Valuation of Soil Productivity in Farmland Prices

Abstract

Purpose: This study examines how commodity prices mediate the relationship between soil productivity and farmland values to better understand the dynamic economic value of soil quality.
Methodology: The authors use a hedonic pricing model to analyze land values derived from about 88,000 Illinois farmland sales transactions from 2000-2022, interacting soil productivity measures with spatially-interpolated commodity prices to separate the effects of market conditions from the marginal productivity of soil.
Findings: Premiums for farmland with high soil productivity ratings vary significantly with commodity prices. The marginal product of increased soil productivity was twice as large from 2018 to 2022 than in the 2000-2005 base period.
Originality: This research introduces a novel approach to assess soil quality premiums by interacting soil quality measures with expected output prices, allowing the data to reveal distinct technology-driven changes in soil value capitalization.

Keywords: farmland valuation, soil productivity, commodity prices, hedonic pricing
Article classification: Research article

1 Introduction

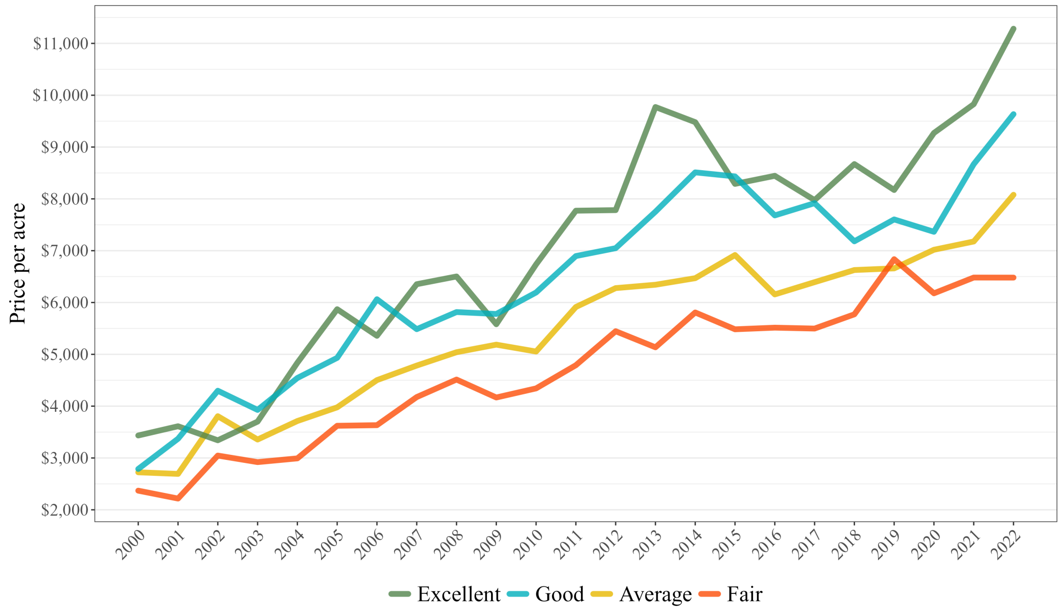
Farmland constitutes a significant portion of agricultural wealth in the United States, accounting for over 80 percent of total farm sector assets in 2023 (Litkowski et al., 2023). Soil quality is a significant determinant of farmland value due to its influence on both the capacity to generate agricultural output and the perception of long-term land viability. Previous studies have established a strong correlation between farmland values and soil quality in the Corn Belt and other major agricultural regions of the US (Nickerson et al., 2012; King and Sinden, 1988; Gardner and Barrows, 1985; Palmquist and Danielson, 1989; Miranowski and Hammes, 1984; Huang et al., 2006).

Though soil quality is often thought to be an immutable characteristic of farmland, the relationship between soil productivity – the ability of soil to generate agricultural output – and land value is not necessarily static. Figure 1 shows average per-acre farmland values in Illinois from 2000 to 2022 for four ordinal categories of soils: "Fair", "Average", "Good" and "Excellent," as classified by appraisers based on soil productivity (ISPFMRA, 2025). Not only have land values grown over time, but the price differences between the lowest and highest productivity land have also grown. In 2000, Excellent land only cost about $1,000 more than Fair land, about 45% higher. By 2022, the premium for Excellent land was at least six times larger than Fair land, about 70% higher. Moreover, Excellent land commanded a higher average price than Good land in 2013 but not in 2017 and 2019.

Why might soil quality become more or less valuable over time? This paper examines the degree to which changes in commodity prices change how soil productivity capitalizes into land values. In our theoretical framework, we demonstrate that the premium for soil productivity in a hedonic regression can change due to technological advancements that enable more output to generated from the soil, shifts in the expected output price, or both. A traditional hedonic regression cannot determine whether changes in the contribution of soil productivity to land values are due to changes in the the production technology linking soil quality to crop output or favorable commodity prices. For instance, recent work points to soil conservation practices having a positive impact on land values by allowing soil productivity to be enhanced or better maintained (Telles et al., 2018, 2022; Chen et al., 2023), but coincidental changes in the expected prices of commodities may also have increased the premium for soil productivity.

In this paper, we modify the traditional hedonic approach to decompose the premium for soil quality into two components: productive and non-productive. The productive component is identified by the coefficient on the interaction between a measure of expected output price and the soil productivity measure in the regression model. The non-productive component is the value of soil productivity to land values that is independent of commodity

Figure 1: Average annual real per-acre price of Illinois farmland by soil productivity category, 2000-2022



Note: Values are in 2010 USD.

output value and is identified by the coefficient on the soil productivity measure that is not interacted with prices. The advantage of this approach is being able to examine whether the productive component of the premium, related to the marginal product of soil, has changed over time because of shifts in the production technology. Relevant technological change here encompasses all aspects of crop production activity that interact with soil quality, including crop inputs, farm management strategies, and agricultural policy. Our theoretical framework highlights the role of commodity prices in valuation of this productive component.

Using transaction-level data from Illinois farmland sales between 2000 and 2022, we find that a sizable portion of the soil productivity premium in farmland values is impacted by commodity prices. In particular, more than 50% of the soil productivity premium for land categorized as Good and about 90% of the premium for land deemed Excellent is related to variation in commodity prices. This suggests that commodity prices have a substantial impact on how soil productivity is capitalized into farmland values over time. Using the productive component of the premium to measure the economic value of soil productivity, we then investigate whether returns to improving soil productivity have changed over time. We find that, relative to 2000-2005, the marginal return to using Excellent land (relative to lower productivity land) was twice as large after 2018, suggesting that technological change has increased the marginal returns to soil over time.

The determinants of farmland values have long been a focal point of agricultural economics, with a large literature examining numerous factors (Borchers et al., 2014). Many papers assess the capitalization of financial and policy aspects of farming like credit access and government payments into land values (Huang et al., 2006; Devadoss and Manchu, 2007; Ifft et al., 2015; Featherstone et al., 2017). Farmland values are also thought to incorporate environmental amenity and disamenity values (Wasson et al., 2013), including the expected impacts of climate change (Schlenker et al., 2005; Massetti and Mendelsohn, 2011; Severen et al., 2018). In addition, proximity to urban areas has long been recognized as an important determinant of farmland value (Chicoine, 1981; Sklenicka et al., 2013; Livanis et al., 2006; Zhang and Nickerson, 2015).

Among the many contributing factors to farmland's value, soil productivity has been relatively understudied, in part because soil productivity measures typically do not vary over time. An existing literature has documented positive impacts of soil productivity improvements on land values (Miranowski and Hammes, 1984; King and Sinden, 1988; Palmquist and Danielson, 1989), though some studies (e.g. Gardner and Barrows, 1985) find investments in soil productivity are not capitalized in farmland values. More recently, studies have found that specific soil conservation practices, such as no-till, are positively associated with land values (Telles et al., 2018, 2022; Chen et al., 2023).

