

ESSAYS ON AGRICULTURAL LAND USE: TRADEOFFS, INFORMATION, AND
INCENTIVES IN PRECISION AGRICULTURE AND WIND ENERGY

By

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ABSTRACT

Agricultural land plays a critical role not only in food production, but also in advancing environmental sustainability and renewable energy goals. Given these diverse functions, landowners face complex decisions that require balancing agricultural productivity with environmental objectives. Their decisions can be shaped by the quality of information guiding expected returns and varying policy and market incentives. This dissertation investigates how agricultural landowners make land use and management decisions when faced with tradeoffs, imperfect information, and differing incentives.

The first chapter examines the tradeoff that landowners' face between farming and conservation. It focuses on estimating the opportunity cost of precision conservation, a practice that converts low-yielding areas into conservation area while minimizing foregone revenue. Using fine-scale yield maps from Michigan corn and soybean fields from 2020 to 2024, we calculate the opportunity costs of foregone yields, yield effects on adjacent cropland, and input cost savings. Assuming a 10-year conservation period under a corn-soybean rotation, results show that precision conservation improves profitability in 19 of 29 fields, with an average annualized profit increase of \$74/ac. Compared to whole-field conservation, precision conservation substantially reduces costs of conservation. On average, the opportunity costs of whole-field conservation is \$235/ac higher than that of precision conservation, with differences ranging from \$135/acre lower to \$349/acre higher.

The second chapter evaluates how different sources of information affect the profitability of variable rate nitrogen (VRN) application. Utilizing 17 field-years data from 13 Midwest fields during 2021-2023, it compares VRN prescriptions based on remotely-sensed early-season

vegetative vigor (NDVI) and historical yield maps. Applying linear regression and spatial discontinuity analysis, the study finds a heterogeneous treatment effect, with profitability gains from NDVI compared to yield history prescriptions ranging from $-\$410 \text{ ha}^{-1}$ to $\$350 \text{ ha}^{-1}$. NDVI-based prescriptions were more profitable when weather conditions diverged from historical trends and remained stable throughout the season (e.g., 2021), while yield history outperformed when early-season signals failed to persist and conditions ultimately reverted to historical norms (e.g., 2023). These results highlight the value of adapting nitrogen management to seasonal weather conditions by combining long-term yield patterns with real-time crop vigor signals.

The third chapter examines the effects of two overlapping policy interventions on wind energy development in Michigan: the revision of Public Act 116, which eased land-use restrictions on preserved farmland, and the Wind Energy Resource Zone designation under Public Act 295, which supported infrastructure development in areas with high wind potential. Employing a difference-in-differences framework, the analysis spans townships and cities in Michigan, Minnesota, and Wisconsin from 2000 to 2023. The findings indicate that the PA116 revision had no statistically significant effect, whereas the Wind Zone designation led to an additional 90 megawatts (MW) of installed electrical generation capacity. These results underscore the varying effectiveness of land-use policies. Because the farmland preservation program offered limited economic incentives to begin with, loosening its restrictions had minimal impact. In contrast, the proactive designation of Wind Zones with clear development signals and coordinated infrastructure planning significantly accelerated wind turbine deployment in Michigan.

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CHAPTER 1. OPPORTUNITY COST OF PRECISION CONSERVATION ¹

Abstract: Conservation practices provide public benefits such as improved water quality and biodiversity, but the associated private costs are often borne by farmers. Typically, the largest of these is the opportunity cost of potential revenue lost due to taking land out of production. Precision agriculture technologies can help reduce these costs by identifying low-yielding areas, thereby minimizing foregone revenue. This study estimates the opportunity cost of such precision conservation on 29 commercial corn and soybean fields in Michigan, USA, using fine-scale yield maps collected between 2020 and 2024. Opportunity costs are calculated by assessing foregone yields and input cost savings within conservation areas plus any crop yield changes on nearby cropland. Results show that on average precision conservation enhances profitability for corn fields but not for soybeans. Under a corn-soybean crop rotation, precision conservation improves profitability in 19 of 29 fields, as opportunity costs in most cases turned out to be negative. The annualized opportunity cost is -\$74/ac on average, ranging from -\$424/acre to \$233/acre. By contrast, whole-field conservation on the same fields would lead to far higher foregone yields, resulting in the differences in opportunity cost that average \$235/acre, with a range from -\$135/acre to \$349/acre. Precision conservation that targets low-yielding field areas can be profitable in many instances without subsidy, although subsidies may help attract early adopters.

¹ This chapter is based on work intended for publication in collaboration with Scott M. Swinton and Bruno Basso

1.1 Introduction

Crop production and biodiversity conservation vie for limited land. Homogenous and simplified agricultural fields produce high yields, but they aggravate biodiversity losses, which can lead to reductions in ecosystem services (Landis, 2017). Conservation areas within agricultural fields can deliver environmental benefits including reduced nutrient and sediment export (Schulte et al., 2017; Zhou et al., 2014; Helmers et al., 2012), wildlife habitat (King and Savidge, 1995; Lane et al., 2020), and enhanced soil productivity (De et al., 2020; Li et al., 2018). Balancing land use between crop production and conservation becomes important amid rising food demand and heightened environmental concerns.

Shifting land from crop production to conservation imposes opportunity costs on farmers, who forgo potential crop yields. Research has shown that opportunity costs increase when conservation is implemented on higher-yielding land, as the foregone yields are greater (Tyndall et al., 2013; McConnell and Burger, 2011). Arbuckle Jr. and Rosesch-McNally (2015) highlights that these costs are a significant concern for farmers considering prairie strips, which cut across crop fields. Compensating farmers for these opportunity costs often requires substantial subsidies, creating financial burdens on government programs. Given these challenges, more cost-effective conservation strategies are needed.

Precision conservation targets low yielding zones of a crop field. It offers a potential solution for achieving a harmonious balance between environmental conservation and agricultural productivity. Leveraging spatial technologies such as global positioning systems (GPS), remote sensing, and geographic information systems (GIS), precision conservation allows for targeting specific areas that either minimize producers' costs or address significant environmental impacts, such as soil erosion or water quality improvement. This targeted approach allows farmers to

simultaneously engage in both farming and conservation. This conservation strategy diverges from conventional conservation policy, which focuses on conserving entire fields (Swinton, 2022) or else on prairie strips that have similar consequences for foregone yield.

Agronomic research has demonstrated significant yield variability within fields and has shown that low-yielding areas can be reliably identified for targeted conservation (Brandes et al., 2016; McConnell and Burger Jr., 2017; Basso, 2021). While these findings support the potential of precision conservation, its costs under farmer management remain underexplored. Existing studies on conservation costs typically rely on accounting approaches using average land rent values (Tyndall et al., 2013; Meng et al., 2022), pre-conservation yield data (McConnell and Burger, 2011; Jeffrey et al., 2014; Capmourteres et al., 2018), or randomized experiments (Pywell, et al., 2015). However, these methods fail to account for the strategic placement of conservation areas on low-yielding land and the potential yield changes in adjacent cropland after conservation implementation. To date, no research has estimated the opportunity cost of precision conservation areas using statistical methods to predict foregone yield and the associated changes in net revenue.

This study aims to fill that gap by estimating the opportunity costs of converting low-yielding areas into conservation areas on 29 commercial corn and soybean fields in Michigan, USA. We consider three main components of opportunity cost. The first is the foregone profit within the conservation area due to the absence of crop cultivation. By modeling yield as a function of distance from the conservation area, we capture the inherent characteristics of low-yielding areas, where yield tends to be lower closer to these areas and gradually increases with distance from the low-yielding zone.

The second component is the potential impact of conservation areas on crop yields on adjacent cropland. Conservation areas may increase nearby crop yields by providing habitat for

beneficial insects (Pywell et al., 2015; Kordbachch et al., 2020; Kemmerling et al., 2022) or by enhancing soil health (Dutter et al., 2023; Senaviratne et al., 2012). Alternatively, they may reduce yields by harboring pests (Fiedler and Landis, 2007), fostering weeds (Hirsh et al., 2013), or competing for water and nutrients with crops (Anderson et al., 2009). As the literature offers no consensus on the net impact of conservation areas, our study provides an important assessment of these dynamics on farm fields. We examine how the impact of conservation areas evolves as the ecosystems within them mature, and we estimate the resulting yield changes in the surrounding cropland.

In addition to the ecological impact generated within conservation areas, crop yields near conservation areas may be affected by increased wildlife attracted to these areas. Wildlife related crop damage can pose significant concern for farmers (McGowan et al., 2006; McKee et al., 2020), with deer being the most commonly reported source of damage in field crops (U. S. Department of Agriculture [USDA], 2002; Wywialowski, 1994). Deer typically graze along wooded field edges (McGowan et al., 2006), where yields are often lower than the field average (Robinson, et al., 2022; Fincham et al., 2023). When conservation areas are placed along field edges, deer may shift their foraging deeper into the field, where yields are higher, potentially increasing overall crop losses. To assess this impact, we use the distance to the nearest wooded edge as a proxy for deer abundance and examine whether crop yields decline following the establishment of conservation areas.

The third component of opportunity cost includes input cost savings and implementation costs. Input cost savings reduce opportunity costs, as conservation areas are no longer cultivated and inputs such as seeds and fertilizers are no longer applied. On the other hand, the cost of implementing conservation areas increases opportunity costs. Implementation costs include technical expenses for precision conservation such as identifying ideal conservation areas or using

GPS devices, as well as costs associated with purchasing seed mixes, planting, and maintaining the conservation areas.

To account for price fluctuations and market risks, we use Monte Carlo simulations to generate hypothetical price trajectories over a 10-year period. These simulations, based on a Geometric Brownian Motion (GBM) model, reflect the random nature of price movements and capture correlations among grain prices and input costs for corn and soybeans. By integrating these simulated prices with yield response distributions, we simulate ten-year conservation opportunity costs for precision conservation under a corn-soybean rotation. The costs are aggregated and annualized to evaluate the financial variability and risks of precision conservation. We compare these annualized costs to the opportunity costs of whole-field conservation and the payments provided by government conservation programs.

1.2 Conceptual Model

In this section, we develop a conceptual model to capture various factors that affect a farmer's decision to implement conservation area. We model effects of conservation areas on crop productivity and construct the opportunity cost of conservation by comparing the gross margins with and without conservation areas. We assume that the conservation area does not influence the farmer's other practices or underlying field site characteristics.

Assume there are two types of land within a field: area I , which is relatively high-yielding crop land, and area J , a low-yielding area identified as potential conservation area. Assume further that the field is divided into a grid, with individual grid cells within area I labeled as i and those within area J labeled as j (Figure 1.1).

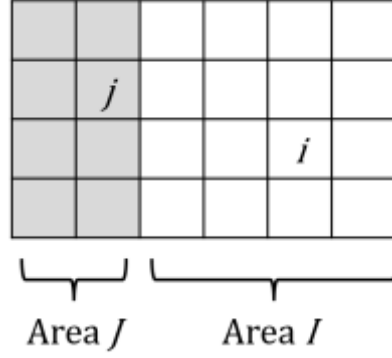


Figure 1.1: Representation of a field divided into crop area and conservation area

A potential conservation area, cell j , correlates to crop yield in cell i through two pathways. Since conservation areas are strategically placed in low yielding zones, yield increases with the distance from conservation cell j to crop area cell i (D_{ij}). D_{ij} represents a proxy for an unobserved and time-invariant spatial gradient of land quality between conservation area and crop area, which remains constant regardless of whether the area j is used for conservation or crop production.

When a farmer converts part of a field into a conservation area, the crop yield outside the conservation area may be influenced by ecosystem services or disservices from the conservation area j . These effects can include positive ecosystem services, such as pollinator habitat or active carbon, as well as negative impacts such as increased weed or pest pressure (Zhang et al 2007). Although we cannot directly measure each ecosystem service associated with a conservation area, examining how the proximity and maturity of conservation areas affect crop yield allows us to capture the overall impact of these areas on crop profitability.

The ecosystem services and/or disservices evolve and intensify progressively over time as the ecosystem develops within conservation areas (Hirsh et al., 2013; Morandin and Kremen, 2013; Kordbacheh, et al., 2020; Dutter, 2022). The maturity of a conservation area is represented by its age at time t (age_t). As the distance between crop area i and the conservation area increases, the ecosystem services and disservices to crop tend to diminish (Nekola and White, 1999; Morlon et

al., 2008; Mitchell et al., 2015; Kemmerling et al., 2022). This varying magnitude of ecosystem services/disservices on crop area i is captured by the distance variable D_{ij} .

Crop yield y is also affected by inputs (x), weather conditions (*weather*), and site-specific characteristics (*site*). Site characteristics include topography and static soil attributes that only change over extended temporal scales, such as the quantity of soil organic carbon and the soil pH. While these site characteristics themselves are time-invariant, their interaction with weather conditions or age of conservation area can lead to varying effects on crop yield. For example, topographic features like hilltops may improve drainage and have a positive impact during periods of excessive rain (Basso et al., 2009). Similarly, proximity to woodland is a fixed site characteristic, but when used as a proxy for deer abundance, it can interact with time-varying factors, such as age of conservation area, resulting in different impacts on yield over time. Considering these factors, the yield in crop area i is,

$$y_{it} = f(D_{ij}, age_{jt}, x_{it}, weather_{it}, site_{it}) \quad (1)$$

The crop yield that would have occurred in conservation area j without establishment of the conservation area is projected using the same function as yield on area i , and the yield becomes zero once the area is put into conservation. In the absence of a conservation area, the maturity of the conservation area (age_{jt}) is set to zero, as no conservation area exists.

$$y_{jt} = \begin{cases} f(x_{jt}, weather_{jt}, site_{jt}, D_{jj}, age_{jt} = 0), & \text{without conservation area} \\ 0 & , \text{with conservation area} \end{cases} \quad (2)$$

Assuming that grain price (p_t) and input costs ($c(x_{it})$) are given, the total gross margin of the field differs depending on whether a conservation area is implemented. In the scenario without the implementation of conservation area, the total gross margin is the sum of the gross margins in area i and j . Conversely, once a conservation area is implemented, the gross margin excludes yield

from area j but incorporates any yield changes in area i resulting ecosystem services or disservices from the conservation area as it matures ($age_{ji}=t$).

$gross\ margin_t =$

$$\begin{cases} (p_t * y_{it|D_{ij},age_{jt}=0} - c(x_{it})) + (p_t * y_{jt|D_{jj},age_{jt}=0} - c(x_{jt})), & \text{without conservation area} \\ p_t * y_{it|D_{ij},age_{jt}=t} - c(x_{it}) & , \text{with conservation area} \end{cases} \quad (3)$$

The opportunity cost of implementing a conservation area is then the difference in gross margin between the same field at time t , without the conservation area and with it. In other words, it is the difference between the counterfactual gross margin without the conservation area and the observed gross margin with it. The opportunity cost at time t is,

$$OppCost_t = \sum_{i=1}^I \sum_{j=1}^J p_t * y_{jt|D_{jj},age_{jt}=0} - c(x_{jt}) + p_t * (y_{it|D_{ij},age_{jt}=0} - y_{it|D_{ij},age_{jt}=t}) \quad (4)$$

The disparity in profit between scenarios with and without a conservation area comes from 1) the foregone gross margin inside the conservation area incurred by allocating land to conservation rather than production and 2) the crop revenue change outside the conservation area resulting from the ecological influence of the conservation area. The opportunity cost of conserving area j rises with an increase in grain prices and falls with higher crop input costs. Ecosystem services that enhance yields reduce these opportunity costs, while those disservices that lower yields increase them.

When considering conservation over multiple years, the net present value of opportunity cost must also account for the one-time establishment cost ($EstCost$) incurred in the first year ($t=0$) and the annual opportunity costs ($OppCost_t$) up to final period T . Using the discount parameter δ , the net present value of total opportunity cost is,

$$Total\ OppCost = \sum_{t=0}^T OppCost_t * \delta^t + EstCost \quad (5)$$

Total opportunity costs over period T are amortized to represent annual costs, enabling comparison with other government programs, which are typically reported on per-acre, per-year basis.

1.3 Experimental design

This study analyzes the opportunity costs of precision conservation using experimental data collected and provided by the Digital Agriculture Lab (Principal investigator: Bruno Basso) at Michigan State University. Prior to implementing conservation areas, the Digital Agriculture Lab identified low-yield areas suitable for potential conservation, based on historical yield, total production costs, and grain prices. They calculated an indicative gross margin value for each cell and crop within a field by multiplying historical yield data by grain prices and then subtracting total input costs. The grain prices and input costs reported in 2020 were used to calculate gross margins for all prior years. The annual gross margin was then averaged across years with available yield maps. A cell where the average gross margin fell below -\$15/ac was identified as unprofitable. After removing unprofitable pockets smaller than 2 acres within the profitable area, the unprofitable area was initially suggested to a farmer as a potential conservation area. The suggested area example is illustrated in the left panel of Figure 1.2.



Note: In the left picture, the yellow shaded area represents the conservation area initially suggested based on the profit. The right picture shows the finalized conservation area chosen by a farmer, marked with an orange header.

Figure 1.2: Aerial image of a field with conservation area

Based on the suggested low-yielding areas, farmers selected the location and size of conservation areas balancing anticipated negative profitability with farming practicability (e.g., right panel of Figure 1.2). On average, farmers allocated 16% (median: 15%) of their field area to conservation. The distribution of conservation area shares across fields is provided in the chapter Appendix. Participating farmers were responsible for establishing the conservation areas, typically carried out in fall after the crop harvest in 2020. They planted the areas in native perennial plants only once, in the first year of participation. Commonly planted species included Indian grass (*Sorghastrum nutans*), big bluestem (*Andropogon gerardii*), and bergamot (*Monarda fistu losa*). These species were chosen for their low maintenance requirements and additional benefits, such as preventing soil erosion and supporting wildlife. While the seeds were provided to the farmers free of charge, the actual seed costs amounted to \$250 per acre. Participation in the project required a commitment to maintaining the conservation area for a minimum of five years. The participating farmers received a payment of \$175/ac/year for the retired acres.

1.4 Empirical Methods and Data

To analyze the opportunity costs of precision conservation, we estimate the forgone yield within

conservation areas and any yield changes outside conservation areas using the estimated yield response model. Based on these yield changes, we calculate the opportunity costs for 10-year periods under corn-soybean rotation. To account for price uncertainty, we employ Monte Carlo simulations. We compare the opportunity costs of precision conservation with those of whole-field conservation to evaluate cost-effectiveness of precision conservation.

1.4.1 Yield response function estimation

To evaluate the ecological impact of conservation areas on agricultural yield and quantify the associated opportunity cost, we begin by estimating a yield response model based on Equation (1). This model uses the distance and age of the conservation area as proxies for the ecosystem services or disservices provided by the conservation area. It also accounts for other factors, including site characteristics and farming practices. Field by year fixed effects capture farming practices, such as input use, that are applied uniformly for each field but adjusted each year. Site characteristics ($site_i$) include variables such as edge effects and headlands, while weather conditions ($weather_{it}$) account for factors like growing degree days and growing season precipitation. Detailed information on variables and their sources is provided in the following data section.

The distance variable (D_{id}) is generated for each grid cell within a field, with the grid cell serving as our unit of analysis. This variable is designed to capture three effects: proximity to the conservation area, its size, and its spatial configuration. To fully represent these factors, we define D_{id} as the total size of conservation areas within specific distance intervals (d) from each grid cell. This approach allows us to model nonlinear distance impacts on yield, capturing how different sizes and spatial arrangements of conservation areas influence yield at varying distances.

We incorporate two distance intervals: 0-10m and 10-50m. These intervals are determined based on the preliminary results, estimated using only data from periods prior to conservation

implementation. To test the robustness of our distance variable definition, we compare models using different definitions: 1) size of conservation area with various distance intervals (every 10, 20, and 50 meters), 2) distance to the nearest conservation area, and 3) the aggregate size of conservation areas weighted by their inverse distances from each crop cell. Results remain robust across these distance definitions, as presented in the chapter Appendix.

Measuring the ecological effect of conservation areas on crop yield is complicated by the fact that conservation areas are intentionally located where crop yields are low. Hence, we need to disentangle the yield effect due to ecosystem services emanating from the conservation area (whether positive or negative) from the yield effect due to its site characteristics. Because conservation areas were selected for low crop yields, the pure site effect based on distance D_{ij} from conservation area j to crop at site i is likely to be positive, meaning that yield would increase with distance from the conservation area. To capture the ecosystem services effect (if any), we rely on the assumption that ecosystem services such as pollination and natural biocontrol of crop pests will increase over early years as the conservation area matures and becomes able to provide habitat for beneficial or malign species. Hence, we interact distance from crop area i to conservation area j (D_{ij}) with the conservation area's age (age_{jt}). The coefficient on this interaction term allows us to examine how the impact of conservation area evolves over time, alongside the constant impact from the site characteristics, as shown in Equation (6).

$$y_{it} = \alpha \cdot age_t + \sum_d \beta_d \cdot D_{id} + \sum_d \gamma_d \cdot age_t \cdot D_{id} + \lambda_1 site_i + \lambda_2 weather_{it} + \lambda_3 Field_i \quad (6)$$

We test the validity of the estimated model using k-fold cross validation (Fushiki, 2011), in which the data is randomly divided into 10 equal subsets. For each iteration, one subset serves as the test set, while the model is trained on the remaining nine subsets. Model performance is then evaluated by comparing the predicted values with the actual values in the test set. This process is

repeated ten times, once for each subset, and we report the average R-squared value and Root Mean Squared Error (RMSE) across all iterations.

To assess whether conservation areas lead to increased deer-related damage on crop yield, we examine yield differences between areas located within 500 meters of the nearest woodland and those situated beyond that distance. We use proximity to woodland as a proxy for deer presence, based on research findings that wooded cover influences deer habitat use (Long et al., 2005; Heit et al., 2023). We choose a 500m threshold based on the estimates of the annual home range size of nonmigratory white-tailed deer, which range from 146 ac to 1,828 ac (Marchinton and Hirth, 1984; Pusateri, 2003). This distance is also sufficient to help isolate other potential ecological impact associated with proximity to woodland areas.

To estimate the potential yield impact associated with deer activity, we estimate Equation (7). We interact the distance from crop area i to conservation area j (D_{ij}) with two binary variables, one indicating whether the cell is located within 500m of woodland (*near_wood*), and the other indicating whether it is from the period after the conservation areas were implemented. We choose to use the binary indicator *after*, rather than the full set of age variables. Our rationale is that including multiple interaction terms between *age* and *near_wood* variables increases the number of parameters, which can lead to unstable estimates due to small sample sizes in some subgroups. Also, including many interaction terms increases the likelihood of Type 1 errors (List et al., 2016). Using a simpler *after* indicator allows for more stable estimation while still capturing the key temporal difference. The estimated coefficient γ_d allows us to assess whether there is any difference in yield near the conservation area conditional on proximity to woodland. We present the estimation results with the full set of age variables instead of the binary variable *after* in the chapter Appendix.

$$y_{it} = \sum_d \beta_d \cdot D_{id} + \sum_d \gamma_d \cdot after \cdot D_{id} + \sum_d \gamma_d \cdot after \cdot near_wood \cdot D_{id} + \lambda_1 site_i + \lambda_2 weather_{it} + \lambda_3 Field_i \quad (7)$$

1.4.2 Data

The data set covers five years of yield maps (2020 - 2024) from 52 commercial corn and soybean fields located on two Michigan farms. Corn and soybeans were planted on these fields following farmers' crop rotation schedules. Because not all fields grew both corn and soybeans during the study period, the opportunity cost simulation under a corn-soybean rotation was limited to the 29 fields that did. We use data from the remaining fields to estimate the yield response functions.

Each field is divided into grid cells of 9m by 9m (30ft by 30ft). Each grid cell serves as an observation unit for this analysis, and the average yield is computed for each cell. A cell is categorized as a conservation area if a conservation measure is installed on the majority of that cell. This issue arises from overlaying a square grid on the field, causing conservation and crop areas not to align perfectly with the grid. We exclude two types of cells from the analysis: 1) cells classified as conservation areas, defined as having more than 50% conservation coverage, but containing yield data from the remaining portion, and 2) cells defined as cropped areas but lacking yield data. The dropped cells account for 1.4% of the entire sample. After cleaning, the dataset includes 934,825 observations in total over the five years of analysis.

Site characteristics ($site_i$) include edge, headland, as well as soil characteristics. Crop yields are often lower on field edges due to greater environmental stresses, such as wind exposure, shading, and uneven application of inputs. In headlands, where farmers turn their equipment around, frequent machinery traffic leads to soil compaction, further contributing to yield reduction. To control for these effects, we generate the dummy variable, $edge1$, by assigning a value of 1 to cells located at the outermost edge of the field. To examine how the impact of the edge changes as

we move further into the field, we also identify cells 50m from the outermost edge of the field (*edge2*). The average value of the *edge1* variable across the full sample is 0.1, indicating that 10% of observations are located within 10 meters of the field edge. Similarly, the average of *edge2* is 0.4, suggesting that around 40% of observations are within 50 meters of the edge (Table 1.1).

We further categorize the type of edge based on the adjacent land: 1) neighboring field, 2) developed land such as houses or paved roads, and 3) grassland or woodland. We generate the dummy variable, *headland*, by identifying cells situated within 20 meters of the headland side of the edge. The 20 meter value arises from the width of the input applicators used by participating farmers. The average value of the *headland* variable is 0.1, indicating around 10% of observations are located in the headland. To examine the potential deer damage, distance to the nearest wood is calculated. We draw soil characteristics from the Soil Survey Geographic Database (SSURGO, 2020), including the amount of soil organic carbon (SOC in g/m²) and available water storage (AWS in cm) in the top 100 cm of soil. SOC contributes to soil fertility as it affects soil capacity to retain water and nutrients while mitigating topsoil loss (Reeves et al., 1997; Robertson et al., 2014). AWS represents the maximum amount of plant-available water a soil can provide, a critical factor influencing corn yield (Leeper et al., 1974).

All the sample fields are rainfed. As a proxy for soil moisture data, we use the Topographic Wetness Index (TWI). The TWI measures potential water accumulation based on landscape position and slope, providing an estimate of soil moisture across the field. A higher value of TWI indicates that water is more likely to accumulate and persist in an area, while a lower one suggests that water is less likely to persist. Using elevation data from the US Geological Survey's Digital Elevation Model (DEM), the average Topographic Wetness Index is generated for each grid cell (Gessler et al., 1995). We use daily weather data at a resolution of 800m from the Parameter-

elevation Relationships on Independent Slopes Model (PRISM, 2025) to construct the growing degree days (GDD) and Total Precipitation variables for the duration of the growing season, spanning from April through September. To capture potential non-linear effects of weather on crop outcomes, we include both the linear and squared terms of GDD and precipitation in the analysis.

Table 1.1 presents the average values of variables used in the estimation model. The average of the D_{10} variable reflects the number of conservation area cells located within 10 meters of a crop cell. The average D_{10} is 0.3 for Farm A and 0.2 for Farm B, indicating that on average each crop cell has approximately 0.3 and 0.2 conservation area cells within a 10 meter radius, respectively. Similarly, the D_{50} variable captures the number of conservation area cells located between 10 and 50 meters from a crop cell. The average D_{50} is 4.2 for Farm A and 3.9 for Farm B, suggesting that each crop cell is surrounded by roughly 4.2 and 3.9 conservation area cells within the 10-50 meter interval.

Table 1.1: Mean values of grid cell data from 52 fields, two Michigan farms, 2020-24

Variables in conceptual model	Empirical model	Farm A (n = 800,195)	Farm B (n = 134,630)
<i>Yield</i>	Yield (bu/ac)	Corn: 148 Soybeans: 49	Corn: 177 Soybeans: 64
<i>Distance</i>	D_{10}	0.3	0.2
	D_{50}	4.2	3.9
<i>Site</i>	Edge1	0.1	0.1
	Edge2	0.4	0.4
	Headland	0.1	0.1
	SOC (g/m ²)	7329	7606
	AWS (cm)	147	149
	TWI	-19	-19
	Distance_wood (m)	413	278
<i>Weather</i>	GDD (April-Sept)	1490	1479
	Precipitation (mm)	616	514

1.4.3 Opportunity cost calculation

The opportunity cost of the conservation area is defined as the sum of three key components: 1)

the foregone gross margin from crops not grown inside the conservation area, 2) changes in revenue in the cultivated area due to the presence of the conservation area, and 3) the cost of establishing the conservation area. Specifically, the foregone gross margin on the conservation area entails the lost revenue from crop yield minus the input costs saved by not applying inputs to the conservation area.

We compute the foregone yield within the conservation area and the yield changes outside of the conservation area based on the estimated yield function (Equation 6). The foregone yield within conservation areas is calculated by extrapolating the estimated yield function under the assumption that the conservation area is not yet implemented ($age_{jt}=0$). The yield change outside of conservation area is calculated using the estimated coefficients of the distance-age interaction term. These two yield values are then converted into opportunity costs using grain prices and input costs.

The total cost of establishing and maintaining conservation areas includes labor, machinery use, and seed expenses. Establishment involves tillage and planting, with annual mowing required for maintenance. The associated costs are calculated using custom hire rates from the Iowa Farm Custom Rates Survey (Plastina and Johanns, 2024), which account for both labor and machinery expenses. Although seeds for the conservation area were provided to farmers at no cost during this project, their market value was \$250/acre. Since perennial species were planted, seed and implementation costs were incurred only in the initial year. The total establishment cost for the initial year is \$283/acre, with the annual maintenance cost of mowing at \$25/acre thereafter.

