased to high, and low increased to moderately high) (table 3). However, for this analysis, the initial classification of the leaching component of the SVI before artificial drainage was analyzed in order to be consistent with the other watersheds. This paper was intended to evaluate the effects of inherent soil properties separately from artificial drainage. A separate article analyzes the suitability of the SVI specifically for artificially drained cropland (Baffaut et al. 2020).

Scientists who participated in the SVI evaluations interpreted the results based on their knowledge of vulnerability and conservation needs in their respective watershed. Did the SVI vulnerability across the watershed correspond to the relative risks of pollutant transport by runoff and leaching in these fields? Was the SVI useful to assess conservation needs in the watersheds (i.e., was the SVI able to identify land that needed conservation practices before being used to grow crops)? Finally, was it helpful to decide where to focus conservation or planning efforts? Answers to the first two questions relied primarily on knowledge of the watershed. Answers to the last question relied on whether the distributions of vulnerability to runoff and leaching spanned the four classes or were skewed toward one or two classes. In the latter case, the index would be less useful to plan conservation.

Effect of Slope and Hydrologic Soil Group on SVI Distribution. Prior SVI validation results (Chan et al. 2017) showed a strong impact of slope on the SVI. Given that the definition of vulnerability to runoff gives an important role to slope, and to hydrologic soil group for the leaching component, it was important to consider to what extent slope and hydrologic soil group were the major drivers in these watersheds. The effects of slope on the runoff component of the SVI and of hydrologic soil group on the leaching component were considered across all the CEAP sites in this analysis. Linear regression analysis between the fractions of watershed in each SVI category and the fractions of watershed in each slope category for the runoff component, and in each hydrologic soil group for the leaching component, were conducted. In each case, the coefficient of determination (r^2) and the regression slope were determined using Excel (Microsoft, Redmond, Washington) and its statistical package. Significance of the coefficient of determination and of the slope were assessed at the 0.05 probability. For analysis of vulnerability to runoff, the sites were grouped based on the three slope categories presented earlier (table 1)—steep slopes, flat slopes, and mixed slopes. The Mark Twain Lake watershed and Riesel ARS sites were separately analyzed because they also represented areas dominated by a single hydrologic soil group (i.e., poorly drained D soils).

Table 2
Criteria for four classes of soil runoff potential (USDA NRCS 2016).

Soil runoff potential	Hydrologic soil group A	B	C	D
Low	All area	Slope* < 4	Slope < 2	Slope < 2; K-factor† < 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

*Slope measured as percentage.

†K-factor refers to the soil erodibility factor (K) found in the Universal Soil Loss Equation.

Table 3
Criteria for four classes of soil leaching potential (USDA NRCS 2016).

Soil leaching potential*†	Hydrologic soil group A	B	C	D
Low	None	None	None	All except organic soils
Moderate	None	Slope ≤ 12 and K-factor‡ ≥ 0.24 or slope > 12	All except organic soils	None
Moderately high	Slope > 12	3 ≤ slope ≤ 12 and K-factor < 0.24	None	None
High	Slope ≤ 12 or soils classified as organic	Slope < 3 and K-factor < 0.24 or soils classified as organic	Soils classified as organic	Soils classified as organic

*If the coarse fragment content of the soil is greater than 30% by weight, the soil leaching potential is increased by two levels (moderate and moderately high increased to high, and low increased to moderately high). If the coarse fragment content is greater than 10% but less than 30%, the soil leaching potential is increased one level.

†Artificial drainage of any type increases leaching potential by two classes (moderate and moderately high increases to high, and low increases to moderately high).

‡K-factor refers to the soil erodibility factor (K) found in the Universal Soil Loss Equation.

Another alternative is to calculate a representative slope for each soil map unit based on the fraction of that map unit within the study area. In essence, the slope is calculated as the average (mean, median, or 75th percentile) cell value of an unfilled (i.e., unconditioned) DEM. This SVI calculation method was incorporated in the Agricultural Conservation Planning Framework (ACPF) tool, a set of custom-developed agricultural conservation planning tools at watershed scale (HUC12 watersheds), developed to be used with ArcGIS software (Tomer et al. 2013). These tools can be used to generate detailed maps that identify areas where different conservation practices can be located. The SVI results using ACPF-calculated slope were compared with SVI results using cell-by-cell calculated slope for all 13 sites. Three means of calculating a representative slope for the map unit using ACPF were considered: 75th percentile slope, mean slope, and median slope.

