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Modification of the Soil Vulnerability Index to account for increased erosion risk from winter precipitation in the southern United States

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Abstract: The Soil Vulnerability Index for Cultivated Cropland (SVI-cc) developed by the USDA Natural Resources Conservation Service uses Soil Survey Geographic (SSURGO) soil properties to classify cultivated cropland into four levels of vulnerability to sediment and nutrient losses: Low, Moderate, Moderately High, and High. SVI-cc includes multiple components, including the runoff component, which is based on the risk of sediment from cropland being discharged into streams. Prior evaluation across 13 watersheds showed that SVI worked well. However, there was interest in determining how precipitation characteristics may influence vulnerability. The objective of this research was to evaluate the effects of rainfall seasonal characteristics on the runoff component of SVI and propose improvements to the SVI vulnerability classification, if needed. The study simulated sediment yields using calibrated models developed with the Soil and Water Assessment Tool for three Conservation Effects Assessment Project (CEAP) watersheds in Missouri, Ohio, and Pennsylvania. Sediment yields from cropland were simulated using 1985 to 2014 precipitation data from 11 CEAP watersheds spanning Vermont in the North to Texas, Georgia, and Mississippi in the South. The relationships between sediment loss and rainfall erosivity were inconclusive. However, the relationships between sediment loss and rainfall amounts showed that the risks of sediment discharge into streams increase or decrease depending on winter precipitation amounts and that this effect is more pronounced for steeper land. We propose to modify the SVI classification ruleset by increasing vulnerability by one class in regions with similar winter and summer precipitation amounts, which is characterized by low correlation ($r^2 < 0.5$) between monthly precipitation and erosivity. Doing so would alert conservation managers and landowners to the need for conservation practices that protect against winter erosion such as cover crops, a winter cash crop, appropriate residue management, and careful winter grazing, in addition to practices that are useful all year round such as terraces, grass waterways, and conservation rotations.

Key words: CEAP—precipitation—rainfall erosivity—sediment loss—Soil Vulnerability Index—winter

Effective management of agricultural landscapes is essential to combat the detrimental impacts of sediment-laden runoff, which substantially degrade water quality and ecosystem health (Yasarer et al. 2020). The assessment of critical source areas, where nutrient or sediment losses are most pronounced, is a fundamental step in designing and locating conservation efforts that minimize the impact of agricultural runoff (Ghebremichael et al. 2013; Liu et al. 2016; Babaei et al. 2019). In this context, the Soil Vulnerability Index for Cultivated Cropland, Version 3.0 (SVI-cc, hereafter designated as "SVI") (USDA NRCS 2021), a GIS-based tool developed by the USDA Natural Resources Conservation Service (NRCS), has emerged as a valuable tool due to its simplicity, ease of use, and ability to provide quick insights into soil vulnerability (Chan et al. 2017; Thompson et al. 2020; Lee et al. 2023).

The SVI evaluates the risk to stream water quality from soil erosion on cropland and subsequent sediment and nutrient transport by water. It provides a standardized approach for assessing the inherent susceptibility of soils to soil erosion and nutrient loss (Lee et al. 2018; Thompson et al. 2020). By considering slope, hydrologic soil group, and soil erodibility, the SVI classifies landscapes into four vulnerability classes: Low, Moderate, Moderately High, and High (Thompson et al. 2020). Vulnerability classes and the SVI ruleset were defined based on simulated average annual sediment losses without any conservation practices at thousands of National Resources Inventory points (Thompson et al. 2020). Nutrient thresholds were defined afterward. This classification system highlights the hydrologically sensitive areas and critical source areas, where soil erosion and nutrient runoff are most likely to occur, helping decision-makers prioritize interventions (Baffaut et al. 2020; Yasarer et al. 2020). The USDA NRCS uses the SVI to assign a Conservation Effects Assessment Project (CEAP) Conservation Benefit Index (CCBI) (USDA NRCS 2021) baseline, which assumes no conservation practice. When combined with the number of Avoid, Control, and/or Trap (ACT) conservation practices implemented in a field, the SVI

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is used to assess what priority to assign to conservation efforts given what is already in place (USDA NRCS 2021). Rainfall is not directly considered in this process.

The SVI considers the rainfall erosivity by limiting its applicability to regions where the annual value of the Universal Soil Loss Equation (USLE) R-factor (annual erosivity) is greater than 250 (measured in English unit of [hundreds ft-tn] in ac^{-1} hr^{-1} yr^{-1}) (USDA NRCS 2021). However, by not considering the seasonality of rainfall amount and erosivity, the SVI oversimplifies the complex interactions between precipitation characteristics and soil erosion processes (Phung et al. 2023). As different geographic regions experience varied precipitation patterns, intensities, and frequencies, these variations can have notable influences on the erosive potential of soils. Phung et al. (2023) found that varied precipitation amounts and intensities relative to six different physiographic and hydrologic sites increased or decreased soil loss risk, which is also influenced by field slope and precipitation seasonality. The most pronounced impact stemmed from differences in maximum 30-minute rainfall among the regions. Not accounting for the influence of precipitation characteristics on soil vulnerability may undermine the accuracy of the SVI and hamper its utility in guiding effective conservation measures.

Therefore, this research aims to evaluate and address this critical limitation in the SVI's ruleset using measured and modeled data. Specifically, our goals were (1) to determine if the SVI ruleset needs adjustment as a function of precipitation seasonal characteristics, and (2) to propose an adjustment to the SVI ruleset that incorporates precipitation seasonal characteristics as a determinant of soil vulnerability. By investigating the interaction between precipitation patterns and soil loss potential, we seek to enhance the SVI's ability to provide reliable assessments of soil vulnerability across a broad range of cultivated agricultural landscapes.

Materials and Methods

Figure 1 provides a graphical representation of our methodology. To determine whether the SVI ruleset needs adjustment as a function of precipitation seasonal characteristics, we focused on sediment yield, which is the main indicator variable used to define the vulnerability classes of the SVI (Thompson et al. 2020; USDA NRCS 2021). We modeled sediment yields from the cropland units of three watersheds (figure 2), each simulated under eleven 1985 to 2014 precipitation data sets. Each of the three watersheds has a previously calibrated and validated model that simulates daily sediment yield using local precipitation. Precipitation data sets were gathered from five CEAP (Duriancik et al. 2008; Baffaut et al. 2021) watershed sites and from National Oceanic and Atmospheric Administration (NOAA) stations (supplemental table S1). For this study, we defined soil vulnerability as the sensitivity of sediment yield to either precipitation amount or rainfall erosivity (the R-factor of the Revised Universal Soil Loss Equation 2 [RUSLE2]) (USDA ARS 2013), that is, the regression slope between sediment yield and precipitation amount or R-factor. We regressed average annual monthly sediment yield against both average annual monthly precipitation and average annual monthly R-factor, by season—summer (April through September) representing periods with significant ground cover, and winter (October through March) indicating seasons with less ground cover, and by region. We then statistically compared the regression slopes to determine whether the risk of erosion was greater in certain regions and for certain seasons.

The 72 km² Goodwater Creek Experimental Watershed (GCEW) is in northeast Missouri; it is a headwater watershed in the Mark Twain Lake/Salt River Basin. The watershed has predominantly poorly drained claypan soils (hydrologic soil group D), which have characteristically high soil runoff potential. Land use includes crop-

Figure 1
Methodology flow chart.