Our paper reconsiders the role of soil quality by examining the intersection between soil productivity and commodity prices to isolate the role of technological progress related to soil quality in land markets. We first recognize that the value of improvements to soil are inextricably linked to both the value of agricultural production generated by that soil and the prices of agricultural commodities. According to the theory laid out by Ladd and Martin

(1976), hedonic coefficients represent both the impact of expected output prices and the marginal product of that characteristic in the production function. Accordingly, a substantial body of literature on land values, government support, and ethanol demand indicates that changes in farm profitability driven by commodity price changes are a significant factor influencing land values in the US Midwest (Latruffe and Le Mouël, 2009; Roberts et al., 2003; Kropp and Peckham, 2015; Featherstone et al., 2017; Blomendahl et al., 2011; Gardner and Sampson, 2022). Thus, the actual value of soil productivity is difficult to isolate without considering how commodity prices mediate the value of soil in farmland prices.

However, previous papers have often used cross-sectional data and so cannot distinguish between variation in commodity prices and variation in soil quality. Other analyses choose not to evaluate the contribution of soil, absorbing soil quality in parcel, farm, county, or other spatial fixed effects and commodity prices in temporal fixed effects. By using more than twenty years of land transactions and high resolution spatial commodity price data, our paper decomposes the soil productivity and commodity price components of the soil productivity-land value relationship by interacting soil productivity measures with an estimate of the output price in each township. The coefficient on this interaction more cleanly represents the marginal product of soil productivity without confounding variation from output prices. We can then track this coefficient over time to detect changes in the marginal product of soil, which would imply changes in production technology to better exploit soil productivity for crop production.

Our paper contributes to the ongoing discussion on the need for investment in soil productivity. In recent years, there has been a surge of interest in promoting agricultural practices to maintain, enhance, and even regenerate soil quality of agricultural land (e.g. Lehmann et al., 2020; Schreefel et al., 2020). Without a generalized understanding of the long-run value of soil improvements, it is difficult to assess how, where, and when such practices will be adopted. Simply, investments to improve the long-run state of soil productivity must be profitable for both farmers and land owners to adopt them. Our modeling suggests that the value of enhancements to soil productivity strongly depends on price dynamics in agricultural commodity markets and our empirical results show the productive component of farmland values associated with soil productivity can change significantly over time. A strong market for commodities could increase the incentives to increase soil productivity whereas weak commodity prices might lead to less adoption of soil conservation practices.

2 Theoretical Framework

For the farm, land is an input. Thus, the demand for farmland intended for agriculture is a factor demand related to the farm's production and profit functions. Ladd and Martin (1976) use the linear characteristics model to set up the profit function of a multi-product firm expressed as total revenue generated from multiple outputs minus total input costs, where each input contributes to output production through its attributes. The first-order conditions for profit maximization says that input prices paid by firm i in time t, such as the land price (L_{it}), are a linear function of the amount of the characteristics the input yields (x_{it}^j):

$$L_{it} = \sum_{j=1}^{J} \beta_{it}^j x_{it}^j. \tag{1}$$

The coefficient β_{it}^j is the value of marginal product equal to $\bar{p}_{it} \frac{\partial F}{\partial x_{it}^j}$, that is the expected output price for the farm product ($\bar{p}_{it}$) multiplied by the marginal product of that characteristic ($\frac{\partial F}{\partial x_{it}^j}$) and F is the production function. This linear relationship is predicted to exist in levels because of the theoretical model posited by Ladd and Martin (1976), motivating a linear regression approach using the variables in levels.

Ladd and Martin (1976) assume that $\beta_{it}^j = \beta^j$, that the hedonic coefficient is constant across time and space and can be estimated as a regression parameter. This is accurate if we assume that the marginal product of the characteristic is the same in all i and t and, most importantly, that the expected output price is the same in all i and t. Many hedonic analyses do make this parameter constant and implicitly impose both assumptions. Given the volatility of commodity prices, this is only likely to hold in analyses using cross-sectional data of limited geographic scope; output prices must be static with limited variation over space.

Indeed, many hedonic analyses of farmland consider cases where these output price assumptions almost certainly will not hold. First, studies often consider multiple years of data, meaning $\bar{p}_{it}$ will vary across time, inducing variation in β^j_{it}. A characteristic x_{it} may be capitalized into land values differently over time simply because output price expectations change over time. Second, previous analyses consider large regions like the US Midwest with sufficient spatial variation in crop prices, where $\bar{p}_{it}$ likely varies over both i and t. Shifts in the spatial distribution of prices, such as those induced by new demand sources like the opening of ethanol plants (e.g., McNew and Griffith, 2005; Wu et al., 2017; Gardner and Sampson, 2022), will also change β^j_{it} even if the marginal product of that characteristic is constant.

Consider soil productivity (S_i) as a characteristic. Farmland derives some value from soil productivity's contribution to commodity output ($\frac{\partial F}{\partial S_i}$) and because that commodity itself is valued at the expected market price ($\bar{p}_{it}$). To understand the value of soil improvements to land, it is not enough to consider how much output a level of soil quality will produce for any commodity. Rather, the value of soil quality is mediated by the commodity prices that are expected by the markets. As a consequence, a typical regression analysis using farmland prices and soil quality measures will estimate a constant β^S that reflects only the average price conditions in-sample. Without disentangling the effects of $\bar{p}_{it}$ from the marginal product of soil $\frac{\partial F}{\partial S_i}$, it is impossible to know whether soil quality is capitalizing into land prices more because of higher expected prices or improvements in technology.

In this paper, we isolate the marginal product of soil by defining measures of expected output prices and soil productivity and interacting them to estimate the marginal value of soil productivity. Modifying Equation 1, we obtain:

$$L_{it} = \beta^S(\bar{p}_{it} \times S_i) + \sum_{j=1}^{J-1} \beta_{it}^j x_{it}^j \tag{2}$$

where $\bar{p}_{it}$ is an estimate of the expected output price and β^S is a new coefficient that is moved by changes in $\frac{\partial F}{\partial S_i}$ and not changes in $\bar{p}_{it}$. First, the coefficient is no longer a weighted average of market conditions and now helps us understand the value of soil improvements independent of market conditions. Second, we can now track changes in $\frac{\partial F}{\partial S_i}$ over time by estimating equation 2 for different periods of time to see whether β^S is changing. With this approach, we can more confidently ascertain whether production technology changes associated with soil quality have allowed farmers to generate greater value from the same soil quality.

Apart from understanding changes in $\frac{\partial F}{\partial S_i}$, a more accurate assessment of β^S allows us to understand how valuable soil improvements are in different market environments. Contrasting results like Gardner and Barrows (1985) may be explained by the fact that the impact of soil improvements is highly conditional on the behavior of commodity markets. By allowing the soil productivity premium to vary with market conditions, we can understand how the profitability of soil improvements may be varying over time.

3 Data

3.1 Land Transactions

Data on farmland transactions are obtained from the Illinois Department of Revenue (IDOR) and span the years 2000 to 2022. The dataset includes over 180,000 farmland transactions, representing more than one billion acres. From these data, we select only arm's-length transactions involving parcels of ten acres or more. "Arm's-length" transactions are conducted in the open market between unrelated parties. This excludes sales involving seller financing or non-monetary considerations, ensuring that the declared price reflects the true market value of the property. Restricting the sample to parcels larger than ten acres eliminates farmland that may sold for conversion to non-agricultural uses. We also exclude parcels that sold for less than $1,000 or more than $40,000 per acre or are larger than 1,300 acres. After cleaning the data, we have 88,850 records to use in our analysis. Transaction-level data has particular advantages over estimated land values, as it has less measurement error than estimates from appraisers or experts (Bigelow and Jodlowski, 2025).

Transactions are reported to IDOR via the PTAX-203 form, a mandatory real estate transfer declaration required in the state of Illinois. This form contains the parcel size, location (survey township, county), declared sales price, property use, and buyer-seller relationship. PTAX-203 is self-reported at the time of sale and processed by local assessment offices. The PTAX-203 data enable the identification of transactions with consistent agricultural use (both current and intended), the calculation of the parcel-level price per acre, and the geographic assignment of each transaction to a public survey or political township, the most granular unit identifiable in the data. Public survey townships are roughly six-by-six mile gridded survey areas. Political townships are geographic regions of roughly similar size that may not or may not share boundaries with survey townships. Each transaction was linked to its corresponding township using both reported information and geographic shapefiles from the Illinois Public Land Survey System (PLSS).[1] Our final sample consists of median transacted land prices for 22,599 township-year observations.

