# Technical Report Documentation Page

| 1. Report No. | 2. Government Accession No. | 3. Recipient's Catalog No. |
|---|---|---|
| agg2.70304 | | |

| 4. Title and Subtitle | 5. Report Date |
|---|---|
| The impact of soil erosion on corn yields: A spatial regression analysis | February 2026 |
| | 6. Performing Organization Code |
| 7. Author(s) | 8. Performing Organization Report No. |
| Le Chen, T. Edward Yu, HannahWilliams | |
| 9. Performing Organization Name and Address | 10. Work Unit No. (TRAIS) |
| Center of Excellence for: Alternative Jet Fuels and Environment<br>The University of Tennessee Knoxville, Knoxville, Tennessee, USA | 11. Contract or Grant No.<br>13-C-AJFE-UTENN-025 |
| 12. Sponsoring Agency Name and Address | 13. Type of Report and Period Covered |
| Federal Aviation Administration<br>Office of Environment and Energy | Journal Article |
| | 14. Sponsoring Agency Code |

15. Supplementary Notes

Chen, L., Yu, T. E., & Williams, H. (2026). The impact of soil erosion on corn yields: A spatial regression analysis. Agrosystems, Geosciences & Environment, 9, e70304. https://doi.org/10.1002/agg2.70304

16. Abstract

This study examines the impact of soil erosion on corn (Zea mays L.) yield across counties in the US Midwest. Using a novel county-level panel dataset that includes information on water erosion and corn yield, we analyze the direct and spatial spillover effects of erosion using a spatial regression framework. We find that increases in soil erosion have a statistically significant negative impact on corn yield. In addition, we find evidence of significant spatial spillover effects, indicating that erosion in one county can adversely affect agricultural productivity in surrounding areas. These findings confirm that the negative effects of soil erosion extend beyond the site of origin and are spatially diffused across regions. This study provides new empirical evidence on the broader yield-related consequences of soil erosion and highlights the importance of landscape-level conservation strategies to mitigate its long-term agricultural impacts.

| 17. Key Words | 18. Distribution Statement |
|---|---|
| ASCENT | This is an open access article under the terms of the Creative Commons Attribution-NonCommercial-NoDerivs License, which permits use and distribution in any medium, provided the original work is properly cited, the use is non-commercial |

| 19. Security Classif. (of this report) | 20. Security Classif. (of this page) | 21. No. of Pages | 22. Price |
|---|---|---|---|
| Unclassified | Unclassified | | |

**Form DOT F 1700.7** (8-72) Reproduction of completed page authorized

Received: 15 July 2025 | Accepted: 22 December 2025

DOI: 10.1002/agg2.70304

Agrosystems, Geosciences & Environment OPEN ACCESS

ORIGINAL ARTICLE

Agrosystems

# The impact of soil erosion on corn yields: A spatial regression analysis

Le Chen[1] | T. Edward Yu[1] | Hannah Williams[2]

[1]Department of Agricultural and Resource Economics, The University of Tennessee Knoxville Institute of Agriculture, Knoxville, Tennessee, USA

[2]Carbon Direct, New York, New York, USA

**Correspondence**
Le Chen, Department of Agricultural and Resource Economics, The University of Tennessee Knoxville Institute of Agriculture, 308B Morgan Hall, 2621 Morgan Circle Drive, Knoxville, TN, USA.
Email: lchen62@utk.edu

Assigned to Associate Editor Xi Zhang.

**Funding information**
US Federal Aviation Administration Office of Environment and Energy; FAA Center of Excellence for Alternative Jet Fuels and the Environment, Grant/Award Number: 13-C-AJFE-UTenn-025

## Abstract

This study examines the impact of soil erosion on corn (*Zea mays* L.) yield across counties in the US Midwest. Using a novel county-level panel dataset that includes information on water erosion and corn yield, we analyze the direct and spatial spillover effects of erosion using a spatial regression framework. We find that increases in soil erosion have a statistically significant negative impact on corn yield. In addition, we find evidence of significant spatial spillover effects, indicating that erosion in one county can adversely affect agricultural productivity in surrounding areas. These findings confirm that the negative effects of soil erosion extend beyond the site of origin and are spatially diffused across regions. This study provides new empirical evidence on the broader yield-related consequences of soil erosion and highlights the importance of landscape-level conservation strategies to mitigate its long-term agricultural impacts.

## Plain Language Summary

Soil erosion can wash away the fertile top layer of soil, making it harder for crops to grow. This study looks at how water erosion affects corn yields in the U.S. Midwest. Using a long-term dataset covering over 500 counties and 25 years, we find that soil erosion not only lowers crop yields in the county where it happens but also affects nearby counties. These findings show that erosion is a shared problem across regions. Better soil conservation efforts that include cooperation between counties could help protect farmland and support long-term crop production.

**Abbreviations:** AIC, Akaike information criterion; BU, bushels; GDD, growing degree days; HDD, harmful degree days; ID, inverse distance; MLE, maximum likelihood estimation; NASS, National Agricultural Statistics Service; NRI, National Resources Inventory; NRCS, Natural Resources Conservation Service; SAR, spatial autoregressive model; SARAR, spatial autoregressive with autoregressive disturbances model; SDM, spatial Durbin model; SEM, spatial error model; USDA, United States Department of Agriculture.

## 1 | INTRODUCTION

Soil erosion has increasingly become a major concern in agricultural sustainability and environmental conservation. It is recognized as one of the most serious environmental challenges affecting global agriculture (Pimentel, 2006). Soil erosion involves the breakdown, detachment, transport, and redistribution of soil particles by forces such as water runoff, wind, or gravity. This widespread phenomenon adversely affects soil productivity in various agricultural ecosystems (Lal & Stewart, 1990; Pimentel, 1993; Pimentel & Kounang, 1998). It is estimated that nearly one-third of the world's cultivable land has been lost to erosion, with the total global productive land loss approximated at 6.7 million ha and an annual productive soil layer loss of 24 million t (DeLong et al., 2015; Komissarov & Ogura, 2020; Pimentel et al., 1995). The economic implications are also severe, with soil erosion costing the US economy approximately $37.6 billion annually due to reduced productivity (Komissarov & Ogura, 2020; Uri & Lewis, 1998; Uri, 2000).

