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CONSERVATION IN PRACTICE

Mapping the Soil Vulnerability Index across broad spatial extents to guide conservation efforts

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THE NEED FOR TARGETED AGRICULTURAL CONSERVATION

The 2008 Gulf of Mexico Hypoxia Action Plan was developed in response to national water quality impairments that were largely caused by agricultural land uses within and around the US Corn Belt (Alexander et al. 2008; Mississippi River Gulf of Mexico Watershed Nutrient Task Force 2008). The plan prompted states to create nutrient reduction strategies to achieve a 45% reduction in total nitrogen (N) and total phosphorus (P) loads into the Mississippi River, and thereby alleviate the hypoxic zone in the Gulf of Mexico (Mississippi River Gulf of Mexico Watershed Nutrient Task Force 2008). Similar to other state strategies, the Iowa Nutrient Reduction Strategy (INRS) promotes the widespread and voluntary adoption of best management practices (BMPs) to achieve nutrient reduction goals. The INRS establishes goals of 41% and 29% reductions in total N and total P, respectively, from nonpoint sources from a 1980 to 1996 baseline (Iowa Department of Agriculture and Land Stewardship et al. 2017). These goals are largely dependent on regional conservation funding and infrastructure to inform and incentivize BMP adoption at individual farm scales (Zimmerman et al. 2019a).

Although billions of dollars have been spent to promote conservation, Iowa continues to be a primary contributor to Gulf of Mexico hypoxia, and there is little evidence of progress toward meeting environmental quality goals (Schilling et al. 2020; Jones et al. 2018; Robertson et al. 2014; Alexander et al. 2008; Tomer and Locke 2011; Osmond et al. 2012). Lack of success at broad-scale conservation efforts can be blamed on a complex mix of social, economic, and ecological barriers (Atwell et al. 2009; Osmond et al. 2012; Mattia et al. 2018; Zimmerman et al. 2019a); however, the historical lack of spatial precision and consideration of hydrologic processes in BMP application is likely a significant factor (Osmond et al. 2012; Tomer and Locke 2011). Effective conservation involves strategic management of watersheds through the implementation of BMPs in a precise and scientific manner.

Fortunately, conservation communities now recognize targeted conservation as a powerful tool that can more effectively and efficiently protect waterbodies (Burger et al. 2019; Zimmerman et al. 2019b; Tomer et al. 2013; Tuppad et al. 2010). By focusing time and resources on areas more vulnerable to soil and nutrient loss, targeted conservation can allow for the joint alignment of environmental and economic objectives, especially if landowners incorporate yield information and incentive programs by implementing BMPs on less-profitable lands (Burger et al. 2019; Zimmerman et al. 2019b). Technological advancements, such as remotely sensed data, have allowed scientists to more easily model hydrologic processes (e.g., Soil and Water Assessment Tool [SWAT]), and develop geospatial planning tools such as the Agricultural Conservation Planning Framework (ACPF). The ACPF database and ArcGIS Toolbox (Esri 2019) allow users to identify agricultural fields where runoff potential is high and then identify opportunities for implementing BMPs in those fields (Tomer et al. 2015). While powerful, downsides of ACPF and other geospatial planning and hydrologic modeling tools are their limited spatial extent and required level of expertise for use. Accessible and accurate methods for identifying environmentally vulnerable areas across broad spatial extents are needed for the widespread application of targeted conservation.

In this exercise, we used high-resolution (2 to 10 m [6.6 to 32.8 ft]), open-source geospatial data from the state of Iowa, the USDA Natural Resources Conservation Service (NRCS), and ACPF to characterize the vulnerability of individual farm fields to runoff and leaching across Iowa. We specifically used the Soil Vulnerability Index (SVI) to categorize the runoff and leaching potential of individual agricultural fields based on slope, hydrologic soil group, and soil erodibility (K-factor). Unlike more resource intensive hydrologic models that require significant time and expertise, the SVI is a USDA NRCS developed index that can be easily applied with open source data and a basic knowledge of ArcGIS (USDA NRCS 2012). Similar to ACPF, SVI can be used to guide and improve watershed management by researchers, watershed planners, conservation agronomists, and soil and water conservationists including those working for agricultural agencies, commodity groups, and industries. SVI can provide a basis for further spatial analysis in research and/or local watershed planning, and inform investments in nutrient management, soil health, and water quality at multiple scales.