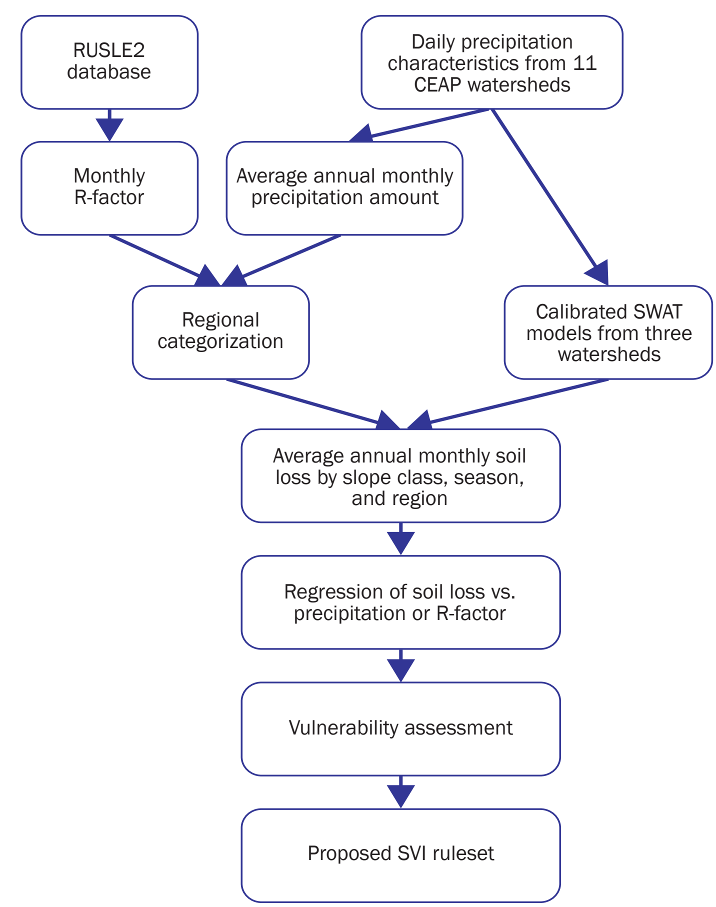
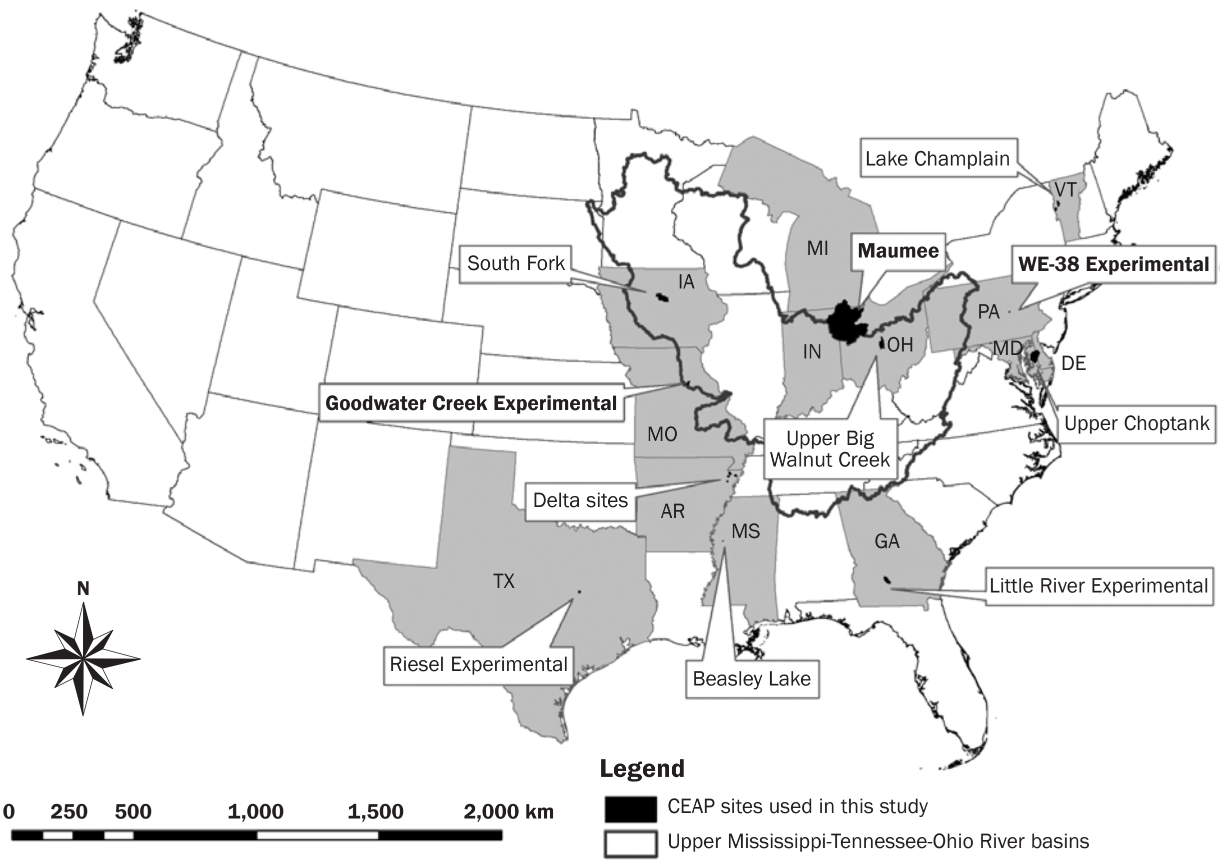


Figure 2

Continental map of the United States indicating the individual CEAP watershed locations included for precipitation characteristics in this study. Bolded names (Goodwater Creek Experimental Watershed, Missouri; Maumee River watershed, Ohio; and WE-38 Experimental watershed, Pennsylvania) represent the sites having calibrated SWAT models used for simulating sediment yield.



land (72%), pasture (16%), woodland (8%), and developed area (4%) (Lerch et al. 2008) with cropland mostly located on land with <4% slope. The dominant cropping system is a corn (*Zea mays* L.)–soybean (*Glycine max* [L.] Merr.) rotation.

The 7 km^2 WE-38 Experimental Watershed located in east-central Pennsylvania is characterized by steep slopes (>6%). Land use includes cropland (55%), woodland (40%), pasture (3%), and developed area (2%). Cropping systems vary by farm operators; most rotate corn and soybeans with other crops, including small grains and, for dairy operations, alfalfa (*Medicago sativa* L.; mixed alfalfa-grass). However, continuous corn represents the dominant cropping system. Slopes in the cultivated portions of WE-38 range from 0% to 18%, with a few hillslopes approaching 32% (Bryant et al. 2011).

The Maumee River Basin, which flows into the western basin of Lake Erie, has a drainage area of over 17,000 km^2. The Maumee River Basin is predominantly characterized by agricultural land use (80%). Due to the region's flat terrain and the presence of clay or poorly drained soils, subsurface drainage systems have been extensively implemented throughout the agricultural land (Kast et al. 2021).

Modeling. Our method used existing watershed Soil and Water Assessment Tool (SWAT) models, which others calibrated for the management in place during the time that weather, discharge, and water quality data were collected (Baffaut et al. 2015; Collick et al. 2016; Gildow et al. 2016). For each model, we developed a No-Practice simulation, which included a No-Practice, watershed-specific management scenario applied to all cropland. We also included a No-Growth simulation, which leaves the land under fallow conditions. The purpose of the No-Practice scenario is to estimate sediment yields without any conservation practices applied so that the resulting sediment yields are comparable to those obtained in the original CEAP study that defined the SVI (USDA NRCS 2012; Thompson et al. 2020). This comparability is crucial as it helps guarantee the accuracy and reliability of the models used in this research by producing outputs that can be compared to established benchmarks. This management scenario included the dominant crop rotation in the original watershed model so that it is representative of the local conditions. The CEAP methodology (USDA NRCS 2012) requires a minimum Soil Tillage Intensity Rating (STIR) for the No-Practice scenario. The STIR serves as an indicator of both the type and the extent of soil disturbance attributed to tillage operations where lower STIR values signify less overall soil disruption (Elhakeem and Papanicolaou 2009). In cases where the dominant rotation did not reach the minimum required value, we added tillage operations to reach the STIR threshold. Supplemental table S1 describes the management specified in the No-Practice models. The purpose of the No-Growth simulations is to eliminate the effect that management has on sediment yields.

