The Dual Damage from Soil Erosion: Lower Yields and Higher Risk in US Agriculture

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Abstract

This study examines the impact of soil erosion on crop yields in the United States (US) using county-level panel data. We use linear panel fixed effects (FE) models and a number of robustness checks to assess how soil erosion affects the mean, variance, skewness, and kurtosis of US corn and soybean yield distributions. Our analysis suggests that soil erosion, specifically caused by both water and wind, has a statistically significant negative impact on mean corn and soybean yields. We also find evidence that counties with higher levels of soil erosion tend to have corn yields with statistically higher variance and kurtosis. This suggests that soil erosion can lead to higher corn yield risks (or more instability in corn yields over time). However, we do not find strong evidence of this risk-increasing-effect for soybean yields. Moreover, our analysis indicate that water-caused erosion tends to have a larger mean-yield-reducing effect compared to wind-caused erosion for soybeans, whereas no strong evidence of this pattern is found in corn. Overall, we estimate that the total damage of soil erosion for corn and soybeans in terms of mean yield reduction and risk increases amounts to around $4.43 billion in 2024. Findings from our analysis provide a better understanding of the economic damage caused by soil erosion since we not only provide evidence of its potential mean-yield-reducing effect, but also provide evidence of its potential risk-increasing effect.

Keywords: Soil Erosion, Crop Yields, Panel Fixed Effects, Yield Risks

JEL classification: Q1, Q2, Q24

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1 Introduction

Soil erosion is a significant threat to agricultural production worldwide primarily due to its role in degrading soils on farmland (Lal and Moldenhauer, 1987; Jang et al., 2021). Much of the economic damage from soil erosion in agriculture can be attributed to on-farm (or on-site) soil degradation that potentially leads to lower farmland productivity, higher input costs, crop yield reductions, lower incomes, and, under extreme erosion, farmland abandonment (Kalantari et al., 2019; Hediger, 2003; Ervin and Mill, 1985; Alewell et al., 2020).[1] Globally, nearly one-third of the world's arable land has been lost to soil erosion over the last four decades, with current annual losses estimated to exceed 24 million acres yearly (Pimentel et al., 1995). From 1955 to 1995, Pimentel et al. (1995) estimated that the annual economic loss due to soil erosion in the United States (US) is $44 billion, including $27 billion from on-site agricultural productivity losses.[2] More recent estimates for the US Corn Belt suggests that erosion-caused topsoil losses in the region resulted in crop yield reductions equivalent to around $2.8 billion annually (Thaler et al., 2021).

Accelerating soil erosion rates negatively affects row crop yields by depleting on-farm soil nutrients, reducing soil organic matter (or soil organic carbon), lowering water-holding capacity, and decreasing effective root depth of the plants (Lal and Moldenhauer,

[1] Notwithstanding that the majority of the effect of soil erosion is on-farm (or on-site), it is important to note that soil erosion has also contributed to off-farm (or off-site) environmental problems mainly through soil runoff and sedimentation in water bodies (Lal, 2001). Runoff and sedimentation can then lead to water quality degradation (e.g., pollution, eutrophication), disruption to fisheries, loss of wildlife habitat and biodiversity, and heightened flood risks (Colombo et al., 2005; Issaka and Ashraf, 2017; Kalantari et al., 2019; Patault et al., 2021; Ferreira et al., 2022; Panagos et al., 2024). Beyond its impacts on water systems, soil erosion also disrupts carbon sequestration and biogeochemical cycles, thereby exacerbating global climate change, food insecurity, and long-term sustainability of agriculture (Lal, 2004, 2005; Van Oost et al., 2007; Quinton et al., 2010; Sartori et al., 2024).

[2] In a separate study, Crosson (1995) suggested a lower figure for the economic damage caused by soil erosion in the US – ranging between $500 to $600 million yearly.

1987; den Biggelaar et al., 2003; Carr et al., 2021; Borrelli et al., 2018; Gu et al., 2018; Ouyang et al., 2018; Thaler et al., 2021; Zhang et al., 2021). Although measuring reductions in mean crop yields is important for estimating direct economic losses due to soil erosion in agriculture (Thaler et al., 2021), another important dimension of loss (or damage) is the potential impact of soil erosion on yield risk or yield variability over time. Since farmers typically do not want large year-to-year variation in yields and income (e.g., farmers are typically risk-averse), increased yield variability is therefore another economic damage from soil erosion that needs to be better understood (and quantified).

This paper aims to address the question of whether and how much soil erosion affects corn and soybean yields in US agriculture. In particular, we quantitatively examine the impact of soil erosion on the four moments of US county-level corn and soybean yield distributions, focusing on its effects on the mean, variance, skewness, and kurtosis of yields. We give insights not only on the impact of soil erosion on mean yields, but also its effect on yield risk (as represented by the combined impact on the variance, skewness, and kurtosis of yields). To achieve the study objectives, we construct a novel county-level data set for the US that includes information on row crop yields (e.g., corn and soybeans), soil erosion, and a number of control variables (e.g., weather variables, etc.). The unique county-level panel data set constructed allows us to estimate linear panel fixed effect (FE) models that can help address potential endogeneity due to time-invariant unobservables. A variety of robustness checks are also conducted using different empirical specifications and alternative estimation procedures (e.g., instrumental variable models) in order to help validate the strength of the results from the linear panel FE models, and address potential endogeneity issues not captured in the linear panel FE models.

There is an extensive body of literature on soil erosion in agriculture. For example, there have been agronomic studies that used small-scale on-farm experiments to show that soil erosion negatively affects mean crop yields, including comparisons of in situ field plots (or transects) with simulated erosion (e.g., through removal of the top soil or desurfacing) versus those without erosion (Gollany et al., 1992; Schertz et al., 1989; Weesies et al., 1994; Larney et al., 2000; Salako et al., 2007; de la Rosa et al., 2000; Liang et al., 2018). Notwithstanding the preponderance of soil erosion studies that use field experiments, researchers have also utilized greenhouse and laboratory experiments, simulation modeling techniques, statistical approaches, and knowledge-based surveys to show that soil erosion is detrimental to mean crop yields (Lal, 1998).

In addition to its effect on mean yields, there are several field studies that also investigate the impact of soil erosion on yield variability (or what crop scientists typically call yield stability), where the main yield variability measure is generally based on the variance or standard deviation of yields (Lin et al., 1986). In general, the literature mostly indicates that soil erosion increases yield variability and promotes yield instability, although there may be heterogeneity in soil erosion effects depending on a number of contextual factors (i.e., such as cropping systems used, tillage used, whether a farm is organic or not, and the soil properties of the field) (Knapp and van der Heijden, 2018; Lawes et al., 2009; Waqas et al., 2020; Grover et al., 2009; Lal, 2010).

Outside of the literature that explored the effects of soil erosion on mean yields and yield variability, there are also a number of studies that examined the potential on-farm economic impact of soil erosion. These economic studies typically focus on how soil erosion can lead to farm income losses or the costs associated with rehabilitating or managing eroded farmlands (Seitz et al., 1979; Walker, 1982; Baffoe et al., 1987; Pagoulatos et al., 1989; Goetz, 1997; Dissart et al., 2000; Hediger, 2003). Other economic research focuses on the impact of soil erosion control investments on land prices (Ervin and Mill, 1985; Hertzler et al., 1985; Sen Chakraborty et al., 2023).

In light of past studies on soil erosion in row crop agriculture, our study contributes to the literature in a couple of ways. First, to the best of our knowledge, there has been no recent observational study that econometrically models how erosion-caused annual soil loss directly affects the moments of crop yield distributions in the US. By carefully examining the impact of soil erosion on the higher moments of the yield distribution (e.g., variance, skewness, and kurtosis), this study provides empirical evidence on whether soil erosion increases production risk in US row crop agriculture. If soil erosion is found to have a yield risk-increasing effect, the total damage caused by erosion can then be more accurately assessed, accounting for both its impact on mean yields and its contribution to higher yield risk.

Our second main contribution is providing inferences on the impact of soil erosion on crop yield distributions over a larger geographical area than most of the previous literature. Previous plot- or field-level studies looking at the effect of soil erosion on crop yields tend to have a narrower geographical scope.[3] The present study utilizes unique county-level soil erosion data from the National Resources Inventory (NRI) survey, combined with crop yield data from the National Agricultural Statistics Service (NASS) surveys. This dataset covers thousands of counties across the US, from the west coast to the east coast (particularly for corn), over a longer time period compared to previous studies. Hence, we have better external validity for our analysis. In addition, the county-level panel data set we constructed reflects actual on-farm behavior (albeit at a more aggregate county-level) since it is not based on small-scale field experiments. Small-scale field experiments do not necessarily represent conditions on-farm, and anal-

[3]Exceptions include studies that used simulation-based models (Bakker et al., 2007) or those that combine biophysical models with macroeconomic models (Panagos et al., 2018) to investigate the yield and economic impact of soil erosion in Europe.

ysis that reflects on-farm conditions (even at a more aggregate level) provides more valuable policy-relevant information.

Lastly, the data utilized in this study allow us to investigate potential heterogeneity in the effect of soil erosion depending on the row crop considered (i.e., corn versus soybeans) and depending on the main cause of soil erosion (i.e., combination of water- and wind-caused erosion versus soil erosion separately caused by water or wind). Thus, our study also contributes to the literature by providing inference on the heterogeneity of soil erosion effects across crops and across causes of erosion, which have not been thoroughly examined in previous literature over a large geographical scale in the US.

Findings from our empirical analysis suggest that soil erosion cumulatively caused by both water and wind can reduce mean corn and soybean yields in the US, and this effect is statistically significant. Moreover, corn-producing counties with higher combined water- and wind-caused soil erosion tend to have statistically larger yield variance and kurtosis. This implies that soil erosion due to both water and wind can increase corn production risk, and this implies more unstable US corn yields over time (i.e., potentially larger downside and upside yield swings). However, we do not find strong evidence of this risk-increasing-effect for the case of soybean yields. We also find evidence that water-caused erosion tends to have a larger mean-yield-reducing effect compared to wind-caused erosion in soybeans (but not for corn). Therefore, our analysis provides evidence on the heterogeneity of the effect of soil erosion depending on the row crop being considered and the cause of soil erosion. We also estimate that the total damage of soil erosion for corn and soybeans in terms of mean yield reduction and risk increases amounts to around $4.43 billion in 2024. These insights provide important information that could help guide row crop producers in their decision-making with regards to adopting soil health practices that can help preempt soil erosion problems, and also whether or not to seek cost-share payments to help alleviate the cost of adopting these practices.

2 Background: Soil Erosion and Crop Yields

The two primary forces driving soil erosion are wind and water. Water erosion refers to the removal of soil from the surface due to rainfall, runoff, snowmelt, and irrigation. Among these, rainwater-driven runoff plays a crucial role, as it transports organic and inorganic soil particles downslope, depositing them in lower landscape areas. The eroded material can either contribute to new soil formation or simply accumulate in streams, lakes, and reservoirs. While all soils experience some degree of water erosion, slight erosion can actually be beneficial for soil formation, whereas severe or accelerated erosion has detrimental effects on both soil quality and the environment. Therefore, understanding the processes and extent of water erosion is essential for developing effective erosion control strategies (Blanco and Lal, 2023). The main factors influencing the rate of soil erosion by water include precipitation, soil type, topography, land use, and land management (Panagos et al., 2015).

More specifically, water-caused erosion strips away the fertile topsoil layer, which is rich in essential nutrients and organic matter needed for healthy crop growth (Pavlů et al., 2022). Consequently, this reduction in topsoil depth weakens the soil's ability to retain water, impedes root penetration, and limits nutrient availability, making it harder for crops like corn and soybeans to achieve high yields (Thompson et al., 1991; Xu and Mermoud, 2001). As a result, crops grown on water-eroded soils may have lower yield potentials, especially under drought conditions, where less water is available for uptake by plant roots due to reduced soil depth and porosity.

Similarly, wind erosion, also known as eolian erosion, is a dynamic process in which soil particles are detached and transported by wind forces. It occurs when wind speed exceeds the soil's resistance to erosion (Webb et al., 2021). The rate and severity of wind erosion are influenced by geological, anthropogenic, and climatic factors. Key variables affecting wind erosion include wind velocity, precipitation levels, surface roughness, soil composition and aggregation, agricultural activities, vegetation cover, and field size (Borrelli et al., 2017). Additionally, abrupt fluctuations in weather patterns can trigger wind erosion events more frequently (Duniway et al., 2019).

Wind erosion is primarily driven by deforestation and agricultural activities. For example, soils that are plowed and have low organic matter content, as well as those that are intensively grazed and trampled upon, are particularly vulnerable to erosion (Wiesmeier et al., 2009). Wind erosion affects crop yield by removing fine soil particles, including clay and organic matter, which are critical for maintaining soil fertility and moisture (Sterk, 2003). This process leaves behind a coarser, less fertile soil profile, reducing the soil's ability to support optimal plant growth. Additionally, the loss of fine particles disrupts soil structure, diminishing its capacity to retain moisture and nutrients essential for corn and soybean development (Colazo and Buschiazzo, 2015; Li et al., 2008).

Furthermore, wind erosion can cause direct plant damage, as wind-blown soil particles may injure seedlings, hinder crop establishment, and increase susceptibility to pests and diseases. Collectively, these factors contribute to consistently lower average yields, particularly in regions with frequent high winds and exposed topsoil (Nordstrom and Hotta, 2004; Zhao et al., 2022; Duniway et al., 2019).

The discussion above indicates that water- and wind-caused soil erosion not only has the potential to significantly reduce mean yields (as have been demonstrated frequently in previous literature), but it also has the potential to heighten production risk in US row crop production through its impacts on the higher moments of the yield distribution. The mechanisms by which water- and wind-caused erosion reduce mean crop yields also likely contribute to whether and how much soil erosion impacts the higher moments of the crop yield distributions (and therefore the risk and stability of yields over time).

For example, since water and wind-related soil erosion can lead to significant soil nutrient loss and reduced moisture holding capacity (both of which are essential for crop health), continuous exposure to erosive factors will result in the soil becoming less fertile and more heterogeneous. This can lead to greater yield variability (or yield variance) over time, which then leads to more unpredictable crop performance across seasons and fields.[4] Fields with higher erosion are prone to lower-than-average yields, particularly under stress conditions (e.g., droughts). This effect increases the likelihood of "left-tail" outcomes in the yield distribution, where crop failures or significant yield reductions are more frequent than bumper crops, resulting in negative skewness. With persistent exposure to soil erosion, yield distributions may exhibit higher kurtosis, reflecting a greater frequency of extreme low-yield events. This leptokurtic distribution pattern suggests that soil erosion can make extreme poor yields more common, while making extremely high yields rare, as the soil quality and structure can no longer support very high yields.

For US farmers, these shifts in the moments of crop yield distributions imply greater challenges in terms of risk management, potentially higher insurance costs, and the need for targeted conservation efforts to maintain soil health and yield stability over time.

[4]However, as briefly noted in the introduction, the literature examining effects of soil erosion on yield variance (or standard deviation) suggests that contextual factors such as tillage systems and inherent soil properties (e.g., soil organic content and water-holding capacity) influences how erosion can impact the stability of yields over time. It is possible that for some cropping systems and soil types, soil erosion do not significantly reduce yield stability over time.