MAPPING THE SOIL VULNERABILITY INDEX

The SVI can be used to characterize cropland runoff and leaching potential with datasets that contain slope information such as digital elevation models (DEMs), land use information, and soils information including hydrologic group, soil erodibility, coarse fragment content, and presence of organic soils. To characterize field-level soil runoff and leaching potential using the SVI across Iowa, we created an ArcGIS-based geoprocessing workflow to analyze large amounts (>125 GB) of high-resolution geospatial data. The ACPF database (Tomer et al. 2013, 2015) consists of field boundaries, land use information, and NRCS gridded Soil Survey Geographic (gSSURGO) 10 m resolution soils data rasters at the hydrologic unit code

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12 (HUC12) watershed level. DEMs were acquired from the Iowa P-Library series (ISU GIS 2016), which are light detection and ranging (LiDAR) point-cloud derived, 2 m (6.6 ft) resolution elevation rasters that have been hydro-conditioned and assembled for the state of Iowa at the HUC12 level (n = 1,615). High resolution DEMs that account for subtle slope differences are necessary for landscapes with low relief, like much of Iowa (Lohani et al. 2020a; Thompson et al. 2020). We used these data as inputs to estimate both SVI indices—soil runoff potential and soil leaching potential—using a custom ArcGIS tool at the HUC12 scale. We analyzed row crop agricultural fields from the ACPF database; specifically, crop fields (e.g., corn [*Zea mays*], soybean [*Glycine max*], alfalfa [*Medicago sativa*], wheat [*Triticum aestivum*], dry beans) larger than 6 ha (15 ac).

Initial SVI classes were estimated at the soil map unit level. To calculate the SVI indices, we first calculated mean percentage slope of each soil map unit from the DEMs. For each soil map unit, slope output is evaluated along with the hydrologic soil group and soil erodibility to classify the runoff potential (table 1) (Thompson et al. 2020). In addition to these parameters, soil leaching potential estimates included the ACPF-based coarse fragment content of the soil and the presence of organic soils in each map unit (table 1) (Thompson et al. 2020). SVI runoff and leaching potential of each field was estimated by examining the area-weighted contributions of the soil map units in the field. Each field was assigned an index value of "High," "Moderately high," "Moderate," or "Low" based on the thresholds of the slope and soil parameters (Thompson et al. 2020). When summarizing by field, each index is estimated in two classes: the "dominant" category was based on the dominant runoff potential class within each field, while "most limiting" uses the most limiting runoff potential class within the field. Additionally, the percentage of the field that each of these classes represent is estimated. Once all HUC12 watersheds were categorized, we aggregated the collection of HUC12 fields to HUC8 field feature classes.

A few caveats should be noted for the data we present. The gSSURGO soils data we used to estimate SVI in Iowa are collected at the county level, which can lead to SVI classification inconsistencies among counties. For example, there is a clear difference in dominant soil runoff potential between Calhoun and Greene counties, and Webster and Boone counties in Iowa (figure 1c). Although NRCS has standardized measurement methods, current soil survey data for each county represent historical soil surveys that have been updated and amended annually by many different soil scientists throughout time (USDA NRCS n.d.). Exact mechanisms or parameters for county-level differences are unclear and difficult to identify. Other caveats of SVI data are discussed in Thompson et al. (2020). Importantly, because SVI is an index that uses relatively few inputs, it does not account for some parameters considered to be important in determining soil and leaching potential in certain geographic locations such as rainfall intensity and topsoil depth, and may be sensitive to slope, complexity of soil profiles, and the presence of artificial drainage (Baffaut et al. 2020a, 2020b; Lohani et al. 2020a; Thompson et al. 2020). We did not use hydrological models or monitoring data to assess its accuracy as others have done with the SVI (Lee et al. 2018; Yasarer et al. 2020; Lohani et al. 2020b), due to the extensive spatial coverage of our output. However, once high-risk areas are

Table 1

Soil vulnerability index (SVI) criteria for surface runoff potential and leaching potential (adapted from Thompson et al. [2020]).

