Soil health investment and Kansas commercial crop farm financial performance

by

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Abstract

Context: Soil health investments are widely promoted for their environmental benefits, but their financial impacts, particularly on farm profitability, remain underexplored and vary widely across studies. Understanding these financial outcomes is crucial for informing farmer decision-making and shaping conservation policy.

Objectives: This study aims to evaluate the relationship between soil health investments, defined as the combined adoption of multiple regenerative or conservation practices, and farm financial performance. It also investigates whether different quantification methods for soil health investments produce consistent farm-level classifications.

Methods: The study uses farm-level data from the Kansas Farm Management Association and a farmer survey on soil health practices. Soil health investments are quantified using three classification methods: agronomic scoring, cluster-based classification, and threshold-based grouping. Financial performance is assessed through (1) a cluster analysis ranking farms based on net farm income ratio, return on assets, profit margin ratio, and (2) net farm income ratio. Ordered logistic regression is applied to determine the likelihood of farms achieving higher financial rankings, while OLS is used for net farm income ratio. The relationship between soil health investment and factors that determine profitability, specifically yield and expenses, are also estimated. To determine the degree to which soil health investment relative to other observable factors predicts farm profitability, we also employ a random forest machine learning analysis.

Results and conclusion: The three classifications used in this study produce different soil health investment rankings across farms, with 10% consistently classified as high, 4% as medium, and 17% as low across all three methods. This variation highlights a key

methodological insight: different classification approaches do not always agree, which has implications for how soil health investment is interpreted and linked to financial outcomes. Only higher agronomic soil health scores are consistently associated with stronger financial performance; lower expenses likely play a role in this relationship. Soil health investments have a weaker predictive power for farm profitability than farm size, structure, operator age, and weather, but can more easily be controlled by farm operators.

Significance: This study underscores the need for standardized soil health measurement to validate survey or practice-based measures. Large, detailed field-level dataset on soil characteristics, practices, input use, and yields would assist in the creation of such measurements.

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Chapter 1 - Introduction

Modern agriculture, while essential for ensuring global food security and supporting rural economies, contribute significantly to environmental degradation, including soil depletion, biodiversity loss, and greenhouse gas emission (Pretty et al., 2001; Sekhar et al., 2024; Wang et al., 2024). As pressure mounts to produce more food on less land, restoring soil health is critical (Alexandratos & Bruinsma, 2012; Montgomery, 2021). In response, approaches like Conservation Agriculture (CA), Regenerative Agriculture (RA), and Climate Smart Agriculture (CSA) have emerged to enhance productivity, resilience, and environmental outcomes (Farooq et al., 2024; Kidson et al., 2024; Patidar, 2022). Although RA and CA may differ in their initial approaches, according to Schreefel et al (2020), they both strongly emphasize the environmental aspect of sustainability, as they share common objectives such as minimizing environmental externalities and optimizing resource management. Schreefel et al (2020), reviewing definitions of RA, found they focus on environmental themes such as soil health and biodiversity. RA practices that enhance soil health provide a practical approach to reversing soil degradation in a way that is both efficient and economically viable (LaCanne & Lundgren, 2018; Montgomery, 2021). CA, on the other hand, offers distinct advantages over conventional agriculture by enhancing soil health, improving carbon sequestration, optimizing natural resource efficiency, and minimizing environmental impacts (Cárceles Rodríguez et al., 2022; Farooq & Siddique, 2015; Smith et al., 1998). Whether it is CA, RA, or CSA, they are inherently connected with soil health, as these practices are designed to enhance productivity, build resilience, and mitigate environmental impacts, many of which are directly tied to soil quality and function. Since many producers adopt one or more practices without fully adhering to RA or CA systems, we use the term soil health practices to encompass the shared principles of these approaches. This terminology maintains a focus on improving soil function, while reflecting the diversity of implementation in practice.

Soil health is defined by the USDA Natural Resources Conservation Service (2025) as "the continued capacity of soil to function as a vital living ecosystem that sustains plants, animals, and humans,". Soil health is crucial for meeting the increasing demands of global food production. As the world population grows, maintaining healthy and productive soil becomes paramount, driving significant investments in soil health initiatives. Given that soil health is closely linked to RA (M. Tahat et al., 2020), sustaining soil vitality necessitates adherence to RA principles. According to Rhodes (2017), Newton et al. (2020), and Khangura et al. (2023a), these principles include minimizing soil disturbance, keeping the soil covered, maintaining living roots in the soil, maximizing plant diversity, and reintroducing livestock. Sherwood and Uphoff (2000) highlight that soil health is crucial not only for immediate agricultural productivity and profitability but also for ensuring long-term sustainability. Maintaining healthy soils supports current farming operations, while safeguarding future yields and economic viability. A major appeal of soil health-building practices is their potential to enhance farm profitability. However, adoption is often hindered by habitual practices, resistance to change, limited knowledge on implementation, and concerns about economic risk during the transition (Montgomery, 2021).

Soil health investments have been widely promoted for their environmental benefits, yet their financial implications remain underexplored. Existing literature provides evidence of the environmental and agronomic benefits of soil health practices (Bergtold et al., 2017; Khangura et al., 2023a; Manzeke-Kangara et al., 2023; McCauley & Barlow, 2023; Myers et al., 2019; Rehberger et al., 2023) but their financial viability across different farming systems and regions remains underexplored. Schnitkey et al. (2024) observed that although cover crops offer environmental benefits, such as reducing nitrogen loading and improving air quality, these do not translate into higher returns for farmers or landowners, with most of the benefits not accruing to them.

Furthermore, while a growing body of literature highlights the benefits of individual soil health practices such as no-till farming (Che et al., 2023; Jayaraman & Dalal, 2022; Khan & Gang Wang, 2023), cover cropping (Bergtold et al., 2017; Fernando et al., 2024; Hughes & Langemeier, 2020; Schön et al., 2024), or crop rotation (Guo et al., 2024; Hassaan et al., 2024; Yang et al., 2024). Much of the existing research tends to isolate these practices in their analyses, rather than examining them as part of a holistic, integrated system. Meta-analyses have extensively evaluated the effects of no-till and other CA practices, providing broad insights into their yield and climate resilience outcomes (Huang et al., 2018; Pittelkow et al., 2015; Steward et al., 2018; Su et al., 2021). While these studies focus primarily on specific practices, this study takes a broader approach by combining a diverse array of soil health strategies, incorporating both RA principles and other conservation-based techniques. The outcome of multiple practices used in concert often exceeds the sum of their individual effects (Khangura et al., 2023a). Dozier et al. (2017) examined the combination of cover cropping and tillage practices and found that cover cropping with tillage reduced soybean yields by 245 kg/ha compared to no-till. Meanwhile, Snapp & Surapur (2018) reported a 3% reduction in corn yield when cover crops were used alongside reduced tillage. Makate et al. (2019), Mutenje et al. (2019), and Sardar et al. (2021) consistently highlight the benefits of adopting multiple CSA practices. Their findings indicate that integrating multiple CSA strategies enhances farm yields, income, and resilience. However, they also emphasize that implementing multiple CSA innovations requires additional resources, which can be a challenge for smallholder farmers. A study by Nouri et al. (2019)

shows that a long-term combination of cover crop and no-till improved the physical properties of soil, such as soil aggregation and moisture retention. The financial impacts of combining them have been understudied in comparison to their individual implementation. This study aims to address this gap by exploring the financial performance of farms that adopt multiple soil health practices simultaneously.

Soil health practices such as no-till, cover cropping, and diversified crop rotations are known to enhance soil fertility, water retention, and carbon sequestration (Khangura et al., 2023b). However, many farmers hesitate to adopt these practices due to uncertainty about financial returns, implementation costs, and risk exposure (Sellars et al., 2023). Existing research on the relationship between soil health practices and farm profitability has yielded highly inconsistent findings, with outcomes varying depending on how soil health investments are modeled. Different methodological approaches often lead to divergent conclusions, with some studies highlighting positive financial impacts (Hughes & Langemeier, 2020; LaCanne & Lundgren, 2018), while others report negligible or even negative effects due to high adoption costs and potential yield trade-offs in certain contexts (Plastina et al., 2018; Schnitkey et al., 2024). For instance, LaCanne and Lundgren (2018) found that regenerative farming systems reduced input costs and improved profitability, while Plastina et al. (2020) reported that in the short run, cover crop adoption increased costs without a clear financial return.

Given these discrepancies and recognizing the need for a more comprehensive understanding of the financial implications of soil health investments, this study addresses two central questions: How can soil health investments be quantified for Kansas commercial crop farming, and are different approaches consistent? Moreover, what is the connection between these soil health investments and farm financial performance? This research seeks to clarify the financial outcomes associated with the adoption of soil health practices and improve measurement techniques for future studies. Kansas commercial crop farms exhibit wide variation in soil health practice adoption, making it an ideal setting to explore whether these investments translate into better financial performance. Given that financial viability is a key factor in farmer decision-making, understanding how soil health impacts profitability is critical for policy, farm management, and conservation incentives. For the purpose of this study, we define soil health investment as the adoption of multiple practices aligned with regenerative agriculture principles. However, because few farms in our data set meet the strict criteria of a complete regenerative system, we use the broader term "soil health investment" to reflect incremental and partial practice adoption.

Chapter 2 - Data

2.1 KFMA

This study leverages a unique dataset from the Kansas Farm Management Association (KFMA), an organization that provides financial analysis and accounting support to its member farms. The dataset offers valuable insights into crop yields and farm economics across a diverse range of agricultural operations, reflecting the state's varied landscape. It encompasses key farm characteristics that influence financial performance and operational efficiency. These variables include demographic factors such as farmer age, which serves as a proxy for experience and risk tolerance, as well as production scale and labor allocation. The scale of operations, measured in acres, accounts for economies of scale, while labor and capital structures are represented by variables such as irrigation use and land ownership status. The number of on-farm workers and the percentage of labor dedicated to crop production further indicate labor intensity in farming operations. Beyond structural characteristics, the dataset incorporates production-specific variables like cattle inventory, which not only affects income diversification but also plays a role in soil health management because their manure can be used as fertilizer, which adds nutrients to the soil.

2.2 Survey of Practices

To complement the KFMA financial records, a comprehensive survey was administered by the KFMA to capture the breadth of soil health and conservation-oriented management practices across participating farms. The survey was designed to assess the presence, the extent, and frequency of adoption of key soil health practices, including no-till farming, reduced or minimum tillage, multi-species and perennial crop rotations, use of both winter and summer cover crops, soil testing, and livestock integration. Designed primarily with yes-or-no questions, the survey facilitated a straightforward assessment of the presence or absence of specific soil health practices (see Appendix Figure A.1). This binary approach enabled a clear analysis of the relationship between soil health strategies and financial performance, ensuring consistency in responses and allowing robust comparisons across different farm operations and regions. The survey responses, collected from farmers across multiple regions, provide critical insights into how soil health practices could contribute to improved farm productivity and long-term profitability.