Ultimately, it is an empirical question whether soil erosion levels generally increase risk in the US agricultural context. The current paper aims to provide empirical evidence on this issue for corn and soybean production in the US.

3 Data and Estimation Strategies

3.1 Data Description

The unique county-level panel data used in this study were collected from various sources. Corn and soybeans account for 87% of US production of grains and oilseeds (Zulauf et al., 2023), and as such, yields from these two crops serve as our two main dependent variables. County-level data on corn and soybean yields, measured in bushels per acre, were obtained from the NASS Quick Stats database. These yield estimates are derived from farmer surveys and field measurements, providing a comprehensive coverage of agricultural productivity across US counties. NASS compiles annual county-level crop data for various grains, including corn and soybeans. However, due to the reliance on sample surveys, not all counties are represented in the data. A minimum threshold is required for publication, and counties that do not meet this threshold are often grouped together under a "Combined Counties" category within their respective Agricultural Statistics District (ASD). To provide broader coverage, some states publish data at the ASD level for key production areas, where detailed county-level data are unavailable. Given these limitations, our analysis only includes counties where both NASS crop yield and (as discussed further below) soil erosion data are available, ensuring consistency throughout the study.

Our main independent variable of interest, annual soil loss data due to erosion (in tons per year), was obtained from the National Resources Inventory (NRI) program, managed by the USDA's Natural Resources Conservation Service (NRCS). The NRI program provides scientifically comprehensive and reliable data on the state, condition, and trends of soil, land, water, and related resources in the US (Larson et al., 1985). It is regarded as the most extensive quantitative effort undertaken to date for evaluating the prevalence and magnitude of soil erosion in the US, and it has been utilized in a number of previous studies (Goodwin and Smith, 2003; Chen et al., 2022). Moreover, the NRI employs a stratified two-stage sampling method, where representative land segments and sample points are selected for assessment. This process utilizes remote sensing techniques in conjunction with field validation to ensure accurate and reliable estimates of soil erosion that is representative across non-federal US lands, including private properties and tribal territories.

The erosion data used in our study include estimates of both water-induced and wind-induced soil erosion. The NRI's soil erosion estimates are partly based on predictive models rather than direct measurements. For water erosion, the Universal Soil Loss Equation (USLE) model was used for erosion estimates prior to 2008, while the Revised USLE (RUSLE2) model was adopted for subsequent years. In contrast, wind erosion estimates were based on the Wind Erosion Equation (WEQ) model. These models calculate average annual rates based on the long-term average climatic conditions, management practices, and land characteristics at each sample site. Erosion data are collected for cropland, including both cultivated and non-cultivated land. The data are reported in terms of annual soil loss (in tons) due to water erosion, wind erosion, and total erosion, which is the sum of the two.

For this study, erosion data from 1987, 1992, 1997, 2002, 2007, 2012, and 2017 are used. Each data point reflects the soil loss recorded in a specific year, with updates every five years capturing the annual soil loss for that specific period. To maintain consistency, all other variables, including the corn and soybean yield variables, were restricted to the same years as the erosion data, even if data were available for other years. This ensures that the analysis consistently reflects the effects of soil erosion on agricultural productivity over time.

Information about several control variables was also collected to account for external factors influencing crop yields. Weather data, including growing degree days (GDD), harmful (or high temperature) degree days (HDD), and precipitation levels, were obtained from the Parameter-Elevation Regressions on Independent Slopes Model (PRISM) climate dataset to serve as the primary controls in our analysis. GDD captures the temperature range favorable for crop growth (8–29°C) over the May to September growing season, while HDD measures high temperatures that can be harmful (above 29°C) during the same period, following thresholds established by Schlenker and Roberts (2009) and Annan and Schlenker (2015). These two variables account for the non-linear effects of temperature on yields. Additionally, we include accumulated precipitation (in mm) over the May to September growing season and a squared precipitation term to account for potential non-linear impacts of moisture on crop yields, as is common in the climate econometrics literature.

Overall, our data sample for corn consists of 12,421 observations from 2,265 counties, covering the following years: 1987, 1992, 1997, 2002, 2007, 2012, and 2017. Similarly, our soybean data comprises 10,418 observations from 1,910 counties for the same years as corn. Summary statistics for the variables used in this research are presented in Table 1 and 2 for corn and soybeans, respectively. Figure 1 and 2 illustrate the spatial coverage of US counties included in the dataset for the separate corn and soybean yield analysis conducted. A county is shaded if at least one year of yield data is available during the estimation period. White counties are excluded due to missing or incomplete records.

Appendix Figures A.1–A.10 provide a visual overview of the spatial and temporal patterns of key variables. Figure A.1 shows histograms of county-level soil erosion, corn yield, and soybean yield for the first and last years of the sample. Figure A.2 plots annual averages of these variables over time. Figure A.3 displays long-term average soil erosion by county, based on total water and wind erosion across all years. Figure A.4 compares soil erosion between the start and end of the study period. Figures A.5 and A.6 present absolute and percentage changes in erosion between early–mid and mid–late periods.[5] Figures A.7 and A.9 show county-level averages of corn and soybean yields, while Figures A.8 and A.10 compare yield distributions between the first and last years. Overall, these figures show sufficient variability in yields and soil erosion levels across counties and over time.

3.2 Estimation: Baseline model

To examine the potential impact of soil erosion on crop yields, we extend the panel fixed-effects regression model in Tack et al. (2015) by incorporating a soil erosion variable in the specification together with the weather and other variables in their specification:

$$Y_{it} = M_1(X_{it}) + \varepsilon_{it} = \alpha S_{it} + \beta W_{it} + \gamma_1 t + \gamma_2 t^2 + \mu_i + \varepsilon_{it}, \tag{1}$$

where Y_{it} represents the yield (for either soybean or corn) in county i in year t,[6] X_{it} in the represents all variables and $M_1(X_{it})$ is the conditional mean function. The variable S_{it} represents the total annual soil loss (in tons) caused by both water and wind erosion, while W_{it} is a vector of weather-related controls, including GDD, HDD, precipitation, and a squared precipitation term. The term $\gamma_1 t + \gamma_2 t^2$ captures the trend component

[5] Figures on soil erosion include only counties used in either the corn or soybean yield estimation.

[6] We define the time index and trend variable by assigning the first year in the time span a value of 1, the second year a value of 2, and so forth. This transformation standardizes the time scale, facilitating the analysis of temporal effects

to account for long-term temporal dynamics affecting all counties the same way, μ_i represents county fixed effects to control for time-invariant county-specific factors, and ε_{it} is the idiosyncratic error term.

Given the potential endogeneity between soil erosion and yield, especially endogeneity due to time-invariant unobservables, it is essential to include county fixed effects in the panel model. County fixed effects (μ_i) account for unobserved, time-invariant factors such as long term soil quality and long-standing farming practices, which may differ across counties but remain constant over time. As noted by studies like Schlenker and Roberts (2009), Deschênes and Greenstone (2007), and Lobell and Burke (2010), including these controls is critical to ensure consistent estimates when analyzing crop productivity relative to environmental factors. Similarly, the time trend terms ($\gamma_1 t+\gamma_2 t^2$) control for national trends that affect all counties equally, such as advances in agricultural technology or changes in policy. Research by Burke and Emerick (2016) highlights the importance of incorporating time-varying factors, such as annual policy changes, technological innovation, to accurately capture their influence on productivity. By including both county fixed effects and time trends, we eliminate omitted variable bias due to county-specific time-invariant unobservables and time-varying national-level shocks, leading to more precise estimates of the effects of soil erosion.

Moreover, to address serial correlation and heteroscedasticity within counties, we cluster the standard errors by county. This approach is recommended in panel data settings where correlations within clusters (in this case, counties) might persist over time, as discussed by Bertrand et al. (2004). Even with data collected at five-year intervals, unobserved factors may introduce correlations across years within a county, making county-level clustering an appropriate choice for robust standard error estimation.

3.3 Estimation: Higher Moment Effects and Cost of Risk

The baseline model above allows one to assess the effect of soil erosion on mean crop yields. To assess the impacts of soil erosion on the higher-order central moments of crop yields, such as variance, skewness, and kurtosis, we use a "residual-based" estimation procedure (Just and Pope, 1979; Antle and Goodger, 1984; Li et al., 2021). In particular, we follow the parametric "residual-based" estimation method as described in Antle and Goodger (1984). In this parametric approach, the mean yield effect is first estimated from the base model (as in equation (1)), after which the residuals ($\widehat{\varepsilon}_{it}$) from the conditional mean estimation are calculated. These residuals are then raised to the second power (for variance), the third power (for skewness), and the fourth power (for kurtosis), and used as dependent variables in separate regressions against the explanatory variables.

The regression models take the following form:

$$(\widehat{\varepsilon}_{it})^p = M_p(X_{it}) + \varphi_{it}^{(p)} = \alpha^{(p)} S_{it} + \beta^{(p)} W_{it} + \gamma_1^{(p)} t + \gamma_2^{(p)} t^2 + \mu_i^{(p)} + \varphi_{it}^{(p)} \tag{2}$$

where $p \in \{2, 3, 4\}$ corresponds to variance, skewness, and kurtosis, respectively; $\varphi_{it}^{(p)}$ is an error term with mean zero; and $M_p(X_{it})$ is the conditional moment function for the higher moments. Therefore, since we are investigating four moments and are looking at yields from two crops (corn and soybeans), we have a total of eight separate regressions for our baseline model results. The residual based approach we use allows for a detailed understanding of how soil erosion affects not only the central tendency of yields, but also the soil erosion effect on the higher order moments of the yield distribution. Hence, we are able to ascertain the impact of soil erosion on yield risk (as determined by the variance, skewness, and kurtosis effects).

To further assess the soil erosion effects on yield risk, in addition to estimating the conditional mean yield model (Equation (1)) and higher-order conditional moments, we also calculate the cost of risk (also called risk premium) following the approach in Shi et al. (2013). A representative decision-maker (i.e., the farmer) is assumed to have constant relative risk aversion (CRRA), as represented by parameter r, and as such their utility function can be represented by the following expression:

$$U(y) = \frac{y^{1-r}}{1-r} \tag{3}$$

We can then assume that the risk aversion parameter is $r = 3$, which corresponds to moderate risk aversion (i.e., given that r is typically in the range of 1 to 5 (Shi et al., 2013)). With this utility function, the cost of risk (measured in the units of the dependent variable Y_{it}, which in our case is bushels per acre) is defined as follows:

$$R(X) = M_1(X) - U^{-1}\left(E\left[U(Y(X))\right]\right). \tag{4}$$

Then from Equation (4), the cost of risk can be simplified to:

$$R(X) \approx \frac{3}{2}\frac{M_2(X)}{M_1(X)} - 2\frac{M_3(X)}{M_1^2(X)} + \frac{5}{2}\frac{M_4(X)}{M_1^3(X)}. \tag{5}$$

From the equation above, we can evaluate how the cost of risk responds to changes in soil erosion levels. To do this, since the cost of risk is defined at a specific point of X, we first fix all the variables in X at its mean (for each year) and then see how the cost of risk changes as the soil erosion values increase (in 0.1 ktons increments). This procedure allows us to observe how the cost of risk is affected by higher soil erosion levels and then compare the contribution of each higher moment (e.g. the variance, skewness, and kurtosis) to the change in the cost of risk. Note that a higher (lower) cost of risk indicates an increase (a reduction) in the farmers' exposure to risk.

3.4 Robustness Checks: Alternative Specifications

3.4.1 Alternative Soil Erosion Variables: Water versus Wind Erosion

As mentioned in the Background section, the mechanisms through which water-caused soil erosion and wind-caused soil erosion affect crop yields are not exactly identical. Additionally, farmers affected by either water or wind erosion may use different production systems. Therefore, we conduct robustness checks where we estimate the same models in Equations (1) and (2) but consider different soil erosion variables, analyzing water-induced erosion and wind-induced erosion separately (rather than combined). This robustness check gives some evidence as to whether water or wind erosion more strongly influence mean yields or yield risk.

3.4.2 Additional Control Variables

For our second robustness check, we use an alternative empirical specification that includes additional control variables on the right side of Equations (1) and (2). That is, we add covariates that also plausibly influence the crop yield outcomes of interest to better tease out the yield effects of soil erosion. The idea is to avoid omitted variable bias by including additional control variables in the specification. However, the disadvantage of including these control variables in the specification is that these controls may be endogenous in and of themselves and therefore add more noise to the estimation.

The additional control variables included in the alternative specification are: farm acres operated, fertilizer expenditures (including lime and soil conditioners, measured in dollars), and federal government program receipts (measured in dollars). We collect data on these additional control variables from the Census of Agriculture, which is available in the NASS database. Each control variable is divided by the number of farm operations reporting, such that each control is reported on a per-farm-operation basis. Additionally, the fertilizer expenditure and government program payment variables are adjusted using the Producer Price Index (PPI) to account for price inflation. Due to data availability for these additional control variables, this robustness check analysis only covers the period from 1997 to 2017. Moreover, it is important to note that these additional control variables are not specifically associated with any particular type of crop producer (i.e., the fertilizer expenditures are for all crop producers, not just, say, for corn or soybeans).

3.5 Robustness Checks: Alternative Estimation Strategies

In addition to the linear panel FE estimation procedure, we also utilize two other estimation strategies as further robustness checks in the study. We implement two instrumental variable (IV) based models – a traditional two-stage least squares (2SLS) procedure and an IV estimation strategy using heteroskedasticity-based instruments. However, since these IV-based models do not necessarily apply to the second step higher moment analysis we used, we focus on implementing the IV-based robustness checks on the mean yield model in Equation (1). Hence, the robustness checks based on the IV-based models in this section only help validate results from our linear panel FE estimation of the mean yield function.

3.5.1 Addressing Residual Endogeneity with 2SLS

In our panel fixed effect approach, we address endogeneity due to unobserved time-invariant variables through county FEs. Morever, endogeneity due to unobserved yearly shocks that affect all counties similarly is addressed through the inclusion of year trends. Hence, unobserved county-specific variables that are time-invariant (or roughly time-invariant or slow-moving), like a county's inherent soil structure and quality, are accounted for. Similarly, if a nationwide change in agricultural policy impacts all counties or if a new agricultural technology is promoted and adopted across the country in a particular year, our time trend terms help capture these effects. Notwithstanding the control of time-invariant and across-county-invariant unobservables, there may be residual endogeneity remaining in our specification if there are time-county-varying unobservables that influence both the soil erosion variable and the yield variable. For example, unobserved input use or soil management practices adopted by farmers likely vary across time and space and are likely to affect both soil erosion levels and yield outcomes in each period (see Lal 2001, Hediger 2003, Dissart et al. 2000, Bakker et al. 2004, Colombo et al. 2005). Moreover, measurement errors in the soil erosion variable (since the soil erosion values are partly based on predictive models), may also contribute to residual endogeneity in our error terms and cause endogeneity issues in the linear panel FE model.