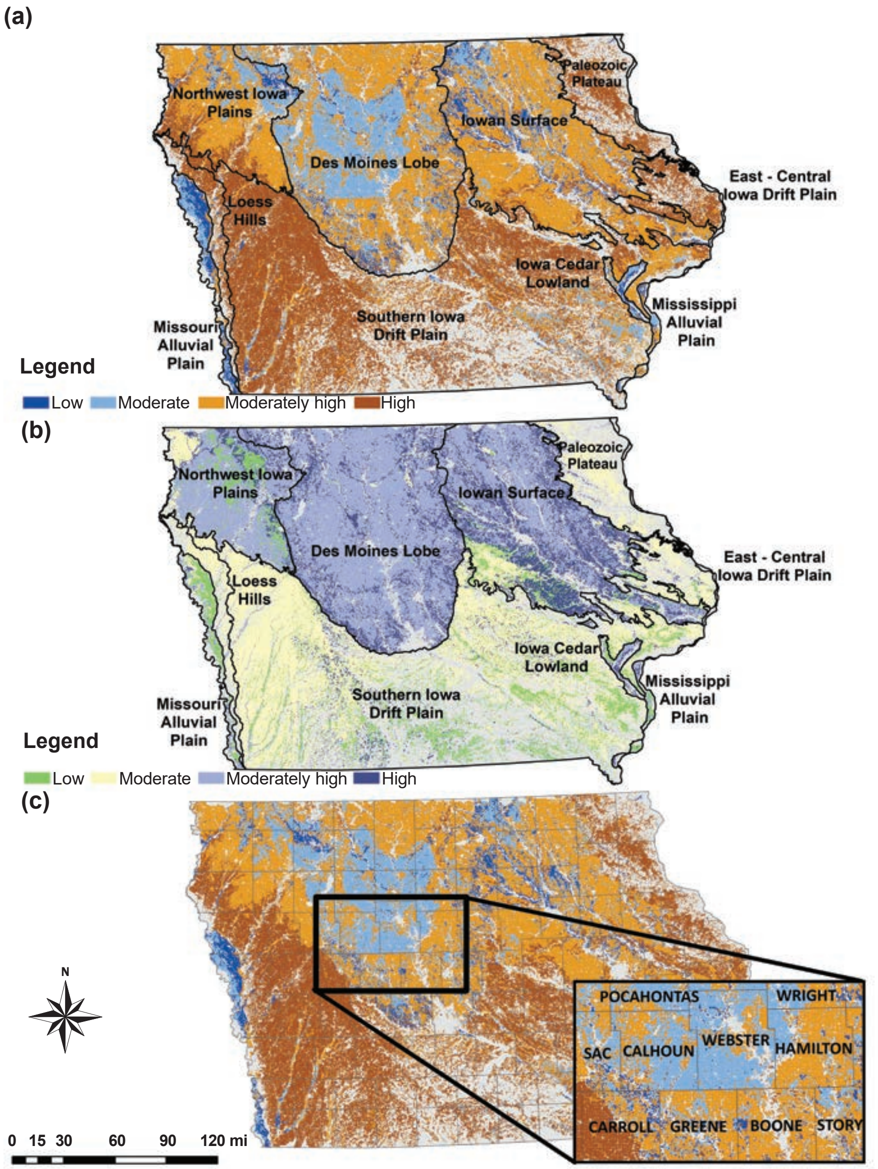
	Hydrologic soil group			
Runoff/leaching	**A**	**B**	**C**	**D**
Soil runoff potential				
Low	All area	Slope < 4	Slope < 2	Slope < 2; K-factor < 0.28
Moderate	None	4 ≤ slope ≤ 6; K-factor < 0.32	2 ≤ slope ≤ 6; K-factor < 0.28	Slope < 2; K-factor ≥ 0.28
Moderately high	None	4 ≤ slope ≤ 6; K-factor ≥ 0.32	2 ≤ slope ≤ 6; K-factor ≥ 0.28	2 ≤ slope ≤ 4
High	None	Slope > 6	Slope > 6	Slope > 4
Soil leaching potential*				
Low	All area	None	None	All except organic soils
Moderate	None or slope > 12	Slope ≤ 12 and K-factor ≥ 0.24	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

Note: All slopes measured as percentage.