The hydrologic soil group is primarily determined based on the rate of infiltration in soils of different textures (USDA NRCS 2007), which decreases from hydrologic soil group A to D, and the presence of a restrictive layer or water table within the first 50 cm of soils, which increases saturation excess runoff. The SVI leaching potential is derived from the infiltration rate and the natural drainage characteristics. For analysis of vulnerability to leaching, the sites were grouped based on the proportion of hydrologic group B soils in the croplands in the watershed. Sites with high proportion (>50%) of B soils were WE-38 and Little River; Goodwin Creek, Choptank, South Fork of Iowa River, and Walnut Creek had proportion of B soils between 20% to 50%; and sites with low proportion (<20%) of B soils were Riesel, Mark Twain Lake, Delta sites, Upper Snake Rock, Beasley, Upper Big Walnut Creek, and Cedar. The different fields of the Water Management Research Center in Arkansas and the subwatersheds in the Mark Twain Lake were considered subsets of each site. To not bias the analysis by the conditions at these two sites, an area-weighted average of the fractions in each slope category, hydrologic soil group, and SVI category were calculated.

Effect of Digital Elevation Model Resolution on SVI Distribution. Multiple studies have shown the importance of DEM for land use planners (Hammer et al. 1991), and the impact of DEM resolution on the outcomes from water quality models (Beeson et al. 2014). Since slope calculated from a DEM was used in this study instead of the SSURGO map unit representative slope, sensitivity to DEM resolution was conducted for all 13 watersheds. For each watershed and each SVI vulnerability category, differences between percentages of cropland area in each watershed obtained with each of three DEM resolutions (30 m, 10 m, and a fine resolution ranging from 1 m to 5 m) were calculated. Results were considered significantly affected by DEM resolution if the percentage of cropland area differed by 5% or more for at least one vulnerability category.

Comparison with Model Outputs. Independent analyses have compared the SVI to modeling results in the Goodwater Creek Experimental Watershed (Chan et al. 2017), which is a watershed within the Mark Twain Lake watershed; Tuckahoe Creek and Greensboro watersheds (Lee et al. 2018), which are within the Choptank River watershed; and Goodwin Creek and Beasley Lake watersheds (Yasarer et al. 2020). In each case, a calibrated model was used to simulate sediment or nutrient transport by runoff or leaching. Since the SVI does not consider management, the model used a single management system appropriate for each watershed on all cropland. Edge-of-field simulated sediment and nutrient transport by runoff and leaching were classified into four classes. Since the studies were independent, they did not use the same thresholds to define vulnerability classes based on model outputs. Yasarer et al. (2020) considered sediment losses and used the thresholds established during the development of the SVI (Thompson et al. 2020). In contrast, Chan et al. (2017) and Lee et al. (2018) used the Jenks natural break method (Jenks 1967) to divide model outputs for spatial units into four classes (high, moderately high, moderate, and low). This method minimizes the variance within each group and maximizes the variance between groups (Jenks 1967).

Simultaneously, the SVI was assessed for the spatially defined cells or units defined by the model using the soil and topographic inputs of the model. The synthesis of these three studies considered two aspects. First, the median values of simulated soil loss and nutrient yields and the SVI vulnerability class should be consistent, meaning distinct and increasing median values for increasing vulnerability. Second, classification by either method should be similar. The similarity rate (i.e., the areal proportion of cropland classified in the same vulnerability class by the SVI and using model outputs) was deemed good if greater than 75%, the criterion used for a good match between model results and SVI classification during SVI development (Thompson et al. 2020). Additionally, the similarity was deemed acceptable if the similarity rate was greater than 65%. In each case, the SVI component used for the comparison was the main pathway for the transport of each constituent: the runoff component for contaminants transported via surface runoff (i.e., sediment, total N, and organic N), and the leaching component for NO_3, which are transported via leaching.

Results and Discussion

Figure 2 shows the SVI vulnerability to runoff in the study sites. The overall SVI calculation was easy to perform with a basic knowledge of ArcGIS software. The input data required for SVI assessment were all publicly available for these US sites. Based on the responses from the local scientists, the SVI was useful for conservation effort targeting in some watersheds and not so useful in others. The relationship between the SVI and slope or soil hydrologic group helped clarify when the SVI was useful or not. Areas with mixed slopes and hydrologic soil groups showed a range of SVI vulnerability, thus providing potential to identify locations where efforts need to focus. In contrast, areas with uniform slope and hydrologic soil group showed uniform SVI vulnerability class such that the SVI was not able to distinguish fields that were more or less vulnerable than others. The following sections describe the impact of slope and hydrologic group distribution on the results and usefulness of the index.

Effect of Slope on SVI Vulnerability to Runoff. Results of the regression between proportions of land in each slope category and in each SVI category are shown in table 4. In many cases, there was a significant relationship between slope category and SVI class. However, there were some exceptions. We provide more details in the following paragraphs.

Slope was the dominant factor for the runoff component of the SVI in watersheds where steep slopes (>6%) were prevalent (WE-38; figure 2). When slope was steep, the corresponding vulnerability to runoff was always high (table 2) regardless of hydrologic soil group and K-factor. Thus, the relationship between fractions of the watershed in each slope category and each class of the runoff component of the SVI was very strong, and the slope distribution explained 95% or more of the variability in vulnerability to runoff (table 4). Yet this was likely an artifact of the r^2 coefficient of determination, which is biased toward high values. While this is correct given the high slopes, SVI indication of vulnerability was not particularly useful. Hillslopes with >6% slope may be consistently and rightfully considered the most vulnerable to runoff, but the SVI was not able to differentiate the greatest problem areas and prioritize efforts, in case of limited resources, for example. Cultivated areas with high vulnerability to runoff in the lower section of WE-38 would benefit from other relevant information such as landscape position (Buda et al. 2009a; Needelman et al. 2001, 2004) and presence of a restrictive layer (Buda et al. 2009b; Gburek et al. 2006), which affect runoff and thus erosion vulnerability.