To address potential residual endogeneity, we employ a 2SLS approach, using Conservation Reserve Program (CRP) cumulative enrollment (in acres) and average rental payment (in $/acre) as instrumental variables (IVs). For an instrument to be valid, it must satisfy two key conditions. First, the relevance condition, which requires that the instrument is sufficiently correlated with the endogenous regressor. Second, the exogeneity condition requires that the instrument affects the outcome variable only through its effect on the endogenous regressor, and is uncorrelated with the idiosyncratic error term. Both IVs are reported based on the fiscal year ending on September 30th, with rental payments disbursed at the beginning of the following fiscal year. CRP is a government-led land conservation program in which farmers are paid to set aside environmentally sensitive portions of their fields, leaving them unplanted. This program plays a critical role in reducing soil erosion through the implementation of conservation practices, such as establishing grasslands and vegetative covers on enrolled non-planted lands. Hansen (2007) estimates that, without CRP, soil erosion would increase by 222 to 248 million tons per year—approximately 11% higher than current levels. This underscores the program's substantial impact in mitigating soil erosion, thereby preserving land productivity and reducing environmental degradation.

Note that we select CRP-related data from the previous year, and therefore, we believe that previous-year CRP enrollment likely satisfies the "relevance condition" for a valid instrument (i.e., CRP enrollment is correlated with soil erosion). Similarly, previous-year average rental payments (i.e., disbursed at the beginning of the current fiscal year) are also likely to satisfy the "relevance condition" since CRP policy specifies that county average CRP rental rates must be set based on non-irrigated cropland rental rates, using a three-year average of NASS data to establish rental payment rates (Hellerstein, 2017). Thus, average rental payments are also likely to satisfy the "relevance condition", as higher rental rates often reflect productive or well-maintained land with better soil quality and lower erosion risk. However, higher rental rates also increase the opportunity cost of conservation, encouraging intensive farming and potentially discouraging soil conservation efforts.

However, for CRP relevant data to be a valid IV, the "exogeneity condition" should also be plausibly satisfied (i.e., CRP enrollment and average rental payments are uncorrelated with unobservables that affect yields). We argue that CRP enrollment at the county-level does not directly influence unobserved time-county-varying factors that influence yields. This is supported by previous studies that have shown that CRP does not statistically influence corn and soybean yields directly (Udawatta et al., 2016). It is also unlikely that current year or lagged year CRP enrollment are correlated with measurement errors in the current year soil erosion variable. The average rental payments are determined by rental rates from previous years, which may reflect long-term historical land productivity rather than current year conditions. Therefore, we believe that the CRP enrollment and average rental payment are potentially valid IVs. Note that we take the logarithm of average rental payments, as it serves as a stronger instrument than the raw value. We also run several diagnostic tests to help determine if the IV we used are strong and valid.

3.5.2 Heteroskedasticity-Based Instruments

To alleviate concerns regarding the validity of CRP cumulative enrollment and average rental payment as IVs — specifically, the concern that these variables may still affect crop yield through channels other than soil erosion — we also implement another alternative IV-based estimation strategies to further validate the robustness of our findings regarding the soil erosion impacts on mean yields.

The approach utilizes heteroskedasticity-based instruments, as proposed by Lewbel (2012). This method is particularly useful for identifying structural parameters in models with endogenous regressors when traditional external instruments are unavailable. The key idea is to extract heteroskedasticity in the error term to generate instruments internally. Identification in Lewbel's approach is achieved under the assumption that the regressors are uncorrelated with the product of heteroskedastic errors, a condition that often holds in models where error correlation arises from unobserved common factors. In practice, instruments are constructed using the residuals from a first-stage regression of each endogenous regressor on all exogenous variables. These residuals are then multiplied by the mean-centered exogenous regressors to form the instruments.

Formally, the first-stage equation takes the form:

$$S_{it} = a + bW_{it} + e_{it}, \tag{6}$$

where S_{it} is the potentially endogenous soil erosion variable, W_{it} represents the exogenous regressors, and e_{it} is the residual. The heteroskedasticity-based instrument proposed by Lewbel (2012) is then constructed as:

$$Z_{it} = (W_{it} - \bar{W}_{it})\widehat{e}_{it}, \tag{7}$$

where $\bar{W}_{it}$ is the mean of W_{it}, and $\widehat{e}_{it}$ is the estimated residual from the first-stage regression. The Lewbel (2012) IV in Equation (7) can then be considered an alternative IV to those IVs based on CRP variables described in the previous section. The use of internally generated heteroskedasticity-based instruments in a two-stage procedure offers an alternative estimation strategy that may help address residual endogeneity arising from time-county-varying unobservables, particularly in the absence of strong external instruments.

Moreover, given the availability of two external CRP-based IVs and the heteroskedasticity-based instruments, we also follow an empirical strategy suggested in Lewbel (2012) and estimate the mean yield model using the following: (1) only the two external IVs; (2) only the internally generated IV following Lewbel (2012); (3) both external IVs and the internally generated IV; (4) one external IV based on CRP enrollment and the internally generated IV; and (5) one external IV based on CRP rental payments and the internally generated IV. All estimation results are followed by diagnostic tests to help determine if the IVs used are strong and valid.

4 Results and Discussion

4.1 Baseline model results

4.1.1 Mean Yield Effects

The estimated parameters using the baseline linear panel FE models are presented in Tables 3 and 4 for corn and soybeans, respectively. The regression results indicate that soil erosion has a statistically significant negative relationship with mean crop yields for both corn and soybeans. That is, counties with higher soil erosion levels due to both water and wind tend to have lower mean yields. For example, the regression result in Table 3 suggest that an additional 1,000 tons in erosion-caused soil losses in a county is associated with a 1.34 bushels per acre reduction in corn mean yield. These results strongly align with the existing literature that shows that erosion reduces the productivity of soils and consequently reduces mean crop yields (den Biggelaar et al., 2001; Badreldin and Lobb, 2023; Zhang et al., 2021).

To better interpret and quantify the estimated impact of combined soil erosion on mean crop yields, we conducted a back-of-the-envelope calculation using the 2017 average erosion levels and information from the 2024 USDA NASS database. In 2017, the average combined soil erosion per county was approximately 0.785 thousand tons for counties with available corn yield data, and 0.763 thousand tons for counties with available soybean yield data. By multiplying these values with the estimated coefficients from the "Mean" column in Tables 3 and 4, respectively, and multiplying further by the total harvested areas, we estimate that soil erosion led to a national yield reduction of approximately 87.2 million bushels for corn and 40.3 million bushels for soybeans. Valuing these yield reduction figures at the 2024 annual average producer received prices—

\$4.27 per bushel for corn and \$11.1 per bushel for soybeans —the estimated mean yield losses due to soil erosion translates to an economic cost of approximately \$372.34 million for corn and \$447.47 million for soybeans. In total, the estimated economic value of the mean corn and soybean yield losses due to soil erosion amounts to roughly \$819.81 million in 2024. These figures underscore the substantial economic burden posed by soil degradation in U.S. agriculture.

These dollar figures highlight the significant economic impact of soil erosion on mean row crop yield losses in the US. Although our estimates are lower than the economic loss values reported by Pimentel et al. (1995) (i.e., their estimates are in the \$44 billion range), there are two key differences to consider. First, their estimates reflect the overall cost of soil erosion to the US economy (not just the economic value of mean yield losses), where they account for both on-site effects (such as crop yield reductions due to lower fertility levels) and off-site effects (such as environmental degradation). In contrast, our estimates focus specifically on the economic value of the yield loss from soil erosion for two major row crops, corn and soybeans. Second, the acres harvested and crop prices have grown rapidly over the past 40 years, likely contributing to the disparity between our estimates and those in earlier studies. Nevertheless, our back-of-the-envelope calculations compare favorably to the more recent loss estimates in Thaler et al. (2021) (e.g., their estimates are around \$500 to \$600 million annually). But note that our estimates cover a larger collection of US corn-producing counties relative to the corn belt region examined in Thaler et al. (2021). Additionally, our yield reduction calculation accounts for soil erosion as estimated by the NRI, which considers both topsoil and deeper soil layers, rather than exclusively focusing on topsoil loss impacts (as in Thaler et al. (2021)).

With regards to the weather variables that serve as controls in Tables 3 and 4, the estimated weather effects on yields largely follow expectations. We find that GDD positively influences the mean yields of both row crops analyzed, and the parameters are statistically significant at the 1% level. This indicates that favorable growing conditions enhance mean yields. Conversely, HDD exhibit a statistically significant negative effect on the mean yields of both corn and soybeans (at the 1% significance level), suggesting that excessive heat accumulation can be detrimental to crop growth. Both precipitation and time trend display significant quadratic effects on mean yields, with coefficients that are statistically significant at the 1% level, capturing the expected nonlinear response to precipitation in both crops.

4.1.2 Higher Moment Effects

When examining higher-order moments of yields, our regression results show mixed findings across the two crops and across the different moments examined. For higher-order moments of corn yield, our findings indicate that the combined effects of water- and wind-caused soil erosion have a statistically significant positive impact on both the variance and kurtosis of yield (see Table 3). For the higher moments of soybean yield, the results are less clear. While the estimates for erosion effects on variance and skewness of soybean yields are positive, they are not statistically significant. Similarly, the estimate for the soil erosion effect on the kurtosis of soybean yields is also insignificant. On balance, our higher moment analysis suggests that soil erosion more likely leads to higher yield risks for corn (i.e., given its statistically significant positive effects on variance and kurtosis on corn yields), but there is no strong evidence of this risk-increasing effect for soybeans. Moreover, it is noteworthy that the estimated impact of soil erosion on all four moments of the yield distribution is generally greater for corn than for soybeans, suggesting that soil erosion likely poses a potentially greater threat to corn production than to soybean production in the US.

For the weather controls, the signs of the parameter estimates in the higher moment analysis generally follow expectations. By and large, GDD reduces the variance and kurtosis of corn and soybean yields, while HDD increases them. This is consistent with expectations that detrimental heat can increase yield variability, while good temperatures reduces yield variability. The signs of the precipitation parameters also largely follow the idea that too much precipitation (e.g. flood conditions) likely increases yield variability. Note however that the estimated weather variable parameters are not always statistically significant in the higher moment analysis (though the variance and kurtosis effects of GDD and HDD are more consistently significant).

4.1.3 Cost of Risk Results

Following Equation (5), we compute the cost of risk separately for corn and soybean yields. Although the estimated effects of soil erosion and other control variables are not statistically significant—particularly for soybeans in higher-order moment regressions—we proceed under the assumption that all coefficients are significant for the purpose of computing the cost of risk.

Soil erosion is assumed to vary between 0 and 1.5 thousand tons (with the actual means in the data around 0.8 thousand tons). County fixed effects are set to their sample mean, and all estimates are evaluated for the year 2017. The remaining covariates are held at either their sample mean or median values, corresponding to the two curves shown in Figures 3 and 4.

The computed cost of risk for corn ranges from 5 to 8.5 bushels per acre over this erosion range, while the corresponding values for soybean yields range from 0.95 to 1.1 bushels per acre. The cost of risk increases linearly as soil erosion increases (though the slope for soybeans tend to be flatter). Furthermore, at the 2017 sample mean of soil erosion levels (e.g., 0.785 for corn and 0.763 for soybeans), the corresponding cost of risk for corn and soybeans are 7.344 and 1.056 bushels per acre, respectively. Multiplying these figures by the 2024 price of both crops (e.g., \$4.27 per bushel for corn and \$11.1 per bushel for soybeans) indicates that the value of the increased risk due to soil erosion is about \$31.36 per acre for corn and \$11.72 per acre for soybeans. These results highlights that the cost of risk associated with soil loss is substantially higher for corn. This finding is consistent with Tables 3 and 4, where the estimated effects of soil erosion on the higher-order moments tend to be larger in the corn yield regressions as compared to the soybean yield regressions.

Using the per-acre cost of risk from the estimates above and multiplying by the harvested acreage—as done in the previous back-of-the-envelope calculation for mean yield losses—the total economic cost of increased risk attributable to soil erosion is estimated at \$2.60 billion for corn and \$1.01 billion for soybean. In total, the estimated economic cost of increased risk due to soil erosion for both crops amounts to approximately \$3.61 billion in 2024. This cost of increased risk due to soil erosion has not been quantified in previous literature. Therefore, with the \$819.81 million estimated losses from mean yield reductions due to soil erosion, we estimate that the total damage of soil erosion in terms of mean yield reduction and risk increases amounts to around \$4.43 billion in 2024.

We also decomposed the cost of risk into the variance effect, skewness effect, and kurtosis effect, consistent with Equation (5) (see Appendix Tables A.11 and A.12). For both crops, we find that majority of the overall risk effect of soil erosion can be largely attributed to the variance effect. The effect of soil erosion on skewness and kurtosis only contributes a small amount to the yield risk effects caused by erosion.

4.2 Robustness checks results

4.2.1 Robustness checks results: Alternative Specifications

The first robustness check we performed involves estimating the baseline model separately for water-induced erosion and wind-induced erosion, as shown in Appendix Tables A.1, A.2, A.3, and A.4. The estimated coefficients for erosion, weather controls, and time trend variables are roughly consistent with those from the baseline model that uses a combined water and wind erosion measure. The detrimental effect of soil erosion on mean yields and yield risk is still generally observed, although the results are sometimes not strongly consistent across runs (e.g., sometimes the significant estimates in the baseline are insignificant or are of the wrong signs).

A second robustness check was conducted by adding three additional control variables – farm acres operated, fertilizer expenditures, and federal government program receipts. The idea is to include these additional controls to help sharpen identification. Results for this robustness check are shown in Tables A.5 and A.6. When these new control variables are included, the estimated effect of soil erosion on the mean yield of corn remains negative but becomes statistically insignificant, while the estimates for variance and kurtosis remain consistent with the baseline model. In the case of soybeans, the estimated effects of soil erosion across all moments are generally robust and remain consistent with the main results. On balance, the findings from this robustness check using additional controls largely tracks the baseline results, though the results are somewhat weaker.

4.2.2 Robustness checks results: Alternative Estimation Strategies

In addition to testing robustness to alternative model specifications, we further assess whether our main findings remain valid when addressing potential endogeneity in the baseline empirical model specified in Equation (1). As part of this analysis, the third robustness check employs two instrumental variables—CRP cumulative enrollment and average rental payment—and implements a two-stage least squares (2SLS) estimation strategy. The results are presented in Tables 5 and 6.

In Table 5, the first-stage regression confirms the relevance of the instruments: CRP cumulative enrollment is negatively associated with soil erosion (significant at the 1% level), while CRP average rent is positively associated (significant at the 5% level). The weak instrument F-statistic indicates that the instruments are strongly correlated with soil erosion, satisfying the relevance condition. The Wu-Hausman test fails to reject the null hypothesis of exogeneity, suggesting that IV estimation may not be strictly necessary in this case. However, we proceed with the IV approach to strengthen the robustness of our findings. Additionally, the overidentification test fails to reject the null hypothesis, indicating that the instruments are valid and satisfy the exclusion restriction. These results suggest that CRP-related variables significantly explain variation in soil erosion. In the second-stage IV regression, the estimated coefficient for soil erosion on corn yield is -2.885, which is significant at the 10% level, supporting the baseline finding that increased erosion reduces mean crop yield. However, the magnitude of the estimated effect is approximately twice as large as that in the baseline model.

The IV estimation results for soybean yield are presented in Table 6, along with the first-stage regression for soil erosion. Diagnostic tests confirm that the instruments are strongly correlated with the endogenous variable, that soil erosion is endogenous, and that the instruments used are valid, thereby supporting the appropriateness of the IV strategy. Our results indicate that an increase of one thousand tons of soil loss leads to a reduction of 2.509 bushels per acre in soybean yield, and this effect is significant at the 1% level. As with the corn results, the soil erosion impact on soybeans tends to be larger using the 2SLS approach relative to the baseline panel fixed effects.

