The Impact of Soil Erosion on Mean Yields and Yield Risk

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Abstract

This study examines the impact of soil erosion on crop yields in the United States using county-level panel data. We use linear panel fixed effects (FE) models to assess how wind and water erosion affect the mean yields of soybeans and corn. The results show that higher soil erosion levels, whether from water, wind, or a combination, lead to significant reductions in mean yields. Additionally, soil erosion contributes to increased variance and kurtosis in corn yields, indicating greater yield instability, though its impact on soybean yield risk is less conclusive. To further explore the complexities of this relationship, we investigate potential nonlinear effects of soil erosion on crop yields. This analysis reveals complex nonlinear impacts of soil erosion, particularly on mean yields. These findings suggest that the relationship between soil erosion and crop yield is more intricate than what linear models can capture. Our study highlights important policy implications, emphasizing the need for targeted soil conservation strategies to mitigate the adverse effects of erosion on crop yields.
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1 Introduction

The intensive use of fertilizers, irrigation, and mechanization has significantly boosted global agricultural output, particularly in the United States (U.S.), where these practices have been key to crop production success. However, this progress has come at a cost. Over 30% of global agricultural land has been degraded by erosion, salinization, and acidification (Lal and Moldenhauer (1987); Jang et al. (2021)). In the last four decades, nearly one-third of the world's arable land has been lost to erosion, with current annual losses exceeding ten million hectares (Pimentel et al. (1995)).

Soil erosion is not only an environmental issue but also a major economic concern, affecting agricultural, forest, and rangeland ecosystems globally (Lal (1994); Pimentel (2006); Seitz et al. (2019); Jang et al. (2021); Chen et al. (2022)). Human activity has exacerbated erosion rates to a level 20 times higher than natural geological rates (Boardman (2021)). This acceleration of soil erosion has severe consequences for farmland and water resources, including sedimentation, pollution, and long-term fertility loss. Given the critical functions of agricultural soils—such as nutrient and water storage and organic matter preservation—soil erosion presents a significant threat to crop productivity.

Water and wind erosion are the primary mechanisms by which soil degradation occurs. Water erosion refers to the removal of the land surface by water, waves, or moving ice, as well as through processes like mass wasting and corrosion. This includes sheet and rill erosion, which occur when soil is removed by rainfall, melting snow, irrigation, or runoff. Often, these processes go unnoticed even when soil loss reaches unsustainable levels (Panagos et al. (2015)). Wind erosion involves the wearing away of the land surface by wind, manifesting in processes like saltation and surface creep, where particles are lifted and transported by the wind (Borrelli et al. (2017); U.S. Department of Agriculture (2020)). Understanding these mechanisms is crucial for assessing soil erosion's impact on agricultural productivity.

The economic cost of soil erosion has been the subject of extensive debate. For example, Pimentel et al. (1995) estimated the annual economic loss in the U.S. to be $44 billion, including $27 billion from on-site productivity losses, while Crosson (1995) suggested a much lower figure, ranging between $500 to $600 million. This discrepancy highlights the variability in estimates due to differing methodologies. Despite efforts to reduce erosion in the U.S.—where erosion rates fell by 35% from 1982 to 2017 (U.S. Department of Agriculture (2020))—the long-term impact on soil productivity and crop yields remains a pressing issue.

Soil erosion has both on-site and off-site effects. On-site, it directly reduces soil productivity by depleting nutrients and organic matter (Lal and Moldenhauer (1987); den Biggelaar et al. (2003); Carr et al. (2021); Zhang et al. (2021)), leading to lower crop yields and increased use of fertilizers (Alt et al. (1989); National Soil Erosion-Soil Productivity Research Planning Committee (1981)). Off-site, erosion results in sediment deposition, waterlogging, and siltation of reservoirs, further exacerbating environmental damage. Yield losses and increased costs of fertilizers are often used as measures of productivity loss, with crop yield serving as a common proxy for soil productivity in studies (den Biggelaar et al. (2003)). While the costs of erosion are significant, the benefits of erosion control are less visible but vital for maintaining soil quality and productivity (Trimble and Crosson (2000); Bakker et al. (2007)).

Despite the extensive literature on soil erosion, most existing studies have focused on small-scale, field-level experiments. Comprehensive regional or national-scale analyses in the U.S. are lacking. For instance, various methods have been employed to assess the impact of erosion, including the comparative-plot method, transect studies, and desurfacing experiments (Bakker et al. (2004); 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)). While these studies provide valuable insights into erosion's effects on productivity, their direct application at larger geographical scales is limited (Bakker et al. (2004)).

Models such as the Universal Soil Loss Equation (USLE), the revised USLE (RUSLE2), and the Water Erosion Prediction Project (WEPP) have been developed to estimate soil erosion rates more reliably (Alewell et al. (2019)). For example, Bakker et al. (2007) used the Pan-European Soil Erosion Risk Assessment (PESERA) model to project yield losses across Europe, while Panagos et al. (2018) integrated biophysical and macroeconomic models to estimate the economic cost of erosion in the European Union. However, there remains a gap in understanding the broader relationship between soil erosion and crop yields, particularly regarding yield stability and risk, which is crucial for long-term agricultural productivity and sustainability (Lal (2010); Šeremešić et al. (2011); Xu et al. (2019); Philip Robertson et al. (2014); Pan et al. (2009)).

This paper aims to fill this gap by investigating how soil erosion affects crop yields at larger geographical scales in the U.S., offering insights into the agricultural and environmental consequences of ongoing land degradation.

The remainder of this article is structured as follows: Section 2 provides a detailed description of the datasets and outlines the empirical strategies used to analyze the impact of soil erosion on crop yields. In Section 3, we present the main model's estimation results, along with various robustness checks to validate our findings. Finally, Section 4 discusses the implications of the results, addresses the limitations of the study, and suggests potential avenues for future research.

2 Data Description

The data used in this study were collected from various county-level sources. The main dependent variables are corn and soybean yields, while the primary explanatory variables are annual soil loss due to erosion and several weather variables.

Annual soil loss data, measured in tons per year, were obtained from the National Resources Inventory (NRI), managed by the USDA's Natural Resources Conservation Service (NRCS). The NRI employs a stratified two-stage sampling method, where 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 across non-federal U.S. lands, including private properties and tribal territories. The data include estimates for both Water Erosion and Wind Erosion, which were introduced in the previous section.

The NRI's soil erosion estimates are based on predictive models rather than direct measurements. For water erosion, the USLE was employed for estimates prior to 2008, while the RUSLE2 was adopted for later years. Wind erosion estimates use the Wind Erosion Equation (WEQ). 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, CRP land, and pastureland.

The NRI program provides scientifically comprehensive and reliable data on the state, condition, and trends of soil, land, water, and related resources in the U.S. (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 U.S. and has been applied in numerous previous studies (Goodwin and Smith (2003) and Chen et al. (2022)).

For this study, erosion data from the years 1987 to 2017 were used, with updates every five years. Each data point reflects the soil loss recorded in a specific year (e.g., 1987, 1992), with updates every five years capturing the annual soil loss for that specific period. To maintain consistency, all other variables were restricted to the same years, 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.

Corn and soybeans account for 87% of U.S. production of grains and oilseeds (Zulauf et al. (2023)). County-level data on corn and soybean yields, measured in bushels per acre, were obtained from the National Agricultural Statistics Service (NASS) Quick Stats database. These yield estimates are derived from farmer surveys and field measurements, providing a comprehensive overview of agricultural productivity across U.S. counties. The goal of this study is to examine the impact of soil erosion on corn and soybean yields, focusing primarily on high-production regions.

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 crop yield and soil erosion data are available, ensuring consistency throughout the study (see

Figures1 and 2).

Several control variables are included to account for external factors influencing crop yields. Weather data, such as growing degree days (GDD), heating degree days (HDD), and precipitation levels, were obtained from the Parameter Elevation Regression on Independent Slopes Model (PRISM) climate dataset. GDD captures the temperature range favorable for crop growth (8–29°C,), while HDD measures high temperatures that can be harmful (above 29°C,), 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.

The study uses Conservation Reserve Program (CRP) cumulative enrollment as an instrumental variable, which is sourced from the Farm Service Agency (FSA), USDA. CRP cumulative enrollment data reflect the total acreage enrolled in the program at the end of each fiscal year. The cumulative CRP enrollment, measured in acres, represents the total land under contract at the end of each fiscal year. This variable helps account for potential endogeneity in the soil loss variables. Details regarding the potential presence of residual endogeneity, based on the fixed-effects model, are explained in the following sections.