Table 1.2: Costs associated with conservation area establishments and maintenance

Tasks		Charge (\$/ac)	Source
Maintenance	Mowing	25	Plastina and Johanns (2024)
	Tillage	20	
Establishment	Planting	13	From this study
	Seed	250	

We first calculate the one-year conservation opportunity costs for corn and soybean fields in 2024. The foregone yield within the conservation area and yield changes outside the conservation area are converted into opportunity costs using farmer-reported grain prices (\$/bu) and input costs (\$/ac) presented in Table 1.3, to reflect differences in management practices that affect crop yield. The input costs reported by the participating farmers exceed the average input costs for the Heartland region reported by the USDA (USDA, 2025). However, since input usage is closely tied to yield outcomes, we opt to using the farmer-reported values. As the farmer reported prices were collected only in 2020, we adjust the prices to 2024\$ using the Producer Price Index for farm products. The input costs for corn are higher than soybeans because corn typically requires more intensive management, including higher fertilizer and pesticide applications, as observed in our sample farms.

Table 1.3: Farmer reported price parameters (in 2024\$)

	Corn		Soybeans	
	Farm A	Farm B	Farm A	Farm B
Grain price (\$/bu)	4.40	5.30	12.60	12.60
Input costs (\$/ac)	534	840	340	478

We then calculate the ten-year conservation opportunity costs assuming a corn-soybean rotation. The objective of this modeling is to reflect the long-term nature of conservation programs, which typically extend beyond a single growing season. By extending the analysis to ten years, we incorporate price fluctuations over time, providing a more realistic representation of market variability and its impact on opportunity costs. By incorporating a corn-soybean rotation, the

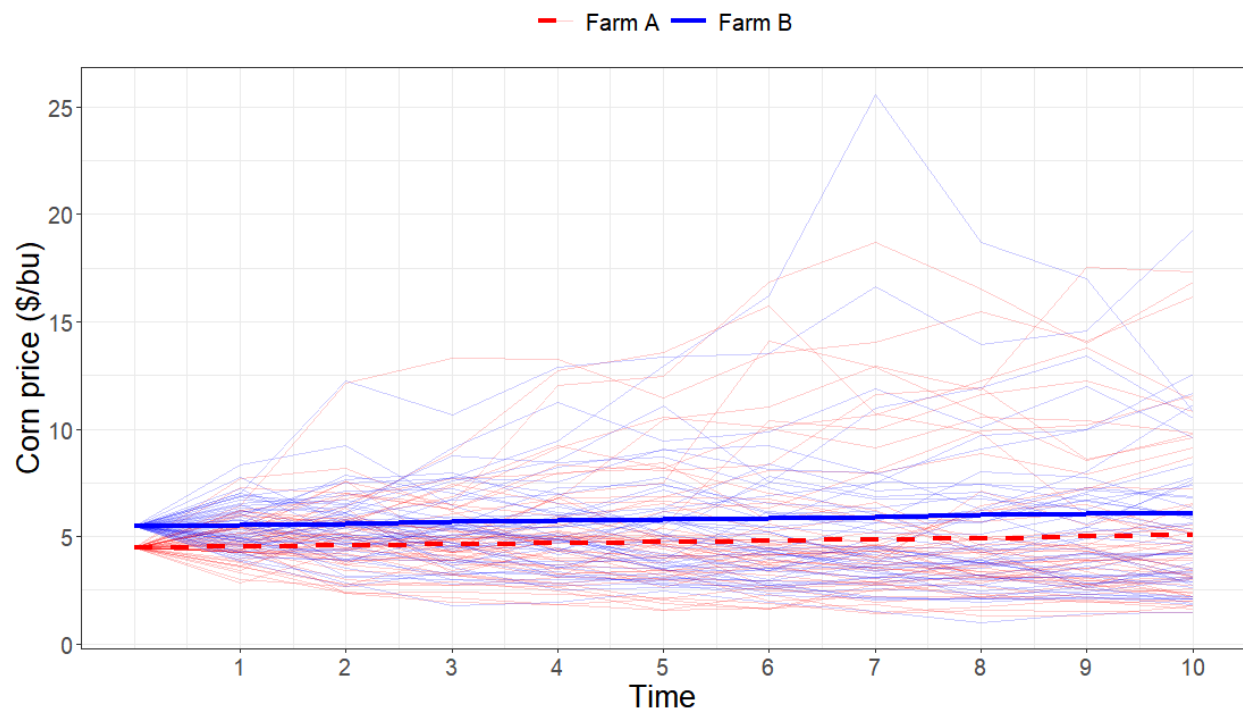
model captures the differing opportunity costs associated with these crops, as corn and soybeans have distinct yield potentials, input costs, and ecological impacts. The amortized results enable comparisons with other long-term conservation initiatives and subsidy programs that are often structured over similar timeframes.

In our model, yield changes due to ecosystem services from conservation areas are observed only over time. We assume the yield effect evolves until the fourth year and remains constant at the fourth-year level thereafter. This assumption aligns with the establishment period of perennials typically planted in conservation areas (Sargent and Carter, 1999). As a robustness check, we also calculate opportunity costs under the assumption that conservation areas have no ecological impact on adjacent cropland. Both the foregone yield within conservation areas and yield changes outside conservation areas are converted into profit using grain prices and input costs.

To account for potential price fluctuations and market risks, we use Monte Carlo simulation to generate hypothetical price scenarios. Price fluctuations are a major component of farm income risk (Sherrick, 2012), alongside yield variability, as they directly influence gross margins and overall profitability. Ignoring price variability would result in an incomplete measurement of profitability risk, overlooking the potential range of financial outcomes for farmers.

Through the simulation, we measure the range of possible profitability outcomes from precision conservation. While farmer-reported values provide accurate information on the actual prices received and input usage, they do not capture variability across years since they were collected only for 2020. To address this limitation, we simulate prices using a Geometric Brownian Motion (GBM) model based on farmer-reported values starting in 2024. We use farmer-reported grain prices and input costs as initial parameters and apply GBM to capture the random walk

behavior of prices, reflecting their tendency to evolve unpredictably over time (Marathe and Ryan, 2007; Turvey, 2007). Parameters for the simulation, including drift rate, volatility, and correlation, are calculated from historical grain price and input cost data for the Heartland region (1975–2023) published by the USDA. All values are deflated to 2024\$, using the Producer Price Index for farm products (BLS, 2024). The simulation incorporates the correlation among corn grain price, soybean grain price, corn input costs, and soybean input costs. We generate 10,000 hypothetical price trajectories for these variables over a 10-year period. Figure 1.3 illustrates the average prices for each time period across the simulations. Using these simulated prices, we calculate 10,000 iterations of 10-year conservation opportunity costs to capture variability and market risks.



Note: The prices in Time before 1 represent farmer reported values. Lighter shaded lines illustrate 50 examples of simulated price trajectories. All values are in 2024\$.

Figure 1.3: Simulated corn prices over time – average of 10,000 simulations with example paths across farms

We calculate 10-year opportunity costs by aggregating annual opportunity costs to the field level. We randomly draw foregone yields and ecological yield benefits from distributions based

on the yield response model. Simultaneously, we apply a set of hypothetical grain prices and input costs from the 10,000 simulated sets derived from the Monte Carlo simulation. Using the randomly drawn yields, simulated prices, and input costs, we calculate the average annual opportunity cost for each field.

In order to evaluate the ten-year conservation opportunity cost of precision conservation under a corn-soybean rotation, we aggregate the estimated annual opportunity costs for each field. We use a 5% discount rate (r) reflecting the real rate of return to owner equity in the farm sector (Erickson et al., 2004). The aggregated opportunity cost over the duration of conservation ($T=10$) is amortized to calculate the annualized opportunity cost of precision conservation (Equation 8).

$$Annual\ OppCost = \frac{r \left[Establish + \sum_{t=cornYear}^T \frac{CornOppCost}{(1+r)^{t-1}} + \sum_{t=soyYear}^T \frac{SoyOppCost}{(1+r)^{t-1}} \right]}{1 - (1+r)^{-T}} \quad (8)$$

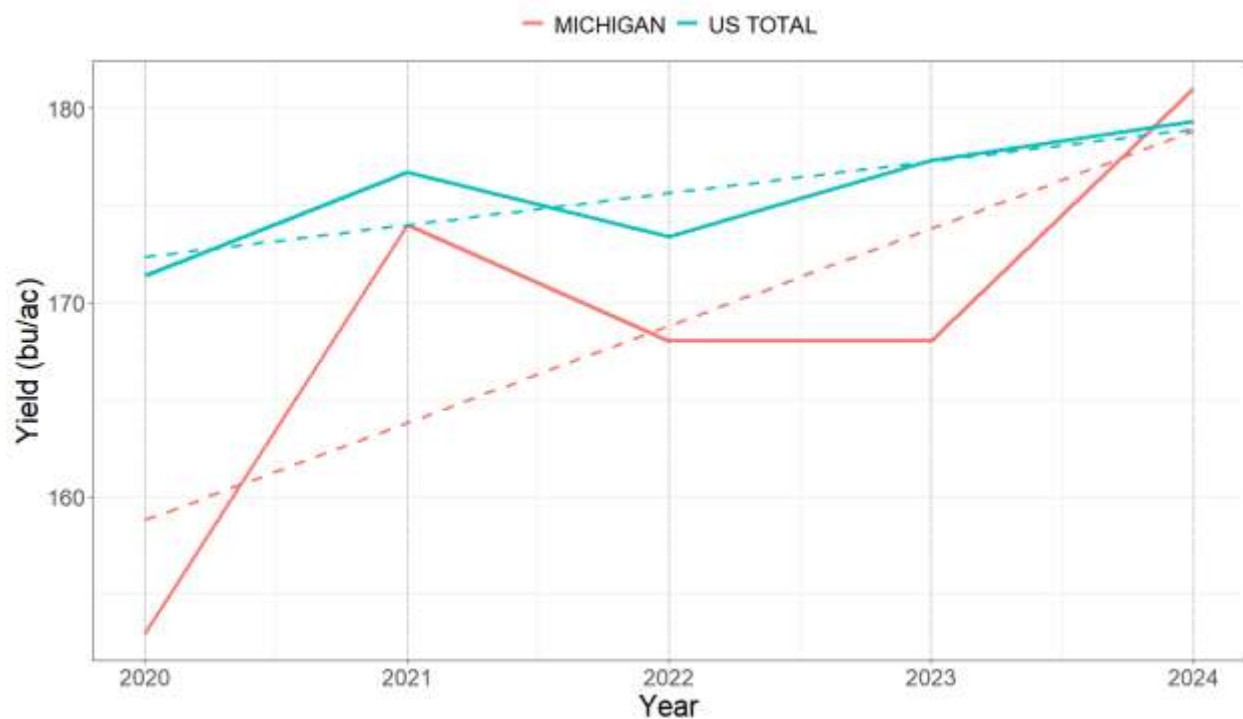
We assume that national grain prices are independent of field-level crop yields, allowing price and yield distributions to be estimated and drawn separately. Although previous studies have shown evidence of a negative price-yield correlation in the Corn Belt (Harwood et al., 1999), this correlation tends to be small in regions like Michigan that are minor producers (Skees et al., 1998). In 2023, Michigan accounted for only 2% of the U.S. value of corn production and 3% for soybeans (USDA, 2024).

To evaluate the cost-effectiveness of precision conservation relative to the whole-field conservation approach, we compare their respective opportunity costs. The opportunity costs of whole-field conservation include the forgone gross margin from both the designated conservation area and the remaining crop area. Thus, the per-acre difference in opportunity costs between whole-field conservation and precision conservation is equal to the forgone gross margin from the crop area under whole-field conservation, minus the ecological yield benefits near conservation

area, plus the implementation costs of the precision conservation area. We estimate forgone gross margin and revenue gain using the estimated yield response function and simulated price trajectories. For implementation costs, we use seed and land preparation expenses, which amount to \$283/ac (Table 1.2).

1.4.3 Representativeness of the study

Although this study is based on two commercial farms in southern Michigan, the data span five growing seasons (2020-2024) and reflect a wide range of weather and production conditions, providing insight into how precision conservation may perform under diverse seasonal scenarios typical of the Upper Midwestern United States. Figure 1.4 illustrates the overall yield trends in Michigan and the U.S. from 2020 to 2024. Detailed monthly temperature and precipitation patterns for the study period are presented in the chapter Appendix. In the first year of conservation (2021), Michigan experienced favorable weather, leading to record high crop yields. However, dry conditions in 2022 resulted in lower yields, while 2023 saw improved weather, but statewide yields remained comparable to those in 2021. In 2024, a warm and wet growing season again produced record-high yields. These weather fluctuations on the sample farms reflect broader variability observed across Michigan, providing a context for examining how opportunity costs evolve over time.



Note: Solid lines indicate average annual yields, while dashed lines indicate linear yield trend from 2020 to 2024

Figure 1.4: Michigan and U.S. Average Corn Yields by Year (2020-2024)

The participating farms follow conventional crop rotations and operate at commercial scale, making them broadly representative of farming systems across the Midwest. The price they received in 2020, which are used as the baseline for both the one-year opportunity cost calculation and the 10-year opportunity cost simulations, reflect typical market conditions. The corn prices they received in 2020 fell within 0.5 standard deviations of the average monthly corn price in Michigan from 2020 to 2024 (Figure 1.5; soybean prices are presented in chapter Appendix), supporting the representativeness of their economic conditions.

While the sample is generally reflective of regional conditions, certain characteristics may lead to conservative estimates of opportunity costs. In particular, both farms reported higher input costs than the USDA Heartland average in 2023. As illustrated in Figure 1.6, the average corn yield of the sample fields in this study (155 bu/ac) is lower than the U.S. average, whereas the average

soybean yield (55 b/ac) is higher. Higher input costs combined with lower corn yield would be expected to reduce forgone revenue within conservation areas, potentially resulting in lower opportunity cost estimates compared to farms using inputs less intensively.

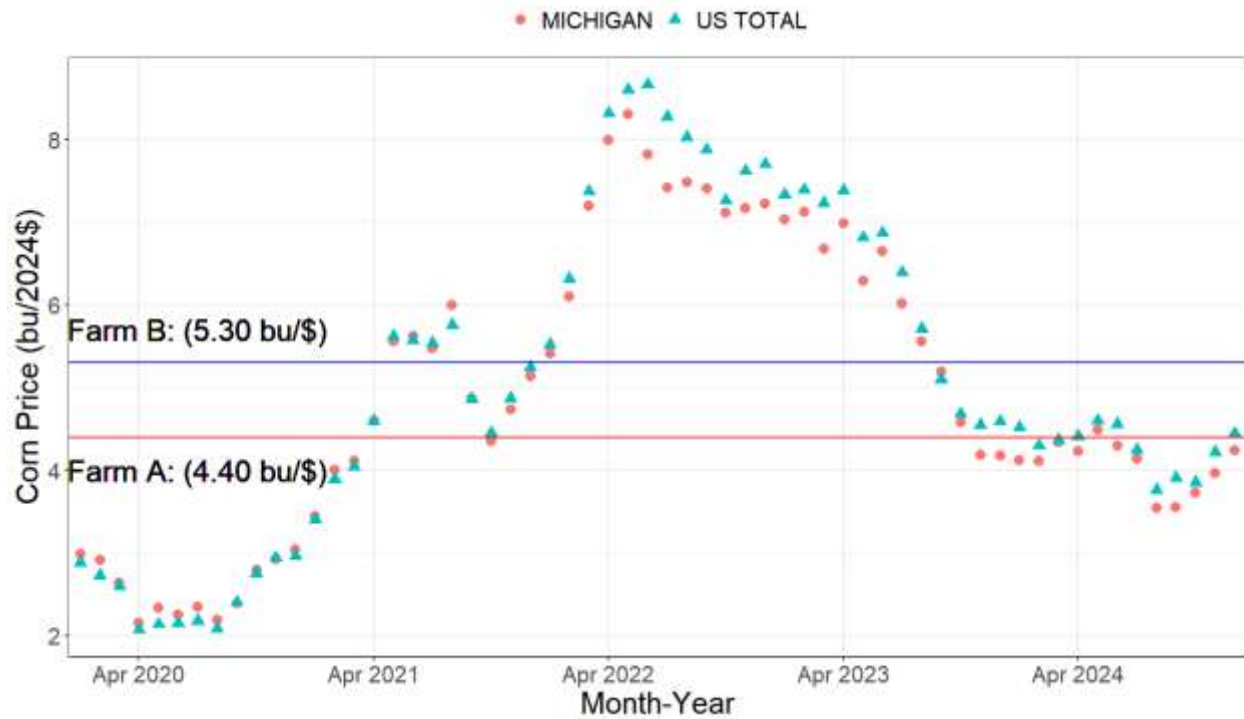


Figure 1.5: Monthly corn prices across Michigan and the US average (2020-2024)

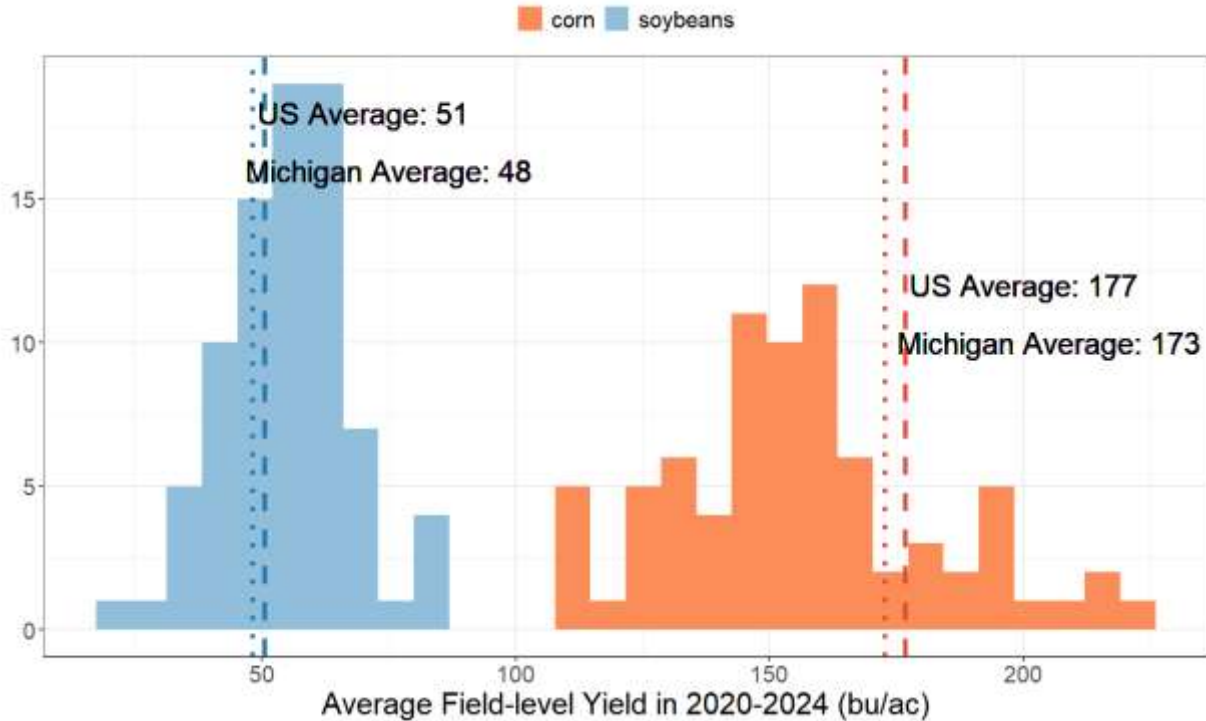


Figure 1.6: Distribution of field-level soybean and corn yields in 2020-2024, 52 Michigan fields

1.5 Results

1.5.1 Estimated yield function

In both corn and soybean, the crop yield near conservation areas is lower (Table 1.4). For corn, yields within 10 meters of the conservation areas are 11 bu/ac lower, and for soybeans, they are 5 bu/ac lower, corresponding to reduced income of \$55/ac and \$65/ac respectively. Between 10 and 50 meters from conservation areas, corn yields are 0.8 bu/ac lower, and soybean yields are 0.2 bu/ac lower. While these differences are statistically significant, the yield changes in the 10-50m interval translate on average to less than \$4/ac for each crop, indicating a slight yield impact beyond 10 meters from conservation areas.

We observe yield impacts that evolve over time in both corn and soybeans within 10 meters of the conservation areas (Figure 1.7). For corn, the distance-age interaction terms increase over time and become statistically significant in year 4. In year 4, the estimated yield impact is 12 bu/ac,

corresponding to a revenue gain of \$60/ac. In contrast, soybeans exhibit an earlier response. The distance-age interaction term is statistically significant and positive beginning year 1 and continues to grow through year 3. The revenue increase from these positive yield impacts amount to \$39 to \$48 per acre. However, the yield impact is statistically insignificant in year 4.

Beyond 10 meters from the conservation area, there is no evidence of a consistent ecological impact over time. In the soybean model, none of the distance-age interaction terms are significant. For corn, the interaction term for the 50 meter interval and Year 1 is significant, but this effect disappears in subsequent years. Given the lack of persistence, we do not interpret these findings as evidence of ecological impact within the 50 meter interval.

We use the estimated coefficients of the distance-age interaction terms to calculate the impact of the conservation area on crop yields outside the conservation area. For the area within 10m from the conservation area, we include all coefficients, even those that are not statistically significant, to capture the full potential effect. This approach allows us to estimate an upper-bound of the possible ecological impact of the conservation area. As there is no consistent evidence of ecological effects beyond 10 meters, we assume no impact beyond this range and exclude the 50 meter interval coefficients from the yield impact calculation.

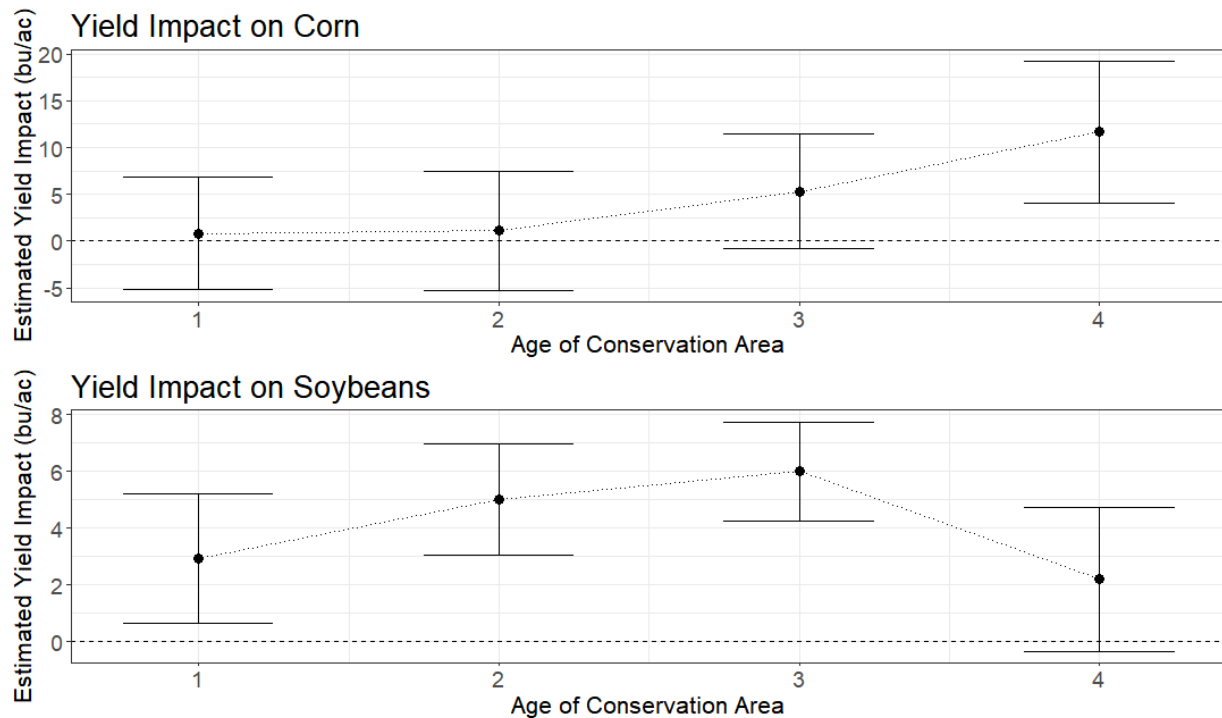
Table 1.4: Estimated effects of conservation areas on yield of corn and soybeans (bu/ac)

Variable	Coefficient (Std. Err.)	
	Corn	Soybeans
D10	-11.3 *** (2.6)	-5.2 *** (0.8)
D10 · Year 1	0.7 (3.5)	2.9 ** (1.4)
D10 · Year 2	0.6 (3.6)	5.0 *** (1.2)
D10 · Year 3	4.9 (3.9)	6.0 *** (1.5)
D10 · Year 4	11.5 ** (4.4)	2.2 (1.5)
D50	-0.9 ** (0.3)	-0.2 ** (0.1)
D50 · Year 1	1.0 ** (0.5)	-0.2 (0.2)
D50 · Year 2	-0.4 (0.5)	0.003 (0.1)
D50 · Year 3	-0.6 (0.4)	0.1 (0.1)
D50 · Year 4	-0.8 (0.5)	0.02 (0.1)
Soil characteristics	Yes	Yes
Site characteristics	Yes	Yes
Weather	Yes	Yes
Field by Year fixed effect	Yes	Yes
R ²	0.60	0.69

***, **, * represent statistical significance at the 1%, 5%, and 10% levels; all standard errors are clustered in the field level.

As we do not measure ecosystem services directly, the exact mechanism driving the observed yield increases remains unknown. However, the positive yield impacts can be partly explained by the role of conservation areas in providing habitat for beneficial species, such as pollinators and natural enemies of pests. Studies have shown that implementing flower strips or hedgerows can enhance pollination services (Albrecht et al., 2020; Schulte et al., 2017), and Kemmerling et al. (2022) observed increased pollination up to 20 meters from prairie strips after one year. While neither corn nor soybeans require pollinators, increased pollination can improve soybean yields (Garibaldi et al., 2021). In addition to pollination, studies have reported natural

biocontrol of soybean aphid (Fox et al, 2004) and of armyworm in corn as well as weed seeds in various crops (Landis et al, 2005).



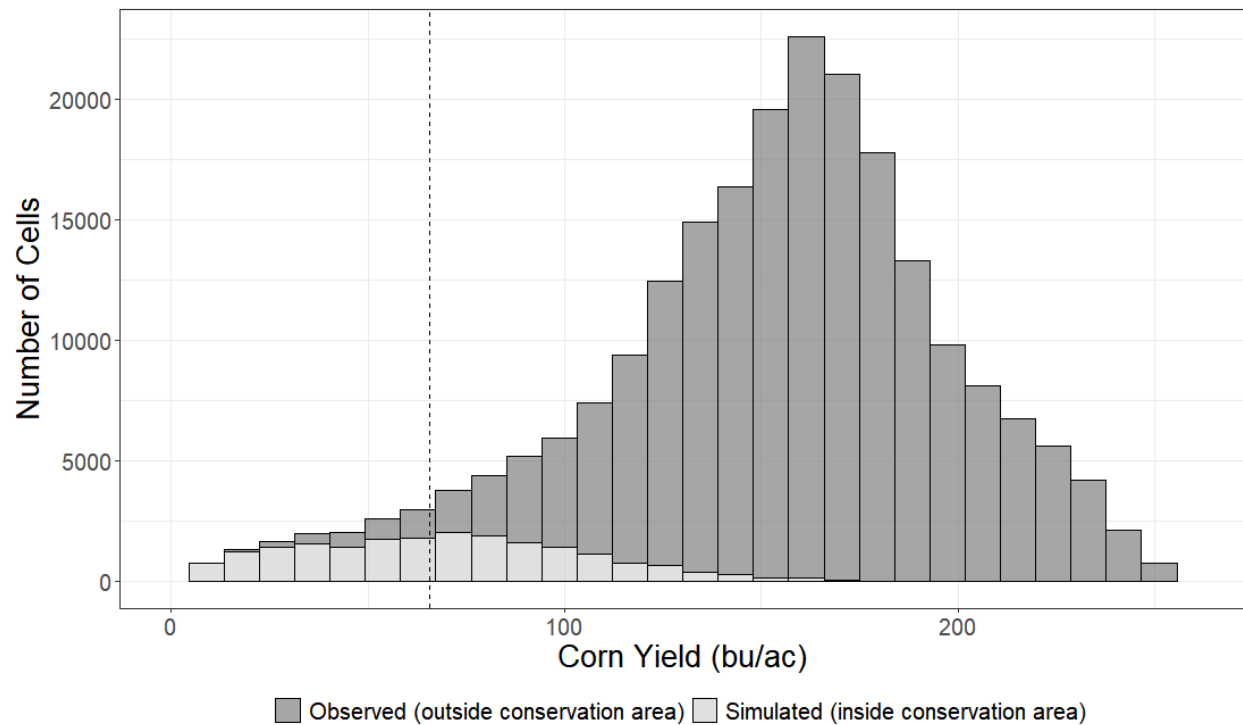
Note: Error bars indicate confidence intervals at 10% level.

Figure 1.7: Estimated ecological yield impact within 10m across age of conservation area

The earlier yield response observed in soybeans compared to corn may be explained by the more immediate benefits of certain ecosystem services, particularly those related to pollinator habitats. While corn is primarily wind-pollinated and does not rely on insect pollinators, soybeans show a modest dependence on pollinators (Morse and Calderone, 2000). Pollinator populations can respond relatively quickly to conservation efforts. Levenson and Tarpy (2023) documented a significant increase in bee population within the first two years of establishing pollinator habitats within agricultural land. In contrast, ecosystem services such as improved soil fertility typically take longer to develop, often requiring more than three years to show measurable effects (Wood and Bowman, 2021).

