ABSTRACT

COORAY, AYESHA LEILANI. Essays on Agricultural Production and Surface Water Quality. (Under the direction of Dr. Junjie Wu and Dr. Roderick Rejesus).

Food and fiber are among our most basic needs as human beings. As such, agriculture is one of the most critical sectors of the economy. As an industry, agriculture is both highly dependent on natural processes and the source of pervasive environmental degradation. The focus of this dissertation is the relationship between agricultural production and water quality in the United States. The goal of the following three chapters is to evaluate how shifts in on-farm production practices can minimize adverse environmental outcomes and improve resilience to climate change and economic shocks. This dissertation aims to generate actionable insights for producers and policymakers that balance economic goals with environmental stewardship.

Chapter 1, *Surface Water Impairment from Storms and Swine in North Carolina*, leverages variation in upstream density of swine feeding operations across surface water monitoring locations in the state of North Carolina and the exogeneity of rainfall to quantify the degree of water quality degradation that occurs from these facilities with the onset of extreme precipitation. I use geospatial stream/river flow data to construct the direction of flow across watersheds in North Carolina and chart the upstream river segments for surface water monitoring locations throughout the state. Combining this information with permitted facility locations, allowed animal counts, and daily precipitation data, I estimate difference-in-difference models. The results of this chapter are important to the sustainability of hog production in North Carolina given the state's susceptibility to hurricanes and projections for more frequent extreme rainfall with climate change. A key contribution of the paper is the close examination of the existing protocols of North Carolina's Swine Waste General Permit and how these stipulations impact public and private incentives within lagoon-spray field waste management systems. In doing so, this chapter is not only able to articulate the impact of hog feeding facilities on water quality but also identify policy implications for North Carolina's Animal Feeding Operations Permit program.

Chapter 2, *The Impact of Conservation Tillage Intensities on Mean Yields and Yield Risk*, examines the productivity and production risk effects of conservation tillage practices in the Piedmont region of North Carolina using long-term field trial data for corn and soybeans. This paper was published in a special issue titled "The Economics of Soil Health" in the journal Soil Security. The paper offers a summary of the trade-offs in yield and yield risk from adopting conservation tillage practices along a spectrum of tillage intensities to corn and soybean growers in North Carolina. Given the short-term investment costs and uncertainty of

benefits from the adoption of conservation agriculture best practices, papers like these, which offer region-specific evaluations of specific practices, contribute to department extension services and offer producers a practical lens by which to evaluate their own production practices.

Finally, Chapter 3, *Cover Crops Adoption and Harmful Algal Blooms* evaluates the impact of agricultural land use and conservation practice adoption in drainage watersheds on harmful algal blooms in freshwater lakes throughout the continental United States. Harmful algal blooms indicate that a waterbody has surpassed its idiosyncratic assimilative capacity for nutrients and is actively impaired. This paper seeks to contribute to the literature by 1) evaluating whether winter cover crops—a conservation practice receiving increasing policy support—reduces the incidence of harmful algal blooms the following summer and 2) examining crop mix in the watershed and the incidence of harmful algal blooms. By evaluating changes in this undesirable phenomenon, the results of this paper offer farmers and policymakers an evaluation of soil health practices as a mitigation measure for nutrient pollution and insight into the types of production should be targeted for conservation expenditure.

Essays on Agricultural Production and Surface Water Quality

by
Ayesha Leilani Cooray

A dissertation submitted to the Graduate Faculty of
North Carolina State University
in partial fulfillment of the
requirements for the Degree of
Doctor of Philosophy

Economics

Raleigh, North Carolina
2025

APPROVED BY:

Dr. Junjie Wu
Co-chair of Advisory Committee

Dr. Roderick Rejesus
Co-chair of Advisory Committee

Dr. Jeffrey Dorfman

Dr. Zachary Brown
External Member

Dr. Spencer Banzhaf

BIOGRAPHY

Ayesha Cooray is an economist passionate about research at the intersection of agricultural production and environmental management. She is dedicated to generating actionable insights for producers and advancing data-driven policy that balances economic and environmental goals. Ayesha earned her Ph.D. in Economics from North Carolina State University and her M.Sc in Local Economic Development from the London School of Economics and Political Science. Her professional experience includes the International Monetary Fund and Bates White Economic Consulting. Upon graduation, Ayesha will be joining the Federal Reserve Bank of Kansas City as an Economist.

ACKNOWLEDGEMENTS

I am deeply grateful to my committee, Junjie Wu, Roderick Rejesus, Jeffrey Dorfman, and Spencer Banzhaf for their incredible mentorship and support. Thank you for demonstrating how to add structure and clarity to nebulous problems; communicating both the formal and informal standards of academia; and kindly but firmly steering me away from work flows that involved large time investments with little rewards. I am incredibly fortunate to have had the opportunity to learn from and collaborate with such talented and dedicated individuals.

Thank you to my incredible village of friends and family both in here in North Carolina and elsewhere. Peter and I are so grateful for the warmth, cheer, and encouragement you have extended us over the past eventful six years. To my in-laws, Jim and Mary, your support and encouragement mean the world to me. I'm so happy to be part of your family. To my own parents, thank you for encouraging me to be ambitious, take risks, work hard, and push my limits. Words can't express my gratitude for your unwavering support, Mommy and Thathi. As they well know, my siblings are the core of my support system. Amila, thank you for always picking up the phone and soothing my various anxieties—no one is there for me as unconditionally as you. Shirmila, your incredible humor, wry pragmatism, and insightful (if sharp) reprimands keep me on track. I never laugh harder than when I'm with you.

To my own little family, I am particularly indebted. Wensleydale, your soft velvety ears have brought me much comfort during late nights and early mornings and your insistence on a walk everyday is a pillar of my health. Thank you for your constant companionship, my most precious pup. Everard, you are the light of my life and give me purpose everyday. Being your mom has forged me into a better version of myself. Undoubtedly, finishing this degree would not have have been possible without the lessons you taught me about discipline, perseverance, and priorities. I love you, my fierce girl.

Finally, thank you to my husband, Peter. You can't finish what you don't start and without you, Peter, I would have never started. Thank you for believing in me when I didn't believe in myself— and for reminding me that there's some good in this world and that it's worth fighting for. This dissertation is dedicated to you.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

Chapter 1

Introduction

Clean water is essential for agricultural production, public health, and the functioning of ecosystems. However, water quality in the United States has been increasingly degraded by anthropogenic activities, particularly agricultural production (Ribaudo and Shortle, 2019; Rossi et al., 2023). The Environmental Protection Agency lists agricultural nonpoint source pollution as the leading cause of water quality impairments on surveyed rivers and streams, the third-largest cause for lakes, the second-largest for wetlands, and a major contributor to contamination of estuaries and groundwater (EPA, 2025). Food and fiber are among our most basic needs as human beings. As such, agriculture is one of the most critical sectors of the economy. The goal of this dissertation is to examine the nexus between agricultural production, water quality, and on-farm production practices

As an industry, agriculture is both highly dependent on natural processes and the source of pervasive environmental degradation. Shifts in temperature, rainfall patterns, and the frequency of extreme weather events with climate change threaten both agricultural production and surface water quality. More frequent and intense rainfall, for example, threatens crop yields and increases the volume of runoff, carrying higher loads of nutrients, sediments, and pesticides into water bodies (EPA, 2025). Given agricultural nonpoint pollution is exempt from the 1972 Clean Water Act, adopting production practices that balance economic viability with environmental stewardship is critical to improving resilience to weather and climate shocks and achieving improvements in water quality. The purpose of the following three chapters is to provide actionable insights to producers and policy-makers on production practices that achieve both outcomes.

Chapter 1, *Surface Water Impairment from Storms and Swine in North Carolina*, leverages variation in upstream density of swine feeding operations across surface water monitoring locations in the state of North Carolina and the exogeneity of rainfall to quantify the degree of water quality degradation that occurs from these facilities with the onset of extreme precipitation. I use geospatial stream/river flow data to construct the direction of flow across watersheds in North Carolina and chart the upstream river segments for surface water monitoring locations throughout the state. Combining this information with permitted facility locations, allowed animal counts, and daily precipitation data, I estimate difference-in-difference models.

The results of this chapter are important to the sustainability of hog production in North Carolina given the state's susceptibility to hurricanes and projections for more frequent extreme rainfall with climate change. A key contribution of the paper is the close examination of the existing protocols of North Carolina's Swine Waste General Permit and how these stipulations impact public and private incentives within lagoon-spray field waste management systems. In doing so, this chapter is not only able to articulate the impact of hog feeding facilities on water quality but also identify policy implications for North Carolina's Animal Feeding Operations Permit program.

Chapter 2, *The Impact of Conservation Tillage Intensities on Mean Yields and Yield Risk*, examines the productivity and production risk effects of conservation tillage practices in the Piedmont region of North Carolina using long-term field trial data for corn and soybeans. This paper was published in a special issue titled "The Economics of Soil Health" in the journal Soil Security. The paper offers a summary of the trade-offs in yield and yield risk from adopting conservation tillage practices along a spectrum of tillage intensities to corn and soybean growers in North Carolina. Given the short-term investment costs and uncertainty of benefits from the adoption of conservation agriculture best practices, papers like these, which offer region-specific evaluations of specific practices, contribute to department extension services and offer producers a practical lens by which to evaluate their own production practices.

Finally, Chapter 3, *Cover Crop Adoption and Harmful Algal Blooms* evaluates the impact of agricultural land use and conservation practice adoption in drainage watersheds on harmful algal blooms in freshwater lakes throughout the continental United States. This paper seeks to contribute to the literature by 1) examining agricultural land use and the incidence of cyanobacterial blooms and 2) evaluating whether the adoption of agricultural best practices that provide winter cover can reduce cyanobacterial blooms. By evaluating changes in this undesirable phenomenon, the results of this paper offer farmers and policymakers an evaluation of soil health practices as a mitigation measure for nutrient pollution and insight into the types of production should be targeted for conservation expenditure.

References

1. Ribaudo, Marc, and James Shortle. "Reflections on 40 years of applied economics research on agriculture and water quality." Agricultural and Resource Economics Review 48, no. 3 (2019): 519-530.

2. Del Rossi, Gemma, Mohammad Mainul Hoque, Yongjie Ji, and Catherine L. Kling. "The economics of nutrient pollution from agriculture." Annual Review of Resource Economics 15, no. 1 (2023): 105-130.

3. United States Environmental Protection Agency. "Nutrient Pollution." Accessed May 23, 2024. `https://www.epa.gov/nutrientpollution`.

Chapter 2

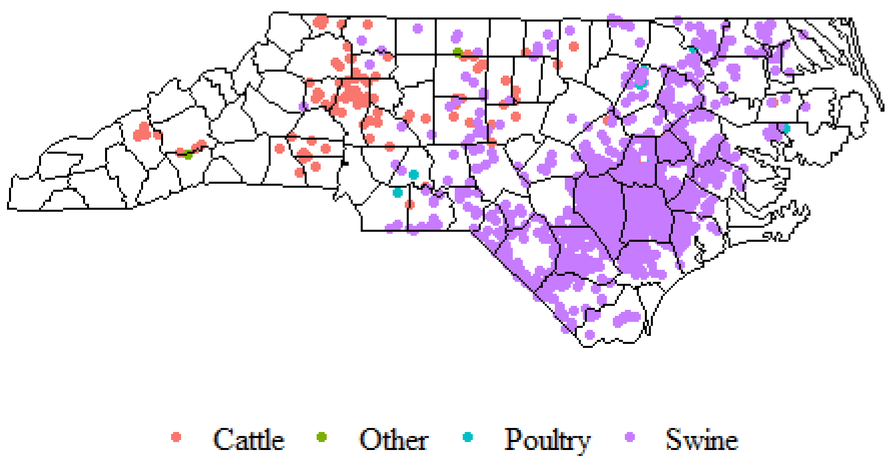
Surface Water Impairment from Storms and Swine in North Carolina

2.1 Introduction

High-profile incidents of flooding, catastrophic lagoon overflows, and thousands of animal deaths during Hurricane Floyd in 1999, Hurricane Matthew in 2016, and most recently Hurricane Florence in 2018 have put a spotlight on the environmental risks associated with hog production and extreme precipitation in North Carolina (Davis, 2018; Maher and Kesling, 2018; Pierre-Louis, 2018; Oglesby, 2021). Swine waste contains microbial pathogens, hormones, antibiotics, and chemicals that endanger human and animal health (US EPA, 2024). As such, hog feeding operations are regulated by the North Carolina Department of Environmental Quality ("NC DEQ") which operates a permit program designed to minimize environmental damage from these facilities (NC DEQ, n.d.). The purpose of this paper is to quantify the impact of hog feeding operations on surface water quality given existing permit protocols in North Carolina, examine the role of precipitation in exacerbating outcomes, and evaluate the mechanisms by which these operations contribute to surface water impairment.

North Carolina is the third largest producer of hogs in the United States. Structural change within the hog industry in the mid-1980s and early 1990s shifted hog production from small, independently-owned operations toward fewer, larger, and more densely-clustered operations (Harun et al., 2013; Montefiore et al., 2022). Figure 1 illustrates the degree of agglomeration in swine production in North Carolina— just three counties in the eastern part of the state account for the majority of production (Zering, 2020). The geographic concentration of these facilities on the coastal plain compound concerns regarding flooding and runoff from these operations (Wing et al., 2002; Shelby, 2002; Oglesby, 2021). The state's low-elevation coast is one of the highest impact zones for hurricanes in the world (Paerl et al., 2019; NC Department of Public Safety, n.d.). Furthermore, climate change threatens to increase the intensity and frequency of heavy rains from hurricanes, tropical storms, and other weather systems like thunderstorms and Nor'easters in North Carolina (Kunkel et al., 2020). Annual precipitation across the state is projected to increase in the coming decades with a greater portion of rainfall occurring in extreme events (Paerl et al., 2019; Kunkel et al., 2020).

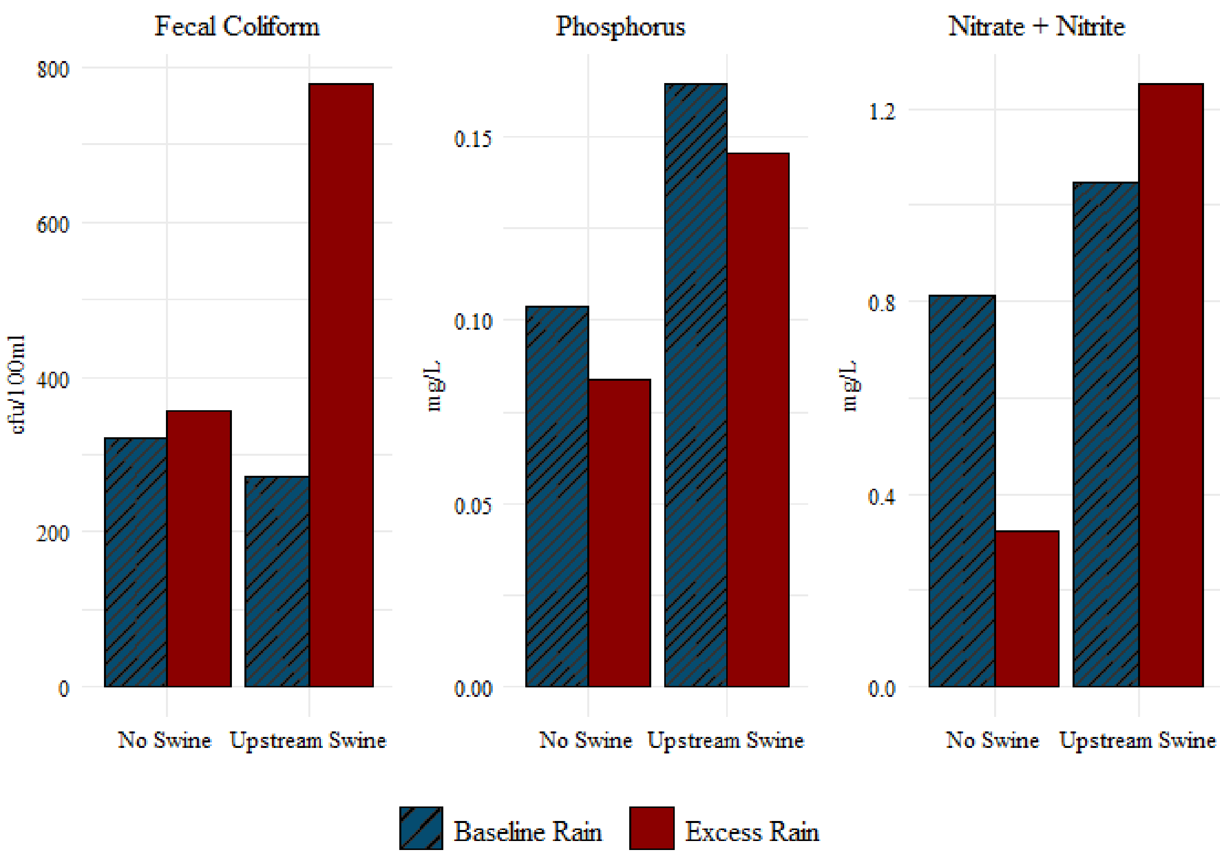
Figure 2.1: Animal Feeding Operations by County in North Carolina



Note: Map of animal feeding operations permitted by NC DEQ. All facilities utilize liquid waste systems (e.g., store waste in a lagoon or pond).

There are several avenues by which extreme precipitation can trigger water quality impairment from swine feeding operations. Hog feeding facilities in North Carolina employ lagoon-spray field systems that flush urine and feces from barns into large open-air lagoons for storage and treatment (Iriaghomo et al., 2022; Montefiore et al., 2022). Within the lagoon, the waste separates into a liquid slurry layer and a solid sludge layer where anaerobic bacteria and microbes break down the chemical compounds of the waste (Liu, 2021). To manage lagoon water levels and recycle nutrients, operators spray lagoon slurry onto adjacent fields as fertilizer (Wang and Baerenklau, 2015; Iriaghomo et al., 2022). However, extreme precipitation can cause lagoons to breach or overflow and release untreated waste into the surrounding landscape. Heavy rain can also cause rivers and streams to rise, flooding lagoons and mixing lagoon slurry with floodwater. Finally, precipitation that occurs before crops in field uptake nutrients and neutralize pathogens causes runoff from spray fields that contaminates waterways (Ribaudo et al., 2003; Wang and Baerenklau, 2015; Shea et al., 2022).

Figure 2.2: Surface Water Quality in North Carolina before and after Extreme Precipitation



Note: Average concentrations of water quality indicators at locations within 5 miles downstream of swine feeding operations versus others throughout North Carolina. Excess rain refers to samples taken within a week of 3 or more inches of 24-hour precipitation while baseline refers to samples taken after rainfall events lower than 3 inches.

Figure 2 compares the average level of fecal coliform, phosphorus, and nitrogen concentrations in surface water at locations within 5 miles downstream of hog feeding facilities and locations with no hog facilities within 5 miles upstream. For each group, Figure 2 shows the average level of these water quality indicators at baseline precipitation (e.g. samples taken after precipitation events below 3 inches) and within a week after the onset of 3 or more inches of rainfall. All samples were taken between 2019 and 2023. Figure 2 suggests that locations downstream of hog feeding facilities experience worse water quality with the onset of excessive precipitation than other locations in North Carolina. For example, while the level of fecal coliform in surface water downstream of hog feeding facilities is lower than other locations at baseline precipitation, it surpasses the level of fecal coliform at other monitoring locations with the onset of heavy precipitation. The concentration of nitrates in surface water declines with excessive precipitation at locations with no upstream swine feeding facilities while the concentration of nitrates in surface water increases with excessive precipitation at locations downstream of swine feeding facilities. These observations are puzzling given the strict operations protocols stipulated by NC DEQ's swine waste general permit which is designed to circumvent adverse water quality outcomes from hog production.

The operations protocol mandated by NC DEQ's swine waste general permit are the legacy of high-profile environmental catastrophes in which multiple lagoons discharged untreated swine waste into the surrounding environment via lagoon breaches, overflows, and flooding. The current permit requires facilities to operate and maintain lagoons to contain all the waste generated by its operations, a foot of additional freeboard, and runoff from a 25-year, 24-hour rainfall event[1]. Land application of waste is forbidden during rainfall and within 12 hours of a National Weather Service hurricane, tropical storm, or flood watch warning for a facility's county. The permit further forbids spraying lagoon slurry on land that is flooded, saturated with water, frozen, or snow-covered. Inspections of lagoons and runoff control measures are required monthly and after all 24-hour rainfall events greater than 1 inch. Facilities are required to have a Certified Animal Waste Management Plan (CAWMP) developed by a technical specialist to ensure that waste application on fields does not exceed agronomic rates. The permit also mandates the designation of a certified operator-in-charge to ensure compliance with these protocols. This individual is responsible for evaluating lagoon levels, overseeing the land application of waste, and collecting information required by the permit including the date, time, and weather conditions each time waste is sprayed.

The North Carolina Pork Council claims permit requirements circumvent environmental damage from swine feeding operations, emphasizing the permit's strict protocols around lagoon management in preventing overflows (NC Pork Council, 2020; NC Pork Council; 2024). Environmental groups allege otherwise, accusing operators of illegal manure application ahead of storms and asserting that runoff from manure-applied fields contribute pathogens and nutrients to local waterways (Waterkeeper Alliance 2019; Environmental Health News, 2021). The extent to which hog feeding facilities contribute to surface water quality impairment continues to be fiercely debated in North Carolina. The ongoing debate highlights a fundamental tension

[1]While the rainfall associated with this definition varies slightly across the state, the average level of precipitation associated with a 25-year, 24-hour rainfall event in North Carolina is 7 inches of precipitation within 24 hours (NOAA, 2012).

within the lagoon-spray field waste management system. The land application of manure (e.g. spraying lagoon slurry) is essential to maintaining lagoon capacity and preventing overflows for facilities seeking to maximize their hog production. This creates private and public incentives around the application of swine slurry beyond the recycling of nutrients.

Lagoon overflows are environmentally catastrophic. Given the state's history of widespread lagoon overflows during hurricanes, NC DEQ includes a qualification within the swine waste general permit that allows operators to temporarily lower lagoon levels, via spraying, during the annual hurricane season to provide additional storage for extreme rainfall[2]. In addition, the permit requires any facilities with overflows or lagoon breaches to issue a press release. Facilities with overflows or lagoon levels that are persistently high are subjected to enhanced regulatory and public scrutiny. As a result, the anticipation of heavy precipitation can motivate facility operators to apply manure in excess of what they would otherwise to increase lagoon capacity and avoid overflows (Hendricks et al., 2019). In the lead up to Hurricane Florence, for example, facility operators pumped down lagoon levels to absorb at least 2 feet of rain by spraying adjacent fields (Associated Press, 2018). This behavior in and of itself has the potential to exacerbate water quality outcomes from hog feeding facilities from excessive precipitation.

The goal of this paper is to rigorously evaluate the net impact of hog feeding facilities on surface water quality in North Carolina and whether extreme precipitation triggers adverse environmental outcomes. To do so, we use the U.S. Environmental Protection Agency's Water Quality Portal to obtain inorganic nitrogen, phosphorus, and fecal coliform samples from surface water monitoring locations throughout North Carolina from 2019 through 2023. We construct a river/stream direction flow network for each Hydrologic Unit Code 8-level watershed using the U.S. Geological Survey's National Hydrography Dataset and use NC DEQ's list of permitted animal feeding facilities to construct measures of upstream swine density across monitoring locations in our water quality sampling data. Using daily precipitation data from Oregon State University's Parameter-elevation Regressions on Independent Slopes Model, we estimate difference-in-difference models. Our analysis leverages variation in the upstream density of swine feeding operations across surface water monitoring locations and the exogeneity of the timing and magnitude of rainfall to identify the impact of swine feeding operations on surface water quality.

The results of this paper offer policymakers an evaluation of the efficacy of the current North Carolina general swine waste permit in protecting the state's surface waters. We go on to examine mechanisms for

[2]From June 15 to October 31, the N.C. Swine Waste General Permit allows drawdowns of lagoon levels to no more than 8 inches below the stop pump level as long as manure application adheres to each facility's CAWMP which forbids application of swine waste in excess of what plants can be reasonably expected to uptake.

water pollution from swine feeding operations and discuss the policy implications of our results for the North Carolina swine waste general permit. The results of this paper are important to the sustainability of hog production in North Carolina given projections for more frequent extreme rainfall with climate change. It is imperative to understand whether adjustments to the swine waste general permit could mitigate adverse water quality outcomes.

The paper is organized as follows: Section 1 reviews the literature examining water pollution from animal feeding operations; Section 2 discusses the construction of the upstream river/stream flow segment for monitoring locations and explains our data processing steps and assumptions for the water quality monitoring data, daily precipitation data, and animal feeding operation permit data; Sections 3 and 4 introduce our methodology and results; Section 5 discusses the mechanisms for surface water quality impairment from hog feeding facilities while Section 6 evaluates the policy implications of our results for NC DEQ's permit program. Finally, Section 7 summarizes our conclusions and discusses the limitations of our study.

2.2 Literature Review

The literature evaluating the environmental impacts of animal feeding operations is extensive and spans several disciplines including epidemiology and public health, environmental science, and public policy. While a large and important literature evaluates the impact of animal feeding operations on air quality, we focus on research examining water pollution in the discussion that follows. The ecological and environmental science literature evaluating the effect of hog feeding operations on water quality identify the contribution of excess nutrients (Weldon and Hornbuckle, 2006; Mallin et al., 2015), pathogens (Sapkota et al., 2007; Mallin et al., 2015; Heaney et al., 2015; Mallin et al., 2019; Christenson et al., 2022), and veterinary pharmaceuticals (Metcalfe et al.,2003; Campagnolo et al. 2002; Bernot et al., 2013) as means of impairment. In the late 1990s, several papers examined water quality and river ecology in the Cape Fear and White Oak watersheds in North Carolina following incidents of large lagoon overflows and breaches at hog facilities (Burkholder et al., 1997; Mallin et al., 1997; Mallin, 2000). These studies identify elevated phosphorus and fecal coliform, extensive fish deaths, and increased algal production as consequences of flooding and runoff from swine feeding operations. While illustrative, these papers rely on a site-sampling methodology and statistical analysis that does not explicitly control for confounding variables, specific attributes of the size and density of animal feeding operations, or the degree of rainfall associated with each sample across sites. As such, extracting specific policy implications for the state's animal permitting program is difficult.

Within agricultural and environmental economics[3], an emerging literature uses reduced-form econometrics and nationally-available water quality monitoring data to directly estimate the effect of policies and programs related to water quality improvement and agricultural practices on ambient water quality (Keiser Shapiro, 2019; Liu et al., 2022; Paudel Crago, 2020; Raff and Meyer, 2021; Hsieh and Gramig, 2023). Raff and Meyer (2021) evaluate the effect of animal feeding operations on water quality by comparing changes in phosphorus and ammonia concentrations across watersheds in Wisconsin with varying degrees of expansion of concentrated animal feeding operations (predominantly dairy cow facilities) from 1995 to 2017. Controlling for annual precipitation, land-use patterns, and land cover, the authors conclude that increasing CAFO presence and intensity leads to significantly higher levels of nutrients in surface water readings at the watershed-level. To date, no papers have used intra-annual variation in precipitation to isolate the impact of animal feeding operations on water quality degradation. This paper seeks to contribute to the literature by examining the role of precipitation in activating water pollution from swine feeding operations in North Carolina.

2.3 Data

To conduct our analysis, we rely use geospatial river/stream data to construct a direction of river/stream flow for surface water monitoring stations through out North Carolina. In doing so, we are able to construct a database at the monitoring location and sampling data level that includes upstream animal densities, daily precipitation, exposure to wastewater facilities, and county-level economic and agricultural production data. In the following section, we discuss the variable construction process for each variable required for our empirical specification.

2.3.1 Water Quality Monitoring Data

Surface water quality sampling data from streams, river, and lake monitoring locations in North Carolina were obtained via the Environmental Protection Agency (EPA)'s Water Quality Portal from 2019 through 2023. Physical/chemical sample results data was downloaded separately from site data and merged using the unique identifier for each monitoring location. Only records with numeric measurements and a media

[3]There are a number of studies that use hedonic price models to evaluate property values in the vicinity of animal feeding operations (Herriges, Secchi, and Babcock 2005; Ready and Abdalla 2005; Isakson and Ecker 2008)— but water quality degradation is just one of many nuisances from animal feeding operations that influence housing prices (e.g. odor, air quality, etc.).

Table 2.1: Descriptive Statistics

Statistic	N	Mean	St. Dev.	Min	Max
Fecal Coliform (cfu/100ml)	6,960	315.347	668.537	0.000	12,000.000
ln(Fecal Coliform)	6,959	4.682	1.481	0.000	9.393
Nitrates (N mg/L)	6,159	0.831	1.786	0.020	28.000
ln(Nitrates)	6,159	−1.022	1.239	−3.912	3.332
Phosphorus (P mg/L)	7,639	0.110	0.211	0.000	7.200
ln(Phosphorus)	7,426	−2.658	0.839	−4.605	1.974
Daily Precipitation (in)	20,758	0.109	0.277	0.000	3.352
After Excess Rain Indicator	20,758	0.018	0.133	0	1
Swine Indicator	20,758	0.118	0.323	0	1
Swine Count (1000s)	20,758	0.970	3.585	0.000	30.008
Cattle Indicator	20,758	0.046	0.210	0	1
Cattle Count (1000s)	20,758	0.035	0.226	0.000	2.650
Poultry Indicator	20,758	0.001	0.035	0	1
Poultry Count (10,000s)	20,758	0.025	0.714	0.000	20.200
Other Animals Indicator	20,758	0.003	0.058	0	1
Other Animal Count (1000s)	20,758	0.003	0.051	0.000	0.874
Wastewater Facilities Count	20,758	0.834	1.744	0	58
County Corn Yield (bu/ac)	14,759	122.888	25.595	55.000	204.000
County Soybean Yield (bu/ac)	15,601	35.835	6.133	19.500	57.000
County GDP (millions, 2017 dollars)	20,758	14,033.130	27,577.580	102.683	129,565.500
Population (10,000s)	20,758	20.450	28.551	0.324	119.028

type identified as “Water” were included in our sample. Since there is overlap across data repositories within the Water Quality Portal, we dropped duplicate records by defining a unique sample of each water quality measure using the following attributes: sampling location, sampling date, sampling time, sampling equipment, sampling depth, unit of measurement, filtered/unfiltered category [4], and laboratory analytical method. Three percent of the data represented the exact same type of measurement but recorded slightly different sampling values. The average measurement across these records was taken. To obtain a single reading for each water quality measure at each location and date, we averaged records at each sampling location and date across sampling depth, time, and sample collection equipment and kept only those records that used the most common type of laboratory analytical method for each type of water quality characteristic.

The EPA identifies nitrogen, phosphorus, organic matter, sediments, pathogens, hormones, and antibiotics as potential water pollutants from animal feeding operations (EPA, 2024). As such, we selected three water quality measures to include in our analysis: Nitrate and nitrite, phosphorus, and fecal coliform. Fecal coliform refers to a group of bacteria that occurs in the intestines of warm-blooded animals. High levels of fecal coliform

[4] Both a filtered and unfiltered sample is taken for water quality indicators that are metals. According to EPA guidelines (EPA, 1991), metal is considered dissolved if it remains in solution after filtration through a 0.45 micromolar (uM) filter. Suspended metals are those that remain on the 0.45 M filter. Unfiltered samples thus represent the total level of the compound collected in the sample. In our analysis, we included only unfiltered nitrogen and phosphorus samples.

indicate the presence of untreated sewage and other types of pathogenic bacteria and viruses (Holcomb and Stewart, 2020). Nitrate and nitrite are plant-accessible forms of inorganic nitrogen which, along with phosphorus, are nutrients that promote plant growth. In excess amounts, inorganic nitrogen and phosphorus accelerate aquatic plant growth, deplete dissolved oxygen, and harm aquatic life in surface water (EPA, 1997; NOAA, 2024)[5]. These characteristics are collected monthly though sampling from March through December of 2020 was reduced due to the COVID-19 pandemic restrictions. See Table 1 above for summary statistics of the concentration of water quality indicators. Appendix A Figure 1 displays the distribution of concentrations of fecal coliform, nitrate and nitrite, and phosphorus over the period of analysis.

2.3.2 Watershed River/Stream Network

Using the EPA and U.S. Geological Survey's National Hydrography Plus Dataset (NHD Plus) for the continental United States, we obtain a map of the river/stream network across the state of North Carolina. Each river/stream segment in the dataset has a unique identifier and includes the upstream and downstream node for each segment. By linking each river segment's downstream node with another river segment's upstream node, we built a directed graph for each river segment in the state of North Carolina. We use these constructs to establish the entire upstream flow network within the HUC8-level watershed for each monitoring location for which we have water quality sampling data.

2.3.3 Animal Feeding Operations Permit Data

Animal feeding operation permit data for facilities permitted from 2019 through 2023 is published by the North Carolina Department of Environmental Quality (NC DEQ). The data includes the latitude and longitude, type and allowed count of animal, and number of waste lagoons associated with each facility. Permits are associated with multiple types of regulated activities per animal. See Appendix A Table 1 for a summary of the regulated activities per animal. We sum over the types of regulated activity at each facility to obtain a total number of each type of animal at the facility. Any facilities marked "Inactive" or "Proposed" are excluded in our analysis as are any that exhibit an "Expired" permit status or for which latitude and longitude data are not available. For each facility in our sample, we identify the nearest river segment. If the nearest river segment for a facility is within a certain distance upstream of a monitoring location, the allowable count of animals at that facility is included in our measure of upstream animal density. Table 1

[5] Nitrates dissolve in water more readily than phosphates, which have an attraction for soil particles (EPA, 1997). As a result, nitrates are a better indicator of possible sewage or manure pollution during dry weather (EPA, 1997).

above contains summary statistics for upstream density of swine, cattle, poultry, and other animals within 5 miles upstream across surface water monitoring locations in North Carolina. Appendix A Figure 2 displays the distribution of these variables across monitoring stations.