Figure 2 shows the distribution of farmland parcel size in acres in our sample. The distribution is strongly right-skewed, with most transactions involving small parcels substantially concentrated under 150 acres, particularly in the 10 to 75-acre range. Very few sales involve parcels larger than 500 acres. This right skewness indicates that small to mid-sized farmland parcels dominate the market, while large-scale sales are relatively infrequent. From an analytical perspective, the skewness suggests that summary statistics, such as the mean parcel size, may be heavily influenced by a few large outliers; therefore, measures like the

[1]For two counties in our sample that do not have political townships, Johnson and Williamson, the transactions are summarized at the county level instead of the township level.

median may be more informative. The spatial distribution of the parcel sizes in Illinois townships in our sample is presented in Figure 3. Most townships exhibit median parcel sizes between 25 and 100 acres, with larger parcels, larger than 300 acres, concentrated in specific rural or peripheral regions of the state.

Figure 2: Distribution of Farmland Parcel Sizes in Illinois (2000–2022)

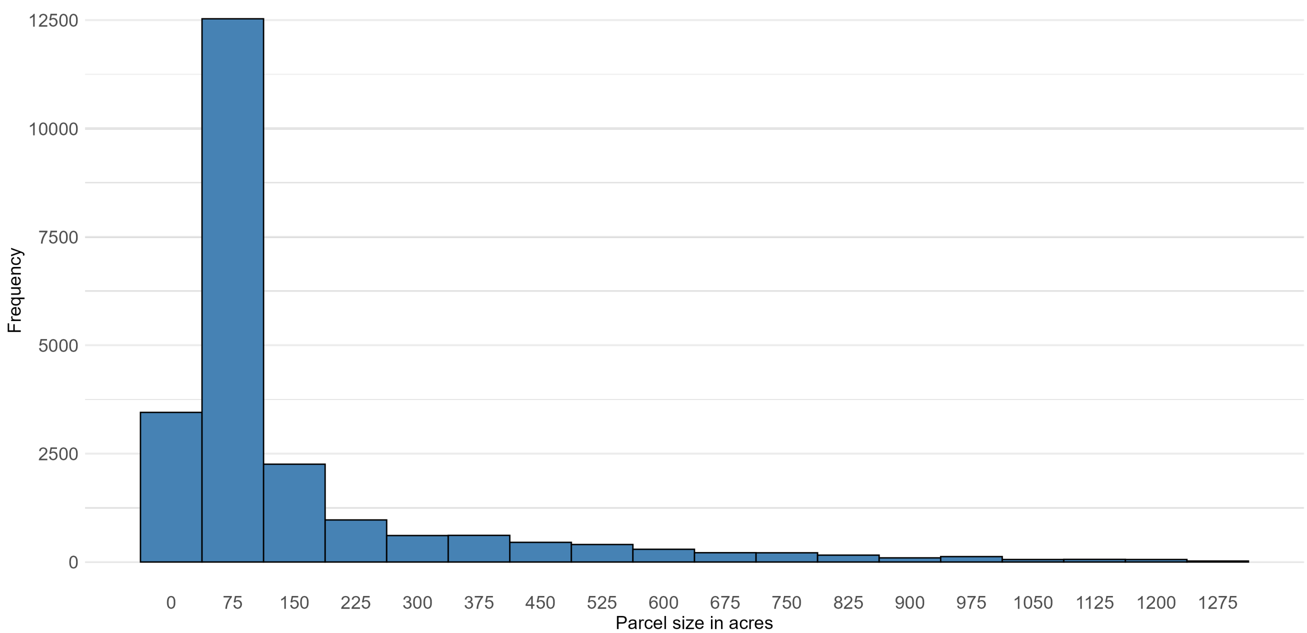
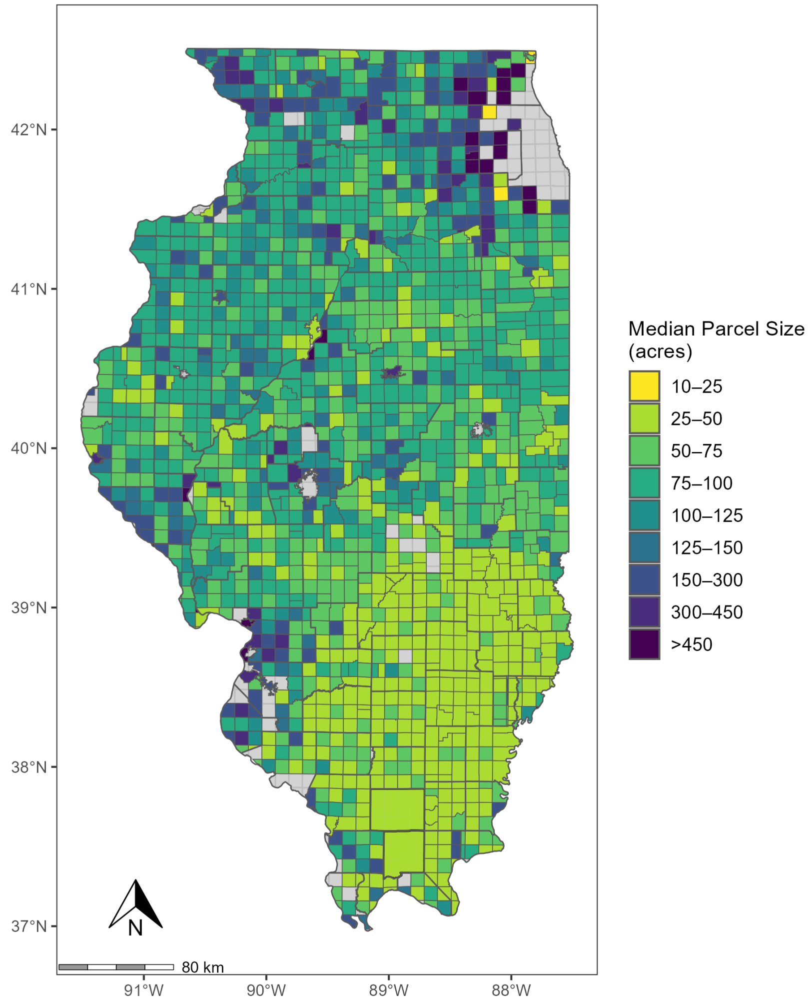