In watersheds with flat slopes (<2%), the only factors that could affect the runoff component of the SVI was the hydrologic soil group and the K-factor value relative to the 0.28 threshold. However, all these watersheds had large proportions of hydrological soil group D soils and, in most cases, the K-factor was <0.28, which resulted in equal and large fractions of land with low slopes and low vulnerability to runoff, and consequently high values of r^2 between fractions of watershed (or cropland) in each slope and SVI category (table 4). All the watersheds with flat slopes and poorly drained soils were artificially drained. Vulnerability to leaching was therefore raised by two classes, thus compressing four classes into two classes. Baffaut et al. (2020) made a separate evaluation of the SVI in the presence of artificial drainage, which brings additional complexity for the leaching component (per SVI definition, table 3), but also for the runoff component. In Goodwin, the lack of discernment of the SVI may not be as important because the vulnerability to runoff was recognized, and most of the highly vulnerable land went out of cultivation at the dawn of the twenty-first century. However, if it was cropped, as it had been in the nineteenth until the mid-twentieth century, gully formation and sheet erosion would increase as historical pictures demonstrate (Kuhnle et al. 1996; Wilson et al. 2015). Other parameters such as clay content have been successful predictors of the susceptibility to gully erosion (Grissinger and Murphey 1989).

For watersheds with mixed slopes (Cedar Creek and Little River), the vulnerability to runoff was affected by the two other factors: hydrologic soil group and K-factor. The resulting relationship between fractions of watershed in each slope category and each SVI category was weak (r^2 = 0.024), and the regression slope was not significantly different from 0 (table 4). Incidentally, it is in these watersheds that scientists agreed most with the SVI outcomes, finding that vulnerability to runoff was well described by the SVI.

Both Mark Twain Lake and Riesel were representative of mixed slopes but were dominated by a single hydrologic soil group (D; table 1) and K-factors >0.28. Definitions of SVI given in table 2 implied that soils in the lowest slope category had a moderate vulnerability due to runoff, those with 2% to 4% slope had a moderately high vulnerability, and everything with >4% slope had a high vulnerability due to runoff. Since the

Figure 2
Soil Vulnerability Index (SVI) runoff potential for 13 sites.