2.3.4 Precipitation Data

Daily precipitation was acquired at the zip code level for each monitoring location from Oregon State University's Parameter-elevation Regressions on Independent Slopes Model (PRISM) via Aaron Smith and Seunghyun Lee's Ag Data portal. In addition to daily precipitation, we construct the cumulative sum of the past 7-days of precipitation for each day in our period of analysis from 2019 through 2023. See Appendix A Figure 2 for a histogram of precipitation values over the period of analysis.

2.3.5 Wastewater Treatment Facilities and County-level Covariates

To isolate the impact of upstream swine density and precipitation, our estimation must account for variables that could vary across monitoring locations and impact the level of fecal coliform, nitrogen, and phosphorus in surface water with the onset of precipitation. To do so, we include the number of wastewater treatment facilities within 5 miles upstream, county GDP, and county population for each monitoring location. In the nitrates and phosphorus specifications, we also include county-level corn and soybean yields. The location of wastewater treatment facilities in the state of North Carolina was obtained via the NC DEQ. As with upstream animal densities, we identified the nearest river/stream segment to each wastewater treatment facility and used our constructed upstream stream/river network for each monitoring location to evaluate the number of wastewater facilities upstream (along the river/stream segment) for each monitoring location. County-level GDP and population data was obtained from the U.S. Census Bureau while county-level corn and soybean yields were obtained from the U.S. Department of Agriculture's National Agricultural Statistics service. See Table 1 for summary statistics and Appendix A Figure 2 for the distributions of these variables within the period of analysis.

2.4 Empirical Strategy

The objective of this paper is to quantify the impact of swine feeding operations on surface water quality given existing permit protocols in North Carolina and examine the role of precipitation in exacerbating outcomes.

To do so, we employ a dynamic two-way fixed effects difference-in-difference estimation framework. In our setting, runoff or flooding from upstream hogs represent the treatment, the timing of treatment is determined exogenously by the onset of excess precipitation, and the level of nitrates, phosphorus, and fecal coliform in surface water are the outcome variables. In terms of conditional expectations, the difference-in-difference estimator for our model is:

$$\delta = (E[Y_t After] - E[Y_t Baseline) - (E[Y_u After] - E[Y_u | Baseline) \tag{2.1}$$

where $After$ refers to water quality samples within a week after the onset of excess precipitation and $Baseline$ refers to all other days. Monitoring locations downstream of hog feeding operations are considered treated, t, while those with no hogs upstream or not proximate to swine feeding operations are considered untreated, u.

To estimate δ, we use the following empirical specification for each water quality indicator:

$$Y_{it} = \alpha + \gamma After_{it} + \lambda Swine_i + \delta(After * Swine)_{it} + \beta X_{it} + \epsilon_{it} \tag{2.2}$$

where i represents a monitoring location and t represents the sampling date. $Swine_i$ is an indicator variable equal to 1 if there are hog facilities within 5 miles upstream (along the river) and zero otherwise. $After_{it}$ is equal to 1 if the water quality reading was taken within a week of excess precipitation (3 inches or more). X_{it} is a vector of station and time varying controls. In this model, λ represents the baseline effect of having swine upstream; γ represents the average effect of runoff or flooding from excess precipitation across monitoring stations; and δ represents the additional impact from upstream swine on fecal coliform, phosphorus, and nitrate concentrations that occurs with excess precipitation (e.g. runoff from swine farms). We use this estimation to examine how the combined effect of runoff from excess precipitation and hog feeding operations, δ, changes across thresholds of extreme precipitation and with distance upstream.

The identification assumption of our model is, absent treatment (runoff from swine feeding operations with precipitation) and controlling for other covariates, the concentration of fecal coliform, nitrates, and phosphorus follow parallel trends across surface water monitoring locations across North Carolina. As such, to isolate the impact of upstream swine density and precipitation, our estimation must include covariates X_{it} which both vary across monitoring locations and could impact the level of fecal coliform, nitrogen, and phosphorus with the onset of precipitation. To do so, we include indicator variables for upstream permitted cattle density, upstream permitted poultry, and upstream other animals[6]. We also include the number of wastewater treatment facilities within 5 miles upstream, county GDP, and county population. In the nitrates and phosphorus specifications, we include county-level corn and soybean yields in X_{it} as fertilizer application for these crops could impact the level of nutrients in nearby surface water. All specifications contain HUC8-level watershed and annual fixed effects in X_{it} and use robust standard errors.

2.5 Results

Results from our baseline difference-in-difference estimation are displayed below in Table 2. The results are particularly striking for fecal coliform. As expected, excess precipitation increases the average level of fecal coliform across monitoring locations in North Carolina (by 64%) and monitoring locations downstream of hog facilities have a higher baseline level of fecal coliform (by 19%). The coefficient on the interaction indicates that being downstream of hog feeding operations and excessive precipitation increases the fecal coliform concentrations by an additional 140%. These results are significant at the 1% level and indicate that extreme precipitation activates significant contamination from swine feeding operations. Monitoring stations downstream of hog facilities in the week following a rainfall event of 3 inches or more have almost four times as much fecal coliform in sampled surface water than they do at baseline precipitation.

Below, Figure 3 illustrates the predicted value of fecal coliform at baseline precipitation and after extreme precipitation for monitoring locations downstream of swine and otherwise. To contextualize our results, we include the Recreational Water Quality Criteria (RWCQ) safety thresholds for primary and non-primary contact recreation. The North Carolina Department of Health and Human Services calculates the RWQC to identify the level of contamination in surface waters that endangers human health using national EPA standards (NCDHHS, 2022). Primary contact recreation refers to swimming [7] while non-primary contact recreation represents boating, canoeing, and kayaking (U.S. EPA, 2012). For E. coli, the major species of fecal coliform bacteria, the RWQCs for primary and non-primary contact recreation are 126 cfu/100ml and

[6]The distributions for upstream permitted swine, cattle, poultry, and other animals are highly skewed to the right with most monitoring locations recording zero. As such, we use indicator variables in our baseline specification but include the results of specifications using continuous upstream animal densities in Appendix A Table 2. Note that this specification does not result in positive, significant coefficients on the interaction between upstream swine and after excess precipitation (contrary to our main result). To evaluate this result further, we explore how the treatment effect changes with the density of upstream swine. The results are contained in Appendix A Table 3. Moving from no upstream swine to 250 upstream swine results in large, significant treatment effect. However, as the density of upstream swine increases to 500 and 1000, the treatment effect is relatively unchanged. Finally, at 2000 hogs upstream, the treatment effect is negative and not significant. Appendix A Figure 3 illustrates this effect. We suspect that these results are related to the strong right skew of the data and the spatial clustering of hog feeding facilities (e.g. once a monitoring location is downstream of some swine feeding operations, it downstream of many swine feeding operations).

[7]Primary contact recreation refers to "activities when immersion and ingestion are likely and there is a high degree of bodily contact with the water (e.g. swimming)."

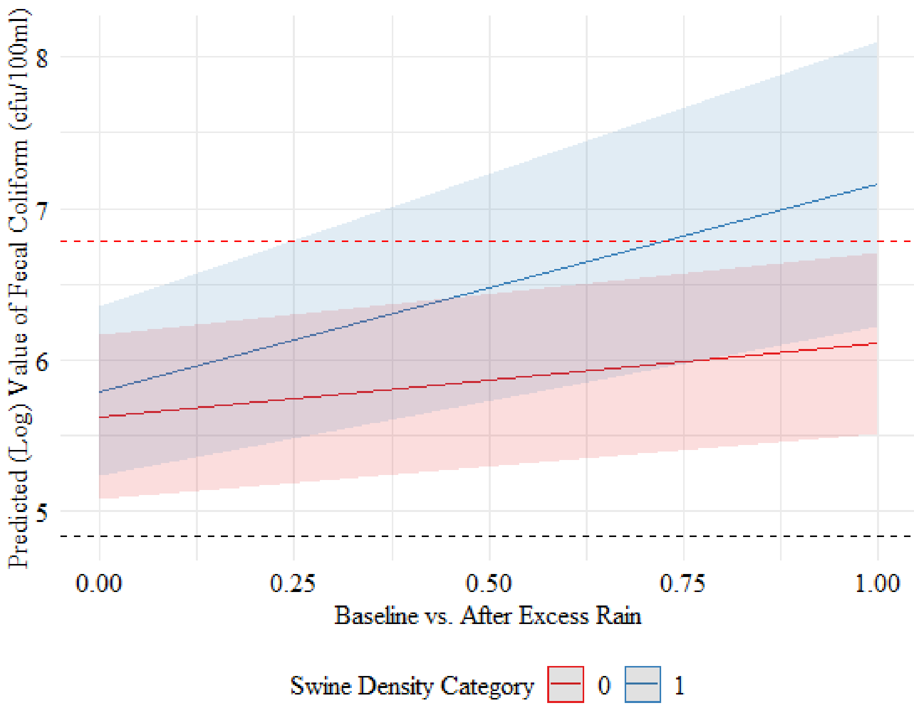
Table 2.2: Results - Water Quality Indicators - Precipitation and Swine Density

	Dependent variable:		
	F. Coliform ((cfu/100ml))	Nitrates ((mg/L))	Phosphorus ((mg/L))
After Excess Rain	0.492***	−0.276*	0.201***
	(0.117)	(0.162)	(0.073)
After Excess Rain*Upstream Swine	0.876***	0.194	−0.153
	(0.325)	(0.374)	(0.199)
Upstream Swine	0.177***	0.122*	0.249***
	(0.065)	(0.064)	(0.041)
Upstream Cattle	0.248***	0.516***	−0.035
	(0.088)	(0.088)	(0.071)
No. of Upstream Wastewater Facilities	−0.028*	0.059**	0.013
	(0.017)	(0.025)	(0.011)
Observations	6,959	3,644	4,969
R^2	0.175	0.338	0.287
Adjusted R^2	0.168	0.330	0.280
Residual Std. Error	1.351	1.031	0.702
F Statistic	24.388***	39.990***	41.341***
Note:			*p<0.1; **p<0.05; ***p<0.01

886 cfu/100ml respectively. Figure 4 illustrates that the level of fecal coliform for both groups of monitoring locations exceeds the RWQC for primary contact even before excessive rainfall. With extreme precipitation, the level of fecal coliform at surface water monitoring locations downstream of swine feeding operations exceeds the non-primary contact RWQC while the surface water at locations not proximate to swine do not.

To further examine how precipitation exacerbates fecal coliform contamination, we repeat our estimation using varying thresholds for extreme precipitation. These results are contained in Appendix A Table 4. Below, Figure 5 illustrates how the effect of runoff from hog facilities during excess precipitation changes with the level of extreme precipitation. At 1 inch or more of precipitation, the additional impact on the level of fecal coliform from being downstream of hog feeding facilities following extreme precipitation is not statistically significant. At 2 inches or more of 24-hour precipitation, the effect of runoff from swine facilities on fecal coliform becomes positive and significant. This effect peaks at 3 inches or more of 24-hour precipitation before declining beyond 4 inches or more. The water quality monitoring data do not contain

Figure 2.3: Fecal Coliform after Extreme Precipitation - Locations with No versus Some Upstream Hog Feeding Facilities

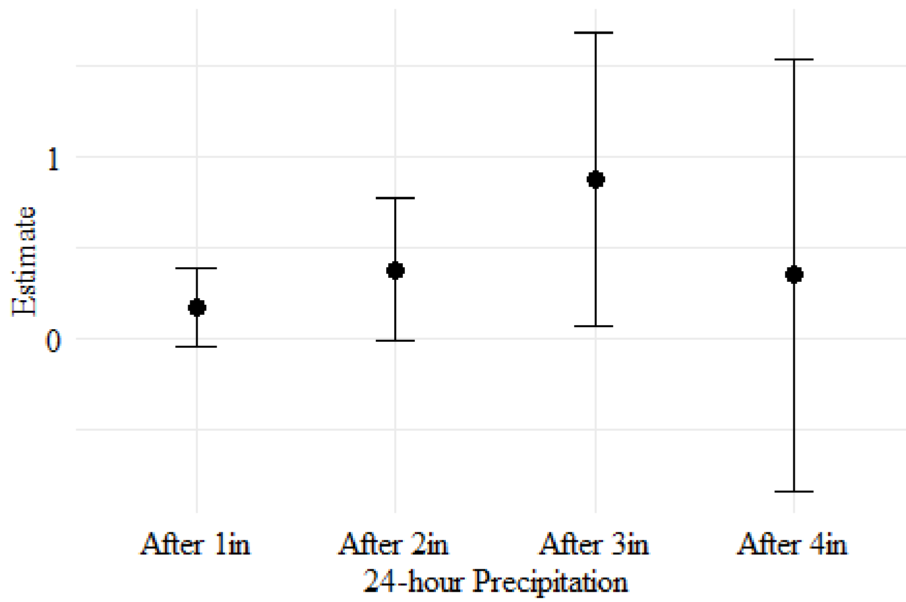


Note: The black dotted line represents the RWQC for primary recreation (e.g. swimming) while the red dotted line represents the RWQC for non-primary recreation (e.g. boating, canoeing, and kayaking). At baseline precipitation, the level of fecal coliform in surface water at both locations downstream of swine feeding operations and others exceed the safety threshold for swimming. After extreme precipitation, surface water at monitoring locations downstream of swine feeding operations exceed the safety threshold for non-primary contact recreation.

many observations following rainfall events of 4 inches or more. Most days with more than 4 inches or more of 24-hour precipitation in our timeframe occurred during 2020 when water quality sampling was reduced due to the Covid-19 pandemic. As result, we are unable to draw strong conclusions about the nature of the treatment effect beyond 3 inches of rainfall.

Appendix A Table 5 contains results of specifications exploring the effect of distance upstream on our treatment effect. At 5-miles, 8-miles, and 10-miles upstream, the effect of runoff from hog facilities from excess precipitation is large, positive, and significant at the 5% level. However, Figure 6 below illustrates that this effect attenuates with distance. This result is in line with our expectations. As distance between the monitoring location and hog facilities increase, there is more opportunity for dilution and decay to decrease the level of fecal coliform. Furthermore, as distance upstream increases, the monitoring location and hog feeding facilities are less likely to be experiencing the same level of precipitation.

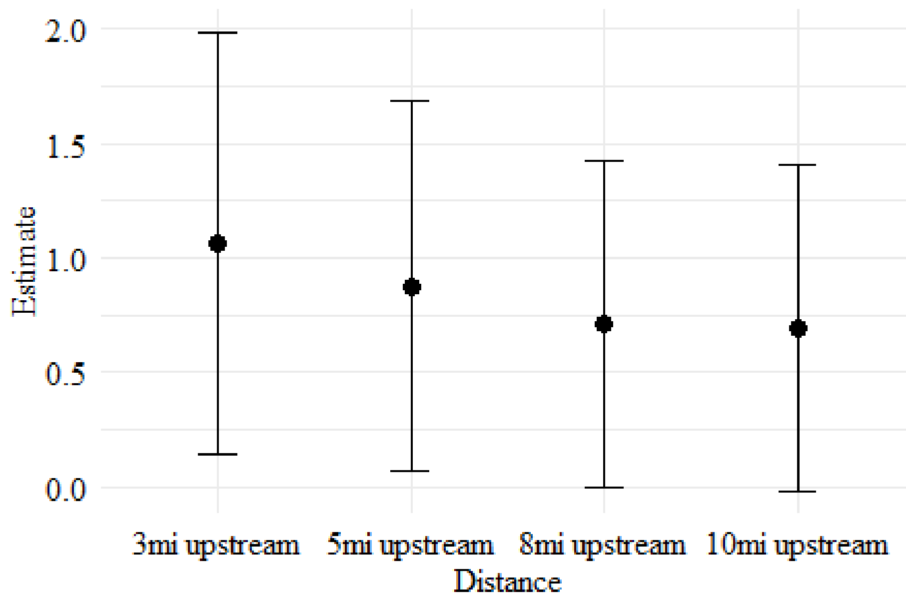
Figure 2.4: Effect of Upstream Swine after Extreme Precipitation as Threshold for Excess Precipitation Increases



Note: In the baseline specification 3 inches of precipitation is used as the definition for extreme precipitation. All samples collected within a week of an extreme precipitation event are considered observations in the post-treatment period. This figure illustrates how the treatment effect changes with varying definitions for the threshold of extreme precipitation.

The relationship between nutrients and swine feeding operations are different from that of fecal coliform. Above, Table 2 contains the results of our specification evaluating the concentration of nitrates and phosphorus give upstream swine and excess precipitation. Unlike with fecal coliform, excess precipitation does not appear to activate nutrient pollution from swine feeding operations. Runoff from excess precipitation increases the concentration of phosphorus in surface water by 22% across monitoring locations in North Carolina while being downstream of hog feeding facilities increases the concentration of phosphorus 28%. These effects are significant at the 1% level. However, the interaction of excess precipitation and upstream swine is not significant. For nitrates, concentrations downstream of hog feeding facilities are only moderately higher than others while the onset of excess precipitation actually reduces the concentration of nitrates in surface water across monitoring locations in North Carolina (note, though, that these effects are only significant at the 10% level). As with phosphorus, the interaction of excess precipitation and upstream swine is not significant. In the nitrates specification, surface water samples from monitoring locations downstream of cattle operations contain higher levels of nitrates (statistically significant at the 1% level) relative to other monitoring locations in North Carolina.

Figure 2.5: Effect of Upstream Swine after Extreme Precipitation as Threshold for Excess Precipitation Increases



Note: In the baseline specification an indicator variable for the presence of permitted swine within 5 miles upstream to indicate proximity to swine feeding operations. This figure illustrates how the treatment effect changes as distance upstream increases.

The chemical properties of these compounds offer insight into interpreting these results. Nitrate ions are made of three oxygen atoms bonded to a central nitrogen atom. As a result, hydrogen atoms in water molecules are strongly attracted to nitrate ions and they easily dissolve and are transported by water (EPA, 1997). As such, a large volume of precipitation can very quickly transport nitrates further away. Phosphates, on the other hand, have a strong affinity for soil particles due to their negative charge (EPA, 1997). If soils on the field are at or near capacity for phosphates, precipitation can cause runoff into surface waters. These dynamics are common to all monitoring stations in North Carolina with the onset of excess precipitation. The increased concentration of nutrients at monitoring locations downstream of swine and cattle relative to others suggest that impairment from these facilities occurs at lower levels of precipitation than a 3-inch rainfall event. The high level of nitrates downstream of cattle feeding operations is potentially related to the high level of ammonia present in cow manure and urine. When dissolved in surface water, ammonia quickly breaks down as bacteria convert it to nitrate and nitrite.

2.6 Mechanisms for Water Quality Impairment

Our analysis indicates that excessive precipitation activates significant fecal coliform contamination from hog feeding facilities. Monitoring stations downstream of hog facilities in the week following a rainfall event of 3 inches or more have almost four times as much fecal coliform in sampled surface water than they do at baseline precipitation. The North Carolina Swine Waste General Permit requires operators to maintain lagoons to contain all the waste generated by hogs plus an additional foot of freeboard and the runoff from a 25-year, 24-hour rainfall event. While the rainfall associated with this definition varies slightly across the state, the average level of precipitation associated with a 25-year, 24-hour rainfall event in North Carolina is 7 inches of precipitation within 24 hours (NOAA, 2012). The 3 inches of precipitation used in our analysis is far below this threshold and yet triggers significant fecal coliform contamination at monitoring location downstream of hog feeding facilities. Furthermore, the water quality sampling data within our study period does not contain any observations occurring after a rainfall event higher than 4 inches of precipitation. As such, we conclude that the fecal coliform contamination identified by our analysis occurs at levels of precipitation lower than is excused by the 25-year, 24-hour precipitation rule. Thus, despite the best practice protocols and restrictions outlined by the N.C. Swine Waste General Permit, excess precipitation appears to trigger significant water quality impairment from hog feeding facilities.

There are two potential mechanisms for this surface water impairment: lagoon overflows and runoff from manure applied fields. The North Carolina Pork Council has been vocal in its assurance that strict permitting protocols have reduced lagoon breaches and overflows to nearly none. Within our period of analysis, there were two reported lagoon breaches resulting from improper lagoon management. In December of 2019, a facility spilled an estimated 1 million gallons of hog waste into the Trent River via Tuckahoe Creek and in June of 2020 a facility discharged 3 million gallons of feces into nearby water resources. Though these breaches very likely contributed significant fecal coliform to surface water, neither was precipitated by excessive rain. As a result, any impacts from these breaches are not included in the effect of excess precipitation and hog feeding facilities identified in our study.

The other mechanism for fecal coliform contamination is runoff from spray fields. While the Swine Waste General Permit forbids spraying during rainfall, after the issuance of storm warnings for the county, and on flooded fields, all other applications are allowed so long nutrients are not applied above agronomic rates and manure application is in line with siting requirements outlined in the permit. There are both private and public incentives to allow operators to spray fields ahead of extreme weather. Given the dire environmental consequences associated with overflows (particularly multiple overflows), NC DEQ allows operators to pump down lagoons during the annual hurricane season to create lagoon capacity. From the individual operator perspective, lagoon overflows trigger enhanced scrutiny from both the public and NC DEQ. Increasing lagoon capacity in anticipation of heavy rainfall decreases the chances of this outcome. However, spraying fields ahead of excessive rainfall, particularly if using slurry past the stop-pump level of lagoons, can result in the application of manure that has not been sufficiently treated (Iriaghomo et al., 2022). If field conditions are too wet to neutralize pathogens (EPA, 1997), fecal coliform can survive on field and then runoff with rainwater to surrounding waterways even if the land application occurs prior to rainfall or the issuance of a storm warning.

2.7 Policy Implications

Our results quantify the net effect of upstream hog feeding operations on concentrations of fecal coliform, nitrates, and phosphorus given excessive precipitation. However, we are unable to distinguish between impacts that are the result of behavior compliant with the N.C. Swine Waste General Permit and impacts that are the result of noncompliant behavior. As such, we cannot identify which specific features of the Swine Waste General Permit are responsible for adverse water quality outcomes and should be revised. However, the NC DEQ already requires facilities to collect the information needed to answer this question.

Operators-in-charge are required to record the amount, timing, and weather conditions each time they spray; keep daily precipitation records from rain gauges; and record weekly lagoon waste levels on forms supplied by or approved by the NC DEQ. However, the extent to which NC DEQ assesses this information is unclear from the permit language. During an inspection and upon request, facilities are required to allow NC DEQ to access to records kept under the conditions of the permit. However, NC DEQ does not otherwise specify a collection schedule for this data beyond the submission of an annual report affirming compliance with protocols. By collecting and analyzing this information, the NC DEQ could establish the degree of compliance and whether compliant or non-compliant behaviors drive water quality impairment with extreme precipitation. Furthermore, at present, the installation of automatic flow meters and irrigation pump equipment designed to automatically stop with precipitation are required only upon notification from the director of the animal feeding operation permit program. Requiring these technologies in addition to digital rainfall monitoring systems could automate data collection, saving operators-in-charge time spent manually entering and collating data and ensuring accurate and timely reporting of critical information.

2.8 Conclusion

This paper set out to quantify the impact of hog feeding operations on surface water quality given existing permit protocols in North Carolina, examine the role of precipitation in exacerbating outcomes, and evaluate whether the current regulatory/permit system adequately protects state water resources. Our results identify significant fecal coliform contamination at monitoring locations downstream of hog feeding facilities following extreme precipitation events of 2 inches or more. The level of fecal coliform at monitoring stations downstream of hog feeding facilities in the aftermath of extreme precipitation events of 3 inches or more of excess precipitation is almost four times greater than that at baseline precipitation. This result is robust at 5-miles, 8-miles, and 10-miles upstream but attenuates with distance. The level of fecal coliform contamination identified by our analysis exceeds the EPA's safety standards for drinking, swimming, boating, and kayaking. These results suggest that the current regulatory paradigm does not circumvent adverse environmental impacts from hog feeding operations in North Carolina.

A key limitation of our study is the inability to distinguish between the impacts of hog feeding operations facilities that are compliant with the N.C. Swine Waste General Permit and those that are not which makes evaluating specific permit guidelines difficult. Given both the public and private incentives around managing lagoon levels, the most likely mechanism for the fecal coliform contamination identified in our analysis is runoff from spray fields. NC DEQ requires the collection of the information to evaluate compliance but does not specify a regular schedule for collecting or evaluating this data. Requiring hog feeding operations to use automated irrigation, rainfall monitoring, and lagoon level recording equipment could save operators time spent manually collating data and allow NC DEQ to evaluate whether the land application guidelines during the hurricane season or spraying ahead of anticipated excess precipitation allowed by the permit drive adverse water quality downstream of hog feeding facilities with the onset of extreme precipitation.

This paper uses a simple estimation procedure to provide a preliminary analysis of the impact of hog feeding operations on surface water quality indicators in North Carolina. Future work includes further evaluation of heterogeneity across watershed characteristics and seasonality within surface water quality samples. Future research direction includes constructing distance-weighted upstream swine densities and evaluating spatial spillovers from hog feeding operations. In addition, future work should evaluate the evolution of permit requirements for cattle and poultry and how these facilities contribute to surface water quality impairment. While hog feeding facilities have received the lion's share of media attention, other categories of animals are less publicly scrutinized and could be related to the generally high level of fecal coliform observed in surface water across North Carolina.

2.9 References

1. Associated Press. "Hurricane Could Flood Many Waste Sites, Creating Toxic Brew." WUNC, September 12, 2018. https://www.wunc.org/environment/2018-09-12/hurricane-could-flood-many-waste-sites-creating-toxic-brew

2. Bernot, Melody J., Lora Smith, and Jeff Frey. "Human and veterinary pharmaceutical abundance and transport in a rural central Indiana stream influenced by confined animal feeding operations (CAFOs)." Science of the total environment 445 (2013): 219-230.

3. Burkholder, JoAnn M., Michael A. Mallin, Howard B. Glasgow Jr, L. Michael Larsen, Matthew R. McIver, G. Christopher Shank, Nora Deamer-Melia et al. "Impacts to a coastal river and estuary from rupture of a large swine waste holding lagoon." Journal of Environmental Quality 26, no. 6 (1997): 1451-1466.

4. Burkholder, JoAnn, Bob Libra, Peter Weyer, Susan Heathcote, Dana Kolpin, Peter S. Thorne, and Michael Wichman. "Impacts of waste from concentrated animal feeding operations on water quality." Environmental Health Perspectives 115, no. 2 (2007): 308-312.

5. Callaway, Brantly, Andrew Goodman-Bacon, and Pedro HC Sant'Anna. Difference-in-differences with a continuous treatment. No. w32117. National Bureau of Economic Research, 2024.

6. Campagnolo, Enzo R., Kammy R. Johnson, Adam Karpati, Carol S. Rubin, Dana W. Kolpin, Michael T. Meyer, J. Emilio Esteban et al. "Antimicrobial residues in animal waste and water resources proximal to large-scale swine and poultry feeding operations." Science of the Total Environment 299, no. 1-3 (2002): 89-95.

7. Christenson, Elizabeth, Lindsay Wickersham, Megan Jacob, and Jill Stewart. "A watershed study assessing effects of commercial hog operations on microbial water quality in North Carolina, USA." Science of the Total Environment 838 (2022): 156085.

8. Davis, Wynne. "Overflowing Hog Lagoons Raise Environmental Concerns in North Carolina." NPR, September 22, 2018. Heard on Weekend Edition Saturday. `https://www.npr.org/2018/09/22/650698240/hurricane-s-aftermath-floods-hog-lago\\ons-in-north-carolina`

9. Deviney, Alison V., John J. Classen, and Jacklyn A. Bruce. "Pathways to sustainable transitions in a complex agricultural system: a case study of swine waste management in North Carolina." Frontiers in Sustainable Food Systems 7 (2024): 1292326.

10. Harun, SM Rafael, and Yelena Ogneva-Himmelberger. "Distribution of industrial farms in the United States and socioeconomic, health, and environmental characteristics of counties." Geography Journal 2013, no. 1 (2013): 385893.

11. Heaney, Christopher D., Kevin Myers, Steve Wing, Devon Hall, Dothula Baron, and Jill R. Stewart. "Source tracking swine fecal waste in surface water proximal to swine concentrated animal feeding operations." Science of the total environment 511 (2015): 676-683.

12. Hendricks, G. S., S. Shukla, F. M. Roka, R. P. Sishodia, T. A. Obreza, G. J. Hochmuth, and J. Colee. "Economic and environmental consequences of overfertilization under extreme weather conditions." Journal of Soil and Water Conservation 74, no. 2 (2019): 160-171.

13. Holcomb, David A., and Jill R. Stewart. "Microbial indicators of fecal pollution: recent progress and challenges in assessing water quality." Current Environmental Health Reports 7 (2020): 311-324.

14. Hsieh, Hsin-Chieh, and Benjamin M. Gramig. "Estimating the impact of cover crop adoption on ambient nitrogen concentration in the upper Mississippi River drainage." Applied Economic Perspectives and Policy 46, no. 2 (2024): 609-626.

15. Iriaghomo, Anjel, Breanna Sorrells, Lise Montefiore, Piyush Patil, Natalie Nelson, and Mahmoud Sharara. "How Does Nitrogen Move Through a Swine Farm with a Lagoon-Sprayfield System?" North Carolina State University Extension AG-927, June 13, 2022. https://content.ces.ncsu.edu/how-does-nitrogen-move-through-a-swine-farm\\-with-a-lagoon-sprayfield-system

16. Keiser, D. A., Shapiro, J. S. (2019). Consequences of the Clean Water Act and the Demand for Water Quality. The Quarterly Journal of Economics, 134 (1), 349–396.

17. Kunkel, K.E., D.R. Easterling, A. Ballinger, S. Bililign, S.M. Champion, D.R. Corbett, K.D. Dello, J. Dissen, G.M. Lackmann, R.A. Luettich, Jr., L.B. Perry, W.A. Robinson, L.E. Stevens, B.C. Stewart, and A.J. Terando, 2020: North Carolina Climate Science Report. North Carolina Institute for Climate Studies, 233 pp. https://ncics.org/nccsr

18. Liu, P., Wang, Y., Zhang, W. (2022). The influence of the Environmental Quality Incentives Program on local water quality. American Journal of Agricultural Economics, ajae.12316.

19. Liu, Qiang, Yifu Li, Fan Yang, Xuran Liu, Dongbo Wang, Qiuxiang Xu, Yi Zhang, and Qi Yang. "Understanding the mechanism of how anaerobic fermentation deteriorates sludge dewaterability." Chemical Engineering Journal 404 (2021): 127026.

20. Maher, Kris, and Ben Kesling. "Florence Flooding Hits North Carolina Hog Farms Hard: More than 5,000 Animals Have Died and Dozens of Waste Lagoons Have Overflowed." Wall Street Journal, September 19, 2018. https://www.wsj.com/articles/florence-flooding-hits-north-carolina-hog-farms-hard-1537398585

21. Mallin, Michael A., JoAnn M. Burkholder, Lawrence B. Cahoon, Amy E. Grogan, Denise M. Sanger, and Erik Smith. "An environmental assessment of the North and South Carolina coasts." In World Seas: an Environmental Evaluation, pp. 405-426. Academic Press, 2019.

22. Mallin, Michael A., JoAnn M. Burkholder, Matthew R. McIver, G. Christopher Shank, Howard B. Glasgow Jr, Brant W. Touchette, and Jeffrey Springer. Comparative effects of poultry and swine waste lagoon spills on the quality of receiving stream waters. Vol. 26, no. 6. American Society of Agronomy, Crop Science Society of America, and Soil Science Society of America, 1997.

23. Mallin, Michael A., Martin H. Posey, Matthew R., McIver, Douglas C. Parsons, Scott H. Ensign, and Troy D. Alphin. "Impacts and recovery from multiple hurricanes in a piedmont–coastal plain river system: Human development of floodplains greatly compounds the impacts of hurricanes on water quality and aquatic life." BioScience 52, no. 11 (2002): 999-1010.

24. Mallin, Michael A., Matthew R. McIver, Anna R. Robuck, and Amanda Kahn Dickens. "Industrial swine and poultry production causes chronic nutrient and fecal microbial stream pollution." Water, Air, Soil Pollution 226 (2015): 1-13.

25. Metcalfe, Chris, Alistair Boxall, Kathrin Fenner, Dana Kolpin, Mark Servos, Eric Silberhorn, and Jane Staveley. "Exposure assessment of veterinary medicines in aquatic systems." Veterinary medicines in the environment (2009): 57-96.

26. Montefiore, Lise R., Natalie G. Nelson, Amanda Dean, and Mahmoud Sharara. "Reconstructing the historical expansion of industrial swine production from Landsat imagery." Scientific reports 12, no. 1 (2022): 1736.

27. National Ocean Service. "What is Eutrophication?" National Oceanic and Atmospheric Administration. Last modified January 18, 2024. https://oceanservice.noaa.gov/facts/eutrophication.html

28. North Carolina Department of Environmental Quality. "Animal Feeding Operations Rules and Statutes." NC DEQ. Accessed June 24, 2024. https://www.deq.nc.gov/about/divisions/water-resources/regulations-guidance/animal-feeding-ope\\rations-rules-and-statutes

29. North Carolina Department of Environmental Quality. “List of Permitted Animal Facilities – 4 -5-2019.” NC DEQ. 2019. Accessed 04 Dec 2023, https://www.deq.nc.gov/about/divisions/water-resources/permitting/animal-feeding-operations/animal-facility-map

30. North Carolina Department of Health and Human Services, Division of Public Health. Recreational Water Quality Advisory: Report and Recommendations. Accessed August 15, 2024. https://epi.dph.ncdhhs.gov/cd/docs/RecreationalWaterQuality\\Advisory-Report_Final.pdf

31. North Carolina Department of Public Safety. ”Hurricanes.” ReadyNC. Accessed June 25, 2024. https://www.readync.gov/stay-informed/north-carolina-hazar\\ds/hurricanes

32. Oglesby, Cameron. ”Hurricane Season Spurs Hog Waste Worries in North Carolina.” Environmental Health News. Last modified May 17, 2021. https://www.ehn.org/north-carolina-hurricanes-hog-farms-2652972415.html

33. Paerl, Hans W., Nathan S. Hall, Alexandria G. Hounshell, Richard A. Luettich Jr, Karen L. Rossignol, Christopher L. Osburn, and Jerad Bales. ”Recent increase in catastrophic tropical cyclone flooding in coastal North Carolina, USA: Long-term observations suggest a regime shift.” Scientific Reports 9, no. 1 (2019): 10620.