We ran each model with 11 daily precipitation input data sets from the 11 CEAP sites (figure 2) from 1985 to 2014 (30 years) with 1982 to 1984 for model warmup, with and without growing crops. This approach was designed to evaluate the model results under a consistent set of conditions, varying only in precipitation, to isolate and understand the impact of precipitation variability on sediment yield. Importantly, this methodology does not aim to simulate actual watershed conditions but rather to examine how changes in precipitation influence sediment yield and the extent to which such variability affects the SVI predictions, given that SVI does not incorporate precipitation into its model. Overall, this approach allows for a focused investigation into the sensitivity of SVI predictions of precipitation events. Monthly maximum half-hour precipitations of the SWAT climate input file were adjusted to reflect the precipitation characteristics of each of the 11 precipitation data sets. The adjustment involved modifying the maximum half-hour precipitation (RAINHMX parameter) within the .wgn files of the model, which were taken from the SWAT weather database by selecting the weather station closest to the precipitation gauge. All other input parameters and input variables of the models remained unchanged, including temperature and other weather characteristics. This was necessary to keep planting and harvest operations consistent with temperatures in the watershed. For each slope class of the SVI runoff component (0% to 2%; 2% to 4%; 4% to 6%; and >6%), we calculated spatial and temporal average monthly sediment yields for the watersheds' cropland, which accounted for erosion from runoff and from snowmelt.

Monthly Precipitation and Rainfall Erosivity. We used the 1985 to 2014 gap filled and quality controlled daily precipitation data for Goodwater Creek, Missouri; Beasley Lake, Mississippi; WE-38 watershed, Pennsylvania; Choptank watershed, Maryland; and Little River watershed, Georgia. The precipitation data for the other six sites were downloaded from the NOAA daily data, using the NOAA rain gauge closest to the centroid of the CEAP watershed. The rainfall erosivities (the RUSLE2 R-factors) from all the sites were extracted from the database associated with RUSLE2 (USDA ARS 2013), which provides average annual monthly R-factors for each county. We selected the county that accounts for the largest portion of each CEAP watershed area. It should be noted that the precipitation data used to calculate the R-factor in RUSLE2 ranges from 1960 to 1989, with extensions up to 1999 in certain cases, while the precipitation data for this study spans from 1985 to 2014. For comparison purposes, this study opted for the R-factor values from RUSLE2 as they represent the most current and widely accepted metrics across the United States, including US federal agencies such as USDA NRCS. In addition, the RUSLE2 R-factors calculations exclude events less than 12 mm (0.5 in) and events that have a return period >50 years, while these simulations include all events.

Data Analysis. We evaluated the regressions of average annual monthly runoff and sediment yield with monthly precipitation on one hand, and monthly R-factor on the other. After initial discovery of the resulting data sets, we identified that the annual precipitation distribution had an influence on sediment yield. Two sets of annual precipitation were identified by correlating R-factor with average monthly precipitation. This was used as the criterion to separate all the sites into two sets: one for which there was no correlation between monthly precipitation and monthly R-factor, located in the southern United States (hereafter called "South"), and one for which the coefficient of determination was greater than 0.5 (central and northern United States, hereafter called "North"). We also divided the data into two seasons per year: one season having a growing canopy and good ground cover (summer, April through September) and one with little ground cover (winter, October through March). For each slope class, we calculated regression slopes of average annual monthly sediment yield versus precipitation amount and R-factor for each combination of season and precipitation distribution. The *t*-test was used to determine if these slopes were significantly different using the methodology proposed by Andrade and Estévez-Pérez (2014). Similar slopes would indicate that the environment (seasonal distribution of monthly precipitation and land cover) does not affect the vulnerability. A significantly different slope for at least one of these combinations would indicate that the SVI ruleset could use some adjustment as a function of the environmental conditions (precipitation or R-factor) for at least one set of sites. This analysis was conducted with growing crops and under No-Growth conditions.

Finally, we calculated the average annual and seasonal sediment yield with growing crops obtained with each precipitation data set for each slope class and compared those to the thresholds defined by Phung et al. (2023) for each watershed. The thresholds by Phung et al. (2023) differ slightly from the CEAP SVI thresholds (USDA NRCS 2012, 2021) to account for the fact that SWAT output results cannot directly be compared to the values used for the development of SVI, which are edge-of-field values simulated with the Agricultural Policy Environmental Extender (APEX) (USDA NRCS 2012). The Phung et al. (2023) thresholds were determined using a decision tree method to maximize the match between SVI classification and the classification based on SWAT simulated sediment yields (Phung et al. 2023). The resulting sediment thresholds varied for each calibrated watershed model: 0.8, 4.6, and 10.3 Mg ha^{-1} for GCEW; 3.3, 10.9, and 18.6 Mg ha^{-1} for WE-38; and 5.8, 15.6, and 25.4 Mg ha^{-1} for Maumee. We assigned an SVI classification based on the average annual sediment yield relative to these thresholds for each slope class and for each set of precipitation data sets (North and South).

Results and Discussion

Classification of Data Sets. The regression between average annual monthly R-factor and monthly precipitation shows a different behavior at the sites located in Vermont, Ohio, Maryland, Pennsylvania, Iowa, and Missouri compared to Georgia, Mississippi, Arkansas, and Texas, hereafter referred to as "North" and "South," respectively. Labeling the North and South groups is a convention limited to this article. It refers to the geographic location of these sites relative to the set of 11 sites and does not imply that all sites in the North or South would behave similarly. In the North, greater summer precipitation (April through September) coincides with greater rain intensity and greater R-factor. These sites experience less rainfall-equivalent precipitation amount and intensity in the winter. As a result, the regression between monthly R-factor and precipitation is strong (i.e., $r^2 > 0.5$) (table 1). In the South, summer and winter precipitation amounts are similar (table 2), but summer and winter intensities and R-factors differ. As a result, the strongest correlation between monthly precipitation and monthly R-factor at these southern sites has an r^2 of 0.24. In addition, rain events are more intense in the South than they are in the North for both seasons: winter and summer average R-factors in the South are greater than in the North (table 2). In summary, winter precipitation in the North is less intense than in summer in terms of erosive power; it consists of lighter rainfall events as well as snowfall events. Winter precipitation amounts in the South are similar to summer precipitation, and include large, erosive events.

Vulnerability of Cropland to Precipitation. The average monthly simulated sediment loss showed a more pronounced correlation with average monthly precipitation amounts (tables 3 to 5) than with erosivity, indicated by the monthly R-factors (table 6). Under fallow conditions, the sediment yields were higher of course, and the correlation of sediment yields versus precipitation amounts or R-factors were more pronounced in the summer, but not always in the winter (table 7). Some regression slopes of sediment yield versus R-factors were negative, which did not happen under growing crops. Since SVI was based on sediment yields obtained with growing crops but no conservation practice, we used those conditions to present the analysis and highlight the results under fallow conditions when necessary. Figure 3 shows the simulated average monthly sediment yields as a function of average monthly precipitation amount for the No-Practice scenario in each watershed for the 0% to 2% slope. We show the results for this slope class because it is a common slope class for cropland, and one found in each of the modeled watersheds. Charts for the three other slope classes are shown in supplemental figures S2 to S4.