Beyond capturing discrete practice adoption, the survey also incorporated several qualitative elements to contextualize farmer decision-making. Farmers were asked to characterize their level of conservation adoption relative to peers in their county, identify motivations for cover cropping, and indicate the importance of soil health in economic decision-making using a five-point Likert scale. Questions about workshop participation, testing frequency for both chemical (NPK) and biological soil properties, and implementation of "other conservation practices" not explicitly listed provided additional dimensions of engagement. Importantly, the survey included livestock-related questions, such as whether cover crops or crop residues are grazed, whether rotational grazing is practiced, and whether annual forage crops are planted for grazing, all central components of regenerative systems. This broader framing allows us to analyze soil health as part of a systems-level management strategy, rather than a set of isolated practices, offering a more accurate foundation for evaluating both environmental and financial outcomes.

3.3 Weather

Additionally, we include weather-related variables that are critical for understanding how climate conditions impact farm productivity and financial outcomes. These include Extreme

Degree-Days (EDD), Growing Degree-Days (GDD), and total precipitation. EDD measures the cumulative exposure of crops to extreme heat, specifically the number of degrees by which daily maximum temperatures exceed a certain threshold, capturing the stress that high temperatures can impose on plant growth and yield. GDD, on the other hand, tracks the accumulation of heat units needed for crop development by summing daily average temperatures above a base level throughout the growing season. It serves as an indicator of how conducive the climate is to plant growth over time. Precipitation data accounts for total rainfall during the growing period, which is essential for understanding water availability and its effect on both crop performance and soil management practices. These climate metrics from the PRISM Weather Database are constructed following Sajid et al., (2023) and enable a nuanced assessment of how extreme heat and seasonal temperature variations influence farm financial performance. Together, this comprehensive dataset and survey provide a robust foundation for analyzing the interplay between conservation strategies, environmental conditions, and farm economic performance.

Table 2.1 Descriptive Statistics of the Variables Used Across Different Analyses

	Farms	Mean	Std. Dev.	Min	Max
Net Farm Income Ratio	438	.101	.153	-.524	.611
Return on Assets	438	-.002	.073	-.347	.531
Profit Margin Ratio	438	-.033	.191	-.821	.558
Operating Expense Ratio	438	.779	.15	.27	1.195
Age	438	59.963	13.901	21	94
Size	438	22.306	20.303	.8	225.201
Irrigation	438	.203	.403	0	1
Land Owned	438	.345	.286	0	1

Workers	438	1.536	1.314	.1	10.5
Percentage of Labor to Crop	438	.848	.195	0	1
Cattle Inventory	438	50.345	86.267	0	620
EDD	438	44.314	12.753	12.77	65.395
GDD	438	1674.339	59.594	1393.108	1775.451
Precipitation	438	477.416	69.483	374.29	694.407

Chapter 3 - Methodology

3.1 Quantifying Soil Health Investment

Previous research has measured soil health investment using various qualitative and quantitative methods. Dong and Mitchell (2023) measure sustainable practice adoption using a composite index derived from 73 practices. They apply Principal Component Analysis (PCA) to reduce dimensionality and Data Envelopment Analysis (DEA) to rank farms based on adoption intensity, creating a 0 to 100 scale that quantifies sustainability levels. Soil organic carbon (SOC) serves as a widely used metric for assessing soil health improvements and carbon sequestration potential in regenerative agriculture (Dash et al., 2024). Another critical indicator is soil biological activity and microbial diversity, particularly the presence and diversity of soil microbes such as mycorrhizal fungi, which signal soil health investment (Shah et al., 2024). Remote sensing techniques, such as the Normalized Difference Water Index (NDWI), provide a means of tracking changes in water retention across agricultural landscapes (Tian et al., 2024).

To our knowledge, there are no studies linking either SOC, soil biological activity, or NDWI to farm financial outcomes. To measure soil health investment in a more straightforward yet rigorous manner and easily link it to farm financial performance, this study adopts three different approaches based on the conservation and regenerative practices implemented by KFMA farmers.

3.1.1 Agronomic Scoring

This approach uses agronomic principles (Chang et al., 2022; McDaniel & Middleton, 2024; Pires et al., 2022) to develop a "Soil Health Practices Scorecard". The scorecard was developed in collaboration with soil health researchers from the Kansas State University Regenerative Agriculture team, drawing on expert consultation and regionally validated best practices. This structured scoring system is based on survey responses from farmers across different regions of Kansas and aligns with the Kansas Farm Management Association (KFMA) regional classifications. The scorecard is designed to quantify the degree of soil health practice adoption using a weighted scoring system that accounts for five core principles of regenerative agriculture. Each principle is operationalized into measurable indicators, and farms are assigned scores based on the extent of their implementation.

The scoring system follows a 0–15-point scale, where higher scores correspond to more intensive adoption of soil health practices. No-till practices are evaluated on a 0–3-point scale, reflecting the extent of reduced or continuous no-till implementation. Crop rotation practices are assessed on a 0–4-point scale, with adjustments for regional precipitation patterns, recognizing that higher rainfall regions can support more diverse cropping systems (Di Falco & Chavas, 2008). Grazing practices are scored on a 0–3-point scale, capturing whether rotational grazing and crop residue retention are implemented as part of the system. Cover cropping is rated on a 0–2-point scale, with considerations for regional differences in drought adaptation strategies. Finally, soil testing, a critical component of soil health management, is assigned a 0–3-point scale, based on the frequency and comprehensiveness of soil health assessments. Table 3.1 outlines the score-based classification system and explains the practical meaning behind each category. This scorecard approach not only provides a quantitative measure of soil health investment but also allows for meaningful comparisons across different farming operations and environmental conditions. More details regarding the soil health practice scorecard can be found in Appendix Figure A.2.

Table 3.1 Score and Classification

Score Range	Classification	Interpretation
0 – 6 points	Low	Limited or inconsistent implementation of soil health practices; significant improvement needed.
7 – 10 points	Moderate	Moderate implementation of key soil health practices.
11 – 15 points	High	Strong and consistent commitment to soil health practices.

3.1.2 Cluster-based Classification

While the agronomic scorecard is a parametric, expert-driven classification based on predefined principles of regenerative agriculture, the clustering method offers a non-parametric, emergent classification derived directly from observed adoption patterns. This approach employs unsupervised machine learning, specifically k-means clustering, to categorize farms based on their conservation practices. Cluster analysis is a statistical method that groups data into distinct groups based on specific criteria. The k-means algorithm divides data into k distinct clusters by identifying natural patterns within the dataset (Mucherino et al., 2009). Cluster analysis has been used in previous research to categorize farms practicing conservation agriculture (Ferdinand & Baret, 2024). Ifft and Jodlowski (2024) used CART, a type of cluster analysis, to figure out which conservation practices are most related to crop insurance use. The goal is to create clusters where the farms share similar characteristics while maintaining differences from those in other clusters (Dolnicar & Grün, 2022). This technique minimizes within-group variation while maximizing variation between groups, allowing for a more precise classification of soil health practices categories (Everitt, 2011). In this methodology, farms are assigned binary values (1 for presence, 0 for absence) for each soil health practice. The k-means algorithm then groups farms into three clusters based on their similarities in practice adoption, ensuring that farms within the same cluster exhibit more homogeneity in their management strategies than those in other groups. The k-means algorithm is widely used for clustering and is among the most widely used techniques for exploratory classification and unsupervised learning.(Wu et al., 2008).

3.1.2.1 K-Means Clustering Algorithm

Given a dataset $D = \{pi \mid i = 1, \dots, n\}$, where each pi represents a farm characterized by the adoption of different soil health practices, K-Means clustering groups these farms into k distinct clusters by minimizing intra-cluster variance (Qi et al., 2016).

Algorithm Steps

Initialization: Select k random initial cluster centers $\{m_1, m_2, \dots, m_k\}$

Assignment Step: Assign each farm pi to the cluster with the closest centroid using Euclidean distance.

Update Step: Recalculate each cluster centroid mj using:

$$mj = \frac{\sum pi \in Cjpi}{\mid Cj \mid}$$

where Cj is the set of farms assigned to cluster j, and $|Cj|$ is the number of farms in that cluster.

Convergence: STATA automatically iterates the K-Means process until cluster assignments stabilize, ensuring that the centroids reach a convergence point. For this study, we set $k = 3$ to classify farms into high, medium, and low-adopter groups.

Objective Function for Clustering

K-Means clustering seeks to minimize the sum of squared errors (SSE):

$$SSE = \sum_{j=1}^{k} \sum_{i=1}^{n} \delta_{ij} ||pi - mj||^2$$

where:

k is the number of clusters.

n is the total number of farms.

pi is the soil health profile of farm i.

mj is the centroid of cluster j.

δij is an indicator variable:

- δij = 1 if farm pi belongs to cluster j.
- δij = 0 otherwise.
- $||pi - mj||^2$ is the squared Euclidean distance between a farm and its assigned cluster center.

This function ensures that each farm is assigned to the cluster whose centroid is closest (Qi et al., 2016). This data-driven approach allows for an objective and emergent classification of farms, capturing natural patterns in practice adoption. By leveraging computational techniques, this method reduces potential biases associated with manually assigning thresholds and provides a robust classification system rooted in empirical clustering patterns.

3.1.3 Threshold-Based Classification

In this ad hoc classification system, farms were assigned to different intensity levels based on the number and type of soil health practices they implement. A similar approach was used in Silva et al. (2023) to group farms based on counts and types of conservation methods implemented, showing that practice diversity often supersedes certification labels. Also, Thomas (2024) used a similar comparative framework for evaluating conservation practices based on their potential for carbon sequestration and cost to producers. In our approach, five key conservation practices aligning with the regenerative principles serve as the basis for classification: continuous no-till/reduced tillage, crop rotations, cover cropping, grazing practices, and soil health assessment. Farms that implement all five practices or at least four, including continuous no-till, are categorized as high-intensity operations, reflecting a strong commitment to soil health. Farms that adopt at least three out of the five practices, or those implementing four out of five but using reduced tillage instead of continuous no-till, are classified as medium-intensity. The remaining farms, which do not meet thresholds for high or medium intensity, are classified as low-intensity operations (see Appendix Figure B.3 for more details about this approach). This approach provides a structured yet flexible means of categorizing farms, ensuring that classifications reflect both the diversity and depth of soil health practice adoption (Thomas, 2024).

In summary, this section presents a comprehensive methodological approach to quantify soil health investment. The study employs three distinct classification strategies, score-based, cluster-based, and threshold-based, to evaluate conservation practices across farms.This multi-method approach allows for a broader and more reliable characterization of soil health practice adoption, laying the foundation for the subsequent econometric analysis of financial outcomes. Specifically, the different soil health investment categorizations are incorporated individually as an independent variable in regression analysis to assess whether farms with higher adoption of soil health practices demonstrate improved financial outcomes.

3.2 Assessing Farm Financial Performance

Farm financial performance is often evaluated using a single financial metric, such as total cost, gross income, benefit-cost ratio, gross margin, net farm income ratio, or asset turnover ratio (M. Langemeier, 2016; Sánchez et al., 2022). For instance, Purdy et al. (1997) used the mean return on equity to assess the impact of risk and specialization on financial performance, while Langemeier (2005) employed the economic total expense ratio to evaluate the effects of adopting reduced tillage practices. However, relying on a single financial indicator has been criticized for its limitations in providing a comprehensive assessment. Recent research suggests that using multiple financial metrics provides a more holistic view of farm performance. Wolf and Karszes (2023) argued that a single ratio alone may lack meaning and fail to support effective decision-making when measuring financial risk and resiliency in U.S. dairy farms. Similarly, Hadrich and Olson (2011) examined farm size and performance and found that relying on a single indicator, such as return on assets, does not adequately capture the complexity of farm size and financial performance. They suggest using multiple financial indicators to provide a more holistic evaluation. Yi and Ifft (2019) further emphasize the inconsistencies that arise when assessing financial performance in the dairy industry using only one metric, such as return on equity, asset turnover ratio, or net income.