Based on k-fold cross-validation, the corn yield model achieves an average R-squared value of 0.77 and a Root Mean Squared Error (RMSE) of 24. For the soybean yield model, the average R-squared value is 0.83, with an RMSE of 8. These RMSE values represent approximately 15% of the sample average yield for corn and soybean, reflecting the predictive error of extrapolated yields within conservation areas.

We extrapolate yields within conservation areas using the estimated yield response function. Since land produces crops only when not placed into conservation use, we set the age of the conservation area to zero for extrapolation. Conservation areas are typically located in historically low-profit areas, resulting in estimated yields that are lower than those outside conservation areas. Figure 1.8 illustrates that precision conservation areas are concentrated in the lower tail of the corn yield distribution, highlighting their strategic placement in low-productivity zones. The estimated average corn yield within conservation areas is 66 bu/ac (standard deviation = 38), compared to the observed average of 159 bu/ac (standard deviation = 34) outside conservation areas. Similarly, the estimated average soybean yield inside conservation areas is 24 bu/ac (standard deviation = 14), compared to the observed average of 55 bu/ac (standard deviation = 14) outside conservation areas.



Note: Light shaded bars indicate the number of cells in conservation area and dark shaded bars indicate number of cells in crop area. Dashed line represents the average of simulated yield within conservation area and the solid line represents the average of yield in crop area.

Figure 1.8: Corn yield distribution across observed and simulated yield

1.5.1.1 Deer damage

The results indicate no statistically significant differences in yields near conservation areas between areas located within 500m of woodland and those farther away, suggesting that conservation areas did not contribute to increased deer-related crop damage (Table 1.5). We present the estimation results with full set of age variables instead of the binary variable *after* in the chapter Appendix.

Table 1.5: Estimated effects of deer damage on yield near conservation area (bu/acre)

Variable	Coefficient (Std. Err.)	
	Corn	Soybeans
D10	-11.2 *** (2.7)	-5.1 *** (0.8)
D10 · after	0.7 (5.2)	2.6 (1.8)
D10 · after · near_wood	3.6 (4.3)	0.8 (1.7)
D50	-0.8 ** (0.4)	-0.2 ** (0.1)
D50 · after	-0.6 (0.4)	-0.1 (0.2)
D50 · after · near_wood	0.3 (0.3)	0.002 (0.1)
Soil characteristics	Yes	Yes
Site characteristics	Yes	Yes
Weather	Yes	Yes
Field by Year fixed effect	Yes	Yes
R ²	0.60	0.69

***, **, * represent statistical significance at the 1%, 5%, and 10% levels; all standard errors are clustered in the field level.

1.5.2 Opportunity costs

We calculate the opportunity costs for three scenarios: corn fields in 2024, soybean fields in 2024, and 10-year conservation under a corn-soybean rotation. For the 2024 opportunity costs, we use farmer-reported prices reported from 2020, adjusted to 2024 dollars as presented in Table 1.3, while for the 10-year opportunity costs, prices are simulated using Monte Carlo simulations to account for variability in prices. Finally, we compare the opportunity costs of precision conservation with those of whole-field conservation to evaluate their relative cost-effectiveness.

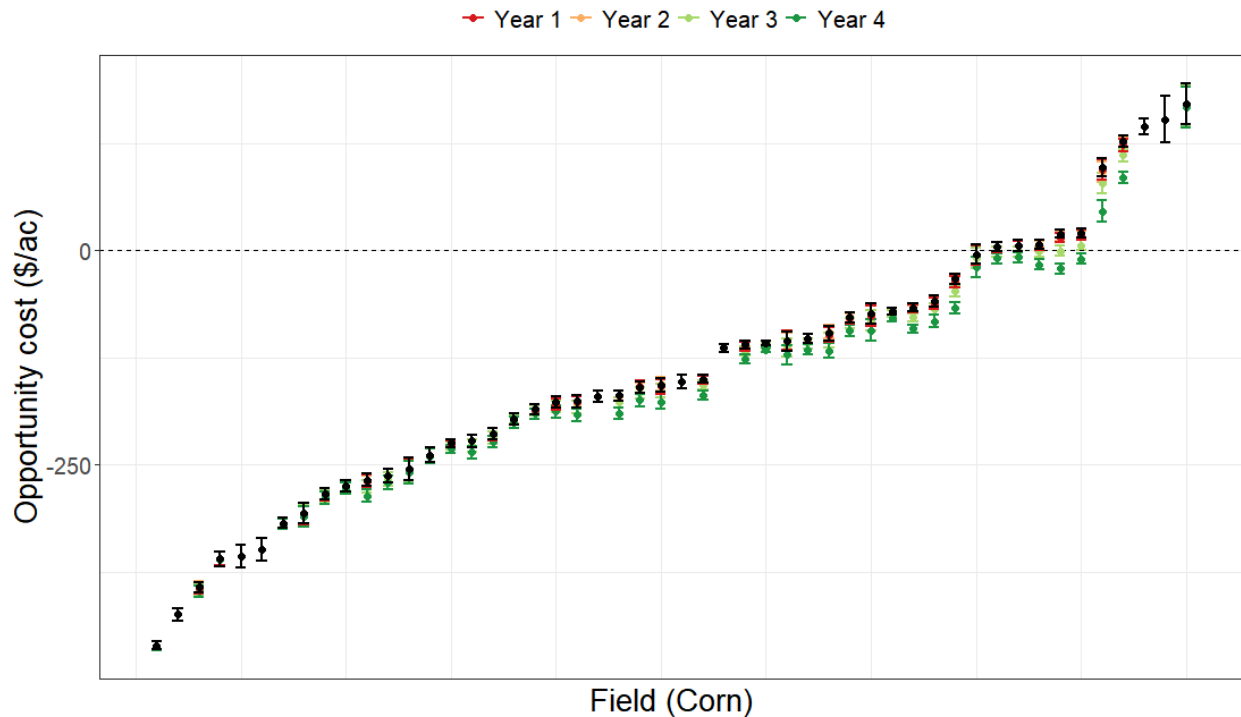
1.5.2.1 Corn fields in 2024

Without considering the ecological yield benefits on nearby crops, the opportunity costs of precision conservation range from -\$460/ac to \$171/ac. The negative average of -\$144 per acre of conservation area, indicates that for most sample fields, implementing precision conservation in a corn field enhances profitability by removing low-yielding land from production, even without

any subsidies or ecological benefits. The estimated foregone yield inside the conservation area is 80 bu/ac, which is insufficient to offset the farmer-reported input costs of corn (Table 1.3). Consequently, converting low-yielding crop area into conservation use proves cost-effective in most instances.

Analyzing the opportunity costs across the 50 fields where corn was planted, we find that 80% of fields (40 out of 50 fields) have negative opportunity costs (Figure 1.9). The estimated foregone yield inside the conservation area has a high, positive correlation of 0.81 with the average actual yield outside the conservation area, so corn fields with higher overall yields tend to incur higher opportunity costs when their relatively lower-yield areas are converted to conservation use.

With positive yield benefits from conservation areas, crop yields near conservation areas increase over time, reducing the opportunity costs of precision conservation. However, the magnitude of the effect is marginal. As the ecosystems within conservation areas mature, the yield benefit increases, resulting in the lowest opportunity costs in year 4. In year 1, the yield benefit is modest (1 bu/ac increase) and statistically insignificant. By Year 4, however, yield benefit increases to 11 bu/ac within 10m of conservation area. When we convert the yield benefits in terms of revenue increase per acre of conservation area, the average revenue increase amounts to on average \$14/ac of affected area in year 4, which is 9% of the average opportunity cost of precision conservation in year 4.



Note: Black points indicate estimated opportunity costs without considering ecological impact. Colored points represent opportunity costs 1 year after (red), 2 years after (yellow), 3 years after (light green), and 4 years after (green) implementing conservation areas. Error bars indicate 95% confidence intervals; standard errors are bootstrapped (N=1,000) and fields are ordered from the lowest to the highest opportunity cost.

Figure 1.9: Estimated opportunity cost of conservation area by maturity across 50 corn fields in 2024

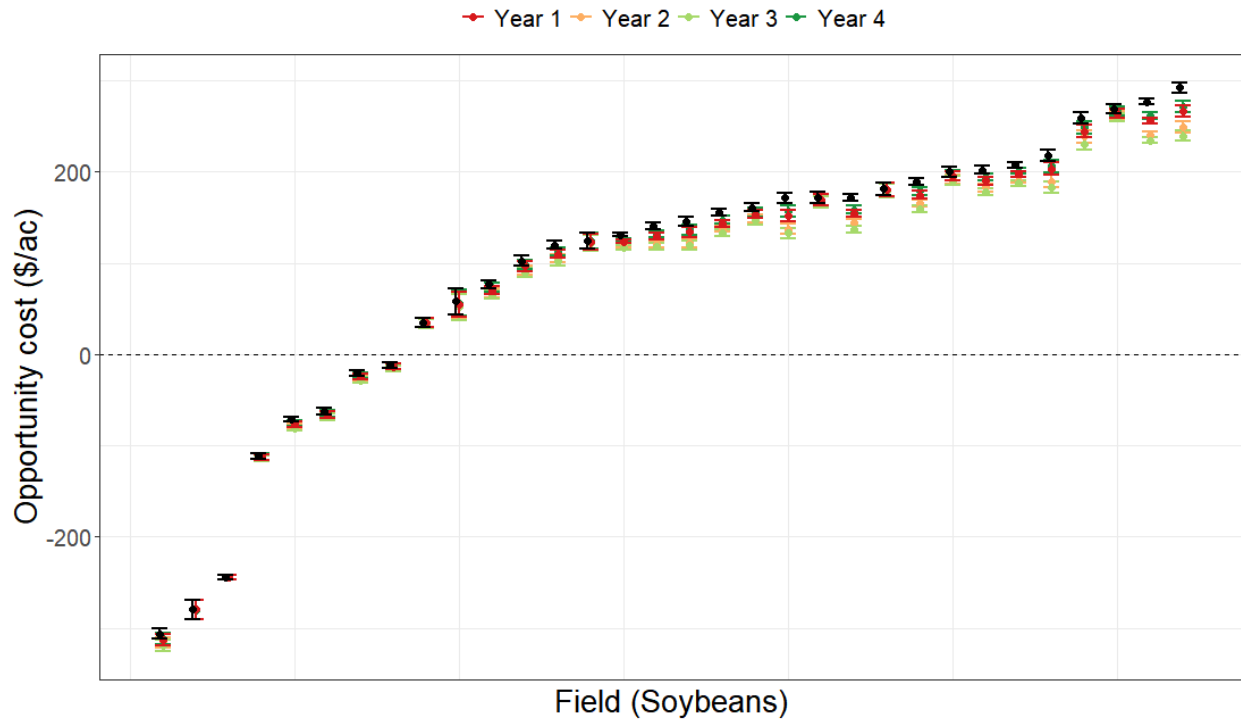
1.5.2.2 Soybeans fields in 2024

The opportunity costs of precision conservation on soybean fields differ from those on corn fields in two respects. First, input costs are lower in soybeans, resulting in higher foregone revenue within conservation area. Second, as they age, the conservation areas affect the yields of nearby soybean plants growing within ten meters only up to year 3. In year 4, the yield benefit declines to the year 1 level.

The total opportunity cost without considering the ecological impacts in soybean fields is \$92/ac on average, ranging from -\$306/ac to \$292/ac. The average foregone soybean yield within conservation areas is 30 bushels per acre, exceeding the break-even yield, meaning conservation

areas reduce profits when they remove soybeans from production. Across 32 soybean fields, over 71% (23 out of 32 fields) have positive opportunity costs, with the full set ranging from -\$352/ac to \$253/ac (Figure 1.10). Similar to corn, the estimated foregone yield within conservation areas has a high, positive correlation of 0.88 with the average yield outside conservation areas, so soybean fields with higher overall yields tend to incur higher opportunity costs when implementing precision conservation.

Ecological yield impacts on crops adjacent to conservation areas partially offset these costs by increasing yields. Each additional grid cell (0.02 acres) of conservation area within 10 meters of crops raises yields approximately by 2 bu/ac annually until Year 3. Since the ecological impact only affects crops within 10 meters, conservation areas farther from crops do not provide this benefit. The average ecological yield impact per acre of conservation area is 0.6 bu/ac, equivalent to \$7.8 in additional revenue per acre of conservation area at the 2024 soybean price.



Note: Error bars indicate 95% confidence intervals; standard errors are bootstrapped (N=1000). Fields are ranked by mean opportunity cost in the first year. Black points and error bars show costs without ecological yield benefits.

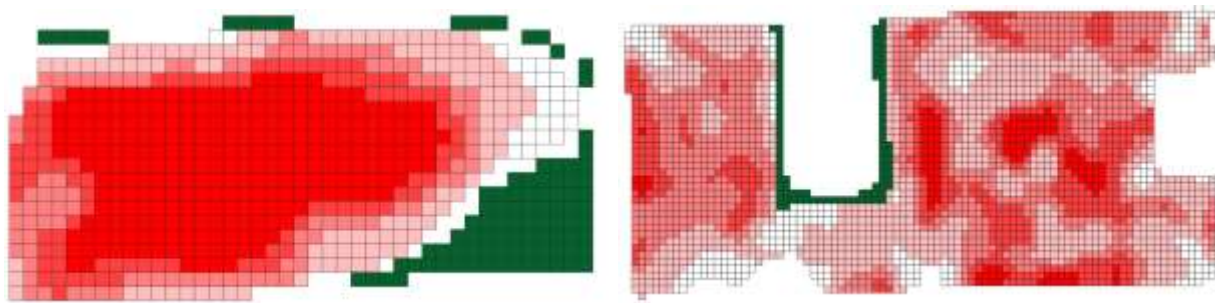
Figure 1.10: Estimated opportunity cost of conservation area across 32 soybean fields in 2024

1.5.2.3 Configuration of conservation area

The extent of ecological yield benefits varies across fields depending on the configuration of conservation areas. Since yield benefits occur only within 10 meters of conservation areas, adding conservation area beyond that distance provides no additional benefits and reduces the average yield benefit per acre of conservation area. To illustrate, Fields A and B (Figure 1.11) have similar conservation area sizes—1.92 acres and 1.90 acres, respectively, differing by only 0.02 acres (equivalent to one grid cell). However, the configuration differs significantly: Field A has more clustered conservation areas, while Field B has a more dispersed configuration with long strips measuring 9.14 m (30 ft) in width.

Despite having similar total conservation area, the ecological benefits differ substantially

between fields A and B. In Year 4, when corn yield benefits are most pronounced, we observe a yield benefit of 1 bushel per acre of conservation area in Field A, while Field B experiences a 5 bu/ac increase. For soybeans, the peak benefits occur in Year 3, with Field A showing a 0.5 bu/ac increase and Field B showing a 4 bu/ac increase. These findings align with the existing literature, which suggests that the optimal configuration of ecosystem service-providing areas consists of smaller patches distributed across the landscape (Bianchi and van der Werf, 2003; Zhang et al., 2010).



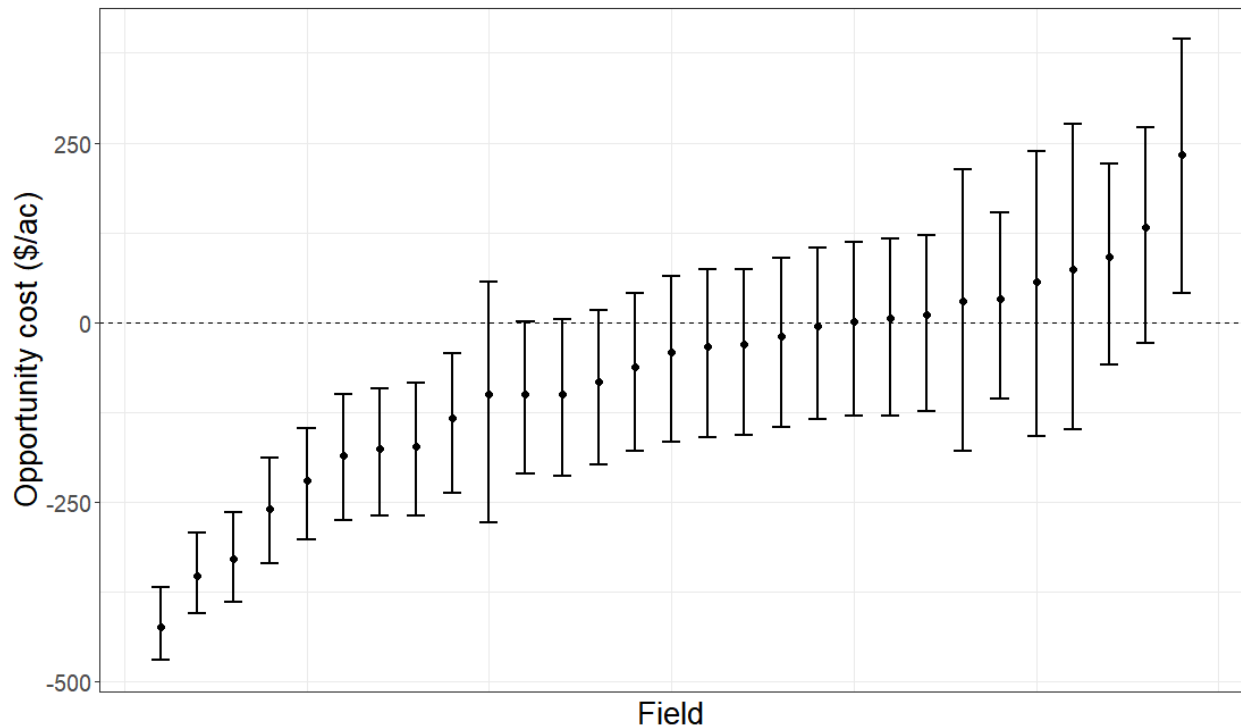
Note: Red hues indicate crop yield, with darker red higher yield. Green cells indicate conservation area.

Figure 1.11: Yield maps of Field A and B illustrate different yield effects of conservation areas

1.5.2.4 10-year conservation opportunity costs under corn-soybean rotation

The opportunity costs of precision conservation under a corn-soybean crop rotation reflect its opportunity cost under each crop, as shown above. When starting with a corn year, the ten-year conservation opportunity costs range from -\$424/ac to \$233/ac, with an average of -\$74/acre. In 19 out of the 29 fields analyzed under corn-soybean rotations, implementing precision conservation improves field profitability by strategically removing unproductive land from production. When starting with a soybean year, the differences compared to corn starting year is marginal. The results range from -\$419/ac to \$238/ac, with an average of -\$70/ac. Precision conservation improves profitability in 18 out of the 29 fields under soybean-corn rotations. In this paper, we present the results with corn as starting year. The results with soybeans as starting year

are presented in the chapter Appendix.



Note: Fields are ordered from the lowest to the highest opportunity costs of precision conservation. Error bars mark the 75th and 25th quantiles from 10,000 simulations.

Figure 1.12: Opportunity costs of 10-year precision conservation under corn-soybean rotation, for 29 Michigan fields

Input cost savings and forgone revenue within the conservation area comprise the largest components of total opportunity costs, averaging \$494/ac and \$367/ac respectively (Figure 1.13), underscoring that effectively selecting low-yielding areas is critical to making precision conservation economically viable. As examined in the previous section, positive yield effects on crops adjacent to conservation areas reduce the opportunity costs. However, the magnitude of this effect is relatively small. On average, these ecological benefits lower the annual cost by \$8.50 per acre of conservation area, with the largest observed reduction reaching \$25/ac. Estimates of opportunity costs excluding the ecological benefits are provided in the Appendix.

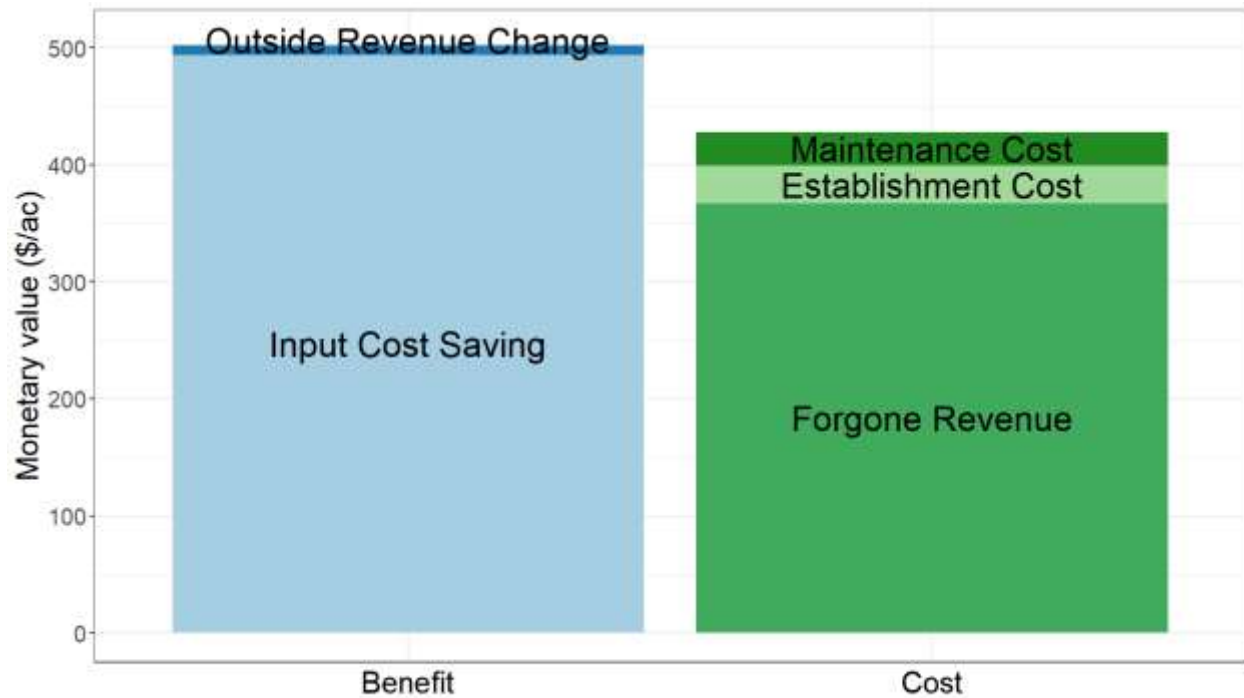
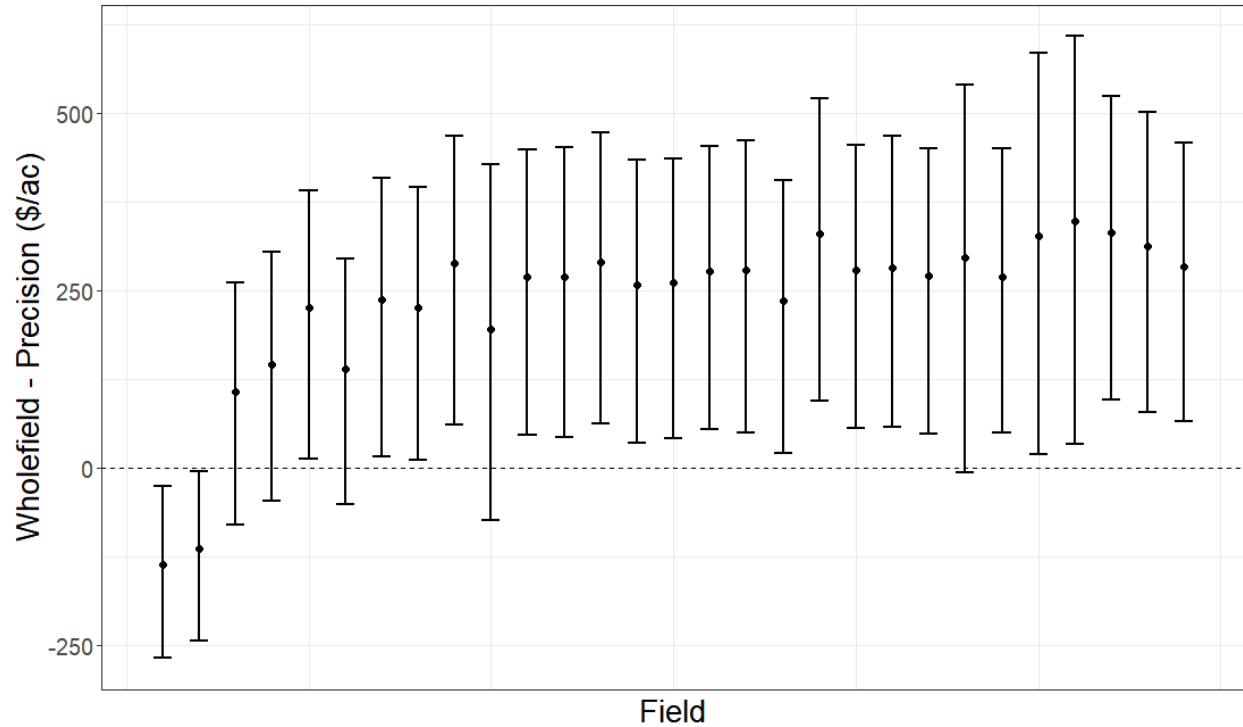


Figure 1.13: Breakdown of opportunity costs, averaged across 29 Michigan fields

1.5.2.5 Cost difference compared to whole-field conservation

Precision conservation significantly reduces conservation costs by targeting unproductive zones rather than removing entire fields from production. On average, precision conservation is \$235/ac less expensive than whole-field conservation. The cost difference ranges from -\$135/ac to \$349/ac, with only two fields where whole-field conservation is more cost-effective, due to higher implementation costs associated with precision conservation. In 27 out of 29 fields (93%), whole-field conservation is more expensive compared to precision conservation. This finding underscores the cost-saving potential of precision conservation compared to whole-field conservation, particularly when low-yielding areas are targeted effectively.



Note: Fields are ordered from the lowest to the highest opportunity costs of precision conservation. Points indicate the average of total simulations. Error bars mark the 75th and 25th quantiles from 10,000 simulations of the cost difference.

Figure 1.14: Difference in annualized opportunity cost of whole field conservation and precision conservation, simulated 10-year corn-soybean rotations, 29 Michigan fields

1.6 Discussion and Conclusion

While agricultural conservation delivers numerous public benefits, such as improved water quality, biodiversity, and carbon sequestration, it often imposes private costs on the farmers who ultimately decide whether to adopt these practices. This study focuses on the economic viability of precision conservation from the farmer's perspective. By quantifying private costs, we offer insights into where conservation can be implemented with minimal or even negative cost to producers, thereby increasing the likelihood of voluntary adoption and long-term sustainability.

Analysis of 29 commercial fields in Michigan shows that precision conservation fully covered its costs in most cases, so the opportunity costs were largely negative. Specifically, implementing precision conservation on corn-soybean rotation field over a simulated 10-year

period increases profit by \$74/ac on average. As precision conservation does not incur net costs for 65 % of these fields (19 out of 29), it is profitable even in the absence of subsidies. Compared to conventional conservation methods that convert entire fields to conservation, precision conservation is more cost-effective on 93% (27 out of 29) of fields, averaging of \$235/ac lower cost than whole-field conservation.

In precision conservation, where only low-yielding areas are designated for conservation, marginal land can typically be conserved even without subsidy, as retiring these marginal cropland areas often increases profitability. Precision conservation can be economically self-sustaining, especially when compared to conventional whole-field conservation approaches. For instance, the average Conservation Reserve Program (CRP) payment rate for the sample fields was \$140/acre in 2024 (USDA, 2024), which would incentivize conservation on only two fields in our sample if the entire field were to put into conservation. However, if the same payment were applied to precision conservation, it would be sufficient to incentivize conservation on all sample fields.

As of mid 2025, there are several subsidy programs supporting part-of-field conservation. New CRP initiatives allow part-of-field conservation through prairie strips (CP-43) and subsidies for practices such as Field Border (NRCS Code 386) and Filter Strips (NRCS Code 393). These programs compensate farmers for foregone income, with CP-43 set at 90% of standard CRP rates and NRCS programs offering compensation rates that vary by county. In counties where our sample farms are located, the average payment for prairie strip CRP is \$130/ac, and for NRCS Field Border and Filter Strips programs the payment ranges from \$41/ac to \$60/ac depending on the practices. Both programs also provide cost-sharing for establishment costs, making current subsidy levels higher than the estimated opportunity costs of conservation for most sample fields.

Conserving low-yielding areas within a field can reduce the private costs of conservation,

but its environmental benefits require further investigation. Tyndall et al. (2013) estimated the ecosystem benefits of prairie strips in central Iowa at \$359/acre (2012\$), focusing on water quality improvements such as reduced sediment, phosphorus, and nitrogen retention. Similarly, Johnson et al. (2016) calculated that riparian CRP land in Iowa's Indian Creek watershed provides ecosystem benefits valued at \$4,478–\$6,401/acre over 10 years (2013\$), accounting for flood damage reduction, water quality improvements, and greenhouse gas mitigation. Further research is needed to explore how ecosystem services differ when conservation targets low-yielding areas and only small parts of fields are converted, as well as to evaluate the associated value of the ecosystem services.

By targeting low-yielding areas and conserving land at a relatively low cost, precision conservation can serve as a cost-effective tool for promoting sustainable agricultural practices. Our results show that the opportunity costs of precision conservation are negative in most of the fields studied, indicating that retiring low-yielding cropland can often be economically beneficial for producers. In spite of these favorable private returns, subsidies may still be needed to trigger initial adoption due to behavioral and economic considerations. On the behavioral side, decision-makers may be discouraged by upfront implementation costs and may undervalue long-term benefits, which reduces the likelihood of adoption (De Groote and Verboven, 2019). Because precision conservation may generate positive externalities, such as increased biodiversity, it may be optimal to offer higher subsidies early on to overcome initial inertia and promote socially desirable levels of adoption (Langer and Lemoine, 2022).