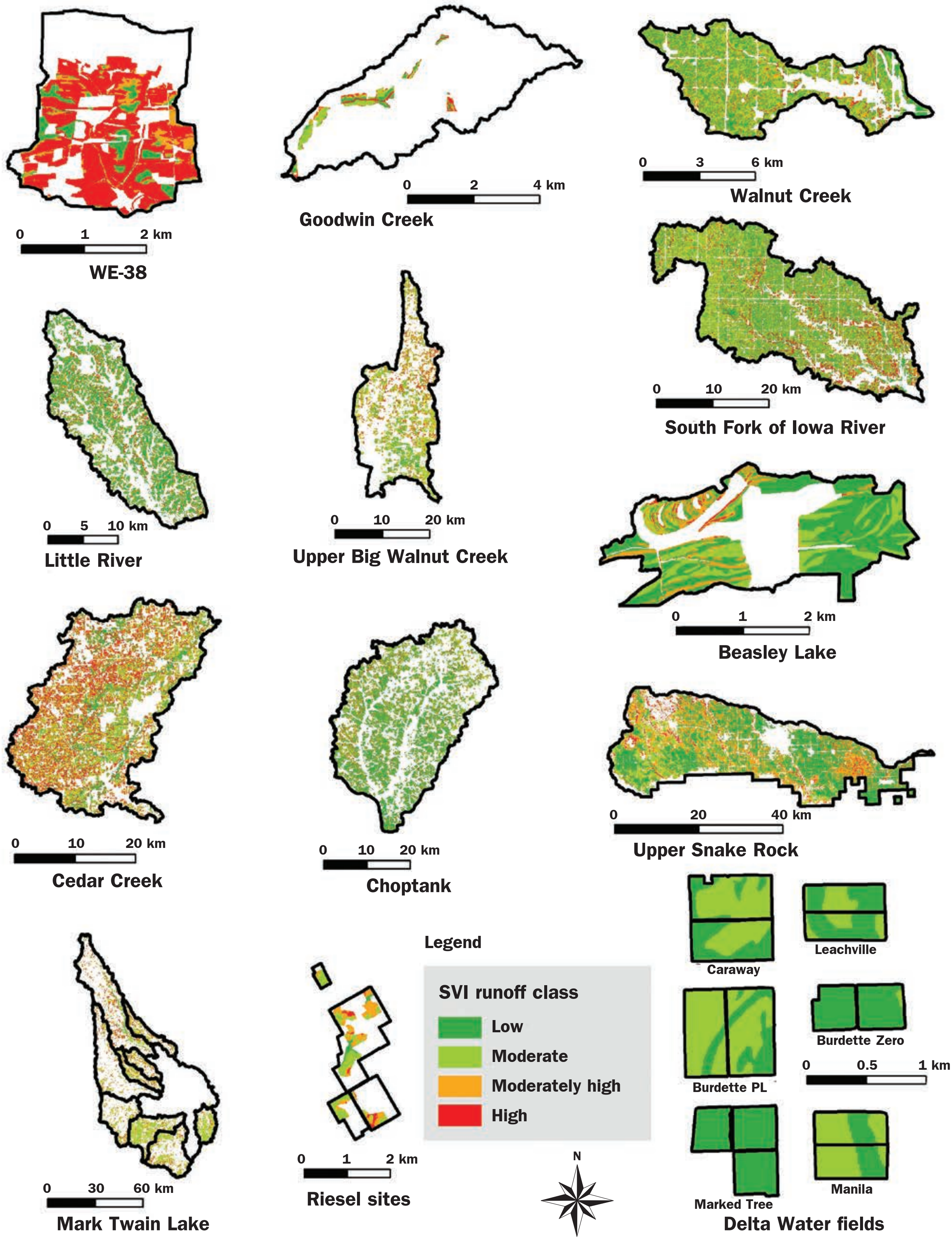


Table 4

Relationship between the fractions of watershed in each slope category (10 m digital elevation model [DEM]) and in each category of the runoff component of the Soil Vulnerability Index (SVI); and the fractions of watershed in each hydrologic soil group (HSG) category and each category of the SVI leaching component using a 10 m DEM.

Slope/HSG category	Number of sites	Number of data points	r^2	Regression slope	Standard error of regression slope
Dominant slope condition					
Steep slopes	1	4	0.95**	0.90**	0.15
Flat slopes, artificial drainage	8	28	0.68**	0.54**	0.07
Mixed slopes	2	8	0.02	0.18	0.54
Mixed slopes (uniform hydrologic soil group)	2	6	0.98**	0.90**	0.06
All watersheds	13	50	0.38**	0.48**	0.09
Fraction of HSG B soils					
High (>50%)	2	8	0.14	–0.44	0.44
Moderate (20% to 50%)	4	16	0.21	0.54	0.28
Low (<20%)	7	26	0.99**	0.99**	0.02
All watersheds	13	50	0.50**	0.74**	0.11

**Indicates significance at the 0.05 level of the slope or coefficient of determination at the 0.05 level.

hydrologic soil group and the K-factor were uniform across these two watersheds, the only factor controlling risk of degradation by runoff as indicated by the SVI was the slope. This was confirmed by aerial photos showing signs of soil degradation or presence of terraces on the steepest cropped land (Chan et al. 2017). However, rills have also been observed on areas with <2% slope in Mark Twain Lake watershed where the argillic horizon was close to the surface (<10 cm), a sign of vulnerability to soil erosion linked to concentrated flow. These were observed in no-till areas, i.e., where a conservation practice to limit soil erosion had already been implemented but was not sufficient to prevent degradation. They certainly also occurred on tilled areas, but tillage regularly erased them. With a low or moderate SVI vulnerability to runoff, the need for conservation measures may be overlooked. Additional information may provide the missing information to describe accurately the vulnerability to runoff under these very vulnerable conditions. For example, landscape features such as slope length (Chaplot and Bissonnais 2003; Jamison and Peters 1967), depth to a restrictive layer (Buda et al. 2009b; Gburek et al. 2006), depth to claypan (Chan et al. 2017), spatial scale of landscape pattern change over distance (Fiener et al. 2011), or landscape dissecting features that disrupt runoff energies (Jencso and McGlynn 2011) have been shown to increase vulnerability to runoff.

Results from the SVI tool within the ACPF framework varied depending on the dominant slope of the site (table 5). Results were examined with regards to the slope class breaks used for calculating the SVI. If the range of slope metrics by map unit did not cross a SVI class threshold (for example, low relief landscapes with dominant steep or flat slopes), the resulting SVI class distribution did not alter substantially (table 5). Incorporating SVI tool into ACPF can thus provide flexibility in using the different slope preferences based on topographic parameters. When calculating the SVI within the ACPF, all the inputs were calculated on a map unit basis within the study area. As expected, calculating the SVI using an average cell DEM slope within each map unit reduced the variability of the SVI calculated using DEM-derived cell-by-cell slope determination (table 5). Doing so may bring consistency to a tool that was intended to be a reclassification of SSURGO soil map unit attributes. The flexibility of selecting one or several slope averaging methods seems to provide results close to those calculated on a cell-by-cell basis.