As an additional robustness check, we use 2SLS to estimate the impact of water- and wind-induced soil erosion on the mean yields of corn and soybeans, as reported in Tables A.7 and A.8. In each case, the weak identification test is rejected, while the overidentification test is not rejected at conventional significance levels, confirming that the selected instruments in each 2SLS estimation are both relevant and valid. Moreover, all 2SLS estimates are consistent with the findings from Tables 5 and 6. That is, counties experiencing more severe soil erosion—regardless of whether it is caused by water or wind—suffer significantly lower corn and soybean yields.

Finally, we implement the Lewbel (2012) heteroskedasticity-based IV procedure as another robustness check to determine if the effect of soil erosion on mean yield still holds when residual time–county varying unobservables are addressed using this econometric procedure. Parameter estimates using the heteroskedasticity-based instrumental variable procedure proposed by Lewbel (2012) are reported in Appendix Tables A.9 and A.10. Overall, the results from the various heteroskedasticity-based IV models for both corn and soybeans still support our main inferences from the baseline panel fixed effects model. That is, counties experiencing higher levels of soil erosion tend to suffer statistically significant mean yield losses. Our heteroskedasticity-based IV models also support the inference from the baseline panel fixed effects model that the negative impact of soil erosion on mean crop yields tend to be stronger for corn than soybeans.

5 Conclusions

Agricultural success hinges significantly on the health of soils, making it a pivotal factor in production agriculture. Soils play a multifaceted role, including nutrient and water storage and the preservation of organic matter, all of which are essential for bolstering farm productivity. Consequently, soil degradation, particularly through erosion, poses a substantial threat to the efficacy of agricultural soils in fulfilling their functions and enhancing productivity.

This study investigates the impact of soil erosion on crop yields in the US using county-level panel data. Our analysis revealed that counties with higher levels of soil erosion, whether due to water, wind, or a combination of both, tend to experience more significant reductions in mean crop yields. Specifically, both the linear FE models and the IV-based models consistently indicate a statistically significant negative impact of soil erosion on mean yields of corn and soybeans. Our higher moment analysis further reveals that soil erosion leads to an increase in the variance and kurtosis for corn yields, highlighting that soil erosion increases yield risk in US corn production. However, this pattern does not strongly hold for soybean yield risk, suggesting a more complex or less pronounced impact of soil erosion on soybean yield variability. Our calculations indicate that water- and wind-caused soil erosion in the US results in economic losses amounting to around \$4.43 billion in 2024 for corn and soybeans, with mean yield reductions accounting for around \$820 million and cost of increased risk accounting for \$3.61 billion.

Our findings have important implications for policymakers and stakeholders in agriculture. Understanding the overall impact of soil erosion on agricultural productivity – both due to mean yield losses and risk increases – is crucial for justifying support for taxpayer-funded government programs that help encourage adoption of practices that can alleviate soil erosion problems in agriculture. Our results demonstrate the magnitude of economic damages that soil erosion can cause in US row crop agriculture and provide further justification for support of federal cost-share programs, like the Environmental Quality Incentives Program (EQIP), and state-level cost-share programs that encourage adoption of practices that can help mitigate soil erosion in farmer fields. These programs are key for increased adoption of effective soil erosion mitigation strategies that can help safeguard the continued growth of US agriculture.

By quantifying both average yield losses and increased production risk due to erosion, our findings highlight the economic rationale for investing in soil conservation to mitigate its adverse effects on agricultural productivity. These results can help policymakers better assess the returns to conservation efforts and support sustained funding for soil health initiatives. National and state-level programs that promote erosion control play a vital role in stabilizing crop production, ensuring long-term food security, and enhancing the resilience of agricultural systems.

While this study provides new empirical evidence on the detrimental effects of soil erosion on crop yields, it is not without limitations. First, our analysis uses aggregate county-level data rather than individual farm-level data. Future research utilizing more granular farm-level data could provide deeper insights into the impact of soil erosion on yield and yield risk. Second, our data does not extend beyond 2017, and examining more recent trends could help better capture the evolving dynamics of soil erosion and crop yields in the context of changing climate conditions and agricultural practices. More in-depth research along the lines of the suggestions above can further aid policymakers and stakeholders in finding funding support for the development of targeted strategies to protect soil resources and ensure long-term agricultural sustainability.

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Tables and Figures

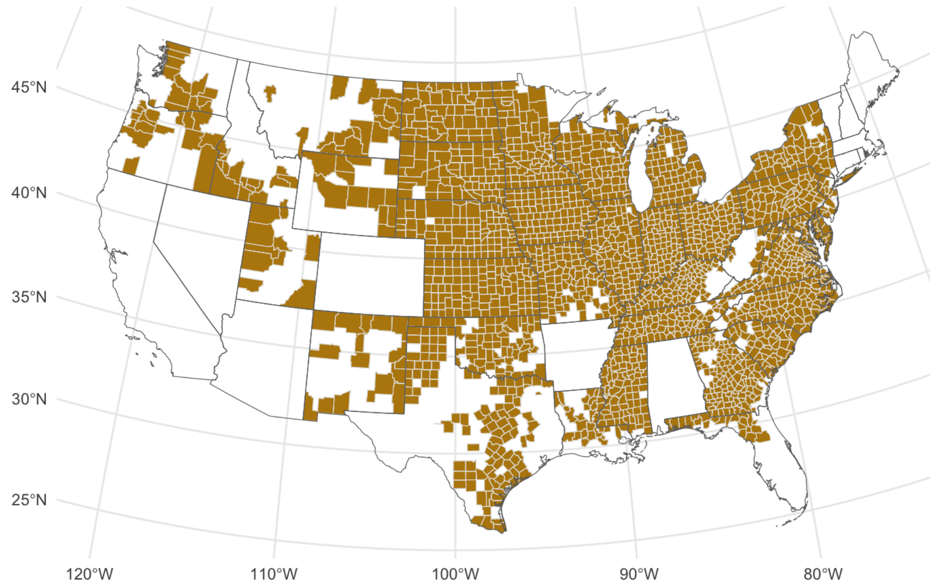

Figure 1: Spatial coverage of observed counties for corn yield data

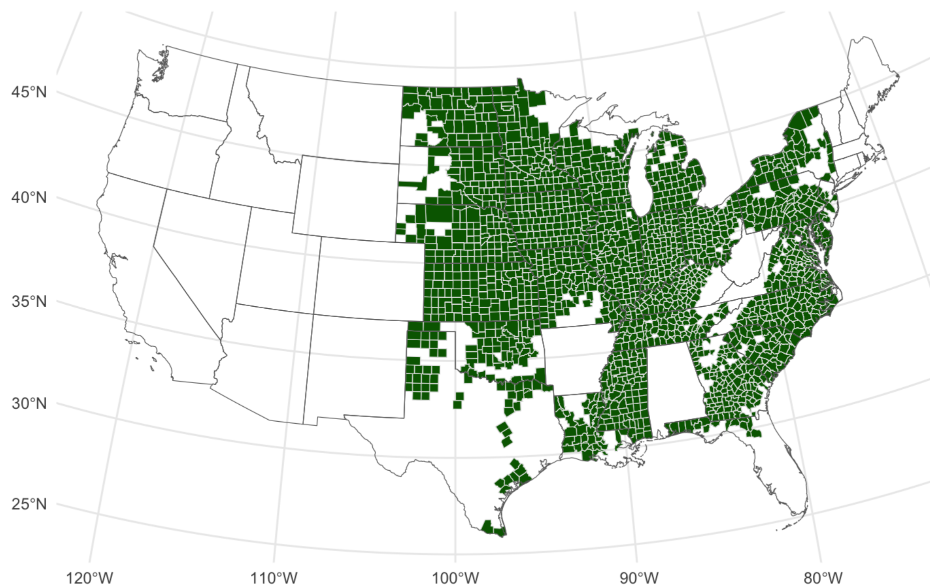

Figure 2: Spatial coverage of observed counties for soybean yield data

Note: Shaded counties indicate those with available data for all variables. Unshaded counties are excluded due to missing or incomplete records.

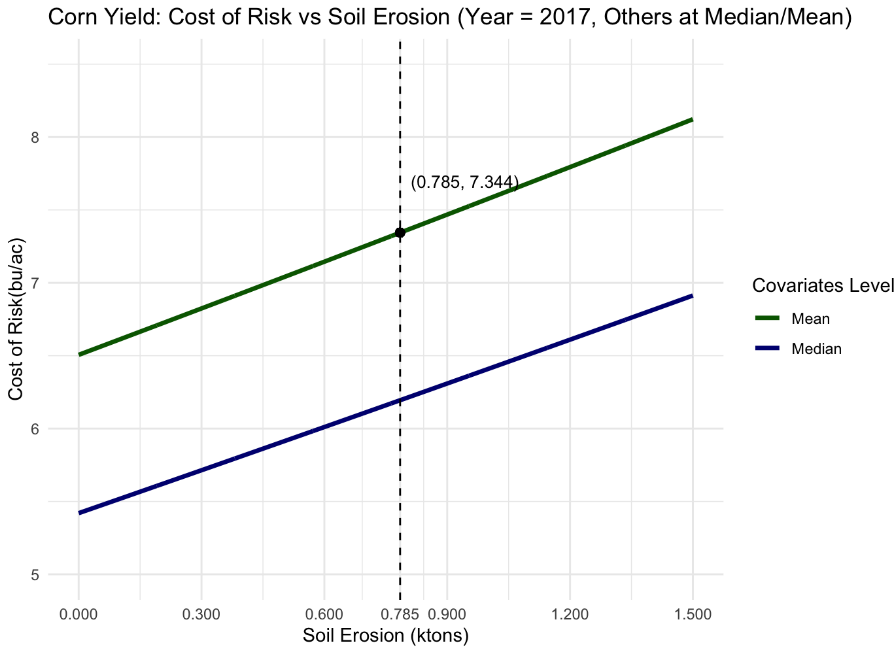

Figure 3: Corn Yield Cost of Risk

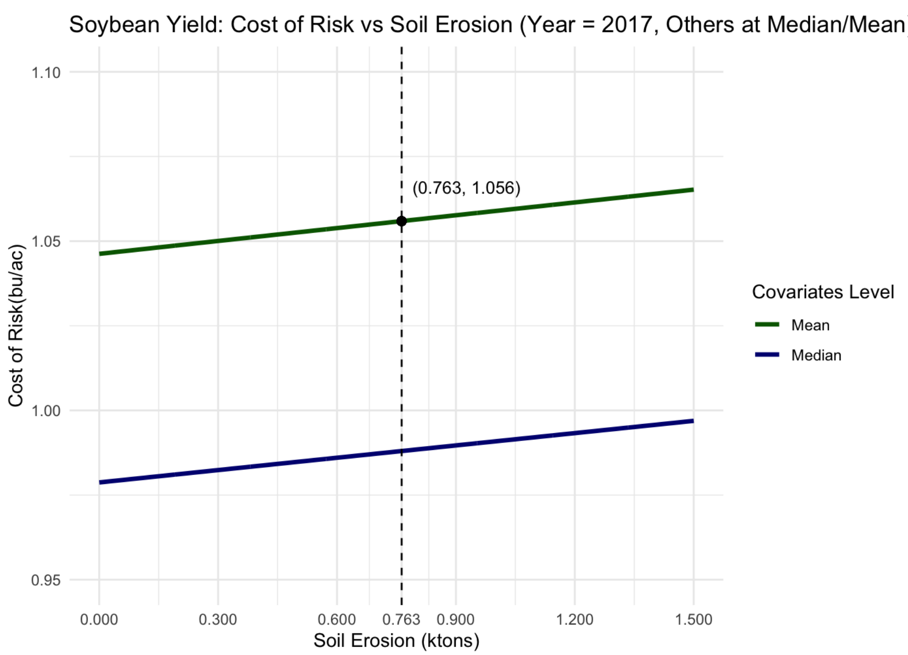

Figure 4: Soybean Yield Cost of Risk

Note: The vertical dashed line represents the average erosion level across all counties in 2017.

Table 1: Corn: Summary Statistics of Variables

Variable	Mean	Standard Deviation	Median	25th Percentile	75th Percentile
Corn Yield (Bu/Acre)	116.347	39.939	115.000	88.000	142.700
Soil Erosion (10^3Tons)	0.830	1.215	0.451	0.162	1.017
GDD (10^{3}˚C·day)	2.179	0.449	2.168	1.834	2.516
HDD (10^{3}˚C·day)	0.058	0.050	0.046	0.017	0.088
Precipitation (10^3mm)	0.549	0.163	0.554	0.449	0.655
Number of years: 7					
Number of counties: 2,265					

Table 2: Soybean: Summary Statistics of Variables

Variable	Mean	Standard Deviation	Median	25th Percentile	75th Percentile
Soybean Yield (Bu/Acre)	36.111	11.013	36.000	28.100	44.000
Soil Erosion (10^3Tons)	0.797	1.047	0.478	0.191	1.009
GDD (10^3˚C·day)	2.206	0.418	2.208	1.887	2.526
HDD (10^3˚C·day)	0.056	0.045	0.046	0.018	0.086
Precipitation (10^3 mm)	0.572	0.143	0.569	0.471	0.665
Number of years: 7					
Number of counties: 1,910					

Table 3: Effects of Combined Water and Wind Erosion on Mean, Variance, Skewness, and Kurtosis of Corn Yield

	Mean	Variance	Skewness	Kurtosis
Soil Erosion	-1.340^{*}	82.662^{***}	1,478.150	$350{,}142.800^{**}$
	(0.774)	(23.455)	(2,295.625)	(137,494.600)
GDD	23.472^{***}	-575.518^{***}	3,503.856	$-1{,}686{,}594.000^{***}$
	(2.246)	(57.537)	(5,443.237)	(375,061.700)
HDD	-523.532^{***}	$4{,}783.725^{***}$	−5,570.423	$14{,}934{,}048.000^{***}$
	(18.084)	(491.201)	(44,830.310)	(2,611,316.000)
Precipitation	58.581^{***}	−478.242	2,811.570	−637,326.100
	(12.616)	(356.333)	(34,479.920)	(2,533,455.000)
Precipitation^2	-33.274^{***}	254.838	5,532.842	426,894.100
	(9.937)	(270.981)	(26,103.820)	(1,883,845.000)
Time Trend	-5.327^{***}	49.305^{***}	−112.152	$185{,}856.900^{**}$
	(0.444)	(13.487)	(1,150.942)	(92,942.180)
Time Trend^2	1.639^{***}	0.395	−157.827	−1,779.939
	(0.054)	(1.696)	(136.938)	(10,386.550)
County FE	Yes	Yes	Yes	Yes
Clustered SE (fips)	Yes	Yes	Yes	Yes
Observations	12,421	12,421	12,421	12,421
R^2	0.475	0.057	0.003	0.013
Adjusted R^2	0.357	−0.154	−0.220	−0.207

Note: *p<0.1; **p<0.05; ***p<0.01. Standard errors in parentheses.