While this study focuses on private costs, future research is needed to explore how precision conservation can target areas that maximize environmental benefits. As these strategies evolve, conservation programs could transition from offering broad subsidies for adoption to

performance-based payments that directly reward environmental outcomes, aligning public investments more closely with ecological gains.

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APPENDIX 1

In section A1.1, we present the distribution of the shares of field area allocated to conservation across 29 fields in the sample. The average share of field area converted to conservation is 16% (median: 15%), ranging from a minimum of 1% to a maximum of 66%.

In section A1.2, we present supplementary figures for section 1.4.3 Representativeness of the study, including monthly temperature and precipitation from 2020 to 2024, and soybean prices.

In section A1.3, we present yield response regression estimations under varying distance definitions. All models use pre-conservation data to establish baseline response functions, excluding any time-evolving effects of conservation areas. The estimations include 45,833 cells from 16 corn fields and 66,070 cells from 17 soybean fields. Across all specifications, the results consistently show that the impact of conservation areas becomes statistically insignificant beyond 50m from conservation areas.

In section A1.4, we present estimation results using interaction terms between proximity to woodland (*near_wood*) and the full set of age variables, rather than a simple binary indicator for the post-conservation period. This specification allows us to test for potential deer-related crop damage after conservation areas are established. The results suggest that there is no evidence of significant deer damage on crops near conservation areas.

In section A1.5, we present estimated opportunity costs of 10-year conservation under a soybean-corn rotation across 29 fields. The results are consistent with the estimates based on a rotation beginning with corn. On average, starting the crop rotation with soybeans results in opportunity costs that are approximately \$4 per acre lower than in rotations that begin with a corn crop.

A1.1 Distribution of the conservation area share

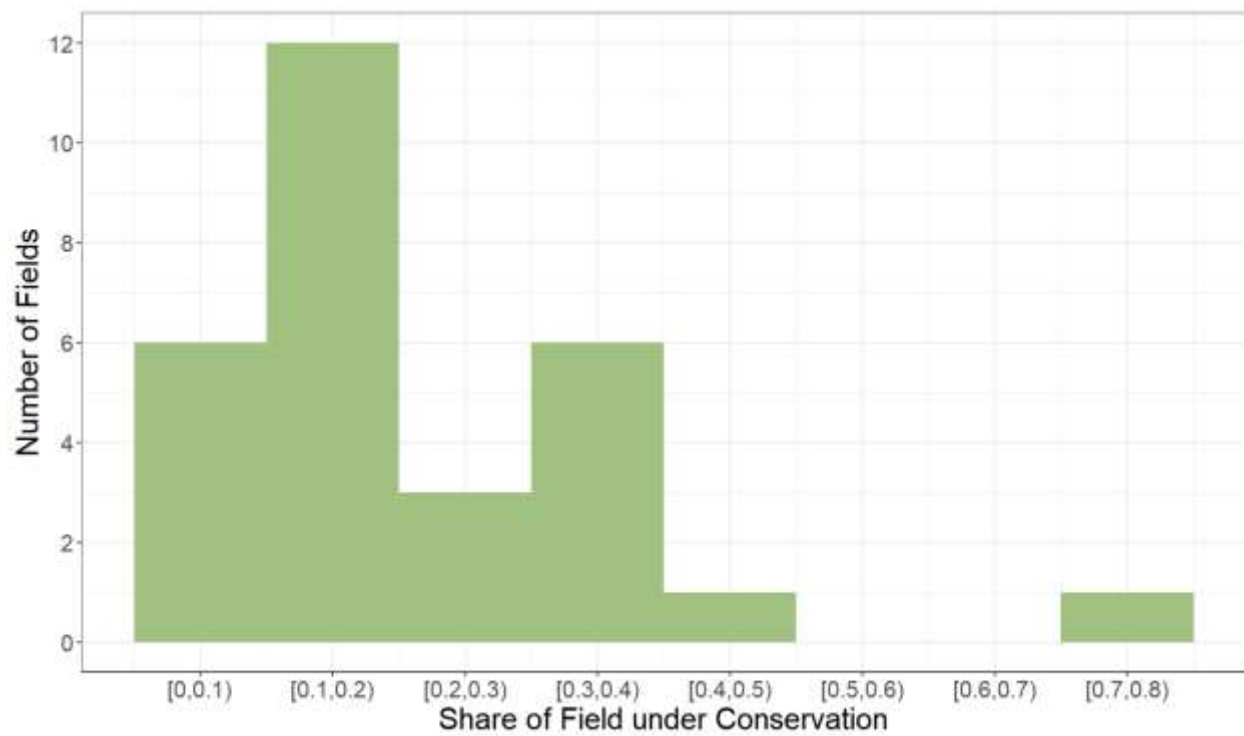
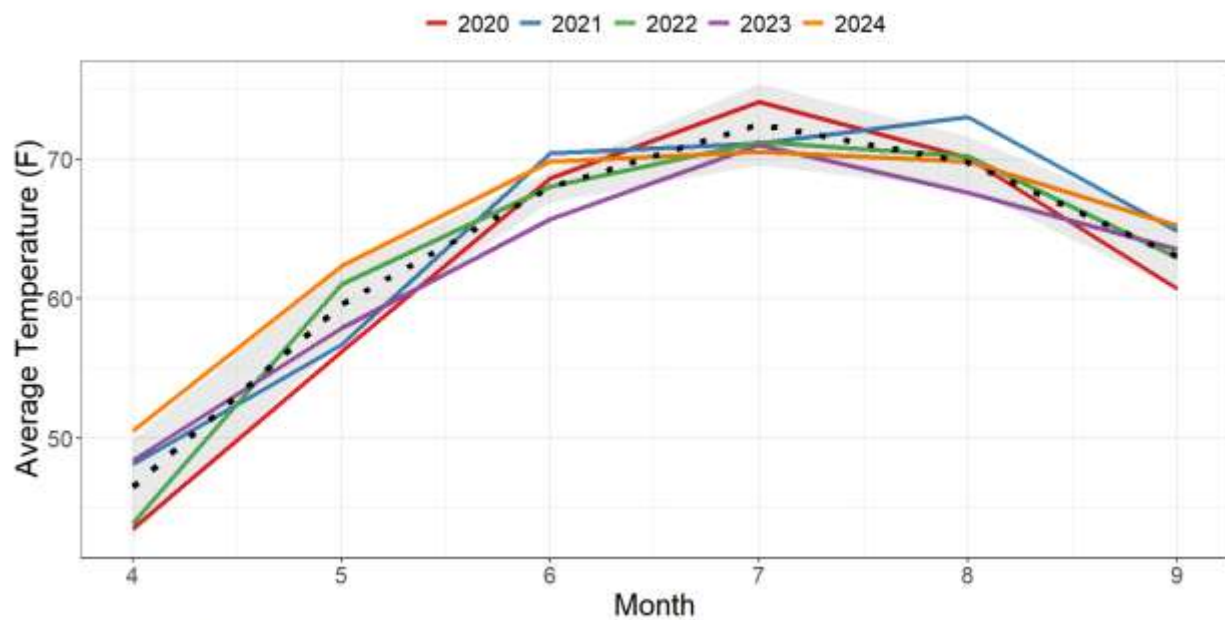


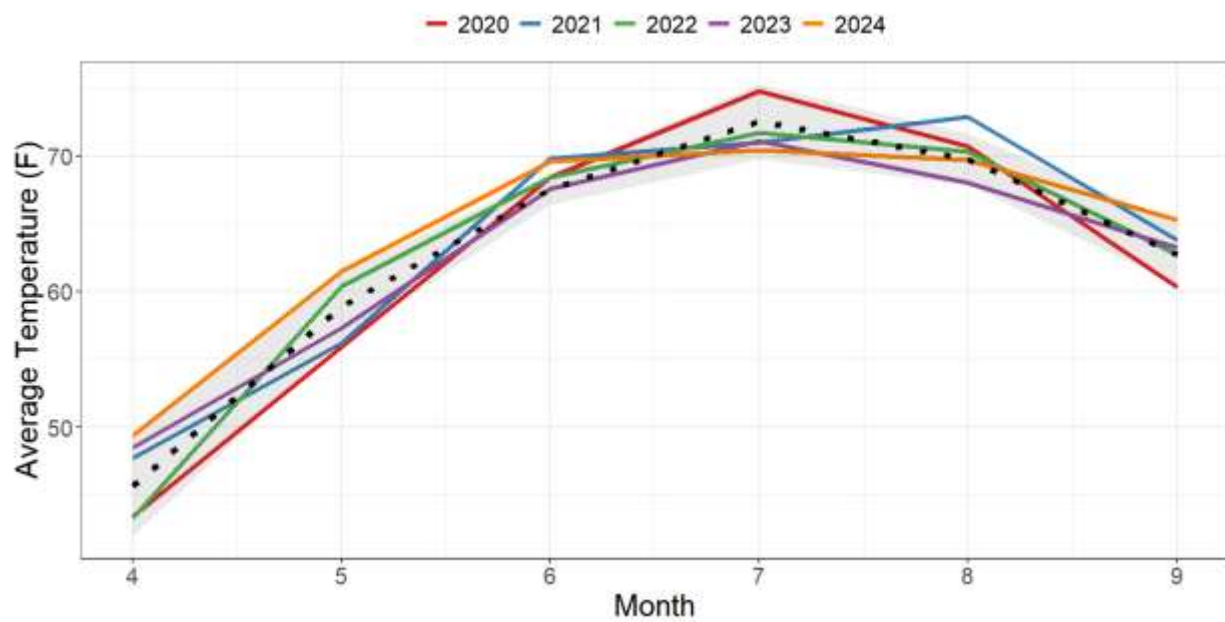
Figure A1.1: Distribution of conservation area share across 29 fields

A1.2 Weather pattern in 2020-2024

Farm A's Location by County

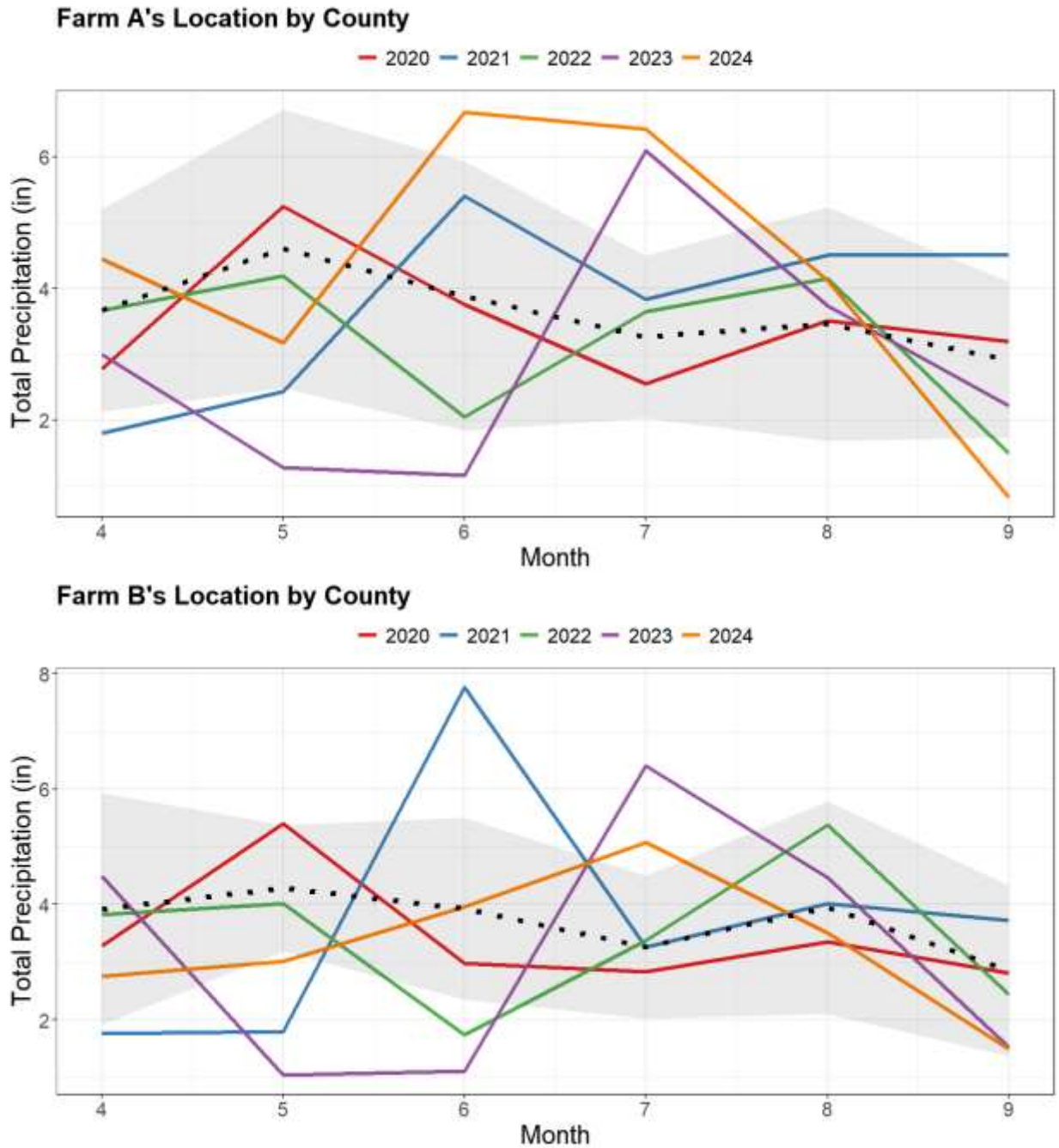


Farm B's Location by County



Note: Black dotted lines represent the past 10-year average temperature from 2010 to 2021, and the gray shaded area indicates one standard deviation from this average.

Figure A1.2: Average monthly temperature, two counties in Michigan



Note: Black dotted lines represent the past 10-year average precipitation from 2010 to 2021, and the gray shaded area indicates one standard deviation from this average.

Figure A1.3: Average monthly precipitation, two counties in Michigan

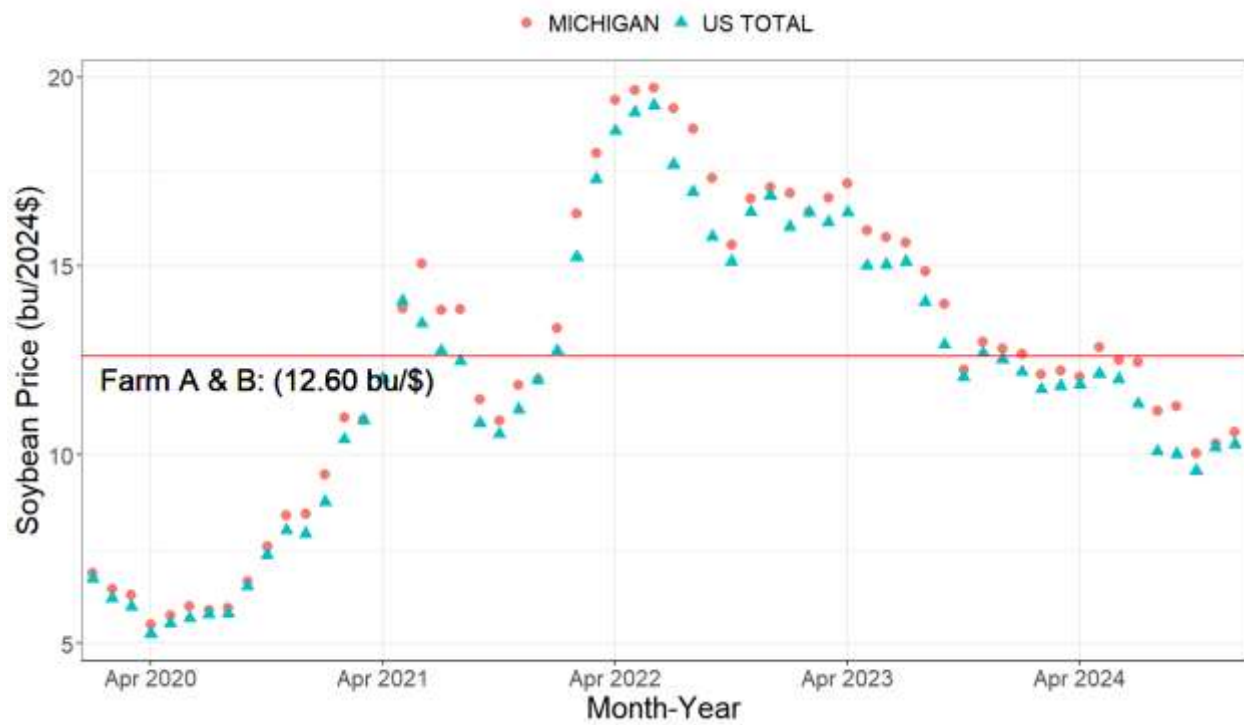
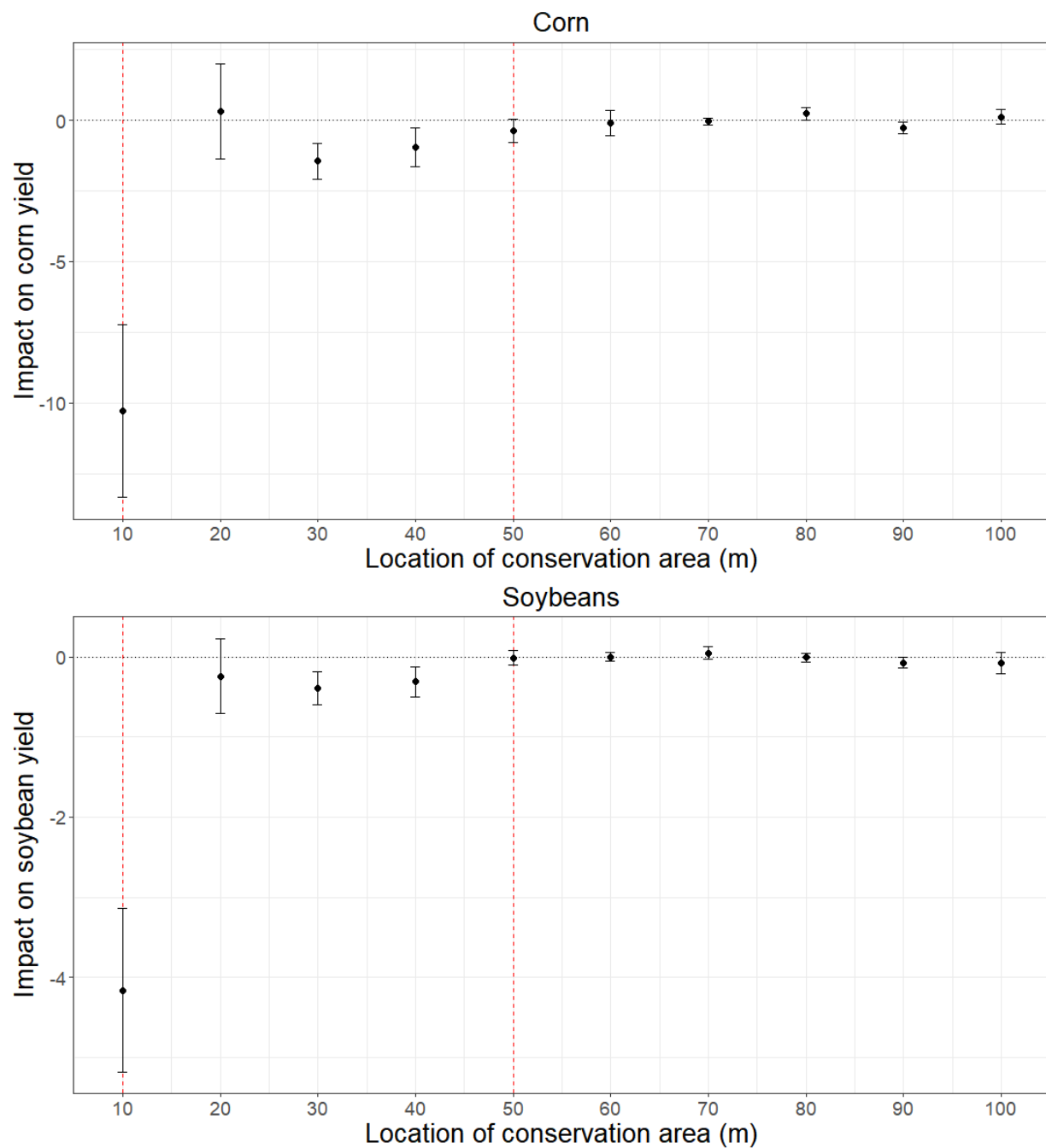


Figure A1.4: Monthly soybean prices across Michigan and the U.S average (2020-2024)

A1.3 Yield response estimations under varying distance definitions

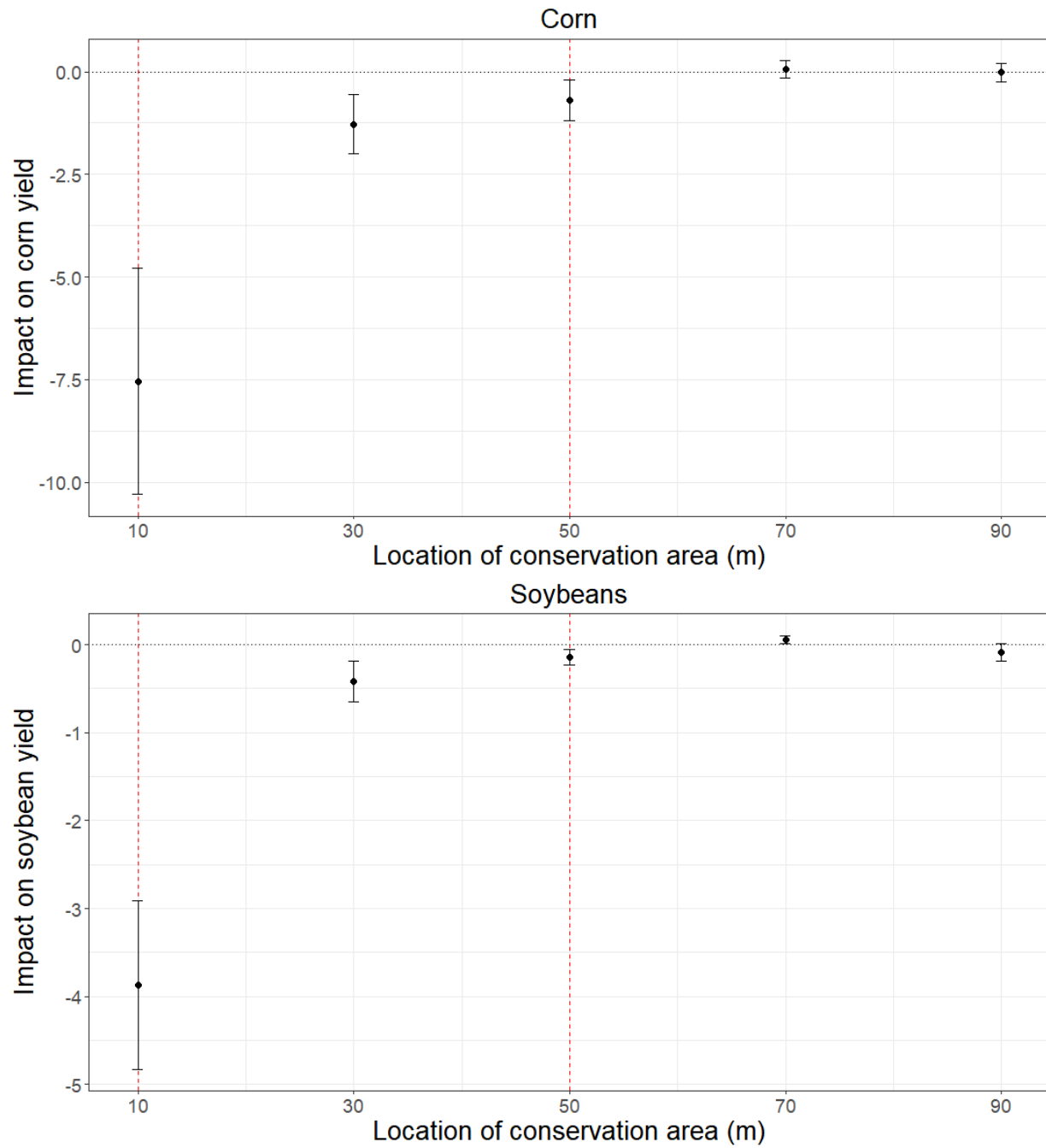
A1.3.1 Yield response estimation to conservation area size by 10m interval



Note: Error bars indicate 90% confidence intervals; standard errors are clustered at the field level.

Figure A1.5: Estimated yield impact of conservation areas using 10m distance intervals

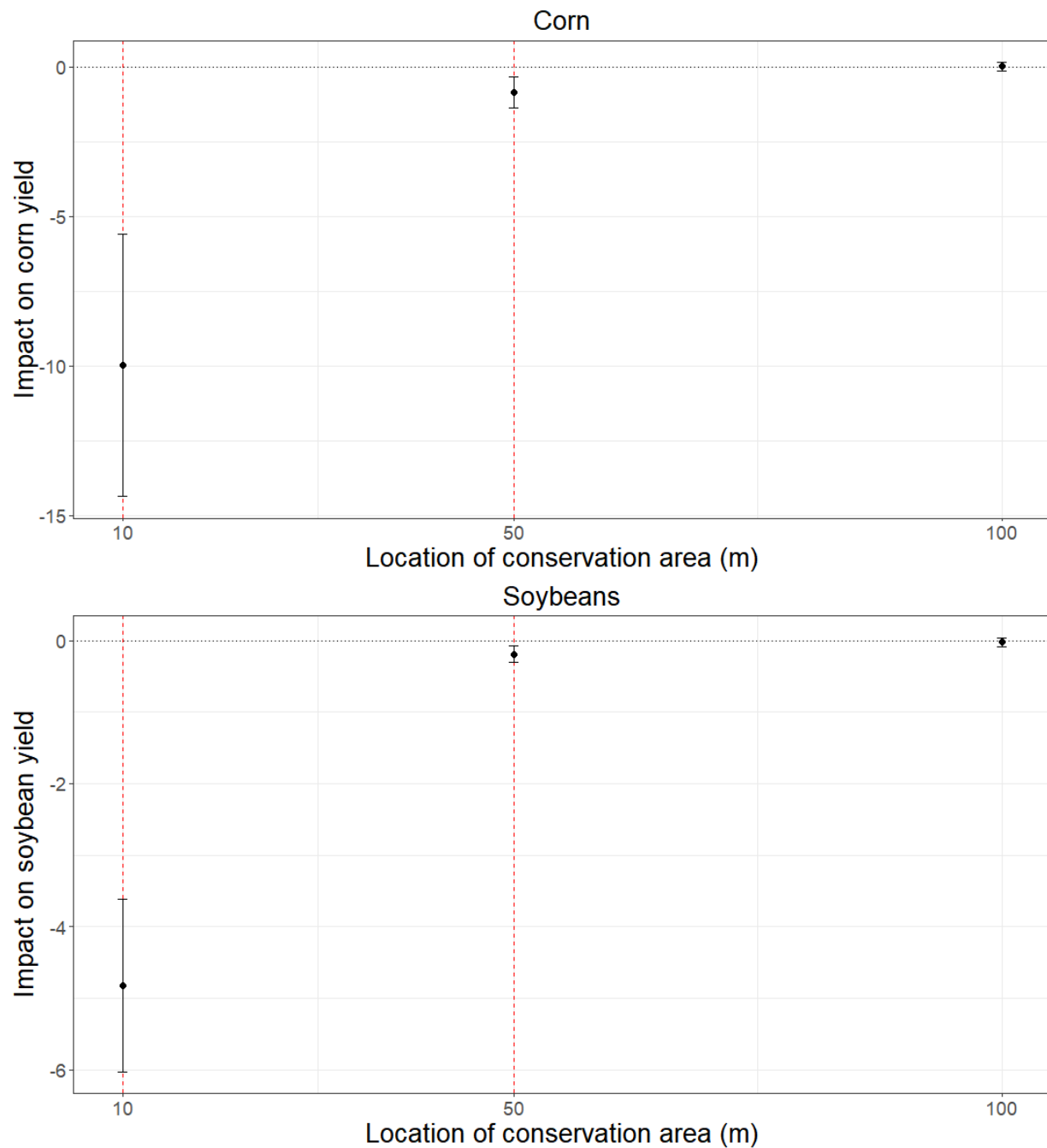
A1.3.2 Yield response estimation to conservation area size by 20m interval



Note: Error bars indicate 90% confidence intervals; standard errors are clustered at the field level.