34. Paudel, Jayash, and Christine L. Crago. ”Environmental externalities from agriculture: evidence from water quality in the United States.” American Journal of Agricultural Economics 103, no. 1 (2021): 185-210.

35. Pierre-Louis, Kendra. ”Lagoons of Pig Waste Are Overflowing After Florence. Yes, That’s as Nasty as It Sounds.” New York Times, September 19, 2018. https://www.nytimes.com/2018/09/19/climate/florence-hog-farms.html

36. PRISM Climate Group, Oregon State University. https://prism.oregonstate.edu. Data created 4 Feb 2014. Accessed 04 Dec 2023.

37. Raff, Zach, and Andrew Meyer. ”CAFOs and surface water quality: evidence from Wisconsin.” American Journal of Agricultural Economics 104, no. 1 (2022): 161-189.

38. Ribaudo, Marc, and James Shortle. ”Reflections on 40 years of applied economics research on agriculture and water quality.” Agricultural and Resource Economics Review 48, no. 3 (2019): 519-530.

39. Ribaudo, Marc, Jonathan D. Kaplan, Lee A. Christensen, Noel Gollehon, Robert Johansson, Vincent E. Breneman, Marcel Aillery, Jean Agapoff, and Mark Peters. ”Manure management for water quality costs to animal feeding operations of applying manure nutrients to land.” USDA-ERS Agricultural Economic Report 824 (2003).

40. Sapkota, Amy R., Frank C. Curriero, Kristen E. Gibson, and Kellogg J. Schwab. ”Antibiotic-resistant enterococci and fecal indicators in surface water and groundwater impacted by a concentrated swine feeding operation.” Environmental Health Perspectives 115, no. 7 (2007): 1040-1045.

41. Shea, Kelly, Danica Schaffer-Smith, and Rebecca L. Muenich. ”Using remote sensing to identify liquid manure applications in eastern North Carolina.” Journal of Environmental Management 317 (2022): 115334.

42. Shelby, Jennifer Duvall. ”Evaluation of Hydrology and Water Quality in a Large Watershed in North Carolina’s Lower Coastal Plain Following the Hurricanes and Related Storms of 1999.” (2002).

43. Sneeringer, Stacy. ”Does animal feeding operation pollution hurt public health? A national longitudinal study of health externalities identified by geographic shifts in livestock production.” American Journal of Agricultural Economics 91, no. 1 (2009): 124-137.

44. Surrusco, Emilie Karrick. ”The Storm Moved on, But North Carolina’s Hog Waste Didn’t.” Earthjustice. Last modified January 9, 2019. https://earthjustice.org/article/hog-waste-creates-problems-for-north-carolina-residents

45. U.S. Environmental Protection Agency. "Animal Feeding Operations (AFOs)." EPA. Last modified May 1, 2024. https://www.epa.gov/npdes/animal-feeding-operatio\\ns-afos

46. U.S. Environmental Protection Agency. An Approach for Applying EPA's 2012 Recreational Water Quality Criteria Recommendation to Non-primary Contact Exposure Scenarios – White Paper. EPA 823-B-22-001. Washington, DC: U.S. Environmental Protection Agency, 2022. Accessed August 8, 2024. https://www.epa.gov/system/files/documents/2022-01/rec-criteria-white-paper-final.pdf

47. U.S. Environmental Protection Agency. An Approach for Applying EPA's 2012 Recreational Water Quality Criteria Recommendation to Non-primary Contact Exposure Scenarios – White Paper. EPA 823-B-22-001. Washington, DC: U.S. Environmental Protection Agency, 2022. Accessed August 8, 2024. https://www.epa.gov/system/files/documents/2022-01/rec-criteria-white-paper-final.pdf

48. U.S. Environmental Protection Agency. Recreational Water Quality Criteria. EPA 820-F-12-058. Washington, DC: U.S. Environmental Protection Agency, 2012. Accessed August 8, 2024. https://www.epa.gov/sites/production/files/2015-10/documents/rwqc2012.pdf

49. U.S. Environmental Protection Agency. Volunteer Stream Monitoring: A Methods Manual. EPA 841-B-97-003. Washington, DC: Environmental Protection Agency, November 1997.

50. U.S. Environmental Protection Agency. Water Quality Portal. Available online. Accessed Dec 03, 2023. https://www.waterqualitydata.us/

51. U.S. National Weather Atmospheric Administration. "Precipitation-Frequency Atlas of the United States." Multiple Volumes, National Weather Service, Silver Spring Maryland (14). 2012.

52. Wang, Jingjing, and Kenneth A. Baerenklau. "How inefficient are nutrient application limits? A dynamic analysis of groundwater nitrate pollution from concentrated animal feeding operations." Applied Economic Perspectives and Policy 37, no. 1 (2015): 130-150.

53. Weldon, Mark B., and Keri C. Hornbuckle. "Concentrated animal feeding operations, row crops, and their relationship to nitrate in eastern Iowa Rivers." Environmental science technology 40, no. 10 (2006): 3168-3173.

54. Welles, Jacqueline S., and John J. Classen. "Flood Vulnerability Assessment of Eastern North Carolina Industrial Swine Operations Using GIS Methodologies." In 2021 ASABE Annual International Virtual Meeting, p. 1. American Society of Agricultural and Biological Engineers, 2021.

55. Wendee, Nicole. "CAFOs and Environmental Justice: The Case of North Carolina." Environmental Health Perspectives 121, no. 6 (2013): a182–a189.

56. Wing, Steve, Stephanie Freedman, and Lawrence Band. "The potential impact of flooding on confined animal feeding operations in eastern North Carolina." Environmental Health Perspectives 110, no. 4 (2002): 387-391.

57. Zering, Kelly. Economics of Swine Production: Budgets and Costs. N.C. State Extension, June 2024. Accessed August 15, 2024. https://cals.ncsu.edu/agricultural\\-and-resource-economics/wp-content/uploads/sites/46/2024/06/econ-of-swine\\-production-budgets.pdf

Chapter 3

The Impact of Conservation Tillage Intensities on Mean Yields and Yield Risk

3.1 Introduction

Farmers till their land for various reasons — to control weeds, to incorporate crop residue in the soil, to facilitate application of manure and fertilizer, or to prepare the soil for planting. Their choice of tillage practice, in terms of intensity and timing, has implications for the long-term health of agricultural soils (Stevens, 2018; Ogieriakhi and Woodward, 2022). Conventional tillage practices are intensive in removing post-harvest crop residue, as breaking up the earth disrupts weed and pest cycles, and exposed soils warm up more quickly in the spring (Claassen et al., 2018). With these benefits come both private and public costs. Private costs are the acquisition and maintenance of tillage machinery, as well as the associated fuel and labor costs incurred, when conventionally tilling (Lal et al., 2007). Public costs are environmental — removing crop residue leads to increased vulnerability of the soil to wind and water erosion, as well as increased incidence of soil runoff and sedimentation in nearby water bodies (Claassen et al., 2018; Mamo and Johnson, 2022). Over time, soil erosion removes the productive topsoil from fields, degrading soils and leading to increased reliance on fertilizer to supply crops with adequate nutrients (Kopittke, 2019). Furthermore, eroded soil, along with excess fertilizer and chemicals remaining in the soil (e.g., not absorbed by the plant), can wind up as sediment in streams, rivers, and lakes, contributing to widespread water pollution (Shortle et al., 2012).

Circumventing the environmental damages from intensive tillage operations has been a focus of soil and tillage research since the 1930s (Cusser et al., 2020; Daigh et al., 2018; Derpsch et al., 2010). These research efforts spurred the development of less-intensive conservation tillage practices as an alternative to the conventional tillage approach. Conservation tillage practices are those that maintain or improve the productivity of soils over time, as well as combat erosion and water pollution (Bergtold and Sailus, 2020, p. 11). The Conservation Technology Information Center (CTIC) defines conservation tillage as any tillage and planting system that leaves at least 30% of the soil surface covered by residue after planting. By leaving a higher level of crop residue on surfaces, conservation tillage practices minimize soil disturbance and establish ground cover, which consequently reduces susceptibility to erosion and nutrient leaching (Blanco-Canqui and Lal, 2009). Minimizing soil disturbance enhances the accumulation of organic material, promotes microbial activity, and may facilitate carbon sequestration in soils (Karlen et al., 1994; Haddaway et al., 2017). In particular, the "no-till" practice is the least intensive tillage practice and involves the complete absence of tillage operations from harvest to planting the subsequent cash crop.

It is important to note that with technological advances in herbicides and glyphosate-resistant crops, the need for plow-based conventional tillage techniques to control weeds has diminished over time (Cusser et al., 2020). Thus, with the availability of herbicide-tolerant seeds, conservation tillage has become more widely adopted in corn (Zea mays, L.) and soybean (Glycine max, L. Merr.) production, the two most widely cultivated crops in the United States (US) (Claassen et al., 2018). Nonetheless, the relatively widespread adoption of conservation tillage practices in corn and soybean production systems disguise inconsistent use over time. Many farmers report having used conservation tillage on their corn and soybean acres at a point in time, but most farmers alternate conservation tillage practices with conventional practices (Claassen et al., 2018). Continuous use of conservation tillage remains limited. For example, while almost 50% of corn and soybean acreage was no-till at some time from 2013 to 2017, only 20% of these acres were continuously no-till (Claassen et al., 2018). The environmental and agronomic benefits from organic matter accumulation and potential carbon sequestration occur only with minimal disruption to the soil surface over time (e.g., continuous no-till; See Claassen and Wade, 2017). While environmental gains accrue over long time scales, the resumption of conventional tillage operations can rapidly undo them (Johnson et al., 2005; Lal, 2007; Haddaway, 2017; Wade and Claassen, 2017). Reverting no-till acres to conventionally tilled acres thus not only forgo immediate environmental benefits (e.g., erosion control) but also erases potential environmental benefits from years of regenerative practice (e.g., like potential soil carbon sequestration) (Sawadgo and Plastina, 2022).

Soil health is an "impure" public good— a good with both private and public benefits (Mason and Plantinga, 2011; Mezzatesta et al., 2013). Given the environmental benefits from conservation tillage, this practice is foremost among soil health practices supported by the US Department of Agriculture's (USDA's) various working lands conservation programs (e.g., the Environmental Quality Incentive Program (EQIP), etc.). However, while federal cost-share programs can bridge the gap between privately and publicly optimal levels of conservation effort, widespread adoption of continuous conservation tillage hinges on whether private net benefits from adoption outweigh direct and indirect costs of implementation (Rejesus et al., 2021). Conservation tillage can reduce farm operating costs via decreased fuel, labor, and machinery costs (Lal et al., 2007). However, these reduced costs are often offset if adoption entails the acquisition of new planting machinery or increases expenditure on herbicides to control weeds (Kaval, 2004). Indirect costs of adoption are time and effort on the part of the farmer to learn how to implement a new practice effectively. In addition, private net benefits from adoption depend on how conservation tillage impacts crop yields.

Establishing the conditions under which conservation tillage practices achieve yield benefits relative to conventional practices has been an important goal of the soil and tillage literature. However, results from corn and corn-soybean rotation field trials are mixed. While many studies have shown that no-till adoption results in lower yields (Griffith et al., 1988; Cox et al., 1992; Al-Kaisi et al., 2004; Anapalli et al., 2018; Patel et al., 2019; Dougherty et al., 2020), others have shown no difference (Dick and Van Doren, 1985; Dam et al., 2005; Archer and Reicosky, 2009; Fiorini et al., 2020) or an increase in yields (Wagger and Denton, 1989; Cassel et al., 1995; Hussain et al., 1999; Beyaert et al., 2002; Idowu et al., 2019). Reduced yields are attributed to delayed plant emergence and poor stand development because of lower soil temperatures resulting from more crop residue in the soil. Increased yields are attributed to greater soil moisture availability, improved water filtration, and enhanced soil stability. Conservation tillage can also improve resilience to soil crusting, whereby precipitation and temperature conditions lead to a hard crust following heavy rain, which can inhibit stand development and lead to lower yields (Cassel et al., 1995).

In a global meta-analysis on tillage and crop rotation practices, Pittelkow et al. (2015) evaluate over 600 field trials, spanning a variety of crops, to identify the conditions under which conservation tillage yields more relative to conventional tillage practices. Their analysis suggests that yield differences for corn and soybeans are largest in the first 1–2 years post-adoption. For corn, differences decline or become negligible in the following years whereas differences equalize after five years or more for soybeans. Focusing on trials in the US and Canada, DeFelice et al. (2006) evaluate 61 corn and 43 soybean trials and find that the national average difference in corn and soybean yields between no-till and conventional tillage systems are negligible. However, they find evidence of geographic heterogeneity: no-till had greater yield benefits in the southern and western US, similar yields in the central US, and lower yield benefits in the northern US and Canada. For soybeans, Toliver et al. (2012)'s meta-analysis of tillage experiments across the US also finds regional variation, particularly that differences between no-till and tillage yields in the southern regions of the US were larger than in northern regions. They conclude that soil and climate factors interact with tillage practices to produce differential impacts on yields, influencing risk and expected returns.

While many studies focus on the impact of tillage on mean yields, comparatively few evaluate impact of tillage operations on yield risk and stability. Risk neutral farmers will undertake a technology investment if the expected revenue resulting from the technology is greater than the expected cost. However, surveys of farm operators suggest that while most farmers accept that conservation tillage systems have the potential to reduce their costs, perceived yield risk is an important barrier to adoption (Kaval, 2004; Sattler and Nagel, 2010; Ramsey et al., 2019). Pedersen and Lauer (2003) report that soybean yield stability is not affected by tillage practices in their four-year study in Wisconsin. Rusinamhodzi et al. (2011) report no observable differences in corn yield stability between reduced tillage practices compared with conventional moldboard plowing in their meta-analysis of 26 studies across the world. Moreover, soil and tillage field trials evaluating yield stability in corn and soybeans under no-till focus mainly on changes in mean yield and variance but ignore higher-order risk effects (e.g., reduction in exposure to adverse events in the tails of yield distributions).

The literature is further limited by a dearth of long-term studies. While the soil and tillage literature evaluating conservation tillage is extensive, there are few studies that span more than 10 years (Pittelkow et al., 2015; Cusser et al., 2020). Given the potential gradual accumulation of soil organic carbon, microbial biomass, and structural integrity, yield increases from continuous implementation of conservation tillage may only emerge with time. DeFelice et al. (2006) warn that experiments conducted for a short number of years do not provide fair comparisons to conventional tillage as soils have not yet had time to stabilize. In their survey analysis, Saak et al. (2021) find that adopters are more likely to report beneficial profit, cost, and yield outcomes as adoption years increase. Cusser et al. (2020) uses a moving window approach to investigate the development and stability of continuous no-till compared to conventional till agriculture over a 29-year period in the upper Midwest. Their results indicate that over a decade (or more) is needed to detect the consistent effects of no-till. Importantly, they conclude that statistically significant, but likely misleading, short-term trends can produce findings that deter from adopting optimal tillage practices that maximize yields and profits in the long-term.

Of the few long-term studies available in the literature, only Daigh et al. (2018), Mathers (2022), and Mathers et al. (2023) consider whether tillage practices impact yield stability. Daigh et al. (2018) found no significant differences in yield stability between no-till and conventional chisel plow tillage treatments in continuous corn and corn-soybean rotations. However, the Daigh et al. (2018) study only examines yields and their stability from 2009 through 2013 at eight long-term sites (tillage treatment durations range from 8 to 51 years). Mathers (2022) and Mathers et al. (2023) did, however, identify differences in yield stability based on corn tillage systems with more stable yields observed for no-till than for conventional tillage in the North Carolina Piedmont. Other long-term studies evaluate the mean yield effect of no-till vis-à-vis a baseline conventional tillage practice (e.g., chisel plowing) with mixed results (Karlen et al., 2013; Sindelar et al., 2015; Al-Kaisi et al., 2015).

Given the difficulty of sustaining long-term agronomic trials, existing long-term tillage studies have been concentrated in the Corn Belt, where corn and soybeans are most commonly produced in the US. However, results from these trials offer limited guidance for corn and soybean producers in different climate zones. Furthermore, aside from Mathers (2022) and Mathers et al. (2023), we have not found any long-term studies that discuss how mean yield and yield risk change with reductions in tillage intensity. Tillage operations represent a wide set of options with respect to machinery, number of passes, and timing. Understanding how mean yield and yield risk change along a spectrum of operations could offer critical insights to producers and researchers.

In light of the discussion above, the main objective of our analysis is to evaluate the impact of conservation tillage practices – with varying levels of tillage intensity and timing – on the mean yield and yield risk of corn-soybean rotations in North Carolina. To achieve this objective, we use long-term (30-year) field trial data from experiments implemented at North Carolina State University's Upper Piedmont Research Station in Reidsville, North Carolina (Roper et al., 2016; Mathers et al., 2023). Nine tillage treatments were replicated four times in a randomized complete block design. The treatments included no-till, in-row subsoiling, chisel-till in the fall, chisel-till in the spring, disk plow in the spring, chisel-till plus disk in the fall, chisel-till plus disk in the spring, moldboard plow plus disk in the fall, and moldboard plow plus disk in the spring. The nine treatments vary in intensity (i.e., from no-till (with the highest residue cover) to the moldboard plow treatments (with the lowest residue cover)), and timing (i.e., Spring versus Fall tillage operations).

The main contribution of this paper is further understanding of how long-term mean yields and yield risk respond to long-term use of tillage practices of various intensities and timing. More specifically, this paper contributes to the literature in the following ways: (1) this study uses a unique long-term field trial data set (e.g., 30 years) that has information about tillage practices with varying intensities, (2) this study provides new empirical evidence on the long-term effects of various tillage practices on mean yields and yield risk in an area that has been understudied in the past (i.e., Southeastern US) using moment-based methods, and (3) this study provides further insights as to the long-term productivity and risk effects of a continuum of tillage practices used (i.e., rather than just a "binary" effect of no-till versus conventional till). The paper is organized as follows: Section 2 introduces the field trial and data. Section 3 reviews the parametric and nonparametric moment-based approaches implemented and explains our empirical specification. Sections 4 and 5 present the results and discussion of our findings. Finally, Section 6 discusses implications for on-farm decision-making and the limitations of our analysis.

3.2 Data

The field trial was implemented at North Carolina State University's Upper Piedmont Research Station in Reidsville, North Carolina. Nine tillage treatments were replicated four times in a randomized block design. See Appendix B Table 1 for details on the site and soil characteristics in the experiment location. The treatments included no-till, in-row subsoiling, chisel-fall, chisel-spring, disk-spring, chisel plus disk - fall, chisel plus disk - spring, moldboard plow plus disk - fall, and moldboard plow plus disk - spring. The no-till treatment involves the absence of tillage operations from harvest to planting. The in-row subsoiling treatment uses an in-row subsoiler to cut through residue with minimal disturbance and involves non-inversion tillage in a narrow strip along the row (NRCS, 2006). The chisel plow treatments use a plow with narrow, double-ended shovels (chisel points) to rip through and stir soil but does not invert and pulverize soil (NRCS, 2006). The chisel plow plus disk treatments extends the chisel treatments by employing a disk plow to prepare the seedbed by pulverizing soil and residue without inversion. The disk plow treatment uses the disk plow alone (without first employing a chisel or moldboard plow to invert the soil). Finally, the moldboard plow plus disk treatments uses a moldboard plow to thoroughly lift and invert soil and residue, followed by the use of a disk plow for seedbed preparation.

These treatments result in various levels of residue cover. Crop residue is any vegetative material remaining after harvesting (Al-Kaisi et al., 2002). Residue cover refers to the percentage of the field covered by crop residue after tillage operations, thus acting as a proxy for tillage intensity (DeDecker, 2014). As previously mentioned, CTIC defines conservation tillage as any tillage and planting system that leaves at least 30 percent of the soil surface covered by residue after planting. A high residue cover post-treatment implies lower tillage intensity while low residue cover post-treatment indicates high tillage intensity. Together, the treatments in the field trial represent a range of tillage intensities (White et al., 2009; Mathers, 2022). The highest residue cover (lowest intensity) treatment is the no-till treatment (residue cover of 92%). The lowest residue cover (highest intensity) treatment is the moldboard plow plus disk treatments (residue cover of 6%). The in-row subsoiling treatment (residue cover of 70%), chisel treatments (residue cover of 45%), disk treatment (residue cover of 22%), and chisel plus disk treatments (residue cover of 18%) form the continuum of tillage intensity. Using the CTIC's definition for conservation tillage, the no-till, in-row subsoiling, and chisel treatments can be characterized as conservation tillage treatments. The disk, chisel plus disk, and moldboard plow plus disk treatments represent conventional tillage treatments. See Table 1 for a summary of tillage treatments, residue covers, and tillage categories.

Each of the tillage treatments in the field trial can be further categorized as primary and secondary tillage. Primary tillage is meant to cut and incorporate crop residue, making it more susceptible to decomposition (NRCS, 2006; Al-Kaisi and Hanna, 2010). These operations are typically done in the Fall post-harvest but can be performed in the Spring. As primary tillage operations do not always provide an ideal seedbed for planting, secondary tillage treatments are meant to prepare seedbeds for planting (NRCS, 2006; Al-Kaisi and Hanna, 2010). Primary and secondary tillage treatments can be stacked and staggered. In the experiment, the use of the moldboard plow and chisel plow represent primary tillage operations while the use of the disk plow and in-row subsoiling tillage treatments represent secondary tillage operations (which is primarily done in the spring).

The timing of primary tillage operations can also make a difference in the environmental and agronomic outcomes observed. Spring tillage offers erosion control during the winter but soil moisture evaporation following spring tillage can result in yield reductions if rainfall is low (Al-Kaisi and Hanna, 2010). All chisel and moldboard plow treatments were performed in the Spring and Fall so that any differential impacts in yields can be observed. The chisel plus disk and moldboard plow plus disk treatments were both followed with disking in the Spring. Chisel plow treatments were performed with and without disking in the Spring to evaluate the effect of a rougher seedbed. For the in-row subsoiling treatment, an in-row parabolic subsoiler shank was attached ahead of the planter so both the in-row subsoiling and planting operations were performed on the same pass. Given the typical Spring implementation in timing the secondary tillage practice (e.g., disk and in-row subsoiling), Fall treatments for the disk plow and in-row subsoiling tillage practice were not conducted in the experiment. No-till planting was performed using a ripple-coulter followed by double-disk opener. Tillage direction alternated every year.

Descriptive statistics for corn and soybean yield under each tillage treatment over the field trial period are displayed in Appendix B Tables 2-4 and illustrated in Appendix B Figures 1-10. The data used to produce Appendix B Tables 2-4 and Appendix B Figures 1-10 are based on earlier work of Roper et al. (2016), Mathers (2022), and Mathers et al. (2023). For both corn and soybeans average annual field trial yields across treatments coincide well with the county average (See Figures 1 and 2)[1]. Corn and soybean yields under different tillage treatments and over the time period covered by the study are presented in Appendix B Figures 1-8. The study was initially designed for continuous corn. As a result, the first three years of the experiment, 1987-1989, were planted as continuous corn. However, as soybeans become more economically important in the region, a corn-soybean rotation was introduced in 1990. In 2006, corn was planted instead of soybeans.

Corn was planted at a density of 30,000 seeds ac1 and soybeans were planted at 137,500 seeds ac1 (per industry standards) and both crops were planted with a common row spacing of 37.8in. Please see Appendix B Table 5 for specific planting dates. While precise dates for tillage passes are not known, the experimental procedure indicates that Spring tillage treatments were conducted in the days before planting while Fall treatments would have occurred soon after harvest in October. Chemical pesticides were used to manage pest infestations and lime, P, and K were applied to both crops according to the specifications set forth by the North Carolina Department of Agriculture and Consumer Services soil test recommendations. Nitrogen was applied to corn plots twice— prior to planting at a rate of 19.63 lbs. N ac-1 and then 4-5 weeks after emergence at rate of 140.07 lbs. N ac-1. These rates are greater than the North Carolina State University's Extension recommendations (Osmond et al., 2020; Mathers et al., 2023). This was to ensure yield differences were the result of soil management and not nutrient deficiency (Mathers et al., 2023). Soybeans were not

[1]For corn, yields in the field trial are lower than the county-level average in 2015 and 2017. For soybeans, yields in the field trial are much higher than the county-level average in 1996 and 2000. Given the differences in the county yields as compared to the field trial yield in these years, we ran robustness checks of the baseline models excluding 2015 and 2017 for corn, and 1996 and 2000 for soybeans. Results from these runs with excluded years are still consistent with our main results (See Appendix B Tables 6-7).

treated with nitrogen. In 1998 and 2002, there were soybean crop failures. In 2014, there are only three replications of the in-row subsoiler, chisel plus disk spring, and moldboard plus disk fall treatments due to deer damage on three plots[2].

3.3 Methodology

To investigate the impact of tillage intensities on mean yield and yield risk, we use the parametric moment-based framework of Antle (1983) for estimating stochastic production functions in agriculture. This framework has been used to identify and quantify the effect of a variety of factors (e.g., technologies, crop varieties, weather, etc.) on agricultural production risk (Li, Rejesus, and Zheng; 2021). An advantage of the framework is that it extends the prevailing methodology in the soil and tillage literature which only typically uses the first and second moments to characterize crop yield stability (Daigh et al., 2018). Additionally examining tillage effects on the third and fourth of the yield distribution can give more insight on how tillage influences the tails of the yield distribution (i.e., better capturing the higher order risk effects).

The first moment, the conditional mean in this framework, allows us to discern differences in the average productivity between tillage treatments. The second moment, variance, gives information about the overall variability of the corn or soybean yields around the mean. Generally, a reduction in variance from one tillage treatment to another suggests less variability. But note that the nature of the variance is that it provides insight on both the "upside" and "downside" risk. The third moment, skewness, measures possible asymmetry of the yield distribution. Thus, negative skewness captures "downside risk" or exposure to losses located in the lower tail of the distribution (while positive skewness depicts "upside risk" or exposure to outcomes in the upper tail of the distribution). The fourth moment, kurtosis, measures whether the thickness in the tails of the distribution departs from a normal distribution. Thicker tails in the yield distribution implies increased exposure to rare (or tail) events.

In our model, yields are represented by the function, μ, of the input vector, X, and stochastic disturbance term, ϵ:

$$yield = \mu(X) + \epsilon \tag{3.1}$$

where ϵ is i.i.d and $E[\epsilon|X] = 0$. The first moment (i.e., the mean yield) of this production function can be represented as follows: $M_1(X) = E[\mu(X)]$ with higher moments generally expressed as:

$$\hat{\epsilon}^i = [yield - \mu(X)]^i = M_i(X) + v_i, \;\; \forall i = 2, 3, 4 \tag{3.2}$$

[2]Given some of the crop failures discussed here, it is important to more clearly explain the total number of corn and soybean observations used in our analysis. Note that the field trial ran from 1987 to 2018. This suggests 32 years of data. The "30" referenced in the text are the years for which we actually have data (e.g., excluding 1998 and 2002 for which there were soybean crop failures). Given that in a particular crop year we have 9 treatments and 4 replications (per treatment), the field trial includes 36 plot observations per year. Therefore, with 30 years of available data, 30 x 36 gives us a total 1080 observations. Subtracting the 3 replications (1 replication for 3 treatments) for which there was deer damage in 2014 gives us a total of 1,077 observations. Of these 1,077 total observations, the count for corn is 648 and count for soybeans is 429. Hence, the sum of corn and soybean observations is 1,077.

where $\hat{\epsilon}^i$ is the i^{th} power of the predicted residuals from the model specification in (1). The term $M_i(X)$ is the i^{th} moment function, and v_i is the error term. Thus, $\hat{\epsilon}^i$ in equation (2) represents the variance when i = 2, skewness when i = 3, and kurtosis when i = 4.[3]

To estimate these mean and higher order central moments of yields, we estimate the moments of the yield distribution as a linear function of independent variables:

$$yield = X\beta_1 + \epsilon \tag{3.3}$$

$$\hat{\epsilon}^i = X\beta_i + v_i, \ \ \forall i = 2, 3, 4 \tag{3.4}$$

In the absence of endogeneity, the equations above can be consistently and efficiently estimated using ordinary least squares (OLS) with heteroskedasticity-robust standard errors (Antle, 1983). A parametric moment-based framework allows for a flexible and robust modeling of production output and the approach is widely used in the field of agricultural economics (i.e., specifically in the production risk management area).

The framework in equations (3) and (4) assumes a linear functional form for the conditional mean and higher order central moments. As is well known, traditional parametric methods suffer from the risk of misspecification. When assumed parametric functional forms are not consistent with underlying data generating processes, estimates are inconsistent and hypothesis tests misleading. To evaluate this potential threat to identification, we also apply Li, Rejesus, and Zheng's (2021) recently developed nonparametric estimation and inference procedure. The proposed nonparametric approach allows for the estimation of production risk and implementation of hypothesis testing without imposing strong parametric assumptions. Their methodology uses the kernel method to estimate the conditional moments and allows for the use of ordered categorical variables. One key advantage of the Li, Rejesus, and Zheng (2021) nonparametric procedure is the use of the leave-one-out, least-squares cross-validation (CV) method to select the smoothing parameters which is entirely data-driven (Li, Rejesus, and Zheng, 2021; Racine and Li, 2004). Between both the traditional (Antle, 1983) and the Li, Rejesus, and Zheng (2021) frameworks, we have two estimation approaches to achieve the study objective and at the same time evaluate the robustness of our results.

We estimate the following specification for corn and soybean yields:

$$yield_{it} = \alpha + \Sigma_{k=2}^{9} \cdot tillage_{it}^{k} + \gamma \cdot rotation_{it} + \lambda \cdot trend_t + \epsilon_{it} \tag{3.5}$$

where crop yield ($yield_{it}$) in plot i and year t are modeled as a function of k tillage treatment dummy variables ($tillage_{it}^{k}$), a crop rotation dummy ($rotation_{it}$), and a time trend ($trend_{it}$; i.e., the number of years since the start of the experiment). Please see Appendix B Tables 2-4 for descriptions and summary statistics

[3]See Chavas (2004, p. 111), Shi et al. (2013, in their supplementary materials), and Wang et al. (2021, p. 1114) for references that follow the same general exposition of the higher moment function in equation (2). In our empirical context, this is a generalized representation of the higher moments where the yield variable can be considered as a vector of yields for a particular field under the same tillage treatment.

for each variable. Corn and soybean yields are estimated separately as the agronomic literature suggests heterogeneity in the way different crops respond to tillage treatment and to avoid potentially biasing the results (Shapiro et al., 2001; Wilhelm and Wortmann, 2004; Toliver et al., 2012; Pittelkow et al., 2015).

Tillage treatments are represented via k binary (i.e., dummy) variables, $tillage^k_{it}$, which takes on the value of one (1) if the kth tillage treatment is applied in plot i for year t, and zero otherwise. As already mentioned above, there are nine tillage treatments (k = 1, . . . , 9) as follows: Fall moldboard plow plus disk (k=1), Spring moldboard plow plus disk (k=2), Fall chisel plow plus disk (k=3), Spring chisel plow plus disk (k=4), Spring disk plow (k=5), Fall chisel plow (k=6), Spring chisel plow (k=7), In-row sub-soiling (k=8), and no-till (k=9). Note that the omitted tillage treatment category in equation (5) is the Fall moldboard plow plus disk treatment (k=1), which represents the most environmentally damaging treatment (i.e., as the moldboard plow plus disk treatment is the most intensive tillage treatment and Fall tillage treatments leave fields bare over winter and more susceptible to erosion). Hence, the β_2 to β_9 parameters estimated in equation (5) are interpreted relative to the omitted Fall moldboard plow plus disk treatment (k=1). The tillage treatments from k=2 to k=9 are then ordered from most intensive to least intensive with Spring treatments of the same intensity following Fall treatments so that the impacts on crop yields (and yield risk) as tillage treatments decrease in intensity (or increase in residue levels) can be more clearly observed. As the use of moldboard plows has declined over the past few decades (Reicosky and Archer, 2007), a specification using the Fall chisel plow plus disk treatment as the omitted treatment category is also included in the Appendix B to provide easier comparisons to the more common conventional practice in the present day (see Appendix B Tables 8 and 9).

The control variable $rotation_{it}$ is a binary (i.e., dummy) variable that takes on the value of 1 if a different crop was planted the year before. For the majority of the experiment, corn and soybeans were planted in rotation. As a result, the variable $rotation_{it}$ is always 1 in the soybean specification as all soybean years are preceded by years in which corn was planted. However, not all corn years were preceded by soybeans. The first three years of the experiment, 1987-1989, were planted as continuous corn. Furthermore, in 2006, corn was planted instead of soybeans resulting in no rotation for 2006 and 2007. As corn and soybeans are seen as complementary in a crop rotation, we expect that having had soybeans planted in the year preceding will likely influence crop yields and yield risk (and therefore needs to be included as a control variable in the specification). Finally, $trend_t$ is constructed by subtracting the start year of the experiment from the year associated with yields. This linear time trend is included as a control to capture the trajectory of yields in response to time-varying omitted variables (i.e., like unobserved technological advancements such as varietal improvement over time).

3.4 Results

3.4.1 Mean Yield Benefits

Tables 2 and 3 show the parameter estimates from the corn and soybean moment-based models that allow for evaluating the effect of different tillage intensities on mean yield and yield risk. Our results indicate that the choice of tillage treatment statistically significantly increases mean yields for corn and soybeans (at the

1% significance level). For both crops, tillage treatments with reduced tillage intensity are associated with larger yield benefits.