Figure 3: Illinois Median Parcel Size in Acres



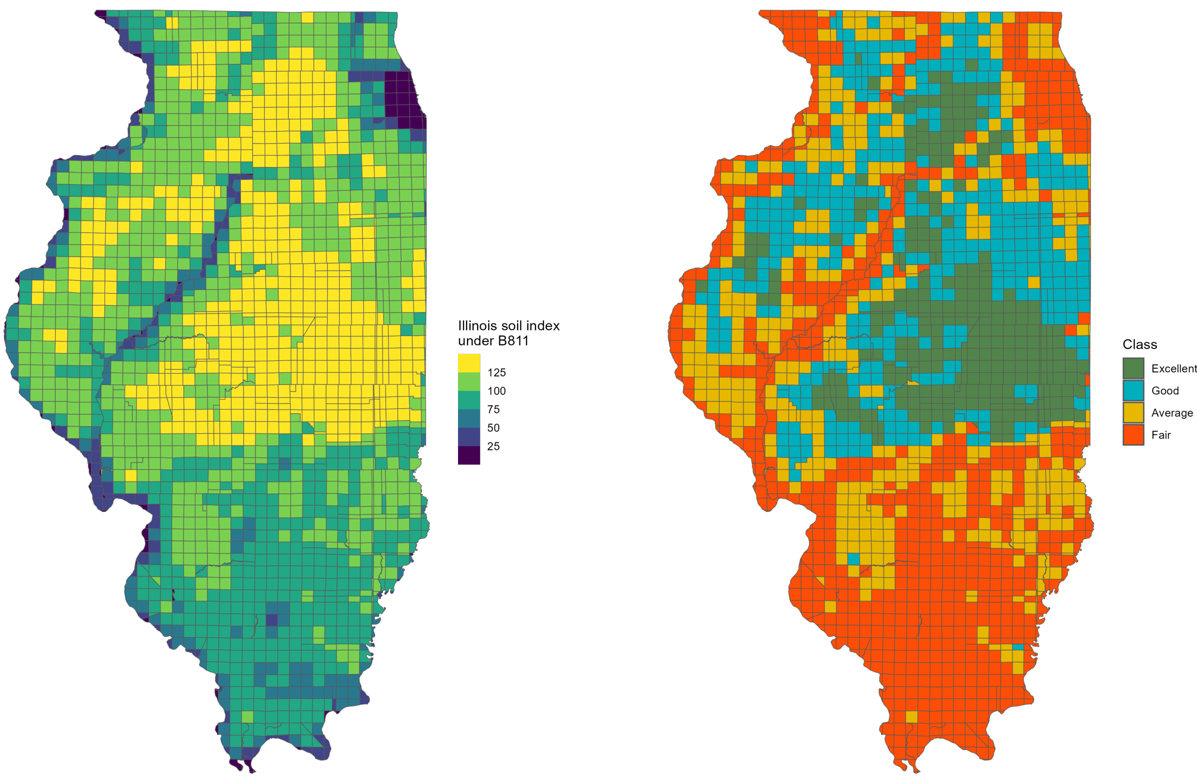
Note: Areas in gray have no transactions in our sample. Johnson and Williamson Counties only have transactions that can be merged to the county level.

3.2 Soil Productivity

To measure soil productivity, we use the soil productivity index (PI) from Bulletin 811, Optimum Crop Productivity Ratings for Illinois Soils, developed by Olson and Lang (2000). The index provides a standardized measure of the crop yield potential across soil types. Township-level PIs were calculated by taking the area-weighted average of the soil productivity index (PI) within each township. These ratings are based on data from the

National Soils Database maintained by the Natural Resources Conservation Service (NRCS), which includes detailed information on soil types, distributions, and suitability for agricultural production. Figure 4a shows the spatial distribution of the soil PI across the state of Illinois. The soil PI benchmarks soil types against Muscatine soil—the most productive type of soil in Illinois—using weighted relative yields aggregated across crops to generate a soil productivity rating (Olson and Lang, 2000).

Figure 4: Bulletin 811 PI in Illinois



(a) PI Index

(b) Appraiser Classification

The soil classification system developed by the Illinois Society of Professional Farm Managers and Rural Appraisers (ISPFMRA) groups soils into four quality categories: 'Fair' (PI < 100), 'Average' (PI 100–117), 'Good' (PI 117–133), and 'Excellent' (PI > 133) (ISPFMRA, 2025). In our dataset, 6,976 observations fall into the 'Fair' category, 5,094 in 'Average', 5,214 in 'Good' and 3,919 in 'Excellent'. This classification enables us to study the non-linear impacts of soil productivity on land values using classification cut-offs familiar to the market to define where non-linearities may occur.

3.3 Output Prices

To estimate the expected output price, we obtain daily cash prices for corn and soybeans from Bloomberg for the period 2000 to 2022. These prices are aggregated to calendar year averages at the township level. Bloomberg's data are sourced from various points along the grain marketing chain—including country elevators, ethanol plants, feed mills, and river terminals—providing a comprehensive reflection of spatially-dispersed commodity demand.

To assign prices to all points in the grid of townships in Illinois, we applied an inverse distance weighted (IDW) interpolation procedure. This method utilizes observed cash price data from known locations to estimate prices at unobserved locations, accounting for the effect of physical distance. Specifically, the IDW process assumes any meaningful deviations from a consistent, smooth spatial price gradient over space are captured in the observed data. In other words, the observed price data reflect the expected price adjustments due to spatial heterogeneity, and these patterns are preserved and extended through the interpolation process.

The interpolation begins with a set of observed data points $(lat_i, long_i, p_i)$, where p_i is the known cash price at coordinates $(lat_i, long_i)$. For a target location $(lat_0, long_0)$, the weight w_i for each observed point is calculated as the reciprocal of the distance between the observed point and the target location, raised to a power ρ:

$$w_i = \frac{1}{(\text{distance}((lat_0, long_0), (lat_i, long_i)))^{\rho}}. \tag{3}$$

The interpolated price for each township, p_0, is computed as a weighted average of the observed prices:

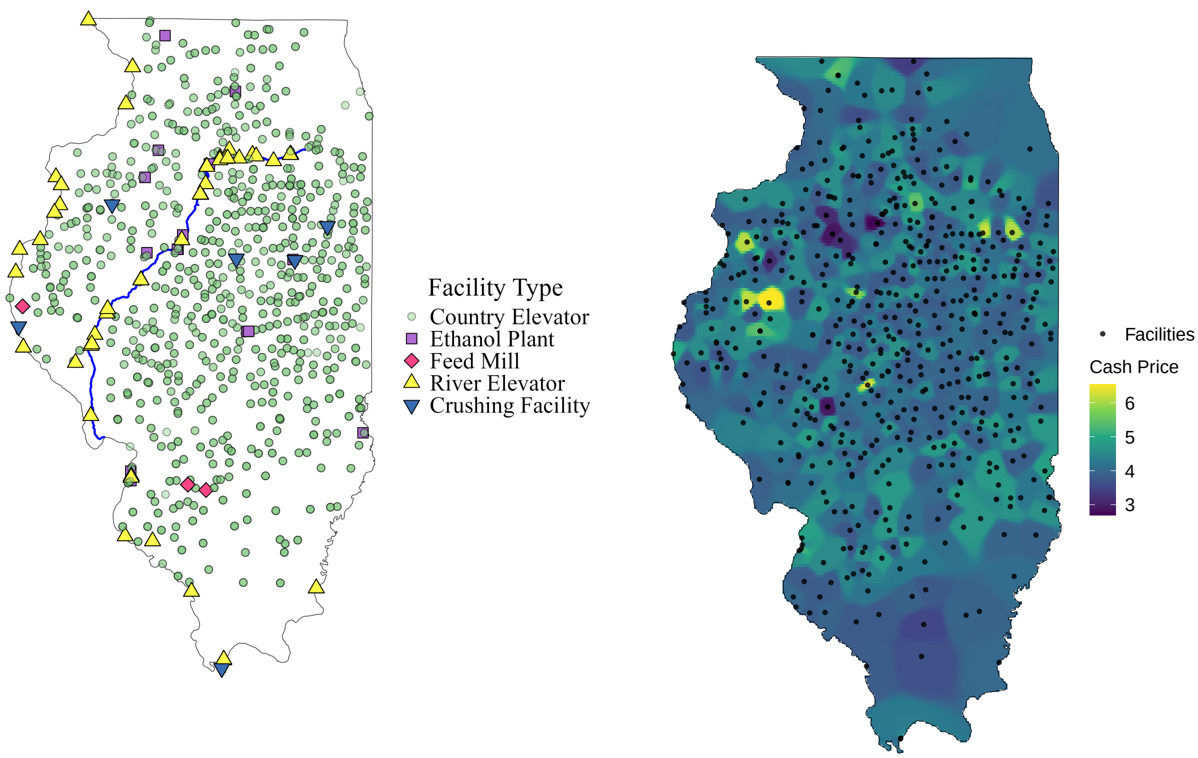
$$p_0 = \frac{\sum(w_i p_i)}{\sum w_i}. \tag{4}$$

Facilities that post prices, including country elevators, ethanol plants, feed mills, river elevators, and crushing facilities, are relatively consistently distributed throughout Illinois, as shown in Figure 5a. These serve as the input for the interpolation process that assigns prices to all possible locations in each year. The price gradient shown in Figure 5b provides an example of this process averaged across all years. The interpolation process is influenced by the power parameter $\rho = 10$, which controls the weight of nearby points; lower values of ρ give less emphasis to closer locations, resulting in smoother interpolated surfaces. By incorporating spatial proximity, this method ensures that the interpolated values align with observed spatial patterns, allowing us to accurately assign commodity prices to all farmland locations.