Figure A1.6: Estimated yield impact of conservation areas using 20m distance intervals

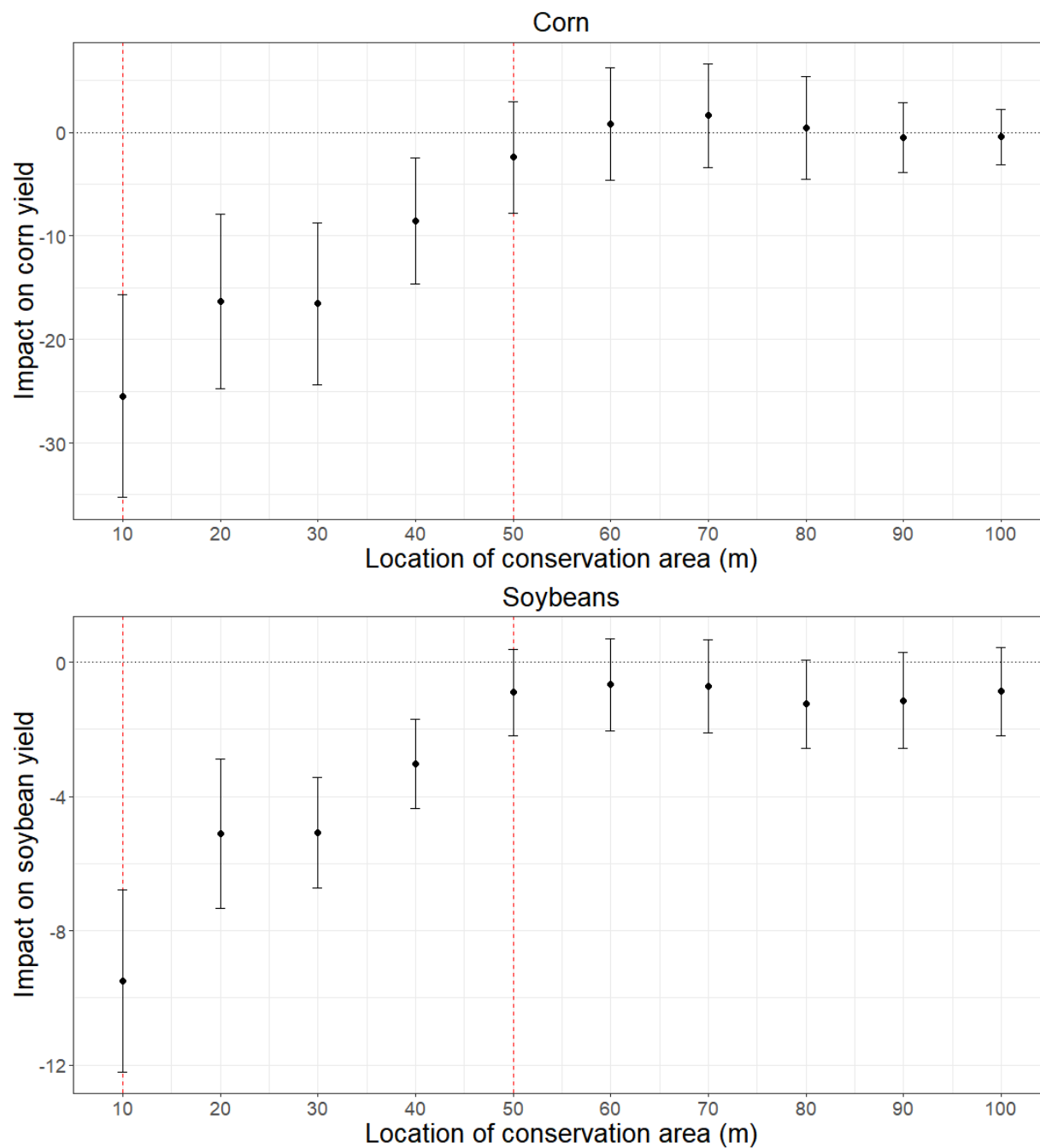
A1.3.3 Yield response estimation to conservation area size by 50m interval



Note: Error bars indicate 90% confidence intervals; standard errors are clustered at the field level.

Figure A1.7: Estimated yield impact of conservation areas using 50m distance intervals

A1.3.4 Yield response estimation using a binary distance variable to the nearest conservation area



Note: Error bars indicate 90% confidence intervals; standard errors are clustered at the field level. The reference category for the binary distance variables is set to 100 meters or greater.

Figure A1.8: Estimated yield impact of conservation areas using binary distance variables

A1.3.5 Yield response to inverse distance-weighted conservation area size

Table A1.1: Estimated corn yield effect (bu/ac) by different distance decay parameters

Variable	Conservation area definitions		
	$\frac{area}{d}$	$\frac{area}{d^2}$	$\frac{area}{d^3}$
	($\gamma = 1$)	($\gamma = 2$)	($\gamma = 3$)
Conservation area	-14.8 ** (5.2)	-570.3 *** (167.1)	-9150.0 *** (234.3)
headland	-19.8 *** (3.7)	-18.3 *** (3.5)	-18.7 *** (3.5)
edge1 (10m, outmost)	-52.8 *** (7.5)	-52.0 *** (7.8)	-55.1 *** (8.4)
edge1 (10m, outmost) · field	31.9 *** (6.7)	31.0 *** (6.8)	33.2 *** (7.0)
edge1 (10m, outmost) · developed	28.1 *** (7.0)	26.5 *** (7.1)	29.5 *** (7.6)
edge2 (10 - 20m)	-25.8 *** (6.7)	-25.7 *** (7.2)	-28.4 *** (7.8)
edge2 (10 - 20m) · field	14.6 ** (6.0)	14.5 ** (6.4)	16.4 ** (6.6)
edge2 (10 - 20m) · developed	8.9 (7.3)	8.5 (7.6)	10.8 (8.0)
Soil characteristics	Yes	Yes	Yes
Weather	Yes	Yes	Yes
R ²	0.42	0.42	0.42

***, **, * represent statistical significance at the 1%, 5%, and 10% levels and all standard errors are clustered in the field level.

Table A1.2: Estimated soybean yield effect (bu/ac) by different distance decay parameters

Variable	Conservation area definitions		
	$\frac{area}{d}$	$\frac{area}{d^2}$	$\frac{area}{d^3}$
	($\gamma = 1$)	($\gamma = 2$)	($\gamma = 3$)
Conservation area	-5.7 ** (2.1)	-198.8 *** (52.8)	-3131.0 *** (599.2)
headland	-6.1 *** (0.9)	-5.5 *** (0.9)	-5.5 *** (0.8)
edge1 (10m, outmost)	-11.8 *** (1.5)	-11.8 *** (1.6)	-12.4 *** (1.6)
edge1 (10m, outmost) · field	1.2 (1.9)	1.1 (1.9)	1.7 (1.9)
edge1 (10m, outmost) · developed	2.1 (1.4)	1.8 (1.3)	2.3 * (1.1)
edge2 (10 - 20m)	-6.6 *** (0.9)	-6.8 *** (1.0)	-7.3 *** (1.0)
edge2 (10 - 20m) · field	1.4 (0.8)	1.6 (0.9)	2.0 * (1.0)
edge2 (10 - 20m) · developed	1.8 ** (0.8)	2.0 ** (0.7)	2.3 *** (0.7)
Soil characteristics	Yes	Yes	Yes
Weather	Yes	Yes	Yes
R ²	0.56	0.56	0.56

***, **, * represent statistical significance at the 1%, 5%, and 10% levels and all standard errors are clustered in the field level.

A1.4 Yield response estimation to deer damage across years

Table A1.3: Estimated effects of near wood on yield near conservation area (bu/ac)

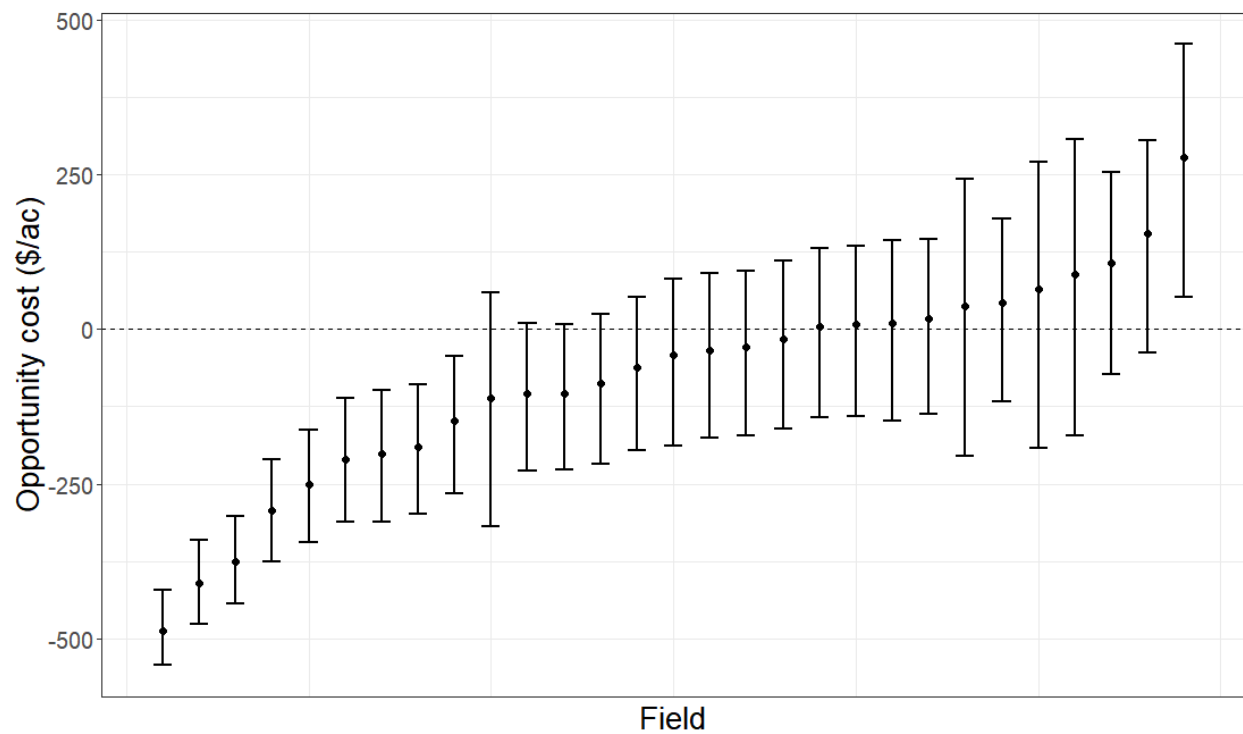
Variable	Coefficient (Std. Err.)	
	Corn	Soybeans
D10	-11.5 ** (4.7)	-4.7 *** (1.4)
D10 · Year 1	2.9 (4.9)	1.8 (2.5)
D10 · Year 2	2.9 (6.7)	5.0 ** (2.1)
D10 · Year 3	0.7 (6.9)	0.1 (2.5)
D10 · Year 4	-6.8 (11.1)	2.4 (3.2)
D10 · Year 1 · near_wood	-2.2 (4.1)	0.9 (2.2)
D10 · Year 2 · near_wood	-1.3 (4.7)	-0.4 (1.9)
D10 · Year 3 · near_wood	6.8 (7.3)	5.6 ** (2.5)
D10 · Year 4 · near_wood	19.8 (12.2)	-1.1 (3.0)
D50	-0.8 ** (0.4)	-0.2 * (0.1)
D50 · Year 1	1.3 *** (0.4)	-0.2 (0.2)
D50 · Year 2	-0.9 (0.5)	0.2 (0.2)
D50 · Year 3	-0.9 * (0.5)	0.4 (0.1)
D50 · Year 4	-0.6 (0.6)	0.02 (0.2)
D50 · Year 1 · near_wood	-0.5 ** (0.2)	-0.03 (0.2)
D50 · Year 2 · near_wood	0.6 * (0.4)	-0.1 (0.1)
D50 · Year 3 · near_wood	0.4 (0.6)	-0.2 *** (0.1)
D50 · Year 4 · near_wood	-0.4 (0.4)	0.1 (0.2)
Soil and site characteristics	Yes	Yes
Weather	Yes	Yes
Field by Year fixed effect	Yes	Yes
R ²	0.60	0.69

Table A1.3 (cont'd)

Note: ***, **, * represent statistical significance at the 1%, 5%, and 10% levels; all standard errors are clustered in the field level.

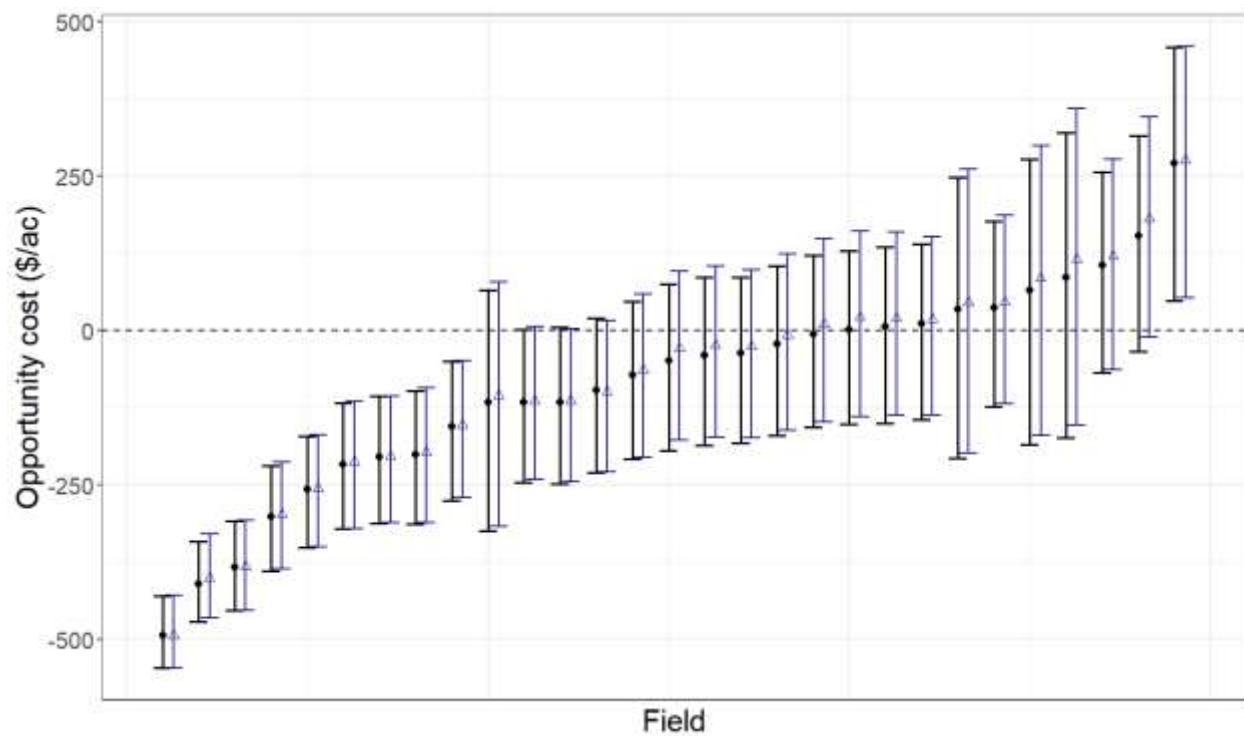
For corn, we observe statistically significant differences near woodland in years 1 and 2 within 50 meters of conservation areas; however, the yield impact is marginal at less than 1 bu/ac. For soybeans, we find a statistically significant difference in year 3. Within 10 meters of conservation areas, yields are 6 bu/ac higher near woodland, while within 50 meters, yields are 0.2 bu/ac lower. Since all yield differences are either marginal (less than 1 bu/ac) or positive, we conclude that there is no evidence of significant deer damage associated with proximity to conservation areas.

A1.5 10-year conservation opportunity costs under soybean-corn rotation



Note: Fields are ordered from the lowest to the highest opportunity costs of precision conservation. Error bars mark the 75th and 25th quantiles from 10,000 simulations.

Figure A1.9: Opportunity costs of 10-year precision conservation under soybean-corn rotation, for 29 fields



Note: Fields are ordered from the lowest to the highest opportunity costs of precision conservation. Error bars mark the 75th and 25th quantiles from 10,000 simulations. Navy error bars with triangular points indicate opportunity cost estimates excluding ecological impacts.

Figure A1.10: Opportunity costs of 10-year precision conservation with and without ecological impacts, for 29 Michigan fields

CHAPTER 2.

COMPARING PROFITABILITY OF VARIABLE RATE NITROGEN PRESCRIPTIONS

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Lee, S. W., Swinton, S. M., and Basso, B. 2025. “Comparing profitability of variable rate nitrogen prescriptions.” *Precision Agriculture*, 26(4): 1-19. <https://doi.org/10.1007/s11119-025-10256-y>

Abstract: As sensing technology and spatial data analysis become more accessible and advanced, nitrogen management is shifting from reliance on traditional soil sampling to the use of remotely sensed imagery and yield maps. While studies often compare variable rate nitrogen (VRN) fertilization to uniform rates, the profitability of information sources guiding VRN recommendations remains unclear. This study fills that gap by investigating the *ex post* profitability of variable rate nitrogen prescriptions derived from different sources of information. Utilizing 17 field-years of data from 13 Midwest fields during 2021-2023, we compared nitrogen prescriptions based on early season vegetative vigor to ones based on yield history. We developed a quasi-experimental design to mitigate non-random treatment assignment and employed complementary analytical methods – spatial linear regression and spatial discontinuity analysis, which were designed to be easily expandable and replicable. Our finding revealed a heterogeneous treatment effect, with estimated profitability ranging from \$-410 ha⁻¹ to \$350 ha⁻¹ for prescriptions based on remote sensing data compared to yield history. In 2021, when unusually favorable weather conditions continued throughout the season, in-season NDVI information proved to be more profitable. In contrast, in 2023, yield history-based prescriptions were more profitable, as early season weather patterns failed to persist. Given the way that seasonal moisture availability enables N uptake and crop yield response, these findings highlight the profitability of adapting VRN

management to seasonal weather variability by supplementing long-term yield response information from yield history with early season crop vigor from NDVI. The two information sources complement one another, depending on whether early season growing conditions persist until grain fill is complete.

2.1 Introduction

Variable rate fertilization is one of the notable advancements in modern agricultural technology, offering the potential to tailor nutrient applications to the specific needs of crops within different areas of a field. While this tailored approach can lead to increased productivity and more efficient use of inputs (Swinton and Lowenberg-DeBoer, 1998; Roberts et al., 2000; Basso et al., 2016a, b), the implementation of variable rate fertilization also introduces new costs, particularly related to the acquisition and analysis of site-specific information required to generate fertilization prescriptions. Among the various nutrients applied using variable rate fertilization, nitrogen (N) presents unique management challenges because its highly leachable nature and complexity to account for N mineralized in the soil by microbes, making it difficult to predict its availability to the crops throughout their growing cycle.

Information cost has not been a major focus in traditional uniform rate nitrogen recommendations, which primarily rely on data from state-level research experiments. Even as N recommendations from land-grant universities evolved from a nutrient replacement, yield goal approach to a maximum return to N approach (Sawyer et al., 2006), soil tests continued to be the key information source. However, the high cost of grid soil sampling began to trigger the search for alternatives (Hurley et al., 2001; Koch et al., 2004). Initially, the alternatives focused on less dense sampling schemes based on topographical or soil type zones (Fiez et al., 1994), which still relied on soil test nutrient levels to guide recommendations for variable rate fertilization. For

sidedress N applications in a growing crop like corn, spatially sampled soil and leaf tissue tests may be accurate (Tremblay et al., 2011), but they are costly and time-consuming to analyze and convert into an N application map. A less costly, more timely alternative was needed.

Two major information sources have become available to farmers to meet the need for detailed in-field, site-specific data to inform variable rate nitrogen (VRN) recommendations. The first type of information is the yield history (YH) accumulated from yield maps of past crop performance (Park et al., 2024; Khakbazan et al., 2021; Laboski and Peters, 2012). Although this type of information does not account for the current season, it reflects historical yield trends and averages. The second class of new information comes from sensing technologies. The most widely used sensing technologies in agriculture use spectral reflectance captured remotely by satellite, airplane, or drone. Converting such information into measures like the Normalized Difference Vegetation Index (NDVI) enables assessment of vegetative vigor as an indicator of nitrogen needs (Holland and Schepers, 2010; Solie et al., 2012). Remotely sensed images captured during the season provide real-time information of current crop conditions. By combining data from historical yield maps with just-in-time measures of vegetative vigor, new algorithms aim to enhance the predictive accuracy of nitrogen prescriptions (Maestrini and Basso, 2018; Pedersen et al., 2023).

Given the information costs associated with VRN, several studies have attempted to assess which information sources contribute most to farm profit. Evaluating returns to alternative information sources for VRN prescriptions has commonly been conducted through randomized field trials. These trials estimate the yield response function and assess how well information explains the optimal nitrogen rate (Hurley et al., 2001; Schmidt et al., 2011), or else they randomly assign different prescriptions across field strips to estimate the treatment effect of each information source (Stefanini et al., 2019; Boyer et al., 2011). While randomized experiments can effectively

control for confounding factors, they are costly to implement (Aggarwal, 1995; Grassini et al., 2015). Some studies have utilized crop growth simulation models to predict profitability under various scenarios (Watkinson et al., 1998; Pedersen et al., 2021). However, this approach has limitations in expanding analyses to other fields and time periods, as models may require recalibration or rely on inputs that are difficult to obtain in commercial agricultural settings. (Boote et al., 1996).

In this paper, we introduce a quasi-experimental method that utilizes nonexperimental VRN data to compare the value of two information sources for VRN prescriptions, offering an alternative approach to randomized field experiments and crop growth simulation models. To compare prescriptions based on remotely sensed data with those based on yield history, we propose two analytical methods: linear regression and spatial discontinuity analysis. We demonstrate their use on 13 fields where variable rate nitrogen was applied during 2021-23. This research addresses gaps in the current literature by 1) comparing information sources underpinning two VRN prescriptions, and 2) proposing quasi-experimental methods that are easy to replicate and expand.

2.2 Conceptual framework

Consider a farm field that is partitioned into a grid. A variable rate nitrogen (VRN) applicator allows each cell to receive a different rate of nitrogen fertilizer, based on the information provided.

In this setup, the gross margin (π) of a cell i at time t is calculated as follows:

$$\pi_{i,t} = P_Y * Y(N_{i,t}(info_t), site_i, weather_t) - P_N * N_{i,t}(info_t) - c(info_t) \quad (1)$$

A gross margin measures revenue minus selected costs. It measures the profitability of specific management actions under the *ceteris paribus* assumption that all other factors hold constant. In this case, revenue is from crop sales. The relevant selected costs include nitrogen fertilizer and variable rate nitrogen application (c) which depends on source of information ($info$). P_Y and P_N

refer to the expected prices of the crop and of fertilizer nitrogen. The crop yield (Y) is a function of fertilizer nitrogen N , site characteristics (*site*) such as soil properties and topography, and *weather*. The amount of nitrogen fertilizer applied depends on the choice of information (*info*) that guides the fertilizer recommendations.

We assume that the farmer's objective in choosing the information to acquire is to maximize the expected gross margin from the entire field. Because the yield response to applied N is conditional on annually variable weather conditions, different information sources offer distinct comparative advantages in prescribing the N rate. For example, N recommendations based on yield history reflect typical long-term conditions shaped by past weather patterns. In contrast, recommendations based on current-season vegetative vigor provide real-time crop condition up to the time of image capture. This in-season information may be more effective when current conditions deviate from historical averages and persist throughout the growing season.

In the following sections, we investigate the *ex post* profitability of two information sources by analyzing the gross margin calculated based on Equation (1), omitting the cost of variable rate nitrogen application. Results can be interpreted as the farmer's implied willingness to pay for a specific source of VRN recommendation information. As outlined in Equation (1), farmers base their fertilization decision on expected yield and prices. Note that the decision that appeared optimal before the season began (*ex ante*) may not yield the highest profit after it ends (*ex post*). The final outcome will depend on the weather and prices that come to pass. Nonetheless, final outcomes are what determine farm profitability over the long term. In this paper, we propose methods to examine the realized gross margin and compare which source of information yielded higher profit *ex post*.

2.3 Data

Data collection was undertaken in partnership with three farmers via an on-farm research approach that is gaining momentum worldwide (Lacoste et al., 2022). We utilized corn yield data from 13 fields located on two farms in Michigan and one farm in Indiana, covering the period from 2021 to 2023. The dataset includes 17 field-years, with data from 10 fields in 2021, 3 fields in 2022, and 4 fields in 2023. Due to crop rotation practices and uneven data availability, only four of the fields were included in multiple years.

Raw yield monitor data provided by participating farmers were processed to generate cleaned yield maps for each year. First, the data points located outside the field boundary were removed. Then, outliers were removed using a median-based filtering approach. For each year and crop, the median yield value was calculated after excluding data points with zero yield. Observations with yield values less than 10% of the median or greater than three times the median were excluded from the dataset (Maestrini and Basso, 2018; Maestrini and Basso, 2021). To address duplicate spatial entries, data points with identical latitude and longitude coordinates were averaged to generate a single representative. Each field was divided into a grid, where the width of each cell was set equal to the width of the fertilizer applicator. The average yield value was calculated for each grid cell. Each grid cell served as an observation unit for this analysis, with a total of 10,439 samples examined.

The nitrogen rate was varied solely for the second side-dress nitrogen application. Nitrogen fertilizers are typically applied to a corn crop at multiple times during the year, including prior to planting, at planting, and one or more times at side-dress when the crop is growing. In this on-farm experiment, the participating farmers maintained the uniform nitrogen rates for the preplant and

first side-dress applications but adjusted the nitrogen rate for the second side-dress application based on the given prescription.

The gross margin calculations utilized USDA corn prices from Michigan and Indiana (USDA, 2023a; 2023b), and the nitrogen fertilizer price was sourced from the USDA Agricultural Marketing Service's Illinois Production Cost Report (USDA, 2023b). The different corn prices reflect differences in the price basis, which nets out transportation costs between local elevators and major markets (like Chicago). Due to globally integrated supply chains, wholesale fertilizer prices tend to be more geographically uniform within a region (Bekkerman et al., 2020; USDA, 2022a). Since side-dress nitrogen was applied as 28% liquid nitrogen fertilizer, we calculated the nitrogen price by dividing the liquid nitrogen price by 0.28, under the assumption that the fertilizer's only value derived from its 28% nitrogen content. Prices for each year were adjusted to 2023 dollars using the Consumer Price Index, with the specific prices applied in the calculations presented in Table 2.1. Acknowledging that the prices of corn and nitrogen could have varied, we also conducted a price sensitivity analysis using data from the same sources covering the 25 years 2009 through 2023.

Table 2.1: Corn and nitrogen price used to calculate gross margin for base analysis

Year	Corn price (\$ kg ⁻¹)		Nitrogen price (\$ kg ⁻¹)
	Indiana	Michigan	
2021	0.19	0.17	2.13
2022	0.27	0.25	2.58
2023	0.27	0.26	1.42

Based on the theoretical model (Equation 1), we incorporated weather and site characteristics variables to control for additional factors that influence profitability. We used daily weather data at a resolution of 800m from the Parameter-elevation Relationships on Independent

Slopes Model (PRISM) dataset to construct the growing degree days (GDD)¹, total precipitation, and number of days with maximum temperature below 15°C during the growing season, spanning from April through September. The site characteristics, including available water storage and soil organic carbon at 20-50 cm soil depth, as well as the National Commodity Crop Productivity Index (NCCPI) of corn, were sourced from Soil Survey Geographic Database (SSURGO).

Descriptive statistics of the data used in the analysis are presented in Table 2.2. For the entire sample, the average corn yield is 11.7 Mg ha⁻¹, with a standard deviation of 2.9. The average gross margin from corn over the cost of the second side-dress nitrogen application is 2590 \$ ha⁻¹, with a standard deviation of 950.

Table 2.2: Descriptive statistics for key variable rate nitrogen profitability variables, 17 field-years, Michigan and Indiana, from 2021 to 2023 (n=10,439)

Variable	Average	Std. Dev.	Min	Max
Gross margin (\$ ha ⁻¹)	2590	950	-148	4240
Yield (Mg ha ⁻¹)	11.7	2.9	0.31	17.3
2 nd sidedress N rate (kg ha ⁻¹)	51.1	41	0	123
<i>Information sources</i>				
NDVI level (Low=1, Med=2, High=3)	2.15	0.71	1	3
YH level (Low=1, Med=2, High=3)	1.92	0.47	1	3
<i>Weather</i>				
Growing degree days (Apr-Sep)	1526	91	1393	1704
Total precipitation (mm; Apr-Sep)	602	68	503	746
Max temp below 15°C (days during Apr-Sep)	26.6	3.36	20	32
<i>Site characteristics</i>				
Available water storage (mm)	46.6	5.87	24.1	98.3
Soil organic carbon (g/m ²)	2277	1311	711	17226
NCCPI	0.64	0.05	0.14	0.82

¹ $GDD = \sum \text{Max}[\text{avg temp } (^\circ\text{C}) - 10, 0]$

2.3.1 Nitrogen prescriptions

Each farmer provided geo-referenced yield maps from past seasons in electronic format, which were used to construct yield history maps. Although the number of years varies among farmers, all provided a minimum of three historical yield maps. Three levels of historical yield (high, medium, and low) were established based on the average of normalized yields (Blackmore, 2000; Basso et al., 2007). For each field and year, yields were normalized, and then the multi-year mean of these normalized yields was calculated. If the average normalized yield exceeds 0.2, it was classified as high; if it falls below -0.2, it was classified as low. Values in between were categorized as medium. Additional details can be found in Maestrini and Basso (2021).

The NDVI data set measures the crop vegetative vigor using remote sensing imagery (transformed into the Normalized Differential Vegetation Index). Data for the NDVI recommendation algorithm were collected after the first nitrogen side-dress application. NDVI levels are classified into three levels (high, medium, and low) using Iso Unsupervised Classification in ArcGIS.

Both the levels of YH and the NDVI data classifications were integrated into the SALUS crop growth model (Basso et al., 2006) to generate a nitrogen rate prescription for each field. Three nitrogen fertilizer levels (high, medium, low) were prescribed for each field as described in Basso et al., (2011, 2016a, b). The specific rate of nitrogen at each level varies by field. From the SALUS model, a single prescription was generated for each field. Depending on circumstances, the prescription aligned with either NDVI or YH information, or both when NDVI and YH provided the same recommendation. All prescriptions were provided to farmers free of charge.