Our estimation sample for corn consists of 13666 observations from 2426 counties. Similarly, our estimation sample for soybeans comprises 11042 observations from 1980 counties, covering the same period. Summary statistics for the variables used in this research are presented in Table 1 and 2.

3 Empirical Specification and Estimation Strategies

In this section, we outline the empirical framework used to examine the effects of soil erosion on crop yields. We first introduce the baseline model and discuss the potential endogeneity between soil erosion and yield, addressed through a Two-Stage Least Squares (2SLS) approach using instrumental variables. Next, we explore potential nonlinearity in the relationship between soil erosion and yield by applying popular machine learning techniques, including LASSO-based variable selection, to capture the complexities and nonlinearity inherent in the data.

3.1 Baseline model

To investigate the potential impact of soil erosion on crop yields, we employ a two-way fixed effects (TWFE) panel regression model, specified as follows:

$$y_{it} = \alpha S_{it} + \beta W_{it} + \gamma_t + \mu_i + \varepsilon_{it}, \tag{3.1}$$

where y_{it} represents the crop yield (either soybean or corn) for county i in year t. The variable S_{it} captures the annual soil loss due to water or wind erosion, or a combination of both, while W_{it} is a vector of weather-related controls, including growing degree days (GDD), heating degree days (HDD), precipitation, and its squared term. γ_t represents the year fixed effect to account for time-specific shocks, μ_i is the county fixed effect 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, it is essential to control for both county and year 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 unbiased estimates when analyzing crop productivity in relation to environmental factors.

Similarly, year fixed effects (γ_t) 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 and year fixed effects, we mitigate the risk of omitted variable bias, 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.

In the subsequent section, we introduce an Instrumental Variable (IV) approach to further address potential endogeneity. This will be followed by non-linear model specifications to capture potential non-linear relationships between soil erosion and crop yields.

In the existing literature, higher-order central moments of crop yields, such as variance, skewness, and kurtosis, are often estimated using a "residual-based" method. This approach allows for analyzing not only the mean of the yield but also its distribution and variability. Parametric methods for such estimations are used by Just and Pope (1979) and Antle and Goodger (1984), while nonparametric methods are applied by Li et al. (2021). Initially, the mean yield is estimated from the base model, 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. This allows for a detailed understanding of how factors like soil erosion affect not just the central tendency of yields but also their variability and distribution.

To validate our findings, we focus separately on crops like soybeans and corn, as comparing the effects of erosion across different crops could complicate interpretation. Specifically, we assess the impact of water-induced erosion, wind-induced erosion, and their combined effects on both the mean yield and yield risk (i.e., variance, skewness, and kurtosis). This leads to 24 separate regression estimations, all based on the same model structure((3.1)). This comprehensive approach ensures that we can rigorously evaluate the effect of different types of soil erosion on various dimensions of crop yield outcomes.

3.2 Robustness checks

3.2.1 Endogeneity with TSLS

When examining the impact of soil erosion on crop yields, reverse causality, measurement error, and omitted variable bias are primary sources of endogeneity. To address these issues, we employ CRP cumulative enrollment as an instrumental variable (IV) for soil erosion.

Reverse causality arises when higher crop yields encourage farmers to implement more aggressive soil conservation measures, thereby reducing soil erosion. As noted by Deininger and Byerlee (2012), higher crop yields can incentivize farmers to adopt soil conservation practices, such as using cover crops or no-till farming, which help reduce erosion (Chen et al. (2022); Chen et al. (2023)). Similarly, Antle and Capalbo (2001) highlights the feedback loop between land productivity and conservation measures. If high yields encourage practices that preserve soil quality, this can lower erosion rates. However, high levels of erosion may negatively impact yields, creating a simultaneity issue. This interplay suggests that the relationship between yield and erosion is bidirectional, leading to correlation between soil erosion and the error term and introducing bias.

Measurement error is another source of endogeneity. Soil erosion data is often subject to measurement errors, leading to an imperfect correlation between the observed variables and the true values. The NRI soil erosion data potentially contain measurement errors due to the reliance on predictive models and sampling techniques. These sources of error mean that the soil erosion estimates might not accurately reflect the actual erosion conditions, potentially leading to endogeneity if these measurement errors are correlated with other variables in the analysis.

Omitted variable bias also poses a challenge in this context. Factors such as soil quality, land management practices, and government policies that are not directly observed may influence both soil erosion and crop yields. Although we consider within-county and within-year fixed effects, these can only control for time-invariant county characteristics and common shocks across years. They do not account for time-varying, county-specific unobserved factors. For instance, suppose a county has inherently poor soil quality. The county fixed effect can control for this, isolating the impact of time-varying factors like soil erosion. Similarly, if a nationwide change in agricultural policy affects all counties in a particular year, year fixed effects will control for this. However, if a county adopts a new, more effective soil conservation technique over time that improves both soil quality and yields, this time-varying, county-specific factor is not accounted for by the two-way fixed effects model and may bias the estimated effect of soil erosion on yields. For example, better farming techniques or the use of fertilizers could enhance yields while simultaneously reducing the impact of soil erosion (Pimentel (2006)). If these omitted variables are correlated with the included independent variables (e.g., erosion), the estimated coefficients will be biased. When such factors are present and correlated with soil erosion and crop yields, additional methods such as instrumental variables (IV) are needed.

CRP enrollment is a government-led land conservation program that plays a critical role in reducing soil erosion through the implementation of conservation practices, such as establishing grasslands and vegetative covers on enrolled lands. Hansen (2007) estimates that, without CRP, soil erosion would increase by 222 to 248 million tons per year—approximately 11

Although CRP contributes to environmental benefits like erosion control and water quality improvement, Udawatta et al. (2016) found that it does not significantly alter soybean or corn yields. Since CRP enrollment is not directly influenced by current-year crop yields, it is suitable for addressing the issue of reverse causality. Additionally, CRP enrollment, being a policy-driven and exogenous instrument, is related to soil erosion but not to measurement error in soil erosion data. By serving as a proxy for soil conservation practices, CRP enrollment helps to alleviate the endogeneity problem caused by measurement error. Furthermore, farmers' decisions to participate in CRP are typically based on long-term land use and economic incentives rather than short-term changes in crop yields. This supports the use of CRP cumulative enrollment as a valid IV to reduce omitted variable bias by isolating the component of soil erosion that is independent of short-term yield fluctuations.

Therefore, we employ a Two-Stage Least Squares (2SLS) approach, using CRP enrollment as an IV to reestimate our model (3.1).

3.2.2 Regression with Polynomials and Interactions

Many models are available for estimating the conditional mean or higher-order moments. However, it is often difficult to determine in advance which explanatory variables will provide the best fit, particularly for higher-order moments. The method we employ allows for data-driven selection of appropriate series terms and interaction terms among variables, incorporating non-parametric regression techniques. This approach is especially helpful when researchers are uncertain about the importance of variables or transformations, encouraging the exploration of a wide range of controls.

The baseline model (3.1) can be viewed as a simplified approximation of a more general functional form. To allow for greater flexibility, explanatory variables may include nonlinear transformations.

Recognizing the potential nonlinear effects of soil erosion on crop yield(Hsiang

(2016)), we extend our analysis beyond the standard baseline model to capture these complexities. Conventional agricultural economics models often rely on intuition to suggest a set of important variables, but this may overlook crucial variables or their appropriate functional forms. While linear panel models are commonly used, they risk introducing bias and misspecification when dealing with more complex empirical relationships. Conversely, applying a complex model to a simpler empirical situation with more nuisance variables can result in poor fit and inflated standard errors. Thus, selecting the appropriate model is essential to achieving valid estimation results.

We employ LASSO-based variable selection techniques to explore nonlinear relationships between soil erosion and yield. LASSO, proposed by Tibshirani (1996), is a widely used shrinkage method that assumes a sparse structure in the parameter vector, meaning only a small, unknown subset of variables has significantly non-zero coefficients, while the rest are reduced to zero. By applying a penalty on the absolute values of the coefficients in the least squares objective function, LASSO effectively selects variables, making it particularly advantageous for high-dimensional models.