Soil erosion on farmland is of particular concern because it adversely affects on-site crop productivity by reducing the availability of water, nutrients, and organic matter (Pimentel et al., 1987). The removal of the topsoil layer, which is rich in nutrients and organic matter, diminishes the soil's ability to support crop growth. The loss of soil fertility also forces farmers to increase reliance on chemical fertilizers to sustain production, raising input costs and contributing to environmental pollution (Jiang et al., 2020). Additionally, eroded soils often become compacted and less aerated, further restricting root growth and limiting the plant's ability to access essential nutrients and moisture (Al-Kaisi et al., 2002; Lal & Moldenhauer, 1987; Zhao et al., 2012). These factors together reduce crop emergence and plant growth, potentially lowering yields and threatening agricultural productivity and long-term food security (Edwin & Muthu, 2020).

Given the potential impact of soil erosion on agricultural productivity, there is a large literature that has investigated the effects of soil erosion levels on crop yields (see among others, Bakker et al., 2005; Den Biggelaar et al., 2001; De la Rosa et al., 2000; Edwin & Muthu, 2020; Larney et al., 2008; Tan et al., 2005; Zhao et al., 2012). Most previous studies confirmed the negative impacts of soil erosion on land productivity by depleting topsoil, nutrients, and soil structure, with impacts varying based on crop, soil type, and conservation practices. For example, utilizing crop yield and soil erosion data across the United States and Canada, Den Biggelaar et al. (2001) estimated that maize yield losses range from 0.04 to 0.15 Mg $ha^{-1}cm^{-1}$ of topsoil lost and wheat yield losses range from 0.005 to 0.14 Mg $ha^{-1}cm^{-1}$ of topsoil lost, with yield varying by soil type and fertilizer use. Tan et al. (2005) estimated soil nutrient depletion due to soil erosion for nitrogen (N), phosphorus (P), and potassium (K) in major crop production systems (wheat, rice, maize, and barley) for the year 2000. They found that the nutrient deficits could translate into a potential annual total production loss of 1136 Tg per year (1 Tg = 1 billion kg).

Despite the robust literature on the direct effects of soil erosion on agricultural productivity, limited research has explored its spillover impacts on surrounding agricultural fields. Soil erosion is inherently a spatial process, wherein displaced soil, nutrients, and sediments move beyond the eroded site, affecting adjacent farmlands (de Vente et al., 2008; Farhan & Nawaiseh, 2015; Patil & Patil, 2018). Moreover, off-site effects of soil erosion contribute to environmental degradation, such as water pollution and sediment accumulation in rivers, increasing the risk of flooding and reducing water quality (Buntley & Bell, 1976; Pimentel et al., 1987; Uri, 2000). Sediment deposition, changes in nutrient distribution, degrading shared water resources, and land use conversion can create complex interactions across a landscape that traditional yield-impact studies often overlook (Jiang et al., 2020). Last, given the spatially diffuse nature of soil erosion, failing to account for spatial dependence in empirical models can lead to misleading inferences. For example, Yun and Gramig (2022) emphasize that spatial correlation in agricultural data may arise from spatial aggregation of environmental data, unobserved regional characteristics, or biophysical spillovers. When such correlation is ignored, model estimates may be biased or inefficient. Addressing this literature gap is crucial for understanding the cumulative effects of soil erosion on agricultural productivity at a regional scale and designing effective soil conservation policies that consider both direct and indirect effects.

The objective of this study is to fill this gap by addressing the impact of soil erosion on crop yield using spatial statistical analysis, with an emphasis on both direct and spillover effects. We utilize unique county-level data for annual soil loss caused by erosion (in tons/acre) from the National Resources Inventory (NRI) program of the US Department of Agriculture (USDA) Natural Resources Conservation Service (NRCS) and county-level data on corn yield from the USDA National Agricultural Statistics Service (NASS) for the census years 1992, 1997, 2002, 2007, 2012, and 2017. The resulting panel dataset used in the study covers 559 counties over eight states in the US Corn Belt. Based on this panel dataset, we apply a spatial regression approach to analyze the broader influence of soil erosion on crop yield beyond the area where it occurs, considering how erosion-induced changes in soil quality affect neighboring areas.

Our study contributes to the literature in a couple of ways. First, to the best of our knowledge, there has been no study that econometrically examines the spatial spillover effects of soil erosion on corn yields using a spatial regression framework. Existing literature largely investigates the direct impacts of erosion on crop productivity, overlooking how erosion in one area can degrade surrounding farmland and influence broader agricultural landscapes. Our study fills this critical gap by explicitly modeling these interconnections, providing new empirical evidence on how soil degradation extends beyond individual fields and affects regional agricultural output. Our study therefore offers a more comprehensive understanding of how erosion in one location can influence crop productivity in adjacent areas, emphasizing the need for a regional perspective in the development of more effective soil conservation strategies.

Second, using unique county-level soil erosion data combined with the crop yield dataset, this study econometrically evaluates the impact of soil erosion on agricultural productivity over a wider geographical region and over a longer time period compared to the previous literature. Given the geographic scope of the dataset, we are able to investigate the aggregate county-level effects of soil erosion on corn yield in the US major agricultural production region rather than for a specific plots (e.g., as is usually the case for agronomic field trial studies). By examining a larger spatial and temporal scale, our study contributes to the understanding of long-term productivity losses associated with soil erosion.

The rest of this article is organized as follows. Section 2 provides a detailed description of the data sources and our empirical approach. Section 3 provides a detailed discussion of the estimation results. Lastly, implications, limitations, and future research directions are presented in the concluding section.

## 2 | METHODS AND MATERIALS

### 2.1 | Data

The data used in this study are collected from a variety of sources. First, the dependent variable, the average corn yield at the county level, is collected from the USDA-NASS database. The corn yield estimates are derived from farmer surveys and field measurements, providing a comprehensive overview of agricultural productivity across US counties. Specifically, we select the US Corn Belt as the study area. According to the USDA, the Corn Belt is composed of eight Midwestern states: Indiana, Illinois, Iowa, Michigan, Minnesota, Missouri, Ohio, and Wisconsin. The US Midwest is one of the most agriculturally productive regions in the world and "consistently affects the global economy" (U.S. Department of Agriculture, 2024). Additionally, about 80% of all US corn and soybeans (*Glycine max* (L.) Merr.) are produced in the Corn Belt (U.S. Department of Agriculture, Economic Research Service, 2023).