2.4 Methods

From a single set of grid cell based prescriptions, we generated pseudo-treatment variables by leveraging the fact that the prescription algorithm integrated two sets of information, NDVI and YH. Given that the treatment was not randomly assigned, we developed a quasi-experimental design employing two methodologies to control for confounding factors that may affect gross margin as well as for potential selection bias into each treatment.

The cost of generating nitrogen prescriptions and associated information was omitted in order to calculate the value added by each information source, independent of any assumed fee structure. By excluding associated costs, such as marketing margins or service fees that commercial agricultural service providers may charge, the value of the information itself is isolated. Under this assumption, the estimated contribution of each information source to gross margin can be interpreted as the maximum amount a farmer would be willing to pay for a prescription based on that source.

2.4.1 Creation of pseudo-treatment variables

As all the nitrogen prescriptions given to farmers are based on the combination of NDVI and YH, we generated treatment variables according to the correspondence between each information source and the nitrogen rate applied in each cell. For each treatment, we created a binary variable taking the value of 1 if the rate was prescribed following that information source or zero otherwise. For example, if the cell received the high nitrogen rate and its NDVI level was also high, the value of the NDVI treatment variable for that cell is 1. If the same cell had a high YH level, then its YH treatment variable also equals 1. However, if the cell received the low nitrogen rate and its YH was low but its NDVI level was high, the value of the NDVI treatment variable for that cell is 0 while the value of the YH treatment variable is 1.

Figure 2.1 describes two examples of how the pseudo-treatment variables are generated. Cell A, which has high NDVI and medium YH, received high nitrogen rate. So its NDVI treatment variable is 1 because its nitrogen recommendation is consistent with NDVI information, whereas its YH treatment variable is 0 because YH alone would not have given a high nitrogen recommendation. On the other hand, Cell B received medium nitrogen rate and both of its NDVI and YH levels are medium. Therefore, the NDVI and YH treatment variables are both 1.

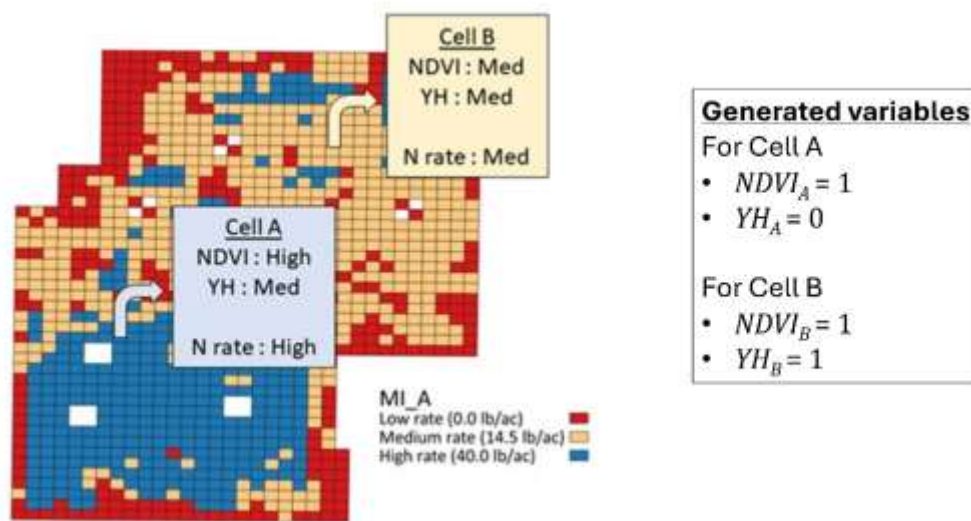


Figure 2.1: Example of pseudo-treatment variable creation

2.4.2. Estimation strategies

Although we can generate pseudo-treatment variables, their non-random assignment calls for care in statistically estimating the treatment effect. Profitability is influenced by numerous factors such as soil characteristics, topography, and plant vigor, all of which also influence VRN prescriptions. These shared factors create many confounding variables that can impact both treatment assignments and profitability. Non-random treatment assignment increases the likelihood of systematic differences in these confounding variables between the treatment and control groups, affecting profitability beyond the treatment itself. For example, if a prescription uses yield history

to target high-yield areas, cells treated based on yield history will inherently differ in characteristics from untreated cells, as they have historically produced higher yields in the past.

We propose two estimation strategies to control for the confounding effects of nonrandom treatment assignment: linear regression and spatial discontinuity analysis. Given that the gross margin is closely related to applied nitrogen rate, site characteristics, and weather conditions, the proposed estimation strategies control for the effects other than the choice of information utilized for prescription and allows us to examine the treatment effect while holding all other factors equal. Linear regression incorporates covariates to capture non-treatment effects on gross margin, while spatial discontinuity analysis leverages the fact that contiguous cells can be assumed to have similar characteristics.

2.4.2.1 Linear regression

The profitability of each treatment is estimated with the following equation.

$$\pi_{it} = \sum_{FieldYear=j} (\beta_{1j}NDVI_{it} + \beta_{2j}YH_{it}) * FieldYear_{it} + \gamma_1 X_{it} + \gamma_2 Field_i + \gamma_3 Year_t \quad (2)$$

For each grid cell i within field j , the dependent variable is the gross margin of corn revenue minus the cost of nitrogen fertilizer. $NDVI_{it}$ and YH_{it} indicate the NDVI treatment and YH treatment respectively. The effects of the prescription information sources are interacted with field-year indicator variable ($FieldYear_i$), representing the differential impacts of the information contingent on field and year. X_{it} is a vector of all confounding variables that are specific to each cell and year, including NDVI and YH levels, total applied nitrogen rates, site characteristics, and weather conditions. γ_1 is a vector of coefficients capturing the correlation between confounding variables and gross margin. $Field_i$ represents a binary variable to identify each field controlling for all field-specific effects such as the farmer, soil type, and location with γ_2 representing their

effects on gross margin. $Year_i$ represents year fixed effects, capturing factors that impact all fields uniformly within a given year, such as weather patterns and market conditions and γ_3 represents the year effects on gross margin.

The effects of the NDVI treatment and YH treatment of field-year j are represented by the coefficients β_{1j} and β_{2j} respectively in Equation (2). The standard errors are clustered by field to account for the more highly correlated random errors that prevail within a field compared to between fields. This method is characterized by its ease of implementation, its capacity to control for the effects of non-treatment variables that may be correlated with the gross margin, and its ready statistical interpretation.

2.4.2.2 Spatial discontinuity analysis

This method compares the gross margin responses of adjacent grid cells under the assumption that all site characteristics are virtually identical except for the information used to make the nitrogen prescription. Specifically, we focus on comparing pairs of cells that received the same nitrogen rate. By doing so, we isolate the impact of information choice on gross margin, as any difference observed between adjacent cells with different information choices can be attributed to the information used for nitrogen prescription.

This approach bears resemblance to the spatial regression discontinuity design (Keele and Titiunik, 2015), which also involves the consideration of spatial factors. However, we cannot classify this method as the spatial regression discontinuity design because the spatial factor alone in this approach does not dictate the treatment assignment. Rather, the spatial component is only used as the basis for assuming similarity between two adjacent cells.

We consider “rook” neighbors, which are grid cells that share a side of non-zero length. As a robustness check, results using “queen” neighbors, grid cells that share either a side or a corner,

are presented in the Appendix. Cell i is defined as a YH treated unit and cell j is defined as an NDVI treated unit if the following conditions are met: 1) they have received the same nitrogen rate, 2) cell i is prescribed following YH level, 3) cell j is prescribed following NDVI level, and 4) the YH and NDVI levels of cells i and j do not match. The fourth condition ensures that we exclude cases when both the NDVI and YH method prescribe the same nitrogen rate. We then compare the yield averages of two samples using a paired t-test by field-year.

This method uses two tactics to address the limitations of linear regression that there may be unobserved heterogeneity, and the treatment assignment is not random. First, it avoids the problem of capturing all relevant variables by assuming that closely located cells have only marginal differences in site characteristics. Second, treatment assignments are independent of other cell characteristics.

2.4.2.3 Price sensitivity analysis

In order to evaluate the robustness of our findings to deviations in market prices from those that prevailed in 2021-23, we conducted a price sensitivity analysis. We evaluated the extremes of the corn to nitrogen price ratio over the past 15 years. Prices for Michigan corn, Indiana corn, and nitrogen from 2009 to 2024 are adjusted to 2023 dollars using the consumer price index (BLS, 2024). From these two series of adjusted prices, we selected the maximum and minimum values from each series, forming two sets of prices: one with maximum corn and minimum nitrogen price (the minimum $\frac{P_N}{P_Y}$), and another with minimum corn and maximum nitrogen prices (the maximum $\frac{P_N}{P_Y}$) (Table 2.3).

Table 2.3: Prices used for sensitivity analysis (in 2023 dollars)

		Minimum	2021	Maximum
Nitrogen price (\$ kg ⁻¹)		0.99	1.23	2.27
Corn price (\$ kg ⁻¹)	Michigan	0.15	0.23	0.31
	Indiana	0.16	0.24	0.34
Price ratio ($\frac{P_N}{P_Y}$)	Michigan	0.06	0.10	0.27
	Indiana	0.05	0.09	0.26

The N fertilizer to corn price ratio utilized in the sensitivity analysis spans from 0.05 to 0.27, representing scenarios where the nitrogen price is 5% of the corn price to cases where the nitrogen price exceeds 25% of the corn price. The prices used for this sensitivity analysis align with the range specified in *Tri-State Fertilizer Recommendations* (Culman et al., 2020). These recommendations indicate suggested nitrogen rates for Michigan within a ratio range of 0.05 to 0.20, and for Indiana, within a ratio range of 0.08 to 0.33 (Camberato et al., 2021).

We then performed regression and spatial discontinuity analysis using these newly selected prices, following the same methodology as before. We examined the outcomes across fields to assess the robustness of the results.

2.5 Results

2.5.1 Linear regression results

In the estimated model for the linear regression method, the outcome variable is the gross margin (\$ ha⁻¹). We control for variables that assign the treatment, NDVI and YH levels, as well as field fixed effect, applied nitrogen rate, growing degree days, total precipitation, days with maximum temperature below 15 °C, and site characteristics: available water storage, soil organic carbon, and the National Commodity Crop Productivity Index (NCCPI) of corn (as a measure of site soil quality). Standard errors are clustered at the field, to account for unobserved correlation within a field. The description of the complete estimated model is presented in the Appendix.

The results (Table 2.4) show how nitrogen prescriptions based on different information sources impact average gross margins. The last column presents the relative effectiveness of NDVI based prescriptions compared to those based on YH, where the positive value indicates that NDVI based prescription resulted in a higher gross margin than YH. In 2021 and 2022, no clear pattern emerged regarding which information source was more effective. In 2023, YH outperformed NDVI in three out of four fields and in the other field, while in the remaining field, the difference between NDVI and YH was not statistically significant.

Table 2.4: Linear regression estimated treatment variable coefficients (\$ ha⁻¹) by prescription method

Year	Farm	Field	Coefficient (clustered standard error)		NDVI-YH (clustered std. err.)
			NDVI	YH	
2021	MI_A	1	68 *** (20)	-110 * (60)	178 *** (63)
		2	663 *** (50)	313 *** (118)	350 *** (103)
		3	323 *** (28)	105 *** (18)	218 *** (38)
	MI_B	1	-148 *** (25)	-68 ** (33)	-80 *** (20)
		2	23 (55)	-8 (40)	30 (48)
		3	-95 (105)	-13 (58)	-83 (88)
	IN_A	4	-253 *** (78)	-93 ** (28)	-160 ** (65)
		1	-165 *** (60)	93 *** (20)	-258 *** (73)
		2	-90 * (53)	-160 *** (18)	70 (60)
		3	25 (-75)	28 (28)	-1 (65)
2022	MI_B	5	-78 *** (13)	-30 *** (15)	-48 *** (18)
		6	5 (13)	-63 *** (18)	68 *** (13)
		7	-10 (10)	-25 ** (10)	15 (13)
2023	MI_A	2	-70 ** (33)	-10 (70)	-60 (90)
		1	-33 (33)	123 ** (58)	-155 *** (55)
	MI_B	2	-98 (95)	210 *** (38)	-308 *** (80)
		3	-33 (60)	378 *** (58)	-410 *** (40)

***, **, * indicate significance level at less than 1%, 5%, and 10% respectively.

2.5.2 Spatial discontinuity design results

We sampled adjacent pairs that received the same nitrogen rate but differed in their prescription information sources. A total of 2013 pairs meet the comparison criteria, although the number of pairs varies across fields. Table 2.5 presents the average gross margins of cells that received nitrogen based on NDVI and YH. The last column shows the difference in gross margin between NDVI based prescription and YH based prescriptions, where positive values indicate that NDVI resulted in higher gross margins than YH. In 2021 and 2022, using NDVI led to higher gross margin than YH in five fields, while the remaining fields showed no statistically significant difference between NDVI and YH. In 2023, YH was more effective than NDVI in one field, while in the other three fields, the difference was not statistically significant.

Table 2.5: Spatial discontinuity average gross margin by information source: Paired t-test results

Year	Farm	Field (number of compared pairs)	Average gross margin (\$ ha ⁻¹)		NDVI – YH (std. err.)
			NDVI	YH	
2021	MI_A	1 (326)	1913	1875	38 ** (18)
		2 (64)	2198	2145	53 (83)
		3 (133)	2863	2720	143 *** (33)
	MI_B	1 (219)	3688	3645	43 *** (15)
		2 (200)	3493	3428	65 *** (13)
		3 (31)	1028	1098	-28 (70)
		4 (219)	2940	2900	40 ** (10)
	IN_A	1 (111)	3268	3298	-28 (23)
		2 (11)	3058	3113	-58 (125)
		3 (80)	3218	3258	-38 (35)
2022	MI_B	5 (179)	2803	2823	-20 (13)
		6 (170)	2853	2828	25 * (15)
		7 (157)	2963	2693	20 (18)
2023	MI_A	2 (31)	1083	1270	-185 *** (53)
		1 (31)	878	918	-40 (38)
	MI_B	2 (49)	888	898	-10 (20)
		3 (12)	1028	1098	-28 (70)

***, **, * indicate significance level at less than 1%, 5%, and 10% respectively.

2.5.3 Sensitivity analysis results

Within the range of prices during 2009-23, the results are robust to variations in corn and nitrogen prices. When we use the minimum nitrogen price and maximum corn price (minimum $\frac{P_N}{P_C}$), the

differences in gross margin effects between NDVI and YH increase. Conversely, with the maximum nitrogen price and minimum corn price (maximum $\frac{P_N}{P_C}$), the differences between NDVI and YH decrease. However, the difference in relative prices was never sufficient to alter which information source contributed to the higher gross margin. Detailed results are presented in Appendix.

2.6 Discussion

2.6.1 Temporal weather patterns and the value of agronomic information

The effects of different information sources on gross margins are analyzed using two analytical approaches: linear regression and spatial discontinuity analysis. In this discussion, we focus on cases where both methods yielded consistent results. The linear regression method compares gross margin across the entire sample while controlling for the effects of covariates. However, potential unobserved factors influencing both gross margins and treatment assignment may still introduce bias, given the non-random nature of treatment. Spatial discontinuity analysis, which limits the comparison to the neighboring cells, mitigates some of these concerns. However due to the small number of comparable samples, the standard errors for the spatial discontinuity estimates are larger than those in the linear regression, making the results more conservative in determining which information source is more effective. To assess the robustness of our findings, we compare the results from both methods. Considering cases where at least one method indicated statistically significant relative effectiveness, linear regression and spatial discontinuity analysis produced consistent results in 65% of the fields (11 out of 17 cases).

In Michigan Farm A, NDVI outperformed YH in three out of four cases, but all of these cases occurred in 2021. For Field 2, NDVI performed better in 2021, whereas YH performed better in 2023, demonstrating intertemporal variation. This shift was also observed in Michigan Farm B.

In 2021, there was no statistical difference between NDVI and YH in all four fields. However, in 2023, YH outperformed NDVI in three of the four fields with available data. In 2022, no consistent pattern emerged regarding which method was superior, as it involved different fields. Similarly, on the Indiana farm in 2021, YH performed better in one out of three fields, while in the other two fields, there was no statistically significant difference between the two methods.

Table 2.6: Summary of results from regression and spatial discontinuity analysis

Year	Farm	Field	Linear Regression	Spatial Discontinuity	Consistent Results
2021	MI_A	1	NDVI ***	NDVI **	NDVI
		2	NDVI ***	NDVI	NDVI
		3	NDVI ***	NDVI ***	NDVI
	MI_B	1	YH ***	NDVI ***	-
		2	NDVI	NDVI ***	NDVI
		3	YH	NDVI	-
		4	YH **	NDVI **	-
	IN_A	1	YH ***	YH	YH
		2	NDVI	YH	-
		3	YH	YH	-
2022	MI_B	5	YH **	YH	YH
		6	NDVI ***	NDVI *	NDVI
		7	NDVI	NDVI	-
2023	MI_A	2	YH	YH ***	YH
	MI_B	1	YH **	YH	YH
		2	YH ***	YH	YH
		3	YH ***	YH	YH

***, **, * indicate significance level at less than 1%, 5%, and 10% respectively.

The heterogeneity in the effectiveness of different information sources correlates with how the weather and subsequently crop conditions diverge from historical trends. The sample years (2021–2023) represent a range of variability in weather conditions. In 2021, corn yields in Michigan and Indiana marked record highs, owing to favorable weather conditions, causing yields to diverge positively from the historical trend. In 2022 and 2023, corn yields in Michigan came back to the historical trend due to dry conditions (Figure 2.2).

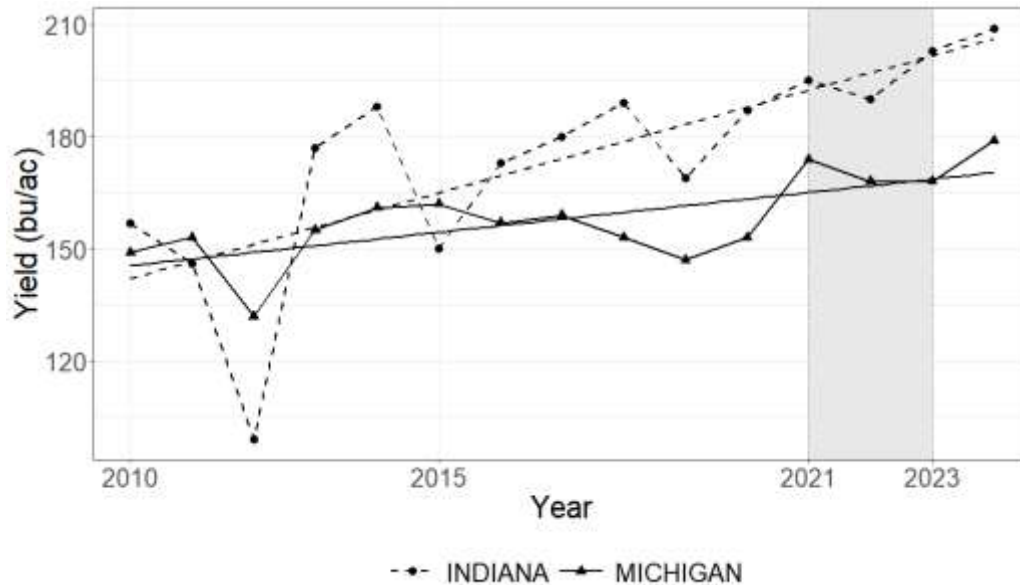
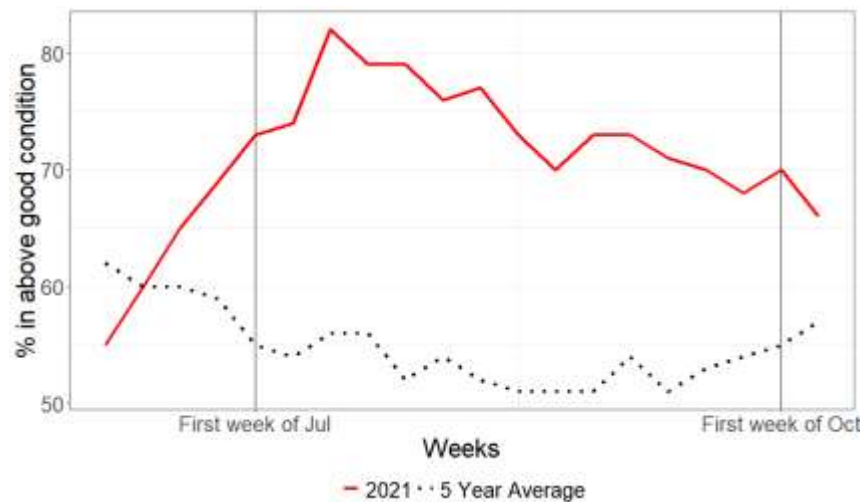


Figure 2.2: Annual corn yield in Indiana and Michigan, 2005-24 (Source: USDA)

NDVI-based nitrogen prescriptions were more profitable than those based on yield history (YH) in 2021, whereas YH outperformed NDVI in 2023; no clear pattern was evident in 2022. NDVI, which provides in-season information on vegetation growth, proved to be more effective in 2021 by enabling higher nitrogen application under favorable weather conditions, resulting in greater gross margins compared to YH-based prescriptions. Figures 2.3 and 2.4 illustrate weekly corn crop conditions in Michigan during 2021 and 2023, showing the percentage of planted corn rated as good or excellent. The NDVI image was collected after the first side-dressing, around the first week of July. In 2021, crop conditions at that time were significantly better than the five-year average and remained favorable throughout the season (Figure 2.3). Consequently, in-season information allowed for more responsive nitrogen management, outperforming historical data in optimizing input use.

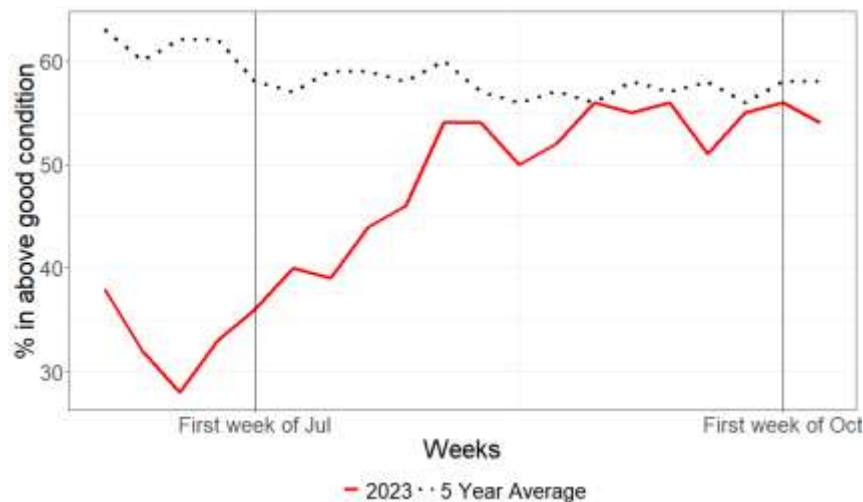
In contrast, YH-based prescriptions were more effective in 2023 by reducing excessive nitrogen applications, leading to higher gross margins than NDVI-based prescriptions. When in-season data was collected, crop conditions were below the five-year average due to early-season

drought (Figure 2.4). However, as the season progressed, weather conditions improved, and crop conditions converged to historical norms. In 2023, nitrogen prescriptions based on early-season NDVI underestimated crop needs, as actual crop conditions later aligned more closely with historical averages.



Data source: USDA QuickStat (<https://quickstats.nass.usda.gov/>); figure reproduced by the author

Figure 2.3: Weekly crop conditions in 2021



Data source: USDA QuickStat (<https://quickstats.nass.usda.gov/>); figure reproduced by the author

Figure 2.4: Weekly crop conditions in 2023

2.6.2 Potential measurement error from yield data cleaning

Yield monitor data cleaning is an important step in preparing spatial gross margin analysis. Yield data collected from commercial combines often contain measurement errors arising from factors such as GPS signal drift, operational errors, and flow delays between crop intake and grain flow measurement (Blackmore and Moore, 1999; Sun et al., 2013). While these sources of error are well recognized, perfect correction is particularly challenging in commercial production settings, where detailed calibration procedures and machine-specific metadata are often unavailable. Our cleaning process addresses these challenges pragmatically by removing extreme outliers based on data-driven thresholds and assuming flow delay is consistent within each field.

We acknowledge that this approach may not eliminate all sources of measurement errors. However, because these errors are consistent within fields and not systematically correlated with treatment assignment, they do not bias our estimation of treatment effects (Hausman, 2001). Any remaining measurement error in yield may only increase standard errors and reduce statistical significance (Hausman, 2001). Moreover, since our analysis focuses on relative differences in gross margins rather than absolute values, any residual measurement error in the yield data would not compromise the validity of our conclusions.

2.7 Conclusion

Variable rate nitrogen (VRN) application is a promising method for reducing excess nitrogen fertilizer and mitigating environmental pollution. However, the need for farmers to choose among new forms of timely and spatially detailed information to calculate recommended fertilizer rates calls for a critical evaluation of their respective contributions to profitability. While several methods based on low-cost and site-specific information sources, such as yield maps and remotely sensed images have been proposed for N rate prescription, comparative analyses of their

profitability remain scarce in the literature. Existing studies often rely on data from randomized field experiments, which hinder our ability to compare prescriptions.

To address this gap, we proposed two methods that compare the profitability of nitrogen fertilizer prescriptions based on remotely sensed imagery and yield history using non-randomized data. We utilized gridded yield maps from 17 field-years from 13 commercial corn fields across three years. By using cells from gridded yield maps as a unit of observation, we can incorporate within-field variation more effectively, allowing for higher statistical efficiency. The estimated profitability of prescriptions based on NDVI compared to yield history ranges from \$-410 ha⁻¹ to \$350 ha⁻¹, indicating a heterogenous treatment effect across fields.

The effectiveness of nitrogen prescription methods varied across years, with NDVI-based prescriptions proving more profitable when early season crop growth deviated from the historical mean in a manner that persisted. This occurred in 2021, when unusually favorable early season conditions continued for the rest of the growing season. By contrast, yield history (YH)-based prescriptions were more profitable when early season conditions failed to deviate from the norm or failed to carry on, as was the case in 2023. In 2021, favorable early-season crop conditions that persisted allowed NDVI to optimize nitrogen application, leading to higher gross margins. By contrast, in 2023, early-season drought conditions caused NDVI-based prescriptions to underestimate nitrogen needs, whereas YH-based prescriptions, which accounted for long-term trends, resulted in more efficient nitrogen use and higher profitability. Given the way that seasonal moisture availability enables N uptake and crop yield response, these findings highlight the profitability of adapting VRN management to seasonal weather variability by supplementing long-term yield response information from yield history with early season crop vigor from NDVI. The

two information sources complement one another, depending on whether early season growing conditions persist until grain fill is complete.

This finding underscores how the value of information can be context-dependent. In zones where yield is unstable, varying significantly from year to year, spatial yield patterns are strongly driven by soil-climate interaction (Maestrini and Basso, 2021). In such context, the better predictor of yield can shift depending on annual weather conditions. Maestrini and Basso (2018) demonstrated that historical yield maps were more reliable in stable zones, areas where yield is relatively consistent across years, while NDVI performed better in unstable zones, where yield is more sensitive to annual weather variation. These results emphasize the need to strategically integrate different information sources to better account for both spatial and temporal variability in crop performance.

This paper contributes to the literature in two ways. First, we develop a quasi-experimental method, using the data from an on-farm experiment and apply two analytical methods: linear regression and a novel application of spatial discontinuity analysis. These methods are easily expandable and replicable, allowing other researchers to apply and build upon our approach in diverse agricultural contexts. Second, we compare the effects of different VRN prescriptions on crop yields, a topic that has been relatively unexplored in existing research.

This study provides an exploratory analysis based on 17 field-years of data, suggesting three avenues for future research. First, expanding the dataset to include more years and fields would allow for a more comprehensive assessment of the long-term profitability of different information sources under varying weather conditions, facilitating the identification of specific weather patterns that drive profitability. Second, the profitability analysis could be deepened by incorporating a range of possible information costs. The current gross margin over fertilizer costs

provides the necessary base of measuring potential ability to pay for YH and NDVI information. Additional research that explores information costs would contribute further toward assessing profitability of VRN prescriptions. Third, the more complete profitability analysis emerging from these two research advances would set a more accurate base for measuring the environmental value of developing information-based VRN recommendations that abate excess N fertilization.

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APPENDIX 2

A version of this Appendix was previously published as Supplementary Material in *Precision Agriculture* and is reproduced with the permission of the journal and co-authors.

Lee, S. W., Swinton, S. M., and Basso, B. 2025. “Comparing profitability of variable rate nitrogen prescriptions. [Supplementary Material 1]” *Precision Agriculture*, 26(4): 1-19. <https://doi.org/10.1007/s11119-025-10256-y>

In this appendix, we outline the algorithm used to prescribe nitrogen and the results of the price sensitivity analysis. Table A2.1 presents the nitrogen prescription algorithm based on the combination of in-season NDVI imagery and historical yield. In Table A2-A5, we examine the robustness of our results to different corn and nitrogen prices.

Table A2.1: Nitrogen prescription algorithm

Assignment criteria		Prescribed level of N	Chosen information
NDVI	YH, Stability ¹		
High	High	High	-
	Medium	High	NDVI
	Low	Low	YH
Medium	High	Medium	NDVI
	Medium	Medium	-
	Low	Medium	NDVI
		Low	YH
Low	High	Low	NDVI
	Medium	Medium	YH
		Low	NDVI
	Low	Low	-

¹: Stability indicates the temporal variance of crop yield and it is calculated following Maestrini and Basso (2018)².