This approach allows us to consider a broad set of candidate variables—including raw regressors, interaction terms, and transformations—while retaining only the most relevant factors. By doing so, we reduce the risk of overfitting and enhance the robustness of our yield and risk estimates. Since LASSO shrinks the coefficients of less relevant variables to zero, it effectively selects a subset of the most important variables, making it a sparse modeling technique.

As discussed by Belloni et al. (2013), sparse modeling techniques, such as LASSO, best subset selection, and stepwise selection, are widely used in both economics and statistics to identify explanatory variables with the highest predictive power from a larger set of potential regressors.

Despite its extensive application in economics, Leeb and Pötscher (2005) highlighted that inference (i.e., hypothesis testing and confidence intervals) drawn from data-driven models like LASSO can be invalid if the selection process is not accounted for. Additionally, LASSO estimates introduce shrinkage bias due to the penalty in the loss function. As a result, the estimator does not have a limiting distribution, so it cannot be used directly for statistical inference.

To solve this issue, we implement the debiased LASSO method, proposed almost simultaneously by van de Geer et al. (2014), Zhang and Zhang (2013), and Javanmard and Montanari (2014). This approach corrects the bias introduced by regularization, enabling valid inference following variable selection. After applying LASSO for variable selection, the initial LASSO estimator is debiased, removing the bias and allowing for uniformly valid inference.

The model we consider takes the form of a series-based approach that incorporates nonlinear components of the soil erosion variables and weather variables. Specifically, the model is specified as follows:

$$y_{it} = \alpha S_{it} + \beta' W_{it}' + \theta' \text{NL\_CONTROLS}_{it}' + \mu_i + \gamma_t + \varepsilon_{it},$$

where NL_CONTROLS_{it} includes nonlinear terms such as higher-order terms and interactions of soil erosion variables and weather variables we considered potentially affect yield[1], all others are the same as defined with (3.1).To maintain consistency

[1]In our model, we consider higher-order terms for variables such as HDD, GDD, precipitation, tons of water erosion, and tons of wind erosion, up to the third power. For the interaction terms between weather variables and erosion variables, we include only the first-order interaction terms:

HDD × GDD, HDD × prep, HDD × tons_water_erosion, HDD × tons_wind_erosion; GDD × prep, GDD × tons_water_erosion, GDD × tons_wind_erosion; prep × tons_water_erosion, prep × tons_wind_erosion.

The rationale for excluding higher-order interaction terms between soil erosion and weather variables is that HDD and GDD already capture the non-linear effects of temperature on crop yield.

with the baseline model, we also address serial correlation and heteroscedasticity within counties by clustering the standard errors at the county level.

Before starting our estimation, the preparation is to eliminate the two-way fixed effect parameters. For simplicity, we will always remove the fixed effects by within-county demeaning and within-year demeaning. Note that removing the fixed effects using other differencing methods could also be accommodated. All two-way demeaned variables are defined as follows:

$$\tilde{x}_{it} = x_{it} - \frac{1}{T_i}\sum_{t} x_{it} - \frac{1}{N_t}\sum_{i} \tilde{x}_{it}$$

where T_i is the number of time periods for county i, N_t is the number of individuals at time t. Similarly, note that the tilde notation ($\tilde{x}_{it}$) will signify deviations from within-county means and within-year means throughout the article.

To simplify, let $d = [\alpha, \beta', \theta']'$ be the parameter vector with a dimension of p. Let $\widetilde{X}_{it} = [\widetilde{S}_{it}, \widetilde{W}'_{it}, \widetilde{\text{NL\_CONTROLS}}'_{it}]'$ be a p vector representing all regressors at year t for county i. We begin the estimation process by minimizing the objective function to obtain the LASSO estimates. Specifically, the coefficient vector $\widehat{d}$ is obtained by

Additionally, we include precipitation squared in the baseline model to address non-linear effects of moisture. Therefore, excluding higher-order interaction terms for these variables to simplify the model.

However, for the interaction between water and wind erosion, we incorporate higher-order terms to capture the combined effects of the two types of erosion. Specifically, we include the following terms:
tons_water_erosion $\times$ tons_wind_erosion; tons_water_erosion^2 $\times$ tons_wind_erosion, tons_water_erosion^3 $\times$ tons_wind_erosion; tons_water_erosion $\times$ tons_wind_erosion^2, tons_water_erosion^2 $\times$ tons_wind_erosion^2; tons_water_erosion^3 $\times$ tons_wind_erosion^2, tons_water_erosion $\times$ tons_wind_erosion^3; tons_water_erosion^2 $\times$ tons_wind_erosion^3, tons_water_erosion^3 $\times$ tons_wind_erosion^3.

The decision not to consider interaction terms involving combined water and wind erosion with other variables is to avoid multicollinearity. The total effect of erosion is simply the sum of water and wind erosion, so we will treat this combined variable as S_{it} in some regression, without including additional interaction terms with other variables to prevent redundancy and multicollinearity in the model.

solving the following optimization problem:

$$\widehat{d} := \text{argmin}_{d\in\mathbb{R}^p}\left\{ \frac{1}{NT}\sum_{t=1}^{T}\left(\tilde{y}_{it} - d'\widetilde{X}_{it}\right)^2 + \lambda \left\|Dd\right\|_1 \right\}. \tag{3.2}$$

Here, D is a diagonal matrix where each diagonal element corresponds to the standard deviation of the associated variable. This standardization ensures that the penalty is uniformly applied across all coefficients, regardless of the scale of the variables. Importantly, to maintain consistency with equation (3.1), we leave the parameters of primary interest from the baseline model unpenalized by setting the first five elements in the diagonal matrix D to zero. This means that these parameters are always included in the model during LASSO estimation.

The tuning parameter λ plays a crucial role in the regularization process and can be chosen using various selection criteria, such as the Schwarz Information Criterion (SBC) or cross-validation (CV). In this analysis, we select λ based on the Bayesian Information Criterion (BIC).

After obtaining the initial LASSO estimates, we proceed to refine these estimates using a debiasing procedure. The debiased LASSO estimates are calculated as follows:

$$\widehat{f} \;=\; \widehat{d} + \frac{1}{NT}\widehat{\Theta}\sum_{t=1}^{T}\sum_{i=1}^{N}\widetilde{X}_{it}\left(\tilde{y}_{it} - \widehat{d}'\widetilde{X}_{it}\right),$$

In this expression, Θ is the inverse or approximate inverse of the sample covariance matrix $\frac{1}{NT}\sum_{t=1}^{T}\sum_{i=1}^{N}\widetilde{X}_{it}'\widetilde{X}_{it}$. However, due to the inclusion of many interaction terms within $\widetilde{X}_{it}$, this sample covariance matrix can often become nonsingular, rendering the direct OLS estimation and inversion of the matrix unfeasible. For constructing an approximate inverse matrix and calculating standard errors, detailed methodologies are provided in van de Geer et al. (2014).

Overall, this section provides a comprehensive econometrics framework for analyzing the impact of soil erosion on crop yields, accounting for both linear and non-linear relationships. By addressing potential endogeneity through 2SLS and incorporating advanced estimation techniques like LASSO, we ensure that our model captures the complexities of the underlying dynamics. The robustness checks further strengthen our conclusions, offering a detailed understanding of the mechanisms through which erosion affects yield outcomes. This empirical approach sets the stage for more detailed interpretations in the next sections.

4 Results and Discussion

4.1 Baseline model results

The estimated parameters using the linear TWFE models are presented in Tables 3 through 8. The regression results indicate that soil erosion—whether through water, wind, or a combination—has a statistically significant relationship with crop yields for both corn and soybeans. Specifically, Tables 3 and 6 show that combined soil erosion has a significant negative effect on both corn and soybean mean yields.

For soybeans, both water and wind erosion have statistically significant negative effects on mean yield. Specifically, a one-ton increase in soil loss due to water, wind, or combined erosion in a county can lead to a decrease in soybean mean yield of 0.001 bushels per acre, as indicated by our TWFE specifications (Tables 6, 7, and 8, Column 'Mean').

However, the results for corn mean yield are mixed. In line with the combined erosion impact, wind erosion has a negative effect on corn mean yield. In contrast, water erosion shows a positive relationship with corn yield, which is counterintuitive. Specifically, a one-ton increase in soil loss due to combined erosion in a county can lead to a decrease in corn mean yield of 0.002 bushels per acre (Table 3, Column 'Mean'). Similarly, a one-ton increase in soil loss due to wind erosion in a county can lead to a decrease in corn mean yield of 0.003 bushels per acre, as indicated by our TWFE specifications (Table 3, Column 'Mean'). Five of the six results align with agronomic studies, which show that soil erosion can degrade soil quality and decrease agricultural productivity (Lal and Moldenhauer (1987); den Biggelaar et al. (2003); Alt et al. (1989); National Soil Erosion-Soil Productivity Research Planning Committee (1981)). However, the positive impact of water erosion on corn mean yield observed in our analysis is likely due to endogeneity issues in the model.