The results confirm that the erosion risk changes with management and with slope. Sediment yields are greater in both GCEW (corn–soybean rotation) and Maumee (continuous soybean) than they are in WE-38 (continuous corn) for the <2% slope class (figure 3). For slopes >2% (supplemental figures S2 to S4), Maumee (continuous soybean) sees greater sediment yields than WE-38 (continuous corn) or GCEW (corn–soybean). Although multiple factors may explain the results, those are consistent with the good ground protection provided by corn residues contrasted with the poor protection provided by soybean residues, and the enhanced benefit of these residues for greater slopes.

For evaluating the risk of seasonal precipitation in one region relative to other seasons or regions, we want to consider the regression slopes of sediment yield versus precipitation amount and R-factor, and significant differences that exist between them. For each of the watersheds and each slope class, the regression slopes for the summer precipitation data sets were similar whether in the North or the South (e.g., 0.008 and 0.01 for GCEW, <2% slope, respectively) (table 3). However, the regression slopes for the winter southern precipitation data sets (figure 3, dash line) were always significantly greater (p = 0.05) from the slopes of the winter northern data sets (figure 3, dot-dash lines). For GCEW and Maumee, they were also greater than the regression slopes for the summer data sets. Thus, winter precipitation in the South poses a greater risk of erosion and its associated contaminant transport.

This corresponds to previous findings about the accuracy of the SVI in Beasley Lake watershed; the SVI ratings were too low for

Table 1
Regression equations between average annual monthly R-factors and precipitation at the 11 sites considered.

Location	Average annual precipitation (mm)	RUSLE2 R-factor (hundreds ft-tn) in ac^{-1} hr^{-1} yr^{-1}	Regression equation	r^2
Iowa	888	167	$y = 0.269x - 2.183$	0.900
Vermont	1,021	93	$y = 0.234x - 12.09$	0.812
Ohio (UBWC)	1,027	144	$y = 0.431x - 24.75$	0.711
Missouri	999	208	$y = 0.409x - 16.78$	0.666
Pennsylvania	1,119	140	$y = 0.328x - 18.85$	0.627
Ohio (Maumee)	940	129	$y = 0.436x - 23.44$	0.557
Maryland	1,167	188	$y = 0.553x - 37.98$	0.502
Georgia	1,196	380	$y = 0.308x + 1.144$	0.242
Texas	1,180	276	$y = -0.191x + 41.79$	0.136
Mississippi	1,290	410	$y = 0.123x + 20.73$	0.058
Arkansas	1,273	310	$y = -0.0015x + 25.59$	<0.001

Table 2
Average monthly precipitation amounts and R-factor at the North and South sites.

	Summer (April to September)		Winter (October to March)	
Site	Precipitation (mm)	R-factor (hundreds ft-tn) in ac^{-1} hr^{-1} yr^{-1}	Precipitation (mm)	R-factor (hundreds ft-tn) in ac^{-1} hr^{-1} yr^{-1}
North sites (VT, MD, PA, OH, IA, MO)	103	21	68	6
South sites (GA, AR, MS, TX)	100	36	106	21

Notes: VT = Vermont. MD = Maryland. PA = Pennsylvania. OH = Ohio. IA = Iowa. MO = Missouri. GA = Georgia. AR = Arkansas. MS = Mississippi. TX = Texas.

Table 3

Slopes and coefficients of determination for the regression of average monthly No-Practice sediment yields in the Goodwater Creek Experimental Watershed versus average monthly precipitation obtained for different groups of precipitation data sets.

Slope class	North—Winter*	North—Summer	South—Winter	South—Summer
<2% slope				
Slope	0.003	0.008	0.014†	0.010
r^2	0.16	0.17	0.33	0.31
2% to 4% slope				
Slope	0.004	0.015	0.022†	0.014
r^2	0.13	0.19	0.30	0.33
4% to 6% slope				
Slope	0.006	0.028	0.042†	0.030
r^2	0.05	0.18	0.26	0.31

*Summer includes April through September months; winter includes October through March.

†Significantly different from the other slopes.

Table 4

Slopes and coefficients of determination for the regression of average monthly No-Practice sediment yields in the Maumee River watershed versus average monthly precipitation obtained for different groups of precipitation data sets.

Slope class	North—Winter*	North—Summer	South—Winter	South—Summer
<2% slope				
Slope	0.001	0.002	0.016†	0.004
r^2	0.01	0.15	0.43	0.21
2% to 4% slope				
Slope	0.003	0.010	0.056†	0.016
r^2	0.01	0.18	0.39	0.22
>6% slope				
Slope	0.003	0.055	0.304†	0.090
r^2	0.000	0.19	0.35	0.21

*Summer includes April through September months; winter includes October through March.

†Significantly different from the other slopes.

what the data showed in terms of sediment yield and erosion (Lohani et al. 2020; Yasarer et al. 2020). Soil loss data in these regions confirm that sediment yields are greater during the winter than when crops are growing. Kuhnle et al. (1996, 2008) showed greater winter precipitation and runoff in the Goodwin Creek Experimental Watershed in Mississippi with similar fine sediment concentrations, thus resulting in greater winter sediment loads. Harmel et al. (2006) showed large winter sediment loss from the Riesel, Texas, watersheds and concluded that small grains and cover crops are important conservation practices against soil loss in the region. Aryal et al. (2018) and Reba et al. (2020) found greater discharge and losses of suspended sediment, total phosphorus (P), and total nitrogen (N) during the nongrowing season (November to April) than the growing season in the Mississippi Delta region of eastern Arkansas. Along with cover crops, they also mentioned flooding fields in winter for waterfowl and groundwater recharge as a conservation practice that targets winter losses. Reasons for these high winter losses include winter precipitation amounts similar to those in the summer, low ground cover at that time, and winter R-factors only slightly smaller than during the summer (table 2).

Regressions of average annual monthly sediment loss with average annual monthly R-factor were inconclusive. Table 6 shows detailed results for GCEW; results for Maumee and WE-38 were very similar (table 7). Substantial scatter was observed around the regression lines, indicating a weak relationship, with correlation coefficients frequently below 0.1 (table 6). Notably, the regression slopes were negative for the winter months in GCEW, which is contrary to expectation and our understanding of the processes that control erosion and sediment transport by water. There was no significant difference between the regression slopes of any season/region combinations for any of the modeled watersheds. This result was undoubtedly surprising as we expected that the R-factor would be a likely candidate variable because it characterizes rainfall in ways that are relevant to erosion and nutrient losses. Even under fallow conditions, which eliminate the impact of management on soil erosion, there was still substantial scatter, some negative regression slopes, and no significant difference between the regression slopes for different season/region combinations (table 7). A lack of consistency between the 1960 to 1989 rainfall data (and up to 1999 in several cases) used to calculate the RUSLE2 R-factors (USDA ARS 2013) and the 1985 to 2014 precipitation inputs used in this study may explain this unexpected result. Given the changes in precipitation characteristics and seasonality from 1960 to 2014 (Giesling et al. 2022; Tobin et al. 2015; Phung et al. 2022), there may be a discrepancy between the two. Indeed, Dabney et al. (2012) recognized the need to update the R-factors to account for changes in precipitation characteristics. Yet, another explanation may be that R-factor calculations use subdaily data but exclude both small events with depths less than 12 mm (0.5 in) (USDA ARS 2013) and very large events with a return period of 50 years or greater (USDA ARS 2013). It excludes small events because their erosive power is small. It excludes very large events because extreme precipitation would affect the average erosive power of annual rainfall at one site, which is the basis for conservation needs assessment and what the R-factor describes (USDA ARS 2013). The thinking in policy design was that average conditions, not extreme events, should drive the amount of conservation needed in crop fields. If extreme events cause damage, rebuilding the practice may be cheaper than designing for greater than average erosive power. The four precipitation data sets that show poor correlation between precipitation and R-factors

Table 5
Slopes and coefficients of determination for the regression of average monthly No-Practice sediment yields in the WE-38 Experimental watershed versus average monthly precipitation obtained for different groups of precipitation data sets.