Table 4: Effects of Combined Water and Wind Erosion on Mean, Variance, Skewness, and Kurtosis of Soybean Yield

	Mean	Variance	Skewness	Kurtosis
Soil Erosion	-0.614^{***}	0.287	8.054	-198.053
	(0.202)	(1.138)	(20.595)	(287.828)
GDD	6.658^{***}	-16.286^{***}	-118.039	$-2{,}058.059^{**}$
	(0.583)	(3.737)	(74.417)	(958.216)
HDD	-127.013^{***}	171.571^{***}	$2{,}232.357^{***}$	$19{,}120.240^{**}$
	(4.128)	(27.182)	(650.949)	(8,391.444)
Precipitation	42.221^{***}	-18.843	$-1{,}638.897^{**}$	$-11{,}127.510$
	(3.752)	(27.758)	(697.383)	(10,545.970)
Precipitation^2	-25.187^{***}	11.465	$1{,}477.287^{**}$	8,785.868
	(3.056)	(22.282)	(576.215)	(8,665.888)
Time Trend	-0.711^{***}	4.482^{***}	-3.799	422.304^{*}
	(0.132)	(0.905)	(17.397)	(218.771)
Time Trend^2	0.392^{***}	-0.281^{**}	1.494	-19.442
	(0.017)	(0.112)	(2.178)	(26.312)
County FE	Yes	Yes	Yes	Yes
Clustered SE (fips)	Yes	Yes	Yes	Yes
Observations	10,418	10,418	10,418	10,418
R^2	0.561	0.030	0.009	0.007
Adjusted R^2	0.462	-0.189	-0.214	-0.217

Note: *p<0.1; **p<0.05; ***p<0.01. Standard errors in parentheses.

Table 5: 2SLS Estimation of the Effects of Combined Water and Wind Erosion on Mean Corn Yield

	Soil Erosion First Stage	Yield IV Estimation
CRP Enrollment	-0.013^{***}	
	(0.001)	
CRP Rent	0.040	
	(0.028)	
Soil Erosion		-2.885^{*}
		(1.751)
GDD	0.084^{**}	23.847^{***}
	(0.035)	(2.259)
HDD	0.123	-523.248^{***}
	(0.196)	(18.045)
Precipitation	0.251	59.177^{***}
	(0.201)	(12.608)
Precipitation^2	-0.146	-33.658^{***}
	(0.154)	(9.924)
Time Trend	-0.119^{***}	-5.706^{***}
	(0.010)	(0.567)
Time Trend^2	0.008^{***}	1.673^{***}
	(0.001)	(0.063)
Diagnostic Tests		
	Test Statistic	p-value
Wu-Hausamn	1.282	0.258
Kleibergen–Paap LM (under-ID)	62.926	0.000
Kleibergen–Paap Wald F(weak-ID)	55.544	
Hansen J	0.244	0.621
County FE	Yes	Yes
Clustered SE (fips)	Yes	Yes
Observations	12,421	12,421
R^2	0.270	0.474

Note: *p<0.1; **p<0.05; ***p<0.01. Standard errors in parentheses. Wu–Hausman statistic is used to check for the endogeneity of soil erosion variable. Kleibergen–Paap rk LM test evaluates underidentification. Weak instrument test is assessed via the Kleibergen–Paap rk Wald F statistic, compared to Stock–Yogo weak-ID critical values (10% = 19.93, 15% = 11.59). Hansen J statistic tests overidentifying restrictions.

Table 6: 2SLS Estimation of the Effects of Combined Water and Wind Erosion on Mean Soybean Yield

	Soil Erosion First Stage	Yield IV Estimation
CRP Enrollment	-0.011^{***}	
	(0.001)	
CRP Rent	-0.050^{**}	
	(0.025)	
Soil Erosion		-2.509^{***}
		(0.707)
GDD	0.029	6.930^{***}
	(0.032)	(0.580)
HDD	0.495^{***}	-125.644^{***}
	(0.173)	(4.215)
Precipitation	0.202	42.373^{***}
	(0.169)	(3.765)
Precipitation^2	-0.075	-25.134^{***}
	(0.127)	(3.069)
Time Trend	-0.145^{***}	-1.150^{***}
	(0.012)	(0.208)
Time Trend^2	0.013^{***}	0.433^{***}
	(0.001)	(0.023)
Diagnostic Tests		
	Test Statistic	p-value
Wu-Hausamn	9.397	0.002
Kleibergen–Paap LM(under-ID)	52.475	0.000
Kleibergen–Paap Wald F(weak-ID)	40.357	
Hansen J stat	0.536	0.464
County FE	Yes	Yes
Clustered SE (fips)	Yes	Yes
Observations	10,418	10,418
R^2	0.261	0.557

Note: *p<0.1; **p<0.05; ***p<0.01. Standard errors in parentheses. Wu–Hausman statistic is used to check for the endogeneity of soil erosion variable. Kleibergen–Paap rk LM test evaluates underidentification. Weak instrument test is assessed via the Kleibergen–Paap rk Wald F statistic, compared to Stock–Yogo weak-ID critical values (10% = 19.93, 15% = 11.59). Hansen J statistic tests overidentifying restrictions.

Appendix

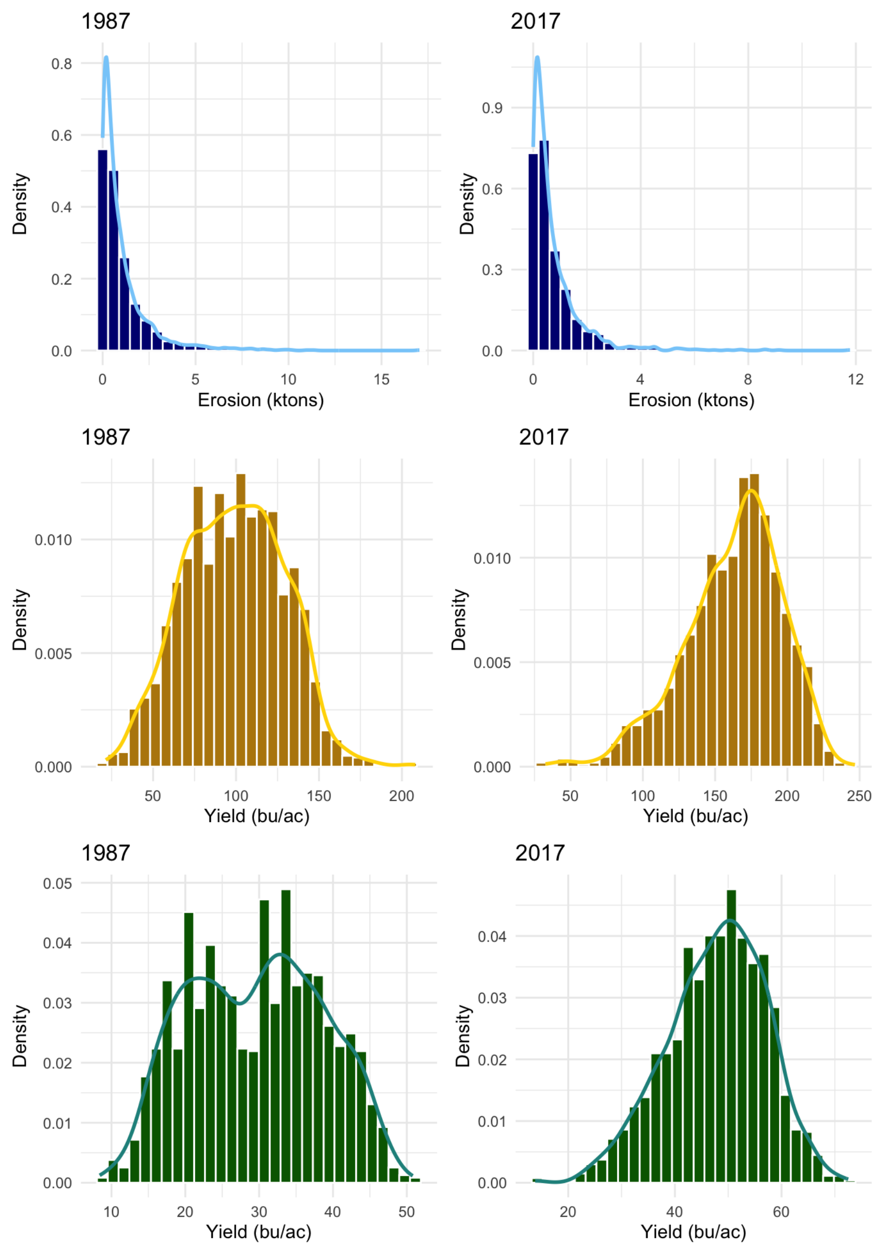

Figure A.1: Density distributions of crop yield and soil erosion

*Note:*Rows correspond to soil erosion (top), corn yield (middle), and soybean yield (bottom). Within each row, the two panels show distributions for the first and last years, with kernel density curves overlaid to highlight changes over time.

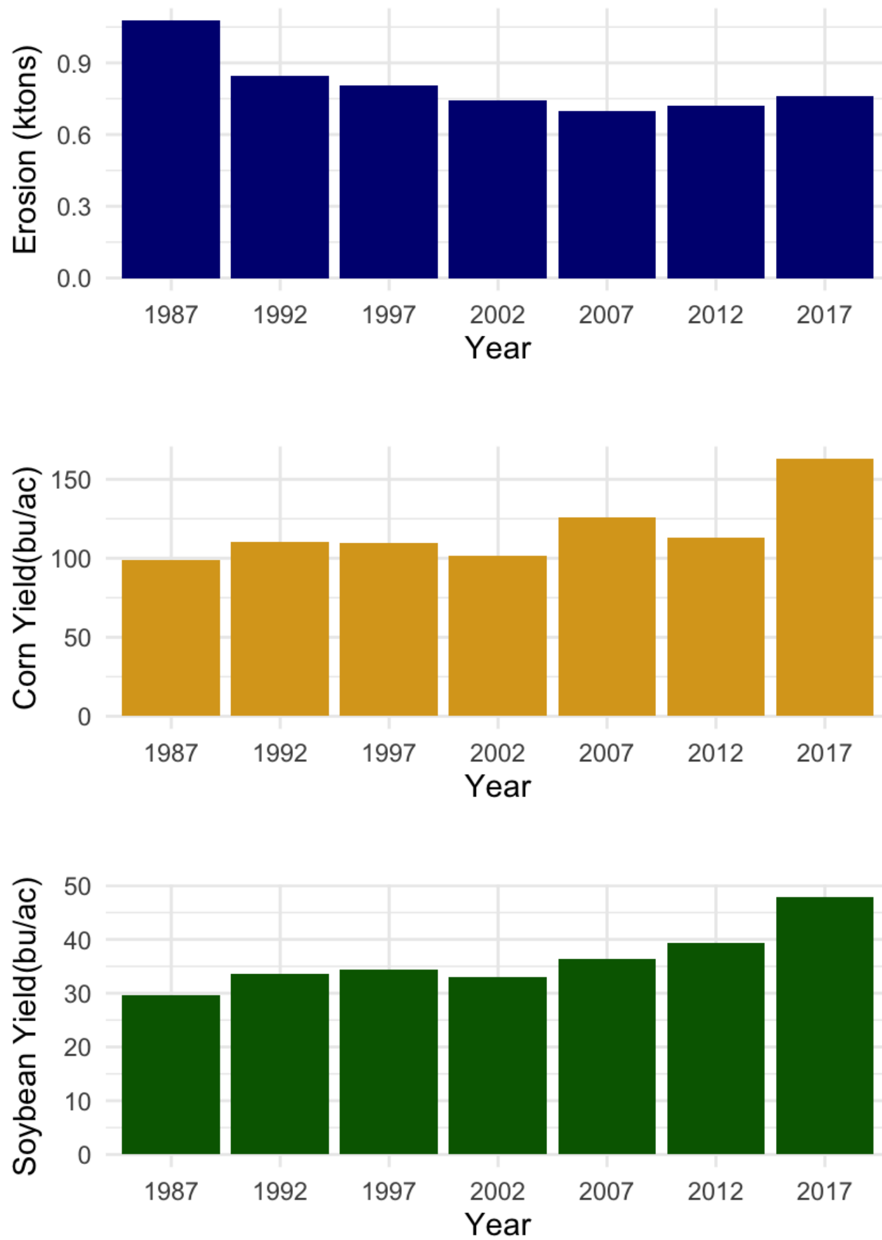

Figure A.2: Annual Average Trends of Soil Erosion, Corn Yield, and Soybean Yield

*Note:*Each panel shows the yearly average across all counties in the dataset. Soil erosion is measured in kilotons, and crop yields are in bushels per acre. Rows correspond to soil erosion (top), corn yield (middle), and soybean yield (bottom).

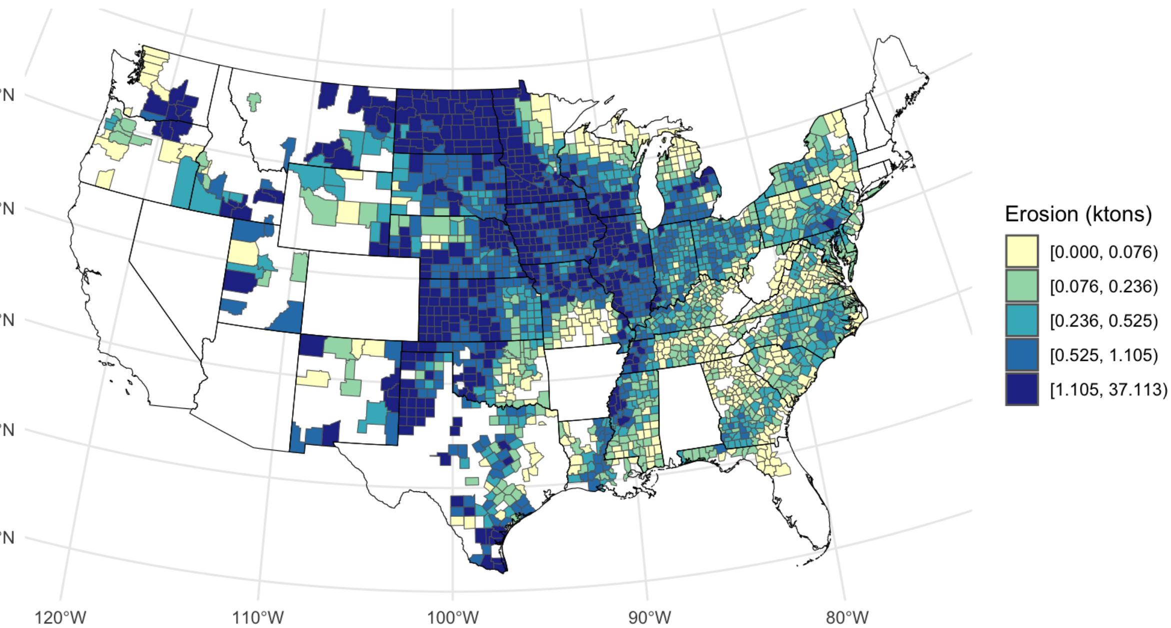

Figure A.3: Average soil erosion across counties

Note: Soil erosion values are averaged across all available years for each county. Only counties used in either the corn or soybean yield estimations are included. The maps show the spatial distribution of long-term average soil erosion.