After collecting corn yield data, we then gather information for our main explanatory variable of interest—measures of soil erosion levels. We use the county-level data for annual soil loss caused by erosion (in tons/acre) collected from the NRI program of the USDA NRCS for the census years 1997, 2002, 2007, 2012, and 2017. The NRI program provides comprehensive data on the condition, trends, and status of land, soil, water, and other resources in the United States (Chen et al., 2022; Doetterl et al., 2012; Kertis, 2006; Larson et al., 1983). The soil erosion data from the NRI are collected through a continuous inventory process, with observations recorded annually during the growing season from a selected subset of foundational sample segments originally established in the 1997 NRI. To construct its dataset, the NRI employs a stratified two-stage, unequal probability area sampling design. In this approach, the first-stage sampling units consist of defined land segments, while the second-stage sampling units are specific points within these segments. Nationwide, the foundational sample consists of approximately 300,000 land segments and 800,000 sample points. Data collection relies on remote sensing (primarily through photo interpretation), along with administrative records and field investigations. Additionally, direct on-site measurements of soil characteristics from a subset of locations are also used to validate the remote sensing data.

To assess soil erosion levels, the NRI incorporates several key soil characteristics, such as the universal K-factor (a measure of soil erodibility), the soil loss tolerance rate ($T$), and other indicators of land susceptibility to erosion. These variables are integrated into two well-established erosion models: (1) the universal soil loss equation for water erosion and (2) the wind erosion equation for wind erosion, providing estimates of average annual soil loss. The NRI's methodology represents one of the most comprehensive quantitative efforts to measure both the occurrence and extent of soil erosion across the United States. As a result, it has been widely used in previous research (see among others, Chen et al., 2022; Cruse et al., 2006; Goodwin & Smith, 2003; Hernandez et al., 2013). The dataset primarily distinguishes between two types of erosion: (1) water erosion, which refers to the displacement of soil due to rainfall and surface runoff, and (2) wind erosion, which involves the detachment, transport, and redeposition of soil particles by wind forces. After spatially visualizing both the water erosion rate and wind erosion rate across the United States, we found that wind erosion has a negligible impact in our study area. Due to the prominence of water erosion in the Corn Belt counties, we proceeded with using the county water erosion rate as a measure of soil erosion in this study. Maps of both the wind erosion rate and water erosion rate can be found in Figure 1.

In addition to data on water erosion and corn yields, we also collect the weather data from the parameter-elevation regression on independent slopes model climate dataset. Specifically, we include the number of growing degree days (GDD) (8°C–29°C), harmful degree days (HDD) (above 29°C), precipitation, and a squared precipitation term as

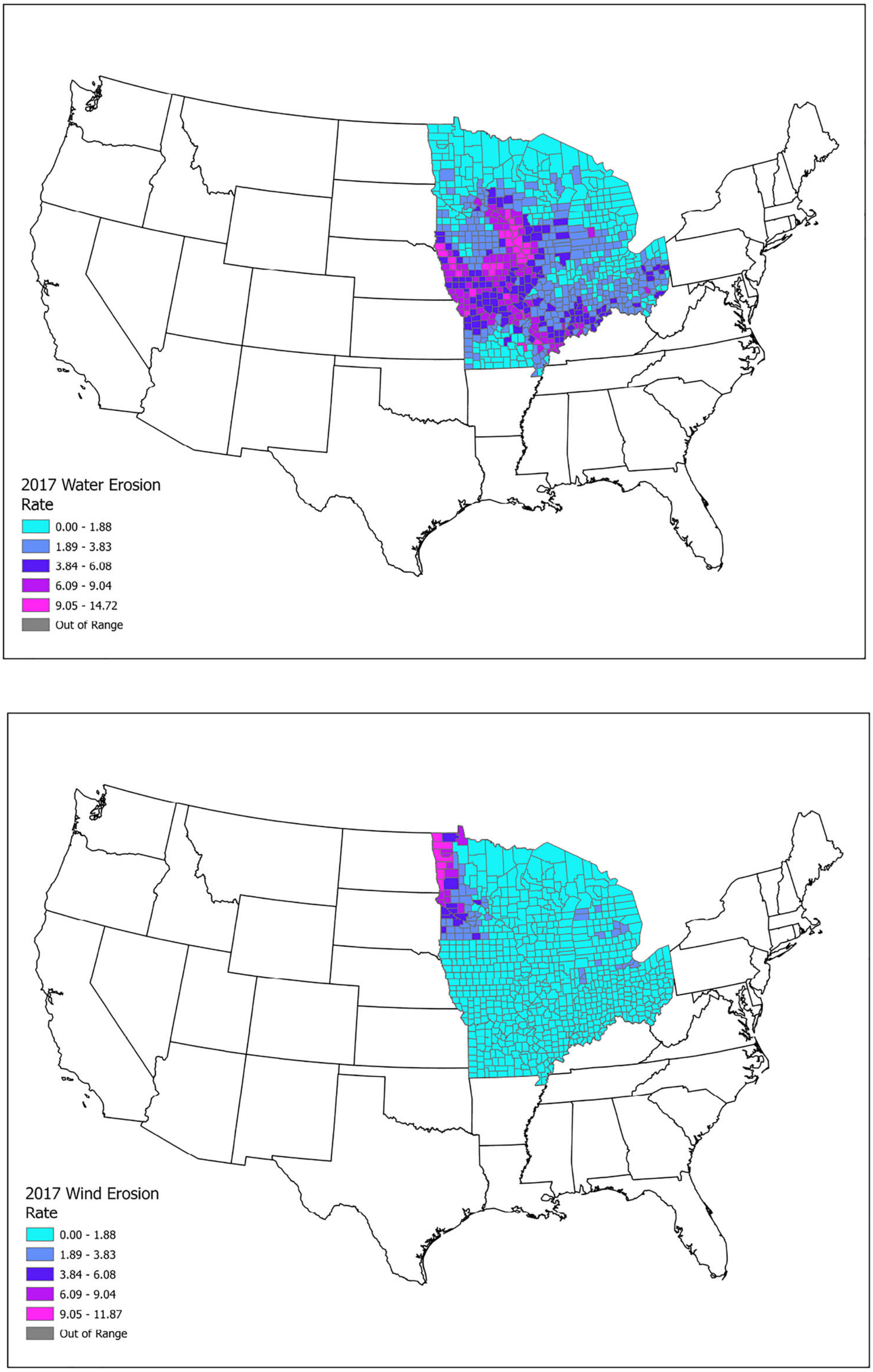


**FIGURE 1** Comparison of 2017 water and wind erosion rate.

control variables in our empirical model specification as these variables can directly affect county-level corn yield and vary over time and across counties. Degree days are typically defined as the number of degrees that the daily temperature is above a specific threshold per day, accumulated over a defined period of time, and have been used in the climate econometrics literature to quantify cumulative temperature exposure within specific thresholds and capture the nonlinear effects of temperature on agricultural outcomes(Annan & Schlenker, 2015; Chen et al., 2022; Ortiz-Bobea, 2021; Schlenker & Roberts, 2006, 2009). Following thresholds established by Schlenker and Roberts (2009), the GDD we use