Few studies have adopted a combined financial metric approach. Wolf et al. (2016) integrated measures of profitability, solvency, and liquidity to assess dairy farm profitability across different herd sizes. Additionally, Jansson and Lagerkvist (2013) developed two key performance indicators, economic sustainability, and loan-to-value ratios, to measure the long-term economic sustainability of agricultural firms. This study follows the methodology of Yi and Ifft (2019), who applied a clustering approach to categorize New York dairy farms based on Net Dairy Income, Return on Equity, and Asset Turnover Ratio. Their study explored the relationship between financial performance and factors such as labor-use efficiency, labor costs, and investment in labor-saving equipment. Similar clustering methods have been used by other researchers. Beranová et al., (2013) utilized agglomerative hierarchical clustering to group farms based on ten financial metrics, identifying the key determinants of agricultural enterprises' financial performance and their impact under various economic conditions.

Following Yi and Ifft (2019) , this study applies K-means clustering as describe previously to categorize farms into three financial performance levels: high, medium, and low. Our goal with K-means clustering is to divide the farms into three groups based on three key financial indicators; Net Farm Income Ratio (NFIR), Return on Assets (ROA), and Profit Margin Ratio (PMR). The financial indicators selected for this study are widely recognized as essential measures of financial performance in farm management. ROA assesses how efficiently farm assets are used to generate net income. It also reflects management effectiveness in capital deployment, as efficiency does not necessarily imply optimal capital positioning. ROA is often considered the most comprehensive measure of farm operating performance (Miller et al., 2001). NFIR represents the proportion of revenue that remains after deducting all expenses, excluding unpaid labor and management. This metric provides insight into farm profitability relative to its revenue base. PMR measures operating profit as a percentage of total revenue. By adding interest back to net farm income, this metric isolates the profitability of agricultural operations from financing considerations, which can vary significantly across farms (Purdy & Langemeier, 1995).

The K-means Clustering Algorithm itself does not automatically rank farms. To establish performance categories, we assess the average NFIR and the average operating expense ratio (OER) for each cluster. NFIR assesses the relationship between profit and gross revenue, revealing the remainder after deducting all expenses, excluding unpaid labor and management, while OER is a key financial efficiency metric that measures the proportion of a farm's gross income spent on operating expenses. Farms with the highest NFIR and lowest OER are classified as high-performing, while those with the lowest NFIR and highest operating expense ratio are deemed low-performing. The remaining farms are categorized as medium-performing.

Finally, two primary outcome variables are used to evaluate the relationship between soil health investment intensity and farm financial performance. The first is the ordinal financial performance rank, derived from cluster analysis based on multiple financial indicators. The second is the Net Farm Income Ratio (NFIR), which captures profitability as a proportion of gross revenue. Together, these outcomes offer both a relative and absolute lens on financial success, forming the basis for the subsequent empirical analysis.

3.3 Regression Analysis

To evaluate the relationship between soil health investment intensity and farm financial performance, this study employs two complementary regression approaches. The first is an ordered logit model, which is appropriate for modeling the ordinal financial performance rank derived from cluster analysis. Second, ordinary least squares (OLS) regression is used to assess relationships involving continuous measures of financial performance or productivity, allowing for a more direct interpretation of how variation in soil health intensity and other farm-level characteristics are associated with financial or efficiency outcomes. By using both modeling strategies, the analysis provides a robust and comprehensive examination of how conservation behavior relates to farm profitability and efficiency

When attempting to forecast ordinal responses, such as our financial rank from the K-means clustering, conventional linear regression models often prove inadequate. These models operate under the assumption that the outcome variable is measured on an interval scale, which does not hold for ordinal outcome variables. Consequently, the fundamental assumptions upon which linear regression hinges are not met, potentially leading to inaccuracies in reflecting the underlying relationships within the dataset (*IBM Documentation*, 2023). In contrast, ordinal regression models, such as the ordinal logit model, are specifically designed to handle ordinal outcomes effectively. (Gnardellis et al., 2023; Jayawardena et al., 2023).

3.3.1 Ordered Logit Regression Analysis

In our framework, we assume that each farm has a continuous measure of financial performance ($Y*$) that is influenced by the intensity of soil health practices and other covariates and that the financial rank from the cluster analysis (Y) is an ordinal categorization of this latent variable. The continuous financial performance is modeled as:

$$Y_i^* = \beta_0 + \beta^\top X_i + \varepsilon_i$$

where:

Y_i^* is the latent financial performance of a farm i

X_i is the vector of independent variables listed in Table 3.1

$\beta^\top$ is the corresponding vector of coefficients

β_0 is the intercept, and

ε_i is an error term assumed to follow a logistic distribution.

The probability of a commercial crop farm being grouped into the low-, middle-, or high-performance category can be defined as:

$$Y_i = j \;\; if \;\; a_{j-1} < Y_i^* \leq a_j, \qquad j = 1, 2, 3$$

With the conventions

$$a_0 = -\infty \;\; and \;\; a_3 = +\infty$$

Hence, Yi = 1 corresponds to low-performing farms, Yi = 2 to medium-performing, and Yi = 3 to high-performing farms.

The cumulative probability that a farm falls in a financial rank at or below category j is given by:

$$P(Y_i \leq j \mid X_i) = F(a_j - \beta_0 - \beta^\top X_i)$$

$F(\cdot)$ is the logistic cumulative distribution function (CDF), defined as:

$$F(z) = \frac{1}{1 + e^{-z}}$$

The probability that the observed financial rank is exactly j is the difference between two consecutive cumulative probabilities:

$$P(Y_i = j \mid X_i) = F(a_j - \beta_0 - \beta^\top X_i) - F(a_{j-1} - \beta_0 \beta^\top X_i)$$

Equivalently, the model can be expressed in terms of the cumulative log odds:

$$\log\left(\frac{P(Y_i \leq j \mid X_i)}{1 - P(Y_i \leq j \mid X_i)}\right) = a_j - \beta_0 - \beta^\top X_i$$

In this representation, a positive $\beta 1$ implies that a higher level in the soil health investment measure shifts the distribution of Y^* to the right, thereby increasing the likelihood of a farm being in a higher financial rank.

3.3.2 Ordinary Least Squares Regression Analysis

To analyze the relationship between soil health investments and key individual farm financial performance metrics, this study employs Ordinary Least Squares (OLS) regression. OLS is a widely used econometric technique for estimating linear relationships between dependent and independent variables (Ayanlowo E. A et al., 2024), making it well-suited for evaluating how soil health practices are related to net farm income ratio, operating expense ratio and crop yield. This method minimizes the sum of squared residuals, ensuring that the estimates are Best Linear Unbiased Estimates (BLUE) under the assumptions of homoscedasticity and no autocorrelation in the error terms.

The general form of the OLS regression model used in this study is:

$$Y_{ic} = \beta_0 + \beta_1 SHI_{ic} + \gamma X_{ic} + \epsilon_{ic}$$

where:

Y_{ic} represents the dependent variable for farm i in county c , which includes farm income ratio, operating expense ratio or crop yield, depending on the specific model.

SHI_{ic} denotes soil health investment, measured using various classification approaches.

Xic is a vector of control variables listed in Table 3.1

β_0 is the intercept, while β_1 captures the relationship between soil health investment and the dependent variable.

γ is the corresponding vector of coefficients for the control variables.

ϵ_{ic} represents the error term, capturing unobserved factors that may influence farm performance.

We also used OLS to evaluate the relationship between individual soil health practices, mainly no-till, reduced tillage, cover crop, and crop rotation with key farm financial and productivity metric. To address potential spatial correlation in the data, standard errors are clustered at the county level. Clustering at this level accounts for within-county correlations in farm outcomes, mitigating the risk of overstating statistical significance due to geographic similarities in soil quality, and market conditions. This adjustment enhances the robustness of the estimated relationships by allowing for arbitrary correlation in error terms within counties.

Following prior literature emphasizing the importance of multi-year averages for farm profitability analysis (Kingwell et al., 2013; Wimalasuriya, 1999; Wolf et al., 2020), we estimate an OLS model using the three-year average net farm income ratio to assess the consistency of financial performance over time. Furthermore, to better understand how soil health investments may be associated with financial performance, we examine potential mechanisms through which these practices could influence farm-level outcomes. Specifically, we focus on two operational indicators: input efficiency, measured by the operating expense ratio (OER), and crop-specific productivity, measured by yields for corn, sorghum, and soybeans. These outcomes represent plausible pathways through which soil health practices such as improved nutrient cycling, water retention, and soil structure could contribute to economic performance. We estimate a series of OLS regression models to assess the relationship between soil health investment levels and each of these operational outcomes. This approach allows us to evaluate whether differences in financial performance may be partly explained by differences in efficiency and crop yields across farms with varying degrees of soil health investment.

3.4 Random Forest

To assess the relative importance of explanatory variables, we employ a random forest model (Breiman, 2001), a non-parametric ensemble learning method well-suited for handling high-dimensional, nonlinear data structures. The random forest analysis was implemented to identify the most influential predictors of soil health investment using a supervised classification approach. Prior to model fitting, the dataset was cleaned by removing observations with missing values and encoding categorical variables such as the soil health classification outcome as numeric factors. Random forests construct an ensemble of decision trees by repeatedly sampling subsets of the data and predictor variables, which helps reduce overfitting and improve generalization. Feature importance, which refers to the process of identifying and ordering the input variables based on their relative importance to the model's predictive performance, was assessed using Gini impurity reduction, a measure of how each variable decreases classification error across the ensemble. This allowed us to rank explanatory variables based on their contribution to predictive accuracy, offering insights into which farm characteristics or practices are most strongly associated with the net farm income ratio.

3.5 Robustness Check

To account for spatial dependence in farm-level data, we apply a spatial HAC estimator as proposed by Conley (1999), which provides consistent standard errors in the presence of both heteroskedasticity and spatial autocorrelation.

Chapter 4 - Results

4.1 Key Insights from the Survey

The survey results provide an overview of soil health investments among KFMA farmers, capturing key trends in conservation practices and management decisions. A total of 438 responses were used in the analysis, based on completeness and successful matching with KFMA financial records. Figure 4.1 illustrates the distribution of farms across different KFMA regions, providing context for regional variations in soil health investments. Of the 438 farms included in our analysis, the distribution varies across Kansas. The Southeast region has the highest number of farms, with 163, followed by North Central region with 130 farms. The South Central and Northeast regions have 59 and 58 farms, respectively. The Southwest region accounts for 21 farms, while the Northwest region has the fewest, with only 7 farms. Additionally, Table 4.1 summarizes key survey responses, illustrating the distribution of soil health investment levels and the prevalence of specific soil health practices.