² Maestrini, B., and Basso, B. (2018) Drivers of within-field spatial and temporal variability of crop yield across the US Midwest. *Scientific Reports* 8:1-0.

Table A2.2: Linear regression analysis results (\$ ha⁻¹) with minimum nitrogen price and maximum corn price (the minimum $\frac{P_N}{P_Y}$)

Year	Farm	Field	Coefficient (clustered standard error)		NDVI-YH (clustered std. err.)
			NDVI	YH	
2021	MI_A	1	62 ** (27)	126 (72)	175 ** (62)
		2	768 *** (54)	288 *** (141)	383 *** (133)
		3	356 ** (37)	146 *** (27)	210 *** (54)
	MI_B	1	-203 *** (37)	-91 ** (42)	-111 *** (22)
		2	44 (67)	30 (44)	15 (59)
		3	-86 (121)	20 (77)	-106 (101)
	IN_A	4	-294 *** (89)	-84 *** (32)	-208 *** (77)
		1	-200 *** (72)	114 *** (25)	-312 *** (86)
		2	-94 (62)	-190 *** (22)	96 (69)
		3	40 (89)	40 (37)	0.5 (104)
2022	MI_B	5	-89 *** (15)	-40 ** (17)	-52 *** (20)
		6	7 (15)	-82 *** (20)	89 ** (15)
		7	-7 (12)	-32 *** (12)	25 * (15)
	MI_A	2	-242 *** (42)	64 (94)	-306 *** (124)
	MI_B	1	-84 ** (35)	-136 ** (67)	54 (64)
		2	-153 (116)	109 ** (44)	-262 *** (84)
2023	MI_B	3	-96 (69)	425 *** (67)	-524 *** (49)

***, **, * indicate significance level at less than 1%, 5%, and 10% respectively.

Table A2.3: Linear regression analysis results (\$ ha⁻¹) with maximum nitrogen price and minimum corn price (the maximum $\frac{P_N}{P_Y}$)

Year	Farm	Field	Coefficient (clustered standard error)		NDVI-YH (clustered std. err.)
			NDVI	YH	
2021	MI_A	1	30 ** (12)	-62 * (25)	175 *** (62)
		2	373 *** (27)	185 *** (69)	185 *** (64)
		3	173 *** (17)	69 *** (12)	104 *** (27)
	MI_B	1	-99 *** (17)	-44 ** (20)	-54 *** (10)
		2	22 (32)	12 (22)	10 (30)
		3	-42 (59)	10 (37)	-49 (49)
		4	-141 *** (44)	-42 *** (15)	-99 *** (37)
	IN_A	1	-104 *** (35)	54 *** (12)	-158 *** (42)
		2	-49 (30)	-84 *** (10)	35 (35)
		3	7 (42)	22 (17)	-15 (49)
2022	MI_B	5	-44 *** (7)	-20 ** (7)	-25 ** (10)
		6	2 (7)	-40 *** (10)	42 *** (7)
		7	-5 (5)	-17 *** (5)	12 * (7)
2023	MI_A	2	-119 *** (20)	32 (44)	-151 ** (59)
		1	-40 ** (17)	-67 * (32)	-27 (32)
	MI_B	2	-74 (57)	52 ** (22)	-126 *** (40)
		3	-47 (35)	205 *** (32)	-252 *** (25)

***, **, * indicate significance level at less than 1%, 5%, and 10% respectively.

Table A2.4: Spatial discontinuity analysis results with minimum nitrogen price and maximum corn price (the minimum $\frac{P_N}{P_Y}$)

Year	Farm	Field (number of compared pairs)	Average gross margin (\$ ha ⁻¹)		NDVI – YH (std. err.)
			NDVI	YH	
2021	MI_A	1 (326)	2384	2340	44 ** (22)
		2 (64)	2723	2661	64 (96)
		3 (133)	3506	3336	170 *** (40)
	MI_B	1 (219)	4510	4458	52 *** (20)
		2 (200)	4277	4201	77 *** (15)
		3 (31)	4013	3993	20 (42)
		4 (219)	3622	3573	49 *** (12)
	IN_A	1 (111)	4203	4238	-35 (30)
		2 (11)	3944	4013	-72 (153)
		3 (80)	4136	4183	-47 (42)
2022	MI_B	5 (179)	3773	3798	-25 (17)
		6 (170)	3828	3795	32 * (17)
		7 (157)	3657	3635	22 (22)
2023	MI_A	2 (31)	2491	2827	-339 * (96)
		1 (31)	2229	2300	-72 (49)
	MI_B	2 (49)	2254	2273	-20 (37)
		3 (12)	2511	2637	-126 (79)

***, **, * indicate significance level at less than 1%, 5%, and 10% respectively.

Table A2.5: Spatial discontinuity analysis results with maximum nitrogen price and minimum corn price (the maximum $\frac{P_N}{P_Y}$)

Year	Farm	Field (number of compared pairs)	Average gross margin (\$ ha ⁻¹)		NDVI – YH (std. err.)
			NDVI	YH	
2021	MI_A	1 (326)	857	835	22 ** (10)
		2 (64)	1018	988	30 (47)
		3 (133)	1411	1327	82 *** (20)
		1 (219)	1833	1809	25 *** (10)
	MI_B	2 (200)	1717	1680	37 *** (7)
		3 (31)	1658	1651	10 (20)
		4 (219)	1404	1379	25 *** (7)
		1 (111)	1559	1574	-17 (12)
	IN_A	2 (11)	1433	1465	-32 (72)
		3 (80)	1537	1559	-22 (-20)
		5 (179)	1525	1537	-12 (7)
	MI_B	6 (170)	1557	1542	15 * (10)
		7 (157)	1473	1463	12 (10)
2023	MI_A	2 (31)	882	1045	-163 *** (47)
		1 (31)	689	724	-35 (25)
	MI_B	2 (49)	694	704	-10 (17)
		3 (12)	818	880	-62 (37)

***, **, * indicate significance level at less than 1%, 5%, and 10% respectively.

CHAPTER 3. ASSESSING THE IMPACT OF POLICY SHIFTS ON WIND TURBINE DEPLOYMENT ¹

Abstract: This paper evaluates the impact of two concurrent policy interventions on wind energy development in Michigan: The revision of Public Act 116, which removed land-use restrictions on preserved farmland, and the Wind Energy Resource Zone designation under Public Act 295, which facilitated infrastructure expansion in high wind potential areas. Using a difference-in-differences approach, we analyze townships and cities in three Midwest states—Michigan, Minnesota, and Wisconsin—from 2000 to 2023. The results show that the PA116 revision did not have statistically significant impact while the Wind Zone designation contributed an additional 90 MW across the Wind Zone. These findings highlight that land-use policies can vary in effectiveness. Relaxing a weakly constraining preservation program had little effect, whereas strategically designated areas with clear development guidance and infrastructure support significantly promoted wind turbine installation.

3.1 Introduction

As demand for clean energy sources increases, wind energy infrastructure is being deployed at scale across the U.S. Midwest. Wind energy requires large, flat, and unobstructed areas, conditions that frequently coincide with productive agricultural land. In the Midwest, the overlap is especially pronounced, with 94% of wind turbines being installed on cropland (Maguire et al., 2024). This spatial overlap between land suitable for wind energy and land used for agriculture creates a context in which renewable energy projects are sited on farmland, raising important considerations for how land-use policies interact.

¹ This chapter is based on work intended for publication in collaboration with Scott M. Swinton,

In addition to overlapping geographically, policies may also overlap in time. Multiple policies are often implemented as part of a “policy mix” or “policy package” to enhance overall effectiveness and address the limitations of individual measures (Cunningham et al., 2009; Howlett and Rayner, 2013; Justen et al., 2014). This approach is especially important in the energy and environmental policy, where challenges are cross-sectoral and require coordinated interventions (Kern et al., 2019; Duffy and Cook, 2019).

Michigan provides an example of spatial and temporal policy overlap. In 2008, the state introduced several major policies to accelerate wind energy development. These included a Renewable Portfolio Standard (RPS) mandate, which was introduced alongside Clean and Renewable Energy and Energy Waste Reduction Act (Public Act 295) and the revision of Farmland and Open Space Preservation Act (Public Act 116). These policies share the same objective of promoting wind energy but operate through different institutional mechanisms. Public Act 295 provided infrastructure by facilitating transmission planning in high-potential wind areas. The revision of Public Act 116 removed a potential land constraint by permitting wind turbine construction on preserved farmland. These policies were implemented concurrently and targeted overlapping land, where preserved farmland coincided with high wind energy potential.

In this paper, we disentangle the independent and joint effects of these two concurrent renewable energy policies. This paper provides empirical evidence on how policy shapes renewable energy siting in spatially constrained settings where land is both agriculturally productive and technically suitable for renewable energy infrastructure. We explore how these two policies interacted and affected total installed wind power capacity across county subdivisions from 2000 to 2023.

This paper contributes to the growing body of literature on the effects of government policies on renewable energy development. While agricultural land is closely linked to wind power generation, there remains a research gap regarding how agricultural land use policies influence wind power deployment. Most existing studies focus on general wind turbine deployment without considering the agricultural context (Deschenes et al, 2023; Lehmann et al., 2023; Hitaj, 2013; Hasani-Marzooni and Hosseini, 2011). This study addresses this gap by investigating the impact of agricultural land use policies on wind turbine deployment.

The determinants of wind turbine deployment in the existing literature can be broadly categorized into three categories: policy considerations, wind power profitability, and landowner characteristics. Most of the literature examining the impact of policies focuses on the effect of renewable portfolio standards (RPS), which are state-level policies that require utilities to produce or purchase a certain percentage of their electricity from renewable energy sources. Empirical evidence on the effectiveness of RPS varies depending on how RPS is measured. In earlier studies, where RPS is a binary variable (1 when in effect, 0 otherwise), the effect tends to be insignificant (Yin and Powers, 2010) or even negative (Delmas and Montes-Sancho, 2011). However, when state variation in specific RPS provisions are incorporated into the estimation model, such as clauses regarding existing renewable energy infrastructure and Renewable Energy Certificate (REC) trading, researchers tend to find a positive effect of RPS (Yin and Powers, 2010; Joshi, 2021; Deschenes et al., 2023; Greenstone and Nath, 2020; Feldman and Levinson, 2023).

Profitability of wind turbines, the second factor driving their installations, is contingent on several factors including the quantity and consistency of power generation, the efficiency of electricity transmission, and the demand for wind power. Wind speed plays a crucial role, with higher and more consistent speeds resulting in greater power output (U.S. Department of Energy

[DOE], 2023). Geographical features, such as elevation and mountain gaps can also influence wind characteristics (U.S. Energy Information Administration [EIA], 2023). Once electricity is generated, transmission costs are influenced by the distance between the plant and the grid, with greater distance incurring higher costs for the plant owner (Hitaj, 2013). Local factors such as wages and taxes can also affect the profitability of wind turbines by influencing construction and operating costs.

Lastly, the deployment of wind turbines is linked to the decisions of landowners who choose to host wind projects. While profitability is a key consideration for landowners, it is not the sole factor impacting their decisions. Past studies have often focused on state-level analyses of wind turbine deployment, and they either aggregated or overlooked landowner-specific characteristics. One study that included sub-state level variables is Bessette and Mills (2021). Based on a survey of 46 energy professionals who were familiar with wind projects, they found that the percentage of farmers who resided on their farms, the population that worked at home, and the population that voted for Trump were the statistically significant precursors to wind turbine opposition. Winikoff and Parker (2023) observed that an increase in land ownership concentration correlates with a rise in installed wind energy capacity. Studies by Hitaj (2013) and Winikoff and Parker (2023) controlled for such variables as the distance to the nearest city and population density, using them as proxies for the number of people exposed to negative externalities associated with wind energy deployment.

To examine the factors affecting wind turbine deployment, existing literature has employed various statistical models. Hitaj (2013) utilized the Tobit model. However, the Tobit model faces limitations due to the incidental parameter problem which causes biased estimators, leading to the exclusion of fixed effect variables. This omission of fixed effects prevented the Tobit model from

fully leveraging the panel structure of the data. Deschenes et al. (2023), Upton and Snyder (2017), Yin and Powers (2010), Joshi (2021), Winikoff and Parker (2023) employed the linear Two-way Fixed Effect model incorporating a difference-in-differences interpretation. The majority of studies employing panel data focused on state-level capacity, neglecting sub-state level characteristics in their analyses. This limitation hinders a comprehensive understanding of the nuanced factors influencing wind turbine deployment at a more localized level. In this study, we address this gap by leveraging a granular, sub-county level dataset to examine wind turbine deployment patterns across three comparable states.

3.2 Background information

3.2.1 Michigan's Clean, Renewable, and Efficient Energy Act – Public Act 295

On October 6, 2008, the Michigan legislature passed the Clean, Renewable, and Efficient Energy Act, also known as Public Act (PA) 295, which introduced a policy package to accelerate renewable energy deployments in Michigan. It established a Renewable Portfolio Standard (RPS), requiring electricity providers to increase the share of electricity generated from renewable sources. To support compliance, the Act facilitated infrastructure development such as transmission upgrades and allowed utilities to recover associated costs through regulated rates. It also included requirements and incentives to promote energy efficiency.

In addition to the RPS and other state-wide measures, PA295 also promoted wind energy development by prioritizing regions with strong wind generation potential. It created the Wind Energy Resource Zone Board, which was tasked with identifying regions in Michigan with the highest wind energy potential. Based on this designation, the Michigan Public Service Commission was authorized to promote and approve transmission expansion plans within 180 days in those regions, with the goal of streamlining the siting process for new transmission lines. This

provision aimed to align infrastructure development with wind energy potential and to bring projects online more efficiently.

In 2009, a Wind Energy Resource Zone was officially designated (Figure 3.1), and in 2010 a new transmission project was launched in Michigan's Thumb region. The Thumb region is a predominantly agricultural area in the eastern part of the state that extends into Lake Huron. The project involved installing 140 miles of 345 kV transmission lines across this region. The project was completed in phases between 2013 and 2015.



Figure 3.1: Designated High Wind Energy Potential Regions under Clean, Renewable, and Efficient Energy Act (PA295), effective January 2010

3.2.2 Michigan's farmland preservation policy – Public Act 116

Both federal and state governments implement policies to safeguard farmland, including conservation easements, property tax benefits, and non-monetary measures. Conservation easements involve relinquishing land development rights in exchange for compensation,

restricting usage exclusively to agriculture. While the easement approach offers a certain way to preserve land for agriculture, its permanent commitment may deter farmer participation, and it entails higher costs to the state government. Property tax relief programs encourage farmland retention by offering reduced taxes on agricultural land. Certain non-monetary policies also support agriculture. For example, right-to-farm laws protect compliant farmers from nuisance lawsuits. State-level variations exist across policies, with some requiring enrollment and contractual commitments for tax or non-monetary benefits.

Michigan distinguishes itself through a unique farmland preservation program governed by the Farmland and Open Space Preservation Act, commonly known as Public Act (PA) 116. It was established in 1975 and is overseen by the Michigan Department of Agriculture and Rural Development (MDARD). To participate in PA116, landowners must enroll their land by signing an agreement with the state. The program protects one-third of all farmland in Michigan, with over 43,900 agreements.

Under PA116, when the land is enrolled in the program, the state of Michigan acquires development rights to the land, ensuring its dedicated use for agricultural purposes throughout the contract's duration. These agreements span 10 to 90 years with the possibility of extensions for a minimum of seven years. Enrolled landowners receive Michigan income tax credits based on the farm's property tax and the total household income of the landowner. Land enrolled in the program is exempt from special assessment for sewers, water, lights, or non-farm drainage. If the contract is terminated early, a landowner is obligated to repay any tax credits received during the last seven years of the agreement.

On October 7, 2008, the Michigan attorney general's office revised PA116, allowing wind turbines to be constructed on land enrolled in PA116. Under the new ruling, wind turbines may be

placed on the enrolled land if the turbines do not substantially hinder the farming operation. In contrast, states like Wisconsin and Minnesota, which operate programs similar to PA116, do not allow the placement of commercial wind turbines on land enrolled in their farmland preservation programs. Once the land is enrolled in those states, wind turbines cannot be installed unless the landowner chooses to terminate the contract early, thereby repaying a portion or the entirety of the tax benefits received. This divergence in farmland preservation policies provides a unique opportunity for analysis, as states vary in their approaches to wind turbine placement on preserved land.

By exploiting policy variations across time and space, this study examines the impact of two policies in Michigan: the revision of PA116, which allowed wind turbines on preserved farmland and the designation of Wind Zone under PA295, which targeted specific areas for wind development. We evaluate the PA116 revision using a cross-state comparison with Minnesota and Wisconsin, leveraging the fact that all three states operate similar farmland preservation programs that require contractual enrollment, but only Michigan revised its program to allow wind turbines on preserved farmland. This policy divergence allows us to isolate the impact of the PA116 revision by comparing trends across otherwise similar states. For the Wind Zone designation, we use within-state comparisons between designated and non-designated areas in Michigan, which enables us to assess the effects of spatially targeted incentives while accounting for the statewide influence of the PA116 revision. Analyzing these two policies provides insight into how different types of regulatory decisions, one focused on land-use restrictions and the other on spatial planning, shape renewable energy development. The following theoretical model outlines the mechanisms through which these policies affect wind turbine siting decisions.

3.3 Theoretical model

We develop a theoretical framework to identify the key factors influencing wind power installation decisions. We assume that there are two types of agents: developer and landowner. A developer offers a lease payment to a landowner in exchange for a land parcel on which to build wind turbines. A wind turbine can be installed only if a developer's maximum willingness to pay (WTP) meets or exceeds a landowner's minimum willingness to accept (WTA). Below, we describe the factors that influence each party's WTP and WTA.

While investments in wind turbines inherently involve dynamic decision-making, the current analysis adopts a simplified approach by employing a static model where all dynamic prices and costs are annualized or fixed. We assume that all variables remain constant over time, reflecting the long-term expectations held by wind developers and landowners at the time of decision-making. This approach allows the model to capture decisions based on anticipated average conditions, rather than short-term fluctuations. This assumption is consistent with the common contractual arrangement where a landowner transfers all rights for construction and operation to the developer in exchange for a fixed lease payment agreed upon at the time of signing the lease contract (Emanuel and Martin, 2012). For simplicity, we assume that the developer and the landowner use the same discount rate (δ).

A developer's WTP for a lease is determined by the expected profit of the wind turbine project. The expected profit (π_i) from installing turbines on landowner i 's land includes the revenue from selling electricity, offset by the costs of constructing and operating the turbines. Governmental policies, such as subsidies or other incentives, can affect electricity prices or operating costs. This expected profit defines the upper limit of the developer's willingness to pay for the land.

$$E[\pi_i] = \sum_{t=0}^T \delta^t ([e_i(p - c + policy_{dev})] - FC_i) \geq \text{WTP to lease land } i \quad (1)$$

Equation (1) describes a developer's profit, where e represents the amount of electricity generated on land i . The price of electricity generated by wind is denoted by p . Variable c represents the operational cost per unit generated. The developer's revenue is also influenced by policy ($policy_{dev}$) which can affect the market value of wind-generated electricity or operating costs. For example, Renewable Portfolio Standards (RPS) require utilities to source a portion of their electricity from renewables, increasing demand and allowing developers to receive a price premium for renewable energy. FC_i is annualized fixed costs. These costs may vary geographically, reflecting regional differences in topography, wages, and subsidies.

A landowner's WTA for a lease is determined by their net utility change from leasing land for wind turbines. This includes the perceived disamenities associated with having turbines on their property, offset by any additional compensation from governmental policies. A landowner is willing to accept the lease payment offered by the developer as long as the lease payment exceeds the monetized value of their utility change from hosting wind turbine on their land.

$$\text{WTA for lease land } i \geq E[U_i] = \sum_{t=0}^T \delta^t [\frac{\lambda_i}{\mu_i} disamenity_i - policy_{land}] \quad (2)$$

Wind turbines may affect a landowner's personal utility by causing displeasure ($disamenity_i$) due to noise or landscape alterations. Policies ($policy_{land}$) that offer financial compensation for hosting wind turbines can influence the landowner's utility by offsetting these potential disamenities. In Equation (2), μ_i and λ_i represent landowner i 's marginal utility of income and the marginal disutility of wind turbines, respectively and $\frac{\lambda_i}{\mu_i}$ represents the marginal rate of substitution between a disamenity and income, monetizing the perceived disamenity from hosting wind turbines.

As noted at the outset of this section, a wind power development project can only proceed on land i if a developer's maximum WTP for lease exceeds a landowner's minimum WTA.

$$\sum_{t=0}^T \delta^t ([e_i(p - c + policy_{dev})] - FC_i) \geq \sum_{t=0}^T \delta^t [\frac{\lambda_i}{\mu_i} disamenity_i - policy_{land}] \quad (3)$$

The likelihood of wind turbines being installed on land i depends on the probability that the condition specified in Equation (3) is satisfied. Hence, the variables in Equation (3) are all relevant factors that influence decisions in wind turbine installation. Assuming the probability of lease payment is normally distributed, this probability is expressed using the standard normal cumulative distribution function Φ , as shown in Equation (4). Wind turbines are more likely to be situated on land i when there is a broader agreement on the range of lease payments between landowner i and a developer. For instance, an increase in price leads to a higher offer from a developer and therefore increases the probability of wind turbines being constructed. Conversely, when there is an increase in the landowner's marginal disutility from wind turbines, it increases the landowner's minimum acceptable lease payment. This, in turn, narrows the potential range of acceptable lease payments and reduces the probability of wind turbines being built.

$$\begin{aligned} Prob_i(Wind\ Turbine\ Built) \\ = \Phi \left[\sum_{t=0}^T \left\{ \delta^t [e_i(p - c + policy_{dev}) - FC_i - \left(\frac{\lambda_i}{\mu_i} disamenity_i - policy_{land} \right)] \right\} \right] \end{aligned} \quad (4)$$

A policy that increases the net benefit to developers ($policy_{dev}$), by increasing electricity prices or decreasing operating costs raises the likelihood of installation ($\frac{\partial Prob(Wind\ Turbine\ Built)}{\partial Policy_{dev}} > 0$). Similarly, a policy that compensates landowners ($policy_{land}$) and offsets the disamenities associated with wind turbines also increases the likelihood of installation ($\frac{\partial Prob(Wind\ Turbine\ Built)}{\partial Policy_{land}} > 0$). Although the effects of policies targeting developers or landowners are theoretically positive, their marginal impacts remain an empirical question.

While Equation (4) provides the theoretical framework on how policies targeting wind developers and landowner influence wind turbine installation, we estimate a reduced-form specification where installed wind turbine capacity is modeled as a function of the variables in Equations (3) and (4). The following empirical analysis explores the impacts of two policies, PA295 and the revision of PA116, on wind turbine installations. Wind Zone designation under PA295 targets developers by reducing operating costs through the provision of transmission infrastructure. The revision of PA116 targets landowners by compensating them for hosting wind turbines through tax credits. We examine how, and to what extent, the PA116 revision and PA295 influence wind turbine construction on farmland.

3.4 Data

We employ a dataset that spans from 2000 to 2023 and covers Michigan, Minnesota, and Wisconsin. The unit of analysis is county subdivisions, such as townships and cities, and all variables are measured accordingly. As we specifically focus on wind turbines situated on farmland, we construct the dependent variable by combining the data from United States Wind Turbine Database (USWTDB; Hoen et al., 2025) and the Cropland Data Layer (CDL; U.S. Department of Agriculture, 2025). To isolate wind turbines located on farmland, we use a GIS program to connect wind turbine placement with the corresponding land use. In instances where CDL data is unavailable, we utilize National Land Cover Database (NLCD), assuming that the land cover remains constant during periods when CDL data is unavailable. Then the information on wind turbines located on farmland is aggregated at the township/city level based on the boundaries as of 2022.

The dependent variable is newly added wind energy capacity. Instead of total (cumulative) capacity, we use annual added capacity, defined as the wind capacity that became operational in

each calendar year, as the outcome variable to ensure a valid assessment of parallel trend assumption. When the rate of annual additions is similar across township/city, the parallel trends assumption is likely to hold. However, when we use cumulative outcomes, even small differences in the slope of annual additions can lead to increasingly divergent cumulative values over time and this compounding effect can create the appearance of non-parallel trends, even if the underlying trend in annual additions is consistent. By focusing on annual additions, we preserve the linearity of the outcome and enable a clearer comparison of trends. The analysis includes a total of 6268 county subdivisions, including 1580 in Michigan, 2761 in Minnesota, and 1927 in Wisconsin.

Factors influencing a wind power developer's decision to install wind turbines include the amount of electricity that can be generated (e_i), government policy ($policy_{dev}$), and fixed costs for installation (FC_i) (Equation 1). Electricity generation potential is primarily determined by natural characteristics such as wind speed and topography. Fixed costs for installation reflect regional differences in wages and taxes. Since these factors are time-invariant, we control them using the county fixed effect. We do not include electricity prices (p) and operational costs (c) from the analysis, as these factors exhibit little spatial variation within the study area.

Although proximity to transmission infrastructure can introduce spatial variation in wind turbine operating costs (c) by lowering transmission expenses (Lamy et al., 2016), we do not include a transmission line related variable in our analysis due to methodological and data limitations. First, transmission line developments are highly endogenous to wind turbine deployment. While access to transmission infrastructure facilitates wind energy expansion, the construction of wind turbines can, in turn, create congestion in existing lines (LaRiviere and Lyu, 2022; Bell et al., 2016), thereby promoting further transmission investment. One strategy to address this endogeneity is to use lagged variables. However, this would shorten the post-treatment

period available for analysis due to limited historical data. Second, publicly available data on transmission infrastructure with exact transmission line locations is limited to data from Homeland Infrastructure Foundation-Level Data (HIFLD), which includes transmission lines that are currently in operation. However, this dataset does not include information on when the line was constructed, making it unsuitable for our empirical setup. Another publicly available data source includes transmission line construction permits which can be obtained from state Public Service Commissions. However, while Minnesota and Wisconsin require public permitting for high-voltage transmission lines, Michigan does not, resulting in inconsistent coverage of data across states. Taken together, these limitations make the inclusion of detailed transmission line data impractical.

For policies targeting wind power developers, we include variables related to local zoning ordinances, Renewable Portfolio Standards (RPS), and year fixed effects. Local zoning ordinances governing wind turbine installation reflect county or sub-county level policies. Ordinance data is mainly from WINDEXchange (2023) and Lopez and Levine (2022). We include an indicator (*ordinance*) for whether the area has any zoning ordinances related to wind energy in place, but do not account for the specific provisions of the zoning. To address missing values, we cross-referenced local zoning ordinances. The *RPS_GWh* variable is taken from Barbose (2023), where the author measured each state's RPS stringency by considering Renewable Energy Credits (RECs) that would be required given each state's total electricity sales and existing infrastructure. We also include a binary variable indicating whether a state has RPS policy (*RPS_yes*) to account for additional policies bundled with RPS, such as net metering, that are not captured by the renewable energy generation requirement (*RPS_GWh*) alone. We account for the potential impact

of all federal level policies using year fixed effects, as federal policies affect all counties uniformly in a given year.

On the landowners' side, we proxy the perceived amount of disamenity ($\lambda_i \cdot disamenity_i$ in Equation 2) using the local population (*population*), under the assumption that the more people residing near a turbine, the greater the total perceived disamenity. To capture the marginal utility of income (μ_i) that affects landowner's WTA (Equation 2), we include median household income (*income*). Under the assumption of diminishing marginal utility, landowners with higher income have lower marginal utility of income. As a result, they are expected to require a higher lease payment to be willing to accept the wind turbine installation. Other landowner characteristics in township/city level are sourced from the American Community Survey.

Table 3.1: Summary statistics – average and standard deviation of control variables of entire samples

Theoretical variables		Empirical variables	Average	Standard deviation
Developer's side	$policy_{dev,i}$	<i>ordinance</i>	0.18	0.38
		<i>RPS</i> (GWh)	6153	5364
		<i>RPS_yes</i>	0.70	0.35
		Year FE	-	-
	e_i FC_i	County FE	-	-
Landowner's side	$\lambda_i \cdot disamenity_i$	<i>population</i>	3313	16066
	μ_i	<i>income</i>	55297	20114
	$policy_{land,i}$	<i>MI*After2008</i>	0.17	0.37

3.5 Empirical Methods

To disentangle the impact of multiple policies on wind turbine investments, we employ a difference-in-difference (DiD) approach by comparing the total installed wind power capacities in treated county subdivisions with those in the relevant control group. The DiD addresses the

potential endogeneity of the treatment assignment, which may arise if it is selectively adopted by states with high potential benefits. We rely on the assumption that, conditional on covariates, the treatment is unconfounded.

We estimate the impacts of PA116 revision and Wind Energy Resource Zone (hereafter, Wind Zone) designation separately, using different subsets of data to isolate the effects of two distinct policies. This approach is motivated by concern about potential bias arising from “contamination weights” in two-way fixed effects (TWFE) models, as discussed by de Chaisemartin and D’Haultfoeuille (2023). When we include multiple treatments simultaneously in TWFE models, the estimated coefficient for one treatment may incorporate not only a weighted average of its own treatment effects, but also a weighted average of the effects of the other treatment(s). The second term is referred to as “contamination weights”, and it can bias the treatment effect estimator if treatment effects vary across groups or time. In our study, the Wind Zone designation (PA295) was implemented only to a subset of the units that are also exposed to the PA116 revision, creating overlap between the two treatments. This overlap can introduce contamination bias when estimating both treatment effects in the same model, as units exposed to both treatments or only one may be incorrectly used as controls for the other, leading to biased estimates.