For corn (see Table 2), as tillage intensity declines, mean yield benefits increased commensurately. The no-till treatment (92% crop residue) conferred the largest yield benefits: 45.2 bushels per acre relative to the baseline Fall Moldboard plow plus disk treatment. The next least-intensive treatment, in-row subsoiling treatment (70% crop residue) is associated with a 34.4 bushels per acre increase in mean yields relative to the baseline tillage treatment. The Fall and Spring chisel plow treatments (45% crop residue) conferred increases of 31.8 and 29.4 bushels per acre respectively, relative to the baseline treatment. Conventional tillage treatments with lower tillage intensities than the baseline also conferred yield benefits for corn, but these benefits were smaller than those from conservation tillage treatments. The Spring disk plow treatment (22% crop residue) is associated with a 21.2 bushel per acre increase compared to the baseline tillage practice, while the Fall and Spring chisel plow plus disk treatments confer 19.3 and 15.3 more bushels per acre respectively. All of the mean yield results are statistically significant at the 1% level. The yields from the Spring moldboard plow plus disk treatment, which has the same tillage intensity as the baseline, were not significantly different from the baseline treatment's yields (Fall moldboard plow plus disk).

For soybeans (see Table 3), as with corn, all treatments confer mean yield benefits relative to the baseline Fall moldboard plow with disk treatment. However, the increases in mean yields are similar across treatments suggesting these mean soybean yield benefits do not proportionately change with the reductions in tillage intensity. While conservation tillage treatments result in larger mean yields than conventional treatments, differences between Fall tillage treatments are roughly within 3 bushels per acre. The Fall and Spring chisel plow treatments (45% crop residue) confer the largest yield benefits, with about 12 bushels per acre advantage over the base omitted practice, while the no-till and in-row subsoiling treatments result in about a 10 bushel per acre increase relative to the baseline tillage treatment. Of the conventional tillage treatments, the Fall chisel with disk treatment (18% crop residue) and Spring disk plow treatments (22% crop residue) were statistically different from the baseline treatment at the 1% level. The Fall chisel plow plus disk treatment resulted in a mean yield increase in line with the no-till and in-row subsoiling treatments, about 10 bushels per acre. For soybeans, all treatments with a lower tillage intensity than the baseline increase mean yield. However, differences between these benefits are modest across all tillage treatments.

The results for both corn and soybeans indicate that reducing tillage intensity has strong positive mean yield impacts. However, our analysis suggests that reducing tillage intensity does not result in statistically significant reductions in risk. That is, no statistically significant higher moment effects are observed for corn or soybeans (see columns 2, 3, and 4 in Tables 2 and 3). Nonetheless, Mathers et al., (2023), using different statistical techniques on the same data utilized in the present study, were able to show that conservation tillage provided yield stability over more intense forms of tillage under variable weather conditions.

3.4.2 Timing of Tillage Treatment

The trial design also allows us to evaluate how the timing of tillage operations affects mean yields across various tillage intensities. We compared the differences in mean yield outcomes between the Spring versus the Fall implementations of the following: moldboard plow plus disk, chisel plow plus disk, and chisel plow treatments. Appendix B Table 10 displays our results for the Fall minus Spring difference in the mean yield effect of the tillage treatment.

The moldboard plow plus disk (6% crop residue) and chisel plow plus disk treatments (18% crop residue) represent conventional tillage treatments whereas the chisel plow treatment (45% crop residue) falls into the conservation tillage category. The differences between Fall and Spring treatments are small and not statistically different from zero for both corn and soybeans (see Appendix B Table 10). Nonetheless, even with the statistically insignificant difference in yields between Fall and Spring, waiting until Spring for implementing moldboard plow plus disk, chisel plow plus disk, and chisel plow treatments may confer erosion control over the winter when wind and precipitation erosion risk is high (Al-Kaisi, 2013).

3.4.3 Marginal Reductions in Tillage Intensity

One key contribution of the field trial analysis here is the opportunity for us to explore how yield and yield risk potentially changes across a spectrum of tillage intensities. Our results show that, relative to the baseline Fall moldboard plow plus disk treatment, all tillage treatments with lower tillage intensities increase mean yields relative to the baseline Fall moldboard plow plus disk treatment, a high-intensity tillage treatment. For corn, these benefits appear to be monotonically increasing as tillage intensity is reduced. To investigate how yield benefits change as tillage intensity is reduced, we further compare the yield benefit of each tillage treatment with the treatment that is next least intensive (i.e., pairwise comparisons). This results in six comparisons: Fall moldboard plow plus disk (6% crop residue) versus Fall chisel plow plus disk (18% crop residue); Spring chisel plow plus disk (18% crop residue) versus Spring disk plow (22% crop residue); Fall chisel plow plus disk (18% crop residue) versus Fall chisel plow (45% crop residue); Spring disk plow (22% crop residue) versus Spring chisel plow (45% crop residue); Spring chisel plow (45% crop residue) versus Spring in-row subsoiling (70% crop residue); Spring in-row subsoiling (70% crop residue) versus no-till (92% crop residue). The results are shown in Table 4.

We find that adjacent reductions in tillage intensity have a larger increase in corn yields at higher levels of tillage intensity than at lower levels of tillage intensity. That is, for corn, the difference in yield benefit from the Fall moldboard plow plus disk treatment to the Fall chisel plow plus disk treatment is statistically significant at the 1% level. The reduction in tillage intensity (increasing crop residue from 6% to 18%) results in a yield benefit of 19 bushels per acre. Furthermore, the difference in yield benefits from the Fall chisel plow plus disk treatment to the Fall chisel plow treatment is also statistically significant at the 5% level, though the 27% increase in crop residue now only results in a 13 bushel per acre yield increase. However, the difference between the in-row subsoiling treatment and no-till treatment is only significant at the 10% level, and the 22% increase in crop residue only results in an 11 bushel per acre increase. The results for corn suggest diminishing marginal mean yield benefits in response to stepwise reductions in tillage intensity. Tillage intensity reduction is highly impactful to mean yields (i.e., larger positive mean yield increase) at high levels of intensity, but mean yield benefits decline at lower levels of tillage intensity.

For soybeans, only the difference between the Fall moldboard plow plus disk treatment and the Fall chisel plow plus disk treatment (12% increase in crop residue) is statistically significant (at the 1% level). After this initial yield increase as one moves from high tillage intensity to the next lower tillage intensity, further reductions in tillage intensity do not appear to statistically increase mean yields at all.

3.4.4 Nonparametric Moment-based Framework

Results from the nonparametric moment-based framework are presented in Tables 5-6. For both corn and soybeans, the coefficients on mean yield mirror those of the baseline specifications. For both crops, reductions in tillage intensity are associated with increases in mean yields. For corn, these increases were proportional to reductions in tillage intensity. For soybeans, reductions in tillage intensity had a large positive impact on mean yields at high levels of tillage intensity but benefits declined at lower levels of tillage intensity. For soybeans, the results for higher order risk effects were also in line with those from the parametric estimation— no higher order risk effects of tillage treatments were observed. However, for corn, results from the nonparametric framework indicate a number of positive and significant coefficients in the variance and kurtosis functions. These nonparametric results suggest that a number of tillage treatments with lower tillage intensity increases mean yields, but these lower tillage intensity practices may also tend to increase higher-order yield risks (e.g., variance and kurtosis, in particular). Based on the higher order moment results from the traditional parametric framework (i.e., no statistically significant low intensity tillage effects on the higher moments) and the nonparametric framework (i.e., positive and significant effects low intensity tillage effects on the higher moments), one can still safely conclude that lower intensity tillage practices do not offer higher order risk improvements (or risk reduction) for corn and soybean rotations on sandy loam soils in the North Carolina Piedmont.[4]

3.4.5 Long-term Effects of Tillage Treatment on Yields

As a final contribution to the literature, we also evaluate whether yield benefits from lower intensity tillage treatments increase with continued use of the practice over time. Note that in our main empirical specification in equation (5) we include a time trend variable that can represent unobserved technological advancements affecting all plots similarly[5]. The time trend simply represents the number of years since the start of the experiment. As such, one can include additional tillage-by-trend interactions $tillage_{it}^{k} \times trend_t$ in our baseline specification to assess whether the mean yield or higher order moment effect of a particular tillage practice increases the longer one uses it (i.e., for instance, observing larger mean yield effects as the number of years of use increase).

Results from the regression runs of the specification with tillage-by-trend interactions are shown in Appendix B Tables 15-16. For both corn and soybeans, none of the treatment-trend interactions are significant. Therefore, the parameter estimates associated with tillage-by-trend interactions suggest that the mean yield effect of all the different lower intensity tillage treatments do not statistically increase with sustained use.

[4]Moreover, it is important to note that the preponderance of evidence from the parametric and nonparametric estimations for both crops (corn and soybeans) generally support the notion that use of lower intensity tillage practices tend to not affect higher order yield risk (e.g., most coefficients associated with lower intensity treatments are statistically insignificant in the various estimation runs. Hence, we believe that, on balance, it is also fair to say that lower intensity tillage treatments likely do not have substantial higher order risk effects.

[5]To test the robustness of our results with a linear trend specification, we also ran models using a quadratic time trend (See Appendix B Tables 11-12) and annual fixed effects (i.e., annual year dummies excluding 1987) (See Appendix B Tables 13 and 14). Results from these alternative treatments of time trends remain consistent with our main baseline results in Tables 2 and 3.

3.5 Discussion

This paper evaluates the impact of conservation tillage practices – with varying levels of tillage intensity and timing – on the mean yield and yield risk of corn and soybean cultivation on sandy loam soil in the North Carolina Piedmont. Our results indicate that choice of tillage treatment significantly increases mean yields for corn and soybeans in the study area. For corn, these increases were proportional to reductions in tillage intensity. For soybeans, reductions in tillage intensity had a large positive impact on mean yields at high levels of tillage intensity but benefits declined at lower levels of tillage intensity. The timing of tillage treatment did not statistically impact yields and our analysis did not find consistent yield risk reduction as a result of lower intensity tillage practices. We also do not find evidence that mean yield benefits increase with sustained use of lower intensity tillage practices.

There are several avenues for reductions in tillage intensity to improve crop yields. Reducing tillage intensity could facilitate the accumulation of organic material in soil, reduce soil moisture loss, improve soil water infiltration, and prevent crusting all which could improve yield outcomes (Busari et al., 2015; Haddaway et al., 2017; Blanco-Canqui and Ruis, 2018; Mathers et al., 2023). In this study, the differences in yields across tillage treatments are likely due to crusting. Crusting occurs when rain pulverizes soil that then cements into hard layers at the soil surface when the soil dries (Hanna and Tidman, 2000). If significant precipitation events occur between planting and emergence, soil crusts can reduce seedling emergence and therefore final yield (Baumhardt et al., 2004). Soil crusts also reduce rates of infiltration and promote runoff and erosion (Raczkowski et al., 2009). Previous research studies at this site have noted the presence of soil crusting and sealing (Wagger and Denton, 1992, Freese et al., 1993, Cassel et al., 1995; Mathers et al., 2023). We hypothesize that differences in yields across tillage treatments result from high residue low intensity treatments preventing crusting (and forestalling subsequent adverse impacts on plant emergence) by impeding water droplet impact on the soil surface during rainfall events. However, crusting intensity and timing was not systematically recorded over the length of the field trial, so we are unable to explicitly quantify interactions between tillage treatment, prevalence and magnitude of crusting, and yields.

Our results are distinct from other long-term tillage trials evaluating corn and soybean production. Our mean yield results are closest to those of Sindelar et al. (2015) who evaluate the impact of five tillage treatments (chisel plow, disk plow, moldboard plow, no-till, ridge-till, and in-row subsoiling) for continuous corn and a corn-soybean rotation in a 28-year field trial near Lincoln, Nebraska (even though the agroecosystem in their study area is very different from the one here). They find that corn grain yield with no-till resulted in consistent, high grain yields for both corn and soybeans in the final 16 years of their experiment. Unlike our results, they conclude that a lag period exists before consistent yield advantages with no-till are detectable. Similar to our results, they also find smaller differences across tillage systems for soybean yields in the corn-soybean rotation. Meta-analysis of past short-term studies have emphasized significant geographic heterogeneity in the efficacy of conservation tillage treatments for increasing corn and soybean yields (Pittelkow et al., 2015; DeFelice et al., 2006). Nonetheless, our results fit in with observations from past studies that differences between conservation and conventional tillage practices are higher in the southern regions of the US (DeFelice et al., 2006; Toliver et al., 2012).

It is important to note that several other long-term trials do not find consistent benefits from lower-intensity tillage treatments. In their evaluation of corn and soybean production at seven sites in Iowa, Al-Kaisi et al. (2015) report that the yields associated with no-till were less than with conventional tillage in locations with poorly drained soils versus well-drained soils. They conclude that the high amount of crop residue associated with no-till coupled with poorly drained soil conditions reduced soil temperature resulting in delayed seed germination and emergence (Al-Kaisi et al., 2015). Karlen et al., (2013) also find that a conventional tillage treatment, the moldboard plow treatment, had the highest yield in their 30-year field trial in Iowa though they note that yield differences between tillage treatments were quite small. Both of these studies also find that corn-soybean rotations offered yield benefits relative to continuous corn, while our results indicate that rotation carries a corn yield penalty (See Table 2).

Our result that crop rotation reduces corn yields runs counter to common prevailing understanding based on crop rotation field studies in the US Midwest. A number of studies have shown that corn-soybean rotations are usually beneficial such that it increases mean corn yields. However, Hall et al. (2019) suggests that short-term benefits of corn and soybean rotation may also come with some long-term costs in terms of long-term declines in soil organic matter. Thus, given that the data used in the analysis covers over 30 years of data, it could be possible that the rotation effects can reduce soil organic matter in the long-term and result in negative mean yield effects of rotation. Notwithstanding the negative mean yield effect in Table 2, it is important to note that the rotation variable had a statistically significant variance-reducing effect and rotation may be beneficial in terms of reducing yield variance in the study area). Lastly, it should be noted that rotation was not randomly allocated across plots in the experiment. The field trial was initially designed for continuous corn and so for the first three years of the trial only corn was planted (1987-1989). As soybeans became more economically important in the region, rotation with soybeans was introduced (1990-2018). Given the non-random nature of the rotation variable, one cannot draw strong conclusions about its estimated effects on corn yields in Table 2. Nonetheless, to demonstrate that our baseline results for corn yields are robust to the use of rotation, we run an estimation excluding continuous corn years and find that the pattern of results are unchanged (see Appendix B Table 17).

Except for the recent study by Mathers (2022) and Mathers et al. (2023), we have not found any other peer-reviewed paper that have examined how stepwise reductions in tillage intensity (or increases in residue) impact long-term higher-order yield risk (i.e., variance, skewness, and kurtosis) in the Southeastern US. Our results suggest that conservation tillage practice with lower tillage intensities and higher intensities do not provide yield risk reductions for corn and soybeans planted in rotations on sandy loam soils in the North Carolina Piedmont. No yield variance, skewness, or kurtosis impacts were statistically observed in majority of our regression runs. This result is in line with previous studies with shorter time horizons. Daigh et al. (2018) found no significant differences in yield variance between no-till and conventional chisel plow tillage treatments in corn-soybean rotations in their four-year evaluation. In their meta-analysis of 26 short-term tillage studies across the world, Rusinamhodzi et al. (2011) report no observable differences in corn yield stability between reduced tillage practices compared with conventional moldboard plowing.

3.6 Conclusion

This study provides new empirical evidence on the long-term effects of lower intensity (or high residue) tillage practices on mean yields and yield risk for corn and soybean production in an area that has been understudied in the past (i.e., the Southeastern US, specifically in the sandy loam regions of the North Carolina Piedmont). This study provides further insight as to the long-term productivity and risk effects of a continuum of tillage practices such that one can see how marginal reductions in tillage intensity from one tillage treatment to another can affect mean yield outcomes and risk. Our results indicate that choice of tillage treatment significantly impacts mean yields— with lower intensity conservation tillage treatments outperforming conventional tillage practices for both corn and soybeans. For corn, increases in mean yield benefits were commensurate with reductions in intensity. For soybeans, after an initial increase in mean yields, further reductions in tillage intensity were not associated with further yield increases. However, for both corn and soybeans, no yield risk reduction was observed across the different tillage treatments with varying intensities (and residue levels).

While this study provides insight into the mean yield and risk response of corn and soybeans to tillage treatment of various intensities, it is important to acknowledge the study limitations. First, the limited geographical scope of the field trial data means that the regression results may not extend to growers operating in different climates and soil types in other states (i.e., our results are for corn and soybeans planted in well-drained sandy loam soils in the North Carolina Piedmont). Second, although research plots enable implementation of randomized field trials to isolate tillage effects, identical regimes for other factors (e.g., fertilizer and chemical inputs) may not exactly follow actual on-farm commercial operations using the various tillage practices examined in the study (Deines et al., 2019). Some of the practices and inputs used in the field trials may not exactly coincide with actual farmer practices "on-the-farm". Future studies should utilize observational data from actual farms to better characterize how yields respond to no-till and other conservation tillage practices under a variety of management and biophysical conditions (i.e., to cover larger geographical regions). Perhaps satellite-based remote sensing data on tillage practices and farm-level survey data on yields and input use can be combined to undertake an analysis similar to the one used in this paper, but with on-farm observational data.

3.7 References

1. Al-Kaisi, M., 2013. Avoid Tillage this Fall. Iowa State University Extension and Outreach. `https://crops.extension.iastate.edu/cropnews/2013/09/avoid-tillage-fall` (accessed 23 April 2023).

2. Al-Kaisi, M. and Hanna, M., 2010. Fall versus Spring Tillage. Iowa State University Extension and Outreach. https://crops.extension.iastate.edu/cropnews/2010/09/fall-versus-spring-tillage-which-better (accessed 18 October 2022).

3. Al-Kaisi, M. Hanna, M., and Tidman, M., 2002. Methods for Measuring Crop Residue. Iowa State University Extension and Outreach. https://crops.extension.iastate.edu/encyclopedia/methods-measuring-crop-residue (accessed 22 June 2023).

4. Al-Kaisi, M.M. and Yin, X., 2004. Stepwise time response of corn yield and economic return to no tillage. Soil and Tillage Research, 78(1), 91-101.

5. Al-Kaisi, M.M., Archontoulis, S.V., Kwaw-Mensah, D. and Miguez, F., 2015. Tillage and crop rotation effects on corn agronomic response and economic return at seven Iowa locations. Agronomy Journal, 107(4), 1411-1424.

6. Anapalli, S.S., Reddy, K.N. and Jagadamma, S., 2018. Conservation tillage impacts and adaptations in irrigated corn production in a humid climate. Agronomy Journal, 110(6), 2673-2686.

7. Antle, J.M., 1983. Testing the stochastic structure of production: a flexible moment-based approach. Journal of Business and Economic Statistics, 1(3), 192-201.

8. Archer, D.W. and Reicosky, D.C., 2009. Economic performance of alternative tillage systems in the northern Corn Belt. Agronomy Journal, 101(2), 296-304.

9. Baumhardt, R.L., Unger, P.W. and Dao, T.H., 2004. Seedbed surface geometry effects on soil crusting and seedling emergence. Agronomy Journal, 96(4), 1112-1117.

10. Bergtold, J. and Sailus, M., 2020. Conservation Tillage Systems in the Southeast. Sustainable Agriculture Research and Education (SARE), SARE Handbook Series. 15. `https://www.sare.org/wp-content/uploads/Conservation-Tillage-Systems-in-the-Southeast.pdf` (accessed 18 October 2022).

11. Beyaert, R.P., Schott, J.W. and White, P.H., 2002. Tillage effects on corn production in a coarse-textured soil in Southern Ontario. Agronomy Journal, 94(4), 767-774.

12. Blanco-Canqui, H. and Lal, R., 2009. Crop residue removal impacts on soil productivity and environmental quality. Critical reviews in plant science, 28(3), 139-163.

13. Blanco-Canqui, H. and Ruis, S.J., 2018. No-tillage and soil physical environment. Geoderma, 326, 164-200.

14. Busari, M.A., Kukal, S.S., Kaur, A., Bhatt, R. and Dulazi, A.A., 2015. Conservation tillage impacts on soil, crop and the environment. International soil and water conservation research, 3(2), 119-129.

15. Cassel, D. K., Raczkowski, C. W., and Denton, H. P., 1995. Tillage effects on corn production and soil physical conditions. Soil Science Society of America Journal, 59(5), 1436-1443.

16. Chavas, J. P., 2004. Risk Analysis in Theory and Practice. Elsevier Academic Press.

17. Claassen, R., Bowman, M., McFadden, J., Smith, D., and Wallander, S., 2018. Tillage intensity and conservation cropping in the United States (No. 1476-2018-5723).

18. Cox, W. J., Otis, D. J., Van Es, H. M., Gaffney, F. B., Snyder, D. P., Reynolds, K. R., and Van der Grinten, M., 1992. Feasibility of no-tillage and ridge tillage systems in the Northeastern USA. Journal of production agriculture, 5(1), 111-117.

19. Cusser, S., Bahlai, C., Swinton, S. M., Robertson, G. P., and Haddad, N. M., 2020. Long-term research avoids spurious and misleading trends in sustainability attributes of no-till. Global Change Biology, 26(6), 3715-3725.

20. Daigh, A.L., Dick, W.A., Helmers, M.J., Lal, R., Lauer, J.G., Nafziger, E., Pederson, C.H., Strock, J., Villamil, M., Mukherjee, A. and Cruse, R., 2018. Yields and yield stability of no-till and chisel-plow fields in the Midwestern US Corn Belt. Field Crops Research, 218, pp.243-253.

21. Dam, R. F., Mehdi, B. B., Burgess, M. S. E., Madramootoo, C. A., Mehuys, G. R., and Callum, I. R., 2005. Soil bulk density and crop yield under eleven consecutive years of corn with different tillage and residue practices in a sandy loam soil in central Canada. Soil and Tillage Research, 84(1), 41-53.

22. DeDecker, J., 2014. Measure Residue Cover to Protect the Soil. Michigan State University Extension. `https://www.canr.msu.edu/news/measure_residue_cover_to_protect_the_soil` (accessed 22 June 2023)

23. DeFelice, M. S., Carter, P. R., and Mitchell, S. B., 2006. Influence of tillage on corn and soybean yield in the United States and Canada. Crop Management, 5(1), 1-17.

24. Deines, J. M., Wang, S., and Lobell, D. B., 2019. Satellites reveal a small positive yield effect from conservation tillage across the US Corn Belt. Environmental Research Letters, 14(12), 124038.

25. Derpsch, R., Friedrich, T., Kassam, A., and Li, H., 2010. Current status of adoption of no-till farming in the world and some of its main benefits. International journal of agricultural and biological engineering, 3(1), 1-25.

26. Dick, W. A., and Van Doren Jr, D. M., 1985. Continuous tillage and rotation combinations effects on corn, soybean, and oat yields 1. Agronomy Journal, 77(3), 459-465.

27. Dougherty, B.W., Pederson, C.H., Mallarino, A.P., Andersen, D.S., Soupir, M.L., Kanwar, R.S., Helmers, M.J., 2020. Midwestern cropping system effects on drainage water quality and crop yields. Journal of Environmental Quality, 49(1), 38-49.

28. Fiorini, A., Boselli, R., Maris, S.C., Santelli, S., Ardenti, F., Capra, F., and Tabaglio, V., 2020. May conservation tillage enhance soil C and N accumulation without decreasing yield in intensive irrigated croplands? Results from an eight-year maize monoculture. Agriculture, Ecosystems and Environment, 296, 106926.

29. Freese, R.C., Cassel, D.K., and Denton, H.P., 1993. Infiltration in a Piedmont soil under three tillage systems. Journal of Soil and Water Conservation, 48(3), 214-218.

30. Griffith, D.R., Kladivko, E.J., Mannering, J.V., West, T.D., and Parsons, S.D., 1988. Long-term tillage and rotation effects on corn growth and yield on high and low organic matter, poorly drained soils. Agronomy Journal, 80(4), 599-605.

31. Haddaway, N.R., Hedlund, K., Jackson, L.E., Kätterer, T., Lugato, E., Thomsen, I.K., Jørgensen, H.B., and Isberg, P.-E., 2017. How does tillage intensity affect soil organic carbon? A systematic review. Environmental Evidence, 6(1), 1-48.

32. Hall, S.J., Russell, A.E., and Moore, A.R., 2019. Do corn-soybean rotations enhance decomposition of soil organic matter? Plant and Soil, 444, 427-442.

33. Hanna, M. and Tidman, M., 2000. Soil crust-busters. Iowa State University Extension and Outreach. https://crops.extension.iastate.edu/encyclopedia/soil-crust-busters: :text=Soil

34. Hussain, I., Olson, K.R., and Ebelhar, S.A., 1999. Impacts of tillage and no-till on production of maize and soybean on an eroded Illinois silt loam soil. Soil and Tillage Research, 52(1-2), 37-49.

35. Idowu, O.J., Sultana, S., Darapuneni, M., Beck, L., and Steiner, R., 2019. Short-term conservation tillage effects on corn silage yield and soil quality in an irrigated, arid agroecosystem. Agronomy, 9(8), 455.

36. Johnson, J.M.F., Reicosky, D.C., Allmaras, R.R., Sauer, T.J., Venterea, R.T., and Dell, C.J., 2005. Greenhouse gas contributions and mitigation potential of agriculture in the central USA. Soil and Tillage Research, 83(1), 73-94.

37. Karlen, D.L., Wollenhaupt, N.C., Erbach, D.C., Berry, E.C., Swan, J.B., Eash, N.S., and Jordahl, J.L., 1994. Long-term tillage effects on soil quality. Soil and Tillage Research, 32(4), 313-327.

38. Karlen, D.L., Kovar, J.L., Cambardella, C.A., and Colvin, T.S., 2013. Thirty-year tillage effects on crop yield and soil fertility indicators. Soil and Tillage Research, 130, 24-41.

39. Kaval, P., 2004. The profitability of alternative cropping systems: a review of the literature. Journal of Sustainable Agriculture, 23(3), 47-65.

40. Kopittke, P.M., Menzies, N.W., Wang, P., McKenna, B.A., and Lombi, E., 2019. Soil and the intensification of agriculture for global food security. Environment International, 132, 105078.

41. Lal, R., Reicosky, D.C., and Hanson, J.D., 2007. Evolution of the plow over 10,000 years and the rationale for no-till farming. Soil and Tillage Research, 93(1), 1-12.

42. Li, Z., Rejesus, R.M., and Zheng, X., 2021. Nonparametric Estimation and Inference of Production Risk. American Journal of Agricultural Economics, 103(5), 1857-1877.

43. Mamo, M., and Johnson, L., 2022. Crop Residue Removal: Its Effect on Soil and Water Quality. University of Nebraska-Lincoln Institute of Agriculture and Natural Resources. `https://water.unl.edu/article/crop-production/crop-residue-removal-its-effect-soil-and-water-quality` (accessed 23 April 2023).

44. Mason, C., and Plantinga, A., 2011. Contracting for impure public goods: carbon offsets and additionality. National Bureau of Economic Research, w16963.

45. Mathers, C. 2022. Improving Future Agricultural Resiliency of Row Crops through Soil Best Management Practices. PhD Dissertation, NC State University, Raleigh NC.

46. Mathers, C., Heitman, J., Huseth, A., Locke, A., Osmond, D., and Woodley, A., 2023. No-till imparts yield stability and greater cumulative yield under variable weather conditions in the southeastern USA piedmont. Field Crops Research, 292, 108811. https://doi.org/10.1016/j.fcr.2023.108811)

47. Meijer, A.D, Heitman, J.L., White, J.G., Austin, R.E., 2013. Measuring erosion in long-term tillage plots using ground-based lidar. Soil Till. Res. 126:1-10.

48. Mezzatesta, M., Newburn, D.A., and Woodward, R.T., 2013. Additionality and the adoption of farm conservation practices. Land Economics, 89(4), 722-742.

49. Natural Resources Conservation Service., 2006. Tillage Equipment – Pocket Identification Guide. United States Department of Agriculture. `https://www.nrcs.usda.gov/sites/default/files/2023-01/Montana-Tillage-Equipment-Pocket-ID-Guide-2006.pdf` (accessed 18 April 2023).

50. Natural Resources Conservation Service., 2022. Soil Health. United States Department of Agriculture. https://www.nrcs.usda.gov/wps/portal/nrcs/main/soils/health/ (accessed 18 October 2022).

51. Ogieriakhi, M., and Woodward, R., 2022. Understanding Why Farmers Adopt Soil Conservation Tillage: A Systematic Review. Soil Security, 100077.

52. Osmond, D., Gatiboni, L., Kulesza, S., Austin, R., and Crouse, D., 2020. North Carolina Realistic Yield Expectations and Nitrogen Fertilizer Decision Making. North Carolina State University Extension. https://content.ces.ncsu.edu/north-carolina-realistic-yield-expectations-and-nitrogen-fertilizer-decision-making (accessed 15 March 2023)

53. Patel, S., Sawyer, J. E., and Lundvall, J. P., 2019. Can management practices enhance corn productivity in a rye cover crop system? Agronomy Journal, 111(6), 3161-3171.

54. Pedersen, P., and Lauer, J. G., 2003. Corn and soybean response to rotation sequence, row spacing, and tillage system. Agronomy Journal, 95(4), 965-971.

55. Pittelkow, C. M., Linquist, B. A., Lundy, M. E., Liang, X., Van Groenigen, K. J., Lee, J., Van Gestel, N., Six, J., Venterea, R. T., and Van Kessel, C., 2015. When does no-till yield more? A global meta-analysis. Field Crops Research, 183, 156-168.

56. Racine, J., and Li, Q., 2004. Nonparametric estimation of regression functions with both categorical and continuous data. Journal of Econometrics, 119(1), 99-130.

57. Raczkowski, C. W., Reyes, M. R., Reddy, G. B., Busscher, W. J., and Bauer, P. J., 2009. Comparison of conventional and no-tillage corn and soybean production on runoff and erosion in the southeastern US Piedmont. Journal of Soil and Water Conservation, 64(1), 53-60.

58. Ramsey, S. M., Bergtold, J. S., Canales, E., and Williams, J. R., 2019. Effects of farmers' yield-risk perceptions on conservation practice adoption in Kansas. Journal of Agricultural and Resource Economics, 44(1835-2019-1558), 380-403.

59. Reicosky, D. C., and Archer, D. W., 2007. Moldboard plow tillage depth and short-term carbon dioxide release. Soil and Tillage Research, 94(1), 109-121.

60. Rejesus, R. M., Aglasan, S., Knight, L. G., Cavigelli, M. A., Dell, C. J., Lane, E. D., and Hollinger, D. Y., 2021. Economic dimensions of soil health practices that sequester carbon: Promising research directions. Journal of Soil and Water Conservation, 76(3), 55A-60A.

61. Roper, W., D. Osmond, J. Heitman, M. Wagger, C. Reberg-Horton. 2016. Soil Health Indicators Do Not Differentiate Agronomic Systems in North Carolina Soils. Soil Sci. Soc. Amer. J. 81:828-843.

62. Rusinamhodzi, L., Corbeels, M., Van Wijk, M.T., Rufino, M.C., Nyamangara, J. and Giller, K.E., 2011. A meta-analysis of long-term effects of conservation agriculture on maize grain yield under rain-fed conditions. Agronomy for sustainable development, 31(4), 657-673.

63. Saak, A.E., Wang, T., Xu, Z., Kolady, D., Ulrich-Schad, J.D. and Clay, D., 2021. Duration of usage and farmer reported benefits of conservation tillage. Journal of Soil and Water Conservation, 76(1), 65-75.

64. Sattler, C. and Nagel, U.J., 2010. Factors affecting farmers' acceptance of conservation measures—A case study from north-eastern Germany. Land Use Policy, 27(1), 70-77.

65. Sawadgo, W. and Plastina, A., 2022. The Invisible Elephant: Disadoption of Conservation Practices in the United States. Choices, 37(316-2022-392).

66. Shapiro, C.A., Holshouser, D.L., Kranz, W.L., Shelton, D.P., Witkowski, J.F., Jarvi, K.J., Echtenkamp, G.W. and Bolte, J.P., 2001. Tillage and management alternatives for returning conservation reserve program land to crops. Agronomy Journal, 93(4), 850-862.

67. Shi, G., Chavas, J.P. and Lauer, J., 2013. Commercialized transgenic traits, maize productivity and yield risk. Nature Biotechnology, 31(2), 111-114.

68. Shortle, J.S., Ribaudo, M., Horan, R.D. and Blandford, D., 2012. Reforming agricultural nonpoint pollution policy in an increasingly budget-constrained environment. Environmental science and technology, 46(3), 1316-1325.

69. Sindelar, A.J., Schmer, M.R., Jin, V.L., Wienhold, B.J. and Varvel, G.E., 2015. Long-term corn and soybean response to crop rotation and tillage. Agronomy Journal, 107(6), 2241-2252.

70. Stevens, A.W., 2018. The economics of soil health. Food Policy, 80, 1-9.

71. Toliver, D.K., Larson, J.A., Roberts, R.K., English, B.C., De La Torre Ugarte, D.G. and West, T.O., 2012. Effects of no-till on yields as influenced by crop and environmental factors. Agronomy Journal, 104(2), 530-541.

72. Wade, T. and Claassen, R., 2017. Modeling no-till adoption by corn and soybean producers: Insights into sustained adoption. Journal of Agricultural and Applied Economics, 49(2), 186-210.

73. Wagger, M.G. and Denton, H.P., 1989. Influence of cover crop and wheel traffic on soil physical properties in continuous no-till corn. Soil Science Society of America Journal, 53(4), 1206-1210.

74. Wagger, M.G. and Denton, H.P., 1992. Crop and tillage rotations: grain yield, residue cover, and soil water. Soil Science Society of America Journal, 56(4), 1233-1237

75. Wang, R., Rejesus, R. M., and Aglasan, S., 2021. Warming temperatures, yield risk and crop insurance participation. European Review of Agricultural Economics, 104(1), 318-339.