When it comes to yield risk, our regression results indicate that soil erosion, whether caused by water, wind, or a combination of both, leads to an increase in the variance of corn yields. For skewness, all types of erosion exhibit a negative relationship with corn yield, though these effects are not statistically significant. In terms of kurtosis, both combined erosion and water erosion have a significant positive impact on corn yield kurtosis, while the effect of wind erosion is not statistically significant.

For soybean yield risk, the results are less clear. Although the estimates for the variance of soybean yield are positive, they are not statistically significant. Regarding skewness and kurtosis, the signs of the estimates are mixed, with combined and water erosion showing a positive impact, whereas wind erosion exhibits a negative impact on both moments.

To better interpret and understand the magnitude of the estimated impact of combined soil erosion on crop yields, we performed a back-of-the-envelope calculation. Using the average combined soil erosion in 2017 from our dataset and combining it with data from the USDA's NASS Quick Stats database on acres harvested and prices received for soybeans and corn in 2023, we derived the following insights:

- The average combined soil erosion per corn-planted county is 765.96 tons, and per soybean-planted county is 746.54 tons.
- This soil erosion leads to a national loss in corn production in 2023 valued at approximately $788.56 million.
- Similarly, for soybean production, the estimated national loss in 2023 is approximately $866.90 million.

These figures highlight the significant economic impact of soil erosion on U.S. agricultural production. Although these figures differ from those reported by Pimentel et al. (1995) and Crosson (1995), there are two major differences to consider. First, their estimates reflect the overall cost of soil erosion to the U.S. economy, while ours are specific to the production of two major crops. Second, the acres harvested and crop prices have grown rapidly over the past 40 years, contributing to the disparity between the estimates.

4.2 Robustness checks results

Results for mean yields from the 2SLS regression approach, using CRP cumulative enrollment as the IV, are presented in Tables 9–12. The first-stage F-statistics, shown in Tables 9 and 11, indicate that the instrument is strongly correlated with the endogenous regressor, suggesting a valid IV approach.

The findings in Tables 10 and 12 indicate that counties with higher levels of soil erosion—whether through water, wind, or a combination—tend to have lower mean yields for both corn and soybeans. Specifically, all estimates are statistically significant and negative, addressing potential endogeneity concerns, particularly with regard to the impact of water erosion on corn mean yield. The impacts of wind erosion and combined erosion on corn yield are 1 and 1.5 times greater, respectively, than the baseline estimation without the IV. For soybean mean yield, the effects of water, wind, and combined erosion are 19 times, 7 times, and 4 times larger, respectively, than those in the baseline model without the IV.

Notably, the estimated impact of soil erosion caused by water is greater than that caused by wind for both corn and soybean production. Crop yields are more affected by the loss of the topsoil layer due to water-related factors such as irrigation, rainfall, snowmelt, runoff, and poor irrigation practices compared to soil loss from wind-driven processes. However, when comparing corn and soybean mean yields, the estimated impact of water-induced soil erosion is greater for corn than for soybeans. Conversely, wind erosion has a more pronounced effect on soybean yield than on corn. Interestingly, the estimated effects of combined erosion are similar for both crops.

This implies that corn and soybean cultivation is potentially more vulnerable to soil erosion caused by excess moisture (or heavy rainfall) events rather than wind events. Compared to corn, soybean production is more susceptible to wind erosion processes such as surface creep, saltation, and suspension.

The results of the robustness checks using IVs to estimate the effect of soil erosion on yield risk are presented in Tables 10–18. Overall, the estimation results from the IV-FE models are consistent with those of the baseline model. Soil erosion—whether through water, wind, or a combination—has a statistically significant positive relationship with the variance and kurtosis of corn yields (Tables 13 and 15). However, there is still no clear pattern for corn skewness or for any of the higher-order moments of soybean yield.

For the remaining Tables 19 to 26, we evaluate the effect of soil erosion on soybean and corn yields using a panel data model that accounts for potential nonlinear effects. Tables 19 and 20 show a consistent negative sign with statistically significant coefficients for the linear non-interaction terms, aligning with the findings from almost all baseline linear models and IV models for mean yield. Notably, in the case of corn, the magnitude of the debiased LASSO estimates is more than 10 times larger than the baseline estimates; however, it is relatively close to the estimates obtained from the IV models. For soybean mean yield, the debiased LASSO estimates of the linear terms are still larger than those in the baseline model and close to those in the IV model.

This suggests that the inclusion of many higher-order terms of erosion variables and interactions between erosion variables and weather variables, many of which are statistically significant, reveals a more complex nonlinear relationship between soil erosion and crop mean yields.

Finally, in the risk-relevant estimation in Tables 21 to 26, statistically significant estimates for nonlinear terms are rarely found; however, some significance is observed in corn variance and soybean yield skewness. This time, we do not find evidence to support that corn yield variance and kurtosis are significantly affected by soil erosion.

Overall, the results indicate a complex and nonlinear impact of soil erosion on crop yields, with important implications for agricultural productivity and risk management. These findings warrant a detailed interpretation, which we explore in the following conclusion.

5 Conclusions

Agricultural success hinges significantly on the health of soils, making it a pivotal determinant 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 (Chen et al. (2022)).

This study has investigated the impact of soil erosion on crop yields in the United States 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 yield. Specifically, both the linear fixed effects (FE) and instrumental variable fixed effects (IV-FE) models consistently indicate a statistically significant negative impact of soil erosion on corn and soybean mean yields.

Our investigation into yield risk revealed that soil erosion, whether caused by water, wind, or a combination, leads to an increase in the variance and kurtosis of corn yields, highlighting greater yield instability. However, this pattern does not hold for soybean yield risk, suggesting a more complex or less pronounced impact of soil erosion on soybean yield variability.

To better understand the magnitude of soil erosion's impact, we performed a back-of-the-envelope calculation using the average combined soil erosion in 2017 and recent market prices for corn and soybeans. The results indicate substantial national losses in crop production, with estimated losses of approximately \$788.56 million for corn and \$866.90 million for soybeans in 2023. These figures emphasize the significant economic impact of soil erosion on U.S. agricultural production and underscore the importance of effective soil conservation practices and policies.

Our exploration of potential nonlinear effects using the LASSO method provided additional empirical insights into the nonlinear relationships between soil erosion and crop yields. While the nonlinear LASSO model suggests a complex interplay involving higher-order interactions between soil erosion and weather variables, evidence of significant nonlinear effects on yield risk remains limited.

Our findings have important implications for policymakers and stakeholders in agriculture. Understanding the overall impact of soil erosion on agricultural productivity is crucial for developing effective mitigation strategies and policies to safeguard crop yields and ensure food security. Furthermore, our study provides applied economists with a more flexible approach to relax some unnecessarily restrictive assumptions of the linear panel data model, offering a natural approach to capture the complexity of soil erosion's impact on crop yields.

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.

Overall, this study highlights the need for a comprehensive understanding of soil erosion's impact on crop production, taking into account both direct and nonlinear effects. Continued efforts in soil conservation are essential to mitigate the adverse impacts of erosion on crop production and ensure long-term agricultural sustainability. Further research in this area can aid policymakers and stakeholders in developing targeted strategies to protect soil resources and support the agricultural sector.