Slope class	North—Winter*	North—Summer	South—Winter	South—Summer
<2% slope				
Slope	0.002	0.005	0.005	0.004
r^2	0.54	0.30	0.45	0.34
2% to 4% slope				
Slope	0.008	0.021	0.020	0.020
r^2	0.53	0.33	0.47	0.36
4% to 6% slope				
Slope	0.015	0.043	0.040	0.040
r^2	0.53	0.34	0.46	0.36
>6% slope				
Slope	0.044	0.130	0.105	0.107
r^2	0.56	0.37	0.49	0.36

*Summer includes April through September months; winter includes October through March.

Table 6
Slopes and coefficients of determination for the regression of average monthly No-Practice sediment yields in the Goodwater Creek Experimental Watershed versus average monthly R-factors obtained for different groups of precipitation data sets.

Slope class	North—Winter*	North—Summer	South—Winter	South—Summer
<2% slope				
Slope	−0.015	0.002	−0.007	0.012
r^2	0.09	0.01	0.01	0.09
2% to 4% slope				
Slope	−0.023	0.011	−0.012	0.020
r^2	0.10	0.04	0.02	0.12
4% to 6% slope				
Slope	−0.065	0.028	−0.038	0.044
r^2	0.14	0.07	0.04	0.12

*Summer includes April through September months; winter includes October through March.

are all affected by hurricanes. If the erosivity calculations ignore these events, the correlation between R-factor and precipitation will necessarily be lower or even lost. McGehee et al. show increases in erosivity values of up to 20% when small and extreme events are included compared to erosivity values when those are omitted (McGehee et al. 2022).

Effect of Southern and Northern Precipitation Data Sets on Average Annual Sediment Yields. Figures 4 to 6 show how annual and seasonal monthly sediment yields with growing crops obtained with each precipitation data set for each slope class compare to the thresholds defined by Phung et al. (2023) for each watershed. In the GCEW, SVI classified most cropland (90% of cropland area) in the Moderate vulnerability class despite the low slopes because of the hydrologic group D and the High erodibility of all the cropland soils (Phung et al. 2023). Some cropland was in the Moderately High (10%) and High (<1%) categories. Figure 4 shows that only cropland with less than 2% slope and with northern precipitation data sets met the upper average annual threshold of 4.8 Mg ha^{-1} for the Moderate class defined by Phung et al. (2023). Cropland with <2% slope met the SVI classification for Moderate when northern precipitation data sets were used as inputs, whereas it exceeded the 4.8 Mg ha^{-1} threshold when southern precipitation data sets were applied (figure 4). With southern precipitation, cropland vulnerability is classified as Moderately High; that is, it increased one vulnerability class (figure 4). For cropland with greater slopes, the sediment-based

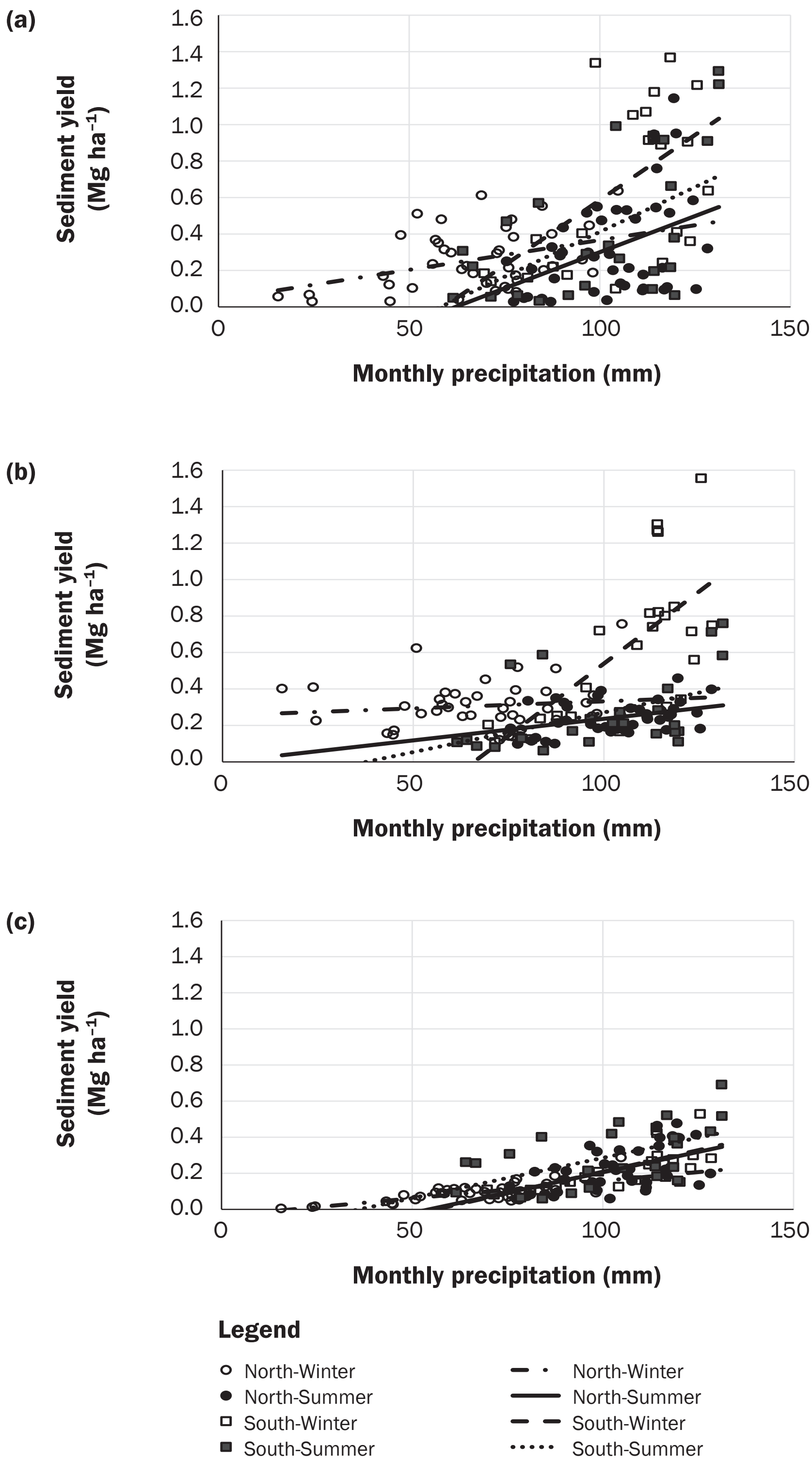
Table 7
Ranges of regression slope and r^2 of sediment versus precipitation amounts and R-factors for the North and South sites, for the No-Practice and fallow scenarios.

	Regression of sediment yield vs. precipitation amount		Regression of sediment yield vs. R-factor	
Site	No-Practice	Fallow	No-Practice	Fallow
GCEW				
Slope	0.003 to 0.042	0.030 to 0.394	−0.065 to 0.044	−0.480 to 0.231
r^2	0.05 to 0.33	0.17 to 0.46	0.006 to 0.144	0.003 to 0.25
Maumee				
Slope	0.001 to 0.304	0.004 to 0.337	−0.082 to 0.250	−0.166 to 0.206
r^2	0.00 to 0.43	0.22 to 0.56	0.00 to 0.06	0.01 to 0.25
WE-38				
Slope	0.002 to 0.130	0.005 to 0.224	0.003 to 0.144	0.006 to 0.280
r^2	0.30 to 0.56	0.47 to 0.80	0.03 to 0.13	0.02 to 0.41

Note: GCEW = Goodwater Creek Experimental Watershed.