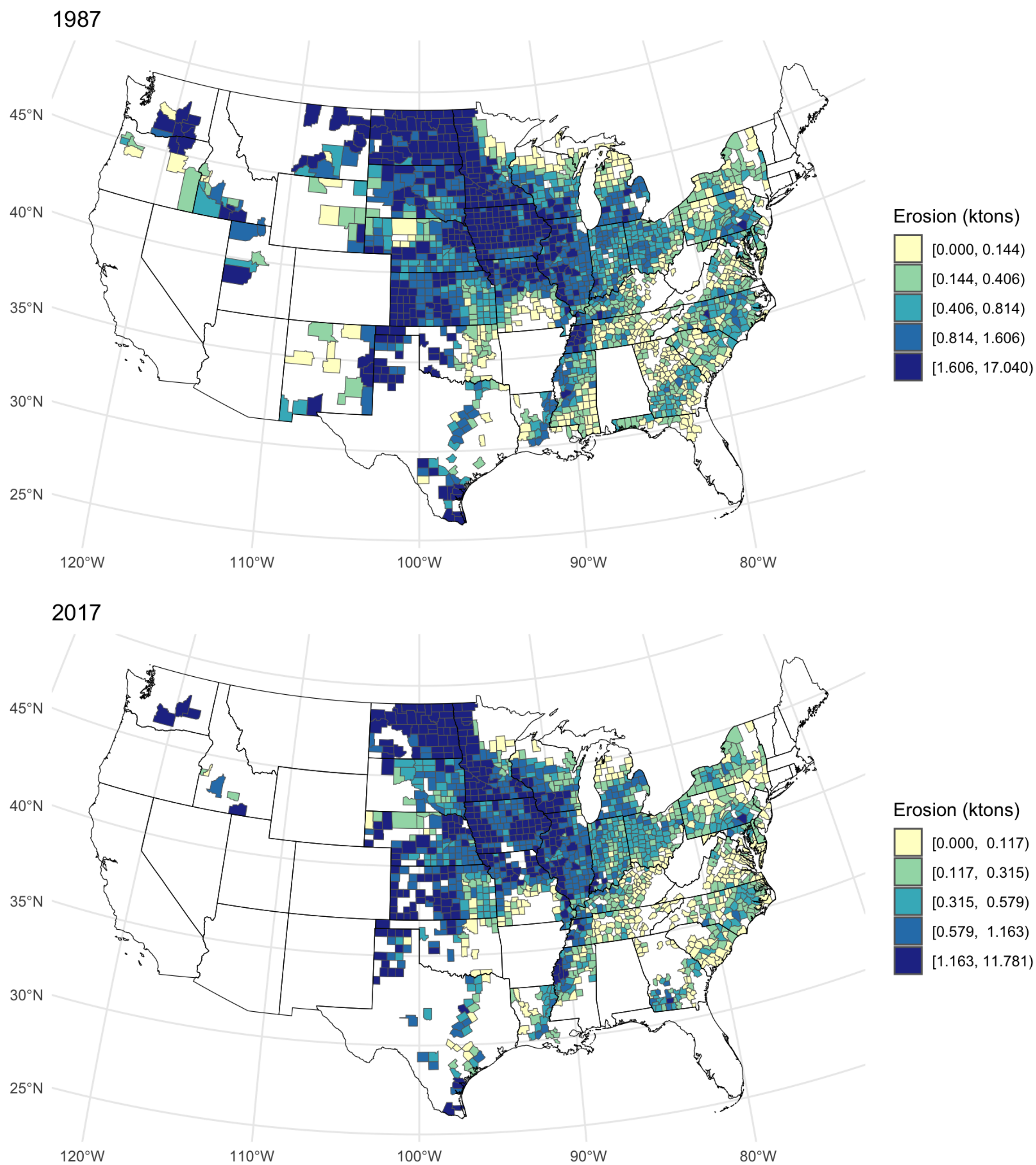

Figure A.4: Spatial distribution of average soil erosion across counties

Note: Soil erosion values represent the first (top) and last (bottom) year of the study period for each county to ensure comparability over time.

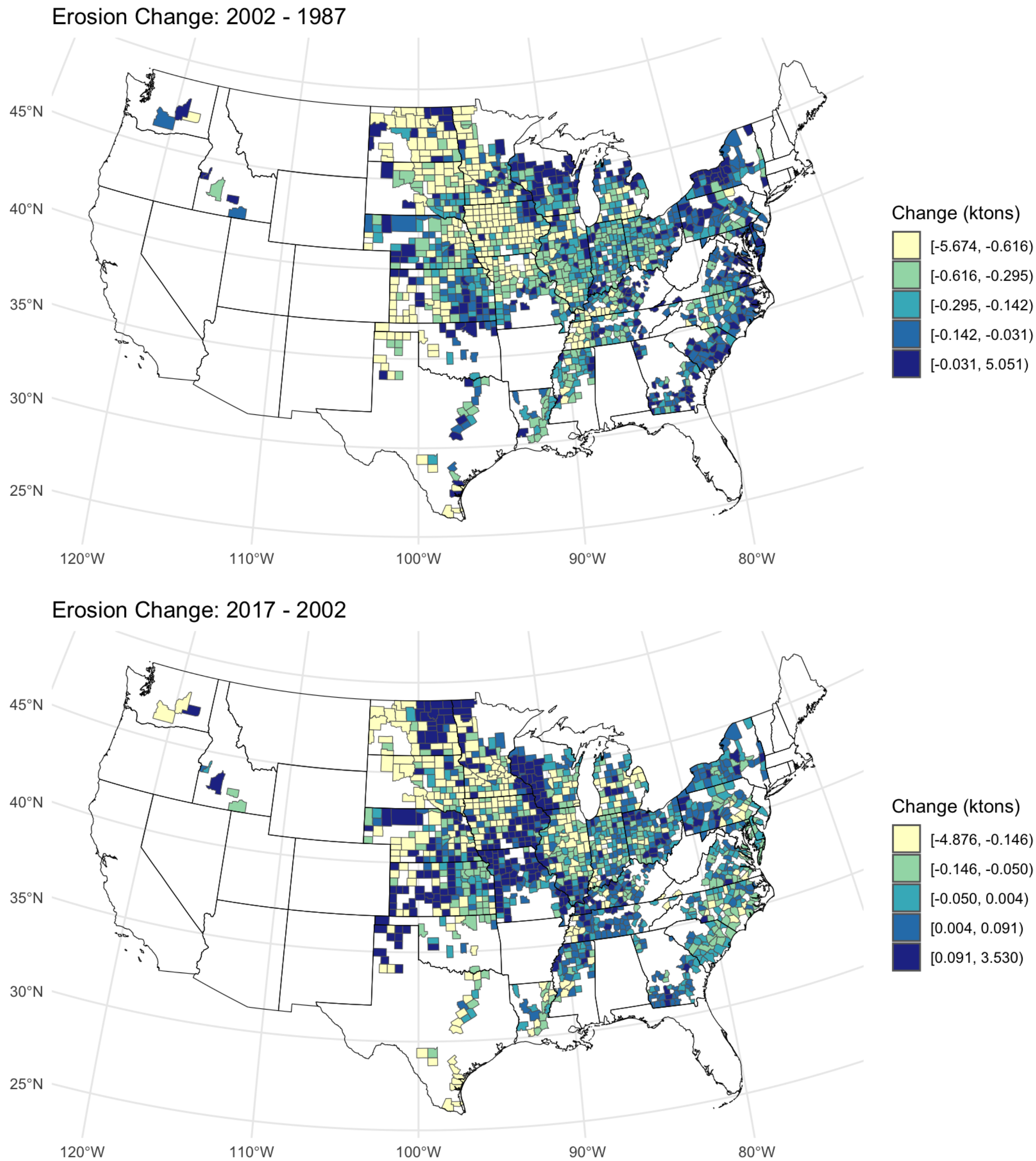

Figure A.5: Spatial distribution of average soil erosion across counties

Note: Maps show level changes in soil erosion (ktons) across counties over two time periods. Top: 1987–2002; Bottom: 2002–2017. Only counties used in corn or soybean yield estimations are included.

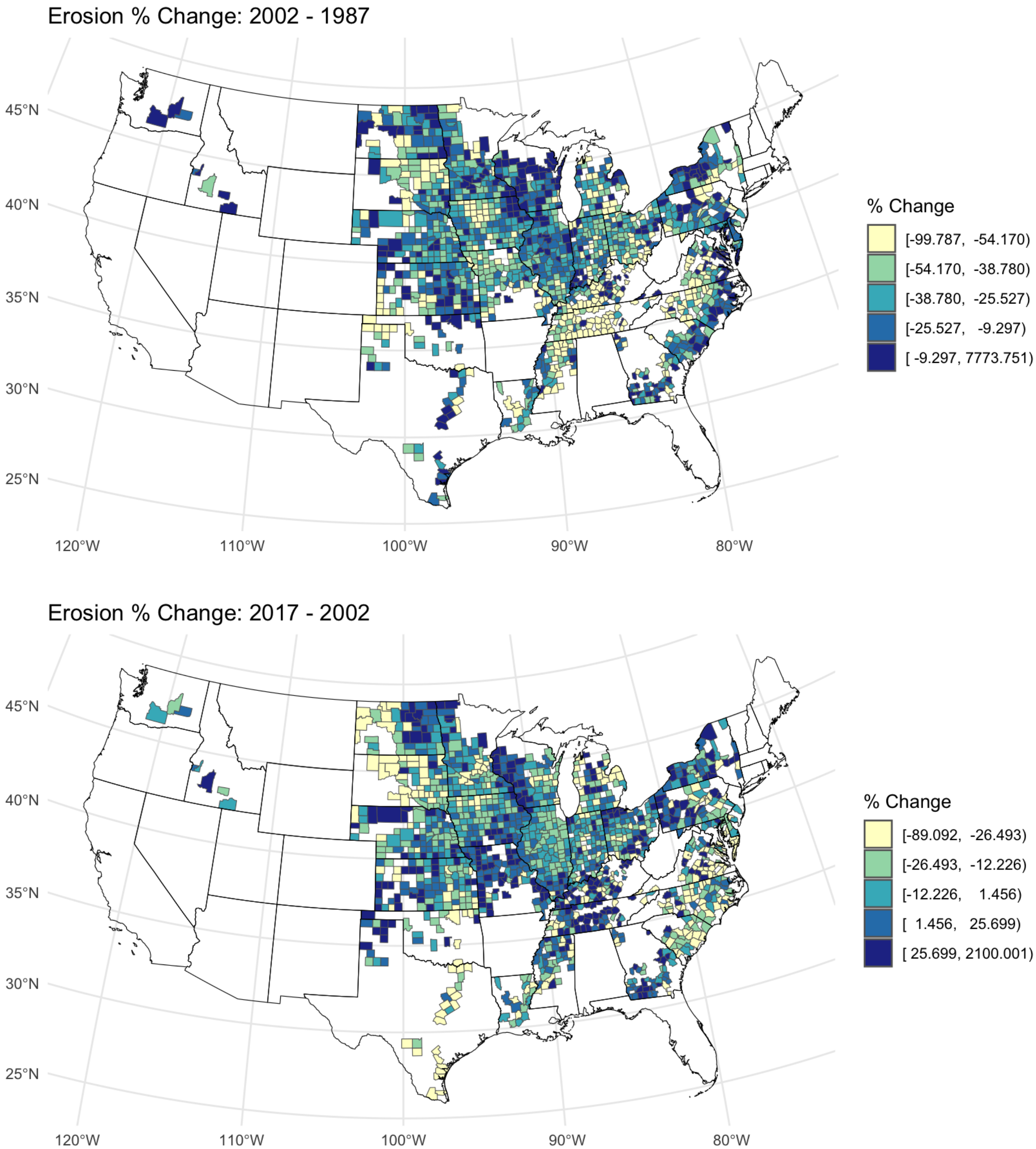

Figure A.6: Spatial distribution of average soil erosion across counties

Note: Maps show percentage changes in soil erosion across counties over two time periods. Top: 1987–2002; Bottom: 2002–2017. Only counties used in corn or soybean yield estimations are included.

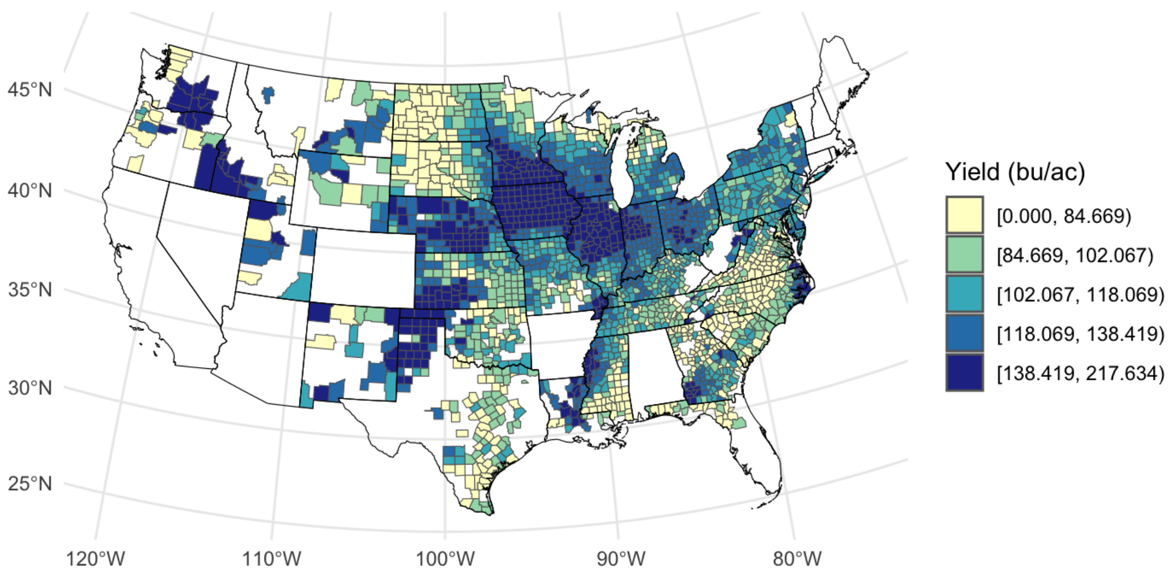

Figure A.7: Spatial distribution of average corn yield across counties

Note: Yield values represent the year-averaged corn yield (in bushels per acre) for each county over the full sample period.