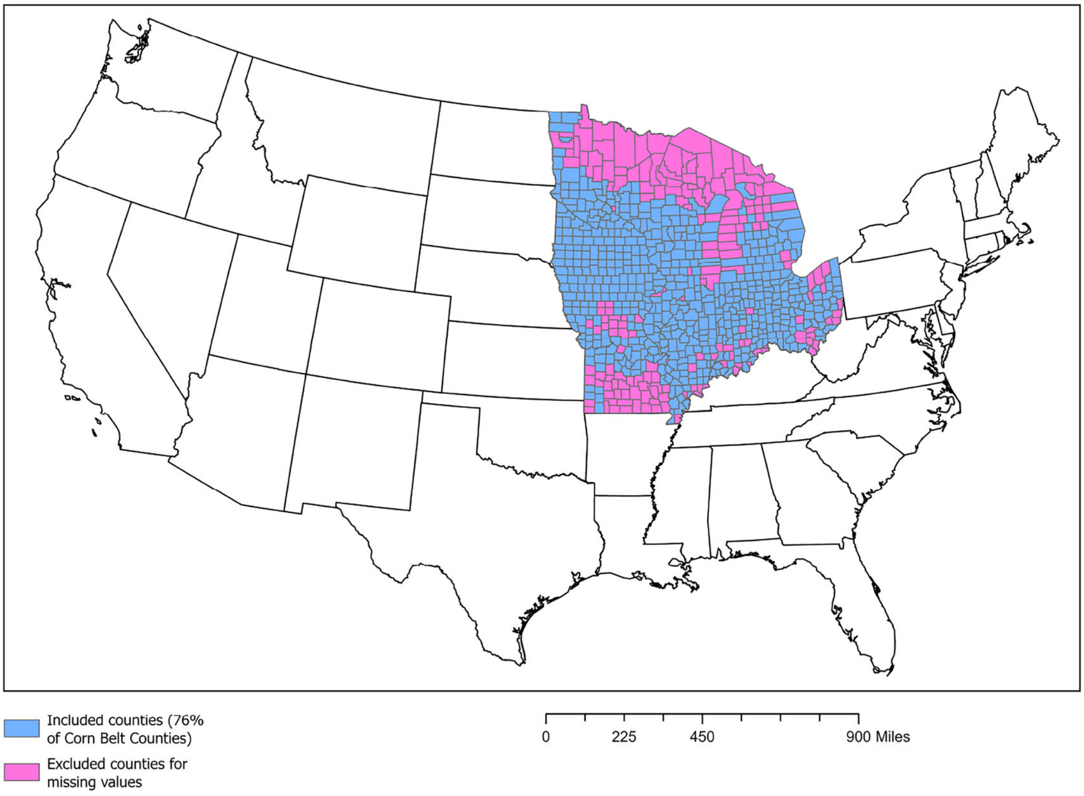


**FIGURE 2** Study area.

are defined as the total degrees by which daily temperature fall within the favorable range for crop growth (8°C–29°C). In contrast, HDD represent temperature exposure that can be harmful (above 29°C) during the same period. Additionally, we include accumulated precipitation and a squared precipitation term to account for potential nonlinear impacts of moisture on crop yield. The degree days and precipitation variables used in this study are aggregated over the months of the growing season from May to September (Schlenker and Roberts, 2009).

To ensure a balanced panel, we exclude counties with missing values of variables of interest from 1992 to 2017 from this analysis. Figure 2 depicts the study area. The sample includes 559 counties per time period (76% of Corn Belt counties), with the total sample across time periods being 3354 observations. Table 1 includes descriptive statistics on the variables of interest for the included counties.

## 2.2 | Geostatistical analysis

We first use the Getis-Ord GI* statistic to identify statistically significant spatial cluster, or spatial autocorrelation, in the water erosion rate variable. This analysis identifies spatial clusters of high values, known as hot spots, and low values, known as cold spots (Esri, 2024). The identification of spatial clustering points to the presence of autocorrelation, which necessitates the control for spatial dependence in the variables of interest by using a spatial regression model. The output creates a feature class including a $z$-score, $p$-value, and confidence interval bins, which can be visualized on a map. These values are used to reject the null hypothesis that the spatial clustering of high or low values present in the data is no different than would be expected in randomly distributed data. Across the time period of the study, the clustering of the water erosion rate is mostly consistent, showing hot spots throughout the Mississippi Delta region and cold spots in the northern reaches of the study area. The example hot spot map for water erosion rate in 2017 is presented in Figure 3.

## 2.3 | Model selection

We then conduct a series of spatial regression models to estimate the impact of soil quality and weather variables on the corn yield in the US Corn Belt. The spatial structure identified through hot spot analysis is conceptualized through a combination of a row-normalized inverse distance (ID) spatial weighting matrix and a row-normalized contiguity spatial weighting matrix. The ID is calculated from the centroid of each spatial unit, in this case, counties. The contiguity matrix is applied to the spatial lags of the variables in the

**TABLE 1** Description and summary statistics of variables.

| Variable | Description | Mean | St. Dev. | Min. | Max. |
|---|---|---|---|---|---|
| Corn yield | County-level total corn yield (BU/acre) | 136.76 | 35.79 | 19.00 | 246.70 |
| Water erosion level | Annual soil loss due to water erosion (tons/acre) | 3.81 | 2.54 | 0.00 | 19.38 |
| GDD | Growing degree days (8°C - 29°C) | 1934.74 | 300.52 | 1074.60 | 2768.00 |
| HDD | Harmful degree days (above 29°C) | 29.51 | 29.13 | 0.12 | 170.21 |
| Prep | Precipitation (growing season average, 1000mm) | 560.29 | 118.66 | 214.53 | 1010.62 |
| Prep_s | Precipitation squared | 328,000.90 | 139,940.40 | 46,021.59 | 1,021,360.00 |

Abbreviations: BU, bushels; Max., maximum; Min., minimum; St. Dev., standard deviation.