In Illinois, the two most important commodity prices are for corn and soybeans price since the vast majority of farmland is devoted to these two crops. Since corn and soybeans are the dominant commodity outputs, we construct a weighted commodity price index based on the interpolated prices in that township and year and the share of corn and soybean land devoted to each of the crops on average. To calculate the rotation share for each township, we use the Cropland Data Layer from 2010 to 2020 and calculate the average share of pixels of cropland for both crops in the whole period (USDA, 2025).[2] Since soybeans yield fewer bushels per acre than corn and have a higher average price, we scale the soybean price by the ratio of the sample average soybean price to average corn price so that we can interpret variation in the resulting price index as roughly approximating changes in the price of corn. In our sample, this ratio is about 0.4.

[2]The Cropland Data Layer does not have reliable data before 2010, thus we are not able to use rotation shares at the township level before 2010. On average, we find that the rotation share is about 45% soybeans and 55% corn and does not change very much over time. See Appendix A.1 for details.

Figure 5: Interpolation of Corn Prices in Illinois, 2000-2022



(a) Illinois grain facilities by type

(b) Corn price distribution, avg. of 2000-2022

Our output price index is constructed as:

$$p_{it} = \alpha_i^{corn} \times p_{it}^{corn} + \alpha_i^{soy} \times p_{it}^{soy} \times \frac{\bar{p}^{corn}}{\bar{p}^{soy}} \tag{5}$$

where α_i^{corn} and α_i^{soy} are the shares calculated from the Cropland Data Layer for the townships in our data. We use sample averages of the corn and soybean prices to determine the price ratio $(\bar{p}^{corn}/\bar{p}^{soy})$.[3]

Table 1 provides a summary of the key variables used in the analysis. The average farmland price per acre in the sample is $6,544.54 with a standard deviation of $5,653.45. The Bulletin 811 productivity index (B811 PI), which serves as the basis for soil classification, has a mean value of 110.22 and a standard deviation of 22.45. The ISPFMRA category class

[3]See Appendix table A.2 for additional results using alternative weightings of the prices.

would classify the this sample mean as “Average”, given a B811 PI value between 100 and 117. Commodity prices also exhibit variation over the study period, with the average corn cash price at \$3.87 per bushel (SD = \$1.59 and the average soybean cash price at \$9.60 per bushel (SD = \$3.14). Our output price index on average in this period is about 17.33.

Table 1: Summary Statistics

	N	Mean	Std. Dev.	Min	Max
Parcel size	22,599	144.947	200.635	11.000	1,280.000
Price per acre	22,599	5,489.769	5,197.790	77.212	46,837.899
B811 PI	22,599	109.540	22.874	0.945	143.867
Corn cash price	22,599	3.706	1.282	1.801	7.113
Soy cash price	22,599	9.232	2.394	4.950	15.101
Output price index	22,599	3.714	1.118	1.000	6.577
Soil class					
Fair	7,613				
Good	5,566				
Average	5,406				
Excellent	4,014				

4 Empirical Strategy

Using Equation 1, our goal is to study the capitalization of soil quality into land values as mediated by commodity prices. This component of land values reflects soil productivity rather than confounding factors that may be correlated with the distribution of soil quality over space. We employ a hedonic pricing model that incorporates soil quality, commodity prices, and township and year fixed effects to account for spatial and temporal heterogeneity. Our first specification decomposes the soil quality premium into non-productive and productive components as follows:

$$L_{it} = \tau_t + \gamma p_{it} + \sum_{k=2}^{K-1} \beta_k^0 S_{ik} + \beta_k^S (S_{ik} \times p_{it}) + \varepsilon_{it} \tag{6}$$

where L_{it} is the median, real price per acre (\$/acre) for township i in year t.[4] The soil productivity class indicator variables, denoted by S_{ik} for each soil class k, is determined using the ISPFMRA classification scheme, where soils are categorized into four classes: Fair (productivity index below 100), Average (100 to 117), Good (117 to 133), and Excellent (greater than 133). In all the models, the Fair category is omitted so that β_k^S is interpreted as the difference between Fair soils and the other classes. Using these indicator variables allows the marginal product of soil to be estimated non-linearly while maintaining ease of interpretation. Year fixed effects, τ_t, capture shocks and trends common across units over time, such as macroeconomic conditions, commodity market conditions, and technological advancements. Finally, ε_{it} is the idiosyncratic error term.

The variable p_{it} is our estimate of the expected output price in township i and year t using real prices in 2010 dollars. Being a proxy for the expected output price, one worry would be that there are too many year-to-year fluctuations in commodity prices for this to accurately reflect the expectations of output prices. As a robustness check on our results, we use averages of both p_{it} and L_{it} in 5-year bins in our regression model to lessen the influence of year-to-year volatility in output prices. In theory, a price averaged every five years is more robust to short-run noise that does not reflect price expectations while still allowing for different regime changes over time (e.g. the passage of the US Renewable Fuel Standard in 2005-2007).

In this first specification, the premium for soil quality in our sample is $\frac{\partial L_{it}}{\partial S_{ik}} = \beta_k^0 + \beta_k^S p_{it}$. Intuitively, β_k^0 is the value of soil productivity when commodities are worthless ($p_{it} = 0$) and so represents the non-productive value of soil quality. However, β_k^S is the premium that is enhanced by commodity prices and so is the productive value, which we know from our theoretical model is closely related to the marginal product of soil quality $\frac{\partial F}{\partial S_i}$. Since the non-productive value β_k^0 is not of interest in this analysis, in our second specification we introduce township fixed effects α_i which absorb the non-productive value. Township fixed

[4]All the prices used in our analysis are adjusted to 2010 dollars.

effects account for other time-invariant factors such as distance to markets or distance to urban areas that might correlate to output price and bias our estimate of β_k^S. Our second specification is then:

$$L_{it} = \tau_t + \alpha_i + \gamma p_{it} + \sum_{k=2}^{K-1} \beta_k^S (S_{ik} \times p_{it}) + \varepsilon_{it} \tag{7}$$

The benefits of studying soil quality and land values with our approach are twofold. First, based on Ladd and Martin (1976), proxying for the expected output price and interacting it with soil quality makes the hedonic coefficient β_k^S vary only with the marginal product of soil quality and not with market conditions. This allows for a more straightforward interpretation of the coefficient as well as an understanding of how commodity prices will or will not enhance the value of soil quality. Second, soil quality measures are typically static and would be collinear with any fixed effects at the level of i (Buck et al., 2014). Yet, including spatial fixed effects can be desirable to control for unobserved, permanent variation across geographic units. By interacting soil quality with commodity prices, β_k^S can be estimated with spatial fixed effects since $(S_{ik} \times p_{it})$ varies over time and space. This allows us to control for unobserved heterogeneity while still studying the capitalization of soil quality into land prices.

Finally, we can use our approach to examine whether the marginal product of soil quality, measured by β_k^S, is changing over time due to changes in the production technology (F in the model). To explore the temporal dynamics of returns to soil quality, we extend our primary specification by introducing five- or six-year bins, enabling us to assess how the relationship between land prices and the interaction of soil productivity classes with commodity cash prices evolves over time. This extended specification is represented as:

$$L_{it} = \alpha_i + \tau_t + \gamma p_{it} + \sum_{k=2}^{K-1} \beta_k^S (S_{ik} \times p_{it}) +$$

$$+ \sum_{j=1}^{J-1} \gamma_j p_{it} \times \mathbb{1}\{t \in j\} + \sum_{k=1}^{K} \beta_{kj}^S (S_{ik} \times p_{it} \times \mathbb{1}\{t \in j\}) + \varepsilon_{it},$$

where there are J bins which divide the sample into four periods: 2000–2005, 2006–2011, 2012–2017, and 2018–2022. The bin 2000-2005 is used as the base category, making the coefficients β_{kj}^S represent the change in the returns to soil class k relative to its returns in 2000-2005 (measured as β_k^S in this regression. The inclusion of these temporal bins allows us to examine improvements in soil management techniques, such as advances in no-till farming, precision agriculture, and enhanced crop rotation practices, that may alter the marginal productivity of soils over time. With 2000–2005 serving as the baseline period, we can identify whether the responsiveness of farmland values to commodity prices has increased or decreased over time and how this responsiveness varies by soil class.