Figure 3

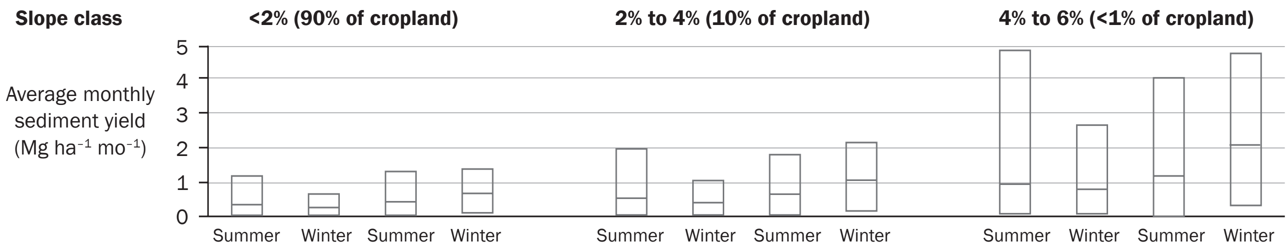
Charts of average monthly sediment yields for a No-Practice management scenario versus average annual monthly precipitation for the 0% to 2% slope class in the (a) Goodwater Creek Experimental Watershed (GCEW), (b) Maumee River watershed (Maumee), and (c) WE-38 Experimental watershed (WE-38). Summer includes April through September months; winter includes October through March.



classification is Moderately High or High. The 2% to 4% slope cropland vulnerability class did not increase, but the average annual sediment yield almost doubled from just above the Low threshold value (5.6 relative to 4.8 Mg ha^{-1} y^{-1}) for Moderately High to just under the upper threshold value (10.1 relative to 10.3 Mg ha^{-1} y^{-1}). The 4% to 6% slope cropland did not increase by one category even though sediment yield doubled, because it was already in the highest vulnerability class.

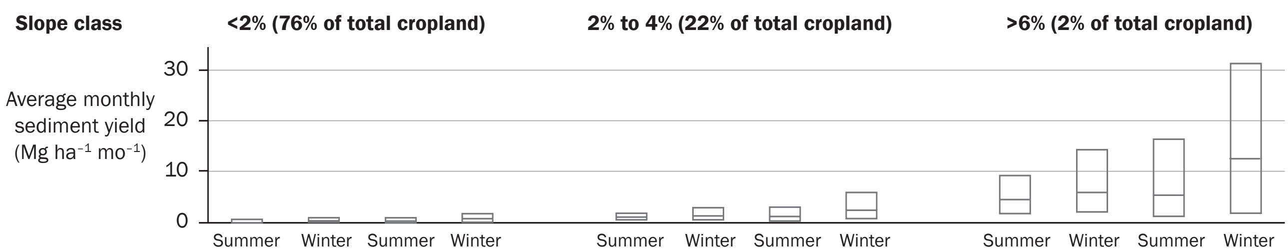
The Maumee River watershed was more complex because slope was not the major factor that affected vulnerability. While SVI classified nearly all (98.98%) cropland with <2% slope in the Low vulnerability class, it also classified some land with greater slopes (including >6%) in the Low vulnerability class because of the hydrologic soil group. Inversely, all the land that SVI classified in the High vulnerability class had slopes >6%. The 2% to 4% cropland increased by one category when the southern precipitation data sets were applied (figure 5). The 0% to 2% slope did not increase in vulnerability class, but the average annual sediment yield obtained with southern precipitation data sets (5.4 Mg ha^{-1} y^{-1}) was very close to the Low/Moderate threshold of 5.8 Mg ha^{-1} y^{-1} for that watershed. Similar results were obtained with the WE-38 watershed model (figure 6). The 2% to 4% and 4% to 6% cropland increased by one vulnerability class, but the 0% to 2% sloped land did not. However, the average annual sediment yield almost doubled for the 0% to 2% land and came very close to the Low/Moderate threshold of 3.3 Mg ha^{-1} y^{-1} for that watershed. In both watersheds, the cropland with slopes >6% did not change vulnerability class because it was already at the highest level under northern precipitation data sets. Given these results, increasing vulnerability by one class in locations characterized by significant rainfall in winter would reflect the need for increased conservation to protect the soil during winter as well as during summer. Conservation practices that address winter conditions include continuous ground cover, which cover crops, winter cash crops (wheat [*Triticum aestivum* L.]), or perennial grass can provide; no-till; avoiding fall tillage if tillage is necessary; and being careful with winter grazing of silage or residues. Of course, other conservation practices that address soil loss

Figure 4
Average (av.) annual monthly and total values of sediment yield for the Goodwater Creek Experimental Watershed, by season and region of the precipitation data sets, classified according to Phung et al. (2023) thresholds of 0.8, 4.8, and 10.3 Mg ha^{-1} y^{-1}, and according to Soil Vulnerability Index (SVI) classification. Each box represents the maximum, mean, and minimum monthly sediment yield.



Geographical group	North	South	North	South	North	South
Av. annual yield (Mg ha^{-1} y^{-1})	3.5	6.5	5.6	10.1	10.4	19.4
Threshold-based SVI	Moderate	Moderately High	Moderately High	Moderately High	High	High
SVI classification for GCEW	Moderate		Moderately High		High	

Figure 5
Average (av.) annual monthly and total values of sediment yield for the Maumee River watershed, by season and region of the precipitation data sets, classified according to the Phung et al. (2023) thresholds of 5.8, 15.6, and 25.4 Mg ha^{-1} y^{-1}, and according to Soil Vulnerability Index (SVI) classification. The 4% to 6% cropland is not featured because this slope class represented a small, nonrepresentative fraction of the cropland. Each box represents the maximum, mean, and minimum monthly sediment yield



Geographical group	North	South	North	South	North	South
Av. annual yield (Mg ha^{-1} y^{-1})	3.3	5.4	12.1	19.7	61.0	106.0
Threshold-based SVI	Low	Low	Moderate	Moderately High	High	High
SVI classification for Maumee	Low		Low (21%), Moderate (72%), Moderately High (7%)		Low (12%), High (88%)	

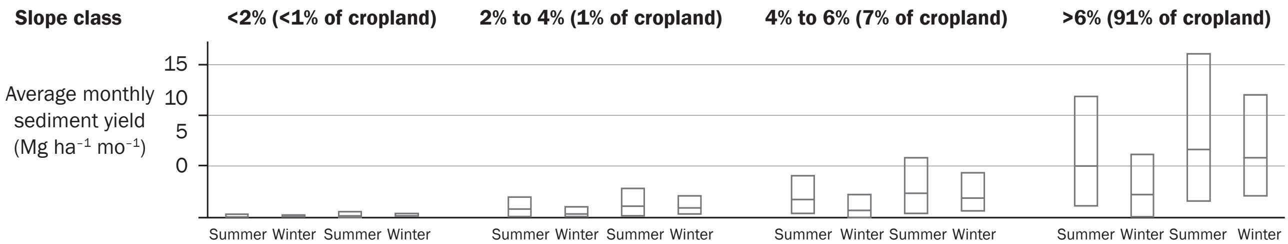
remain useful (grassed waterways, terraces, upland buffers, and others).

Inherent Vulnerability Relationship with Rainfall. These results suggest that the inherent vulnerability (i.e., the ability of cropland to withstand storm events without excessive soil or nutrient losses) does vary with rainfall characteristics and especially with the rainfall winter characteristics. Two land tracks with a similar SVI rating and with the same number of ACT practices, but one located in the North and one in the South, do not have the same conservation requirements and should not have the same priority for conservation investment. Thus, these results contradict the SVI underlying assumption that it is independent of rainfall characteristics.