Figure 4.1 Farms by KFMA Region Distribution

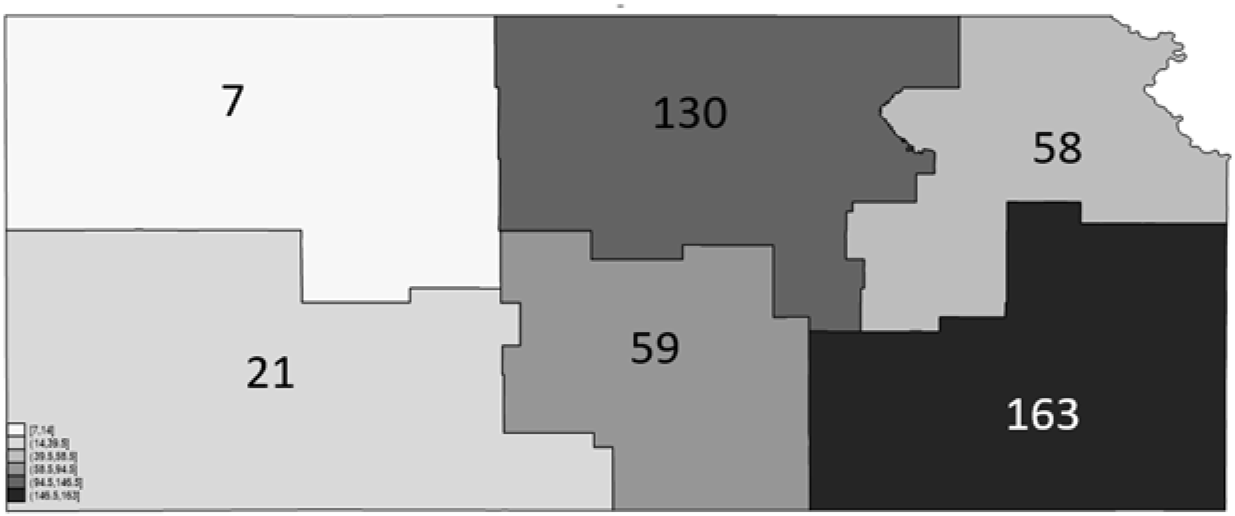


Table 4.1 Soil Health Practice Adoption Among KFMA Members as of 2023

Soil Health Practices	Yes	No
Continuous No-till	256	182
Reduced Tillage	246	192
Cover Crop	199	239
3 or More Crops Rotation	276	162
Graze Cover Crop	114	324
Rotational Grazing	110	328
Workshop on Soil Health	156	282
Soil Test for Biological Matter	134	304
Soil Test for NPK	431	7
Annual Forage Crop	95	343
Grazing Crop Residue	176	262

Total farms: 438

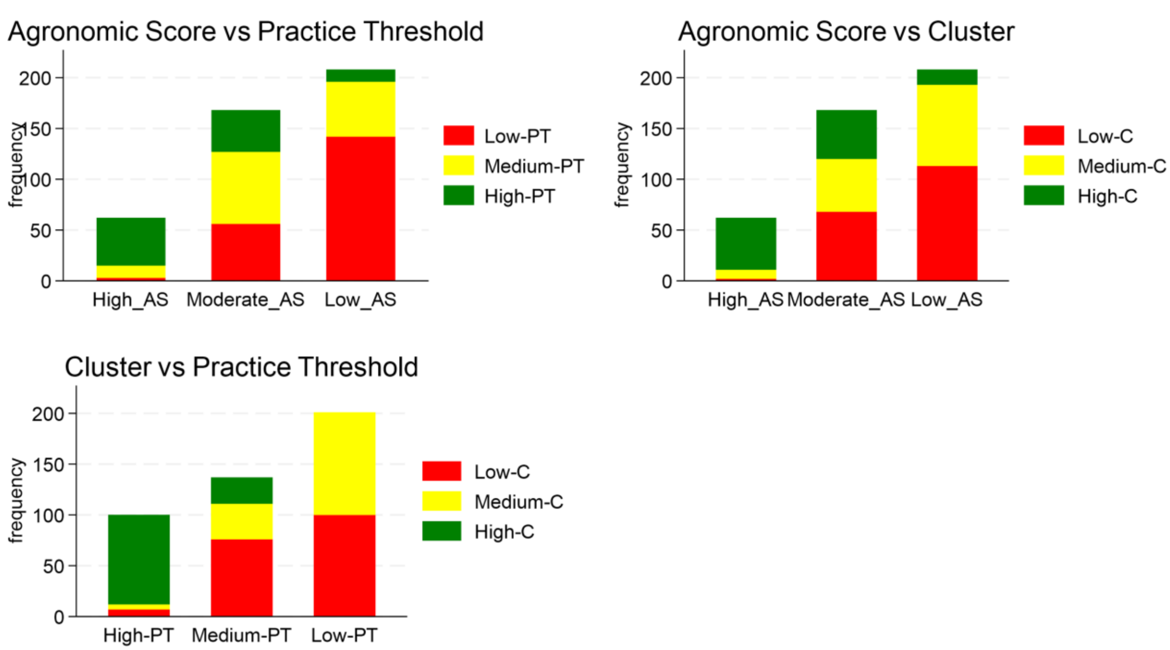
4.2 Soil Health Investment Measures

The classification of soil health investment using the three different approaches yields similar overall distributions but with some notable differences in farm placement across categories. Based on agronomic classification, 47% of farms (208 out of 438) were categorized as low investment, 38% (168 farms) as moderate, and 14% (62 farms) as high. The clustering approach produced a slightly different distribution, with 45% (195 farms) classified as low, 32% (140 farms) as medium, and 24% (103 farms) as high, suggesting that clustering identified a larger share of high-investment farms compared to the agronomic method. Similarly, the threshold-based approach categorized 46% (201 farms) as low, 31% (137 farms) as medium, and

23% (100 farms) as high, aligning closely with clustering in overall distribution. Appendix Table B.1 shows the descriptive statistics of key financial metrics under different approaches to measuring soil health investment.

As shown in Figure 4.2, when cross-tabulating results from different classification methods, discrepancies were most apparent in the medium investment categories. These discrepancies suggest that farmers in these groups exhibit greater variation in their soil health practices, making their classification highly sensitive to the methodology used. Only a small proportion of farms, 10% (42 farms), were consistently classified as high across all three methods, while 4% (17 farms) were consistently placed in the medium category and 17% (76 farms) were consistently classified as low. This variation highlights a key methodological insight: different classification approaches do not always agree, which has implications for how soil health investment is interpreted and linked to financial outcomes.

Figure 4.2 Overlap Between Measures of Soil Health Investment



Note: AS: Agronomic Scoring, C: Cluster, PT: Practice Threshold

Pairwise comparisons reveal somewhat greater consistency between specific methods. For example, between the agronomic score and threshold-based classification, 47 farms (11%) were classified as high in both, 71 (16%) as medium in both, and 142 (32%) as low in both categories. Comparing agronomic score and cluster-based classification, we find 50 farms (11%) classified as high in both, 52 farms (12%) as medium in both, and 114 farms (26%) as low in both. The greatest overlap appears between the threshold and cluster classifications, where 80 farms (18%) were jointly classified as high, 34 (8%) as medium, and 100 (23%) as low.

These patterns reveal that while some farms are consistently classified across methods, particularly those at the extremes of investment (high or low), a substantial share of farms shift categories depending on the classification system used. This inconsistency reinforces the importance of transparency in how soil health investment is measured and cautions against relying on a single classification approach when assessing its relationship to financial or agronomic outcomes. It also underscores the need for further research into more robust or integrative measures of soil health investment that better capture the complexity of farm-level management strategies.

4.3 Relationship Between Financial Ranking, Net Farm Income Ratio, and Soil Health Investment

The ordered logistic regression evaluating the relationship between financial ranking and soil health investment, as shown in Table 4.2, revealed that farms in the high agronomic score category are associated with a 0.675 increase in the log-odds of being in a higher financial rank compared to low agronomic score farms ($p < 0.05$). The positive sign and statistical significance suggest that farms with higher agronomic scores are more likely to fall into better-performing financial categories. This pattern is reinforced in the OLS regression on net farm income ratio, where high agronomic score farms are also associated with a higher average net farm income ratio (NFIR), with a coefficient of 0.056 ($p < 0.05$). This estimate implies that, all else equal, farms in the high agronomic score category tend to report 5.6 percentage points more in net farm income ratio compared to low agronomic score farms. While this analysis does not imply a causal relationship, the positive association is consistent with the hypothesis that farms implementing a greater number of agronomic soil health practices are also performing better financially. In contrast, farms with moderate agronomic scores show no statistically significant difference from the low farms in either model. For the practice threshold and cluster-based classifications, none of the coefficients are statistically significant in either the ordered logit or OLS models. The signs of the coefficients vary, and their magnitudes are smaller compared to those associated with the agronomic score. For example, the NFIR regression shows a small negative coefficient for medium (-0.029) and high (-0.006) farms in the practice threshold, while medium (-0.004) and high (0.014) farms in the cluster-based classifications also exhibit minimal differences from the baseline. These findings indicate that the practice threshold and cluster-based classification methods may be less sensitive to capturing economically meaningful variation in financial outcomes compared to the agronomic score. The R-squared values for the net farm income ratio models are modest but consistent across specifications (ranging from 0.107 to 0.115), suggesting that while soil health investment classifications explain part of the variation in profitability, other farm-level or external factors also play a substantial role.

Table 4.2 Soil Health Investment and 2023 Financial Ranking and Net Farm Income Ratio (NFIR)

	Agronomic Score (AS)		Practice Threshold (PT)		Cluster (C)	
	Financial Rank	NFIR	Financial Rank	NFIR	Financial Rank	NFIR
Moderate_AS	-0.041	0.009				
	(0.207)	(0.016)				
High_AS	0.675**	0.056**				
	(0.326)	(0.026)				
Medium-PT			0.060	-0.029		
			(0.272)	(0.021)		
High-PT			0.037	-0.006		
			(0.240)	(0.018)		
Medium-C					-0.145	-0.004
					(0.258)	(0.021)
High-C					0.085	0.014
					(0.284)	(0.019)
South Central	0.368	0.044**	0.219	0.035	0.252	0.035
	(0.325)	(0.022)	(0.320)	(0.022)	(0.308)	(0.022)
Southwest	0.598	0.024	0.259	-0.003	0.264	0.000
	(0.753)	(0.038)	(0.729)	(0.035)	(0.733)	(0.036)
Northeast	0.728*	0.041	0.518	0.025	0.508	0.024
	(0.406)	(0.025)	(0.395)	(0.024)	(0.396)	(0.025)