76. White, J.G., Walters, R.D., Heitman, J.L., Howard, A.M., Wagger, M.G., 2009. Long-term conservation tillage effects on physical properties and productivity of Southeastern US Piedmont soils. Paper Presented at the ASA-CSSA-ASA Annual Meeting, Pittsburgh, PA. November 1-5, 2009.

77. Wilhelm, W. W., and Wortmann, C. S., 2004. Tillage and rotation interactions for corn and soybean grain yield as affected by precipitation and air temperature. Agronomy Journal, 96(2), 425-432.

3.8 Tables

Table 3.1: Tillage Treatments and Residue Cover

Tillage Treatment	Tillage Category	Residue Cover (%)
1. Fall moldboard plow plus disk	Conventional	6
2. Spring moldboard plow plus disk	Conventional	6
3. Fall chisel plow plus disk	Conventional	18
4. Spring chisel plow plus disk	Conventional	18
5. Spring disk	Conventional	22
6. Fall chisel plow	Mulch	45
7. Spring chisel plow	Mulch	45
8. Spring in-row subsoiling	Strip	70
9. No-till	No-till	92

Note: Data for the figure above drawn from Mathers et al., (2023).

Table 3.2: Corn - Baseline Specification

VARIABLES	(1) Mean	(2) Variance	(3) Skewness	(4) Kurtosis
2. Spring moldboard plow plus disk	5.921	209.9	8,914	2.029e+06
	(6.051)	(337.7)	(36,528)	(3.280e+06)
3. Fall chisel plow plus disk	19.31***	156.4	-15,858	753,672
	(5.988)	(323.3)	(32,948)	(2.759e+06)
4. Spring chisel plow plus disk	15.28**	562.0	13,958	3.776e+06
	(6.449)	(347.1)	(37,793)	(3.194e+06)
5. Spring disk plow	21.17***	327.0	-13,940	1.470e+06
	(6.186)	(327.2)	(33,616)	(2.795e+06)
6. Fall chisel plow	31.83***	50.80	-27,123	-1.171e+06
	(5.862)	(283.6)	(28,507)	(2.284e+06)
7. Spring chisel plow	29.41***	296.1	-22,958	750,164
	(6.151)	(298.3)	(31,815)	(2.505e+06)
8. Spring in-row subsoiling	34.41***	443.7	-37,048	1.485e+06
	(6.318)	(308.8)	(32,548)	(2.458e+06)
9. No-till	45.20***	257.7	-33,653	552,122
	(6.107)	(305.1)	(31,570)	(2.455e+06)
Rotation	-29.13***	-363.2**	4,472	-761,866
	(3.159)	(143.1)	(11,410)	(960,472)
Trend	1.457***	87.68***	655.4	617,812***
	(0.196)	(9.286)	(1,093)	(81,811)
Constant	48.61***	186.6	19,512	-3.062e+06
	(4.822)	(239.3)	(24,486)	(1.998e+06)
Observations	648	648	648	648
R-squared	0.214	0.144	0.008	0.107

Note: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 3.3: Soybean - Baseline Specification

VARIABLES	**(1)** Mean	**(2)** Variance	**(3)** Skewness	**(4)** Kurtosis
2. Spring moldboard plow plus disk	1.087	28.69	928.6	66,755
	(3.578)	(101.8)	(5,316)	(261,991)
3.Fall chisel plow plus disk	9.847***	29.78	-1,999	-45,319
	(3.581)	(88.77)	(4,274)	(177,920)
4.Spring chisel plow plus disk	5.667	0.309	-1,672	-60,017
	(3.516)	(89.80)	(4,361)	(188,149)
5.Spring disk plow	8.726***	-59.50	-2,106	-96,481
	(3.304)	(89.41)	(4,500)	(212,029)
6.Fall chisel plow	12.21***	-6.914	-604.8	26,746
	(3.470)	(99.61)	(5,258)	(263,571)
7.Spring chisel plow	12.13***	-57.54	-3,438	-129,409
	(3.310)	(84.55)	(4,058)	(176,306)
8.Spring in-row subsoiling	10.26***	-96.75	-3,702	-209,281
	(3.201)	(77.99)	(3,657)	(161,822)
9.No-till	10.25***	-18.47	-1,196	-47,254
	(3.434)	(92.58)	(4,398)	(193,080)
trend	-0.579***	-9.218***	-256.5**	-17,905***
	(0.0835)	(2.025)	(100.9)	(4,502)
Constant	38.72***	443.0***	9,069**	614,077***
	(2.984)	(85.10)	(4,302)	(197,101)
Observations	429	429	429	429
R-squared	0.155	0.052	0.019	0.037

Note: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 3.4: Yield Benefit of Different Tillage Practices

	Change in Residue	Yield Benefit (bu/ac)	
VARIABLES		**Corn**	**Soybeans**
Fall moldboard plow plus disk vs. chisel plow plus disk	12	19.313***	9.847***
		(5.988)	(3.581)
Spring chisel plow plus disk vs. disk plow	4	5.885	3.059
		(6.798)	(3.304)
Fall chisel plow plus disk vs. chisel plow	27	12.517**	2.365
		(6.048)	(3.536)
Spring disk plow vs. chisel plow	23	8.240	3.409
		(6.516)	(3.085)
Spring chisel plow vs. in-row subsoiling	25	5.004	-1.877
		(6.641)	(2.976)
Spring in-row subsoiling vs. No-till	22	10.786*	-0.012
		(6.600)	(3.112)

Note: Robust standard errors in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table 3.5: Corn - Nonparametric Specification

VARIABLES	(1) Mean	(2) Variance	(3) Skewness	(4) Kurtosis
2. Spring moldboard plow plus disk	5.92	16.46	-104.71	-20995.17
	(6.1)	(38.29)	(780.04)	(42668.88)
3. Fall chisel plow plus disk	19.34***	276.99***	2318.32	366166.27***
	(6.29)	(74.28)	(2563.8)	(132822.89)
4. Spring chisel plow plus disk	15.29**	83.66	973.59	140280.14
	(6.31)	(56.93)	(1748.11)	(126019.77)
5. Spring disk plow	21.2***	245.44***	4527.48*	441568.8**
	(6.54)	(71.17)	(2532.83)	(216976.54)
6. Fall chisel plow	31.83***	315.07***	1708.47	675625.91**
	(6.24)	(87.98)	(3447.51)	(332434.59)
7. Spring chisel plow	29.42***	120.87**	-1452.98	113148.15
	(6.78)	(58.74)	(1660.17)	(83087.23)
8. Spring in-row subsoiling	34.41***	263.38***	-7160.36	776250.88*
	(6.9)	(96.39)	(4486.85)	(396287.82)
9. No-till	45.2***	227.56***	553.32	337432.3**
	(6.57)	(73.86)	(2790.64)	(156925.97)
Observations	648	648	648	648

Note: Robust standard errors in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

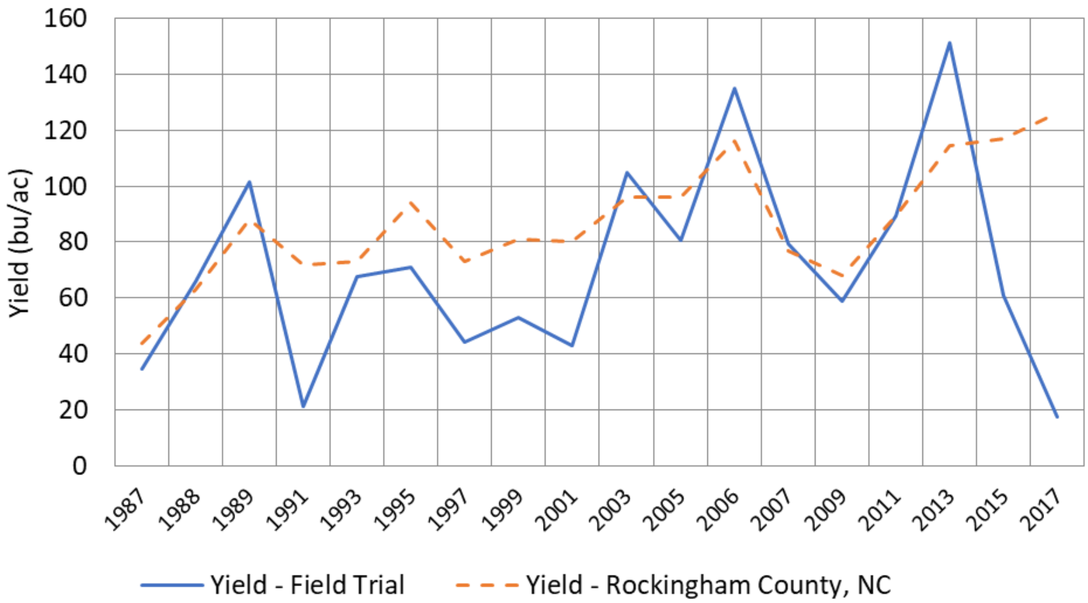
Table 3.6: Soybean - Nonparametric Specification

VARIABLES	**(1)** Mean	**(2)** Variance	**(3)** Skewness	**(4)** Kurtosis
2. Spring moldboard plow plus disk	0.95	-20.94	9.79	-7404.98
	(3.72)	(17.51)	(205.06)	(6971.97)
3. Fall chisel plow plus disk	9.71**	14.48	-387.41	11558.64
	(3.77)	(24.74)	(384.97)	(12278.31)
4. Spring chisel plow plus disk	5.63	12.91	-398.63	8045.93
	(3.81)	(25.52)	(404.37)	(15326.4)
5. Spring disk plow	8.56**	24.01	518.07	15223.53
	(3.52)	(23.68)	(358.36)	(13389.82)
6. Fall chisel plow	12.07***	19.8	17.66	11997.2
	(3.64)	(24.5)	(341.44)	(12792.88)
7. Spring chisel plow	12***	-5.5	-130.12	-753.14
	(3.31)	(19.29)	(260.15)	(7760.23)
8. Spring in-row subsoiling	10.22***	9.8	-117.79	644.47
	(3.39)	(20.43)	(249.6)	(7955.56)
9. No-till	10.08***	31.92	-412.37	12423.28
	(3.75)	(23.93)	(348.56)	(11752.84)
Observations	429	429	429	429

Note: Robust standard errors in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

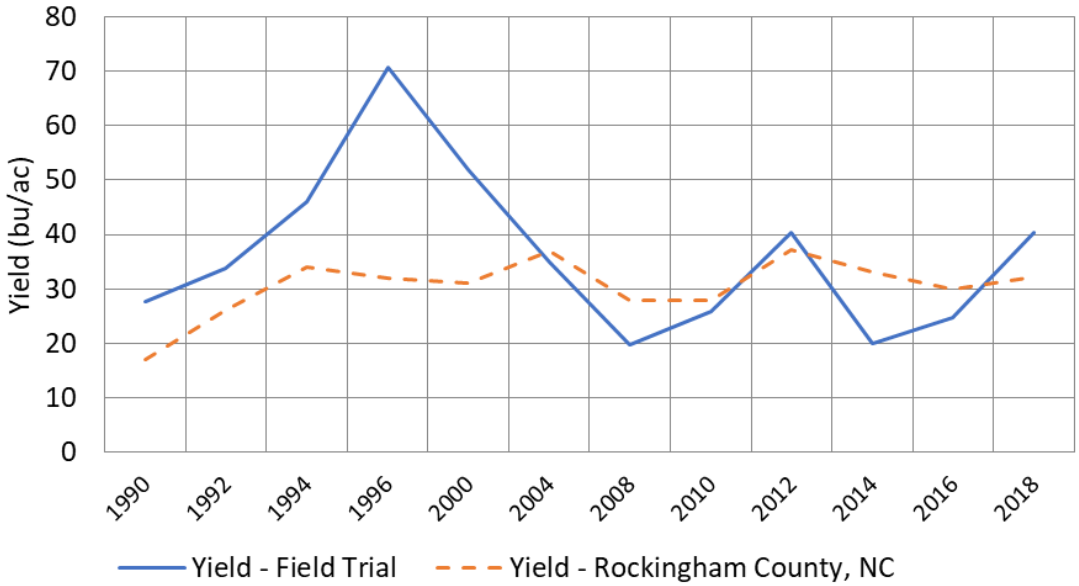
3.9 Figures

Figure 3.1: Corn – Mean Annual Yield – Ave. Field Trial vs. County



Note: Data for the figure above drawn from Mathers et al., (2023).

Figure 3.2: Soybean – Mean Annual Yield – Ave. Field Trial vs. County



Note: Data for the figure above drawn from Mathers et al., (2023).

Chapter 4

Cover Crop Adoption and Algal Blooms

4.1 Introduction

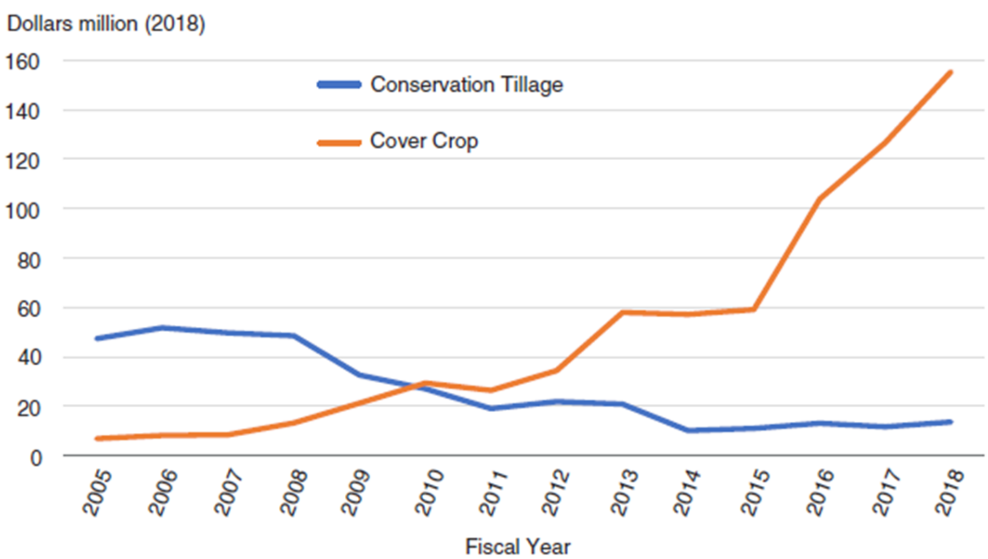
The Environmental Protection Agency (EPA) describes nutrient pollution, or the accumulation of nitrogen and phosphorus in water, as "one of the most widespread, costly, and most challenging environmental problems" confronting the United States (EPA, 2024). These elements can trigger excessive algal growth, resulting in harmful algal blooms that reduce dissolved oxygen available to aquatic life and produce toxins that can harm people, animals, and plants (Urquhart et al., 2017; Schaeffer et al., 2022). The most common form of freshwater harmful algal bloom are comprised of photosynthetic prokaryote cyanobacteria (Graham et al., 2017). Occurring throughout the entirety of the United States, cyanobacterial blooms disrupt fishing and recreation, reduce property values, and threaten safe drinking water sources (Graham et al., 2017; NCCOS, 2025; Wolf and Klaiber, 2017; Zhang et al., 2022; Del Rossi et al., 2023). The purpose of this paper is to examine whether cover crops—an on-farm agricultural production practice receiving increasing conservation funding—reduces the frequency of harmful algal blooms in nearby freshwater lakes.

Agriculture is widely credited with increasing nutrient loads in surface water in the United States (Ribaudo and Shortle, 2019; Metaxoglou Smith, 2022; Del Rossi et al., 2023). The intensive use of fertilizer in crop production is associated with excessive nitrogen and phosphorus concentrations and reduced dissolved oxygen in nearby surface water (Paudel and Crago, 2021; Del Rossi et al., 2023). As agricultural nonpoint pollution is exempt from the 1972 Clean Water Act, the most significant investments in controlling agricultural nonpoint pollution come from USDA federal conservation programs (Shortle et al., 2012; Ribaudo and Shortle, 2019) which use voluntary cost share programs to encourage the adoption of agricultural best practices to achieve environmental improvements.

Reduced tillage and cover crop adoption are conservation practices that have been emphasized to reduce erosion and prevent nutrient runoff into surface waters (Wallander et al., 2021; Chen et al., 2022). Cover crops refer to non-cash crops grown to cover the soil between growing seasons while reduced tillage refers to tillage operations that leave 30% or more of the post-harvest crop residue on the field until spring planting (Wallander et al., 2021). While cover crops and reduced tillage have been shown to mitigate climate-related production risk to producers (Won et al., 2024; Mathers et al., 2023), public benefits from these conservation practices stem primarily from their role as winter soil cover (Schipanski et al., 2014; Blanco-Canqui, 2018; Chen et al., 2022). By covering the soil during the fallow season, cover crops and reduced tillage improve wind and water erosion during the winter months and early spring, reducing agricultural runoff during a precipitation-heavy period (Blanco-Canqui, 2018; Chen et al., 2022).

In the last decade, there has been a significant upward trend in total funding going toward cover crops in federal conservation programs. From 2005 to 2018, funding for cover crops through the Environmental Quality Incentives Program (EQIP) increased from $7 million to more than $155 million while funding for no-till declined substantially (Wallander et al., 2021). See Figure 1 for a depiction of EQIP expenditure from 2005 to 2018. As a result, cover crop adoption expanded significantly over this period. Figure 2 illustrates watershed-level cover crop and reduced tillage acres for 16 states in Midwest from 2008 through 2020. More recently, cover crop adoption featured prominently in the USDA's pandemic relief programming for farmers with the Pandemic Cover Crop Program providing over $59 million in crop insurance premium subsidies for 12.2 million acres of cover crops in 2021 ("Coronavirus and USDA Assistance for Farmers"). In 2022, the USDA announced an investment of $38 million to expand their Cover Crop Initiative in 11 states and a partnership with Farmers for Soil Health to double the number of corn and soybean acres using cover crops to 30 million acres by 2030 (NRCS Press Release, Jan 10, 2022).

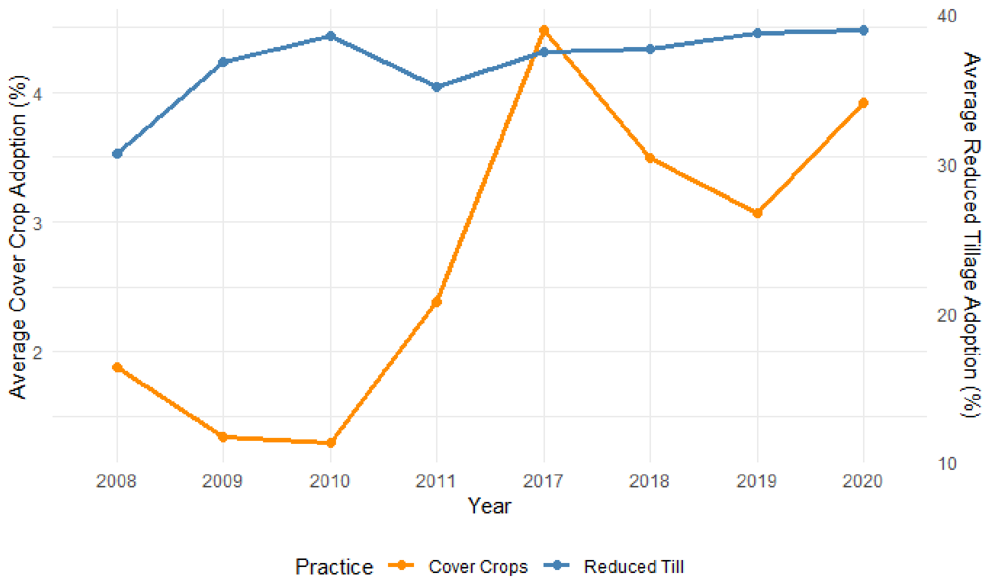
Figure 4.1: EQIP Expenditure on Cover Crops and Reduced Tillage, 2008-2020



Note: Graph depicted is Figure 4 from Wallander et al. (2021). Data depicted is USDA Economic Research Service analysis of NRCS ProTracts data on Environmental Quality Incentive Program obligations.

Given this expansion of public support, it is important to establish whether cover crop adoption delivers public benefits in the form of improved water quality. While a plethora of field trials from the soil and tillage literature evaluate the impact of cover crop adoption on sediment loss and nutrient loss (Martin and Cassel, 1992; Laloy and Bielders, 2010; Blanco-Canqui et al., 2013; Smith, Huang, and Haney, 2017; Blanco-Canqui, 2018), they offer limited insight as to how field-level nutrient and/or sediment loss relate to changes in ambient surface water quality in the aggregate. In addition, the practical implementation of cover crops across farms differs from the fixed management systems employed in field trials (Blanco-Canqui, 2018).

Figure 4.2: Cover Crop and Reduced Till Adoption across Freshwater Lakes in the Midwest



An emerging literature in agricultural economics uses reduced form econometrics to evaluate the impact of agricultural production and conservation programs in the United States on concentrations of nitrogen and phosphorus, dissolved oxygen, and other water quality characteristics in surface water (Paudel and Crago, 2021; Raff Meyer, 2022; Liu et al., 2023; Metaxoglou Smith, 2022; and Hsieh and Gramig, 2024). Hsieh and Gramig (2024) examine cover crop adoption specifically, using river flow direction to construct drainage basins as units of analysis to evaluate whether cover crop adoption across 11 corn belt states from 2008 to 2018 reduce the concentration of nitrates in surface water. Their results highlight the role of spillovers as a unit increase in the percentage of cropland adopting cover crops results in a small but significant decrease in the concentration of inorganic nitrogen for downstream drainage basins but not headwater basins.

The purpose of this paper is to examine whether the winter cover crop adoption in the watershed that drains into freshwater lakes reduces the incidence of cyanobacterial blooms the following summer. The EPA provides remotely-sensed cyanobacterial bloom data for 2,000 lakes throughout the continental United States from 2008-2011 and 2017-2020. Using the U.S. Geological Survey's National Hydrography dataset and the U.S. Department of Agriculture's Crop Layer dataset, we identify the agricultural, urban, and non-agricultural/non-urban land use of each hydrologic unit code-8 watershed that drains into these lakes. We then use the Conservation Technology Information System (CTIC)'s remotely-sensed Operational Tillage Information System (OpTIS) residue cover dataset to estimate panel regressions that control for urban and agricultural land use and weather in the watershed and include lake and annual fixed effects. Given the spatial coverage of OpTIS and temporal coverage of the algal bloom dataset, our analysis comprises 424 freshwater lakes in the Midwest from 2008-2011 and 2017-2020.

The contribution of our paper to the existing literature is the use of an alternative, more direct, measure of environmental harm from nutrient pollution. Past studies evaluate water quality using sampling data of nitrogen, phosphorus, and dissolved oxygen in surface water (Hsieh and Gramig, 2024; Paudel and Crago, 2021). However, the impact of a change in one of these measures varies across watersheds given heterogeneity in soil types, drainage conditions, stream power, and other hydrological conditions (Zhang et al., 2024; Steinman and Denning, 2005; Snelder, Biggs, and Weatherhead, 2004). Harmful algal blooms indicate that a waterbody has exceeded its idiosyncratic assimilative capacity for nutrients and is actively impaired (EPA, 2025). By directly evaluating impacts to an adverse phenomenon, the results of this paper offers policymakers insight as to whether the on-farm implementation of cover crops mitigates direct environmental harm from nutrient pollution.

The paper is organized as follows: Section 2 provides background on harmful algal blooms and the literature that has evaluates them. Section 3 introduces the data. Section 4 presents our methodology and limitations of our empirical strategy. Section 5 presents the results of our regression analyses and discuss the implications. Section 6 concludes and discusses future research directions.

4.2 Background

The incidence of harmful algal blooms are influenced by a variety of factors. Runoff from agricultural fields, wastewater discharge from sewage systems, animal waste from livestock operations, urban stormwater runoff, and atmospheric deposition of nitrogen compounds from fossil fuel burning all contribute to high levels of nitrogen and phosphorus entering waterways (CDC, n.d.). Weather plays a critical role in the occurrence of a harmful algal bloom. Sunlight is essential for the growth of photosynthetic algal species. As such, extended periods of strong sunlight and warmer water temperatures fuel the growth of cyanobacterial blooms and prolong the growing season of cyanobacteria (Kramer et al., 2024; Paerl, 2023). In addition, precipitation facilitates nutrient runoff while rainfall intensity impacts the distance nutrients can travel in waterways (Moore et al., 2008).

Past studies that have examined changes in agricultural land use and the incidence of harmful algal blooms have relied on simulation tools like the Soil and Water Assessment Tool (SWAT) or the Spatially Referenced Regression On Watershed attributes (SPARROW) to provide watershed-specific insight into how changes in land use, land management practices, and climate change impact surface and ground water (Michalak et al., 2013; Kling et al., 2017; Watson et al., 2016; Liu et al., 2024; Nepal and Parajuli, 2025). However, limitations of these tools include reliance on extensive input data, potential inaccuracies in representing hydrological processes within watersheds, and the need for careful calibration (Aloui et al., 2023).

Advances in remote sensing have empowered researchers to examine direct relationships between agricultural land use and the harmful algal blooms. In the United States, remotely-sensed cyanobacterial bloom data is often used to estimate hedonic property value models to estimate the economic costs of water quality degradation (Wolf Klaiber, 2017; Osseni et al., 2021; Zhang et al., 2022). More recently, Tang et al. (2025) examine the impact of agricultural land use on the incidence of harmful algal blooms in China between 2003 and 2019 using remotely-sensed cyanobacterial bloom data. Their results indicate that a 1% increase in cropland leads to a 0.5% increase in the size of HABs in large lakes. Our baseline model for evaluating cyanobacterial blooms is an extension of the fixed effect estimation used by Tang et al., (2025) where harmful algal blooms are modelled as a function of agricultural and urban land use, temperature, and precipitation. We include controls for winter soil cover practices to evaluate whether cover crops mitigate harmful algal blooms.

4.3 Data

The Environmental Protection Agency publishes annual cyanobacterial size and frequency metrics for 2000 lakes throughout the continental United States via its EnviroAtlas data portal. Cyanobacterial bloom data were derived from two European Space Agency satellite sensors: the Medium Resolution Imaging Spectrometer (MERIS) onboard the Envisat satellite for the years 2008-2011 and the Ocean and Land Colour Instrument (OLCI) onboard the Sentinel-3 satellite for the years 2017-2021. Schaeffer et al. (2022) detail the spectral shape algorithm used to construct the cyanobacteria index and field validation procedures. For each lake in the dataset, the frequency of cyanobacterial blooms refers to the percentage of weekly satellite composites exhibiting the presence of cyanobacteria relative to the total number of weekly satellite composites that contained a valid measurement. The results range from 0 to 100 where 0 indicates a cyanobacterial bloom was never detected by the satellite sensor for any pixels that year and 100 indicates a cyanobacterial bloom was detected by the satellite sensor for every week in that year. Distributions of these variables are displayed in Appendix C Table 1. See Table 1 below for descriptive statistics.

Cover crop adoption data was obtained from the Conservation Technology Information System's Operational Tillage Information System (OpTIS) dataset, version 3.0. The OpTIS 3.0 residue cover dataset reports acres of cover crops and reduced tillage adoption at the watershed level (hydrologic unit code-8) for 16 states in the Midwest from 2005 through 2020. OpTIS algorithms use multi-temporal optical satellite observations sourced from multiple platforms, including MODIS sensors on Terra and Aqua, Landsat 5, Landsat 7, Landsat 8, Sentinel 2A, and Sentinel 2B. Hagen et al. (2020) provides a detailed account of how the Normalized Difference Tillage Index and Normalized Difference Vegetation Index algorithms were used to construct the residue and winter crop cover fractions across the satellite imagery.

OpTIS provides the acreage associated with the following winter cover categories: cover crops, no cover crops, perennial (perennial crops such as hay or alfalfa), winter commodity (e.g. commodities like winter wheat), and no data. To construct our measure of cover crop adoption, we take the ratio of cover crop acres to total agricultural acres in each watershed. We similarly construct perennial and winter commodity ratios to include as controls. OpTIS also provides the acreage associated with four levels of residue cover: very low (0–15%), low (16–30%), moderate (31–50%), and high (51–100%) across watersheds. Given that reduced tillage also provides winter soil cover, we include the sum of moderate and high residue cover acres as a ratio to agricultural acres for each watershed as measures for reduced tillage adoption. The distributions of these variables are displayed in Appendix C Table 2. See Table 1 above for descriptive statistics.

Table 4.1: Table 1. Descriptive Statistics

Statistic	N	Mean	St. Dev.	Min	Max
Frequency	3,386	32.321	26.533	0.000	100.000
Extent	3,386	41.363	41.706	0.000	100.000
Corn	3,392	19.643	11.751	0.339	51.114
Soybean	3,392	17.491	10.191	0.00001	46.406
Grain	3,392	3.103	4.558	0.026	46.717
Cotton	254	0.302	0.519	0.00001	2.551
Other Ag	3,392	22.520	14.078	2.062	79.852
Ag land	3,392	62.780	21.063	6.410	96.329
Urban land	3,392	7.152	5.233	1.595	55.414
Non-ag, Non-urban	3,392	30.066	20.784	1.081	90.472
Reduced till	3,392	36.741	9.495	5.912	65.216
Cover crops	3,392	2.734	3.616	0.000	46.159
Winter Commodity	3,392	3.369	8.602	0.000	83.752
Perennial Crop	3,392	4.964	5.748	0.000	33.398
Cum. Precipitation	3,392	31.854	8.726	9.317	77.366
Summer Temperature	3,392	21.197	2.023	16.362	30.247
Max depth	2,752	−17.540	539.082	−9,998.000	81.824
Lake area	3,392	12.198	18.841	1.328	190.178

Given the spatial resolution of the OPTIS data, the HUC8 watershed is the smallest geographic unit to evaluate the drainage area for lakes in the EPA's cyanobacterial bloom dataset. Lakes are the receiving bodies of water within watersheds due to elevation (USGS, 2019). Using the U.S. Geological Survey's Water Boundary and National Hydrography datasets, we examine the direction of river flow through each lake and identify the HUC8 watershed of the inflow point. Given the temporal coverage of the EPA's cyanobacterial bloom data and geographic coverage of OpTIS winter and residue cover data, the data used in our analysis includes 424 lakes in 134 watersheds in 16 states in the Midwest for 8 years, from 2008 through 2011 and 2017 through 2020.

Given the diverse sources of nutrients and environmental factors that catalyze harmful algal blooms, we model the frequency of cyanobacterial blooms as a function of land use and weather as well as our variables of interest. To construct agricultural and urban land use estimates for each drainage watershed, we use the USDA National Agricultural Statistics Service (NASS) Cropland Data Layer (CDL). CDLs are annual raster, geo-referenced, crop-specific land cover data layers produced using satellite imagery and extensive ground reference data (USDA, n.d.). We segment each CDL by the boundaries of our drainage basins and combine pixels associated with different crops, urban and suburban land, forest cover, and wetlands into the following categories: corn, soybean, grain, and urban land use. We then divide the sum of pixels in each category by the sum of pixels in the drainage watershed. These crop variables are thus measures of the ratio of land planted as each category to land in the watershed. Distribution of these variables are displayed in Appendix C Table 3. See Table 1 above for descriptive statistics.

To account for the role of weather, we use Oregon State University's Parameter Elevation Regression on Independent Slopes Model (PRISM) climate data set to construct the mean temperature across June, July, and August for each drainage watershed in each year and cumulative precipitation from October of the previous year through August of each year for each drainage watershed. Distribution of weather controls across lakes are displayed in Appendix C Table 1. See Table 1 above for descriptive statistics.

4.4 Methodology

As in Tang et al. (2025), we use two-way fixed effect model as our main specification for evaluating the incidence of harmful algal blooms as a function of agricultural and urban land use and weather:

$$Hab_{it} = \beta_1 CC_{it-1} + \beta_2 RC_{it-1} + \beta_3 WC_{it-1} + \beta_4 Per_{it-1} + \beta_5 LandUse_{it} + \beta_6 Temp_{it} + \beta_7 PPT_{it} + \beta_8 \lambda_i + \beta_9 \eta_t + \epsilon_{it} \tag{4.1}$$

where Hab_{it} refers to the frequency of a cyanobacterial bloom in lake i and year t. $LandUse_{it}$ is a vector of covariates including ratios of the acres of corn, soybean, cotton, grain, and other crops to total land in the drainage watershed. $Temp_{it}$ refers to the mean temperature across June, July, and August in the drainage watershed for each lake and PPT_{it} represents the cumulative precipitation from October of the previous year through August of year t. We include lake fixed effects to account for time-invariant determinants of lake-level cyanobacterial blooms (e.g. lake surface-area to depth ratios; types of aquatic plant and animal life; elevation etc.) and annual fixed effects to address other unobservable phenomena that could impact blooms (e.g. regional agricultural or climate shocks). We include winter's ratio of acres with winter cover crops (CC_{it-1}), reduced tillage (RC_{it-1}), perennial crops (Per_{it-1}), and winter commodity (WC_{it-1}) acres to total agricultural land to the specification to evaluate the role of winter soil cover in reducing nutrient pollution. The identifying assumption of our estimation is that changes in agricultural land use and soil health practice adoption across drainage watersheds and over time drives changes in the frequency of lake-level cyanobacterial blooms.

There are several threats to identification in our analyses. In our land use estimations, our measure for urban land cover alone does not account for population dynamics within urban zones. Urban areas with larger population density may disproportionately impact water quality relative to those with smaller populations. Furthermore, the estimation does not explicitly control for changes over time in point sources of phosphorus or nitrogen (e.g. wastewater treatment facilities). Future analyses should aggregate census block income and population data into watershed-level variables and include these covariates as an alternative specification. In addition, targeting of impaired watersheds by state-level policymakers threatens identification if implementation of other conservation programming is correlated with cover crop and reduced tillage adoption and reduce nutrient pollution. Future analyses should construct measures of Conservation Reserve Program acreage or EQIP payment expenditure from county-level data to include as covariates in an alternative specification.