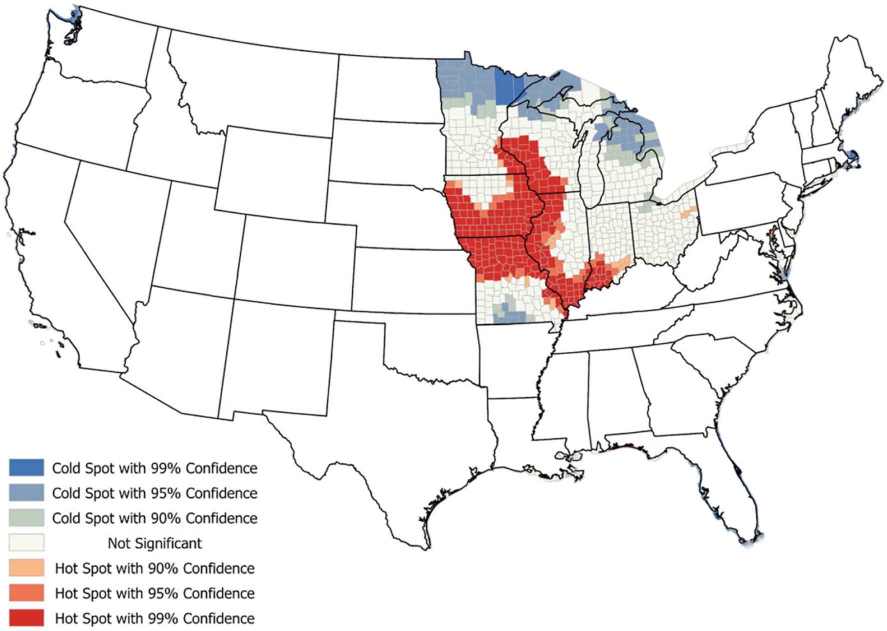


**FIGURE 3** Hot spot map for 2017 water erosion rate.

applicable models. Applying the contiguity matrix to the dependent variables helps the model capture the potential neighboring effects of the omitted socioeconomic variables, such as farming practices, on corn yield (Yun & Gramig, 2022). The ID matrix is applied to spatial lags of the error terms in applicable models, as the measurement errors are spatially correlated. Using different spatial weighting matrices for the variables and the error term is supported by previous work (see among others, Elhorst et al., 2014; Stakhovych & Bijmolt, 2009; Yun & Gramig, 2022).

We use the xsmle package in Stata for model estimation, which was developed for spatial panel regression models. The package uses maximum likelihood estimation (MLE) for several types of spatial models including the spatial Durbin model (SDM), the spatial autoregressive model (SAR), the spatial error model (SEM), and the spatial autoregressive with autoregressive disturbances model (SARAR) (Belotti et al., 2017). Specifically, the SDM incorporates spatial lags of both the dependent and independent variables, allowing for the possibility that both the dependent and explanatory variables in one unit may depend not only on their own values but also on the values in neighboring units. On the other hand, the SAR includes a spatial lag of the dependent variable, accounting for spatial dependence in the outcome variable itself, while the SEM focuses on capturing spatial dependence in the error term, allowing for unobserved factors affecting the dependent variable to exhibit spatial correlation. The SARAR combines both the spatial lag of the dependent variable and spatially autocorrelated error terms.

We first execute the SDM by applying a spatial lag on the dependent and independent variables using the contiguity matrix. Next, we generate the SAR, SARAR, and SEM model types, applying the contiguity matrix on the dependent variable spatial lags (SAR and SARAR) and the ID matrix on the error term spatial lags (SARAR and SEM). The Akaike information criterion (AIC) values of the three alternative models

**TABLE 2** Akaike information criterion (AIC) by model type.

| Model | AIC |
|---|---|
| SAR | 24461.80 |
| SEM | 26807.81 |
| SARAR | 24396.77 |
| SDM | 24400.07 |

Abbreviations: SAR, spatial autoregressive model; SARAR, spatial autoregressive with autoregressive disturbances model; SDM, spatial Durbin model; SEM, spatial error model.

(SAR, SARAR, and SEM) are then compared to the AIC of the SDM model to select the model that balanced both model complexity and goodness of fit.

Table 2 displays the results of the AIC testing outcomes and indicates that the SARAR model performs best when comparing AIC values among all models, that is, the SARAR model has the lowest AIC value. Thus, we proceed with using this model specification which balances both model complexity and good fitness.

## 2.4 | Econometric analysis

To examine the impacts of soil quality and climatic factors on corn yield across the Corn Belt, we employ a SARAR regression model with two-way fixed effects for panel data. This approach accounts for both spatial autocorrelation in the dependent variable and spatial dependence in the error term, leading to robust estimates of the relationships among the variables of interest in the presence of spatial spillovers. Additionally, two-way fixed effects control unobserved heterogeneity across both time and space. We utilize our main empirical specification defined as follows:

$$y_{it} = \rho W y_{it} + \mathbf{X}_{it}\beta + \alpha_i + \delta_t + \epsilon_{it} \tag{1}$$

$$\epsilon_{it} = \lambda \mathbf{W}_H \epsilon_{it} + \mu_{it} \tag{2}$$

In this model, $y_{it}$ denotes the corn yield for county $i$ in year $t$, $\rho W y_{it}$ is the spatial lag term for corn yield where $W$ is the contiguity spatial weight matrix and $\rho$ measures spatial dependence of corn yield. $\mathbf{X}_{it}\beta$ is the matrix of explanatory variables and their coefficients for county $i$ in year $t$, and $\lambda \mathbf{W}_H \epsilon_{it}$ denotes the spatial lag for the error term where $\mathbf{W}_H$ is the ID spatial weight matrix. The spatial fixed effects are represented by $\alpha_i$ for county $i$ and the time fixed effects are represented by $\delta_t$ for year $t$, and $\mu_{it}$ denotes the error term.

As mentioned in the previous section, the independent variables used in the analysis capture climatic, environmental, and soil quality-related factors hypothesized to influence corn yield. Water erosion rate represents a measure of soil quality that could impact agricultural productivity, while HDD and GDD are included to measure cumulative exposure to temperature conditions conducive to or limiting to crop growth. Precipitation and precipitation squared capture the nonlinear effects of rainfall on yield.

We estimate the SARAR two-way fixed effects model using MLE. This estimation approach is well-suited for SARAR models because it accommodates the joint estimation of spatial lag parameters and spatially autocorrelated errors, ensuring efficient and consistent parameter estimates. Unlike two-stage least squares or generalized method of moments (GMM) approaches, which may suffer from inefficiencies in small samples, MLE directly accounts for the structure of the SARAR model and provides robust estimates of both spatial dependence in the dependent variable and error term (LeSage & Pace, 2009). Time fixed effects account for common temporal trends, such as advancements in agricultural technology and efficiency that affect all county corn yields simultaneously. Spatial fixed effects capture time-invariant characteristics specific to each county, such as soil type, historical farming practices, and infrastructure differences. To interpret the estimated coefficients, we calculate direct, indirect, and total effects with the xsmle package, which show how changes in the independent variables affect corn yield in both the focal county and neighboring counties through spatial spillovers.