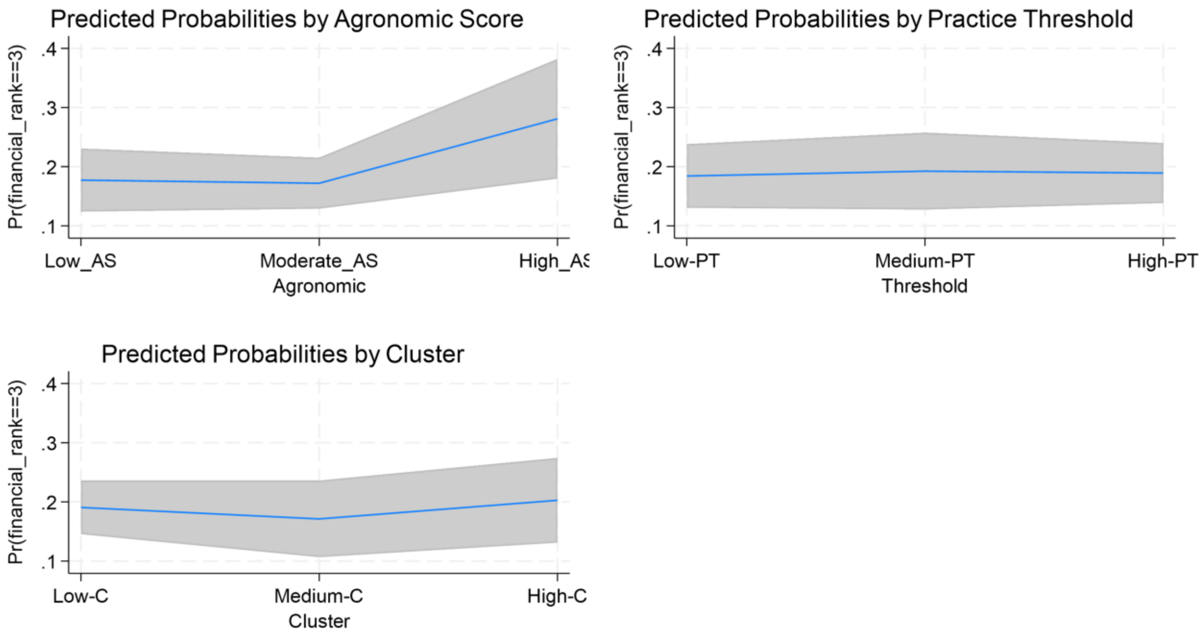
Northeast	0.728*	0.041	0.518	0.025	0.508	0.024
	(0.406)	(0.025)	(0.395)	(0.024)	(0.396)	(0.025)
Northwest	-1.719	-0.081	-2.125*	-0.109	-2.023	-0.108
	(1.349)	(0.084)	(1.290)	(0.078)	(1.283)	(0.080)
Southeast	0.814**	0.058***	0.603**	0.037*	0.597**	0.039**
	(0.322)	(0.020)	(0.302)	(0.019)	(0.303)	(0.019)
Age	-0.042***	-0.002***	-0.042***	-0.002***	-0.042***	-0.002***
	(0.008)	(0.001)	(0.008)	(0.001)	(0.008)	(0.001)
Size	0.016*	0.000	0.015*	0.000	0.016*	0.000
	(0.009)	(0.000)	(0.009)	(0.000)	(0.009)	(0.000)
Irrigation	-0.472*	-0.052**	-0.451*	-0.056**	-0.447*	-0.051**
	(0.258)	(0.021)	(0.264)	(0.022)	(0.258)	(0.021)
Land Owned	1.280***	0.055*	1.192***	0.054	1.204***	0.054*
	(0.418)	(0.031)	(0.423)	(0.033)	(0.425)	(0.032)
Workers	-0.126	-0.014	-0.132	-0.013	-0.148	-0.015
	(0.222)	(0.016)	(0.216)	(0.016)	(0.213)	(0.016)
Workers^2	0.005	0.000	0.006	0.000	0.008	0.000
	(0.022)	(0.002)	(0.021)	(0.002)	(0.021)	(0.002)
Percentage of Labor to Crop	-1.291**	-0.080*	-1.318**	-0.077*	-1.370**	-0.082*
	(0.554)	(0.045)	(0.551)	(0.046)	(0.578)	(0.047)

Cattle Inventory	0.000	0.000	0.001	0.000	0.001	0.000
	(0.001)	(0.000)	(0.001)	(0.000)	(0.001)	(0.000)
EDD	0.003	-0.001	0.002	-0.001	0.002	-0.001
	(0.011)	(0.001)	(0.011)	(0.001)	(0.011)	(0.001)
GDD	-0.002	-0.000	-0.003	-0.000	-0.003	-0.000
	(0.005)	(0.000)	(0.005)	(0.000)	(0.005)	(0.000)
Precipitation	0.005**	0.000	0.005**	0.000	0.005**	0.000
	(0.002)	(0.000)	(0.002)	(0.000)	(0.002)	(0.000)
R-squared		0.115		0.111		0.107
Farms	438	438	438	438	438	438

Note: * p<0.10, ** p<0.05, and *** p<0.01. Models using financial rank as the outcome are estimated with ordered logit; models using net farm income ratio (NFIR) are estimated using Ordinary Least Squares (OLS). Standard errors, shown in parentheses, are clustered at the county level. The low financial rank category, as well as the North Central region, are omitted as the reference group.

To further interpret the ordered logit results, we computed and plotted marginal effects for all three soil health investment measures. For each classification, we estimated the predicted probabilities of a farm falling into low, medium, or high financial performance categories. As shown in Figure 4.3, the clearest trend appears in the agronomic score measure, where the predicted probability of being in the highest financial rank increases substantially from low to high agronomic score, suggesting a strong positive association between agronomic investment and financial performance. In contrast, the practice threshold classification shows no meaningful change in predicted probabilities across investment levels, indicating that this measure does not clearly differentiate financial performance. The clustering-based classification displays a mild U-shaped pattern, with a slight dip at medium and a modest increase at high, but the variation is limited and not statistically distinct. Overall, these findings highlight that while different classification methods of soil health investment provide generally consistent directions of association with financial performance, only the agronomic classification shows a statistically significant relationship, and only at the high investment level.

Figure 4.3 Predicted Probabilities by Different Measures of Soil Health Investment



Note: This graph shows the predicted probabilities of being in a higher financial rank based on the level of investment in soil health.

When considering the 3-year average net farm income ratio as shown in Table 4.3, the relationship with soil health investment shows a consistently positive association, particularly for farms with a high agronomic score. Although this relationship is not statistically significant, the direction and consistency with the main financial rank analysis suggest that farms with higher agronomic scores are associated with better financial performance over time, reinforcing the potential link between sustained soil health investment and improved profitability.

Table 4.3 3-year average NFIR regression results

	Agronomic Score (AS)	Cluster (C)	Practice Threshold (PT)
Moderate_AS	0.006		
	(0.013)		
High_AS	0.036		
	(0.025)		
Medium-C		-0.031*	
		(0.017)	
High-C		-0.004	
		(0.016)	
Medium-PT			-0.018
			(0.018)
High-PT			-0.011
			(0.015)
South Central	0.063**	0.058***	0.055**
	(0.024)	(0.022)	(0.023)
Southwest	0.003	-0.012	-0.015
	(0.046)	(0.045)	(0.047)
Northeast	0.048**	0.036*	0.035*
	(0.020)	(0.018)	(0.018)
Northwest	-0.022	-0.028	-0.040
	(0.075)	(0.070)	(0.072)
Southeast	0.017	0.001	0.002

	(0.021)	(0.017)	(0.018)
Age	-0.002***	-0.002***	-0.002***
	(0.001)	(0.001)	(0.001)
Size	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)
Irrigation	-0.019	-0.017	-0.021
	(0.016)	(0.016)	(0.016)
Land Owned	0.058**	0.056**	0.056**
	(0.028)	(0.026)	(0.028)
Workers	0.002	-0.001	0.003
	(0.011)	(0.011)	(0.010)
Workers^2	-0.001	-0.001	-0.001
	(0.001)	(0.001)	(0.001)
Percentage Labor to Crop	0.053	0.041	0.055*
	(0.033)	(0.033)	(0.032)
Cattle Inventory	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)
EDD	-0.001**	-0.001**	-0.001**
	(0.001)	(0.001)	(0.001)
GDD	-0.000*	-0.000*	-0.000*
	(0.000)	(0.000)	(0.000)
Precipitation	0.000*	0.000**	0.000*
	(0.000)	(0.000)	(0.000)

R-squared	0.107	0.112	0.104
Farms	438	438	438

Note: Standard errors in parentheses. * p<0.10 ** p<0.05 *** p<0.01

4.4 Relationship between Financial Ranking and Individual Soil Health Performance

When analyzing the relationship between individual soil health practices and financial rank, all practices exhibit a positive but non-significant association with higher financial performance as shown in Table 4.4. This suggests that while these conservation practices may contribute to improved farm outcomes, their direct impact on financial standing remains inconclusive within this dataset. The lack of statistical significance indicates that other factors, such as farm management strategies, market conditions, and regional differences, may play a more dominant role in determining financial performance.

Table 4.4 Relationship Between Financial Ranking and Individual Soil Health Practices

	Financial Rank			
Cover Crop	0.182			
	(0.220)			
Crop Rotation		0.061		
		(0.230)		
Continuous No-till			0.157	
			(0.164)	
Reduced Tillage				0.081

				(0.198)	
Grazing Cover Crop					0.165
					(0.294)
South Central	0.231	0.228	0.219	0.198	0.238
	(0.311)	(0.304)	(0.315)	(0.312)	(0.305)
Southwest	0.271	0.266	0.271	0.199	0.300
	(0.733)	(0.734)	(0.723)	(0.710)	(0.730)
Northeast	0.498	0.528	0.516	0.501	0.501
	(0.400)	(0.387)	(0.403)	(0.387)	(0.402)
Northwest	-2.070	-2.093	-2.148	-2.159*	-2.028
	(1.303)	(1.320)	(1.321)	(1.270)	(1.306)
Southeast	0.603**	0.599**	0.634**	0.577*	0.607**
	(0.300)	(0.300)	(0.293)	(0.300)	(0.298)
Age	-0.042***	-0.042***	-0.042***	-0.042***	-0.042***
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
Size	0.016*	0.015*	0.015*	0.015*	0.016*
	(0.009)	(0.008)	(0.008)	(0.008)	(0.009)
Irrigation	-0.447*	-0.460*	-0.451*	-0.470*	-0.443*
	(0.251)	(0.258)	(0.258)	(0.264)	(0.257)
Land Owned	1.232***	1.191***	1.184***	1.187***	1.220***
	(0.425)	(0.425)	(0.424)	(0.427)	(0.428)
Workers	-0.140	-0.136	-0.128	-0.133	-0.142

	(0.216)	(0.213)	(0.214)	(0.218)	(0.218)
Workers^2	0.006	0.006	0.006	0.006	0.007
	(0.021)	(0.021)	(0.021)	(0.022)	(0.022)
Percentage Labor to Crop	-1.318**	-1.317**	-1.342**	-1.312**	-1.283**
	(0.543)	(0.561)	(0.549)	(0.557)	(0.560)
Cattle Inventory	0.001	0.001	0.001	0.001	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
EDD	0.002	0.001	0.003	0.002	0.003
	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)
GDD	-0.003	-0.003	-0.003	-0.003	-0.003
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Precipitation	0.005**	0.005**	0.005**	0.005**	0.005**
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Farms	438	438	438	438	438

Note: Standard errors in parentheses. * $p<0.10$ ** $p<0.05$ *** $p<0.01$

4.5 Individual Financial and Productivity Metrics and Soil Health Investment Measure

To investigate potential mechanisms linking soil health investment to farm performance, the OLS regression results in Table 4.5 reports associations between agronomic score categories and two key operational outcomes: input efficiency, measured by the operating expense ratio (OER), and crop-specific productivity, measured by yields for corn, sorghum, and soybeans. Farms classified as high agronomic score are associated with a 4.7 percentage point lower OER relative to low score farms (p < 0.10). This suggests a potential link between higher soil health investment and improved input efficiency. While not causal, the magnitude of this association is economically meaningful in the context of tight farm margins. For corn yields, high agronomic score farms show an average yield difference of 10.87 bushels per acre above low score farms, though this relationship is not statistically significant. Farms with a moderate score show a smaller, non-significant difference of 1.47 bushels per acre. These positive coefficients suggest that greater soil health investment may be associated with improved corn productivity in some contexts. For soybeans, farms with a moderate score are associated with a 2.89 bushel per acre increase (p < 0.10) compared to low score farms, while high agronomic score farms show a similar, though not statistically significant, positive difference of 2.51 bushels. These yield gains may reflect agronomic improvements such as enhanced soil structure, organic matter, or moisture retention linked with conservation practices. Sorghum on the other hand show no significant association with agronomic score, though the coefficients differ in direction: farms with moderate score are negatively associated with yield (-6.10 bushels), while farms with high score show a positive difference (4.88 bushels), neither of which is statistically significant.