Effect of Hydrologic Soil Group on SVI Vulnerability to Leaching. Hydrologic soil group had a very strong impact on the leaching component of the SVI, and in many cases, the maps of hydrologic soil group and SVI vulnerability to leaching were exactly the same (Riesel, Mark Twain Lake, Delta Research Center fields, and Upper Big Walnut Creek) or very similar (Upper Snake Rock, Beasley, and Cedar Creek). The SVI leaching component changed with slope and soil erodibility K-factor only for soils in the hydrologic soil group B. For soils in the hydrologic soil group A, slope was a factor (table 3), but amounts of A soils were too small in these watersheds, except WE-38, to assess the effect of slope on the SVI for these soils. Grouping watersheds based on their dominant slope characteristics was not as useful for the leaching component of the SVI as it was for the runoff component. Instead, the critical factor was the fraction of soils in hydrologic soil group B (table 4). For those with high proportions (>50%) of hydrologic soil group B soils, the relationship between fractions of watershed in each hydrologic soil group and each SVI leaching vulnerability category was weak (r^2 = 0.14; table 4). In areas with more than 50% hydrologic soil group B, SVI leaching vulnerability changed with soil erodibility K-factor. For those with moderate proportions (20% to 50%) of hydrologic soil group B soils, the relationship between fractions of watershed in each hydrologic soil group and each SVI leaching vulnerability category was weak, but slightly better than watersheds with dominantly B soils (r^2 = 0.21; table 4). The other group of watersheds had low proportions of hydrologic soil group B soils (<20%), and for those, the hydrologic soil group was the main factor driving vulnerability to leaching (r^2 = 0.99; table 4). In areas with hydrologic soil group C and D soils, the leaching component of the SVI changed only if the soil contained enough organic matter to be considered an organic soil. Only the Choptank watershed had soils with organic layers, which resulted in greater vulnerability to leaching, which is further discussed by Baffaut et al. (2020).

Table 5
Comparison of Soil Vulnerability Index (SVI) classes distribution (%) using cell-by-cell slope calculation with SVI distribution using the Agricultural Conservation Planning Framework (ACPF) tool.

Watershed	SVI class*	SVI distribution (%) using cell-by-cell slope	SVI distribution (%) using ACPF tool		
			Mean slope	Median slope	75th percentile slope
WE-38	L	14	9	9	9
	M	0	5	25	0
	MH	12	0	0	0
	H	74	86	66	91
Delta	L	57	57	57	43
	M	43	43	43	32
	MH	0	0	0	14
	H	0	0	0	11
Choptank	L	67	88	93	82
	M	17	7	6	6
	MH	12	5	1	11
	H	4	0	0	1
Upper Snake Rock	L	50	50	50	50
	M	14	6	6	6
	MH	31	42	42	42
	H	5	2	2	2
Goodwin	L	27	2	32	1
	M	39	0	43	0
	MH	15	81	19	51
	H	19	17	6	48
Beasley	L	61	59	65	59
	M	24	17	24	17
	MH	13	19	11	19
	H	2	5	0	5
South Fork of Iowa River	L	38	44	44	44
	M	37	56	56	56
	MH	17	0	0	0
	H	8	0	0	0
Walnut Creek	L	39	28	31	27
	M	38	16	54	12
	MH	19	53	14	58
	H	4	3	1	3
Upper Big Walnut Creek	L	17	17	18	0
	M	42	28	38	0
	MH	31	49	42	80
	H	10	6	2	20
Cedar Creek	L	22	45	45	20
	M	23	54	55	16
	MH	30	1	0	1
	H	25	0	0	63
Little River	L	65	63	64	27
	M	21	23	24	55
	MH	6	13	12	8
	H	8	1	0	10
Riesel	L	6	6	6	5
	M	48	0	49	0
	MH	39	94	45	93
	H	7	0	0	2
Mark Twain Lake	L	0	0	0	0
	M	65	59	66	29
	MH	24	31	27	51
	H	11	10	7	20

*L = low, M = moderate, MH = moderately high, and H = high.

Effect of Digital Elevation Model Resolution on SVI Vulnerability to Runoff. Since the runoff component of the SVI was heavily dependent on slope for many of the watersheds, and since slope was calculated for each cell of the DEM, it was expected that DEM resolution would impact the results for that component of the SVI. As expected, DEM resolution did not affect the results for the leaching component. The SVI leaching component depended primarily on the hydrologic soil group, which is not affected by DEM resolution. For the runoff component, DEM resolution affected the SVI for croplands in 8 out of 13 watersheds when comparing the 10 m and 30 m DEM, which is almost 60% of the watersheds (table 6). Comparison of results obtained with the 10 m DEM and a finer resolution DEM (from 1 m to 5 m depending on availability) showed that croplands in 3 out of the 8 watersheds for which a fine resolution DEM did exist were affected. Watersheds for which a 10 m and a 30 m DEM did not affect SVI results included WE-38, Riesel, Upper Snake Rock, Little River, and Delta Water. For these (except WE-38), a high-resolution (<10 m) DEM was not available for assessment. For WE-38, SVI distribution was similar whether using a 30, 10, or 5 m DEM. This can be explained by the uniform topography in this watershed, which remains steep (>6%) no matter the cell size from which slopes were calculated.