This might explain why the second CEAP I to CEAP II Comparison report (USDA NRCS 2022) shows that out of all the cropland area that exceeds the threshold of 4.5 Mg ha^{-1}, 40% were receiving >1,143 mm of rainfall (table 8). Out of those, 27% were classified in the Low SVI category, which is defined by a sediment loss under No-Practice scenario of <4.5 Mg ha^{-1}. Clearly, the Low SVI rating is not appropriate for these 27%. Thus, inherent soil vulnerability cannot be totally independent of rainfall. Indeed, high rainfall on land with insufficient ground or canopy cover will start a vicious cycle of erosion, which leads to eroded land that is more vulnerable, more erosion, and ultimately completely eroded land when not addressed with appropriate conservation practices. It is therefore justified to modify the runoff

Figure 6

Average (av.) annual monthly and total values of sediment yield for the WE-38 Experimental watershed, by season and region of the precipitation data sets, classified according to the Phung et al. (2023) thresholds of 3.3, 10.9, and 18.6 Mg ha^{-1} y^{-1}, and according to Soil Vulnerability Index (SVI) classification. Each box represents the maximum, mean, and minimum monthly sediment yield.



Geographical group	North	South	North	South	North	South	North	South
Av. annual yield (Mg ha^{-1} y^{-1})	1.9	3.1	8.0	13.8	16.0	27.5	45.4	76.4
Threshold-based SVI	Low	Low	Moderate	Moderately High	Moderately High	High	High	High
SVI classification for WE-38	Low		Moderately High		Moderately High		High	

Table 8

Cultivated cropland exceeding the sediment threshold by Soil Vulnerability Index (SVI) runoff and rainfall (after USDA NRCS [2022], table 23).

	Average annual rainfall (mm)									
	≤381		>381 to ≤635		>635 to ≤889		>889 to ≤1,143		>1,143	
SVI runoff rating	Area (km^2)	% total area	Area (km^2)	% total area	Area (km^2)	% total area	Area (km^2)	% total area	Area (km^2)	% total area
Low	45	9	503	10	1,397	6	1,652	4	12,915	27
Moderate	244	47	617	12	1,202	5	3,707	9	10,097	21
Moderately High	146	28	816	16	10,142	44	15,221	35	13,808	29
High	85	16	3,187	62	10,536	45	22,358	52	10,418	22
Total area	520		5,124		23,276		42,939		47,238	
% of total	0		4		20		36		40	

component of SVI and increase vulnerability by one class in regions where winter conditions augment the erosion risk. In this study, we have not investigated the two subsurface loss components of the SVI, but there is no reason to think that rainfall would not affect the subsurface movement of contaminants in similar ways (Williams et al. 2018).

Adjustment Outcomes in the Southern Watersheds. The Beasley Lake watershed in Mississippi, Riesel watersheds in Texas, Little River Experimental watershed in Georgia, and the Delta sites in Arkansas are the CEAP watersheds located in these southern states. It is therefore useful to consider the implications of the proposed change in SVI ratings in these watersheds. In Beasley, most of the crop fields had a Low or Moderate vulnerability rating due to slopes less than 2%; however, most of the watershed soils are hydrologic group C or D with high K-factors and high risk of soil loss (Lohani et al. 2020). With the original SVI rating criteria, soils in hydrologic group D would never be ranked above Moderate unless they had slopes higher than 2%, and soils in group C would never be ranked as High without a slope greater than 6%. The proposed change in SVI ranking considering precipitation effects would increase Beasley soil ratings to Moderate or Moderately High, which would better match model-simulated sediment yield results and measured runoff and suspended sediment values from cropland (Yasarer et al. 2020; Locke et al. 2020).

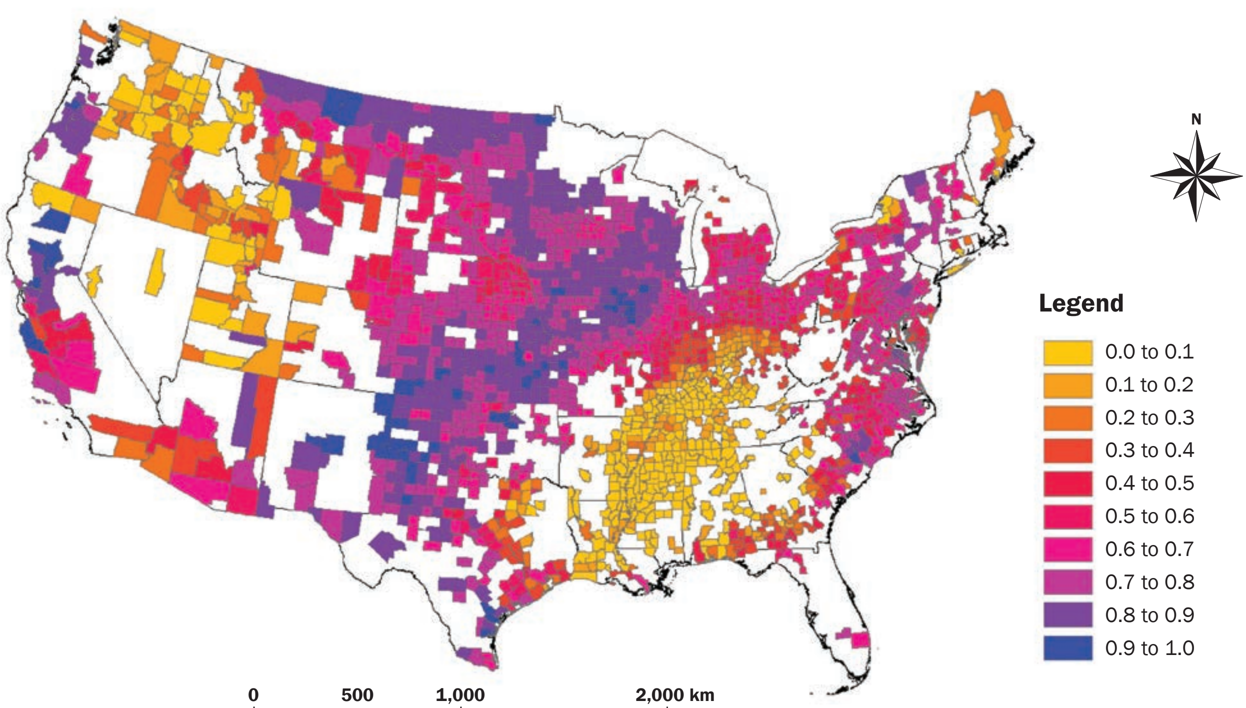
At the Riesel watersheds, many of the fields already had a Moderately High runoff vulnerability rating. Thus, the change would move them into the High category, which is consistent with the average annual sediment yields from 1939 to 1947 under conventional tillage and no conservation practices (36 to 42 Mg ha^{-1}) (Harmel et al. 2006). In the Little River Experimental watershed in Georgia, most of the cropland had a Low runoff vulnerability rating, which would change to a Moderate one. A quarter of the cropland was already in a Moderate category and would switch to a Moderately High rating. Finally, 10% of the watershed had a Moderately High or High rating and would fall in the High category. Those are areas with slopes >2%, erodible soils (soil erodibility >0.28), and C or D hydrologic group; they happen to be close to streams (supplemental figure S5). Settimi et al. (2010) also identified these areas as being at high risk of erosion and water quality degradation, independently of the SVI technology. Whether the rating should be Moderately High or High is difficult to say. The number of implemented practices did not correlate well with the identified risk (Settimi et al. 2010), and other factors (availability of funding, soil health concerns, or subfield concerns, for example) could affect the decision. The reference crop fields used to assess SVI at the Delta sites in Arkansas had a Low or Moderate vulnerability rating (Lohani et al. 2020). The change would increase the vulnerability to Moderate and Moderately High. Thus, one (when classified as Moderate) or two (when classified as Moderately High) ACT conservation practices may be needed to attain an acceptable risk according to the CCBI. No known modeling results exist for these Arkansas sites, and monitoring data include only a few years of data, with most events missed because of equipment malfunction or flooding (Aryal et al. 2018). Thus, they provide unreliable annual sediment yields. However, one site, for which soil erodibility was very high (0.49) for most of the field, had an average event sediment yield of 0.6 Mg ha^{-1} with 14 events being measured over two years and a maximum event load of 128 Mg ha^{-1}. Ongoing monitoring at these sites may provide confirmation or question the increase of vulnerability class.