*Coarse fragments (stones and rocks) in the soil make it easier for water to infiltrate rather than run off. 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 increase 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.

Figure 1

(a) Dominant soil runoff potential, and (b) dominant soil leaching potential in Iowa, United States, with landforms delineated (Prior 1991), as well as (c) an illustration of inconsistencies in dominant soil runoff potential among Iowa counties.



identified through the SVI, runoff and leaching potential can be verified through monitoring data or hydrologic models and combined with field-based knowledge and imagery to determine placement of conservation practices.

SOIL VULNERABILITY INDEX CLASSIFICATIONS IN IOWA

For both soil runoff and leaching potential, approximately 86% of agricultural fields in Iowa had a dominant soil class that represented greater than 50% of the field (figure 1). Processing the data to create SVI outputs for Iowa took roughly a week to complete at the field level. Post-processing and aggregation of the data to the HUC12 and HUC8 level took approximately another week to complete. These data are freely available for use and may be downloaded from the Iowa State University GIS Facility's ACPF project page (https://www.gis.iastate.edu/gisf/projects/acpf).

Using the dominant soil class, 76% of row crop fields (7.724689×10^6 ha [1.908812×10^7 ac]) were classified as having either high or moderately high soil runoff potential, while the remaining 24% were classified as having either moderate or low soil runoff potential (table 2). At the HUC8 and HUC12 level, over 85% of the watersheds were classified as having high or moderately high soil runoff potential, leaving only 15% of the watersheds as moderate or low (table 2 and figure 2). In terms of soil leaching potential, only 50% of row crop fields (5.541369×10^6 ha [1.369302×10^7 ac]) were classified as either high or moderately high, while the other 50% were classified as either moderate or low (table 2). At the HUC8 level, only 34% of watersheds were classified as high or moderately high soil leaching potential, and at the HUC12 level 45% were classified as high or moderately high (table 2; figure 2). Using the most limiting soil class, 92% (9.628479×10^6 ha [2.379249×10^7 ac]) of row crop fields were classified as having either high or moderately high soil runoff potential, leaving only 8% of fields classified as either moderate or low (table 2). At the HUC8 and HUC12 level, over 95% of watersheds were classified as either high or moderately high soil runoff potential, with very few classified as moderate or low (table 2). In terms of soil leaching potential, 79% of row crop fields (8.523451×10^6 ha [2.106191×10^7 ac]) were categorized as high or moderately high, while 21% were either moderate or low (table 2). Soil leaching potential at the HUC8 and HUC12 level was high or moderately high for over 85% of watersheds, while only 15% of the watersheds were classified as moderate or low (table 2).

In areas with steeper topography, slope is the main determinant of the SVI soil runoff potential, whereas hydrologic soil group and K-factor are more determinant of the SVI soil runoff potential in areas of relatively low relief (Lohani et al. 2020a). We see this relationship in Iowa, where the majority of agricultural fields categorized as having high or moderately high soil runoff potential are found in landscapes characterized by generally higher relief and more erodible soils, such as the Loess Hills, Paleozoic Plateau, and Southern Iowa Drift Plain regions of Iowa. Conversely, in the relatively smooth tilled and loamy Des Moines Lobe and Iowan