In watersheds with mixed slopes, high-resolution DEM permitted identifying short but steep slopes such as faces of terraces, gullies, stream banks, or banks along ditches, roads, and rivers as high vulnerability for runoff. Conversely, coarser DEM resolution resulted in increased fractions of watersheds in the lowest category of slopes and a decrease in the fraction of watersheds in the steepest slope categories (figure 3). Thus, there is a possibility that high vulnerability areas (with >6% slope) that require attention could fail to be identified with a coarser DEM. While controlling erosion and nutrient inputs to the water body, steep banks along roads or railways may be of greater importance; however, on the other hand, those areas may need to be buffered for any cropland management program. Hence, masking out noncropped areas should be recommended, especially with fine scale assessments.

Table 6

Distributions of the runoff and leaching components of the Soil Vulnerability Index (SVI) as affected by digital elevation model (DEM) resolution.

		Runoff component of SVI DEM resolution		
Watershed	**SVI class***	**High resolution†**	**10 m**	**30 m**
Goodwin Creek	L	28	27	35
	M	37	39	37
	MH	15	15	20
	H	20	19	8
Mark Twain Lake	L	—	1	1
	M	—	61	64
	MH	—	24	26
	H	—	14	9
Choptank	L	66	67	77
	M	15	17	19
	MH	14	12	4
	H	5	4	0
Beasley	L	52	61	66
	M	21	24	27
	MH	22	13	7
	H	5	2	0
South Fork of Iowa River	L	35	38	46
	M	36	37	39
	MH	19	17	12
	H	10	8	3
Walnut Creek	L	36	39	44
	M	36	38	43
	MH	21	19	12
	H	7	4	1
Upper Big Walnut Creek	L	15	17	20
	M	36	42	52
	MH	33	31	24
	H	16	10	4
Cedar Creek	L	19	22	27
	M	19	23	31
	MH	31	30	28
	H	31	25	14

*L = low, M = moderate, MH = moderately high, and H = high.

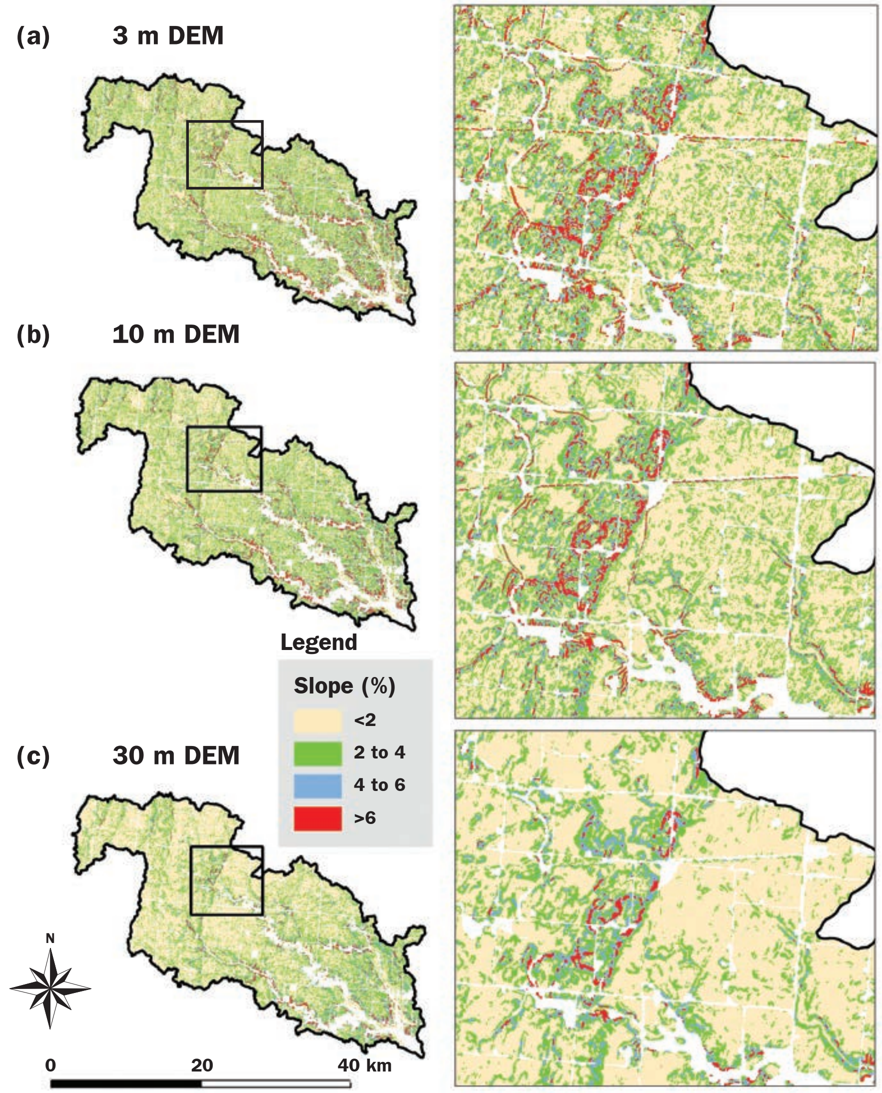
†The high resolution DEM was 1 m for Goodwin Creek watershed; 2 m for Choptank watershed, Cedar Creek watershed, Upper Big Walnut Creek, and Walnut Creek; 1.5 m for Beasley Lake watershed; and 3 m for South Fork of Iowa River.