# 3 | RESULTS AND DISCUSSION

Table 3 summarizes the estimated coefficients of the explanatory variables in Equation (1) and their direct, indirect (i.e., spatial spillover), and total effect. The results indicate that water erosion has a statistically significant and negative effect on corn yield, both within a county and in neighboring counties. The direct effects of water erosion on corn yield generally suggest that counties with higher levels of water erosion tend to have statistically lower corn yield, and this productivity effect is not explained by climate. Specifically, we find that each additional ton per acre of soil loss due to water erosion in a county can lead to a statistically significant decrease of 0.48 BU per acre in its corn yield (where BU is bushels). This finding is consistent with previous literature that have generally discussed the relationship between soil health and crop productivity (Den Biggelaar et al., 2001; Tan et al., 2005). According to these soil and crop yield studies, soil erosion could negatively affect crop yield by depleting topsoil, nutrients, and soil structure. Our study therefore supports the notion of a negative relationship between the major type of soil erosion (i.e., water erosion) and crop yield in the United States.

In addition to the direct effect, there is also a spillover effect of water erosion on corn yield in adjacent coun-

**TABLE 3** Estimated coefficients from the spatial autoregressive with autoregressive disturbances model (SARAR).

| | Corn yield | | | |
|---|---|---|---|---|
| | **Coefficient** | **Direct effect** | **Indirect effect** | **Total effect** |
| Water erosion | −0.3880* | −0.4815* | −1.2175* | −1.6990* |
| | (0.2097) | (0.2537) | (0.6503) | (0.9028) |
| GDD | 0.0023 | 0.0031 | 0.0079 | 0.0110 |
| | (0.0051) | (0.0066) | (0.0166) | (0.0232) |
| HDD | −0.2766*** | −0.3459*** | −0.8726*** | −1.2185*** |
| | (0.0212) | (0.0240) | (0.0610) | (0.0799) |
| Precipitation | 0.0365*** | 0.0471*** | 0.1191*** | 0.1663*** |
| | (0.0125) | (0.0149) | (0.0385) | (0.0533) |
| Precipitation squared | −0.0000** | −0.0000*** | −0.0001*** | −0.0001*** |
| | (0.0000) | (0.0000) | (0.0000) | (0.0000) |
| $\rho$ | 0.7720*** | | | |
| | (0.0606) | | | |
| $\lambda$ | 0.8964*** | | | |
| | (0.0424) | | | |
| County FE | Yes | Yes | Yes | Yes |
| Time FE | Yes | Yes | Yes | Yes |
| Observations | 3354 | 3354 | 3354 | 3354 |

Abbreviations: FE, fixed effects; GDD, growing degree days; HDD, harmful degree days.
$*p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

ties: each additional ton per acre of soil loss due to water erosion can lead to a statistically significant decrease of 1.22 BU per acre in corn yield. Thus, considering the direct and spillover effects of water erosion on corn yield, the total effect of water erosion indicates that each additional ton per acre of water erosion would result in a 1.70 BU per acre decrease in corn yield, suggesting a substantial overall regional impact of water erosion on corn yield in the US Midwest. These findings imply that water erosion is not only a localized phenomenon but also has spatial externalities that affect surrounding agricultural productivity. Our results are consistent with recent studies discussing the interconnected nature of soil and land systems (Farhan & Nawaiseh, 2015; Patil & Patil, 2018). Our study provides new empirical evidence that soil erosion is inherently a spatial phenomenon, whereby displaced soil, nutrients, and sediments are transported beyond the site of origin, impacting agricultural productivity in neighboring areas. Furthermore, soil degradation in one county, especially due to severe erosion, can influence farmland management decisions in adjacent counties. Conversion of marginal lands into less productive or fallow land in response to erosion may trigger similar transitions in nearby regions, further exacerbating degradation across boundaries. The presence of spatial dynamics and strong spillover effects highlights the importance of coordinating soil erosion control and land use planning at broader geographic scales, such as watershed or multi-county regions, to effectively mitigate cascading ecological effects.

With regard to the control variables in the empirical specification, the parameter estimates from our model all follow expectations[1]. Our results indicate that HDD has a significant and negative impact on corn yield, suggesting that higher heat stress (typically reflecting hotter days requiring cooling) reduces corn yield both locally and in surrounding areas. This is consistent with findings in agronomic and climate-economics literature (Lee, 2025; Roberts et al., 2013). We also find that precipitation has a nonlinear effect on yield. The coefficient of precipitation is positive and significant, indicating that moderate rainfall increases yield. However, the squared term of precipitation is negative and significant, confirming the diminishing returns and potential negative effects of excessive rainfall, which is also consistent with the notion that too much rainfall can lead to waterlogging, ponding, and flooding, ultimately reducing crop productivity(Schlenker & Roberts, 2006).

Furthermore, the spatial autoregressive coefficient ($\rho$) is positive and significant, implying strong spatial dependence in corn yield across counties. Our findings suggest that corn yield in one county is significantly influenced by the yield performance in neighboring counties. This could be due to

[1] Based on insights from previous literature, we initially hypothesized that HDD would negatively affect corn yield, while GDD would have a positive effect. In terms of precipitation, we expected that moderate levels of precipitation would be helpful, but too much precipitation (e.g., floods) would be harmful to corn yield

a variety of interrelated factors, such as shared agroclimatic conditions, regional economic linkages, and the diffusion of farming technologies and practices across county boundaries. The significance of the spatial autoregressive coefficient validates the use of a spatial regression framework in our analysis. By using the spatial model that explicitly accounts for both spatial spillover in the dependent variable (i.e., corn yield) and spatial lags of the independent variables (i.e., water erosion and weather), our model captures complex intercounty interactions that would otherwise be omitted in a traditional nonspatial regression setting.

Overall, our results highlight the importance of incorporating spatial spillover effects when evaluating the impact of soil erosion on crop productivity. The large and significant indirect effects of water erosion on corn yield suggest that neighboring counties are economically and ecologically linked in ways that traditional nonspatial models usually overlook. These spillover impacts provide strong justification for regional soil conservation programs, particularly those that promote landscape-level planning and cooperative restoration strategies across county or state boundaries.