4.5 Results

The results from our empirical specification 3.1 are displayed in column 4 in Table 2 below. Columns 1-3 were included to show the effect of including additional winter soil cover controls. Our results indicate winter cover crop adoption does not reduce the frequency of cyanobacterial algal blooms the next year. Indeed, in specifications 1-3, cover crops are associated with increased incidence of cyanobacterial blooms (significant at the 5% level). However, these results are not robust to the inclusion of the ratio of perennial crops to cropland in the watershed. In the Discussion section below, we consider several explanations for this result.

While our results on cover crops are inconclusive, our analysis suggests reduced tillage is associated with a statistically significant decrease in the frequency of cyanobacterial blooms (5% level). A one unit increase in the percentage of agricultural land that adopts reduced tillage is associated with a 0.072 decrease in the frequency of cyanobacterial blooms the following year. This corresponds to a decrease of 0.037 weeks of cyanobacterial blooms a year. This result is robust to the addition of winter soil cover controls. The coefficients on the ratio of winter commodities and perennial crops to agricultural land in the watershed are also negative (significant at the 10% level), suggesting that winter soil cover could be a means to mitigate nutrient pollution.

Crop mix in the watershed also has implications for the frequency of cyanobacterial blooms. Our analysis indicates that a unit increase in the percentage of the watershed planting soybeans is associated with a 0.322 increase in the frequency of cyanobacterial blooms that year. This change corresponds to an increase of 0.17 weeks of cyanobacterial blooms in a year. In addition, a unit increase in the percentage of the watershed planting grains is associated with an increase in the frequency of cyanobacterial blooms of 1.20. This corresponds to an additional 0.62 weeks of cyanobacterial blooms a year. While nitrogen application in corn is associated with increased nutrient pollution (Metaxaglou et al., 2022; Del Rossi et al. 2023), our results do not indicate a significant relationship. This may be related to the fact that the limiting factor for growth in freshwater systems is phosphorus (Paerl et al., 2016; Kramer et al., 2024). Soybeans are phosphorus-fertilizer intensive. This supports our result that increased soybean acreage in the watershed increases the incidence of cyanobacterial blooms. In our analysis, grains as a category include sorghum, barley, and oats. We hypothesize that increased grain acreage in the watershed are associated with increased livestock operations.

Summer temperature appears to be the most important indicator for the incidence of cyanobacterial blooms. An increase of 1 degree celsius in the average summer temperature increases the frequency of cyanobacterial blooms the next year by 1.725 (or 0.90 weeks a year). Our results for cumulative precipitation and urban land use are not significant.

4.6 Discussion

Our results indicate that winter cover crop adoption in the drainage watershed of freshwater lakes in the Midwest is not associated with reductions in the incidence of algal blooms the following summer. In some of

Table 4.2: Table 3. Impact of Crop Mix and Cover Crop adoption on HAB Frequency

	Dependent variable:			
	Frequency of HAB			
	(1)	(2)	(3)	(4)
Cover Crops	0.178**	0.163**	0.146**	0.115
	(0.071)	(0.070)	(0.070)	(0.073)
Reduced Till		−0.077**	−0.063*	−0.072**
		(0.035)	(0.035)	(0.036)
Winter Commodity			−0.289*	−0.248*
			(0.147)	(0.149)
Perennial Crop				−0.220*
				(0.114)
Corn	−0.158	−0.177	−0.176	−0.225
	(0.159)	(0.159)	(0.159)	(0.162)
Soybean	0.369**	0.380**	0.358**	0.322**
	(0.159)	(0.159)	(0.158)	(0.159)
Grain	1.058***	0.949***	1.298***	1.196***
	(0.297)	(0.296)	(0.361)	(0.367)
Urban	0.037	−0.019	0.023	−0.097
	(0.568)	(0.570)	(0.571)	(0.576)
Cum. Precip	−0.064	−0.061	−0.062	−0.077
	(0.049)	(0.050)	(0.050)	(0.050)
Summer Temp	1.701***	1.769***	1.788***	1.725***
	(0.269)	(0.271)	(0.269)	(0.271)
Observations	3,386	3,386	3,386	3,386
R^2	0.022	0.024	0.025	0.026
Adjusted R^2	−0.120	−0.119	−0.117	−0.116
Note:				*p<0.1; **p<0.05; ***p<0.01

our specifications, cover crop adoption is associated with a statistically significant (5% level) increase in the incidence of algal blooms. However, this result is not robust to the inclusion of the ratio of perennial crops to cropland in the watershed. There are several factors that could account for this result.

The first is that our baseline empirical model does not account for spatial spillovers. Possibly, nutrients from upstream watersheds flow into the drainage watersheds of our analysis and bias our estimates. Hsieh and Gramig (2024) needed to account for nitrate spillovers from upstream drainage basins to identify the small but statistically significant decrease in nitrate concentration from cover crop adoption.

Another possibility is endogeneity between water quality, cover crop adoption, and conservation program expenditure. Expenditure on cover crops increased dramatically over our period of analysis. It is possible that state NRCS offices direct EQIP expenditure on cover crops towards impaired watersheds resulting in more cover crop adoption in watersheds with lakes that are severely impaired by cyanobacterial blooms.

Finally, our results on cover crop adoption are impeded by the low level of cover crop adoption overall in the study area. While cover crop adoption expanded rapidly over the period of analysis, the average level of cover crop adoption over drainage watersheds in our sample is still very low, 2.7%. As a comparison, the average level of reduced tillage adoption in our sample is 36.7%. It may be the case that cover crop adoption only achieves reductions in cyanobacterial blooms observable via satellite after reaching a threshold level in the watershed.

While our results do not indicate that cover crops mitigate harmful algal blooms from nutrient pollution, they do support reduced tillage as a production practice that decreases the frequency of cyanobacterial blooms. In addition to winter soil cover, reduced till practices displace tillage practices that disturb or turn over the soil. Negative signs on the coefficients of the other winter soil cover measures suggest that greater adoption of winter soil cover could mitigate nutrient pollution.

To contextualize benefits of fewer cyanobacterial blooms from reduced tillage, we rely on estimates from Zhang et al. 2022 which examines how the frequency of cyanobacterial blooms generate economic costs via residential property values. Their paper uses nearly two decades worth of nationwide data on property sales near US inland lakes along as well as the EPA's satellite-derived measures of the annual frequency of cyanobacterial blooms to estimate hedonic property models and recover the marginal willingness to pay to reduce the frequency of cyanobacterial blooms. They provide estimates for seven climate regions across the United States, including the Upper Midwest which overlaps the geographic span of the lakes included in our analysis.

Table 4.3: Marginal Value of Changes in Agricultural Land Use and Reduced Tillage Operations

Scenario	Per House	Per Lake	Region
Marginal value of a percent increase in agricultural land adopting reduced tillage	$5	$1,137	$358,185
Marginal value of a percent increase in land in the watershed planting soybeans	-$21	-$5,085	-$1,601,882
Marginal value of a percent increase in land in the watershed planting grains	-$77	-$18,888	-$5,949,849

Note: Marginal values are computed using coefficients from column 4 in Table 2 and estimates for the Upper Midwest in Table 7 from Zhang et. al., 2022.

In Table 3, we use their valuations for a one-week reduction in cyanobacterial blooms for the Upper

Midwest and the coefficients we estimate for reduced tillage, grain, and soybeans in Table 2 to compute the marginal value of changes in agricultural land use and reduced tillage adoption at the property, lake, and region levels.

4.7 Conclusion

The purpose of this paper was to evaluate whether winter cover crop adoption reduces the incidence of harmful algal blooms in freshwater lakes. Our results do not indicate that cover crops reduce the frequency of algal blooms though our evaluation is impeded by the very low levels of cover crop adoption overall. The crop mix of the drainage watershed influences the incidence of cyanobacterial blooms. Soybean and grain acreage in the drainage watershed in particular is associated with increased cyanobacterial blooms. The results of this paper support reduced tillage as a conservation practice that mitigates direct environmental harm from nutrient pollution, though the magnitude of the effect is small despite moderate levels of adoption across watersheds.

Extensions to this work include exploring alternative specifications. To evaluate the robustness of our results, we propose to run alternative specifications that include measures of population density (e.g. GDP and population) in addition to urban land use, measures of alternative conservation programming that could introduce ommitted variable bias (e.g. acres enrolled with the Conservation Reserve program), and measures of livestock operations to further examine our result suggesting grain acreage increases the incidence of algal blooms.

In addition, future work includes employing alternative estimation procedures to explore endogeneity between cover crop adoption and conservation targetting in the watershed. In the past, Chen et al., (2022) used Kripfganz and Kiviet (2021)'s kinky least square (KLS) "external-IV-free" estimation to evaluate potential endogeneity in their assessment of cover crop adoption and soil erosion. In this setting, the kinky least square procedure can be used to confine correlation between cover crop adoption and the error term. Evaluating both positive correlation (e.g. increased cover crop adoption due to cyanobacterial bloom activity) and negative correlation with the error term (e.g. other conservation programming is adopted along with cover crops that reduce the incidence of harmful algal blooms) could shed light on whether state-level conservation targetting biases our results.

Finally, future work should explore the role of spillovers across watersheds as in Hsieh and Gramig (2024). Defining neighbors according to direction of river flow and estimating spatial lag regressions could more effectively control for spatial autocorrelation relating to the spatial clustering of crops.

In conclusion, our findings indicate that soybean and grain acreage in drainage watersheds increase the incidence of harmful algal blooms. Reduced tillage is a on-farm conservation practice that can reduce the incidence of harmful algal blooms. While cover crop adoption has expanded rapidly over the sample period, the low levels of adoption overall impede our analysis.

4.8 References

1. Aloui, S., Mazzoni, A., Elomri, A., Aouissi, J., Boufekane, A., Zghibi, A. (2023). A review of Soil and Water Assessment Tool (SWAT) studies of Mediterranean catchments: Applications, feasibility, and future directions. Journal of Environmental Management, 326, 116799.

2. Blanco-Canqui, Humberto, John D. Holman, Alan J. Schlegel, John Tatarko, and Tim M. Shaver. "Replacing fallow with cover crops in a semiarid soil: Effects on soil properties." Soil Science Society of America Journal 77, no. 3 (2013): 1026-1034.

3. Blanco-Canqui, Humberto. "Cover crops and water quality." Agronomy Journal 110, no. 5 (2018): 1633-1647.

4. Chen, Le, Roderick M. Rejesus, Serkan Aglasan, Stephen C. Hagen, and William Salas. "The impact of cover crops on soil erosion in the US Midwest." Journal of Environmental Management 324 (2022): 116168.

5. Del Rossi, Gemma, Mohammad Mainul Hoque, Yongjie Ji, and Catherine L. Kling. "The economics of nutrient pollution from agriculture." Annual Review of Resource Economics 15, no. 1 (2023): 105-130.

6. Graham, Jennifer L., Guy M. Foster, Thomas J. Williams, Ariele R. Kramer, and Theodore D. Harris. Occurrence of cyanobacteria, microcystin, and taste-and-odor compounds in Cheney Reservoir, Kansas, 2001-16. No. 2017-5016. US Geological Survey, 2017.

7. Hagen, S.C., Delgado, G., Ingraham, P., Cooke, I., Emery, R., P. Fisk, J., Melendy, L., Olson, T., Patti, S., Rubin, N. and Ziniti, B., 2020. Mapping conservation management practices and outcomes in the corn belt using the operational tillage information system (OpTIS) and the denitrification–decomposition (DNDC) model. Land, 9(11), p.408.

8. Hsieh, Hsin-Chieh, and Benjamin M. Gramig. "Estimating the impact of cover crop adoption on ambient nitrogen concentration in the upper Mississippi River drainage." Applied Economic Perspectives and Policy 46, no. 2 (2024): 609-626.

9. Kling, C. L., Chaubey, I., Cibin, R., Gassman, P. W., Panagopoulos, Y. (2017). Policy implications from multi-scale watershed models of biofuel crop adoption across the corn belt. JAWRA Journal of the American Water Resources Association, 53(6), 1313-1322.

10. Kramer, B. J., Turk-Kubo, K., Zehr, J. P., Gobler, C. J. (2024). Intensification of harmful cyanobacterial blooms in a eutrophic, temperate lake caused by nitrogen, temperature, and CO2. Science of the Total Environment, 915, 169885.

11. Laloy, Eric, and Charles L. Bielders. "Effect of intercropping period management on runoff and erosion in a maize cropping system." Journal of environmental quality 39, no. 3 (2010): 1001-1008.

12. Liu, D., Huang, L., Jia, L., Li, S., Wang, P. (2024). Evaluation of best management practices for mitigating harmful algal blooms risk in an agricultural lake basin using a watershed model integrated with Bayesian Network approach. Journal of Environmental Management, 364, 121433.

13. Liu, Pengfei, Yu Wang, and Wei Zhang. "The influence of the Environmental Quality Incentives Program on local water quality." American Journal of Agricultural Economics 105, no. 1 (2023): 27-51.

14. Mathers, C., Heitman, J., Huseth, A., Locke, A., Osmond, D. and Woodley, A., 2023. No-till imparts yield stability and greater cumulative yield under variable weather conditions in the southeastern USA piedmont. Field Crops Research, 292, p.108811.

15. Martin, C. K., and D. K. Cassel. "Soil loss and silage yield for three tillage management systems." Journal of production agriculture 5, no. 4 (1992): 581-586.

16. McKay, L., Bondelid, T., Dewald, T., Johnston, J., Moore, R., and Rea, A., 2012, NHDPlus Version 2: User Guide, `https://www.epa.gov/waterdata/nhdplus-national-hydrography-dataset-plus`

17. Metaxoglou, K. and Smith, A., 2022. Nutrient pollution and US agriculture: causal effects, integrated assessment, and implications of climate change (No. w30124). National Bureau of Economic Research.

18. Michalak, A.M., Anderson, E.J., Beletsky, D., Boland, S., Bosch, N.S., Bridgeman, T.B., Chaffin, J.D., Cho, K., Confesor, R., Daloğlu, I. and DePinto, J.V., 2013. Record-setting algal bloom in Lake Erie caused by agricultural and meteorological trends consistent with expected future conditions. Proceedings of the National Academy of Sciences, 110(16), pp.6448-6452.

19. Moore, Stephanie K., Vera L. Trainer, Nathan J. Mantua, Micaela S. Parker, Edward A. Laws, Lorraine C. Backer, and Lora E. Fleming. "Impacts of climate variability and future climate change on harmful algal blooms and human health." In Environmental health, vol. 7, pp. 1-12. BioMed Central, 2008.

20. Nepal, D., Parajuli, P. (2025). Hydrology and water quality evaluation for potential HABs under future climate scenarios. Journal of Environmental Management, 374, 124033.

21. Osseni, Abdel Fawaz, Francois Bareille, and Pierre Dupraz. "Hedonic valuation of harmful algal bloom pollution: Why econometrics matters?." Land Use Policy 107 (2021): 104283.

22. Paerl, Hans W. "Climate change, phytoplankton, and HABs." In Climate change and estuaries, pp. 315-334. CRC Press, 2023.

23. Paerl, Hans W., J. Thad Scott, Mark J. McCarthy, Silvia E. Newell, Wayne S. Gardner, Karl E. Havens, Daniel K. Hoffman, Steven W. Wilhelm, and Wayne A. Wurtsbaugh. "It takes two to tango: when and where dual nutrient (N P) reductions are needed to protect lakes and downstream ecosystems." Environmental science technology 50, no. 20 (2016): 10805-10813.

24. Paudel, J. and Crago, C.L., 2021. Environmental externalities from agriculture: evidence from water quality in the united states. American Journal of Agricultural Economics, 103(1), pp.185-210.

25. PRISM Climate Group, Oregon State University. `https://prism.oregonstate.edu`. Data created 4 Feb 2014. Accessed 04 Dec 2023.

26. Raff, Z. and Meyer, A., 2022. CAFOs and surface water quality: evidence from Wisconsin. American Journal of Agricultural Economics, 104(1), pp.161-189.

27. Ribaudo, Marc, and James Shortle. "Reflections on 40 years of applied economics research on agriculture and water quality." Agricultural and Resource Economics Review 48, no. 3 (2019): 519-530.

28. Schaeffer, Blake A., Erin Urquhart, Megan Coffer, Wilson Salls, Richard P. Stumpf, Keith A. Loftin, and P. Jeremy Werdell. "Satellites quantify the spatial extent of cyanobacterial blooms across the United States at multiple scales." Ecological indicators 140 (2022): 108990.

29. Schipanski, Meagan E., Mary Barbercheck, Margaret R. Douglas, Denise M. Finney, Kristin Haider, Jason P. Kaye, Armen R. Kemanian et al. "A framework for evaluating ecosystem services provided by cover crops in agroecosystems." Agricultural Systems 125 (2014): 12-22.

30. Schindler, D. W. (1977). Evolution of phosphorus limitation in lakes: natural mechanisms compensate for deficiencies of nitrogen and carbon in eutrophied lakes. Science, 195(4275), 260-262.

31. Shortle, James S., Marc Ribaudo, Richard D. Horan, and David Blandford. "Reforming agricultural nonpoint pollution policy in an increasingly budget-constrained environment." Environmental science technology 46, no. 3 (2012): 1316-1325.

32. Smith, D. R., C. Huang, and R. L. Haney. "Phosphorus fertilization, soil stratification, and potential water quality impacts." Journal of Soil and Water Conservation 72, no. 5 (2017): 417-424.

33. Snelder, Ton H., Barry JF Biggs, and Mark A. Weatherhead. "Nutrient concentration criteria and characterization of patterns in trophic state for rivers in heterogeneous landscapes 1." JAWRA Journal of the American Water Resources Association 40, no. 1 (2004): 1-13.

34. Steinman, Alan D., and Rodney Denning. "The role of spatial heterogeneity in the management of freshwater resources." In Ecosystem function in heterogeneous landscapes, pp. 367-387. New York, NY: Springer New York, 2005.

35. Tang, Chuan, Yifeng Guo, and Lian Feng. "Quantifying the Water Quality Impacts of Cropland Farming in China: A Satellite Data Approach." American Journal of Agricultural Economics (2025).

36. Urquhart, Erin A., Blake A. Schaeffer, Richard P. Stumpf, Keith A. Loftin, and P. Jeremy Werdell. "A method for examining temporal changes in cyanobacterial harmful algal bloom spatial extent using satellite remote sensing." Harmful algae 67 (2017): 144-152.

37. U.S. Center for Disease Control. "Harmful Algal Blooms: Contributing Factors and Impacts". Accessed Feb 2, 2024. https://www.cdc.gov/harmful-algal-blooms/about/harmful-algal-blooms-contributing-factors-and-impacts.html#cdc_health_safety_special_topic_how-contributing-factors

38. U.S. Department of Agriculture, National Agricultural Statistics Service. Cropland Data Layer. USDA, https://nassgeodata.gmu.edu/CropScape. Accessed 01/15/2025.

39. U.S. Department of Agriculture, Economic Research Service. "Feed Grains Sector at a Glance. 5 Jan. 2025", https://www.ers.usda.gov/topics/crops/corn-and-other-feed-grains/feed-grains-sector-at-a-glance. Accessed 5 Mar. 2025.

40. U.S. Department of Agriculture. "USDA Offers Expanded Conservation Program Opportunities to Support Climate Smart Agriculture in 2022" Washington, DC. https://www.usda.gov/media/press-releases/2022/01/10/usda-offers-expanded-conservation-program-opportunities-support.

41. U.S. Department of Agriculture. "Coronavirus and USDA Assistance for Farmers." Farmers.gov. Accessed May 23, 2024. https://www.farmers.gov/coronavirus/pandemic-assistance.

42. U.S. Environmental Protection Agency. "Cyanobacteria Index – Frequency". Available via https://enviroatlas.epa.gov/enviroatlas/interactivemap/. Accessed on January 1, 2024.

43. U.S. Environmental Protection Agency. "National Hydrography Dataset Plus, Version 2". Available via https://enviroatlas.epa.gov/enviroatlas/interactivemap/. Accessed on January 1, 2024.

44. U.S. Environmental Protection Agency. "Nonpoint Source: Agriculture" Updated Feb 27, 2025. Accessed May 23, 2024. https://www.epa.gov/nps/nonpoint-source-agriculture.

45. U.S. Environmental Protection Agency. "Nutrient Pollution: The Problem" Updated Nov 5, 2024. Accessed May 23, 2024. https://www.epa.gov/nutrientpollution/problem.

46. U.S. National Center for Coastal Ocean Science. "Harmful Algal Blooms: NOAA State of the Science Fact Sheet" Published March 6, 2025. Accessed on Feb 1, 2025. https://coastalscience.noaa.gov/news/hab-noaa-fact-sheet/#:~:text=Blooms%20of%20toxic%20cyanobacteria%20occur,U.S.%20during%20the%20past%20decade

47. U.S. Geological Survey. National Hydrography Dataset. U.S. Department of the Interior, https://www.usgs.gov/national-hydrography. Accessed 06/01/2024.

48. Wallander, S., Smith, D., Bowman, M., Claassen, R. (2021). Cover crop trends, programs, and practices in the United States.

49. Watson, Susan B., Carol Miller, George Arhonditsis, Gregory L. Boyer, Wayne Carmichael, Murray N. Charlton, Remegio Confesor et al. "The re-eutrophication of Lake Erie: Harmful algal blooms and hypoxia." Harmful algae 56 (2016): 44-66.

50. Wendling, Marina, Lucie Büchi, Camille Amossé, Sokrat Sinaj, Achim Walter, and Raphaël Charles. "Influence of root and leaf traits on the uptake of nutrients in cover crops." Plant and Soil 409 (2016): 419-434.

51. Wolf, D. and Klaiber, H.A., 2017. Bloom and bust: Toxic algae's impact on nearby property values. Ecological economics, 135, pp.209-221.

52. Won, S., Rejesus, R. M., Goodwin, B. K., Aglasan, S. (2024). Understanding the effect of cover crop use on prevented planting losses. American Journal of Agricultural Economics, 106(2), 659-683.

53. Wurtsbaugh, Wayne A., Hans W. Paerl, and Walter K. Dodds. "Nutrients, eutrophication and harmful algal blooms along the freshwater to marine continuum." Wiley Interdisciplinary Reviews: Water 6, no. 5 (2019): e1373.

54. Zhang, J., Phaneuf, D. J., Schaeffer, B. A. (2022). Property values and cyanobacterial algal blooms: Evidence from satellite monitoring of Inland Lakes. Ecological Economics, 199, 107481.

55. Zhang, Z., Huang, J., Chen, S. and Sun, C., 2024. How much nutrient reaches a stream: Insights from a hybrid model and implications for watershed nitrogen export and removal. Journal of Environmental Management, 360, p.121104.

APPENDICES

Appendix A

Surface Water Impairment from Storms and Swine in North Carolina

Table A1: Regulated Activities under North Carolina's AFO Permit Program

Primary Operation	Regulated Activity	Count
Cattle	Cattle - Other	10
Cattle	Cattle - Beef Brood Cow	110
Cattle	Cattle - Beef Feeder	8,151
Cattle	Cattle - Beef Stocker Calf	7,275
Cattle	Cattle - Dairy Calf	4,661
Cattle	Cattle - Dairy Heifer	14,976
Cattle	Cattle - Dry Cow	3,549
Cattle	Cattle - Milk Cow	51,929
Swine	Swine - Boar/Stud	4,932
Swine	Swine - Farrow to Feeder	28,229
Swine	Swine - Farrow to Finish	7,863
Swine	Swine - Farrow to Wean	881,052
Swine	Swine - Feeder to Finish	5,060,610
Swine	Swine - Gilts	47,262
Swine	Swine - Other	19,870
Swine	Swine - Wean to Feeder	2,334,162
Swine	Swine - Wean to Finish	1,175,609
Poultry	Wet Poultry - Layers	6,440,980
Poultry	Wet Poultry - Non-Laying Pullets	750,000
Poultry	Wet Poultry - Other	0
Poultry	Dry Poultry - Laying Chickens	1,400,000
Other	Horses - Horses	22,887
Other	Horses - Other	1,009
Other	Animals Other	810
Other	Sheep - Other	135

Table A2: Results - Water Quality Indicators - Excess Rain and Continuous Animal Density

	Dependent variable:		
	F. Coliform (cfu/100ml)	Nitrates (mg/L)	Phosphorus (mg/L)
After Excess Rain	0.559***	−0.286*	0.210***
	(0.116)	(0.149)	(0.071)
After Excess Rain*Upstream Swine	0.014	0.030	−0.028***
	(0.014)	(0.041)	(0.007)
Upstream Swine	−0.026	0.062**	0.013
	(0.017)	(0.025)	(0.011)
Upstream Cattle	0.039***	0.025***	0.030***
	(0.005)	(0.008)	(0.004)
No. of Upstream Wastewater Facilities	0.209***	0.252***	−0.027
	(0.080)	(0.058)	(0.052)
Observations	6,959	3,644	4,969
R^2	0.179	0.337	0.291
Adjusted R^2	0.172	0.329	0.284
Residual Std. Error	1.348	1.032	0.700
F Statistic	25.038***	39.788***	42.018***

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

Table A3: Fecal Coliform - Precipitation and Swine - Varying Upstream Swine

	Dependent variable:			
	Log of Fecal Coliform (cfu/100ml)			
	250 Pigs	500 Pigs	1000 Pigs	2000 Pigs
	(1)	(2)	(3)	(4)
After Excess Rain	0.496***	0.496***	0.496***	0.540***
	(0.117)	(0.117)	(0.117)	(0.117)
After Excess Rain*Upstream Swine	0.836**	0.836**	0.836**	0.485
	(0.325)	(0.325)	(0.325)	(0.317)
Upstream Swine	0.260***	0.260***	0.260***	0.420***
	(0.065)	(0.065)	(0.065)	(0.069)
Upstream Cattle	0.241***	0.241***	0.241***	0.225**
	(0.088)	(0.088)	(0.088)	(0.088)
No. of Upstream Wastewater Facilities	−0.028*	−0.028*	−0.028*	−0.027
	(0.017)	(0.017)	(0.017)	(0.017)
Observations	6,959	6,959	6,959	6,959
R^2	0.176	0.176	0.176	0.177
Adjusted R^2	0.169	0.169	0.169	0.170
Residual Std. Error	1.350	1.350	1.350	1.349
F Statistic	24.550***	24.550***	24.550***	24.747***

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

Table A4: Fecal Coliform - Precipitation and Swine - Varying Thresholds for Excess Rain

	Dependent variable:			
	Log of Fecal Coliform (cfu/100ml)			
	1 inch	2 inch	3 inch	4 inch
	(1)	(2)	(3)	(4)
After Excess Rain	0.610***	0.272***	0.492***	0.717***
	(0.042)	(0.062)	(0.117)	(0.257)
After Excess Rain*Upstream Swine	0.170	0.381**	0.876***	0.349
	(0.111)	(0.193)	(0.325)	(0.469)
Upstream Swine	0.160**	0.165**	0.177***	0.181***
	(0.067)	(0.066)	(0.065)	(0.065)
Upstream Cattle	0.245***	0.260***	0.248***	0.246***
	(0.085)	(0.088)	(0.088)	(0.088)
No. of Upstream Wastewater Facilities	−0.030*	−0.033*	−0.028*	−0.029*
	(0.016)	(0.017)	(0.017)	(0.017)
Observations	6,959	6,959	6,959	6,959
R^2	0.205	0.176	0.175	0.173
Adjusted R^2	0.198	0.169	0.168	0.166
Residual Std. Error (df = 6898)	1.326	1.350	1.351	1.352
F Statistic (df = 60; 6898)	29.645***	24.524***	24.388***	24.100***

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

Table A5: Fecal Coliform - Precipitation and Swine - Varying Distance Upstream

	Dependent variable:			
	Log of Fecal Coliform (cfu/100ml)			
	3 miles	5 miles	8 miles	10 miles
	(1)	(2)	(3)	(4)
After Excess Rain	0.486***	0.492***	0.493***	0.499***
	(0.116)	(0.117)	(0.120)	(0.120)
After Excess Rain*Upstream Swine	1.061	0.876***	0.712**	0.695**
	(0.317)	(0.325)	(0.277)	(0.277)
Upstream Swine	−0.064	0.177***	0.169***	0.193***
	(0.075)	(0.065)	(0.055)	(0.054)
Upstream Cattle	0.088	0.248***	0.331***	0.349***
	(0.110)	(0.088)	(0.085)	(0.088)
No. of Upstream Wastewater Facilities	−0.077***	−0.028*	−0.009	−0.008
	(0.020)	(0.017)	(0.013)	(0.011)
Observations	6,959	6,959	6,959	6,959
R^2	0.175	0.175	0.175	0.176
Adjusted R^2	0.168	0.168	0.168	0.169
Residual Std. Error	1.350	1.351	1.350	1.350
F Statistic	24.822***	24.388***	24.450***	24.603***

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

Figure A1: Distribution of Water Quality Indicators

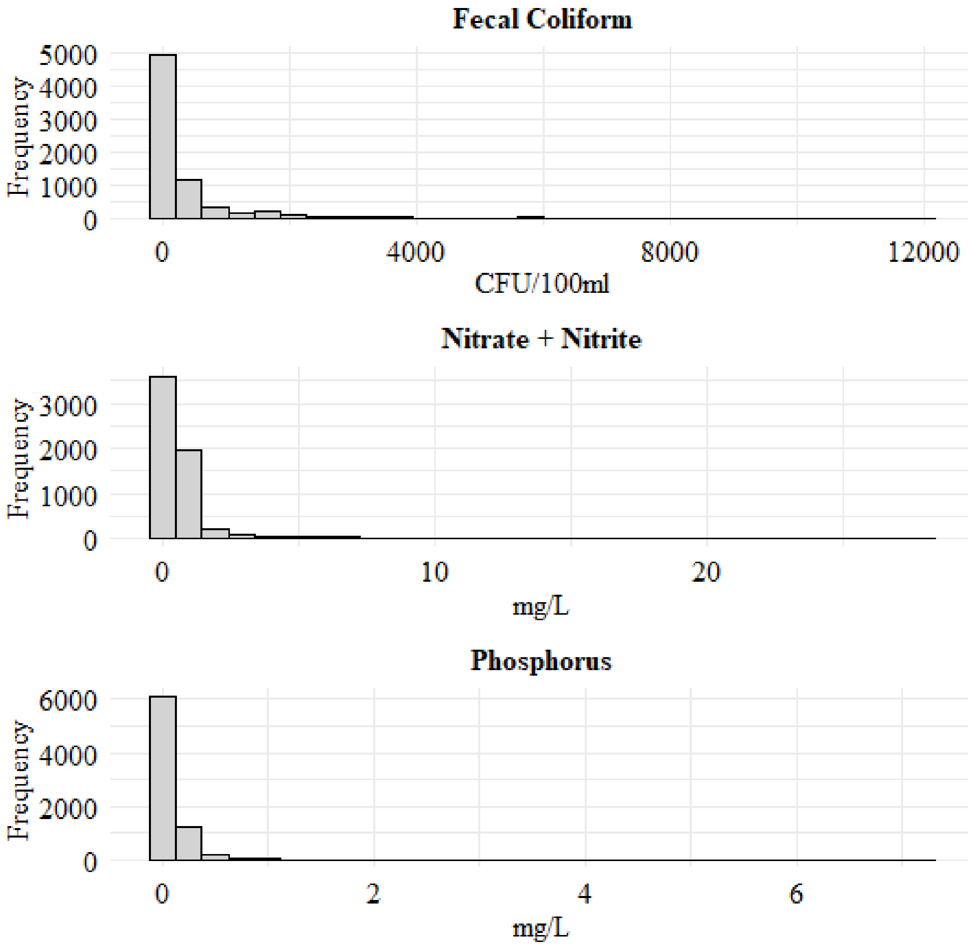


Figure A2: Distribution of Covariates

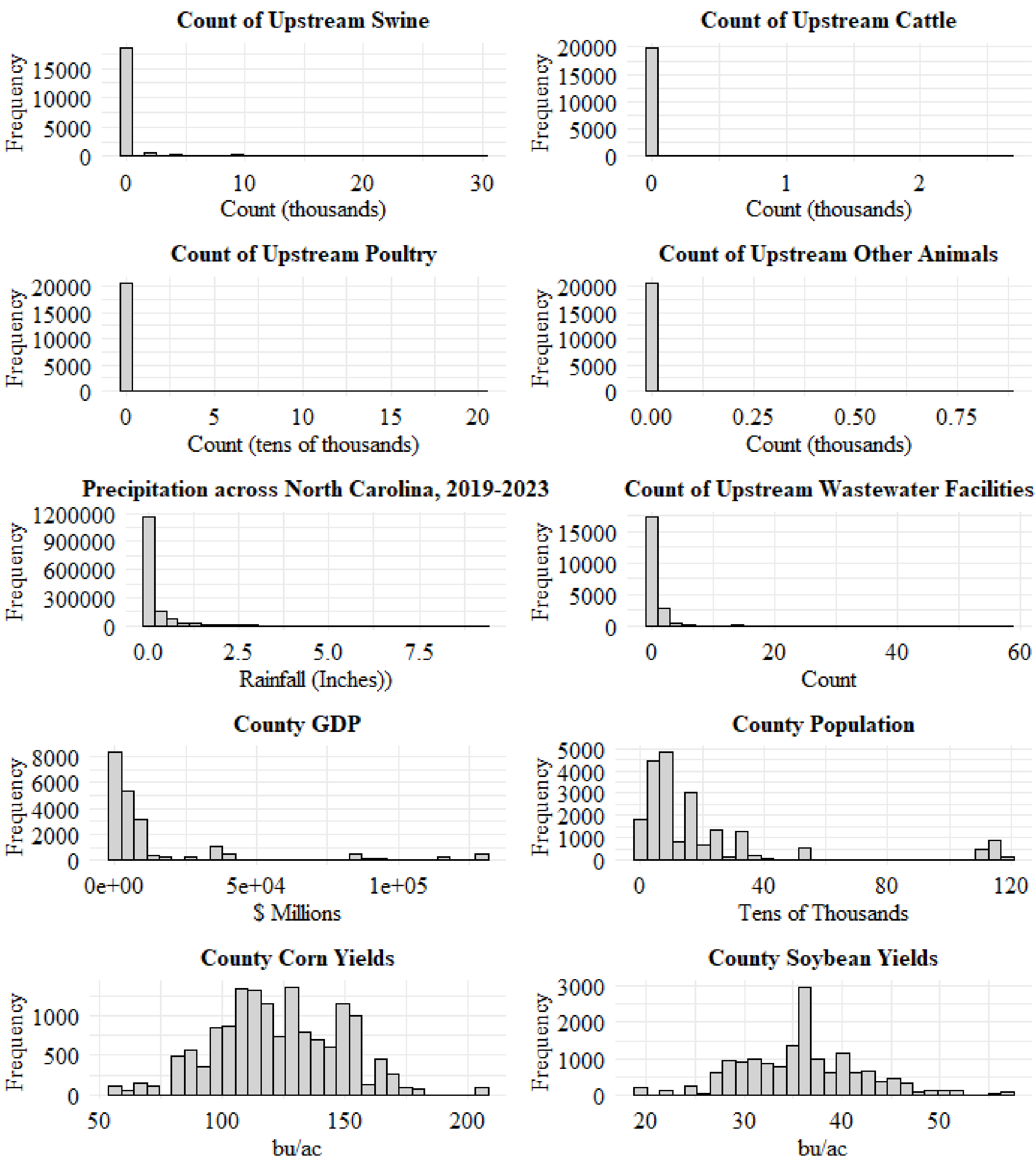
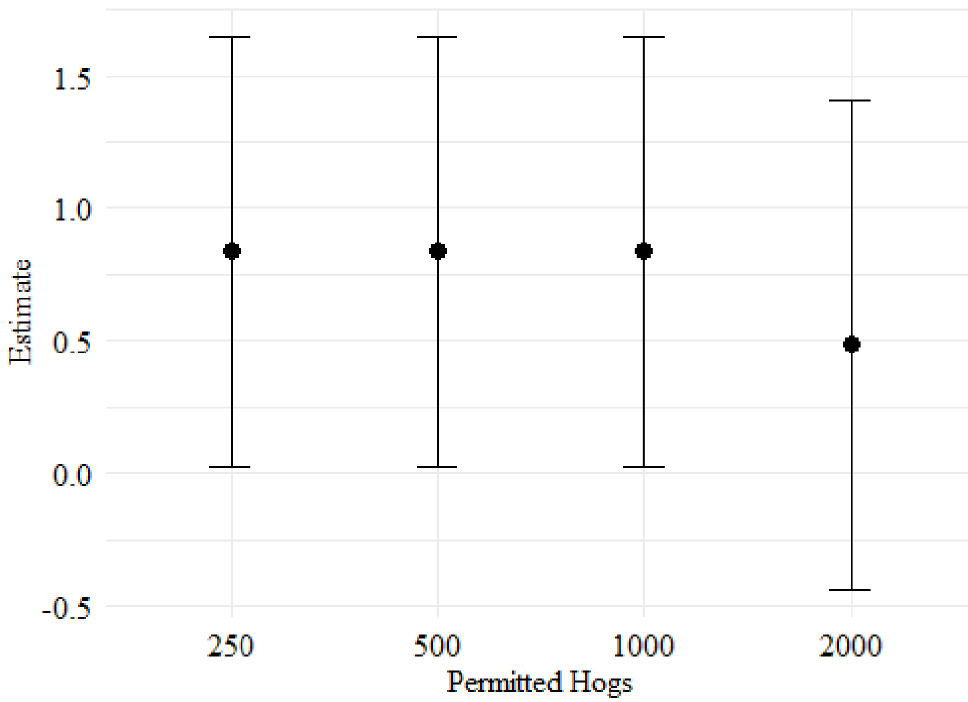


Figure A3: Effect of Extreme Precipitation and Upstream Hogs on Fecal Coliform as Number of Upstream Swine Increases



Appendix B

The Impact of Conservation Tillage Intensities on Mean Yields and Yield Risk

Table B1: Site Characteristics

Variable	**Value**
Soil type	Casville sandy loam
Average sand percentage (%)	62
Average silt percentage (%)	21
Average clay percentage (%)	17
Organic matter content (%)	1.38–3.39
Slope of site (%)	6
Plot size (ft)	19×50
Latitude	36.37979
Longitude	-79.6942
Planting density (seeds ac^{-1}) - Corn	30,000
Planting density (seeds ac^{-1}) - Soybean	137,500

56. Note: Organic matter content is reported as a range based on site variation. Information above attributed to Meijer et al. (2013) and Roper et al. (2016).