Optimal DEM resolution varied with lengths of the features that may cause problems. If gullies need to be identified, a resolution compatible with the width and length of these gullies is preferable. Finest DEM (1 m) in Goodwin Creek watershed was able to identify gullied areas as high vulnerability. Ditch bank erosion may be a significant problem in watersheds like Beasley Lake, and should not be buffered out when using a high-resolution DEM. For sites that have varying slopes across a topo-sequence, the SVI used in combination with a high-resolution DEM gives the ability to identify areas within a field that are of greater concern. While this may not have been the original intent of the SVI, conservation planning may benefit from the ability to identify those areas across a field.

Comparison with Model Outputs. Comparison results between land vulnerability assessed by the SVI and model results were inconsistent from watershed to watershed. In Goodwater Creek watershed (Chan

Figure 3

Slope category ([a] 3 m digital elevation model [DEM], [b] 10 m DEM, and [c] 30 m DEM) for the runoff component of the Soil Vulnerability Index (SVI) in the croplands of the South Fork of Iowa River.



et al. 2017), the ranges of constituent yields (sediment, total N, and total P) for the high, moderately high, and moderate vulnerability classes were distinct and consistent with SVI vulnerability classification (table 7). However, there was no clear differentiation between the total N and total P yields for the low and moderate SVI vulnerability classes. In the well-drained Tuckahoe watershed (Upper Choptank watershed), simulated NO_3 yields in surface runoff and leachate (simulated leaching and NO_3 transport by lateral flow) were inconsistent with SVI classification. Nitrate transported by runoff was smaller for areas with high SVI vulnerability than with low vulnerability (table 7). Average loss of organic N, which is transported by surface runoff, was consistent with SVI ranking. In the poorly drained Greensboro watershed (also in the Upper Choptank watershed), simulated NO_3 yields in surface runoff were inconsistent with SVI classification, while simulated organic N in runoff and leached N yields were consistent. However, there was no or little differentiation between the moderately high and high vulnerability class. Lee et al. (2018) concluded that SVI runoff classification scheme was suited for identifying critical source areas vulnerable to organic N in Greensboro, while the SVI leaching classification scheme was suited for NO_3. In Beasley Lake watershed, sediment yields were not differentiable between SVI classes (table 7) except for the highest vulnerability class, and in Goodwin Creek watershed sediment yields differed only for the moderately high and high vulnerability classes.

Similarity rates between classification based on SVI and model results (table 8) confirmed the previous findings. Overall, similarity rates were good or acceptable when the processes matched the SVI component, but with some exceptions. In Goodwater Creek (Chan et al. 2017), surface runoff causes sediment and nutrient movement. Model based vulnerability was similar to vulnerability based on the runoff component of the SVI (table 8), and was consistent with the judgement of local scientists. In Greensboro, which is dominated by poorly drained soils and has an extensive and dense network of drainage ditches, vulnerability classification based on the leaching component of SVI and model results was similar for leached N. Similarly in Tuckahoe, which has well-drained soils and not as much artificial drainage, classification based on the runoff component of SVI and model results was similar for constituents transported by surface runoff. However, similarity was poor for leached constituents. Lee et al. (2018) attributed this poor similarity to varying soil water capacity across the watershed. In Beasley, which features drainage ditches around each field, similarity of SVI classification and simulated sediment yields, which are controlled by surface runoff processes, was poor. Similarity rate was better in Goodwin, but sediment yields were not fully consistent with SVI classification. Yet, land taken out of production in these two watersheds was land primarily classified with high vulnerability by the SVI, a confirmation of the potential for the SVI to identify high vulnerability areas. Overall, the models showed inconsistent results between SVI classification and average amounts of sediment or nutrients lost per unit area (tables 7 and 8).

Summary and Conclusions

The SVI was developed by the USDA NRCS CEAP to classify cropland vulnerability to runoff and leaching into four categorical classes—low, moderate, moderately high, and high. The SVI calculation required basic ArcGIS tools using easily available input parameters from the SSURGO database and a DEM, and was applicable at scales ranging from a single field to a watershed or region. In this study, SVI maps for 13 watersheds were generated and evaluated by scientists

Table 7
Contaminant loads from hydrologic response units (HRUs) by vulnerability class determined with the Soil Vulnerability Index (SVI).