## 4 | CONCLUSION

The yield of agricultural crops such as corn is closely tied to the biophysical conditions of the land, especially the health and productivity of the soil. Among the many threats to soil health, erosion remains a dominant environmental concern as it depletes fertile topsoil, impairs water and nutrient retention, and reduces long-term soil productivity (Pimentel, 2006; Uri & Lewis, 1998; Uri, 2000). Although the agronomic impacts of soil erosion have been well discussed in experimental literature, empirical evidence quantifying how erosion influences yield across space and over time remains relatively limited, particularly at broader spatial scales. Based on a novel panel dataset with detailed information on county-level water erosion levels and corn yield, we utilize a spatial panel econometric framework to examine the impact of the dominant type of soil erosion (i.e., water erosion) on corn yield across US counties, explicitly accounting for both direct and spatial spillover effects.

Our empirical results indicate that water erosion has a statistically significant and negative impact on corn yield, both within a county and in neighboring counties. This finding provides new empirical evidence that soil erosion is not a purely site-specific issue, but rather a spatially diffuse phenomenon that influences crop productivity across landscapes. By modeling spatial interdependence explicitly, our study captures important ecological and economic linkages that conventional nonspatial models may overlook.

Findings from our study point to several important implications. First, the evidence of large and significant spillover effects highlights the need for regional coordination in soil conservation efforts. Traditional policies targeting individual landowners or counties may fail to internalize the full costs of erosion, particularly when degradation in one area affects neighboring productivity. Government programs like the Environmental Quality Incentives Program, which incentivize practices such as cover cropping and reduced tillage, could be more effective if designed with spatial externalities in mind: supporting not only individual adoption but also encouraging cooperation across entities or watershed boundaries. Second, the strength of the spatial dependence in yield outcomes highlights the potential value of landscape-level planning. From a policy standpoint, soil erosion control should be viewed not just as a local agronomic decision, but also as a regional public good with broader economic and environmental implications.

Even though our study provides a couple of important insights about the spatial dynamics of soil erosion and crop productivity, it is important to acknowledge a number of limitations of this study and discuss potentially fruitful directions for future research. First, although our county-level analysis enables broad coverage and captures regional effects, it lacks the micro-level detail available in field or farm-level datasets. Future research could incorporate more granular data, allowing for capturing within-county heterogeneity and conservation practice adoption. Second, while our spatial model addresses spatial correlation and endogeneity due to omitted spatial effects, further work could explore more advanced identification strategies, such as spatial instrumental variable approaches, to strengthen causal inference. Third, while we focus on corn yield as a key outcome, it would be useful to evaluate whether soil erosion has differential impacts across other crops, production systems, or under varying climate conditions. We leave all these potential research directions for future work.

## AUTHOR CONTRIBUTIONS

**Le Chen**: Conceptualization; data curation; formal analysis; investigation; methodology; supervision; writing—original draft. **T. Edward Yu**: Conceptualization; formal analysis; investigation; methodology; supervision; writing—review and editing. **Hannah Williams**: Formal analysis; methodology; software; visualization; writing—original draft.

## ACKNOWLEDGMENTS

This research was partially funded by the US Federal Aviation Administration Office of Environment and Energy through ASCENT, the FAA Center of Excellence for Alternative Jet Fuels and the Environment, project 104 through FAA Award Number 13-C-AJFE-UTenn-025 under the supervision of Dr. Prem Lobe. Any opinions, findings, conclusions, or recommendations expressed in this material are those of the authors and do not necessarily reflect the views of the FAA.

## CONFLICT OF INTEREST STATEMENT

The authors declare no conflicts of interest.

## ORCID

*Le Chen* https://orcid.org/0009-0003-3871-1203

## REFERENCES


Al-Kaisi, M., Hanna, M., Miller, G., & Tidman, M. (2002). Soil erosion effect on soil productivity. Iowa State University Extension and Outreach.

Annan, F., & Schlenker, W. (2015). Federal crop insurance and the disincentive to adapt to extreme heat. *American Economic Review*, *105*(5), 262–266.

Bakker, M. M., Govers, G., Kosmas, C., Vanacker, V., Van Oost, K., & Rounsevell, M. (2005). Soil erosion as a driver of land-use change. *Agriculture, Ecosystems & Environment*, *105*(3), 467–481.

Belotti, F., Hughes, G., & Mortari, A. P (2017). Spatial panel-data models using stata. *The Stata Journal*, *17*(1), 139–180.

Buntley, G., & Bell, F. (1976). Yield estimates for the major crops grown on the soils of West Tennessee. University of Tennessee Agricultural Experiment Station. https://trace.tennessee.edu/utk_agbulletin/358/

Chen, L., Rejesus, R. M., Aglasan, S., Hagen, S. C., & Salas, W. (2022). The impact of cover crops on soil erosion in the US Midwest. *Journal of Environmental Management*, *324*, 116168.

De la Rosa, D., Moreno, J., Mayol, F., & Bonsón, T. (2000). Assessment of soil erosion vulnerability in western Europe and potential impact on crop productivity due to loss of soil depth using the ImpelERO model. *Agriculture, Ecosystems & Environment*, *81*(3), 179–190.

de Vente, J., Poesen, J., Verstraeten, G., Van Rompaey, A., & Govers, G. (2008). Spatially distributed modelling of soil erosion and sediment yield at regional scales in Spain. *Global and Planetary Change*, *60*(3–4), 393–415.

DeLong, C., Cruse, R., & Wiener, J. (2015). The soil degradation paradox: Compromising our resources when we need them the most. *Sustainability*, *7*(1), 866–879.

Den Biggelaar, C., Lal, R., Wiebe, K., & Breneman, V. (2001). Impact of soil erosion on crop yields in North America. *Advances in Agronomy*, *72*, 1–52.

Doetterl, S., Van Oost, K., & Six, J. (2012). Towards constraining the magnitude of global agricultural sediment and soil organic carbon fluxes. *Earth Surface Processes and Landforms*, *37*(6), 642–655.

Esri. (2024). Hot spot analysis. ArcGIS Pro Tool Reference. https://pro.arcgis.com/en/pro-app/latest/tool-reference/spatial-statistics/hot-spot-analysis.htm

Edwin, G. A., & Muthu, N. (2020). Soil fertility, integrated management, and sustainability. In W. L. Filho, A. M. Azul, L. Brandli, A. L. Salvia, & T. Wall (Eds.), *Life on land* (pp. 939–951). Springer.

Elhorst, J. P. (2014). *Spatial econometrics: From cross-sectional data to spatial panels*. Springer.