Table 4.5. Agronomic Score (AS) and 2023 Individual Financial and Productivity Metrics

	OER	Corn	Sorghum	Soybeans
Moderate_AS	-0.004	1.473	-6.097	2.886*
	(0.016)	(5.146)	(7.803)	(1.545)
High_AS	-0.047*	10.874	4.875	2.511
	(0.025)	(8.477)	(10.017)	(2.418)
South Central	-0.013	-2.100	-0.578	-9.558**

	(0.024)	(11.308)	(6.145)	(4.509)
Southwest	-0.028	-62.077*	-14.277	-3.933
	(0.043)	(31.121)	(12.133)	(19.931)
Northeast	-0.022	21.128	-18.111	7.077**
	(0.023)	(13.420)	(11.504)	(3.435)
Northwest	0.069	-21.803	-57.403*	
	(0.094)	(49.823)	(31.308)	
Southeast	-0.048**	-12.265	10.256	-4.216*
	(0.020)	(9.251)	(6.560)	(2.415)
Age	0.003***	-0.357*	-0.243	0.016
	(0.001)	(0.178)	(0.195)	(0.061)
Size	-0.000	-0.186	0.357	0.096
	(0.000)	(0.282)	(0.313)	(0.088)
Irrigation	0.033	160.072***	30.144***	42.040***
	(0.023)	(9.256)	(6.817)	(2.971)
Land Owned	-0.092***	-4.103	3.525	0.615
	(0.032)	(8.376)	(12.240)	(2.922)
Workers	0.008	14.799**	2.165	2.594
	(0.018)	(6.673)	(8.614)	(2.112)
Workers^2	0.000	-1.365	-0.395	-0.267
	(0.002)	(0.935)	(0.965)	(0.217)
Percentage Labor to Crop	0.012	27.750	58.358***	1.357
	(0.048)	(23.173)	(17.208)	(5.181)

Cattle Inventory	-0.000	-0.038	-0.008	-0.020*
	(0.000)	(0.034)	(0.044)	(0.010)
EDD	0.000	-1.806***	-1.369***	-0.674***
	(0.001)	(0.464)	(0.268)	(0.124)
GDD	0.000	0.164	0.003	0.063
	(0.000)	(0.179)	(0.076)	(0.052)
Precipitation	-0.000*	0.015	0.047	0.052***
	(0.000)	(0.059)	(0.049)	(0.014)
Constant	0.693	-111.582	48.965	-84.034
	(0.617)	(313.457)	(134.666)	(90.077)
R-squared	0.130	0.743	0.381	0.717
Farms	438	354	128	395

Note: Standard errors in parentheses. * p<0.10 ** p<0.05 *** p<0.01

The cluster-based measure of soil health investment does not show any statistically significant relationship with operating expense ratio, or yields of corn, sorghum, and soybeans (Table 4.6). This suggests that, unlike the agronomic classification, the clustering approach may capture broader patterns in soil health investment that do not strongly correlate with individual financial or productivity metrics.

Table 4.6 Cluster-based Classification and 2023 Individual Financial and Productivity Metrics

	OER	Corn	Sorghum	Soybeans
Medium-C	0.018	-7.698	-6.040	-1.245
	(0.017)	(7.834)	(8.843)	(1.974)

High-C	-0.000	-0.627	6.704	-1.638
	(0.018)	(7.651)	(7.486)	(1.750)
South Central	-0.006	-3.385	-1.109	-9.520**
	(0.023)	(11.240)	(5.988)	(4.377)
Southwest	-0.005	-66.123**	-21.296	-4.299
	(0.041)	(30.332)	(12.794)	(19.994)
Northeast	-0.007	17.594	-24.906**	6.520*
	(0.023)	(13.547)	(11.998)	(3.497)
Northwest	0.091	-26.446	-60.545*	
	(0.088)	(51.098)	(33.546)	
Southeast	-0.031*	-16.560*	7.906	-5.629**
	(0.018)	(9.226)	(6.309)	(2.516)
Age	0.003***	-0.328*	-0.212	0.021
	(0.001)	(0.176)	(0.211)	(0.065)
Size	-0.000	-0.189	0.454	0.101
	(0.000)	(0.281)	(0.311)	(0.089)
Irrigation	0.032	160.303***	30.419***	41.724***
	(0.023)	(9.372)	(6.908)	(2.942)
Land Owned	-0.089***	-4.889	1.645	0.213
	(0.033)	(8.056)	(11.240)	(2.876)
Workers	0.010	13.939**	-2.186	2.554
	(0.017)	(6.525)	(10.726)	(2.199)
Workers^2	-0.000	-1.275	0.162	-0.275

	(0.002)	(0.896)	(1.167)	(0.221)
Percentage Labor to Crop	0.019	24.053	51.058**	0.495
	(0.048)	(24.498)	(19.274)	(5.126)
Cattle Inventory	-0.000	-0.034	-0.024	-0.018*
	(0.000)	(0.034)	(0.040)	(0.010)
EDD	0.000	-1.851***	-1.455***	-0.695***
	(0.001)	(0.469)	(0.260)	(0.122)
GDD	0.000	0.155	-0.016	0.051
	(0.000)	(0.184)	(0.078)	(0.052)
Precipitation	-0.000*	0.012	0.053	0.049***
	(0.000)	(0.058)	(0.051)	(0.014)
R-squared	0.125	0.744	0.385	0.715
Farms	438.000	354.000	128.000	395.000

Note: Standard errors in parentheses. * p<0.10 ** p<0.05 *** p<0.01

Table 4.7 shows the practice threshold-based classification results with a significant positive relationship with the operating expense ratio at the medium level compared to the low level. Sorghum, at the medium level, exhibits a significant positive relationship.

Table 4.7 Practice Threshold and 2023 Individual Financial and Productivity Metrics

	OER	Corn	Sorghum	Soybeans
Medium-PT	0.040**	8.623	12.655*	1.597
	(0.018)	(6.925)	(6.344)	(1.552)
High-PT	0.022	5.588	10.456	0.638

	(0.018)	(7.509)	(10.189)	(1.933)
South Central	-0.004	-5.014	-2.011	-9.619**
	(0.023)	(11.244)	(5.971)	(4.392)
Southwest	-0.001	-65.269**	-22.878*	-3.519
	(0.039)	(30.275)	(12.191)	(19.924)
Northeast	-0.007	18.054	-23.824*	6.499*
	(0.022)	(13.640)	(12.005)	(3.456)
Northwest	0.095	-29.196	-70.335**	
	(0.088)	(48.675)	(28.956)	
Southeast	-0.029*	-15.525*	9.134	-5.473**
	(0.017)	(9.067)	(5.774)	(2.451)
Age	0.003***	-0.323*	-0.306	0.020
	(0.001)	(0.178)	(0.186)	(0.062)
Size	-0.000	-0.207	0.468	0.098
	(0.000)	(0.278)	(0.308)	(0.088)
Irrigation	0.038	161.705***	30.617***	42.007***
	(0.024)	(9.670)	(7.091)	(2.904)
Land Owned	-0.090**	-4.334	2.750	0.537
	(0.034)	(8.379)	(13.013)	(2.793)
Workers	0.007	14.864**	-0.954	2.590
	(0.018)	(6.497)	(9.866)	(2.108)
Workers^2	0.000	-1.401	-0.016	-0.280
	(0.002)	(0.906)	(1.051)	(0.218)

Percentage Labor to Crop	0.006	26.317	54.776***	0.865
	(0.048)	(23.017)	(18.117)	(5.125)
Cattle Inventory	-0.000	-0.041	-0.027	-0.021*
	(0.000)	(0.034)	(0.042)	(0.010)
EDD	0.000	-1.823***	-1.430***	-0.682***
	(0.001)	(0.466)	(0.246)	(0.128)
GDD	0.000	0.156	-0.048	0.058
	(0.000)	(0.179)	(0.074)	(0.054)
Precipitation	-0.000*	0.019	0.071	0.051***
	(0.000)	(0.060)	(0.055)	(0.014)
R-squared	0.134	0.744	0.389	0.715
Farms	438	354	128	395

Note: Standard errors in parentheses. * p<0.10 ** p<0.05 *** p<0.01

4.6 Individual Financial and Productivity Metrics with Individual Soil Health Practices

When analyzing individual soil health practices with individual financial and productivity metrics, none of the financial metrics (NFIR and OER) showed statistically significant relationships with any of the practices (Table 4.8). However, several notable associations emerged with crop yields. No-till showed a significant positive relationship with corn yield, while reduced tillage had a significant negative association with corn yield. In the case of sorghum, only continuous no-till and grazing practices had significant positive relationships with yield. Meanwhile, for soybeans, both cover cropping and no-till were positively associated with yield, whereas crop rotation with three or more crops and reduced tillage showed significant negative relationships with soybean yield. These findings highlight how individual soil health practices can have varying effects across different crops, suggesting that the adoption of specific conservation practices may come with both productivity benefits and trade-offs depending on the cropping system. Regarding cover crop, the relationship might depend on the species used as shown by Hughes and Langemeier (2020).

Table 4.8 Regression Analysis with Individual Metrics

		Coefficient	Std. Err	R-squared	Farms
NFIR	Cover Crop	-0.002	(0.015)	0.105	438
	3 or More Crop Rotations	-0.013	(0.017)	0.106	438
	Continuous No-till	0.009	(0.016)	0.106	438
	Reduced Tillage	-0.005	(0.015)	0.105	438
	Grazing	0.012	(0.018)	0.106	438
OER	Cover Crop	0.008	(0.016)	0.123	438
	3 or More Crop Rotations	0.012	(0.017)	0.123	438
	Continuous No-till	-0.005	(0.014)	0.122	438
	Reduced Tillage	-0.004	(0.014)	0.122	438
	Grazing	0.003	(0.018)	0.122	438
Corn	Cover Crop	-1.392	(6.700)	0.742	354
	3 or More Crop Rotations	-3.396	(7.888)	0.742	354
	Continuous No-till	20.259***	(5.867)	0.753	354
	Reduced Tillage	-10.983**	(4.858)	0.746	354

	Grazing	1.979	(5.719)	0.742	354
Sorghum	Cover Crop	7.233	(7.321)	0.377	128
	3 or More Crop Rotations	9.034	(6.650)	0.378	128
	Continuous No-till	11.536*	(6.194)	0.389	128
	Reduced Tillage	-4.912	(9.133)	0.372	128
	Grazing	7.561*	(4.196)	0.375	128
Soybeans	Cover Crop	2.757*	(1.615)	0.717	395
	3 or More Crop Rotations	-5.587***	(1.341)	0.723	395
	Continuous No-till	2.506*	(1.421)	0.717	395
	Reduced Tillage	-1.937*	(1.027)	0.716	395
	Grazing	2.657	(1.628)	0.716	395

Note: Standard errors in parentheses. * p<0.10 ** p<0.05 *** p<0.01. This table is a summary of multiple regression analysis, looking at a single soil health practice at a time. Control variables include region, other farm characteristics, and weather variables.