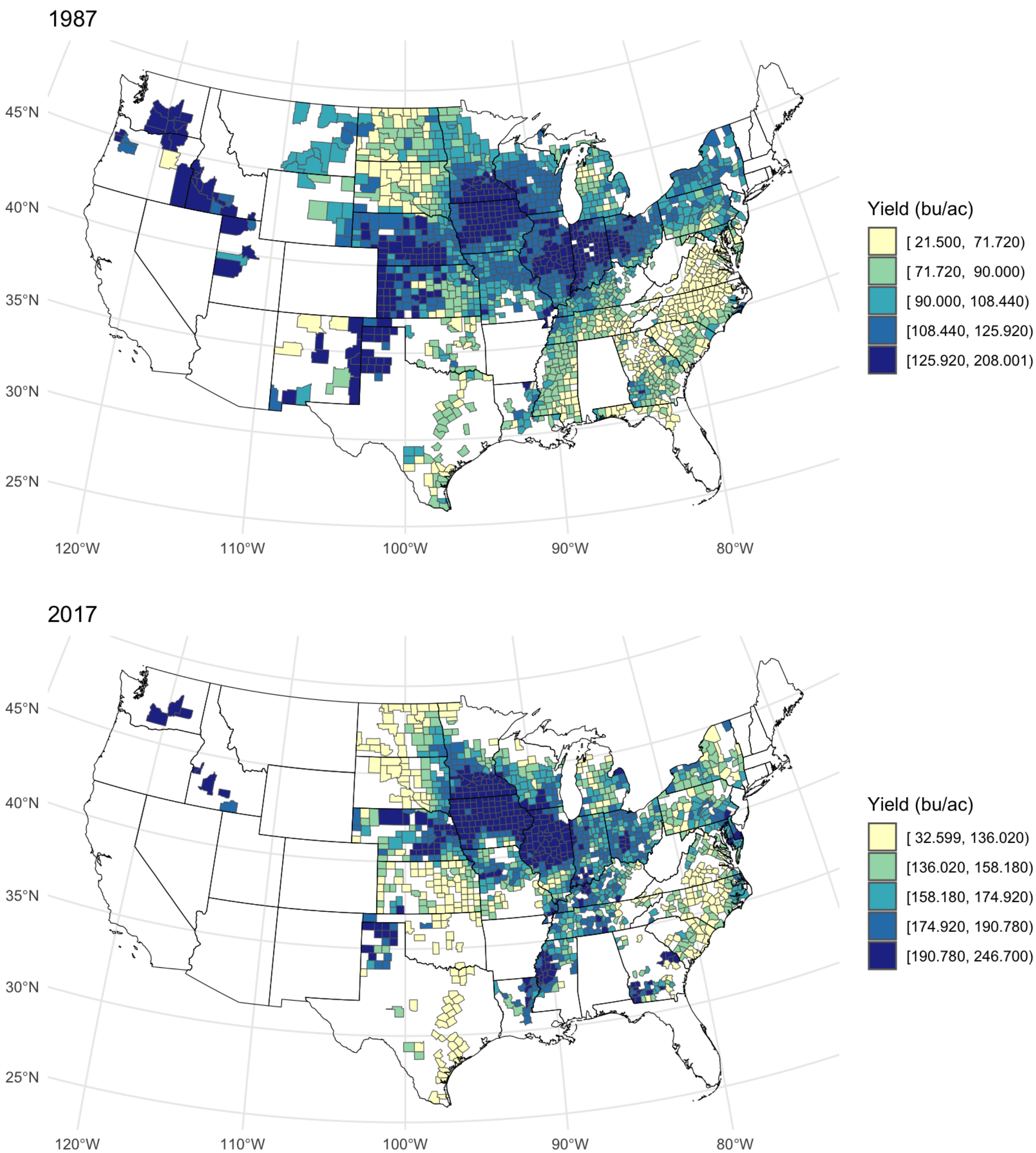

Figure A.8: Spatial distribution of corn yield in the first and last years

Note: Yield values represent the first (top) and last (bottom) year of the study period for each county to ensure comparability over time.

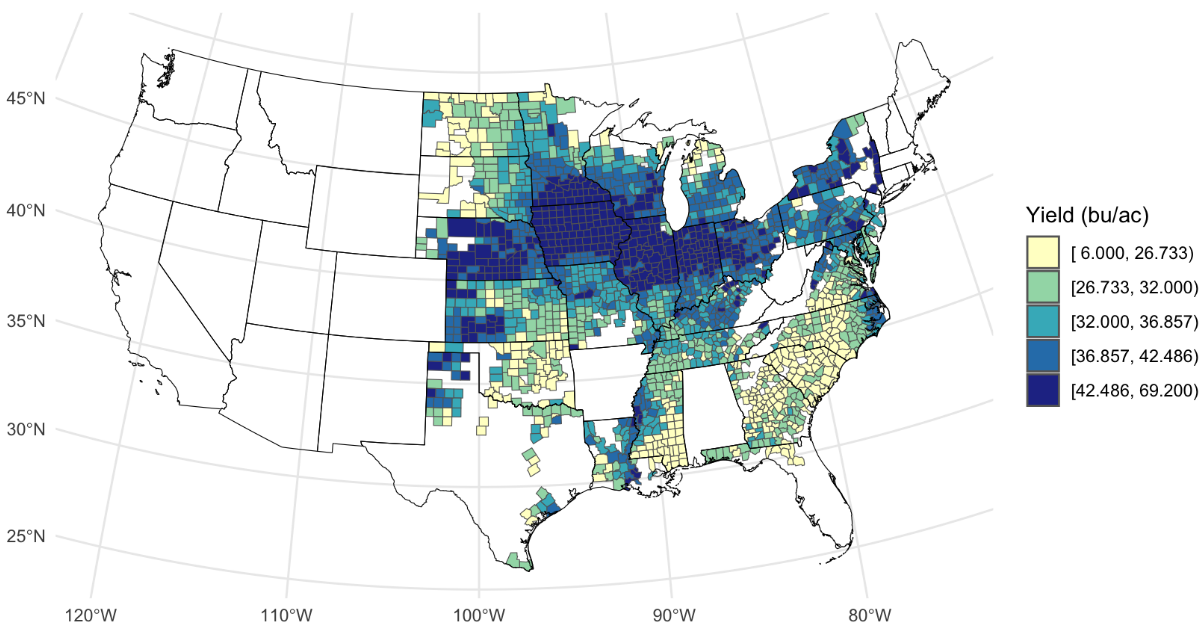

Figure A.9: Spatial distribution of average soybean yield

Note: Yield values represent the year-averaged soybean yield (in bushels per acre) for each county over the full sample period.

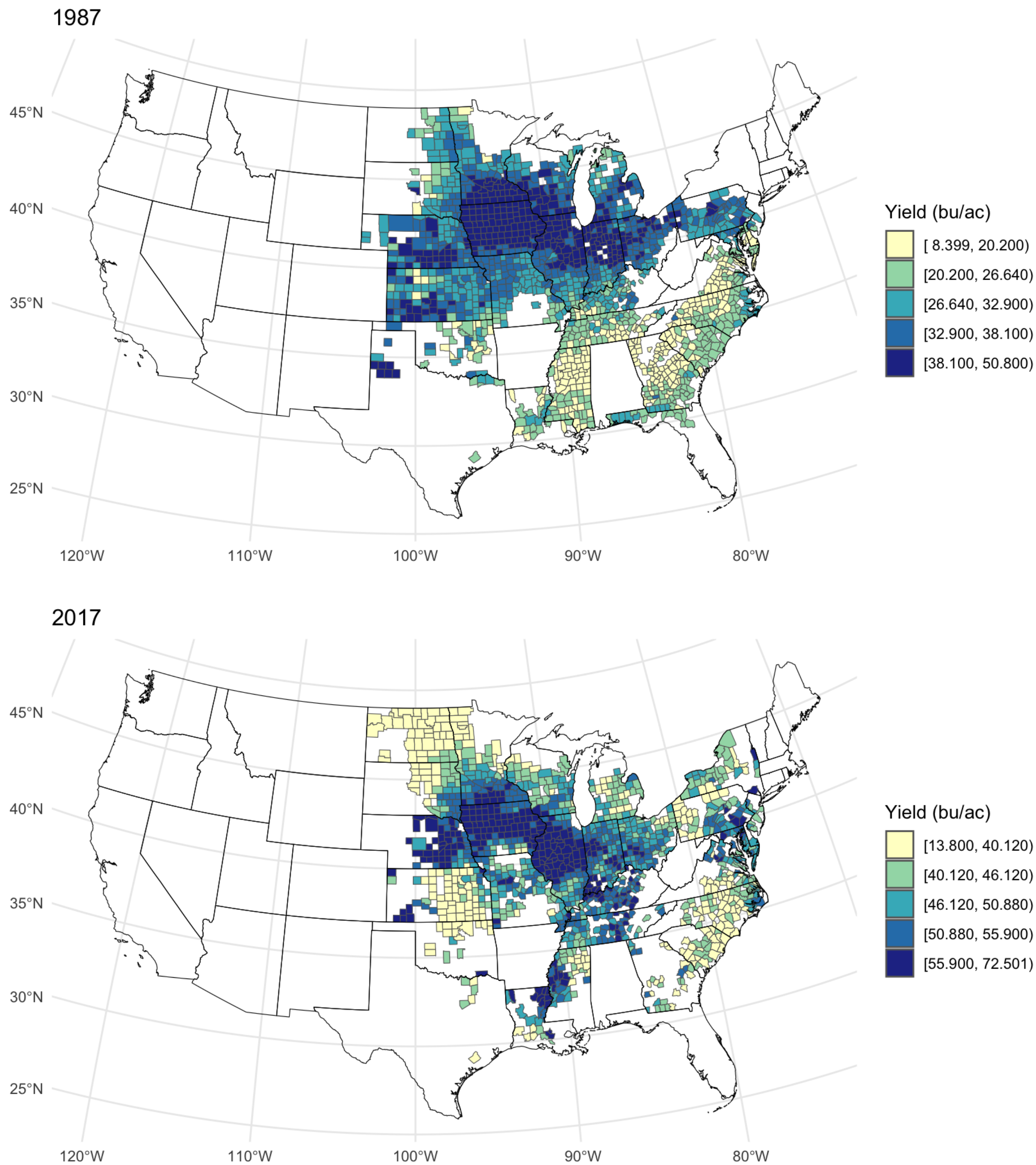

Figure A.10: Spatial distribution of soybean yield in the first and last years

Note: Yield values represent the first (top) and last (bottom) year of the study period for each county to ensure comparability over time.

Table A.1: Effects of Water Erosion on Mean, Variance, Skewness, and Kurtosis of Corn Yield

	Mean	Variance	Skewness	Kurtosis
Water Erosion	2.363*	32.833	−1,102.404	269,111.400*
	(1.230)	(30.393)	(2,343.176)	(149,371.700)
GDD	22.773***	−556.404***	3,980.578	−1,634,374.000***
	(2.244)	(57.132)	(5,367.575)	(367,239.200)
HDD	−523.960***	4,802.129***	−6,843.892	15,029,869.000***
	(18.150)	(492.429)	(45,013.630)	(2,627,130.000)
Precipitation	57.999***	−441.136	1,786.924	−456,007.200
	(12.640)	(363.224)	(34,917.780)	(2,596,635.000)
Precipitation^2	−32.926***	227.352	6,483.165	295,022.400
	(9.952)	(275.734)	(26,387.440)	(1,928,752.000)
Time Trend	−4.673***	33.299**	−590.321	139,980.800
	(0.457)	(13.859)	(1,156.337)	(95,272.470)
Time Trend^2	1.579***	1.841	−115.003	2,359.145
	(0.056)	(1.746)	(139.733)	(10,833.880)
County FE	Yes	Yes	Yes	Yes
Clustered SE (fips)	Yes	Yes	Yes	Yes
Observations	12,421	12,421	12,421	12,421
R^2	0.474	0.055	0.003	0.013
Adjusted R^2	0.357	−0.156	−0.220	−0.208

Note: *p<0.1; **p<0.05; ***p<0.01. Standard errors in parentheses.

Table A.2: Effects of Wind Erosion on Mean, Variance, Skewness, and Kurtosis of Corn Yield

	Mean	Variance	Skewness	Kurtosis
Wind Erosion	-2.236^{**}	91.989^{***}	2,821.609	$363{,}253.800^{**}$
	(0.936)	(28.287)	(2,731.694)	(160,722.100)
GDD	23.335^{***}	-558.994^{***}	3,507.324	$-1{,}625{,}177.000^{***}$
	(2.240)	(57.257)	(5,424.440)	(373,988.000)
HDD	-523.539^{***}	$4{,}761.372^{***}$	−3,578.608	$14{,}885{,}816.000^{***}$
	(18.076)	(491.395)	(44,797.380)	(2,605,108.000)
Precipitation	58.865^{***}	−492.159	4,134.436	−706,299.900
	(12.595)	(355.118)	(34,347.100)	(2,514,885.000)
Precipitation^2	-33.482^{***}	262.991	4,611.915	476,017.300
	(9.922)	(270.055)	(26,011.810)	(1,870,615.000)
Time Trend	-5.240^{***}	39.801^{***}	−228.693	140,354.400
	(0.413)	(12.913)	(1,053.906)	(87,079.200)
Time Trend^2	1.630^{***}	1.279	−145.633	2,411.489
	(0.052)	(1.673)	(130.482)	(10,037.700)
County FE	Yes	Yes	Yes	Yes
Clustered SE (fips)	Yes	Yes	Yes	Yes
Observations	12,421	12,421	12,421	12,421
R^2	0.475	0.057	0.003	0.013
Adjusted R^2	0.357	−0.154	−0.219	−0.208

Note: *p<0.1; **p<0.05; ***p<0.01. Standard errors in parentheses.

Table A.3: Effects of Water Erosion on Mean, Variance, Skewness, and Kurtosis of Soybean Yield

	Mean	Variance	Skewness	Kurtosis
Water Erosion	−0.768**	−4.181**	15.526	−336.816
	(0.317)	(1.911)	(39.651)	(660.302)
GDD	6.681***	−16.133***	−122.825	−2,087.062**
	(0.589)	(3.759)	(76.244)	(994.033)
HDD	−127.278***	174.844***	2,253.010***	19,287.540**
	(4.128)	(27.230)	(652.934)	(8,379.064)
Precipitation	42.213***	−18.235	−1,664.514**	−11,551.410
	(3.758)	(27.777)	(701.116)	(10,650.900)
Precipitation^2	−25.215***	11.383	1,498.490***	9,133.816
	(3.060)	(22.288)	(579.330)	(8,744.296)
Time Trend	−0.682***	3.918***	−3.825	444.430**
	(0.134)	(0.915)	(17.956)	(218.931)
Time Trend^2	0.390***	−0.231**	1.511	−22.510
	(0.017)	(0.113)	(2.211)	(26.248)
County FE	Yes	Yes	Yes	Yes
Clustered SE (fips)	Yes	Yes	Yes	Yes
Observations	10,418	10,418	10,418	10,418
R^2	0.561	0.030	0.009	0.007
Adjusted R^2	0.462	−0.188	−0.214	−0.217

Note: *p<0.1; **p<0.05; ***p<0.01. Standard errors in parentheses.

Table A.4: Effects of Wind Erosion on Mean, Variance, Skewness, and Kurtosis of Soybean Yield

	Mean	Variance	Skewness	Kurtosis
Wind Erosion	-0.549^{**}	2.207	3.670	-126.363
	(0.248)	(1.418)	(24.589)	(347.053)
GDD	6.570^{***}	-16.016^{***}	-116.942	$-2{,}029.135^{**}$
	(0.583)	(3.721)	(74.114)	(943.282)
HDD	-127.188^{***}	169.669^{***}	$2{,}244.752^{***}$	$18{,}800.490^{**}$
	(4.132)	(27.185)	(651.802)	(8,370.261)
Precipitation	42.186^{***}	-18.439	$-1{,}618.678^{**}$	$-10{,}798.680$
	(3.748)	(27.691)	(691.248)	(10,345.390)
Precipitation^2	-25.182^{***}	10.937	$1{,}462.696^{**}$	8,496.859
	(3.053)	(22.224)	(571.625)	(8,507.373)
Time Trend	-0.614^{***}	4.544^{***}	-6.578	453.991^{**}
	(0.122)	(0.862)	(15.768)	(207.722)
Time Trend^2	0.383^{***}	-0.285^{***}	1.764	-22.284
	(0.016)	(0.109)	(2.048)	(25.358)
County FE	Yes	Yes	Yes	Yes
Clustered SE (fips)	Yes	Yes	Yes	Yes
Observations	10,418	10,418	10,418	10,418
R^2	0.561	0.030	0.009	0.007
Adjusted R^2	0.462	-0.189	-0.214	-0.217

Note: *p<0.1; **p<0.05; ***p<0.01. Standard errors in parentheses.