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Tables and Figures

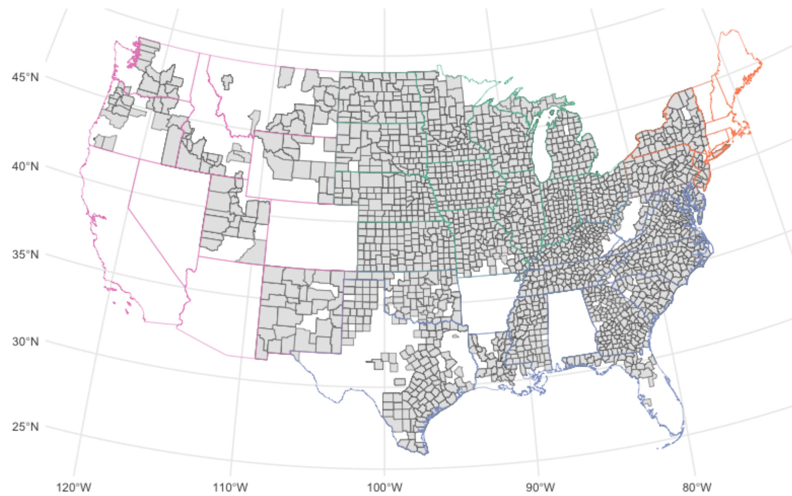

Figure 1: Map of data availability for corn

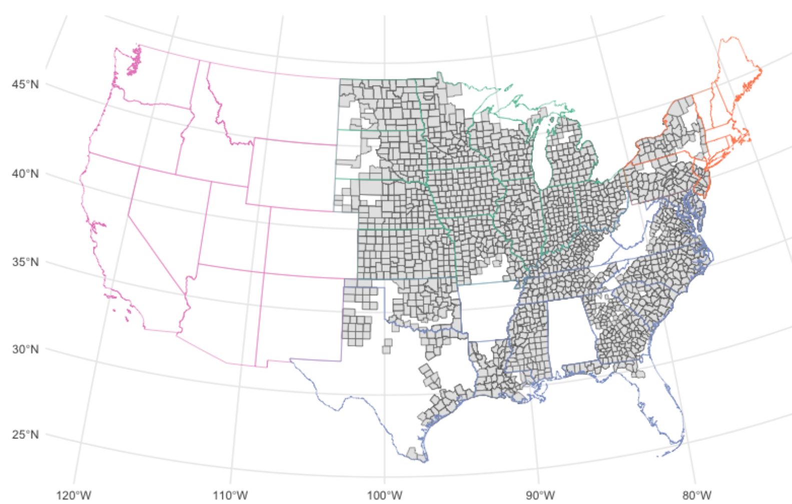

Figure 2: Map of data availability for soybean

Table 1: Corn: Summary Statistics of Variables

Variable	Mean	Standard Deviation	Median	25th percentile	75th percentile
Yield	114.699	40.008	113.000	86.300	141.200
Water Erosion	476.763	550.268	310.290	105.145	637.938
Wind Erosion	307.805	1,007.402	0.000	0.000	91.738
Total Erosion	784.568	1,190.209	408.195	131.475	956.400
GDD	2,191.649	456.596	2,177.172	1,841.692	2,531.688
HDD	60.292	56.344	46.703	17.032	89.195
Precipitation	545.531	169.487	553.210	448.055	654.857

Number of years: 7
Number of counties: 2426

Table 2: Soybean: Summary Statistics of Variables

Variable	Mean	Standard Deviation	Median	25th percentile	75th percentile
Yield	35.712	11.005	35.700	27.800	43.800
Water Erosion	538.451	567.777	374.010	153.860	718.392
Wind Erosion	231.613	846.557	0	0	27.177
Total Erosion	770.063	1,034.427	456.965	173.918	972.938
GDD	2,220.748	423.765	2,222.478	1,899.199	2,543.591
HDD	57.153	45.179	47.157	18.913	87.038
Precipitation	575.674	146.092	571.315	472.601	667.671

Number of years: 7
Number of counties: 1980

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

	Mean	Variance	Skewness	Kurtosis
Soil Erosion	-0.002^{***}	0.068^{***}	-2.640	453.673^{*}
	(0.001)	(0.026)	(3.362)	(256.037)
GDD	0.023^{***}	-0.803^{***}	29.856^{**}	$-3{,}084.437^{***}$
	(0.003)	(0.103)	(11.954)	(935.188)
HDD	-0.420^{***}	1.563^{***}	59.728	1,018.896
	(0.018)	(0.475)	(52.670)	(3,323.488)
Precipitation	0.049^{***}	-0.601^{*}	17.185	$-1{,}566.486$
	(0.012)	(0.353)	(33.660)	(2,750.932)
Precipitation Squared	-0.00002^{**}	0.0004	0.0003	0.964
	(0.00001)	(0.0003)	(0.025)	(2.031)
Observations	13,666	13,666	13,666	13,666
R^2	0.157	0.010	0.002	0.003
Adjusted R^2	-0.026	-0.205	-0.214	-0.214
Note:				*p<0.1; **p<0.05; ***p<0.01

Table 4: Effects of Water Erosion on Mean, Variance, Skewness, and Kurtosis of Corn Yield

	Mean	Variance	Skewness	Kurtosis
Soil Erosion	0.003^{***}	0.058^{**}	-2.009	366.069^{*}
	(0.001)	(0.028)	(2.580)	(208.213)
GDD	0.022^{***}	-0.789^{***}	29.828^{**}	$-3{,}024.607^{***}$
	(0.003)	(0.103)	(11.980)	(946.882)
HDD	-0.420^{***}	1.531^{***}	61.249	982.858
	(0.018)	(0.474)	(53.770)	(3,368.332)
Precipitation	0.048^{***}	-0.566	12.506	$-1{,}137.317$
	(0.012)	(0.361)	(34.205)	(2,877.576)
Precipitation Squared	-0.00002^{**}	0.0004	0.004	0.645
	(0.00001)	(0.0003)	(0.025)	(2.126)
Observations	13,666	13,666	13,666	13,666
R^2	0.156	0.009	0.002	0.002
Adjusted R^2	-0.027	-0.207	-0.215	-0.215
Note:				*p<0.1; **p<0.05; ***p<0.01

Table 5: Effects of Wind Erosion on Mean, Variance, Skewness, and Kurtosis of Corn Yield

	Mean	Variance	Skewness	Kurtosis
Soil Erosion	-0.003^{***}	0.068^{**}	-1.581	458.171
	(0.001)	(0.030)	(4.044)	(294.766)
GDD	0.022^{***}	-0.785^{***}	29.240^{**}	$-3{,}022.215^{***}$
	(0.003)	(0.103)	(11.777)	(926.534)
HDD	-0.420^{***}	1.552^{***}	59.868	975.398
	(0.018)	(0.476)	(52.206)	(3,316.829)
Precipitation	0.049^{***}	-0.611^{*}	19.159	$-1{,}682.774$
	(0.012)	(0.351)	(33.495)	(2,714.512)
Precipitation Squared	-0.00002^{**}	0.0004	-0.001	1.050
	(0.00001)	(0.0003)	(0.025)	(2.004)
Observations	13,666	13,666	13,666	13,666
R^2	0.158	0.010	0.002	0.002
Adjusted R^2	-0.025	-0.205	-0.214	-0.214
Note:				*p<0.1; **p<0.05; ***p<0.01

Table 6: Effects of Water and Wind Erosion on Mean, Variance, Skewness, and Kurtosis of Soybean Yield

	Mean	Variance	Skewness	Kurtosis
Soil Erosion	-0.001^{***}	0.001	0.006	0.011
	(0.0002)	(0.001)	(0.022)	(0.342)
GDD	0.007^{***}	-0.017^{***}	-0.046	-1.397
	(0.001)	(0.006)	(0.114)	(1.977)
HDD	-0.156^{***}	0.139^{***}	2.750^{***}	19.487^{*}
	(0.005)	(0.030)	(0.859)	(11.651)
Precipitation	0.045^{***}	-0.073^{***}	-1.778^{***}	-24.370^{**}
	(0.003)	(0.025)	(0.650)	(12.003)
Precipitation Squared	-0.00003^{***}	0.0001^{***}	0.001^{***}	0.019^{**}
	(0.00000)	(0.00002)	(0.001)	(0.010)
Observations	11,042	11,042	11,042	11,042
R^2	0.327	0.008	0.009	0.004
Adjusted R^2	0.178	-0.210	-0.209	-0.215
Note:				*p<0.1; **p<0.05; ***p<0.01

Table 7: Effects of Water Erosion on Mean, Variance, Skewness, and Kurtosis of Soybean Yield