Overall, the results of this study provide empirical evidence that soil health investments play an important role in improving farm financial performance. The ordered logistic regression results show that farms with higher agronomic soil health scores are associated with medium or high financial rank compared to those with lower soil health investment. Among the three measurement approaches, agronomic scoring emerges as the most reliable predictor of financial success, while the cluster-based and threshold-based classifications exhibit weaker relationships with financial performance. These findings suggest that a structured agronomic scoring approach provides a more accurate representation of soil health investment and its economic benefits.

The OLS regression for net farm income ratio confirms the positive association between soil health investments and profitability, supporting the results of the ordered logistic regression.

The yield and expense ratio analysis further reinforces these findings, as soil health investments are associated with improved operational efficiency, particularly in soybean production, while also being associated with reducing overall expense ratios. The spatial heteroskedasticity and autocorrelation-consistent (Table 4.9) accounts for geographic clustering effects and confirms that the positive financial relationship of soil health investments remains robust even when controlling spatial dependencies. The relationship between soil health investment and the three-year average net farm income ratio shows a consistently positive association, particularly for farms with high agronomic score. Although this relationship is not statistically significant, the direction and consistency with the main financial rank analysis suggest that farms with higher agronomic scores are associated with better financial performance over time, reinforcing the potential link between sustained soil health investment and improved profitability. To further validate these results, a random forest machine learning model was employed to identify the most influential predictors of farm financial performance. As shown in Figure 4, the random forest feature importance confirms that high agronomic scores are among the important predictors of net farm income ratio, reinforcing the reliability of this measurement approach. Other key factors, including land ownership and farm size, also emerge as significant predictors, while regional effects and the negative relationship with farmer age on financial success remain consistent with previous models.

Table 4.9 Spatial heteroskedasticity and autocorrelation-consistent (HAC) for Standard Error

	Agronomic Score (AS)	Practice Threshold (PT)	Cluster(C)
Moderate_AS	0.013		
	(0.024)		

High_AS	0.062*		
	(0.032)		
Medium-PT		-0.029**	
		(0.013)	
High-PT		-0.006	
		(0.018)	
Medium-C			-0.004
			(0.020)
High-C			0.014
			(0.017)
Age	-0.002***	-0.002***	-0.002***
	(0.001)	(0.001)	(0.001)
Size	0.000	0.000	0.000
	(0.001)	(0.000)	(0.000)
Irrigation	-0.042	-0.056***	-0.051***
	(0.031)	(0.020)	(0.019)
Land Owned)	0.058**	0.054**	0.054**
	(0.023)	(0.024)	(0.025)
Workers	-0.013	-0.013	-0.015
	(0.019)	(0.015)	(0.013)
Workers^2	-0.000	0.000	0.000
	(0.002)	(0.002)	(0.002)
Percentage Labor to Crop	-0.077***	-0.077***	-0.082***

	(0.017)	(0.026)	(0.022)
Cattle Inventory	0.000	0.000***	0.000**
	(0.000)	(0.000)	(0.000)
		(0.018)	
EDD		-0.001	-0.001
		(0.001)	(0.001)
GDD		-0.000	-0.000
		(0.000)	(0.000)
Precipitation		0.000	0.000
		(0.000)	(0.000)
			(0.017)
R-squared	0.087	0.097	0.092
Farms	430	438	438

Note: Standard errors in parentheses. * p<0.10 ** p<0.05 *** p<0.01
County FE: YES | Year FE: YES | Conley SE: YES | Spatial Cutoff: 110 KM

Chapter 5 - Conclusion and Discussion

5.1 Conclusion

The findings of this study reveal several critical considerations for interpreting the relationship between soil health investments and farm financial performance. First, there is notable inconsistency across different classification approaches used to define and measure soil health practices, highlighting how methodological choices can significantly shape outcomes and interpretations. This inconsistency also reflects broader challenges in the aggregation of soil health indicators, which remains a subjective and often inconsistent process. Farms that adopt soil health practices, particularly those measured through agronomic scores, show an association with higher profitability, demonstrating that soil health investments can not only be beneficial for environmental sustainability, as some farmers believe, but also contribute to improved financial performance in agriculture. While soil health investments may have the potential to enhance farm profitability, this relationship is contingent upon precise and context-specific measurement, underscoring the need for further large-scale, rigorous research. Evidence from this analysis suggests that soil health practices may lead to operational efficiency gains, although the mechanisms appear relatively weak and indirect. Compared to other farm-level variables such as farm size, structural characteristics, operator demographics, and weather conditions, soil health investments demonstrate a weaker predictive power for financial outcomes. However, unlike these relatively fixed or external factors, soil health practices represent management decisions that are more readily influenced by farmers themselves. This positions them as a potentially strategic lever for improving efficiency and resilience, even if their direct financial returns are more limited or variable.

5.2 Contribution

This study makes important contributions to the growing body of research on soil health practices and financial performance. A major strength of this study is its combination of detailed farm financial records with direct farm survey responses. This integration helps to validate whether self-reported conservation practices align with actual financial outcomes and provide more granular insights into the economic trade-offs and benefits of soil health practices. Additionally, bridge the gap between agronomic assessments and financial performance metrics, offering a holistic view of regenerative agriculture’s impact.

Another key contribution is our systematic comparison of different classification methods for measuring soil health investments. Rather than relying on a single approach, we evaluate expert-based agronomic scoring, clustering techniques, and threshold-based classifications that segment farms based on different levels of soil health investment. By comparing these methods, our study provides new insights into the most effective ways to categorize soil health investments, enhancing future research and policy applications.

Furthermore, this study reveals that different methods of aggregating soil health practices produce inconsistent farm classifications. These discrepancies highlight a key methodological challenge in soil health research: the way soil health investment is measured can meaningfully alter which farms are considered "high" or "low" adopters. By comparing and documenting this instability, we contribute to a more critical understanding of measurement sensitivity in classifying conservation practices and their relationship to financial performance.

5.3 Shortcomings and Limitations

One of the key limitations of this study is the time frame over which financial performance is assessed. While financial metrics such as net farm income, return on assets, and operating profit margins provide valuable insights, they capture performance over a limited period. However, the benefits of regenerative agricultural practices, particularly improvements in soil health, often take several years to materialize (Yu et al., 2024). This discrepancy may result in an underestimation of the long-term financial gains associated with conservation agriculture.

While the KFMA dataset reflects a non-random sample of relatively well-managed farms that voluntarily participate in a financial advisory program, it provides a rare and rigorous basis for linking farm financial records to soil health practices. Although findings may have limited external validity due to the dataset's regional scope, Kansas itself is agriculturally diverse with regions sharing soil quality and cropping systems typical of Corn Belt farms, and others more reliant on irrigation and dryland systems, resembling production environments across the Plains. In this context, the KFMA sample captures a broad range of farm structures and management strategies within one of the most productive agricultural belts in the U.S. Moreover, previous work shows that financial patterns observed in KFMA data are consistent with those from nationally representative samples, such as ARMS (H. Kuethe et al., 2014; Katchova, 2005). Importantly, few datasets offer the depth and quality of financial detail required to study the relationship between soil health practice adoption and economic outcomes. As such, the KFMA dataset enables an analytical rigor that would be nearly impossible to achieve through survey-only approaches, offering valuable insight into the potential financial returns to soil health investments under relatively favorable management conditions.

A further challenge is causality, while the study identifies significant associations between soil health practices and financial performance, establishing a direct causal relationship remains difficult. External factors such as weather variability (Sajid et al., 2024), market conditions, and government subsidies can significantly influence farm profitability. Additionally, farm management decisions are often influenced by multiple interrelated factors, making it challenging to isolate the specific financial impact of regenerative practices.

5.4 Future Research Directions

One of the most critical areas for future research is the long-term financial effects of regenerative agriculture. While this study evaluates financial performance over a limited timeframe, many soil health benefits take years to fully materialize. Future studies should leverage longitudinal datasets to track farm profitability over extended periods, capturing both short-term costs and delayed economic benefits.

The methods for measuring soil health investments in this study primarily rely on survey-based indicators, such as self-reported adoption of cover crops, crop rotations, and reduced tillage. While these metrics provide useful insights, they lack quantitative precision. Future research should integrate biophysical indicators such as Soil organic carbon (SOC), Microbial activity assessments or Remote sensing data to see their relationship with farm profitability.

Furthermore, by combining field-level measurements with survey data, researchers can assess whether self-reported conservation practices accurately reflect actual soil health improvements. This will enhance the reliability of survey instruments and improve the accuracy of financial models linking soil health investments to farm profitability.

5.5 Policy and Management Implications

This study offers various targeted insights for policy and agricultural extension efforts. First, while the relationship between soil health investment and financial performance is not uniformly strong across all measures, we find a positive association when multiple soil health practices are adopted together. This suggests that bundling practices rather than focusing on single interventions may align more closely with profitable farm management. Although our random forest analysis indicates that structural factors like farm size and operator age are stronger predictors of financial outcomes, soil health investments are within the producer’s control, unlike many structural characteristics. This may help explain why younger producers, who are more flexible in their management decisions, appear more willing to adopt soil-building practices.

Second, our results point to the need for more robust, data-driven validation of soil health investment scores. Current practice-based scoring systems rely heavily on self-reported management data. To improve their credibility and usefulness for both researchers and policymakers, these scores should be validated with physical measurements such as soil organic carbon, microbial activity, or other biological indicators. Furthermore, establishing a more definitive relationship between soil health investment and profitability will likely require multi-year, field-level data from precision agriculture systems, which can account for variability across time, weather, and management intensity. Without such data, policy efforts aimed at linking conservation incentives to profitability may remain speculative or uneven in impact.

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Appendix A - Survey Design and Soil Health Investment Scorecard

Appendix Figure A.1 Farmer Survey on Soil Health Practices

Farm Number: KFMA Conservation and Production Practices Survey

* Denotes a definition on the back of survey

Practice	Yes-Y No-N	First year of use	% acres on average
Do you have fields that are typically continuous no-till*?			
Do you have fields where you typically practice no-till on about half* of your rotations?			
Do you have fields where you typically practice reduced or minimum* tillage?			
Do you have fields where you rotate 2 crops?			
Do you have fields where you rotate 3 crops?			
Do you have fields where you rotate 4 or more crops?			
Do you include perennials in your typical crop rotations?			
Do you use winter cover crops? Circle the most typical species: (a) grass/cereal crops (b) legumes (c) mix			
Do you use summer cover crops? Circle the most typical species: (a) grass/cereal crops (b) legumes (c) mix			
If you have cover crops, do you typically graze them?			
Do you use rotational grazing* practices (on any field/land)?			
Do you typically graze crop residue?			
Do you ever plant annual forage crops* for grazing livestock? Circle the most common type (a) single species (b) mix			
Do you regularly test* your soil for NPK and organic matter? How often? (a) Every year (b) every 2 years (c) less than every 2 years			
Do you regularly test* your soil for biological matter, micronutrients, or other soil health factors or indicators*? (for example, Haney test, tests for infiltration, aggregate stability) If yes, how often? (a) Annually (b) every 2 years (c) less than every 2 years			

What are the crops that are planted in sequence in your most common rotation*?