Table B2: Data Description

Variable	Description	Mean	Std. Dev.	Min	Max
Yield - Corn	Harvested bushels per acre, corn	71.12	42.94	1.57	193
Yield - Soybean	Harvested bushels per acre, soybean	36.44	17.64	2.72	102
Fall moldboard plow plus disk	1 if the tillage treatment is Fall moldboard plow plus disk; 0 otherwise	0.11	0.31	0	1
Spring moldboard plow plus disk	2 if the tillage treatment is Spring moldboard plow plus disk; 0 otherwise	0.11	0.31	0	1
Fall chisel plow plus disk	3 if the tillage treatment is Fall chisel plow plus disk; 0 otherwise	0.11	0.31	0	1
Spring chisel plow plus disk	4 if the tillage treatment is Spring chisel plow plus disk; 0 otherwise	0.11	0.31	0	1
Spring disk plow	5 if the tillage treatment is Spring disk plow; 0 otherwise	0.11	0.31	0	1
Fall chisel plow	6 if the tillage treatment is Fall chisel plow; 0 otherwise	0.11	0.31	0	1
Spring chisel plow	7 if the tillage treatment is Spring chisel plow; 0 otherwise	0.11	0.31	0	1
Spring in-row subsoiling	8 if the tillage treatment is In-row subsoiling; 0 otherwise	0.11	0.31	0	1
No-till	9 if the tillage treatment is No-till; 0 otherwise	0.11	0.31	0	1
Rotation	1 if the previous year was planted soybean, 0 if the previous year was planted corn	0.83	0.37	0	1
Trend	Years since start of experiment (e.g. Year of observation - 1987), range 0-31	15.67	9.50	0	31

57. Note: Data for the table above drawn from Mathers et al. (2023).

Table B3: Corn - Summary of Yields

	Yield (bu/ac)			
Treatment	Minimum	Maximum	Mean	Std. Dev.
Fall moldboard plow plus disk	2	158	49	35
Spring moldboard plow plus disk	2	176	55	38
Fall chisel plow plus disk	5	178	68	40
Spring chisel plow plus disk	2	179	64	44
Spring disk plow	4	192	70	42
Fall chisel plow	10	188	80	40
Spring chisel plow	11	190	78	42
Spring in-row subsoiling	7	187	83	45
No-till	13	193	94	43

58. Note: Data for the table above drawn from Mathers et al. (2023).

Table B4: Soybean - Summary of Yields

	Yield (bu/ac)			
Treatment	Minimum	Maximum	Mean	Std. Dev.
Fall moldboard plow plus disk	3	84	29	18
Spring moldboard plow plus disk	4	91	30	19
Fall chisel plow plus disk	10	85	38	18
Spring chisel plow plus disk	10	85	34	18
Spring disk plow	11	94	37	16
Fall chisel plow	5	102	41	18
Spring chisel plow	10	90	41	16
Spring in-row subsoiling	12	78	39	15
No-till	4	89	39	18

59. Note: Data for the table above drawn from Mathers et al. (2023).

Table B5: Planting Dates

Corn				Soybeans			
Year	Planting Date	Year	Planting Date	Year	Planting Date	Year	Planting Date
1987	12-May	2003	21-Apr	1990	25-Apr	2004	25-May
1988	2-May	2005	19-Apr	1992	11-May	2008	8-May
1989	Missing	2006	19-Apr	1994	12-May	2010	8-Jun
1991	24-Apr	2007	17-Apr	1996	24-May	2012	21-May
1993	22-Apr	2009	27-Apr	1998	19-May	2014	7-May
1995	18-Apr	2011	21-Apr	2000	12-May	2016	Missing
1997	17-Apr	2013	26-Apr	2002	15-May	2018	Missing
1999	19-Apr	2015	6-May				
2001	2-May	2017	Missing				

60. Note: Data for the table above drawn from Mathers et al. (2023).

Table B6: Corn - Baseline Specification, excluding 2015 and 2017

VARIABLES	**(1)** Mean	**(2)** Variance	**(3)** Skewness	**(4)** Kurtosis
2. Spring moldboard plow plus disk	6.393	116.6	6,136	650,559
	(5.789)	(234.8)	(20,867)	(1.444e+06)
3.Fall chisel plow plus disk	19.70***	-85.29	2,612	-216,114
	(5.504)	(230.0)	(18,842)	(1.276e+06)
4.Spring chisel plow plus disk	17.33***	282.0	9,268	1.542e+06
	(6.012)	(253.0)	(22,828)	(1.602e+06)
5.Spring disk plow	22.19***	152.8	3,367	712,482
	(5.839)	(243.2)	(20,512)	(1.362e+06)
6.Fall chisel plow	31.41***	-8.333	-10,828	-525,328
	(5.615)	(213.8)	(17,395)	(1.082e+06)
7.Spring chisel plow	30.92***	-25.34	-12,203	-504,378
	(5.590)	(207.1)	(17,878)	(1.155e+06)
8.Spring in-row subsoiling	34.97***	253.2	-19,860	1.020e+06
	(5.974)	(243.2)	(21,301)	(1.372e+06)
9.No-till	45.16***	41.08	-3,359	-220,654
	(5.684)	(223.1)	(17,927)	(1.121e+06)
rotation	-29.59***	-416.5***	4,751	-1.342e+06**
	(3.183)	(117.6)	(9,802)	(581,561)
trend	2.860***	45.60***	871.1	227,029***
	(0.191)	(7.813)	(689.9)	(44,831)
Constant	36.20***	704.3***	1,115	850,595
	(4.488)	(177.9)	(14,857)	(997,799)
Observations	648	648	648	648
R-squared	0.214	0.144	0.008	0.107

Note: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table B7: Soybean - Baseline Specification, excluding 1996 and 2000

VARIABLES	**(1)** Mean	**(2)** Variance	**(3)** Skewness	**(4)** Kurtosis
2. Spring moldboard plow plus disk	0.0212	-8.717	-130.0	-13,373
	(3.028)	(37.94)	(1,196)	(26,145)
3.Fall chisel plow plus disk	8.504***	-0.728	-327.4	-4,751
	(3.062)	(40.13)	(1,265)	(28,246)
4.Spring chisel plow plus disk	4.588	-30.98	-568.2	-27,710
	(2.947)	(35.83)	(1,103)	(24,339)
5.Spring disk plow	8.052***	-57.15*	-938.2	-37,634
	(2.815)	(34.61)	(1,063)	(23,948)
6.Fall chisel plow	10.35***	-67.41*	-1,290	-25,413
	(2.767)	(39.36)	(1,214)	(28,861)
7.Spring chisel plow	11.30***	-64.41*	-1,363	-33,642
	(2.782)	(36.88)	(1,110)	(25,512)
8.Spring in-row subsoiling	9.877***	-71.35**	-1,058	-37,624
	(2.760)	(35.77)	(1,082)	(24,536)
9.No-till	8.539***	-45.35	-1,128	-13,366
	(2.868)	(41.51)	(1,271)	(28,852)
Trend	-0.201***	1.915**	15.82	1,228**
	(0.0635)	(0.815)	(23.27)	(482.9)
Constant	28.35***	144.5***	640.5	42,853**
	(2.426)	(30.39)	(929.9)	(20,476)
Observations	357	357	357	357
R-squared	0.124	0.046	0.013	0.039

Note: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table B8: Corn - Fall Chisel Plow as Baseline Conventional Treatment

(1) **VARIABLES**	(2) Mean	(3) Variance	(4) Skewness	Kurtosis
2.Spring chisel plow plus disk	-4.031	405.6	29,816	3.022e+06
	(6.618)	(358.8)	(38,906)	(3.283e+06)
3.Fall moldboard plow plus disk	-19.31***	-156.4	15,858	-753,672
	(5.988)	(323.3)	(32,948)	(2.759e+06)
4.Spring moldboard plow plus disk	-13.39**	53.41	24,772	1.276e+06
	(6.231)	(349.7)	(37,679)	(3.368e+06)
5.Spring disk plow	1.854	170.6	1,918	716,441
	(6.362)	(339.6)	(34,863)	(2.896e+06)
6.Fall chisel plow	12.52**	-105.6	-11,265	-1.925e+06
	(6.048)	(297.8)	(29,968)	(2.408e+06)
7.Spring chisel plow	10.09	139.6	-7,099	-3,508
	(6.328)	(311.8)	(33,130)	(2.618e+06)
8.Spring in-row subsoiling	15.10**	287.3	-21,190	731,031
	(6.491)	(321.9)	(33,834)	(2.573e+06)
9.No-till	25.88***	101.3	-17,795	-201,550
	(6.285)	(318.4)	(32,895)	(2.570e+06)
Rotation	-29.13***	-363.2**	4,472	-761,866
	(3.159)	(143.1)	(11,410)	(960,472)
Trend	1.457***	87.68***	655.4	617,812***
	(0.196)	(9.286)	(1,093)	(81,811)
Constant	67.92***	343.1	3,654	-2.308e+06
	(5.216)	(260.7)	(25,656)	(2.075e+06)
Observations	648	648	648	648
R-squared	0.214	0.144	0.008	0.107

Note: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table B9: Soybean - Fall Chisel Plow as Baseline Conventional Treatment

VARIABLES	**(1)** Mean	**(2)** Variance	**(3)** Skewness	**(4)** Kurtosis
2.Spring chisel plow plus disk	-4.180	-29.47	327.2	-14,699
	(3.581)	(80.09)	(3,713)	(134,348)
3.Fall moldboard plow plus disk	-9.847***	-29.78	1,999	45,319
	(3.581)	(88.77)	(4,274)	(177,920)
4.Spring moldboard plow plus disk	-8.760**	-1.092	2,928	112,074
	(3.642)	(93.26)	(4,796)	(226,296)
5.Spring disk plow	-1.121	-89.28	-107.0	-51,163
	(3.374)	(79.66)	(3,876)	(166,209)
6.Fall chisel plow	2.365	-36.70	1,394	72,065
	(3.536)	(90.92)	(4,731)	(228,116)
7.Spring chisel plow	2.288	-87.32	-1,439	-84,090
	(3.380)	(74.18)	(3,355)	(117,525)
8.Spring in-row subsoiling	0.411	-126.5*	-1,703	-163,963*
	(3.274)	(66.64)	(2,857)	(94,207)
9.No-till	0.399	-48.25	802.4	-1,935
	(3.501)	(83.20)	(3,758)	(141,362)
trend	-0.579***	-9.218***	-256.5**	-17,905***
	(0.0835)	(2.025)	(100.9)	(4,502)
Constant	48.57***	472.7***	7,070**	568,758***
Observations	429	429	429	429
R-squared	0.155	0.052	0.019	0.037

Note: Robust standard errors in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table B10: Timing: Tillage Treatments in the Spring versus Fall (i.e., Spring-Fall differences)

	Yield Benefit (bu/ac)	
VARIABLES	**Corn**	**Soybeans**
Moldboard plow plus disk	5.921	1.087
	(6.051)	(3.578)
Chisel plow plus disk	-4.031	-4.18
	(6.618)	(3.581)
Chisel plow	-2.424	-0.077
	(6.209)	(3.262)

Note: Robust standard errors in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table B11: Corn - Sensitivity to Time Trend - Quadratic

VARIABLES	(1) Mean	(2) Variance	(3) Skewness	(4) Kurtosis
2. Spring moldboard plow plus disk	5.921	144.5	8,474	909,103
	(5.413)	(260.2)	(25,621)	(2.063e+06)
3.Fall chisel plow plus disk	19.31***	-117.8	-2,287	-824,148
	(5.058)	(239.9)	(22,313)	(1.757e+06)
4.Spring chisel plow plus disk	15.28***	359.0	22,472	2.639e+06
	(5.688)	(293.4)	(29,638)	(2.511e+06)
5.Spring disk plow	21.17***	109.5	2,405	838.3
	(5.367)	(252.3)	(23,381)	(1.795e+06)
6.Fall chisel plow	31.83***	53.79	-18,728	-974,199
	(5.293)	(228.8)	(20,898)	(1.543e+06)
7.Spring chisel plow	29.41***	101.6	-14,185	-467,670
	(5.357)	(232.2)	(21,999)	(1.669e+06)
8.Spring in-row subsoiling	34.41***	217.7	-24,190	-116,646
	(5.509)	(238.0)	(22,320)	(1.591e+06)
9.No-till	45.20***	67.36	-10,021	-918,207
	(5.311)	(230.9)	(20,773)	(1.553e+06)
rotation	-36.93***	93.41	48,051**	2.112e+06*
	(5.028)	(206.1)	(18,745)	(1.263e+06)
trend	23.19***	186.5	-16,899	149,450
	(2.717)	(117.8)	(10,564)	(824,033)
trend_sq	-3.298***	-43.04**	1,441	-118,020
	(0.377)	(17.61)	(1,613)	(130,069)
trend_cub	0.180***	3.036***	-34.27	10,836
	(0.0190)	(0.916)	(85.17)	(6,900)
trend_quad	-0.00319***	-0.0606***	0.120	-237.9**
	(0.000308)	(0.0151)	(1.419)	(114.7)
Constant	19.63***	380.3*	16,761	784,148
	(4.478)	(196.1)	(18,751)	(1.518e+06)
Observations	648	648	648	648
R-squared	0.422	0.130	0.031	0.083

Note: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table B12: Soybean - Sensitivity to Time Trend - Quadratic

VARIABLES	(1) Mean	(2) Variance	(3) Skewness	(4) Kurtosis
2. Spring moldboard plow plus disk	1.184	-10.91	480.7	8,198
	(2.449)	(47.34)	(1,781)	(62,909)
3.Fall chisel plow plus disk	9.943***	26.80	278.6	4,562
	(2.608)	(44.67)	(1,489)	(42,593)
4.Spring chisel plow plus disk	5.667**	-16.04	-573.2	-26,389
	(2.439)	(39.89)	(1,332)	(37,056)
5.Spring disk plow	8.823***	1.222	-118.4	4,193
	(2.502)	(47.30)	(1,617)	(49,109)
6.Fall chisel plow	12.31***	19.87	-661.4	40,446
	(2.580)	(52.37)	(1,984)	(67,817)
7.Spring chisel plow	12.23***	-26.89	-485.4	-27,979
	(2.376)	(40.75)	(1,306)	(36,771)
8.Spring in-row subsoiling	10.26***	-11.08	-1,245	-34,253
	(2.461)	(39.22)	(1,247)	(35,063)
9.No-till	10.34***	105.0*	-1,209	85,437
	(2.914)	(55.89)	(1,971)	(56,040)
trend	22.68***	146.2***	5,096***	140,208**
	(2.441)	(48.39)	(1,784)	(58,394)
trend_sq	-1.932***	-14.86***	-576.4***	-13,671**
	(0.270)	(5.209)	(188.5)	(6,046)
trend_cub	0.0589***	0.582***	24.47***	508.1**
	(0.0116)	(0.217)	(7.703)	(241.2)
trend_quad	-0.000579***	-0.00784**	-0.350***	-6.474*
	(0.000168)	(0.00309)	(0.108)	(3.323)
Constant	-37.63***	-265.7**	-11,106**	-322,285**
	(6.600)	(126.5)	(4,662)	(151,372)
Observations	429	429	429	429
R-squared	0.506	0.061	0.041	0.053

Note: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table B13: Corn - Annual Fixed Effects

VARIABLES	(1) Mean	(2) Variance	(3) Skewness	(4) Kurtosis
2. Spring moldboard plow plus disk	5.921**	40.87	-103.3	-3,236
	(2.983)	(74.38)	(4,168)	(225,250)
3.Fall chisel plow plus disk	19.31***	266.3**	966.3	729,301*
	(3.487)	(111.1)	(7,071)	(428,354)
4.Spring chisel plow plus disk	15.28***	104.1	4,633	316,640
	(3.133)	(87.32)	(6,241)	(285,187)
5.Spring disk plow	21.17***	143.3	853.1	289,188
	(3.222)	(90.26)	(5,492)	(298,388)
6.Fall chisel plow	31.83***	293.9**	-1,034	962,884*
	(3.544)	(119.2)	(8,394)	(490,677)
7.Spring chisel plow	29.41***	38.11	-4,249	33,725
	(2.976)	(75.40)	(4,343)	(231,594)
8.Spring in-row subsoiling	34.41***	279.1	-16,757	2.027e+06
	(3.514)	(169.7)	(18,016)	(1.884e+06)
9.No-till	45.20***	245.1**	959.3	663,056*
	(3.443)	(102.4)	(6,776)	(375,899)
rotation	-17.11***	-193.9**	-3,769	-223,867
	(3.726)	(96.66)	(5,295)	(245,909)
1988.year	31.28***	-3.950	-5,632	-104,769
	(4.402)	(99.84)	(5,618)	(237,461)
1989.year	66.94***	105.9	-4,318	46,781
	(4.750)	(110.6)	(6,143)	(247,093)
1991.year	3.667	60.55	-1,524	-58,939
	(3.166)	(65.73)	(2,904)	(172,418)
1993.year	50.16***	56.88	-1,387	-14,197
	(3.149)	(75.27)	(3,294)	(183,284)
1995.year	53.18***	269.8***	-2,527	245,222
	(4.010)	(98.32)	(4,750)	(232,236)
1997.year	26.75***	2.247	-447.9	-72,175
	(2.887)	(66.74)	(2,974)	(174,855)
1999.year	35.55***	97.77	-1,708	-7,041
	(3.332)	(72.13)	(3,284)	(177,095)
2001.year	25.21***	250.1***	99.36	206,603
	(3.938)	(92.71)	(4,230)	(203,478)
2003.year	87.14***	982.3***	-33,786	5.484e+06
	(6.058)	(355.8)	(37,575)	(3.839e+06)
2005.year	62.82***	519.5***	12,421	1.352e+06*
	(4.828)	(181.9)	(12,373)	(783,288)
2006.year	100.3***	222.1	-3,641	631,885
	(5.091)	(163.3)	(9,783)	(487,761)
2007.year	44.61***	3.701	-1,115	24,124
	(4.427)	(117.1)	(6,511)	(308,663)
2009.year	41.09***	202.2**	-162.8	212,499
	(3.758)	(96.10)	(4,440)	(192,783)
2011.year	71.77***	279.7***	-2,118	247,024
	(4.045)	(98.46)	(4,732)	(210,270)
2013.year	133.7***	569.5***	-8,919	952,421**
	(4.975)	(138.2)	(8,763)	(422,832)
2015.year	43.43***	828.6***	12,208	2.349e+06**
	(5.679)	(212.9)	(16,259)	(960,508)
2017o.year	-	-	-	-
Constant	12.21***	180.1*	6,627	-196,164
	(3.579)	(93.74)	(5,781)	(329,226)
Observations	648	648	648	648
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]

Table B14: Soybean - Sensitivity to Time Trend - Quadratic

VARIABLES	(1) Mean	(2) Variance	(3) Skewness	(4) Kurtosis
2. Spring moldboard plow plus disk	1.325	-26.49	-12.18	-9,644
	(1.994)	(27.16)	(815.6)	(16,128)
3.Fall chisel plow plus disk	10.08***	-21.32	-595.6	-5,140
	(2.023)	(26.94)	(849.1)	(18,446)
4.Spring chisel plow plus disk	5.667***	-20.47	-698.5	-5,192
	(2.038)	(27.40)	(898.4)	(21,214)
5.Spring disk plow	8.964***	-16.80	-56.94	-4,814
	(2.048)	(27.26)	(800.1)	(15,176)
6.Fall chisel plow	12.45***	-18.86	-424.1	-1,430
	(2.035)	(28.62)	(894.7)	(19,028)
7.Spring chisel plow	12.37***	-44.22*	-297.5	-21,278*
	(1.890)	(23.33)	(655.2)	(12,405)
8.Spring in-row subsoiling	10.26***	-22.87	-717.6	-11,102
	(2.024)	(26.34)	(727.5)	(13,944)
9.No-till	10.48***	49.89	-2,067	56,696
	(2.377)	(41.31)	(1,464)	(47,549)
1992.year	6.115***	-39.01*	-393.1	-16,208
	(1.884)	(23.08)	(570.2)	(11,263)
1994.year	18.30***	-45.66**	-600.3	-16,943
	(1.832)	(22.97)	(568.0)	(11,067)
1996.year	43.12***	185.5***	-1,727	118,892***
	(3.177)	(49.56)	(1,717)	(40,120)
2000.year	24.35***	10.98	-806.1	2,710
	(2.238)	(29.96)	(783.0)	(15,417)
2004.year	7.162***	89.69**	-1,364	44,785*
	(2.702)	(38.87)	(1,127)	(24,585)
2008.year	-7.904***	-60.62***	-351.0	-20,775*
	(1.709)	(21.41)	(555.5)	(11,068)
2010.year	-1.796	-25.01	-411.6	-13,103
	(1.990)	(24.32)	(606.6)	(11,622)
2012.year	12.62***	-9.040	-757.0	-4,790
	(2.103)	(28.10)	(712.7)	(14,076)
2014.year	-8.037***	5.180	-277.6	-5,253
	(2.256)	(28.14)	(679.1)	(12,934)
2016.year	-2.840	-46.30**	-468.3	-18,727*
	(1.827)	(21.92)	(555.3)	(10,954)
2018.year	12.61***	45.70	-2,330	63,538
	(2.453)	(47.49)	(1,708)	(60,402)
Constant	19.71***	93.89***	938.4	22,099
	(2.025)	(27.12)	(765.0)	(15,200)
Observations	429	429	429	429
R-squared	0.711	0.204	0.036	0.110

Note: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table B15: Corn - Baseline Specification - Interaction with Trend

VARIABLES	**(1)** Mean	**(2)** Variance	**(3)** Skewness	**(4)** Kurtosis
2. Spring moldboard plow plus disk	3.414	-71.24	-9,249	-2.399e+06
	(9.511)	(383.0)	(38,632)	(3.143e+06)
3.Fall chisel plow plus disk	10.78	225.5	24,762	-413,776
	(10.18)	(425.7)	(39,436)	(2.735e+06)
4.Spring chisel plow plus disk	11.17	32.03	22,607	-489,662
	(9.775)	(381.4)	(40,330)	(2.876e+06)
5.Spring disk plow	19.24*	574.5	17,437	2.169e+06
	(10.54)	(441.8)	(41,003)	(2.818e+06)
6.Fall chisel plow	32.17***	249.8	5,942	795,226
	(9.523)	(354.4)	(31,994)	(2.261e+06)
7.Spring chisel plow	25.08***	-218.3	24,857	-2.208e+06
	(9.375)	(361.7)	(36,004)	(2.502e+06)
8.Spring in-row subsoiling	33.82***	204.5	21,558	-535,831
	(10.25)	(422.8)	(40,124)	(2.780e+06)
9.No-till	45.32***	186.3	33,780	-521,871
	(10.12)	(401.4)	(38,422)	(2.706e+06)
rotation	-29.13***	-345.1**	4,034	-712,624
	(3.170)	(143.2)	(11,571)	(974,517)
trend	1.291**	79.82***	2,926	529,250**
	(0.513)	(25.33)	(2,838)	(227,223)
2. Spring moldboard plow plus disk#c.trend	0.174	19.62	1,020	295,355
	(0.765)	(40.18)	(4,823)	(413,608)
3.Fall chisel plow plus disk#c.trend	0.591	-5.702	-3,510	62,103
	(0.776)	(39.35)	(4,359)	(321,560)
4.Spring chisel plow plus disk#c.trend	0.284	36.77	-1,055	278,196
	(0.787)	(36.51)	(4,607)	(344,999)
5.Spring disk plow#c.trend	0.133	-16.97	-2,364	-58,370
	(0.776)	(37.95)	(4,290)	(334,058)
6.Fall chisel plow#c.trend	-0.0235	-13.83	-2,308	-145,517
	(0.728)	(33.58)	(3,708)	(283,750)
7.Spring chisel plow#c.trend	0.299	35.67	-3,794	195,642
	(0.774)	(35.99)	(4,305)	(311,403)
8.Spring in-row subsoiling#c.trend	0.0405	16.63	-4,077	124,967
	(0.795)	(37.89)	(4,403)	(317,347)
9.No-till#c.trend	-0.00887	4.928	-4,644	54,717
	(0.781)	(37.10)	(4,274)	(317,826)
Constant	51.00***	284.7	-9,736	-1.668e+06
	(6.614)	(263.1)	(24,317)	(1.864e+06)
Observations	648	648	648	648
R-squared	0.216	0.155	0.014	0.117

Note: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table B16: Soybean - Baseline Specification - Interaction with Trend

VARIABLES	(1) Mean	(2) Variance	(3) Skewness	(4) Kurtosis
2. Spring moldboard plow plus disk	1.457	73.90	3,247	203,982
	(8.828)	(257.0)	(13,738)	(645,106)
3.Fall chisel plow plus disk	6.044	93.77	-1,152	358.8
	(8.628)	(233.4)	(11,471)	(457,595)
4.Spring chisel plow plus disk	1.524	65.94	520.0	-10,819
	(8.499)	(233.0)	(11,633)	(489,864)
5.Spring disk plow	6.347	-80.53	-829.2	-139,786
	(7.871)	(228.1)	(11,803)	(547,747)
6.Fall chisel plow	9.542	44.68	5,214	148,690
	(8.257)	(256.2)	(13,927)	(700,499)
7.Spring chisel plow	7.193	-29.36	-2,532	-190,334
	(7.997)	(220.6)	(10,818)	(456,191)
8.Spring in-row subsoiling	6.975	-159.0	-4,045	-436,115
	(7.399)	(193.2)	(9,307)	(394,949)
9.No-till	13.21	16.12	-478.9	-133,106
	(8.216)	(223.9)	(10,898)	(454,298)
trend	-0.693**	-7.949	-176.2	-18,272
	(0.282)	(7.081)	(341.7)	(14,237)
2. Spring moldboard plow plus disk#c.trend	-0.0198	-2.623	-141.2	-8,368
	(0.409)	(10.18)	(523.9)	(23,613)
3.Fall chisel plow plus disk#c.trend	0.219	-3.659	-16.71	-1,759
	(0.392)	(9.339)	(444.6)	(16,994)
4.Spring chisel plow plus disk#c.trend	0.239	-3.807	-89.66	-1,750
	(0.386)	(9.223)	(446.0)	(18,071)
5.Spring disk plow#c.trend	0.137	1.251	-57.79	3,123
	(0.362)	(9.008)	(447.6)	(20,054)
6.Fall chisel plow#c.trend	0.154	-2.904	-313.1	-6,044
	(0.371)	(10.08)	(525.0)	(25,572)
7.Spring chisel plow#c.trend	0.284	-1.703	-13.21	4,490
	(0.361)	(8.862)	(418.1)	(16,900)
8.Spring in-row subsoiling#c.trend	0.190	3.639	38.93	13,846
	(0.342)	(7.902)	(362.7)	(14,710)
9.No-till#c.trend	-0.168	-2.333	-67.98	3,455
	(0.372)	(9.023)	(419.4)	(16,849)
Constant	40.70***	419.8**	7,440	610,963
	(6.014)	(172.7)	(8,754)	(382,125)
Observations	429	429	429	429
R-squared	0.161	0.056	0.019	0.040

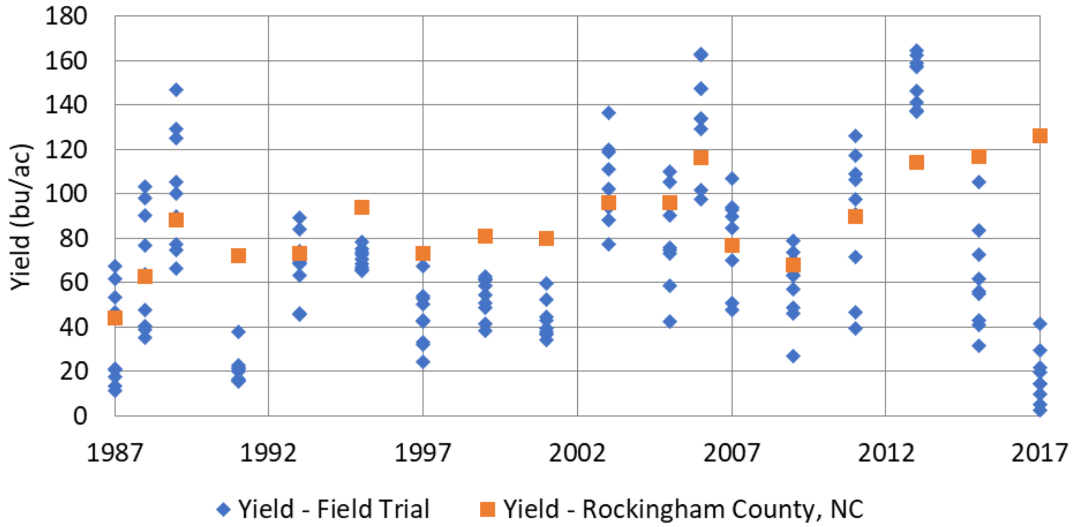
Note: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table B17: Corn - Baseline Specification - Excluding Rotation