5 Results

Table 2 shows coefficient estimates for equations 6 and 7 and contains our main result. In the first column, we estimate the relationship between soil classes and land values without price interactions or spatial fixed effects. Compared to Fair land, the three soil classes capitalize into land values at an increasing rate: Excellent has a much larger premium than Good, Good has a larger premium than Average, and Average is priced at a premium to Fair. The Average, Good and Excellent soil premiums are 13%, 31%, and 41% of the sample average of $5,489.77.

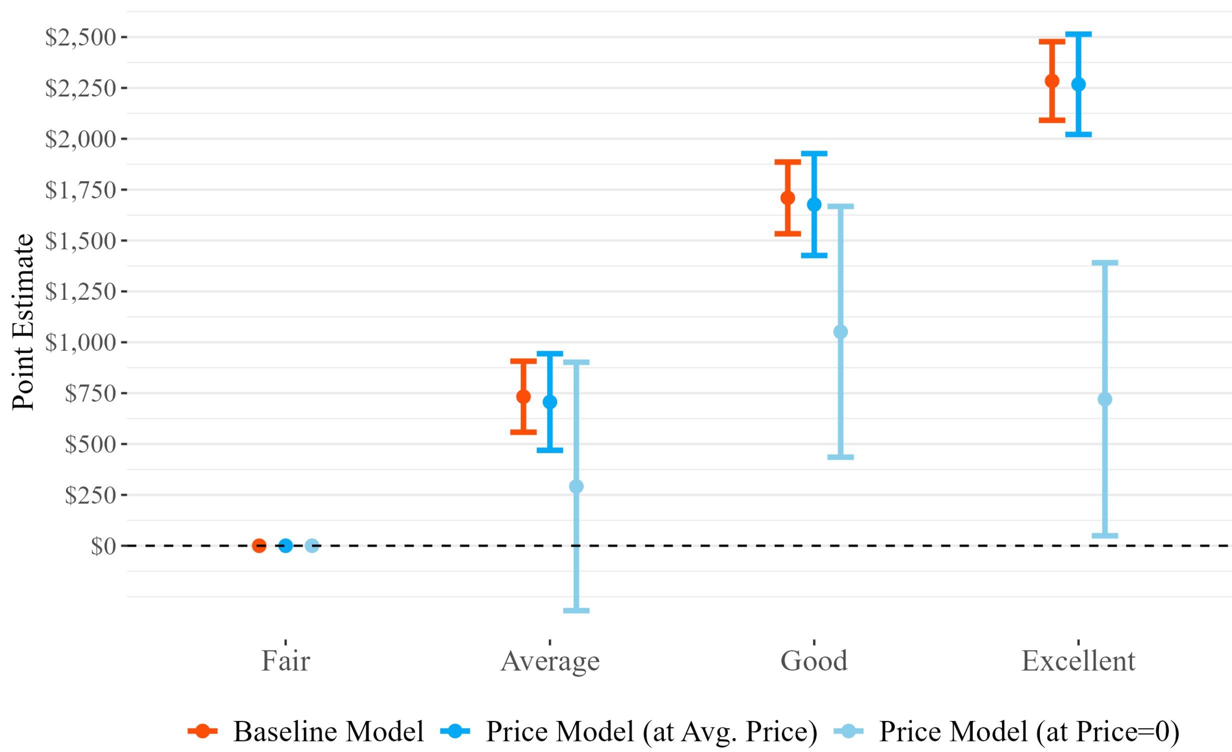
When we introduce output price interaction terms in Column (2), we see that the price interaction term explains portion of the soil class premiums, especially for Excellent We find the highest quality soils, Excellent and Good, are the most enhanced by increases in commodity prices while Average soils have a premium more independent of commodity prices. Including spatial (township) fixed effects as in column (3) causes the soil classes by themselves to drop from the model; the price interactions remain and show the returns to soil productivity while controlling for other spatially constant factors. When spatial fixed effects are included, the coefficients on the price interactions decrease somewhat and the Good premium becomes indistinguishable from Fair, suggesting that there are other spatial factors that might bias the estimates of soil productivity upward.

By assessing the model in column (2) at different values of our price index, we can measure the portion of the soil premium in each category that is influenced by changes in prices. Figure 6 shows the coefficients for the baseline model, shown in column (1) of Table 2, and the price model in column (2) assessed at zero and the sample average, about 3.7. If prices do not explain any of the premium, we would expect the price model assessed at zero to be very similar to the baseline model. This appears to be the case for Average and Good soils since the price interaction term for Fair is indistinguishable from zero and the coefficient for Good when price is zero is indistinguishable from the other models. However, Excellent soils have a significant interaction term and a sizable portion of their premium can be explained by the prices.

Table 2: Soil Classes With and Without Price Interactions

	Price Per Acre (2010 Dollars)		
	(1)	(2)	(3)
Soil Class (Base: Fair Soil)			
Average Soil	732.525***	291.447	
	(120.665)	(310.894)	
Good Soil	1,709.488***	1,051.511***	
	(127.105)	(360.788)	
Excellent Soil	2,284.239***	720.034**	
	(125.854)	(353.408)	
Price Interaction			
Average Soil × Output Price		111.751	53.250
		(80.105)	(79.495)
Good Soil × Output Price		168.413*	140.844
		(88.151)	(86.109)
Excellent Soil × Output Price		416.751***	343.282***
		(93.168)	(93.041)
Year FE	X	X	X
Price Interaction		X	X
Township FE			X
Observations	22,599	22,599	22,599
Adjusted R^2	0.056	0.057	0.126
Note:			*p<0.1; **p<0.05; ***p<0.01

Figure 6: Output price relationship by soil productivity class.



Because not every township will have land transactions every year, using spatial fixed effects might lead to dropping some townships due to collinearity. We may also be concerned that the output prices we are using are too volatile to represent an expected output price since they are only averages of each year. A more realistic assumption may be instead that a multiple-year average is a better proxy for the expected output price. To assess the robustness of our main result to these factors, we estimate versions of the price interaction model with spatial fixed effects where the variables are averages over three and five-year bins. Table 3 shows the price interaction coefficients with the full sample, the sample averaged in 3-year bins, and the sample averaged in 5-year bins. The coefficients on the interaction become stronger when the data is averaged, as Excellent and Good land have even larger premiums in the 3-year and 5-year averages.

We are also interested in whether the relationship between soil classes and land values has changed over time, as this would indicate that changes in production technology have

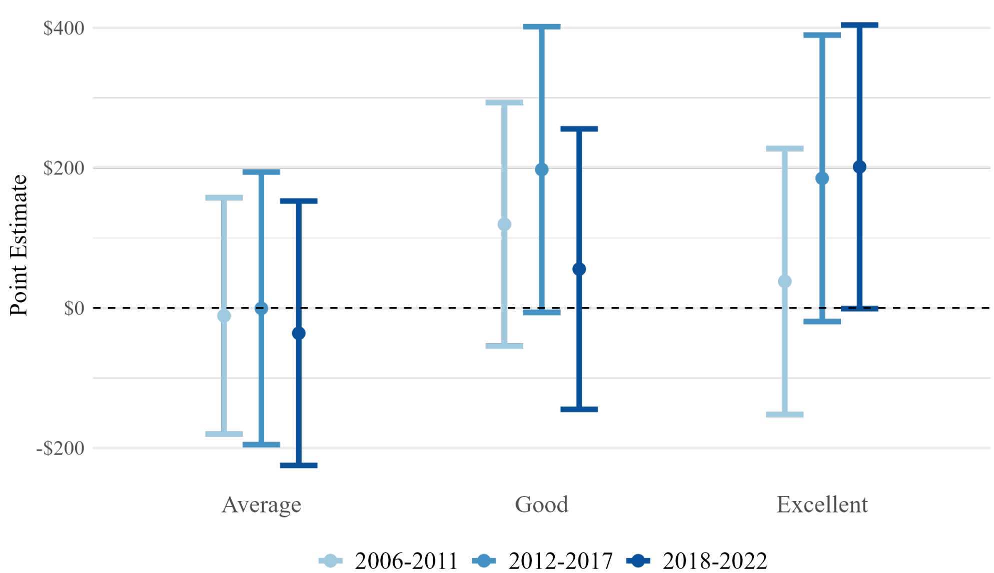
Table 3: Price Interaction Model With 3-Year and 5-Year Averages of Variables