	Mean	Variance	Skewness	Kurtosis
Soil Erosion	-0.001^{***}	0.0004	0.030	0.685
	(0.0003)	(0.002)	(0.045)	(0.938)
GDD	0.007^{***}	-0.017^{***}	-0.045	-1.484
	(0.001)	(0.006)	(0.115)	(2.009)
HDD	-0.156^{***}	0.143^{***}	2.801^{***}	19.996^{*}
	(0.005)	(0.030)	(0.867)	(11.825)
Precipitation	0.045^{***}	-0.071^{***}	-1.809^{***}	-24.727^{**}
	(0.003)	(0.025)	(0.656)	(12.203)
Precipitation Squared	-0.00003^{***}	0.0001^{***}	0.002^{***}	0.020^{**}
	(0.00000)	(0.00002)	(0.001)	(0.010)
Observations	11,042	11,042	11,042	11,042
R^2	0.326	0.008	0.009	0.004
Adjusted R^2	0.178	-0.210	-0.209	-0.215
Note:				*p<0.1; **p<0.05; ***p<0.01

Table 8: Effects of Wind Erosion on Mean, Variance, Skewness, and Kurtosis of Soybean Yield

	Mean	Variance	Skewness	Kurtosis
Soil Erosion	-0.001^{**}	0.001	-0.007	-0.259
	(0.0002)	(0.001)	(0.025)	(0.371)
GDD	0.007^{***}	-0.016^{***}	-0.042	-1.313
	(0.001)	(0.006)	(0.114)	(1.962)
HDD	-0.156^{***}	0.137^{***}	2.750^{***}	19.101^{*}
	(0.005)	(0.030)	(0.857)	(11.524)
Precipitation	0.045^{***}	-0.073^{***}	-1.756^{***}	-24.059^{**}
	(0.003)	(0.025)	(0.642)	(11.694)
Precipitation Squared	-0.00003^{***}	0.0001^{***}	0.001^{***}	0.019^{**}
	(0.00000)	(0.00002)	(0.001)	(0.009)
Observations	11,042	11,042	11,042	11,042
R^2	0.326	0.008	0.009	0.004
Adjusted R^2	0.178	-0.210	-0.209	-0.215
Note:				*p<0.1; **p<0.05; ***p<0.01

Table 9: Effects of Soil erosion on Corn Yield: IV First Stage

Dependent variable:Erosion	Water	Wind	Water & Wind
Crp Cumulative Enrollment	-0.003***	-0.012***	-0.015***
	(0.0004)	(0.002)	(0.002)
GDD	0.143***	0.001	0.144**
	(0.018)	(0.054)	(0.057)
HDD	0.001	-0.142	-0.141
	(0.071)	(0.215)	(0.231)
Precipitation	0.042	0.435**	0.477**
	(0.049)	(0.189)	(0.202)
Precipitation Squared	-0.00002	-0.0003**	-0.0003**
	(0.00004)	(0.0001)	(0.0002)
F-statistic	73.908	202.785	262.742
Observations	13,666	13,666	13,666
R^2	0.032	0.083	0.105
Adjusted R^2	-0.178	-0.116	-0.089
Note:			*p<0.1; **p<0.05; ***p<0.01

Table 10: Effects of Soil erosion on Corn Mean Yield

	Water (No IV)	Water (IV)	Wind (No IV)	Wind (IV)	Water & Wind (No IV)	Water & Wind (IV)
Soil Erosion	0.003***	-0.023**	-0.003***	-0.006**	-0.002***	-0.005**
	(0.001)	(0.010)	(0.001)	(0.003)	(0.001)	(0.002)
GDD	0.022***	0.026***	0.022***	0.023***	0.023***	0.023***
	(0.003)	(0.004)	(0.003)	(0.003)	(0.003)	(0.003)
HDD	-0.420***	-0.420***	-0.420***	-0.421***	-0.420***	-0.421***
	(0.018)	(0.018)	(0.018)	(0.018)	(0.018)	(0.018)
Precipitation	0.048***	0.049***	0.049***	0.050***	0.049***	0.050***
	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)
Precipitation Squared	-0.00002**	-0.00002**	-0.00002**	-0.00002***	-0.00002**	-0.00002***
	(0.00001)	(0.00001)	(0.00001)	(0.00001)	(0.00001)	(0.00001)
Observations	13,666	13,666	13,666	13,666	13,666	13,666
R^2	0.156	0.131	0.158	0.156	0.157	0.155
Adjusted R^2	-0.027	-0.057	-0.025	-0.027	-0.026	-0.029
Note:						*p<0.1; **p<0.05; ***p<0.01

Table 11: Effects of Soil erosion on Soybean Yield: IV First Stage

Dependent variable:Erosion	Water	Wind	Water & Wind
Crp Cumulative Enrollment	-0.003***	-0.008***	-0.011***
	(0.001)	(0.002)	(0.002)
GDD	0.124***	0.049	0.174***
	(0.021)	(0.058)	(0.062)
HDD	0.022	0.499***	0.521**
	(0.097)	(0.189)	(0.217)
Precipitation	0.106*	0.213	0.319**
	(0.054)	(0.149)	(0.155)
Precipitation Squared	-0.0001	-0.0001	-0.0001
	(0.00004)	(0.0001)	(0.0001)
F-statistic	32.041	82.051	113.297
Observations	11,042	11,042	11,042
R^2	0.017	0.043	0.059
Adjusted R^2	-0.199	-0.167	-0.148
Note:			*p<0.1; **p<0.05; ***p<0.01

Table 12: Effects of Soil Erosion on Soybean Mean Yield

	Water (No IV)	Water (IV)	Wind (No IV)	Wind (IV)	Water & Wind (No IV)	Water & Wind (IV)
Soil Erosion	-0.001***	-0.020***	-0.001**	-0.008***	-0.001***	-0.005***
	(0.0003)	(0.004)	(0.0002)	(0.002)	(0.0002)	(0.001)
GDD	0.007***	0.010***	0.007***	0.008***	0.007***	0.008***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
HDD	-0.156***	-0.156***	-0.156***	-0.152***	-0.156***	-0.153***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Precipitation	0.045***	0.046***	0.045***	0.045***	0.045***	0.045***
	(0.003)	(0.003)	(0.003)	(0.004)	(0.003)	(0.003)
Precipitation Squared	-0.00003***	-0.00003***	-0.00003***	-0.00003***	-0.00003***	-0.00003***
	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)
Observations	11,042	11,042	11,042	11,042	11,042	11,042
R^2	0.326	0.210	0.326	0.274	0.327	0.290
Adjusted R^2	0.178	0.037	0.178	0.114	0.178	0.134
Note:						*p<0.1; **p<0.05; ***p<0.01

Table 13: Effects of Soil Erosion on Corn Yield Variance

	Water (No IV)	Water (IV)	Wind (No IV)	Wind (IV)	Water & Wind (No IV)	Water & Wind (IV)
Soil Erosion	0.058**	1.416***	0.068**	0.346***	0.068***	0.263***
	(0.028)	(0.392)	(0.030)	(0.114)	(0.026)	(0.083)
GDD	-0.789***	-1.059***	-0.785***	-0.789***	-0.803***	-0.835***
	(0.103)	(0.129)	(0.103)	(0.105)	(0.103)	(0.106)
HDD	1.531***	1.681***	1.552***	1.617***	1.563***	1.614***
	(0.474)	(0.492)	(0.476)	(0.477)	(0.475)	(0.476)
Precipitation	-0.566	-0.542	-0.611*	-0.716**	-0.601*	-0.679*
	(0.361)	(0.364)	(0.351)	(0.351)	(0.353)	(0.352)
Precipitation Squared	0.0004	0.0004	0.0004	0.001*	0.0004	0.0005*
	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)
Observations	13,666	13,666	13,666	13,666	13,666	13,666
R^2	0.009	0.004	0.010	0.005	0.010	0.007
Adjusted R^2	-0.207	-0.212	-0.205	-0.210	-0.205	-0.209
Note:						*p<0.1; **p<0.05; ***p<0.01

Table 14: Effects of Soil Erosion on Corn Yield Skewness

	Water (No IV)	Water (IV)	Wind (No IV)	Wind (IV)	Water & Wind (No IV)	Water & Wind (IV)
Soil Erosion	-2.009	4.492	-1.581	-3.257	-2.640	-3.656
	(2.580)	(25.834)	(4.044)	(6.625)	(3.362)	(4.957)
GDD	29.828**	30.087**	29.240**	29.268**	29.856**	30.021**
	(11.980)	(13.136)	(11.777)	(11.786)	(11.954)	(11.991)
HDD	61.249	59.904	59.868	59.477	59.728	59.466
	(53.770)	(54.180)	(52.206)	(52.416)	(52.670)	(52.849)
Precipitation	12.506	11.249	19.159	19.788	17.185	17.593
	(34.205)	(33.859)	(33.495)	(33.536)	(33.660)	(33.689)
Precipitation Squared	0.004	0.004	-0.001	-0.002	0.0003	0.00004
	(0.025)	(0.025)	(0.025)	(0.025)	(0.025)	(0.025)
Observations	13,666	13,666	13,666	13,666	13,666	13,666
R^2	0.002	0.003	0.002	0.002	0.002	0.002
Adjusted R^2	-0.215	-0.213	-0.214	-0.215	-0.214	-0.214
Note:						*p<0.1; **p<0.05; ***p<0.01