Farhan, Y., & Nawaiseh, S. (2015). Spatial assessment of soil erosion risk using rusle and gis techniques. *Environmental Earth Sciences*, *74*, 4649–4669.

Cruse, R., Flanagan, D., Frankenberger, J., Gelder, B., Herzmann, D., James, D., Krajewski, W., Kraszewski, M., Laflen, J., Opsomer, J., & Todey, D. (2006). Daily estimates of rainfall, water runoff, and soil erosion in Iowa. *Journal of Soil and Water Conservation*, *61*(4), 191–199.

Goodwin, B. K., & Smith, V. H. (2003). An ex post evaluation of the conservation reserve, federal crop insurance, and other government programs: Program participation and soil erosion. *Journal of Agricultural and Resource Economics*, *28*, 201–216.

Hernandez, M., Nearing, M., Stone, J., Pierson, F., Wei, H., Spaeth, K., Heilman, P., Weltz, M., & Goodrich, D. (2013). Application of a rangeland soil erosion model using national resources inventory data in southeastern Arizona. *Journal of Soil and Water Conservation*, *68*(6), 512–525.

Jiang, C., Zhao, L., Dai, J., Liu, H., Li, Z., Wang, X., Yang, Z., Zhang, H., Wen, M., & Wang, J. (2020). Examining the soil erosion responses to ecological restoration programs and landscape drivers: A spatial econometric perspective. *Journal of Arid Environments*, *183*, 104255.

Kertis, C. A. (2006). *Soil erosion on cropland in the United States: Status and trends for 1982-2003*. Citeseer.

Komissarov, M., & Ogura, S.-I (2020). Soil erosion and radiocesium migration during the snowmelt period in grasslands and forested areas of Miyagi prefecture, Japan. *Environmental Monitoring and Assessment*, *192*(9), 1–15.

Lal, R., & Moldenhauer, W. C (1987). Effects of soil erosion on crop productivity. *Critical Reviews in Plant Sciences*, *5*(4), 303–367.

Lal, R., & Stewart, B. (1990). *Soil degradation*. Springer-Verlag.

Larney, F. J., Janzen, H. H., Olson, A., & Olson, B. (2008). Residual impact of topsoil removal and soil amendments on crop productivity over sixteen years. In *Soils and crops workshop proceedings*. University of Saskatchewan.

Larson, W. E., Pierce, F. J., & Dowdy, R. H (1983). The threat of soil erosion to long-term crop production. *Science*, *219*(4584), 458–465.

Lee, S. (2005). Effects of extreme heat events on crop revenues for US corn and soybeans. *American Journal of Agricultural Economics*, *108*, 176–203.

LeSage, J., & Pace, R. K. (2009). *Introduction to spatial econometrics*. Chapman and Hall/CRC.

Ortiz-Bobea, A. (2021). The empirical analysis of climate change impacts and adaptation in agriculture. In C. B. Barrett & D. R. Just (Eds.), *Handbook of agricultural economics* (vol. 5), pp. 3981–4073. Elsevier.

Patil, R. J., & Patil, R. J. (2018). *Spatial techniques for soil erosion estimation*. Springer.

Pimentel, D. (1993). *World soil erosion and conservation*. Cambridge University Press.

Pimentel, D. (2006). Soil erosion: A food and environmental threat. *Environment, Development and Sustainability*, *8*(1), 119–137.

Pimentel, D., Allen, J., Beers, A., Guinand, L., Linder, R., McLaughlin, P., Meer, B., Musonda, D., Perdue, D., Poisson, S., Siebert, S., Stoner, K., Salazar, R., & Hawkins, A. (1987). World agriculture and soil erosion. *BioScience*, *37*(4), 277–283.

Pimentel, D., Harvey, C., Resosudarmo, P., Sinclair, K., Kurz, D., McNair, M., Crist, S., Shpritz, L., Fitton, L., Saffouri, R., & Blair, R. (1995). sEnvironmental and economic costs of soil erosion and conservation benefits. *Science*, *267*(5201), 1117–1123.

Pimentel, D., & Kounang, N. (1998). Ecology of soil erosion in ecosystems. *Ecosystems*, *1*(5), 416–426.

Roberts, M. J., Schlenker, W., & Eyer, J. (2013). Agronomic weather measures in econometric models of crop yield with implications for climate change. *American Journal of Agricultural Economics*, *95*(2), 236–243.

Schlenker, W., & Roberts, M. J (2006). Nonlinear effects of weather on corn yields. *Review of Agricultural Economics*, *28*(3), 391–398.

Schlenker, W., & Roberts, M. J (2009). Nonlinear temperature effects indicate severe damages to US crop yields under climate change. *Proceedings of the National Academy of Sciences*, *106*(37), 15594–15598.

Stakhovych, S., & Bijmolt, T. H (2009). Specification of spatial models: A simulation study on weights matrices. *Papers in Regional Science*, *88*(2), 389–409.

Tan, Z.-X., Lal, R., & Wiebe, K. D (2005). Global soil nutrient depletion and yield reduction. *Journal of Sustainable Agriculture*, *26*(1), 123–146.

U.S. Department of Agriculture, Economic Research Service. (2023). *Each decade since 1992, both corn and soybean area harvested have increased*. USDA ERS Chart Gallery. https://www.ers.usda.gov/data-products/chart-gallery/gallery/chart-detail/?chartId=108037

U.S. Department of Agriculture. (2024). *Agriculture in the midwest*. USDA Climate Hubs. https://www.climatehubs.usda.gov/hubs/midwest/topic/agriculture-midwest

Uri, N. D (2000). Agriculture and the environment—The problem of soil erosion. *Journal of Sustainable Agriculture*, *16*(4), 71–94.

Uri, N. D., & Lewis, J. A (1998). The dynamics of soil erosion in US agriculture. *Science of the Total Environment*, *218*(1), 45–58.

Yun, S. D., & Gramig, B. M (2022). Spatial panel models of crop yield response to weather: Econometric specification strategies and prediction performance. *Journal of Agricultural and Applied Economics*, *54*(1), 53–71.

Zhao, L., Jin, J., Du, S., & Liu, G. (2012). A quantification of the effects of erosion on the productivity of purple soils. *Journal of Mountain Science*, *9*, 96–104.

**How to cite this article:** Chen, L., Yu, T. E., & Williams, H. (2026). The impact of soil erosion on corn yields: A spatial regression analysis. *Agrosystems, Geosciences & Environment*, *9*, e70304. https://doi.org/10.1002/agg2.70304