Regions Where These Conditions Exist. In this limited study, we separated the 11 precipitation data sets based on the correlation between measured average annual monthly precipitation and average monthly R-factor from the RUSLE2 database. This resulted in two groups: data sets with a $r^2 > 0.5$, which were the most northern data sets among the 11 used in the study, and the others, which were all located in the South (table 1). However, these were only 11 specific precipitation data sets, which is not sufficient to define if and where these conditions exist regionally. We asked the CEAP Cropland modeling team to extract from their APEX runs the average annual monthly erosivity calculated by APEX and the 1986 to 2015 average annual monthly rainfall amounts given as input. These runs use the precipitation record at one single station per county (C. Lester, Natural Resources Specialist, NRCS, personal communication). Note that APEX calculates rainfall erosivity in a different way than for the RUSLE2 database (Williams 1995). One major difference is that it includes the events that are <12 mm and those that have a return period >50 years. In addition, APEX uses daily rainfall and cannot calculate a peak rainfall intensity from subdaily data. To remedy this limitation, it uses the average monthly maximum half-hour intensities provided as input to APEX, makes assumptions about the rainfall distribution and the peak rainfall rate during each event, and introduces a random factor (Williams 1995). The spatial distributions of average annual monthly precipitation and erosivity (supplemental figure S1) match the spatial patterns presented by McGehee et al. (2022). From these, we calculated and mapped the coefficients of determination (r^2) between monthly erosivity and monthly precipitation for all the counties covered by the CEAP 2 Survey (USDA NRCS 2022) (figure 7).

Figure 7 and supplemental table S2 show that the r^2 remained high at the seven study

Figure 7

Coefficients of determination between average annual monthly erosivity index calculated by APEX and precipitation for the CEAP National Resources Inventory points, by county.



sites where the correlation was high (r^2 > 0.5; table 1). Additionally, all the sites that showed poor correlation in table 1 still show poor correlation: Turner County in southwest Georgia (r^2 ~ 0), Sunflower County in Mississippi (r^2 = 0.03), Falls County in Texas (r^2 = 0.30), and Mississippi County in Arkansas (r^2 = 0.02). This independent confirmation that precipitation and erosivity are poorly correlated in these areas also defines a greater region where this is happening. This region includes a large area in the southeast, which could be initially defined as the area influenced by storms that originate in the Gulf of Mexico and moved northeast in a corridor along the Mississippi and Tennessee River. Once in Tennessee, the r^2 are again >0.5. Defining a more precise r^2 threshold and identifying the causes of this poor correlation and possible seasonality factors is beyond the scope of this analysis.

Figure 7 also shows an area in the Pacific Northwest with poor correlation between erosivity index and precipitation. Crop production in this region can be rainfed (the Palouse area) but can also be heavily supplemented by irrigation, for example in the Upper Snake/Rock Watershed in southern Idaho for which both the flow regime and the water quality of the Upper Snake River have been heavily influenced by irrigation withdrawals and irrigation returns from irrigated land (Bjorneberg et al. 2008; Lentz and Lehrsch 2010). The risks to stream water quality are therefore different from those caused by agriculture in the eastern half of the United States where rainfall remains the major driver of sediment and nutrient loss. This study did not include watersheds or precipitation data sets from the western United States.

Vulnerability under a Changing Climate. This study demonstrates the importance of rainfall in assessing vulnerability. This has consequences when thinking about vulnerability under changing climate conditions. A drier climate may decrease vulnerability; a wetter one may increase it. However, these results cannot be translated directly to future climate because temperatures and management remained constant in the model. Under future climate conditions, temperatures would likely be higher, and the same crops may not be planted at the same time or in the same place as represented in the model, which might affect sediment loss. However, given the impact of rainfall on vulnerability, there is a need to assess vulnerability under a changing climate so that conservationists, managers, and policymakers have that information when defining vulnerability.

Limitations and Further Studies. In this study, we have a limited number of sites and precipitation data sets. Specifically, we did not have a calibrated model for a watershed located in the South, nor did we have one for a watershed located in the western United States. Given the importance of winter precipitation in the South and the poor correlation between monthly precipitation and erosivity in the West and in a corridor from the Gulf of Mexico to Tennessee, it would be useful to confirm these results with additional model sites.

The results of this study led us to define the South as the region where the coefficient of determination between average annual monthly precipitation and average annual monthly erosivity was <0.5 (figure 7). However, this was defined based on erosivity values extracted from the APEX runs for the CEAP cropland study. APEX uses a different method and uses assumptions about the rainfall distribution and intensity distribution to calculate the rainfall erosivity. There is a need to further define the region characterized as the South, including recalculating R-factors across the United States from modern, observed, and subdaily data; studying the seasonality of the regressions between precipitation and R-factor; and identifying the cause for the poor correlation.

Nutrients, which were not considered in this study, do pose a water quality risk to receiving water bodies, which can be independent from soil erosion. For example, winter nutrient loss when manure is applied on frozen soil is a known source of vulnerability that is specific to winter conditions in the North. The suitability of SVI and the modification we propose has not been evaluated for nutrient losses and remains to be done. Similarly, the determination of a possible modification remains necessary for the leaching component of SVI. However, there is currently no plan to complete such studies.

Finally, as mentioned above, the R-factor values were not calculated with the precipitation data sets we used for sediment loss simulation. Assessing vulnerability with more modern rainfall data and calculating R-factors consistent with these data, and without excluding any events, will clarify the relationship (or lack thereof) between sediment yield and R-factors. A new study has been initiated to accomplish this.

Summary and Conclusions

The objective of this study was to determine if introducing precipitation as a factor in the SVI classification would improve the suitability of the SVI runoff component to categorize the risk of discharging sediment losses from cropland into a receiving stream. We hypothesized that either precipitation amount or the precipitation erosivity (USLE R-factor) were potential rainfall characteristic candidates. Regressions between average annual monthly sediment yield with or without growing crops and monthly R-factors were not statistically different among the various regions and seasons. This was unexpected and additional investigations are needed using modern rainfall data to drive the models and to calculate monthly erosivity. Thus, it was impossible to assert that R-factors would be a useful factor to introduce in the SVI classification ruleset. We did find that winter precipitation amounts significantly affected the risk of sediment loss in regions where winter and summer precipitation were similar. These regions were also characterized by a poor correlation between average annual precipitation amounts and R-factor values. East of the Rocky Mountains, these regions are in the South along the Mississippi River and Ohio River corridor. Increasing SVI vulnerability by one class in this region helps account for the importance of high winter precipitation amounts and greater event intensity. Conservation managers and landowners would be alerted to the need for conservation practices that specifically protect against winter erosion such as cover crops, a winter cash crop, appropriate residue management, and careful winter grazing, in addition to practices that are useful all year round such as terraces, grassed waterways, and conservation crop rotation.

Supplemental Material

The supplementary material for this article is available online at https://doi.org/10.2489/jswc.2024.00088.

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