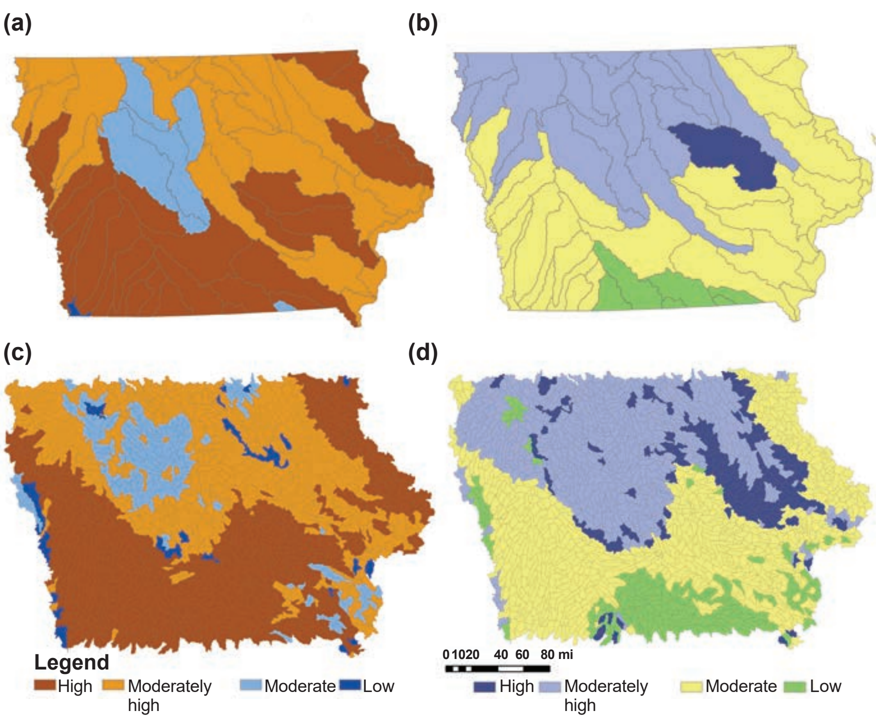
Table 2

Dominant and most limiting soil runoff and leaching potential by field (of 366,636 total), HUC12 (of 1,615 total), HUC8 (of 56 total), hectares, and acres in Iowa, United States, categorized by the Soil Vulnerability Index (SVI).

Runoff/ leaching	SVI category	Fields	HUC12	HUC8	Ha	Ac	% total fields	% total HUC12	% total HUC8
Dominant									
Runoff	High	137,792	761	28	3,526,631	8,714,496	38	47	50
	Moderately high	137,918	640	22	4,198,058	10,373,626	38	40	39
	Moderate	52,263	171	5	1,634,908	4,039,946	14	11	9
	Low	23,840	43	1	638,881	1,578,709	7	3	2
Leaching	High	62,915	185	1	1,665,325	4,115,107	17	11	2
	Moderately high	120,496	551	18	3,876,045	9,577,915	33	34	32
	Moderate	123,174	669	31	3,271,051	8,082,942	34	41	55
	Low	45,218	180	6	1,186,058	2,930,812	12	11	11
Most limiting									
Runoff	High	240,079	1,170	47	6,568,013	16,229,913	65	72	84
	Moderately high	98,976	410	9	3,060,466	7,562,576	27	25	16
	Moderate	11,332	34	0	337,032	832,824	3	2	0
	Low	1,416	1	0	32,967	81,464	<1	<1	0
Leaching	High	232,218	1,279	44	7,012,475	17,328,204	63	79	79
	Moderately high	58,757	143	6	1,510,976	3,733,703	16	9	11
	Moderate	59,080	193	6	1,435,437	3,547,041	16	11	11
	Low	1,748	0	0	39,590	97,828	<1	0	0

Figure 2

(a and c) Dominant soil runoff potential and (b and d) dominant soil leaching potential at the (a and b) HUC8 and (c and d) HUC12 level.



Surface regions, there is a large number of fields categorized as moderate and low soil runoff potential.

Soil leaching potential also follows expected patterns that vary with soils. Fields with a higher leaching potential are found in areas where soils are coarser, and lower leaching potential in areas where soils are finer and denser (Huddleston 1996). Lohani et al. (2020a) determined that the SVI soil leaching potential is more greatly affected by hydrologic soil group than slope. This is likely because hydrologic soil group reflects a soil's ability to infiltrate water (USDA NRCS 2007). We would expect hydrologic soil groups that have a high infiltration rate (low runoff potential) and coarser soils to have a higher leaching potential, and soil groups with a low infiltration rate (high runoff potential) and finer soils to have low leaching potential (USDA NRCS 2007). Our maps show this relationship, as regions dominated by highly erodible loess and clay such as the Loess Hills, Paleozoic Plateau, and Southern Iowa Drift Plain are characterized by moderate and low soil leaching potential (figure 1). Regions in Iowa that are flat to undulating and have more loamy or tilled soils, such as the Des Moines Lobe and Iowan Surface, are characterized by high and moderately high soil leaching potential (figure 1).