How would you characterize your use of 'conservation practices' relative to producers in your county and surrounding counties? 1. More than average 2. Average 3. Less than average.

If you use cover crops, why? (Select more than 1 if relevant)
1. Forage/grazing 2. Weed control 3. Organic Matter. 4. Herbicide reduction 5. Erosion 6. Soil health 7. Other ____________

In the past two years, have you been to a meeting or workshop on soil health? YES NO

How important is soil health to your economic decision making on a scale of 1 to 5? (1=very little, 5=very important) 1 2 3 4 5 (circle one)

Do you implement any other conservation practices that are not included in this table?

Appendix A.2 Soil Health Practices Scorecard

Kansas Regenerative Agriculture Farming Practices Scorecard

Created by: Cesar Guareschi

Review: Charles Rice, Jennifer Ifft, and Delide Joseph

1. **Motivation**

This scorecard uses descriptive categories to evaluate Kansas farmers' adoption of regenerative agriculture practices. The main input is 605 responses to a survey answered by farmers in the northeast (NE), southeast (SE), north-central (NC), south-central (SC), northwest (NW), and southwest (SW) portions of the state of Kansas, according to the KFMA division. The survey can be found at the end of this document.

2. **Methodology**

We defined major practices aligned with the five principles of regenerative agriculture, which are:
- Minimize soil disturbance: reduced or continuous no-tillage
- Keep the soil covered: crop residue, cover crops, mulching
- Maintain living roots in the soil: year-round plant cover, more crops in the rotation
- Maximize plant diversity: more crops in the rotation
- Integrate livestock into the system: rotational grazing preferred
- Consider the context: know your capabilities and limitations

Based on these principles, the scorecard was generated, taking into consideration the answers to these five major principles of conservation farming practices.

3. **The Scorecard**

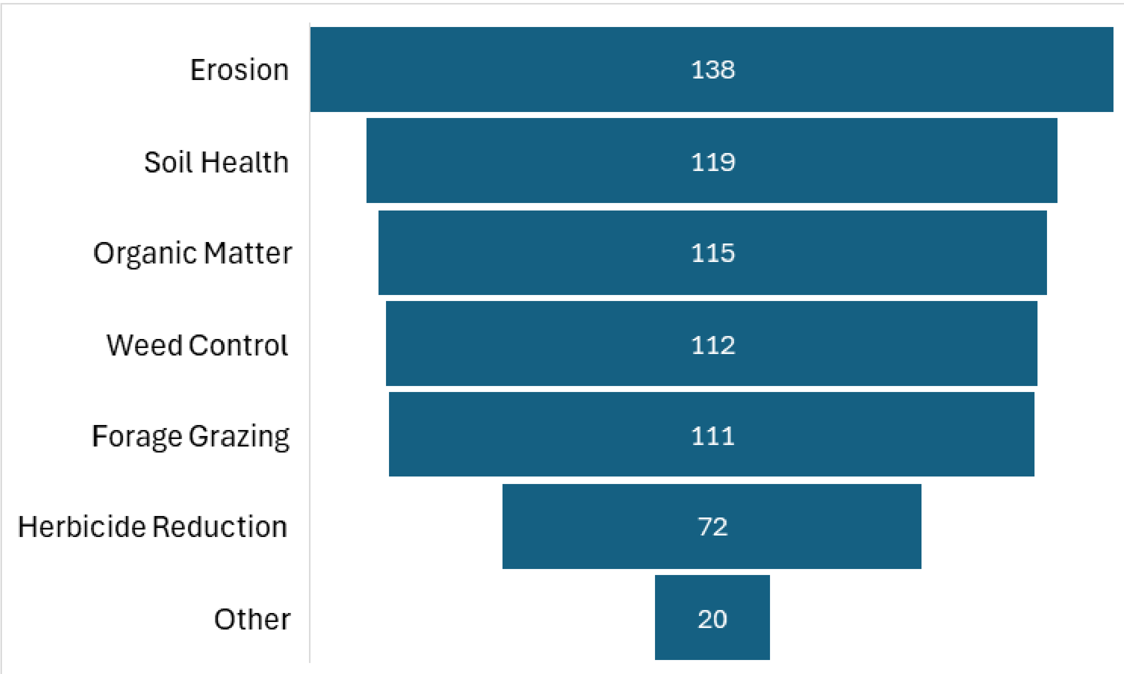
This scorecard will use a 0-15 scoring scale to quantify conservation practices, with further qualitative interpretations for each scoring range.

a. **No-tillage practices (ranging from 0 to 3 points)**
   - **3 points:** Farmer has continuous no-till across all fields, or a significant percentage (>80 %) of reduced/minimum tillage used consistently.
   - **2 points:** Farmer has no-till employed on a significant part of the field (50 – 79%), or a significant percentage of reduced/minimum tillage used consistently.
   - **1 point:** Farmer has only reduced/minimal, and it is only used in some fields, but not consistently or extensively.
   - **0 points:** Farmer does not use no-tillage or reduced/minimum tillage practices.

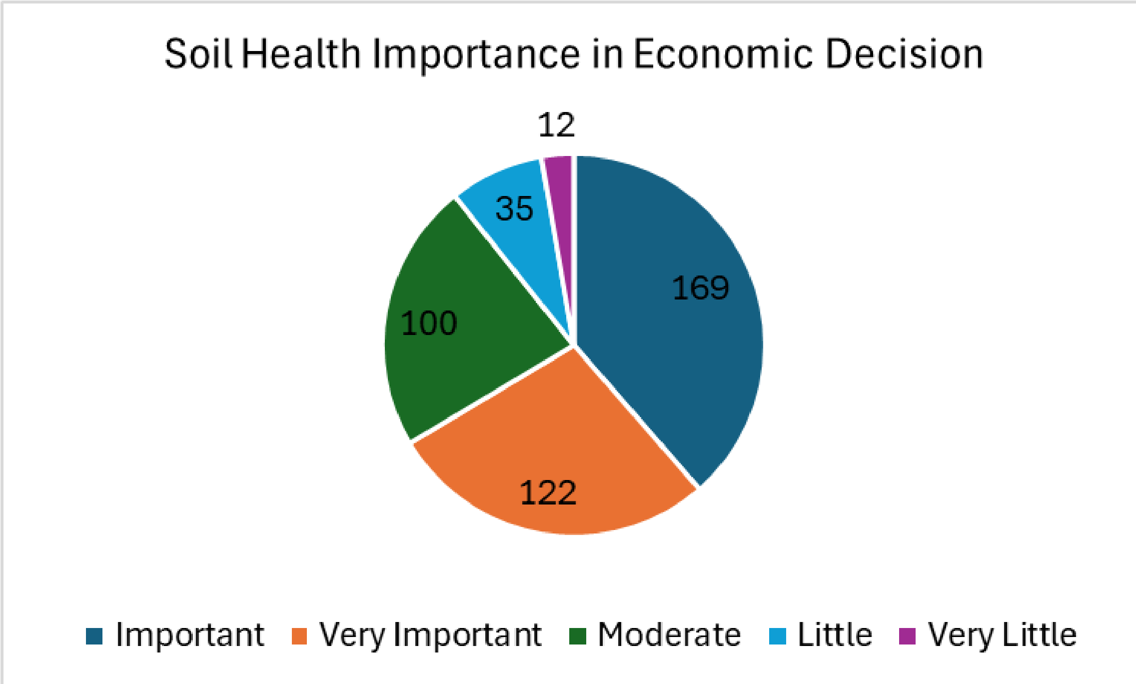
b. **Crop rotations (ranging from 0 to 4 points)**
   In this section, three scorings were created, taking into consideration the precipitation patterns affecting the Kansas regions from east to west. The three sub-categories were divided into: Higher precipitation regions (NE and SE), Moderate precipitation regions (NC and SC), and Lower precipitation regions (NW and SW). The reason for this subdivision is given by the fact that the amount of precipitation received across the different regions may dictate how intensive (number of crops in the rotations) the production systems are.
   - **Higher precipitation regions (NE and SE)**
     - **4 points:** Rotation with 4 or more crops, including perennials
     - **3 points:** Rotation with 3 crops
     - **2 points:** Rotation with 2 crops
     - **1 point:** Less than 2 crops or no crop rotation
   - **Moderate precipitation regions (NC and SC)**
     - **4 points:** Rotation with 3 or more crops
     - **3 points:** Rotation with 2 crops with supplemental irrigation and/or the use of low water-demanding crops

Appendix B - Insights from Survey and Descriptive Statistics under Different Soil Health Classification

Appendix Figure B.1 Cover Crop Adoption: Farmer Counts and Motivations



Appendix Figure B.2 Soil Health Importance in Economic Decision Making



Appendix Figure B.3 Threshold-Based Categorization: Practice and Criteria

Practice	Criteria
Tillage	Continuous no-till
	Reduced Tillage
Crop Rotations	2 or 3; 2 or 3 or 4; 3; 3 or 4; 4
Cover Crops	Winter or summer or both
Grazing	Graze cover crops or residue or annual forage crop or rotational grazing
Management	Test for biological matter or attend soil health workshop or soil health important 4 or 5

Soil health investment levels are based on how many criteria a farm meets:

- **High**: Meets 5 criteria, or 4 including **continuous no-till**
- **Medium**: Meets 3 criteria, or 4 including **reduced tillage**
- **Low**: All other cases

Appendix Table B.1 Summary Statistics Under Different Approaches to Measuring Soil Health.

Rank	Variable	Obs.	Mean	Std. dev.	Min	Max
	Agronomic Scoring					
Low	Net Farm Income Ratio	208	0.102	0.153	-0.397	0.611
	Operating Expense Ratio	208	0.775	0.158	0.342	1.195
Medium	Net Farm Income Ratio	168	0.091	0.158	-0.524	0.552
	Operating Expense Ratio	168	0.792	0.142	0.270	1.175
High	Net Farm Income Ratio	62	0.124	0.141	-0.286	0.412
	Operating Expense Ratio	62	0.760	0.143	0.467	1.189
	Threshold-Based Categorization					
Low	Net Farm Income Ratio	201	0.109	0.158	-0.397	0.611
	Operating Expense Ratio	201	0.765	0.155	0.342	1.144
Medium	Net Farm Income Ratio	137	0.087	0.158	-0.524	0.489
	Operating Expense Ratio	137	0.796	0.150	0.270	1.195
High	Net Farm Income Ratio	100	0.104	0.138	-0.286	0.552
	Operating Expense Ratio	100	0.785	0.138	0.467	1.071
	Cluster-Based Classification					
Low	Net Farm Income Ratio	195	0.096	0.160	-0.346	0.611
	Operating Expense Ratio	195	0.788	0.159	0.342	1.189
Medium	Net Farm Income Ratio	140	0.099	0.158	-0.524	0.552
	Operating Expense Ratio	140	0.773	0.151	0.270	1.195
High	Net Farm Income Ratio	103	0.112	0.137	-0.297	0.448

Operating Expense Ratio	103	0.777	0.135	0.467	1.071