Table 15: Effects of Soil Erosion on Corn Yield Kurtosis

	Water (No IV)	Water (IV)	Wind (No IV)	Wind (IV)	Water & Wind (No IV)	Water & Wind (IV)
Soil Erosion	366.069*	5,727.231**	458.171	1,465.921**	453.673*	1,114.433**
	(208.213)	(2,431.443)	(294.766)	(646.805)	(256.037)	(467.939)
GDD	-3,024.607***	-4,011.041***	-3,022.215***	-3,038.768***	-3,084.437***	-3,192.247***
	(946.882)	(1,069.917)	(926.534)	(929.910)	(935.188)	(948.549)
HDD	982.858	1,166.303	975.398	1,210.829	1,018.896	1,189.069
	(3,368.332)	(3,327.837)	(3,316.829)	(3,330.472)	(3,323.488)	(3,331.895)
Precipitation	-1,137.317	-1,327.455	-1,682.774	-2,061.117	-1,566.486	-1,831.429
	(2,877.576)	(2,804.076)	(2,714.512)	(2,732.755)	(2,750.932)	(2,766.541)
Precipitation Squared	0.645	0.772	1.050	1.320	0.964	1.150
	(2.126)	(2.068)	(2.004)	(2.019)	(2.031)	(2.043)
Observations	13,666	13,666	13,666	13,666	13,666	13,666
R^2	0.002	0.0005	0.002	0.002	0.003	0.002
Adjusted R^2	-0.215	-0.216	-0.214	-0.215	-0.214	-0.214
Note:						*p<0.1; **p<0.05; ***p<0.01

Table 16: Effects of Soil Erosion on Soybean Yield Variance

	Water (No IV)	Water (IV)	Wind (No IV)	Wind (IV)	Water & Wind (No IV)	Water & Wind (IV)
Soil Erosion	0.0004	0.038	0.001	-0.004	0.001	-0.003
	(0.002)	(0.030)	(0.001)	(0.007)	(0.001)	(0.005)
GDD	-0.017***	-0.019**	-0.016***	-0.016**	-0.017***	-0.016**
	(0.006)	(0.009)	(0.006)	(0.006)	(0.006)	(0.006)
HDD	0.143***	0.238***	0.137***	0.139***	0.139***	0.141***
	(0.030)	(0.038)	(0.030)	(0.030)	(0.030)	(0.030)
Precipitation	-0.071***	-0.049*	-0.073***	-0.073***	-0.073***	-0.073***
	(0.025)	(0.030)	(0.025)	(0.025)	(0.025)	(0.025)
Precipitation Squared	0.0001***	0.00004*	0.0001***	0.0001***	0.0001***	0.0001***
	(0.00002)	(0.00002)	(0.00002)	(0.00002)	(0.00002)	(0.00002)
Observations	11,042	11,042	11,042	11,042	11,042	11,042
R^2	0.008	0.047	0.008	0.007	0.008	0.008
Adjusted R^2	-0.210	-0.163	-0.210	-0.211	-0.210	-0.211
Note:						*p<0.1; **p<0.05; ***p<0.01

Table 17: Effects of Soil Erosion on Soybean Yield Skewness

	Water (No IV)	Water (IV)	Wind (No IV)	Wind (IV)	Water & Wind (No IV)	Water & Wind (IV)
Soil Erosion	0.030	1.726**	-0.007	-0.500***	0.006	-0.346***
	(0.045)	(0.749)	(0.025)	(0.186)	(0.022)	(0.116)
GDD	-0.045	0.027	-0.042	-0.012	-0.046	0.020
	(0.115)	(0.167)	(0.114)	(0.120)	(0.114)	(0.122)
HDD	2.801***	3.017***	2.750***	2.990***	2.750***	2.926***
	(0.867)	(1.171)	(0.857)	(0.872)	(0.859)	(0.874)
Precipitation	-1.809***	-2.306**	-1.756***	-1.722***	-1.778***	-1.737***
	(0.656)	(0.950)	(0.642)	(0.645)	(0.650)	(0.654)
Precipitation Squared	0.002***	0.002**	0.001***	0.001***	0.001***	0.001***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Observations	11,042	11,042	11,042	11,042	11,042	11,042
R^2	0.009	0.196	0.009	0.002	0.009	0.003
Adjusted R^2	-0.209	0.019	-0.209	-0.217	-0.209	-0.217
Note:						*p<0.1; **p<0.05; ***p<0.01

Table 18: Effects of Soil Erosion on Soybean Yield Kurtosis

	Water (No IV)	Water (IV)	Wind (No IV)	Wind (IV)	Water & Wind (No IV)	Water & Wind (IV)
Soil Erosion	0.685	31.816	-0.259	0.090	0.011	0.095
	(0.938)	(19.938)	(0.371)	(1.818)	(0.342)	(1.325)
GDD	-1.484	-1.742	-1.313	-1.334	-1.397	-1.413
	(2.009)	(3.762)	(1.962)	(2.002)	(1.977)	(2.065)
HDD	19.996*	63.192**	19.101*	18.932*	19.487*	19.445*
	(11.825)	(24.981)	(11.524)	(11.107)	(11.651)	(11.423)
Precipitation	-24.727**	-35.553	-24.059**	-24.083**	-24.370**	-24.380**
	(12.203)	(24.841)	(11.694)	(11.782)	(12.003)	(12.088)
Precipitation Squared	0.020**	0.028	0.019**	0.019**	0.019**	0.019**
	(0.010)	(0.020)	(0.009)	(0.009)	(0.010)	(0.010)
Observations	11,042	11,042	11,042	11,042	11,042	11,042
R^2	0.004	0.059	0.004	0.004	0.004	0.004
Adjusted R^2	-0.215	-0.148	-0.215	-0.215	-0.215	-0.215
Note:						*p<0.1; **p<0.05; ***p<0.01

Table 19: Effects of Soil Erosion on Corn Mean Yield: Debiased LASSO Results

Variable	Combined Erosion	Water Erosion	Wind Erosion
Combined Erosion Erosion	-0.026***	-0.016*	-0.028***
	(0.006)	(0.007)	(0.007)
HDD	-0.204	-0.196	-0.236
	(0.162)	(0.163)	(0.162)
GDD	0.331***	0.349***	0.314***
	(0.045)	(0.046)	(0.046)
Precipitation	-0.000	0.009	-0.005
	(0.036)	(0.037)	(0.037)
Precipitation^2	0.000220***	0.000***	0.000229***
	(0.0001)	(0.0001)	(0.0001)
HDD^2	0.004***	0.004***	0.004***
	(0.0004)	(0.0004)	(0.0004)
Water Erosion^2	0.0000033	0.000008	-0.0000006
	(0.00000)	(0.00000)	(0.00000)
Wind Erosion^2	0.0000026	-0.000002*	0.0000028
	(0.00000)	(0.00000)	(0.00000)
HDD^3	-0.000002***	-0.000002***	-0.000002***
	(0.00000)	(0.00000)	(0.00000)
HDD $\times$ GDD	-0.000410***	-0.000***	-0.000403***
	(0.0001)	(0.0001)	(0.0001)
HDD $\times$ Precipitation	0.000154	0.000	0.000149
	(0.0001)	(0.0001)	(0.0001)
HDD $\times$ Water Erosion	-0.000173***	-0.000***	-0.000138***
	(0.00003)	(0.00003)	(0.00003)
HDD $\times$ Wind Erosion	0.000017	0.000029	0.000013
	(0.00001)	(0.00002)	(0.00001)
GDD $\times$ Precipitation	-0.0000497***	-0.00005***	-0.0000494***
	(0.00001)	(0.00001)	(0.00001)
GDD $\times$ Water Erosion	0.000017***	0.000015***	0.0000083***
	(0.00000)	(0.00000)	(0.00000)
GDD $\times$ Wind Erosion	0.0000031	-0.0000006	0.000004*
	(0.00000)	(0.00000)	(0.00000)
Precipitation $\times$ Water Erosion	-0.000012**	-0.000012**	-0.0000123**
	(0.00000)	(0.00000)	(0.00000)
Precipitation $\times$ Wind Erosion	-0.0000053	-0.000006*	-0.000005
	(0.00000)	(0.00000)	(0.00000)
Water Erosion $\times$ Wind Erosion	0.0000285*	-0.000009	0.0000262*
	(0.00001)	(0.00001)	(0.00001)