USING THE SOIL VULNERABILITY INDEX FOR TARGETED CONSERVATION: AN IOWA CASE STUDY

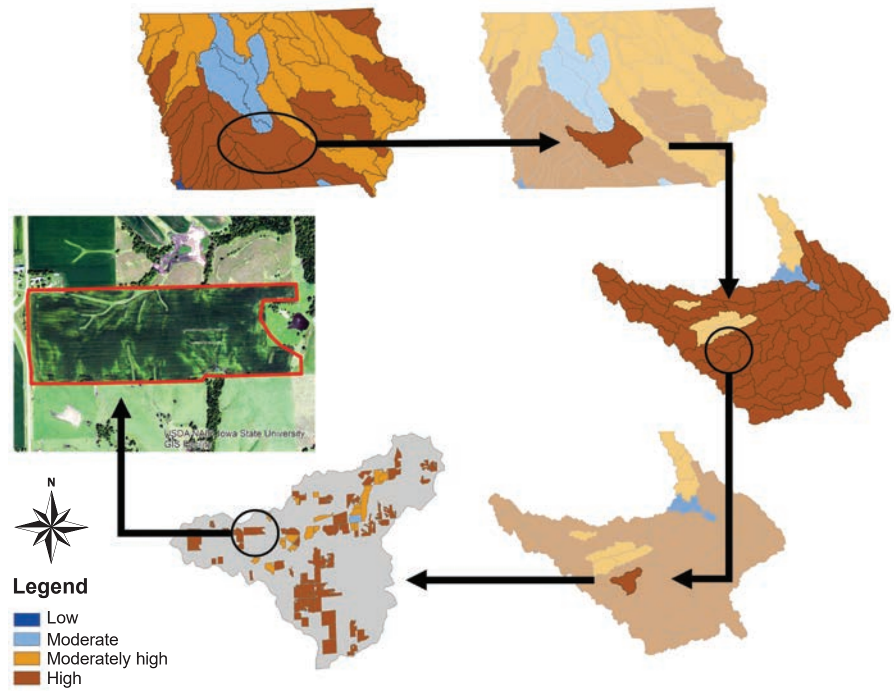
Here we present a method to estimate the SVI at the state level, encompassing over 1,600 HUC12 watersheds and hundreds of thousands of fields in which decisions to target conservation can be more easily made. The SVI has not yet been used across agricultural fields at a state level. Therefore, the data we present are novel and will be valuable to conservation planning at multiple spatial scales in Iowa. Because Iowa is at the crux of national water quality issues (i.e., Gulf hypoxia [Schilling et al. 2020; Jones et al. 2018]), these data will be essential to meeting state and national water quality goals by more cost effectively focusing conservation efforts.

Over 85% of HUC8 and HUC12 watersheds in Iowa were categorized as having either high or moderately high soil runoff potential. Iowa devotes roughly 10 million ha (25 million ac; 70%) of land to row crop agriculture (USDA NASS 2019), and most of that cropland lies within those high and moderately high runoff risk watersheds. Soil leaching potential was high and moderately high in only 50% of HUC8 and HUC12 watersheds. Still, most of the land in those watersheds is also devoted to row crop agriculture. Thus, the areas of Iowa most vulnerable to soil runoff and leaching are dominated by cropping systems that rely on soil health to support Iowa's agricultural economy. This reveals the need for targeted conservation and potential conservation opportunities across Iowa.

To illustrate those opportunities and the utility of our data in guiding conservation and conservation-related research, we identified a HUC8 (07100008) watershed in Iowa with high runoff potential in which to demonstrate how the SVI can be used to target conservation practices (figure 3). Once the HUC8 was selected, all HUC12 watersheds with high runoff potential were identified. We then chose one HUC12 (071000080504) with high runoff potential in which individual agricultural fields with defined runoff potential could be further investigated. We found 65 row crop fields (1,447 ha) out of 85 in the chosen HUC12 (071000080504) watershed classified as having high soil runoff potential (figure 3). These fields would be high priority candidates for managing resource concerns related to soil and water conservation.