	Mean and standard deviation of contaminant load			
SVI category*	**Low**	**Moderate**	**Moderately high**	**High**
Goodwater				
Sediment in surface flow (t ha^{-1})	0.7 (0.4)	1.2 (0.6)	2.2 (0.2)	5.1 (0.6)
Total N in surface flow (kg ha^{-1})	9 (1.7)	11 (2.2)	15 (0.5)	22 (1.3)
Total P in surface flow (kg ha^{-1})	0.7 (0.2)	1.1 (0.3)	1.7 (0.1)	2.9 (0.2)
Tuckahoe				
NO_3-N in surface flow (kg ha^{-1})	0.72 (0.33)	1.42 (0.10)	1.49 (0.26)	0.58 (0.14)
Organic N in surface flow (kg ha^{-1})	10.0 (6.44)	22.47 (5.02)	27.52 (9.83)	38.72 (6.59)
Leached N (kg ha^{-1})	35.78 (8.29)	40.66 (2.79)	36.98 (5.10)	38.98 (5.48)
Greensboro				
NO_3-N in surface flow (kg ha^{-1})	2.92 (2.43)	3.96 (1.19)	6.79 (1.10)	2.08 (0.25)
Organic N in surface flow (kg ha^{-1})	21.40 (10.22)	32.23 (5.40)	43.26 (11.81)	44.58 (3.67)
Leached N (kg ha^{-1})†	7.87 (9.29)	14.12 (7.74)	23.41 (5.80)	26.58 (6.29)
Beasley				
Sediment in surface flow (t ha^{-1})	5.01 (3.7)	5.7 (4.3)	5.4 (4.3)	22 (25)
Goodwin				
Sediment in surface flow (t ha^{-1})	7.4 (2. 5)	7.5 (0.67)	13 (11)	40 (44)

Notes: N = nitrogen. P = phosphorus. NO_3 = nitrate.

*The runoff component of SVI was used for comparison of SVI classes and yields of contaminants in surface runoff. The leaching component of SVI was used for evaluation against leached N yields.

†Includes N leached through the soil profile and transported through subsurface flow.

Table 8
Similarity rate between vulnerability classification based on the Soil Vulnerability Index (SVI) and model outputs.

			Classification similarity rate (%)				
Watershed	**Drainage characteristics**	**Model used**	**Surface runoff sediment**	**Surface runoff total P**	**Surface runoff NO_3-N**	**Surface runoff total N or organic N**	**Leached N**
Goodwater	Poor	SWAT	73	73	—	86	—
Tuckahoe	Fairly good	SWAT	—	—	81	70	14
Greensboro	Poor	SWAT	—	—	34	46	71
Beasley	Poor	AGNPS	45	—	—	—	—
Goodwin	Poor	AGNPS	69	—	—	—	—

Notes: P = phosphorus. NO_3 = nitrate. N = nitrogen. SWAT = Soil and Water Assessment Tool. AGNPS = Annualized Agricultural Non-Point Source.

with knowledge of the watersheds. Major conclusions of the study are the following:

- In watersheds with mixed slopes and hydrologic soil groups, the SVI resulted in vulnerability spread out across the four categories, thus informing where efforts need to focus. The location of areas with high and low vulnerability was consistent with scientists' knowledge of vulnerability in these watersheds.
- In watersheds with uniform hydrologic soil groups, the slope was the dominant factor. In these cases, it was important to use a DEM to calculate the slope instead of using the SSURGO representative slope to obtain more discernment of vulnerability. Two alternatives are possible: using the DEM cell-by-cell method to calculate slope and determining the SVI for each DEM cell, or using the DEM to calculate a median, average, or selected quantile of choice slope for each soil map unit. In the latter case, the SVI was then determined for each soil map unit.
- In areas where both slopes and hydrologic soil group were uniform, and in areas with uniformly elevated slopes, vulnerability was also uniform and the SVI was not able to distinguish areas that were more or less vulnerable than others. Yet, even in these cases, scientists with knowledge of the watersheds have been able to identify factors that affect vulnerability: depth of restrictive layer, clay content, slope length, and landscape position to name a few of those identified within this study.
- The SVI classification was compared with model outputs from AGNPS and SWAT in five sites. The SVI classification matched with model outputs when the predominant mode of nutrient transport matched with the SVI component. SVI runoff classification was consistent with model outputs for sites without artificial drainage (Goodwater and Tuckahoe) where sediment and nutrient movement was primarily through surface runoff. In sites with artificial drainage (Greensboro),

model outputs for leached N were consistent with SVI leaching classification. Model outputs for sediment yields in Beasley and Goodwin were not fully consistent with SVI classification because primary route of sediment loss did not match with the SVI component.

Hence, the SVI can be used as a preliminary assessment tool to identify soil and topography based inherent vulnerability of a watershed and thus help in developing conservation plans and mapping vulnerability in a watershed. However, site specific information on slope length, depth to restrictive layers, landscape position, and historical information could increase the reliability and usefulness of the index. Conclusions from this study are summarized in the SVI synthesis paper by Thompson et al. (2020), along with other companion studies.

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