Note: *p<0.1; **p<0.05; ***p<0.01

Table 20: Effects of Water and Wind Erosion on Soybean Yield: Debiased LASSO Results

Variable	Combined Erosion	Water Erosion	Wind Erosion
Erosion	-0.003*	-0.004*	-0.002
	(0.001)	(0.002)	(0.002)
HDD	-0.036	-0.033	-0.041
	(0.059)	(0.058)	(0.058)
GDD	0.143***	0.148***	0.143***
	(0.014)	(0.014)	(0.015)
Precipitation	0.055***	0.057***	0.056***
	(0.012)	(0.012)	(0.012)
Precipitation^2	-0.000015	-0.000015	-0.000015
	(0.00002)	(0.00002)	(0.00002)
HDD^2	0.002***	0.002***	0.002***
	(0.0003)	(0.0003)	(0.0003)
Water Erosion^2	-	0.0000018**	0.0000013**
		(0.00000)	(0.00000)
Wind Erosion^2	-	0.0000001	0.0000005
		(0.00000)	(0.00000)
HDD^3		-0.000003***	-0.000003***
		(0.00000)	(0.00000)
HDD $\times$ GDD	-	-0.000144***	-
		(0.00004)	
HDD $\times$ Precipitation	0.000064	0.000067	0.000064
	(0.00004)	(0.00004)	(0.00004)
HDD $\times$ Water Erosion	-0.000018*	-0.000019*	-0.000013
	(0.00001)	(0.00001)	(0.00001)
HDD $\times$ Wind Erosion	0.000023*	0.000025*	0.000024*
	(0.00001)	(0.00001)	(0.00001)
GDD $\times$ Water Erosion	-	0.000000	-0.000001*
		(0.00000)	(0.00000)
GDD $\times$ Wind Erosion	-	-0.000001*	-
		(0.00000)	
Precipitation $\times$ Water Erosion		-0.000002	-0.000002
		(0.00000)	(0.00000)
Precipitation $\times$ Wind Erosion	-	-0.000002*	-0.000002*
		(0.00000)	(0.00000)
Water Erosion $\times$ Wind Erosion		0.000001	0.000003
		(0.00000)	(0.00000)

Note: *p<0.1; **p<0.05; ***p<0.01

Table 21: Effects of Water, Wind, and Combined Erosion on Corn Variance: Debiased LASSO Results

Variable	Water Erosion	Wind Erosion	Combined Erosion
Erosion	-0.321	0.481	0.257
	(0.192)	(0.275)	(0.229)
HDD	5.953	6.888	6.013
	(4.139)	(4.189)	(4.185)
GDD	1.441	2.188	1.681
	(1.154)	(1.142)	(1.156)
Precipitation	-1.167	-0.677	-0.870
	(1.160)	(1.180)	(1.172)
Precipitation^2	0.00009	-0.0002	-0.000004
	(0.002)	(0.002)	(0.002)
HDD^2	-0.034*	-0.028*	-0.030*
	(0.013)	(0.014)	(0.014)
HDD $\times$ GDD	0.0015	-	-
	(0.002)		
HDD $\times$ Precipitation	-0.0018	-0.0002	-
	(0.003)	(0.003)	
HDD $\times$ Water Erosion	-0.0009	-	-
	(0.001)		
HDD $\times$ Wind Erosion	-0.0004	-0.0005	-
	(0.001)	(0.0004)	
Precipitation $\times$ Water Erosion	0.0001	-	-
	(0.0001)		
Precipitation $\times$ Wind Erosion	0.0002*	-	-
	(0.0001)		

Note: *p<0.1; **p<0.05; ***p<0.01

Table 22: Effects of Water, Wind, and Combined Erosion on Corn Skewness: Debiased LASSO Results

Variable	Water Erosion	Wind Erosion	Combined Erosion
Erosion	-16.191	-9.168	-14.448
	(22.436)	(38.290)	(31.123)
HDD	1070.906	1068.223	1082.494
	(560.402)	(564.465)	(561.643)
GDD	352.513**	309.979*	330.767*
	(131.873)	(128.166)	(130.822)
Precipitation	-4.331	14.472	17.621
	(124.274)	(126.956)	(125.569)
Precipitation^2	0.244	0.233	0.224
	(0.228)	(0.228)	(0.227)

Note: *p<0.1; **p<0.05; ***p<0.01

Table 23: Effects of Water, Wind, and Combined Erosion on Corn Kurtosis: Debiased LASSO Results

Variable	Water Erosion	Wind Erosion	Combined Erosion
Erosion	325.797	6251.169	4585.025
	(2104.281)	6251.169	(3191.631)
HDD	549.959	7436.013	-1317.196
	(47097.020)	(47390.210)	(47647.190)
GDD	2134.927	8803.137	4251.679
	(11527.650)	(11129.640)	(11327.910)
Precipitation	-7753.838	-5317.895	-6773.851
	(9504.896)	(9839.583)	(9671.565)
Precipitation^2	19.064	18.228	20.160
	(19.768)	(19.878)	(19.752)
HDD^2	-136.543	-120.931	-127.168
	(173.971)	(177.175)	(177.168)

Note: *p<0.1; **p<0.05; ***p<0.01

Table 24: Effects of Water, Wind, and Combined Erosion on Soybean Yield Variance: Debiased LASSO

Variable	Combined Erosion	Water Erosion	Wind Erosion
Erosion	0.0004	-0.0066	0.0090
	(0.011)	(0.013)	(0.017)
HDD	0.2561	0.1769	0.2025
	(0.370)	(0.369)	(0.369)
GDD	-0.1604	-0.1140	-0.1151
	(0.098)	(0.097)	(0.102)
Precipitation	-0.1642	-0.1351	-0.1480
	(0.095)	(0.093)	(0.096)
Precipitation^2	0.0003*	0.0002	0.0002*
	(0.0001)	(0.0001)	(0.0001)

Note: *p<0.1; **p<0.05; ***p<0.01

Table 25: Effects of Water, Wind, and Combined Erosion on Soybean Yield Skewness: Debiased LASSO

Variable	Combined Erosion	Water Erosion	Wind Erosion
Erosion	0.193	0.260	0.117
	(0.201)	(0.318)	(0.367)
HDD	26.232*	26.818**	27.357*
	(10.473)	(10.395)	(10.633)
GDD	6.800***	6.031**	6.553**
	(2.032)	(2.045)	(2.192)
Precipitation	-3.781	-3.876	-3.950
	(2.165)	(2.150)	(2.208)
Precipitation^2	0.006*	0.006*	0.006*
	(0.003)	(0.003)	(0.003)
HDD^2	0.173**	-	-
	(0.063)		
GDD^2	-0.004***	-	-
	(0.001)		
Water Erosion^2	0.00004	-	-
	(0.0001)		
HDD^3	-0.0005**	-	-
	(0.0002)		
HDD $\times$ GDD	-0.017*	-	-
	(0.007)		
HDD $\times$ Precipitation	-0.002	-0.002	-0.001
	(0.007)	(0.007)	(0.006)

Note: *p<0.1; **p<0.05; ***p<0.01

Table 26: Effects of Water, Wind, and Combined Erosion on Soybean Yield Kurtosis: Debiased LASSO

Variable	Combined Erosion	Water Erosion	Wind Erosion
Erosion	0.602	2.753	-2.172
	(3.562)	(7.288)	(6.218)
HDD	26.196	15.148	21.563
	(155.609)	(145.862)	(153.188)
GDD	-11.874	-6.969	-10.242
	(26.138)	(27.031)	(29.796)
Precipitation	-106.346*	-91.057*	-99.818*
	(47.796)	(46.097)	(49.222)
Precipitation^2	0.133*	0.119*	0.126*
	(0.058)	(0.055)	(0.057)

Note: *p<0.1; **p<0.05; ***p<0.01