Table A.5: Effects of Combined Water and Wind Erosion on Mean, Variance, Skewness, and Kurtosis of Corn Yield Extra Control Variables

	Mean	Variance	Skewness	Kurtosis
Soil Erosion	−0.813	92.221***	−717.753	379,260.600***
	(1.044)	(34.799)	(2,828.866)	(141,176.700)
GDD	3.370	−345.196***	42,444.990***	−1,923,361.000***
	(4.618)	(101.603)	(12,639.620)	(501,519.400)
HDD	−556.115***	1,958.695***	17,001.090	6,872,059.000**
	(24.450)	(656.552)	(56,707.700)	(2,856,679.000)
Precipitation	42.218***	−490.861	22,879.370	1,004,634.000
	(15.128)	(353.360)	(40,209.360)	(1,344,931.000)
Precipitation^2	−22.910*	68.922	−16,222.840	−1,245,342.000
	(11.839)	(275.177)	(30,857.260)	(985,511.000)
Time Trend	8.645***	209.546***	−19,095.300***	743,302.900***
	(1.781)	(43.875)	(5,783.665)	(233,627.000)
Time Trend^2	0.647**	−24.859***	2,575.855***	−90,109.500***
	(0.268)	(6.609)	(848.125)	(33,980.150)
Farm Acres	−0.008*	−0.039	12.257	24.021
	(0.004)	(0.099)	(20.106)	(331.504)
Fertilizer Expense	−0.010*	0.150	−4.503	271.995
	(0.006)	(0.148)	(11.027)	(557.989)
Government Subsidy	−0.0003***	−0.004**	−0.074	−12.404**
	(0.0001)	(0.002)	(0.169)	(6.007)
County FE	Yes	Yes	Yes	Yes
Clustered SE (fips)	Yes	Yes	Yes	Yes
Observations	8,428	8,428	8,428	8,428
R^2	0.519	0.054	0.009	0.021
Adjusted R^2	0.357	−0.265	−0.326	−0.309

Note: *p<0.1; **p<0.05; ***p<0.01. Standard errors in parentheses.

Table A.6: Effects of Combined Water and Wind Erosion on Mean, Variance, Skewness, and Kurtosis of Soybean Yield Extra Control Variables

	Mean	Variance	Skewness	Kurtosis
Soil Erosion	-0.567^{*}	-1.349	-18.618	-321.607
	(0.320)	(2.292)	(43.286)	(619.787)
GDD	-6.791^{***}	-3.707	-0.811	1,816.855
	(1.278)	(7.765)	(180.269)	(2,666.916)
HDD	-132.102^{***}	-6.427	1,448.741**	$-9{,}450.519$
	(5.072)	(38.492)	(700.880)	(11,328.670)
Precipitation	49.858***	8.678	$-1{,}050.057$	8,030.003
	(4.452)	(27.118)	(741.882)	(10,249.470)
Precipitation^2	-31.671^{***}	-11.502	901.537	$-5{,}949.654$
	(3.624)	(22.306)	(606.450)	(8,432.997)
Time Trend	3.968***	8.016**	-54.535	253.711
	(0.562)	(3.760)	(89.009)	(1,586.758)
Time Trend^2	-0.108	-1.138^{**}	10.889	-65.098
	(0.082)	(0.558)	(12.822)	(223.147)
Farm Acres	-0.009^{***}	0.028***	0.086	3.101
	(0.002)	(0.010)	(0.248)	(2.882)
Fertilizer Expense	0.014***	0.013	-0.374	6.144*
	(0.002)	(0.010)	(0.258)	(3.573)
Government Subsidy	0.00001	-0.0002	0.001	0.006
	(0.00002)	(0.0001)	(0.002)	(0.027)
County FE	Yes	Yes	Yes	Yes
Clustered SE (fips)	Yes	Yes	Yes	Yes
Observations	7,142	7,142	7,142	7,142
R^2	0.589	0.011	0.004	0.003
Adjusted R^2	0.452	-0.319	-0.329	-0.330

Note: *p<0.1; **p<0.05; ***p<0.01. Standard errors in parentheses.

Table A.7: 2SLS Estimation of the Effects of Water and Wind Erosion on Mean Corn Yield

	Water Erosion	Wind Erosion
Erosion Variable	-15.925^{*}	-3.440
	(9.681)	(2.159)
GDD	25.671^{***}	23.436^{***}
	(2.680)	(2.235)
HDD	-522.554^{***}	-523.411^{***}
	(18.058)	(18.053)
Precipitation	58.506^{***}	59.296^{***}
	(12.701)	(12.599)
Precipitation^2	-33.045^{***}	-33.774^{***}
	(10.007)	(9.915)
Time Trend	-7.183^{***}	-5.371^{***}
	(1.343)	(0.450)
Time Trend^2	1.812^{***}	1.642^{***}
	(0.128)	(0.054)
Diagnostic Tests		
Wu-Hausamn	5.837 (p = 0.016)	0.510 (p = 0.475)
Kleibergen–Paap LM stat (under-ID)	80.601 (p = 0.000)	44.065 (p = 0.000)
Kleibergen–Paap Wald F stat (weak-ID)	38.738	39.013
Hansen J statistic	0.004 (p = 0.951)	0.351 (p = 0.553)
County FE	Yes	Yes
Clustered SE (fips)	Yes	Yes
Observations	12,421	12,421
R^2	0.255	0.466

Note: *p<0.1; **p<0.05; ***p<0.01. Wu–Hausman statistic is used to check for the endogeneity of soil erosion variable. Kleibergen–Paap rk LM test evaluates underidentification. Weak instrument test is assessed via the Kleibergen–Paap rk Wald F statistic, compared to Stock–Yogo weak-ID critical values (10% = 19.93, 15% = 11.59). Hansen J statistic tests overidentifying restrictions.

Table A.8: 2SLS Estimation of the Effects of Water and Wind Erosion on Mean Soybean Yield

	Water Erosion	Wind Erosion
Erosion Variable	-9.092^{***}	-3.432^{***}
	(2.849)	(1.075)
GDD	7.877^{***}	6.569^{***}
	(0.702)	(0.585)
HDD	-125.339^{***}	-125.777^{***}
	(4.297)	(4.211)
Precipitation	42.661^{***}	42.262^{***}
	(3.828)	(3.763)
Precipitation^2	-25.326^{***}	-25.062^{***}
	(3.125)	(3.064)
Time Trend	-1.919^{***}	-0.854^{***}
	(0.439)	(0.151)
Time Trend^2	0.506^{***}	0.405^{***}
	(0.043)	(0.018)
Diagnostic Tests		
Wu-Hausamn	11.810 (p = 0.001)	11.622 (p = 0.001)
Kleibergen–Paap LM(under-ID)	71.065 (p = 0.000)	26.819 (p = 0.000)
Kleibergen–Paap Wald F (weak-ID)	26.835	18.816
Hansen J	1.223 (p = 0.269)	0.341 (p = 0.559)
County FE	Yes	Yes
Clustered SE (fips)	Yes	Yes
Observations	10,418	10,418
R^2	0.537	0.554

Note: *p<0.1; **p<0.05; ***p<0.01. Wu–Hausman statistic is used to check for the endogeneity of soil erosion variable. Kleibergen–Paap rk LM test evaluates underidentification. Weak instrument test is assessed via the Kleibergen–Paap rk Wald F statistic, compared to Stock–Yogo weak-ID critical values (10% = 19.93, 15% = 11.59). Hansen J statistic tests overidentifying restrictions.

Table A.9: 2SLS Estimates of the Effects of Combined Water and Wind Erosion on Mean Corn Yield

	(1) External IV	(2) Lewbel IV	(3) Lewbel + External	(4)CRP Enrl + Lewbel	(5)CRP Rent+ Lewbel
Soil Erosion	-2.885^{*}	-2.269^{*}	-2.456^{**}	-2.466^{**}	-2.269^{*}
	(1.714)	(1.315)	(1.255)	(1.253)	(1.315)
GDD	23.847^{***}	23.698^{***}	23.743^{***}	23.745^{***}	23.698^{***}
	(2.258)	(2.252)	(2.247)	(2.246)	(2.252)
HDD	-523.248^{***}	-523.361^{***}	-523.327^{***}	-523.325^{***}	-523.362^{***}
	(18.036)	(18.052)	(18.049)	(18.049)	(18.052)
Precipitation	59.177^{***}	58.940^{***}	59.012^{***}	59.016^{***}	58.940^{***}
	(12.602)	(12.600)	(12.599)	(12.599)	(12.600)
Precipitation^2	-33.658^{***}	-33.505^{***}	-33.552^{***}	-33.554^{***}	-33.505^{***}
	(9.920)	(9.922)	(9.921)	(9.921)	(9.922)
Time Trend	-5.706^{***}	-5.555^{***}	-5.601^{***}	-5.603^{***}	-5.555^{***}
	(0.567)	(0.513)	(0.497)	(0.497)	(0.513)
Time Trend^2	1.673^{***}	1.660^{***}	1.664^{***}	1.664^{***}	1.660^{***}
	(0.063)	(0.059)	(0.058)	(0.058)	(0.059)
Diagnostic Tests					
Kleibergen–Paap Wald F (weak-ID)	55.544	158.538	117.943	131.059	137.603
Kleibergen–Paap LM (under-ID)	62.926	72.925	103.862	82.563	91.030
p-value (LM stat)	0.000	0.000	0.000	0.000	0.000
Hansen J	0.244	9.241	9.271	9.176	9.337
p-value (J stat)	0.621	0.010	0.234	0.164	0.156
County FE	Yes	Yes	Yes	Yes	Yes
Clustered SE (fips)	Yes	Yes	Yes	Yes	Yes
Observations	12,421	12,421	12,421	12,421	12,421
R^2	0.474	0.474	0.474	0.474	0.474

Note: *p<0.1; **p<0.05; ***p<0.01. Kleibergen–Paap rk LM test evaluates underidentification. Weak instrument test is assessed via the Kleibergen–Paap rk Wald F statistic, compared to Stock–Yogo weak-ID critical values (10% = 19.93, 15% = 11.59). Hansen J statistic tests overidentifying restrictions.

Table A.10: 2SLS Estimates of the Effects of Combined Water and Wind Erosion on Mean Soybean Yield

	(1) External IV	(2) Lewbel IV	(3) Lewbel + External	(4)CRP Enrl + Lewbel	(5) CRP Rent + Lewbel
Soil Erosion	−2.509***	−0.072	−0.660*	−0.674*	−0.061
	(0.706)	(0.348)	(0.348)	(0.349)	(0.346)
GDD	6.930***	6.581***	6.665***	6.667***	6.579***
	(0.579)	(0.586)	(0.582)	(0.582)	(0.587)
HDD	−125.644***	−127.405***	−126.980***	−126.970***	−127.413***
	(4.213)	(4.129)	(4.140)	(4.142)	(4.126)
Precipitation	42.373***	42.177***	42.225***	42.226***	42.177***
	(3.763)	(3.748)	(3.748)	(3.748)	(3.748)
Precipitation^2	−25.134***	−25.202***	−25.186***	−25.185***	−25.203***
	(3.067)	(3.051)	(3.052)	(3.052)	(3.051)
Time Trend	−1.150***	−0.585***	−0.721***	−0.725***	−0.583***
	(0.208)	(0.149)	(0.150)	(0.150)	(0.149)
Time Trend^2	0.433***	0.381***	0.393***	0.394***	0.380***
	(0.023)	(0.018)	(0.018)	(0.018)	(0.018)
Diagnostic Tests					
Kleibergen–Paap Wald F (weak-ID)	40.355	163.632	153.980	167.087	154.990
Kleibergen–Paap LM (under-ID)	52.475	86.915	118.899	91.551	109.897
p-value (LM stat)	0.000	0.000	0.000	0.000	0.000
Hansen J stat	0.536	4.416	19.204	18.484	4.526
p-value (J stat)	0.464	0.491	0.008	0.005	0.606
County FE	Yes	Yes	Yes	Yes	Yes
Clustered SE(fips)	Yes	Yes	Yes	Yes	Yes
Observations	10,418	10,418	10,418	10,418	10,418
R^2	0.557	0.561	0.561	0.561	0.561

Note: *p<0.1; **p<0.05; ***p<0.01. Kleibergen–Paap rk LM test evaluates underidentification. Weak instrument test is assessed via the Kleibergen–Paap rk Wald F statistic, compared to Stock–Yogo weak-ID critical values (10% = 19.93, 15% = 11.59). Hansen J statistic tests overidentifying restrictions.

Table A.11: Estimated Cost of Risk for Corn

Soil Erosion (ktons)	**COR due to Variance(bu/ac)**	**COR due to Skewness(bu/ac)**	**COR due to Kurtosis(bu/ac)**	**COR (bu/ac)**
0.0	4.884	0.862	0.760	6.506
0.1	4.973	0.850	0.789	6.612
0.2	5.061	0.838	0.819	6.718
0.3	5.150	0.826	0.848	6.824
0.4	5.239	0.814	0.878	6.931
0.5	5.328	0.801	0.908	7.038
0.6	5.418	0.789	0.938	7.145
0.7	5.507	0.777	0.969	7.252
0.8	5.597	0.765	0.999	7.360
0.9	5.686	0.752	1.030	7.468
1.0	5.776	0.740	1.060	7.577
1.1	5.867	0.727	1.091	7.685
1.2	5.957	0.715	1.122	7.794
1.3	6.047	0.702	1.154	7.903
1.4	6.138	0.690	1.185	8.013
1.5	6.229	0.677	1.217	8.122

Note: We use the parameter estimates for the mean, variance, skewness, and kurtosis to compute the cost of risk as defined in Equation (5), although some of these estimates are not statistically significant.

Table A.12: Estimated Cost of Risk for Soybean

Soil Erosion (ktons)	**COR due to Variance(bu/ac)**	**COR due to Skewness(bu/ac)**	**COR due to Kurtosis(bu/ac)**	**COR (bu/ac)**
0.0	0.971	−0.014	0.088	1.046
0.1	0.974	−0.014	0.088	1.048
0.2	0.976	−0.015	0.088	1.049
0.3	0.978	−0.016	0.088	1.050
0.4	0.981	−0.017	0.088	1.051
0.5	0.983	−0.018	0.088	1.053
0.6	0.985	−0.019	0.087	1.054
0.7	0.987	−0.019	0.087	1.055
0.8	0.990	−0.020	0.087	1.056
0.9	0.992	−0.021	0.087	1.058
1.0	0.994	−0.022	0.087	1.059
1.1	0.997	−0.023	0.086	1.060
1.2	0.999	−0.024	0.086	1.061
1.3	1.001	−0.025	0.086	1.063
1.4	1.004	−0.026	0.086	1.064
1.5	1.006	−0.026	0.086	1.065

Note: We use the parameter estimates for the mean, variance, skewness, and kurtosis to compute the cost of risk as defined in Equation (5), although some of these estimates are not statistically significant.