To avoid this source of bias, we estimate separate models on subsamples in which only one policy varies. To identify the impact of the PA116 revision, we exclude units that were designated as Wind Zone and compare units that had comparable farmland preservation policies until 2008. To estimate the impact of Wind Zone designation, we restrict the sample to units already exposed to the PA116 revision and compare outcomes between designated and non-designated areas.

3.5.1 Estimating the impact of the PA116 revision

To estimate the impact of PA116 revision, we compare Michigan with Wisconsin and Minnesota. Wisconsin and Minnesota serve as suitable counterfactuals for Michigan, given their geographical proximity and similar agricultural settings. Importantly, their farmland preservation policies closely resemble Michigan's, which is essential for estimating the impact of the 2008 revision to PA 116. All three states require contractual commitment from landowners in exchange for tax benefits, a distinctive feature that shapes how farmland preservation programs operate. Prior to 2008, none of these states permitted wind turbines on preserved farmland. In 2008, Michigan introduced the PA116 revision enabling wind turbines on enrolled lands, while wind turbine installations remained restricted on preserved farmland in Wisconsin and Minnesota. Equation (5) present employed DiD specification for estimating the impact of the PA116 revision.

$$WindCap_{it} = \beta_1 MI_i \cdot Post2008_t + X_{it} + \rho_i + \sigma_t + \epsilon_{it} \quad (5)$$

MI_i is an indicator for treatment group, and $Post2008_t$ is an indicator for years after the policy implementation. X_{it} is a vector of control variables, including an indicator variable for the presence of zoning ordinance, population, median household income, an indicator variable for whether RPS is in place, and the amount of electricity required to come from renewable sources under the RPS (GWh). To address potential reverse causality where wind turbine projects might influence the enactment of zoning ordinances, we include a three-year lag of the zoning ordinance variable ($ordinance_{t-3}$). ρ_i is a county fixed effect to control for time-invariant county characteristics such as landscape and natural amenities. Year fixed effect σ_t control for time-varying impacts that affect all samples such as federal policy or technological advances. The dependent variable, $WindCap_{it}$ represents wind power capacity installed in county-subdivision i during year t . The coefficient of interest β_1 indicates the average treatment effect of PA116 revision.

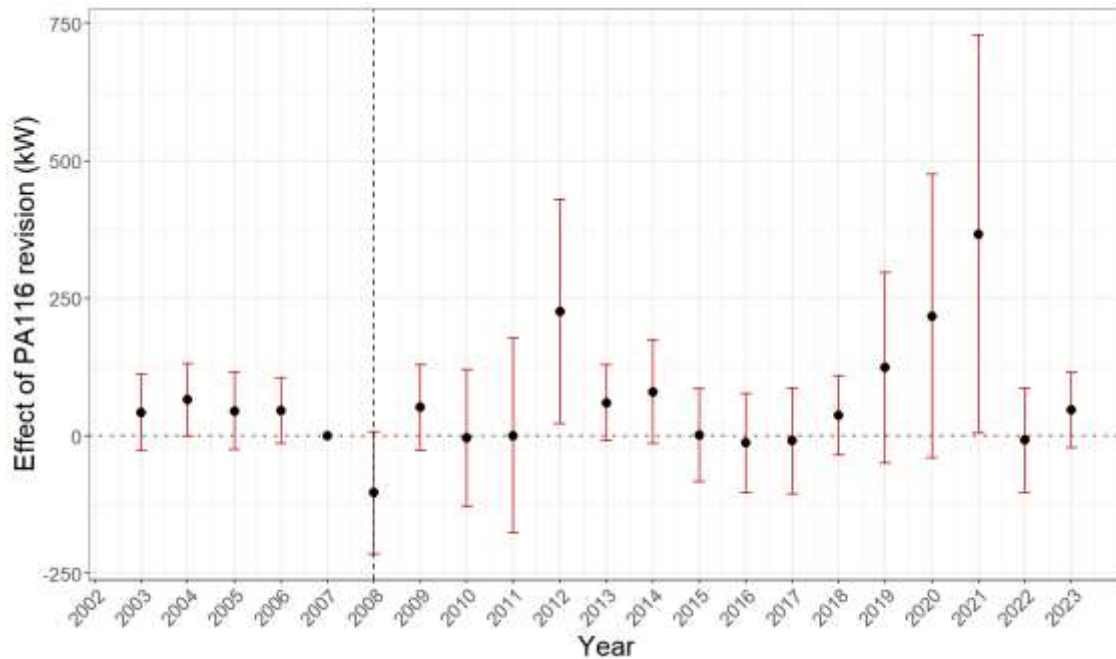
3.5.1.1 Identification strategy for estimating the PA116 Revision's impact

We interpret the estimated effect as causal under the parallel trends assumption that the county subdivisions in Michigan (treated group) and in the other states (non-treated groups) would have followed the same time trend in wind turbine capacity, if there was no policy. To assess the plausibility of the parallel trends assumption, we conduct event study analyses by estimating Equations (6),

$$WindCap_{it} = \sum_{\tau \neq 2007} \gamma_{\tau} MI_i \cdot YEAR_{\tau} + X_{it} + \rho_i + \sigma_t + \epsilon_{it} \quad (6)$$

where $YEAR_{\tau}$ is an indicator variable for the year τ . MI_i is an indicator variable for treated group. MI_i identifies all townships and cities in Michigan that were affected by the PA116 revision in 2008.

Figure 3.2 presents the estimated coefficients γ_{τ} , which capture the average differences in added wind power capacity between treated and control groups over time. To test the validity of the parallel trends assumption, we conduct a Wald test of the null hypothesis that the pre-treatment coefficients jointly equal zero. The test yields a test statistic of 8 with a p-value of 0.11, indicating there are no statistically significant differences between the counties in Michigan and the comparison counties prior to the 2008 policy revision.



Note: Error bars indicate 95% confidence intervals. Standard errors are clustered at township/city level.

Figure 3.2: Estimated effect of PA116 revision from event study – 6187 townships/cities in Michigan, Minnesota, and Wisconsin

The potential concern is the presence of spillover effects between treatment and control groups. Specifically, the treatment may influence not only the treated areas but also the control areas by stimulating wind development more broadly. To assess this possibility, we examine the structure of wind turbine manufacturing industry. Wind turbine suppliers primarily operate at the national scale, with GE Vernova, Vestas, and Siemens Energy AG accounting for nearly 90% of installed capacity in the United States (Wilson, 2023). In Michigan, turbines are sourced from these major manufacturers as well as local firms. In 2010, Michigan accounted for only 0.4% of total installed wind power capacity in the US (EIA, 2025). Given this marginal share, it is unlikely that policy changes in Michigan had any meaningful impact on the broader wind manufacturing market in other states.

Another potential source of spillover effects is the relocation of wind developers in response to the policy change. If wind developers shifted their investment from control areas to treated areas due to the newly enacted policies, such a spillover could lead to overestimation of the treatment effect. To assess this possibility, we examine all operators who constructed wind turbines in Michigan, Wisconsin, and Minnesota between 2002 and 2023, identifying whether any developers were active in more than two states. Although there are no legal barriers preventing out-state construction, we find that no operator constructed wind turbines in more than two states, suggesting that this form of spillover effect is unlikely.

3.5.2 Estimating the impact of the Wind Zone designation under PA295

We examine the effect of the Wind Zone designation, which was implemented in a subset of Michigan townships and cities (Figure 3.1). To estimate the impact of Wind Zone designation, we compare townships and cities that were designated as Wind Zone with those in Michigan that were not designated as Wind Zone. Equation (7) present employed DiD specifications.

$$WindCap_{it} = \beta_2 WindZone_i \cdot Post2008_t + X_{it} + \rho_i + \sigma_t + \epsilon_{it} \quad (7)$$

$WindZone_i$ is an indicator for treated township/city, and $Post2008_t$ is an indicator for years after the policy implementation. X_{it} is a vector of control variables. It includes the same set of controls used in the PA116 revision analysis, excluding the RPS variables. Since the estimation for the Wind Zone designation impact is limited to townships and cities within Michigan, the RPS variables are not included in Equation (7) because they do not vary within the state. All other variables in Equation (7) are defined as in Equation (5). The coefficient of interest β_2 represents the average treatment effect of Wind Zone designation.

We further examine the heterogeneity in the Wind Zone designation treatment effect based on the amount of land enrolled in PA116. While all townships and cities in Michigan were subject to the 2008 PA116 revision, areas with more acres under PA116 may have experienced a greater

change in land-use constraints, with the PA116 revision effectively freeing up more land for potential wind development. To test this, we interact the treatment indicator with $PA116_i$, which is total acres enrolled in PA116 in 2005, 2006, and 2007. We exclude post-2008 enrollment data to avoid endogeneity, as the policy revision could itself influence subsequent enrollment. We begin with 2005 data due to limited data availability prior to that year. Equation (8) presents the specification used to estimate the heterogeneous effect of the Wind Zone designation with respect to previously enrolled PA116 acres.

$$WindCap_{it} = \beta_3 WindZone_i \cdot Post2008_t \cdot PA116_i + \beta_4 WindZone_i \cdot Post2008_t + X_{it} + \rho_i + \sigma_t + \epsilon_{it} \quad (8)$$

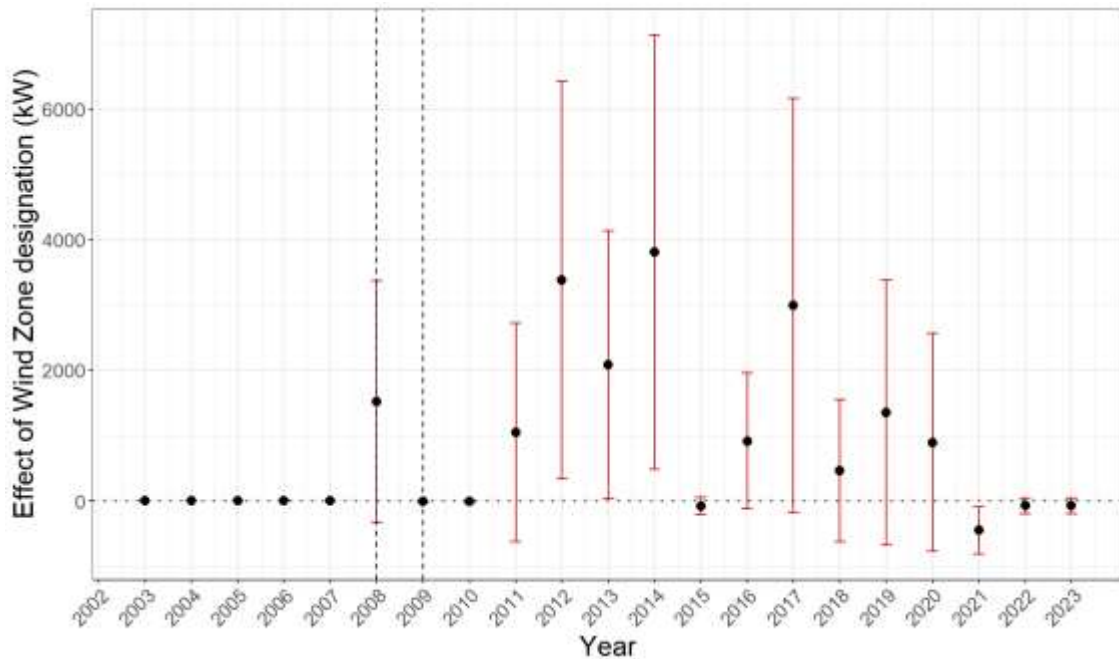
3.5.2.1 Identification strategy for estimating Wind Zone designation impact

As in the previous section, we apply a similar event study specification to test for any statistically significant differences between the Wind Zone designated units and the control units prior to the policy's implementation. Equation (9) presents the specification used for the event study analysis.

$$WindCap_{it} = \sum_{\tau \neq 2007} \omega_{\tau} WindZone_i \cdot YEAR_{\tau} + X_{it} + \rho_i + \sigma_t + \epsilon_{it} \quad (9)$$

$YEAR_{\tau}$ is an indicator variable for the year τ and $WindZone_i$ identifies designated as Wind Zone areas. All other variables are defined as in Equation (8).

Figure 3.3 presents the estimated coefficients ω_{τ} . The estimated results suggest an anticipation effect prior to the official Wind Zone designation. In 2008, when PA295, which established the committee to identify Wind Energy Resource Zones, was enacted, there was a statistically significant increase in newly added wind capacity in areas that would later be officially designated as Wind Zone in 2009. Based on this event study, we assume that the effect of PA295 began in 2008, when the planning process was initiated, rather than in 2009 when the designation was formally announced.



Note: Error bars indicate 95% confidence intervals. Standard errors are clustered at township/city level.

Figure 3.3: Estimated effect of Wind Zone designation from event study – 1580 townships/cities in Michigan

3.5.3 Time discrepancy between policy revision and observed wind turbine increase

The event study results in Figure 3.2 and 3.3 show an increase in wind turbine capacity beginning in 2012. The lag between policy revision and the observed increase in wind capacity likely reflects the time required for planning, permitting, and constructing wind turbines. While the actual construction of a 50 MW wind farm typically takes less than a year, the permitting process requires approvals from various authorities at the local, state, interstate, and federal levels. This process extends over multiple years, with potential delays arising from factors such as litigation and negotiations between developers and landowners (Sud and Ptnaik, 2022). Deschenes et al., (2023) demonstrated that there is a statistically significant effect of RPS on wind capacity after 5 years. Similarly, Greenstone and Nath (2020) utilized a 7-year timeframe following RPS enactment to capture the effects of RPS on electricity prices. Looking specifically at Michigan, Harsh et al. (2008) notes that contract duration often involves multiple years of evaluation or discovery phase

where developers analyze the economic viability of projects and await favorable market conditions before turbine construction. Figure 3.4 illustrates the time discrepancy between agents' decision-making timing and the observed data on wind turbines. Because the PA116 revision and the Wind Zone designation were implemented within a short time span, and wind projects typically require several years to plan and construct, both policies should be considered together when estimating the impact of each. This approach helps account for their temporal overlap and avoids misattributing effects from one policy to the other.

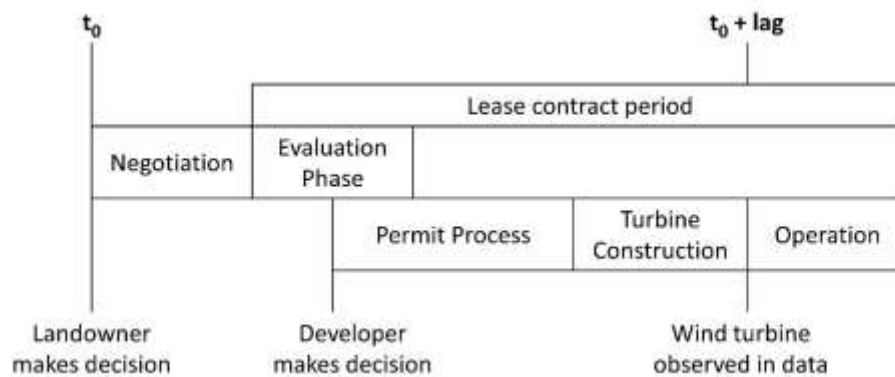


Figure 3.4: Why there is lag between agents' decision making and data on wind turbine installation

3.6 Results and discussion

3.6.1 Policy impact on wind turbine capacity

Table 3.3 presents the estimated results of the difference-in-differences specifications. Column (1) reports the estimated impact of PA116 revision, using townships and cities in Michigan, Minnesota, and Wisconsin, excluding those in Michigan that are designated Wind Zones. Column (2) presents the estimated impact of Wind Zone designation using townships in Michigan.

Following the PA116 revision in 2008, which allowed wind turbines on preserved farmland, Michigan's townships and cities did not experience statistically significant increase in added wind turbine capacity. In Table 3.2, Column (1), the coefficient of the term $MI * Post2008$, indicating

units treated with PA116 revision, is statistically insignificant, suggesting that the policy change did not meaningfully affect siting decisions. The coefficient of the term *income* is -1.20 and statistically significant at the 10% level, indicating that each \$1000 increase in median household income (*income*) is associated with 1.2 kW decrease in added wind capacity. In contrast, the coefficient of the term *RPS_GWh* is 0.01 and statistically significant at the 10% level, indicating a 100 GWh increase in RPS requirement (*RPS_GWh*) leads to a 1kW increase in added wind capacity. Given that Michigan's average RPS requirement since its introduction in 2008 is 9824 GWh (Barbose, 2023), the implied impact of RPS is at about 98 kW per township/city. The indicator variable for having an RPS (*RPS_yes*) is not statistically significant, suggesting that most of the RPS's impact stems from the renewable energy generation requirement, rather than from auxiliary measures such as net metering or other incentives.

The Wind Zone designation significantly boosted wind turbine capacity in the affected townships. The interaction term $WindZone \cdot Post2008$ in Column (2) is statistically significant at 1110 indicating that Wind Zone designation effectively increased the added wind capacity in treated areas. The Wind Zone designation under PA295 led to an average increase of 1110 kW per designated township, totaling about 90 MW across the Wind Zone, which covers only 3% of Michigan's land area. While PA116 revision did not have any significant impact on wind power capacity, the Wind Zone designation had a concentrated and substantial impact.

Table 3.2: Estimated impact of PA116 revision and Wind Zone designation using DiD from 2003 to 2023

	Impact on newly added wind capacity (kW)	
	(1) PA116 revision	(2) Wind Zone designation
<i>MI · Post2008</i>	36.3 (25.1)	-
<i>WindZone · Post2008</i>	-	1110*** (281)
<i>Ordinance (t-3)</i>	-37.5 (44.4)	-320 (205)
<i>population (1000 people)</i>	-0.670 (0.455)	-0.433 (0.899)
<i>income (\$1000)</i>	-1.20* (0.705)	-1.38 (2.42)
<i>RPS_GWh</i>	0.00609* (0.00368)	-
<i>RPS_yes</i>	8.15 (25.5)	-
Number of Township FE	6187 (In MI, MN, WI)	1580 (In MI only)
Number of Year FE	21	21
R squared	0.06	0.07

***, **, * represent statistical significance at the 1%, 5%, and 10% levels; all standard errors are clustered at the township/city level.

We further examine the heterogeneity in the treatment effect based on the amount of land enrolled in PA116. The results suggest that while the Wind Zone designation had a positive impact on wind capacity, this effect did not vary with the level of prior PA116 enrollment. The interaction term between the treatment indicator and PA116 acreage (*WindZone · Post2008 · PA116*) is not statistically significant. This result suggests that although PA116 revision expanded the land

available for potential wind development, within Wind Zone, those areas with more newly available land did not necessarily see greater wind turbine deployment.

Table 3.3: Estimated impact of Wind Zone designation using DiD and interaction with 2005-2007 PA116 acres

	Newly added wind capacity (kW)
	Wind Zone designation
<i>WindZone · Post2008</i>	997*** (315)
<i>WindZone · Post2008 · PA116</i>	1.24 (1.45)
<i>Ordinance (t-3)</i>	-311 (206)
<i>population (1000)</i>	-0.421 (0.892)
<i>income (\$1000)</i>	-1.34 (2.42)
Number of Township FE	1580 (In MI only)
Number of Year FE	21
R squared	0.07

***, **, * represent statistical significance at the 1%, 5%, and 10% levels; all standard errors are clustered at the township/city level.

3.6.2 Robustness check

As discussed in the earlier section, because contamination weights can bias the estimated policy impact when multiple policy indicators are included simultaneously, our preferred specification estimates each policy's impact separately using different subsets of the data. As a robustness check, however, we also report estimates from two model specifications that incorporate both PA116 revision and the Wind Zone designation (Table 3.4). Column 1 presents estimates from the model that includes both PA116 revision and Wind Zone designation simultaneously. Column 2 extends the model by incorporating a heterogeneous Wind Zone impact that varies with PA116-enrolled acres from 2005 to 2007. Column 1 corresponds to the results presented in Table 3.2, and Column 2 aligns with Table 3.3.

The estimated effect of the PA116 revision is consistent across specifications, suggesting that this result is robust to model choice. In contrast, the estimated impact of Wind Zone designation is larger when included alongside the PA116 revision. In the model without heterogeneous impact of Wind Zone designation (Table 3.4, Column 1), the estimated coefficient of $WindZone \cdot Post2008$ is 1165 compared to 1110 in the preferred specification that excludes the impact of PA116 revision (Table 3.2, Column 2). In the model with heterogeneous impact of Wind Zone designation (Table 3.4, Column 2), the coefficient of $WindZone \cdot Post2008$ is 1031, again higher than 997 estimated in the corresponding preferred specification (Table 3.3). In both models, the estimated effect of the Wind Zone designation appears to be upwardly biased, likely due to contamination weights stemming from overlapping treatment timing and the interactions between the policies.

Table 3.4: Estimated impact of PA116 revision and Wind Zone designation using models that include two policies simultaneously

	Impact on newly added wind capacity (kW)	
	(1)	(2)
<i>MI · Post2008</i>	36.1 (25.2)	35.9 (25.2)
<i>WindZone · Post2008</i>	1170 ^{***} (282)	1030 ^{***} (318)
<i>WindZone · Post2008 · PA116</i>	-	1.45 (1.46)
<i>Ordinance (t-3)</i>	-48.9 (47.9)	-47.5 (47.9)
<i>population (1000)</i>	0.0903 (0.368)	0.0926 (0.367)
<i>income (\$1000)</i>	-1.12 (0.718)	-1.12 (0.717)
<i>RPS_GWh</i>	0.00414 (0.00379)	0.00416 (0.00379)
<i>RPS_yes</i>	14.2 (25.7)	14.3 (25.7)
Number of Township FE	6268 (In MI, MN, WI)	6268 (In MI, MN, WI)
Number of Year FE	21	21
R squared	0.06	0.06

***, **, * represent statistical significance at the 1%, 5%, and 10% levels; all standard errors are clustered at the township/city level.

3.6.3 Relative magnitudes of policy incentives from PA116

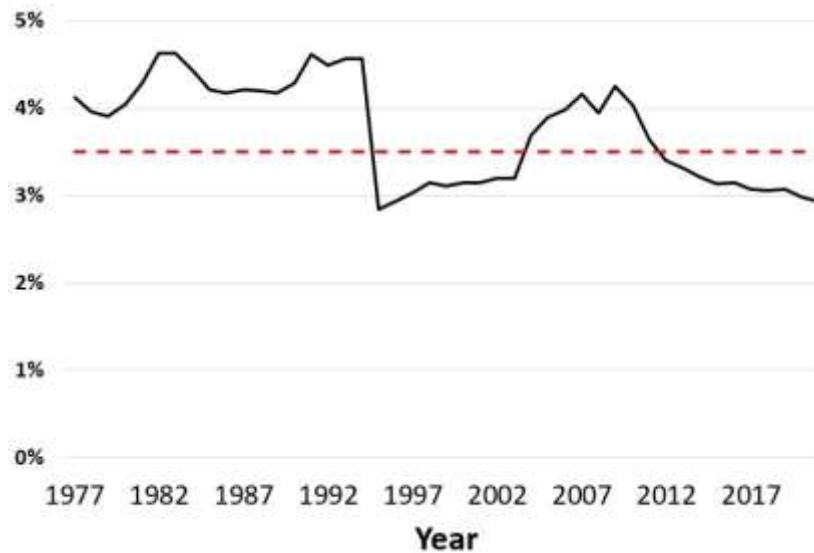
The results indicate that the PA116 revision did not have a statistically significant impact on its own, whereas PA295 did. Moreover, the impact of PA295 did not vary in response to prior PA116 enrollment levels. These findings suggest that increased land availability played a limited role in influencing wind development within the designated Wind Zone. One possible explanation for this

null effect of PA116 revision is that the policy revision did not offer a substantially stronger incentive compared to the previous policy, due to the structure of its tax credit. While the PA116 revision had theoretical potential to influence a landowner's willingness to accept a wind power lease by offering tax credits ($policy_{land}$ in Equation 4), its empirical magnitude appears not to have been large enough to meaningfully affect wind turbine development.

The amount of tax credit offered to PA116 participants is calculated based on property tax and household income, as shown in the equation below.

$$Tax\ credit = Property\ tax - Household\ Income * 3.5\% \quad (10)$$

Under the PA116 program, landowners are eligible for a tax credit only when property taxes exceed 3.5% of household income. However, since 2009, property taxes as a share of personal income in Michigan have been declining and have consistently remained below this 3.5% threshold at the state level (Figure 3.5), suggesting that eligible tax credit amount is likely to be small. Although annual PA116 tax credit data are not publicly available, Harlow (2012) reports that in 2012, \$43.9 million tax credits were issued for 3.2 million enrolled acres, which indicates that approximately \$14 per acre in tax credits was paid to owners of farmland.



Source: US Census Bureau Annual Survey of State and Local Government Finances, 1977-2022 (compiled by the Urban Institute Accessed 2023-11-28)

Figure 3.5: Property taxes as a share of personal income in Michigan have been declining below 3.5%

Compared to the modest tax credit offered through PA116 program, the financial incentive for leasing land for wind turbines is substantially higher, offering landowners a strong motivation to terminate preservation contracts in favor of wind development. The typical lease payment in the U.S. is approximately \$3000 /MW/year, though payments can vary based on location, profitability, and land area (DOE, 2015). In Michigan, wind developers paid nearly \$39 million annually in lease payments as of 2022 (ACP, 2022). Given Michigan’s total installed wind power capacity of 3102 MW in 2022 (State of Michigan, 2022), the average lease payments is estimated to be around \$12000 per MW. Assuming each megawatt of wind capacity requires 79 acres ² (Denholm et al.,

² While wind turbines and associated infrastructure physically occupy a relatively small portion of land (2.5 ac/ MW, Denholm et al., 2009), turbine spacing and setback requirements significantly increase the total land area needed per turbine. In wind energy leasing, although developers typically do not hold rights to the entire area surrounding the turbines, landowners lease larger portions of land to accommodate turbine placement and spacing requirements. As a result, areas beyond the physical footprint of the infrastructure are dedicated to the project. Therefore, in this calculation, we use the total land area required per megawatt of capacity.

2009), this translates to about \$152 per acre. The typical U.S. lease payment of \$3000 per MW translates to approximately \$38 per acre.

The stark contrast between the high wind lease payments and the relatively small PA116 tax credit underscores the limited role of PA116 in influencing wind turbine deployment. While wind lease payments average approximately \$152 per acre in Michigan, the PA116 tax credit amounted to an average of about \$14 per acre. In many cases, landowners may have received no tax credit at all if their property taxes failed to exceed 3.5% of household income. As a result, even after the policy change allowing wind turbines on PA116-enrolled land, the impact was likely limited, as the tax credit remained negligible for many landowners both before and after the revision.

3.7 Conclusions

This study examines the interaction between farmland preservation and wind energy policies in a context where agricultural land overlaps with areas of high wind energy potential. Using sub-county level data from 2000 to 2023 across Michigan, Minnesota, and Wisconsin, and employing a difference-in-differences framework, we evaluate the effects of two policy changes in Michigan: 1) the revision of the PA116 farmland preservation program, which permitted wind turbine installation on preserved farmland, and 2) the designation of Wind Zones under PA295, which prioritized areas for wind energy development and transmission planning.

Our findings offer several contributions to literature. First, while prior studies have emphasized the restrictive effects of land-use regulations, such as setback requirements and environmental zoning, on renewable energy development (O'Brien and Hagerty, 2025; Lehmann and Tafarte, 2024; Meier et al., 2024; Lopez et al., 2023; Winikoff and Parker, 2023; Lauf et al., 2020), we investigate the opposite scenario: whether relaxing such restrictions facilitates wind

turbine deployment. We find that permitting wind turbine on preserved farmland did not lead to a measurable increase in wind turbine capacity.

This stands in contrast to findings from Germany, where expanding the designated priority areas for wind development significantly boosted turbine deployment (Lauf et al., 2020; Meier et al., 2023). In those cases, municipalities typically only permitted wind turbines within the designated priority areas, making the policy binding and highly influential in shaping land use. While this approach is functionally similar to the PA116 revision, as it expands the land area where wind development is legally permissible, the difference lies in how binding the policy is. In Germany, the restrictions were strictly applied. By contrast, before the revision, Michigan's PA116 program did not substantially constrain wind development in practice. Because wind development offered significantly greater financial returns, landowners had flexibility to forgo the PA116 tax credit and opt out of the program. As a result, the PA116 revision did not represent a substantial loosening of constraints on wind development. These findings underscore that for land-use policies to meaningfully shape landowner behavior, especially in the presence of lucrative alternative uses, they must be backed by compelling economic incentives.

Second, we document strong positive effects from the Wind Zone designation, a policy that resembles spatial planning strategies implemented elsewhere, such as Sweden's National Areas of Interest for Wind Power (nationella intresseområden för vindkraft), Australia's Renewable Energy Zone, and Texas' Competitive Renewable Energy Zones (CREZ). The incentives associated with these designations differ by context. In Sweden, the designation expedites the permitting process. In Australia, it reduces operation costs. In Texas, it provides infrastructure in advance of new renewable energy projects. Michigan's Wind Zone designation facilitated infrastructure, making it most comparable to Texas' CREZ. While existing literature on

Texas' CREZ primarily focused on its impact on grid congestion or market outcomes (Fell et al., 2019; LaRiviere and Lyu, 2022), our study provides evidence on how such designations influence the deployment of new wind capacity. We find that areas designated as Wind Zones experienced 90MW increases in newly added capacity. The effect emerged even before the transmission line projects were launched, demonstrating the anticipatory response of developers to policy signals.

Together, these results extend the literature on land-use and renewable energy policy by showing that not all land constraints are equally binding in practice. Because the economic incentives underpinning the farmland preservation program were already weak, relaxing its restrictions had little effect, whereas proactively designating Wind Zones with clearer development signals and infrastructure planning substantially boosted wind turbine installation.

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