	Price Per Acre		
	No Avg.	3-Year Avg.	5-Year Avg.
Soil Class (Base: Fair Soil)			
Average Soil × Output Price	53.250	15.143	−118.368
	(79.495)	(100.962)	(198.113)
Good Soil × Output Price	140.844	104.526	344.385**
	(86.109)	(102.797)	(167.517)
Excellent Soil × Output Price	343.282***	404.527***	589.097***
	(93.041)	(118.133)	(166.838)
Year FE	X	X	X
Price Interaction	X	X	X
Township FE	X	X	X
Observations	22,599	10,696	5,773
Adjusted R^2	0.126	0.186	0.249

*p<0.1; **p<0.05; ***p<0.01
Robust standard errors in parentheses.
Coefficients are interpreted as relative to the Fair soil class.

shifted the marginal returns to increasing soil quality. Whereas a model without price interactions would have coefficients that confound productive and non-productive components of soil quality in land values, our interaction term coefficients already have this variation netted out. Thus, we can interpret changes in these coefficients as related to a broad set of technological improvements. Figure 7 shows the premiums for each soil class for three five-year bins: 2006-2011, 2012-2017, and 2017-2022. The premiums for each soil class in each period are interpreted as those relative to the premiums in 2000-2005; statistical significance indicates the soil quality premium in a period is statistically distinct from the premium in 2000-2005. For Average and Good soil classes, there are no significant differences across time. However, the premium for Excellent soil increases after 2018, indicating an increase in the economic value of Excellent soil related to its marginal agricultural productivity. Relative to the premium for Excellent soil in 2000-2005, the premium is twice as large in the period 2018-2022. Using this approach, we find evidence for technological progress that has raised the marginal returns of using Excellent soil for agricultural production compared to Fair soil.

Figure 7: Soil Class Premiums Across 5-Year Categories Relative to 2000-2005



Note: Coefficients are relative to the coefficients in 2000-2005 and the Fair soil class.

In a supplementary analysis, we test the robustness of our results by using different measures of soil productivity and expected output price. In Table A.2, we compare different weightings of soybean and corn prices and find that our specification is the most conservative. Other weightings of the prices result in larger premiums, suggesting our main specification is a possible lower bound on the effect. In Table A.3, we use a continuous measure of soil productivity and use quantiles of the soil productivity index instead of the appraiser classification. We find that the general pattern of the results is not significantly impacted by these changes.

We also test for the influence of outliers and the existence of a log-log relationship between land prices and output prices in Appendix A.3. When omitting the 99th, 95th and 90th percentiles of land prices, we find that Excellent premium is reduced, likely because the parcels with the highest prices are also Excellent parcels. We do not find any evidence suggesting the same relationship exists in logarithms, as when the land and the output prices are log transformed we see no significant interaction between soil class and output price. This suggests that the relationship is not a proportional relationship and depends on the levels of the prices. Since the first order condition in Ladd and Martin (1976) only suggests that a relationship should exist in levels, a different theoretical model is needed to understand what a log-log relationship would mean in these markets. More details on these results are available in the supplementary appendix.

6 Conclusion

This paper explores the evolving relationship between soil productivity and farmland values. According to our theoretical framework, the expected output price is an important mediating factor impacting how soil productivity capitalizes into land values. Using 22 years of farmland transactions and crop prices in Illinois, we find that the premium for high-quality soils varies significantly with our interacted measure of soil quality and expected output price. In particular, we find the premiums for Good and Excellent soil classes are strongly related to the productive component of soil quality associated with variation in commodity prices. Since our new premiums are interpreted independently of commodity prices, we can use our approach to determine whether the marginal returns to soil productivity have increased over time. We find that the economic value of Excellent soil has roughly doubled relative to its value between 2000 and 2005, suggesting technological progress in how soil productivity is used to generate agricultural output.

Our results have significant implications for future research in farmland markets. Previous hedonic analyses of farmland prices or estimated values have often implicitly made the assumption that hedonic coefficients are constant across time and space. However, this assumption is almost certainly violated when using multiple years of data in markets where output prices vary over space. As output prices vary over time and space, hedonic coefficients will also vary and may lead to incorrect inferences about how capitalization of a characteristic like soil quality changes over time. Our approach in this paper provides a practical way to relax this assumption. By interacting the characteristic with a measure of expected output price, the resulting coefficients can be interpreted independently of market conditions. In the case of soil productivity, this allows us to have a better understanding of how the marginal benefit of soil quality may have changed over time due to technological progress. However, our analytical framework does not address which individuals or firms anticipate, observe, and incorporate the productive component of soil quality in farmland prices. Future work could assess whether the farmland market activity of farmers, farmland investors, or other agents is associated with the productive component of soil quality.

Our results are also relevant to the evolving policy discussion around soil conservation, soil health, and regenerative agriculture. A generalized understanding of the process by which soil productivity capitalizes into farmland prices helps us assess the economic returns to improving soil productivity. Our analysis shows that the returns to bettering soil productivity may depend on the state of commodity markets. Failing to consider how commodity price variation may confound how land values impound the benefits of enhanced soil quality may lead analysts to overstate or understate the returns to changes in practices. In our analysis, soil quality premiums, especially for Good and Excellent soils, are significantly driven by soil productivity that is made more valuable by high commodity prices. Our results do highlight that farmers and land owners may only find some enhancements in soil productivity beneficial to the extent that their benefits can be realized when commodity markets are favorable.

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A Supplementary Analysis

A.1 Output Price Construction

In our theoretical model, we refer to a single, theoretical expected output price $\bar{p}_{it}$. In reality, the relevant prices for farmers in Illinois are the prices for both corn and soybean. Since many farmers in Illinois engage in crop rotation between the two crops, both of the prices will be relevant to their expected value of soil productivity.

To construct an appropriate expected output price for our analysis, we must address the fact that both soybean and corn prices are important to agricultural production in Illinois. One way to address this would be to give each commodity price and equal weight, 0.5, since many parts of Illinois rotate soybeans and corn. Yet, using equal weights would be inaccurate for townships which do not rotate soybeans and corn equally.

In order to weight the most important commodity price for each township, we calculate the share of the corn-soybean rotation devoted to each crop using the Cropland Data Layer for the years 2010-2020 (USDA, 2025). Unfortunately, there is poor satellite coverage before 2010 and calculation of soybean and corn planting at the level of the township are not possible. For each year, we use our township boundaries (both political and PLSS) to calculate the number of pixels devoted to corn and soybeans in each township. We then sum these pixels together and divide the counts by the sum to get the shares. In other words, each share represents the share of the total land for soybean and corn land devoted to that crop.

Figure A.1 shows the average share devoted to corn across Illinois from 2010 to 2020. Table A.1 shows descriptive statistics for the rotation shares for the 1,226 township marked out by the Illinois PLSS. On average, a township plants about 45% of their corn and soybeans area to soybean and 52% to corn. However, there is significant heterogeneity across space. In southern Illinois, more townships rotate more to soybeans while several townships in the north and central Illinois rotate more to corn. The standard deviation of shares within the townships is roughly 0.09 for corn and soybeans, which indicates that these rotation shares did not drastically change over time.