VARIABLES	(1) Mean	(2) Variance	(3) Skewness	(4) Kurtosis
2. Spring moldboard plow plus disk	7.699	238.0	8,820	2.335e+06
	(7.540)	(426.5)	(48,031)	(4.233e+06)
3.Fall chisel plow plus disk	18.71***	6.789	-18,981	348,776
	(7.232)	(407.0)	(43,975)	(3.712e+06)
4.Spring chisel plow plus disk	14.91*	646.8	16,948	4.575e+06
	(8.055)	(442.9)	(50,251)	(4.224e+06)
5.Spring disk plow	18.30**	118.8	-22,914	-145,061
	(7.383)	(390.9)	(42,250)	(3.620e+06)
6.Fall chisel plow	24.72***	-38.59	-26,973	-1.957e+06
	(7.170)	(359.5)	(38,068)	(3.209e+06)
7.Spring chisel plow	26.66***	289.2	-28,259	613,087
	(7.606)	(383.3)	(42,921)	(3.502e+06)
8.Spring in-row subsoiling	26.73***	344.9	-33,689	859,757
	(7.678)	(384.3)	(42,630)	(3.321e+06)
9.No-till	37.84***	213.0	-31,593	232,318
	(7.507)	(383.2)	(41,682)	(3.270e+06)
Trend	1.102***	117.5***	1,706	819,685***
	(0.250)	(11.63)	(1,481)	(113,129)
Constant	28.42***	-642.4**	15,949	-7.131e+06***
	(5.967)	(304.4)	(33,869)	(2.742e+06)
Observations	468	468	468	468
R-squared	0.114	0.198	0.010	0.121

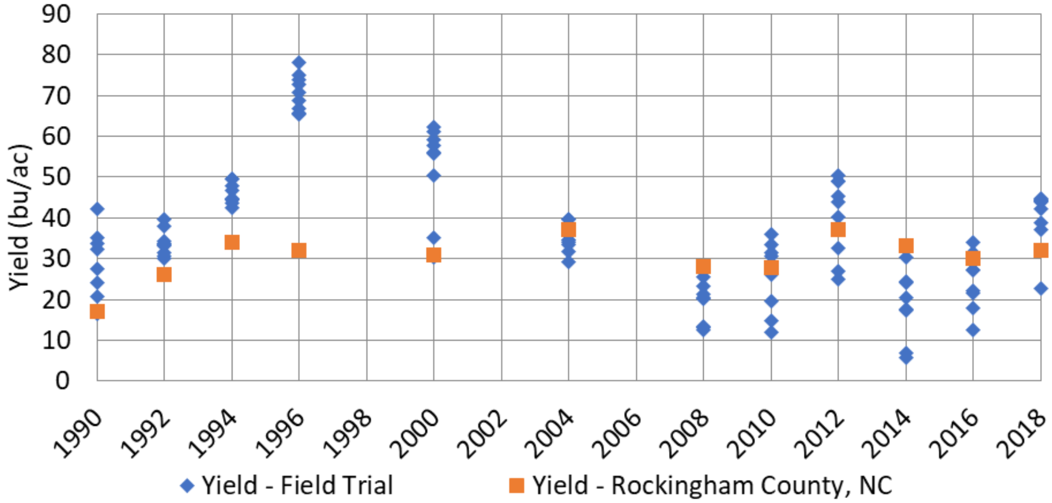
Note: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Figure B1: Corn – Mean Annual Yield – Ave. Field Trial vs. County



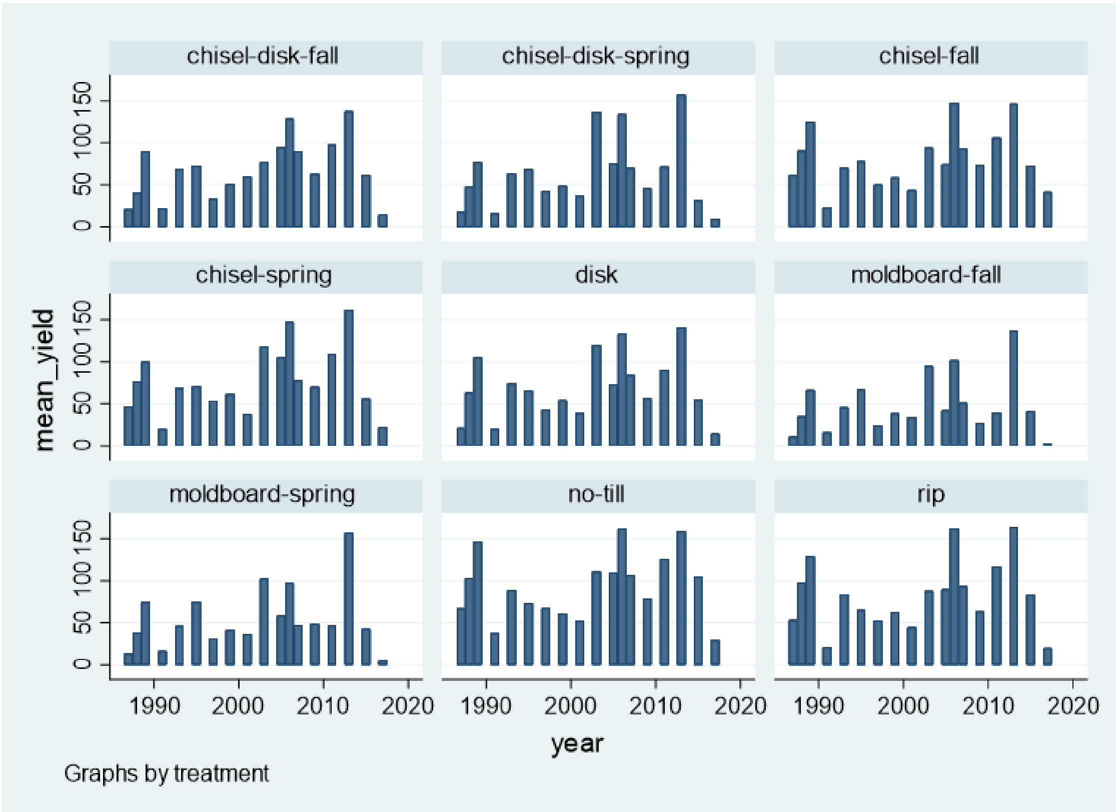
Note: Data for the table above drawn from Mathers et al. (2023).

Figure B2: Soybean – Mean Annual Yield – Ave. Field Trial vs. County



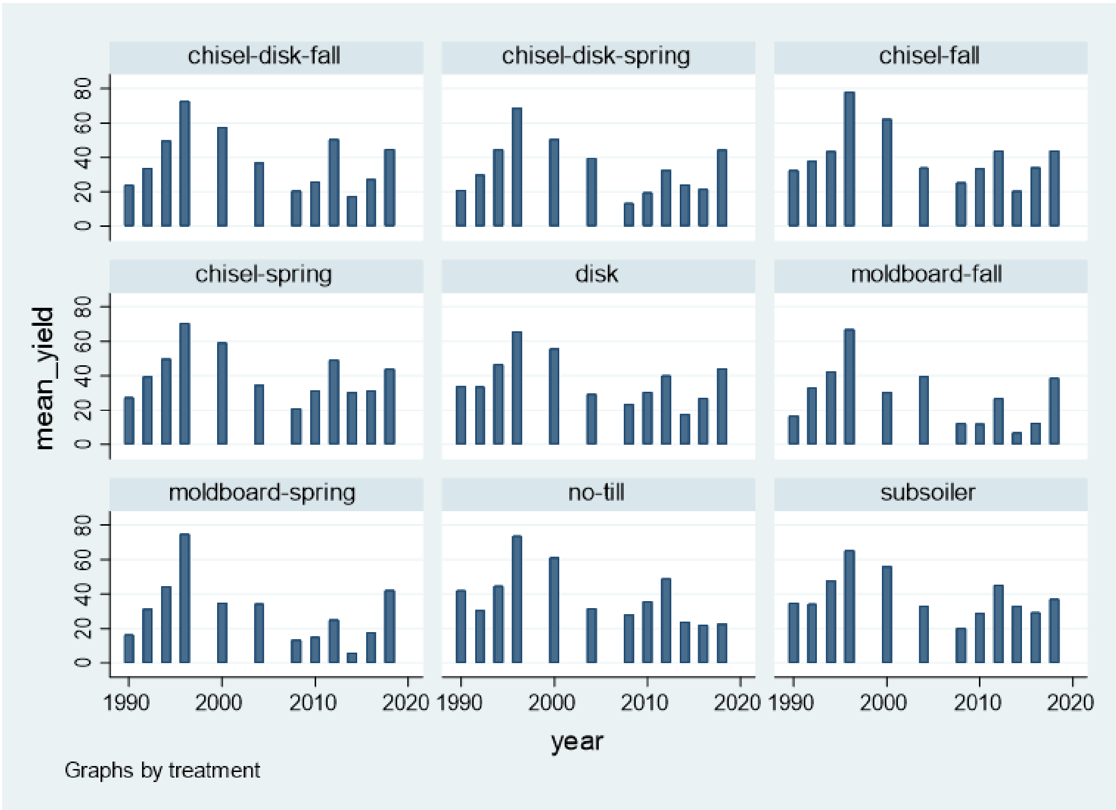
Note: Data for the figure above drawn from Mathers et al., (2023).

Figure B3: Corn – Mean Yield by Tillage Treatment



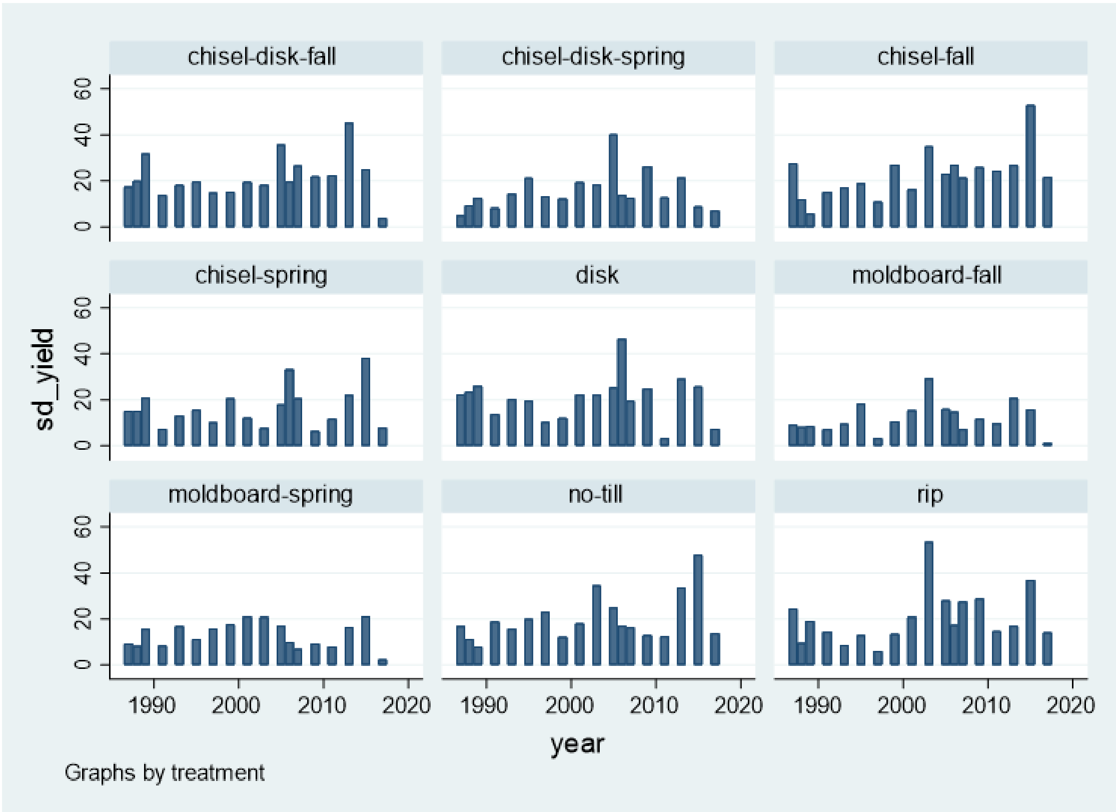
Note: Data for the figure above drawn from Mathers et al., (2023).

Figure B4: Soybean – Mean Yield by Tillage Treatment



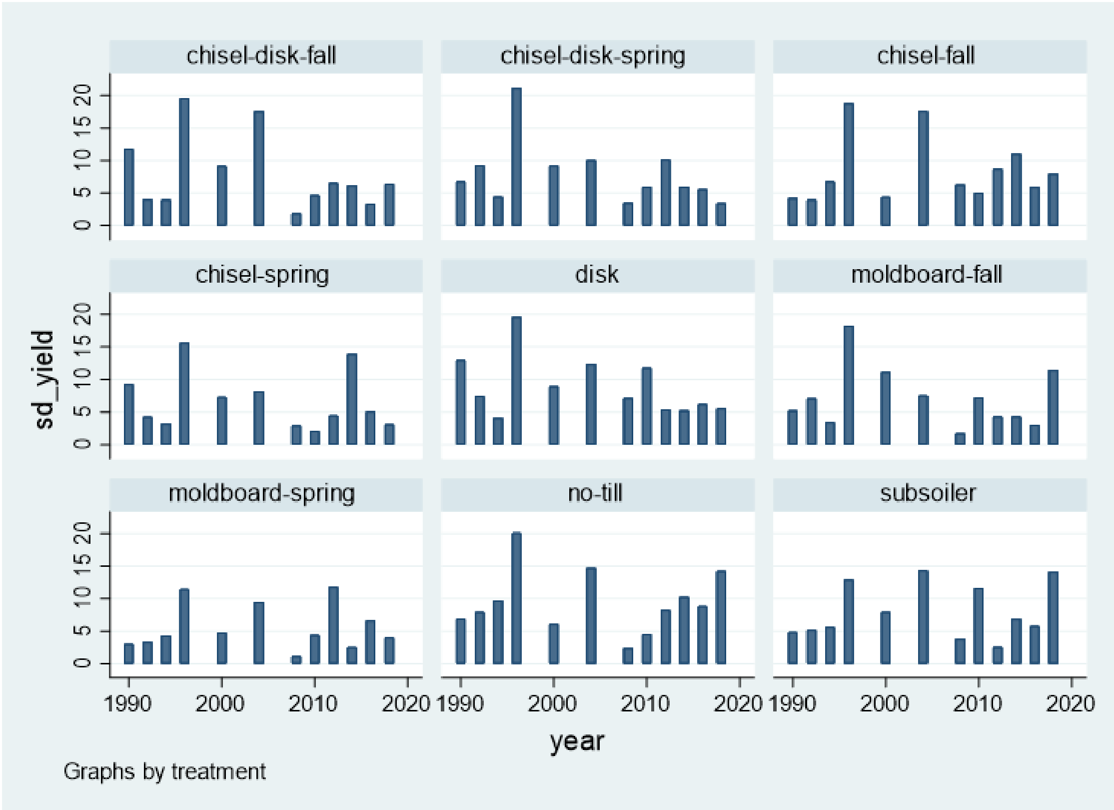
Note: Data for the figure above drawn from Mathers et al., (2023).

Figure B5: Corn – Std. Deviation of Yield by Tillage Treatment



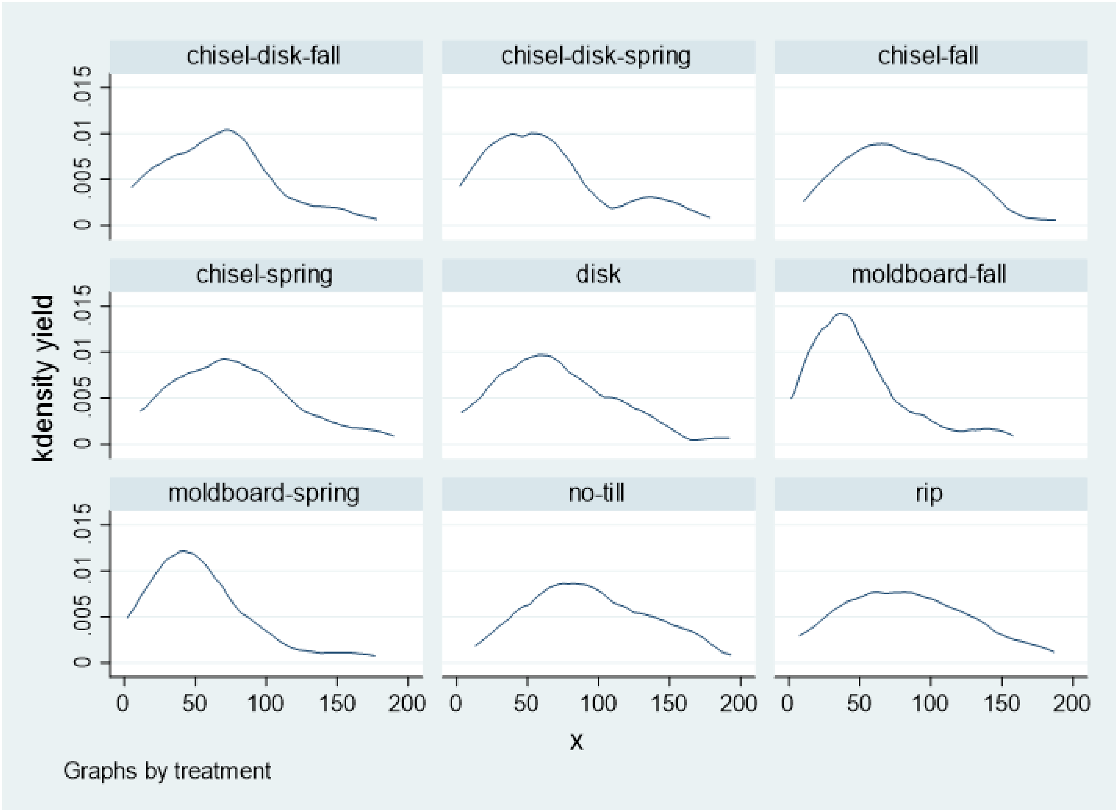
Note: Data for the figure above drawn from Mathers et al., (2023).

Figure B6: Soybean – Std. Deviation of Yield by Tillage Treatment



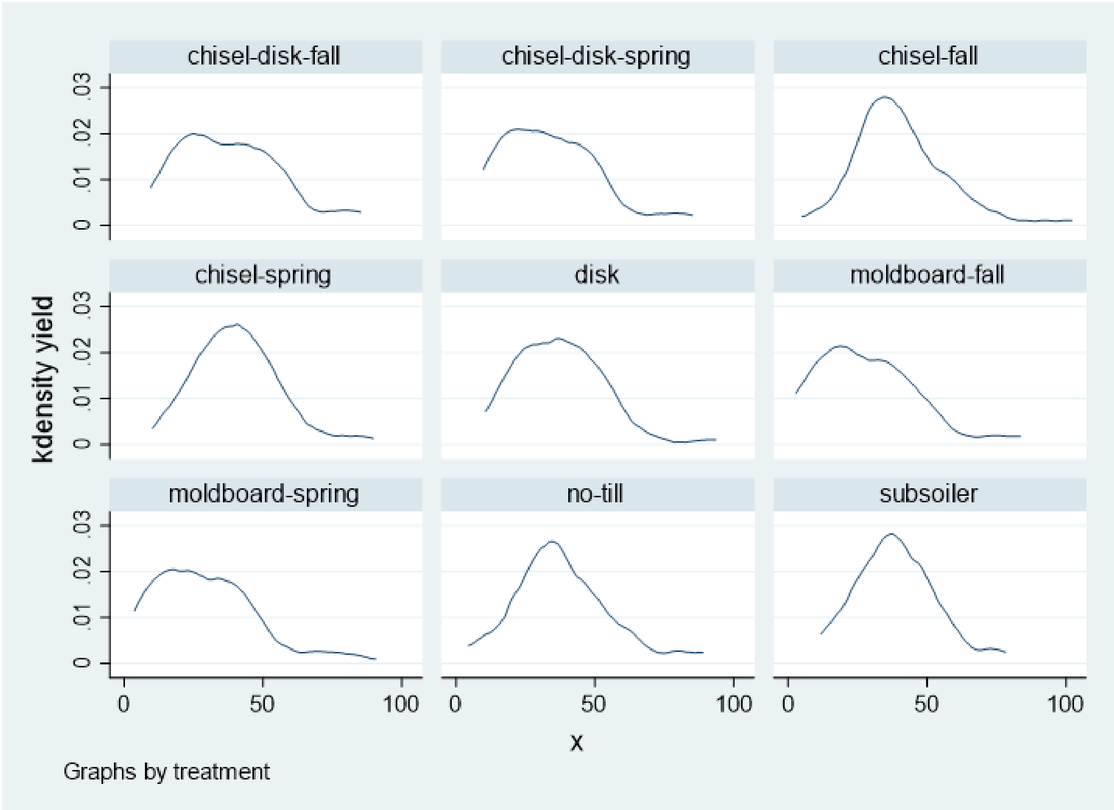
Note: Data for the figure above drawn from Mathers et al., (2023).

Figure B7: Corn – Kernel Density of Yield by Tillage Treatment



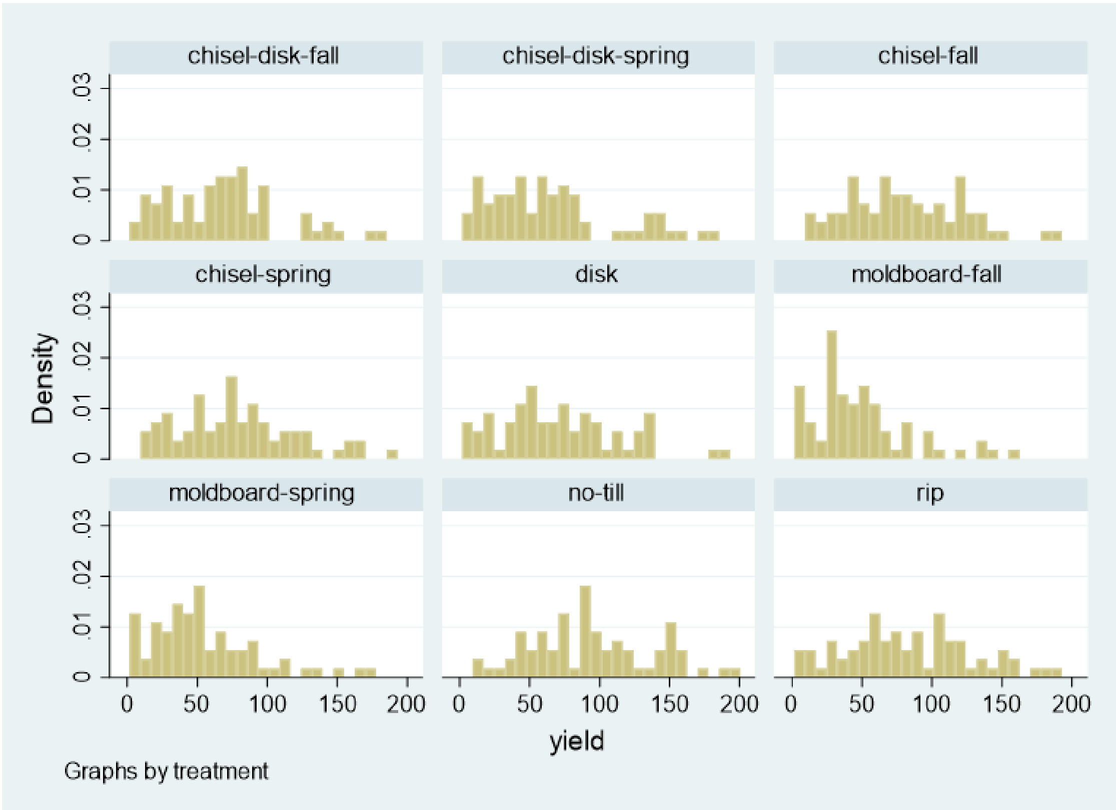
Note: Data for the figure above drawn from Mathers et al., (2023).

Figure B8: Soybean – Kernel Density of Yield by Tillage Treatment



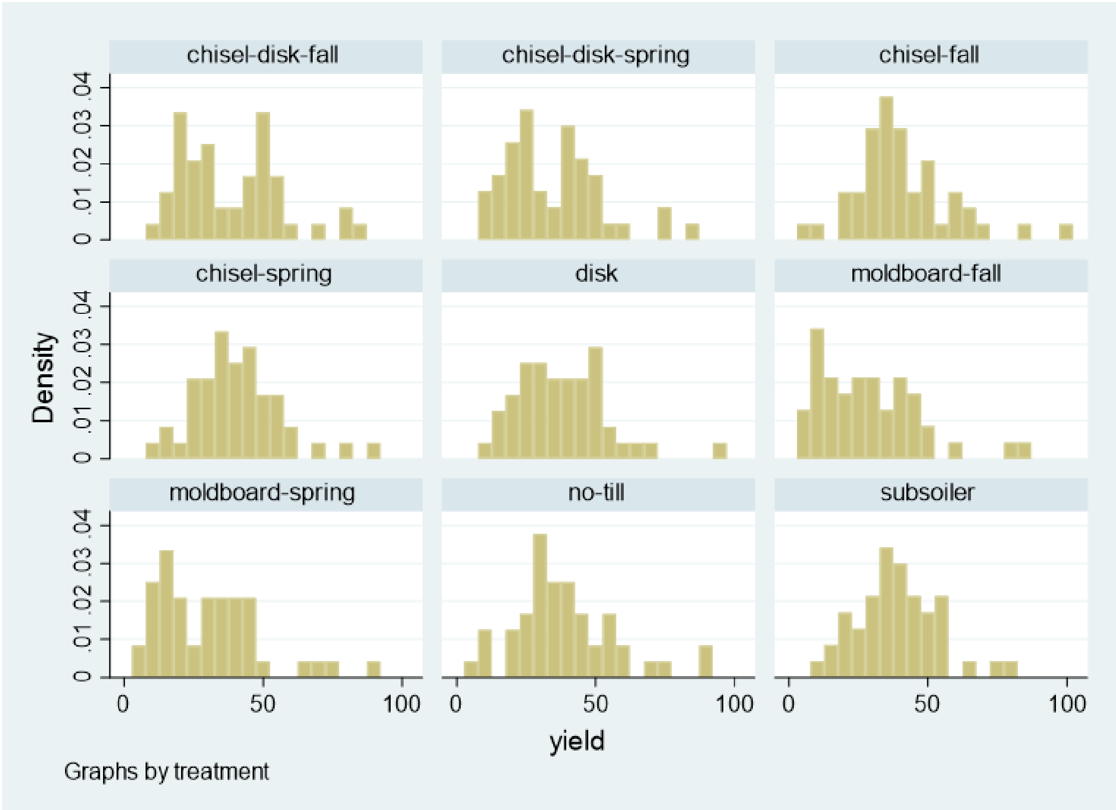
Note: Data for the figure above drawn from Mathers et al., (2023).

Figure B9: Corn – Yields by Tillage Treatment



Note: Data for the figure above drawn from Mathers et al., (2023).

Figure B10: Soybean – Yields by Tillage Treatment



Note: Data for the figure above drawn from Mathers et al., (2023).

Appendix C

Cover Crop Adoption and Algal Blooms

Figure C1: Cyanobacterial Frequency, Extent, Weather Controls, and Lake Size and Depth across Lakes

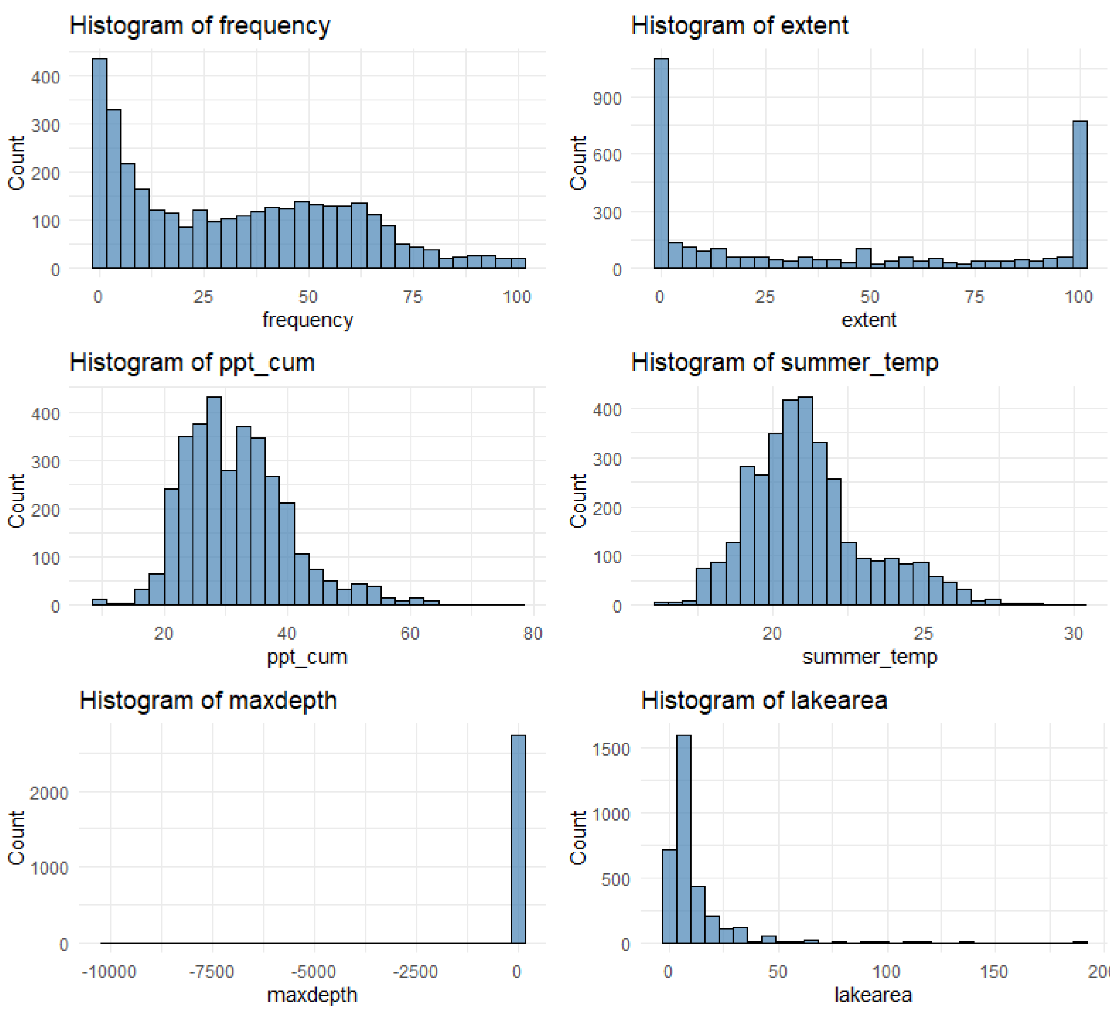


Figure C2: Distributions of Cover Crops, Reduced Till, Winter Commodity, and Perennial Crop Acres across Lakes

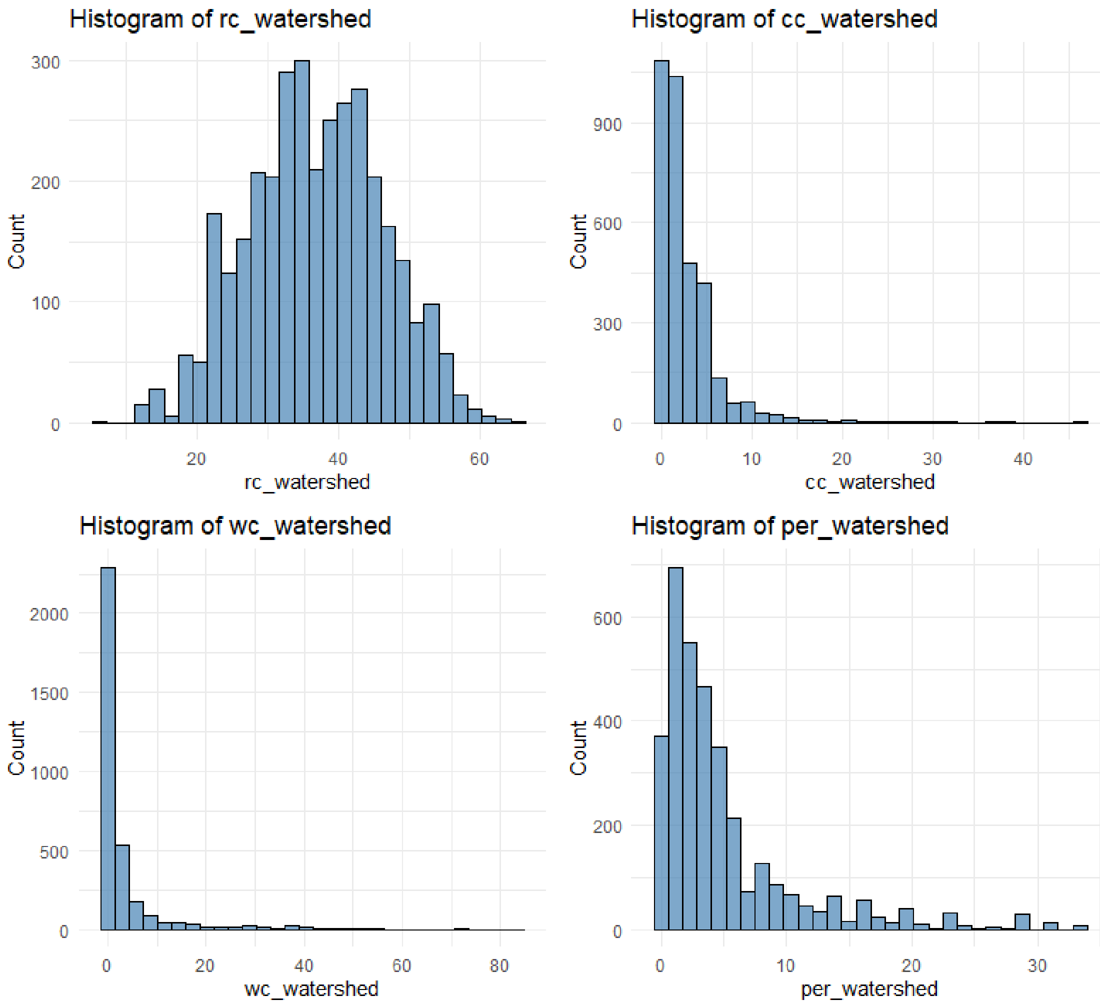


Figure C3: Distributions of Land Use and Crops across Lakes