Figure 3

An illustration of how Soil Vulnerability Index (SVI) data can be used across HUC8 and HUC12 watersheds as well as individual fields in Iowa, United States.



Best management practices such as prairie strips could be placed within these fields to reduce soil and nutrient loss while also enhancing other ecosystem services (i.e., pollination, wildlife habitat, biodiversity) and maintaining crop yields (Schulte et al. 2017). Research has shown that replacing as little as 10% of row crop land in a given catchment with contour prairie strips can reduce sediment loss by 95%, total P loss by 90%, and total N loss by 84% (Helmers et al. 2012; Zhou et al. 2014). If 10% of the row cropped land in each of the 65 fields in this HUC12 was replaced with prairie strips, a total of 144.7 ha (357.6 ac) would be converted. Within the HUC12 (071000080504), we identified a single agricultural field to investigate further (figure 3). This field is 46.5 ha (114.9 ac) of corn/soybean rotation with silty clay loam soils in hydrologic groups C and D. The slopes range from 0% to 14%; however, the majority of the field is characterized by slopes between 0% and 5%. The combination of soil groups with slow infiltration rates and moderate to steep slopes in some areas likely resulted in this field being classified as having high runoff potential. Therefore, conservation practices such as prairie strips, grass waterways, or sediment control basins placed in steeper areas would keep the soil in place and reduce soil runoff.

CONCLUSIONS

There are a variety of tools used to target conservation efforts such as ACPF, SWAT, and Agricultural Policy/Environmental eXtender (APEX). These tools have been used by scientists to understand the effects of strategic land management on hydrologic processes. Zimmerman et al. (2019b) used ACPF to target conservation in a small watershed in Iowa and found that targeting BMPs in fields with higher N loss and opportunity costs was an effective way to meet water quality goals. Tuppad et al. (2010) used SWAT to target BMPs in HUC12 watersheds within the Smoky Hill River watershed in Kansas either at random or based on annual average sediment yield. Tuppad et al. (2010) found that a targeted approach was more effective at reducing nutrient and sediment loading throughout the watershed. Mudgal et al. (2012) used APEX to develop physically based indices for delineating critical management areas within a 34 ha (84 ac) field, and tested the effect of four land management scenarios on surface runoff, as well as on sediment and atrazine loads. Mudgal et al. (2012) found that targeting critical management areas was effective at reducing atrazine loads and could have economic benefits as well.

Although all three of these tools are useful for targeting conservation, they are all limited in their spatial application as they involve complex analyses that require significant resources that are difficult to obtain at state, county, or local resource management levels (Thompson et al. 2020; Chan et al. 2017). An alternative to these tools is the SVI, which can be applied with basic knowledge of ArcGIS and open source data, increasing its accessibility and utility in guiding conservation. Since its development, the SVI has been used to validate and compare other indices and water quality metrics (Chan et al. 2017; Baffaut et al. 2020a; Lohani et al. 2020a; Lohani et al. 2020b), and will be used to streamline the assessment of conservation needs and delivery services in the NRCS Conservation Assessment and Ranking Tool (CART) (Baffaut et al. 2020b). Beyond published literature discussing the SVI's development, improvement, and validation, there have yet to be any studies that demonstrate and test its ability to target conservation.

Overall, we demonstrated SVI methodology for categorizing the vulnerability of Iowa agricultural fields to soil runoff and leaching. SVI data can efficiently and effectively guide soil and water conservation efforts at field, HUC12, HUC8, or statewide level. SVI results should be used to prioritize which watersheds and fields might benefit from conservation efforts, not to target specific placement of practices. More work that validates the ability of SVI results to prioritize watersheds and fields and subsequently improve water and soil health might be beneficial for assessing its effectiveness, but will not change SVI inputs or results. While others have used SVI toward similar outcomes, this is the first time the index has been presented over such a broad spatial extent. Under a targeted conservation framework, these data can be used to help protect soil and water in Iowa and beyond. Our methodology can, furthermore, be applied to any state or region to help protect waterbodies and communities.

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