Figure A.1: Rotation Shares for Illinois PLSS Townships, 2010-2020 Average

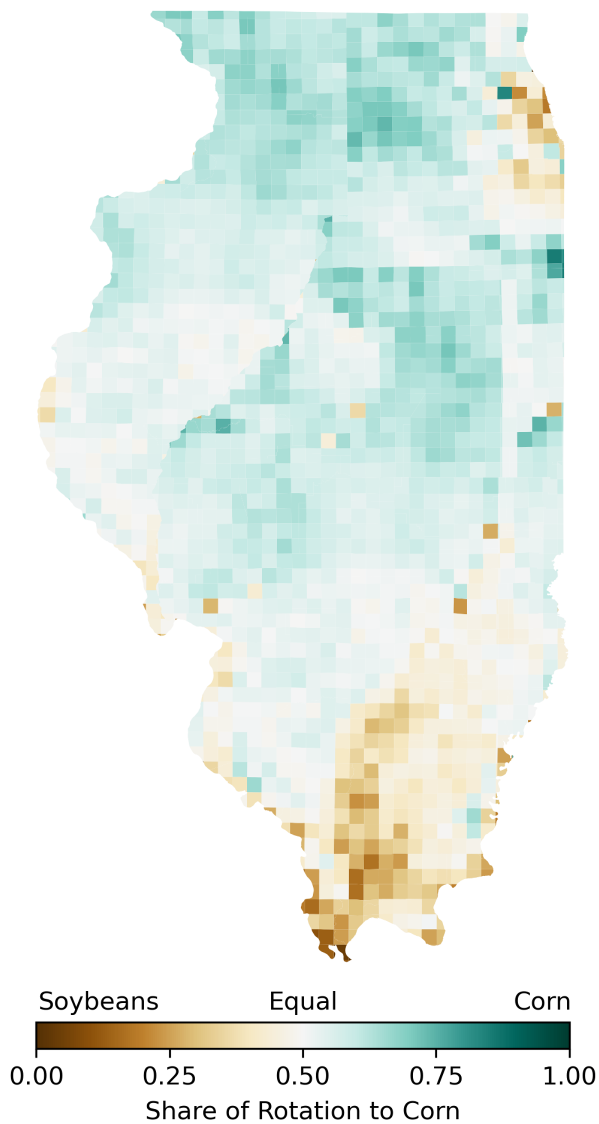

Table A.1: Rotation Descriptive Statistics

	Count	Mean	Std. Dev.	Min	Max
Soybeans	1226	0.468	0.105	0.000	0.984
Corn	1226	0.523	0.109	0.000	0.853

To test the influence of differing weights and scaling, we estimate our main specification using differing output prices. We first estimate our specification using the corn price and the soybean price separately. Next, we use a combined price where each commodity price is weighted equally: $p_{it} = .5p_{it}^{corn} + .5p_{it}^{soy}$. Next, we use a combined price where each commodity is weighted by its rotation share in the township from 2010-2020: $p_{it} = \alpha_i^{corn} \times p_{it}^{corn} + \alpha_i^{soy} \times p_{it}^{soy}$. The last two specifications consider these same two weightings with a scaling term for the soybean price to make it equivalent in value to bushel of corn.

Table A.2 shows the effect of these specifications on the price interaction coefficients. The rotation weighted price without a scaling for soybeans results in the largest coefficients while the 50/50 weights with a scaling for soybeans gives the most conservative results. Our most preferred specification, using rotation weights and the scaling, gives the second most conservative estimates. Thus, the results in our preferred specfication could be underestimating the value of soil, as alternative weightings of the prices could give larger effects. However, in none of the specifications does the pattern change: Average soils are not statistically different than Fair soils and the coefficients become larger as soil quality improves past Fair.

Table A.2: Comparison of Alternative Output Prices

	Corn Price	Soybean Price	50/50 Weighted	Rotation Weighted	50/50 Weight, Scaled	Rotation Weight, Scaled
Average Soil × Price	69.186	38.919	52.080	19.588	55.472	96.340
	(71.606)	(37.529)	(50.206)	(18.832)	(51.435)	(82.187)
Good Soil × Price	176.495**	119.601***	150.531***	58.831***	162.465***	236.022***
	(76.901)	(40.381)	(53.942)	(20.250)	(56.237)	(88.127)
Excellent Soil × Price	366.442***	231.109***	296.553***	114.466***	311.013***	469.429***
	(83.614)	(45.214)	(59.880)	(22.607)	(61.623)	(96.950)
Observations	22,599	22,599	22,599	22,599	22,599	22,599
Adjusted R^2	0.163	0.163	0.163	0.163	0.163	0.163

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

A.2 Alternative Soil Productivity Measures

It may be that the soil classifications we use in our main specifications do not adequately capture the relationship between the soil productivity index and land values. As a robustness check, we estimate the model with a continuous measure of the soil productivity index (PI) and with quartiles of the soil PI instead of our appraiser classification. Table A.3 shows the results of these models. The results show roughly the same pattern as Table 2. A sizable portion of the returns to the soil productivity index depend on variations in output price, especially high values of the soil PI (as in quartile 4). When including fixed effects, the fit of the model improves and the coefficients increase on the price interactions. In particular, the coefficient on the continuous measure increases by about 85% when spatial fixed effects are included.

A.3 Price Outliers

Table A.3: Alternative Constructions of the Soil Productivity Measure

	Price Per Acre		
Continuous Soil PI			
Soil PI, B811	37.152***	14.006***	
	(1.918)	(5.174)	(0.000)
Soil PI, B811 × Output Price		6.127***	5.639***
		(1.309)	(1.340)
Observations	22,599	22,599	22,599
Adjusted R^2	0.102	0.104	0.164
Soil PI Quartile (Base: Soil PI Q1)			
Soil PI Q2	580.772***	−236.679	1,767.525***
	(117.204)	(315.415)	(332.224)
Soil PI Q3	1,591.488***	719.106*	2,554.971***
	(137.188)	(374.542)	(376.216)
Soil PI Q4	2,338.723***	814.292**	2,872.390***
	(120.917)	(342.969)	(398.508)
Price Interactions			
Soil PI Q2 × Output Price		216.173***	176.005**
		(82.633)	(82.934)
Soil PI Q3 × Output Price		226.038**	206.784**
		(90.543)	(88.400)
Soil PI Q4 × Output Price		405.162***	346.247***
		(89.050)	(88.608)
Observations	22,599	22,599	22,599
Adjusted R^2	0.057	0.058	0.125
Year FE	X	X	X
Price Interaction		X	X
Township FE			X

*p<0.1; **p<0.05; ***p<0.01
Robust standard errors in parentheses.
Coefficients are interpreted as relative to the first quartile of the soil PI

Table A.4: Log-Log Model

	Log(Price Per Acre, 2010 Dollars)		
	(1)	(2)	(3)
Average Soil	0.145^{***}	0.129	
	(0.026)	(0.085)	
Good Soil	0.317^{***}	0.305^{***}	
	(0.026)	(0.091)	
Excellent Soil	0.464^{***}	0.462^{***}	
	(0.027)	(0.095)	
Average Soil × Log(Output Price)		0.009	−0.039
		(0.068)	(0.069)
Good Soil × Log(Output Price)		0.004	−0.033
		(0.073)	(0.074)
Excellent Soil × Log(Output Price)		−0.002	−0.066
		(0.079)	(0.079)
Year FE	X	X	X
Price Interaction		X	X
Township FE			X
Observations	22,599	22,599	22,599
Adjusted R^2	0.038	0.038	0.097

Note: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Table A.5: Omitting 90th, 95th, and 99th Percentile of Land Prices

	Price Per Acre (2010 Dollars)			
	All Data	Omit 99th	Omit 95th	Omit 90th
Average Soil × Output Price	53.250	79.649	87.421	100.282**
	(79.495)	(69.587)	(55.157)	(46.087)
Good Soil × Output Price	140.844	229.281***	177.382***	197.562***
	(86.109)	(76.582)	(60.204)	(53.313)
Excellent Soil × Output Price	343.282***	326.784***	235.314***	146.311**
	(93.041)	(84.732)	(66.950)	(59.354)
Percentile Cutoff		25,664.64	15,702.11	11,585.18
Year FE	X	X	X	X
Price Interaction	X	X	X	X
Township FE	X	X	X	X
Observations	22,599	22,373	21,469	20,339
Adjusted R^2	0.126	0.129	0.130	0.130

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