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THREE ESSAYS ON WATER QUALITY POLICY AND
CONSERVATION PRACTICE EVALUATION

BY

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DISSERTATION

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Abstract

Non-point source pollution from agriculture has been identified as the leading cause of water quality impairments in the United States. Excess nutrients (e.g., phosphorus, P, nitrogen, N) degrade waterways, and eutrophication leads to hypoxia or "dead zones" in water bodies. The federal government has invested billions of dollars in voluntary incentive-based conservation programs to encourage farmers and ranchers to adopt conservation practices on their working lands. However, the realized environmental benefits attributed to those conservation programs and practices still remain unclear and incomplete. In this dissertation, I evaluate the effects of the two largest working lands conservation programs (in terms of acreage and spending) and the conservation practice cover crops on ambient water quality.

The first chapter discusses the Conservation Stewardship Program (CSP) in the Illinois River Basin (ILRB), a tributary of the Mississippi River that drains Illinois and smaller areas of Indiana and Wisconsin in the Corn Belt region. The hypoxic zone in the Gulf of Mexico is the result of intensive agriculture in the Midwest that is drained by the Mississippi River. The economics literature has explored the effects of conservation programs on retired lands (e.g., slippage and additionality), and their impacts on ambient water quality have been studied by integrating with engineering simulation models. However, the econometric evidence of the effect of working land conservation programs on ambient water quality remains unknown. The first chapter aims to isolate the impact of the CSP, a cost-share program designed for farm operators who have already adopted some conservation practices and plan to adopt more or expand their use of these practices, on surface water quality (i.e., total

nitrogen) in the IRB. This study found that a ten percent increase in the percentage of land enrolled in CSP reduces ambient nitrogen concentration by 0.5 to 1.0 mg/l in the ILRB. The estimated amount of abatement is equivalent to 12 to 23 percent of the average nitrogen measurements.

In the second chapter, I examine cover crop (CC) adoption to determine how this soil health practice has influenced agricultural non-point source pollution in the U.S. Corn Belt. I use remotely sensed data on practice adoption, and control for hydrological flow direction, weather and land use to estimate the *ex post* impact of CC on total Nitrogen concentrations in surface water while controlling for pollutant spillovers from upstream. At the mean treatment level in the study area (3.2%), a 1% increase in CC adoption results in a 0.05 mg/L (2%) reduction in concentration in the study area. Results provide novel estimates based on observed data that can be compared to biophysical simulations of CC effectiveness.

The last chapter evaluates the effect of the U.S. Department of Agriculture's Natural Resources Conservation Service (NRCS) administered Environmental Quality Incentives Program (EQIP) on ambient water quality (i.e., total inorganic nitrogen). The EQIP is the largest and longest-running agriculture conservation financial and technical assistance program targeting working lands and supports national policy goals to reduce nonpoint source pollution in impaired watersheds. However, the econometric evidence of the effect of working lands agri-environmental programs on ambient water quality remains limited. Recent peer-reviewed research has used EQIP contract data to evaluate the program's impact on water quality, but it has several limitations. Our study provides a more comprehensive analysis than prior work by including the entire program duration and the period before EQIP was first authorized in the 1996 farm bill. The data we employ to identify this effect are watershed-level dollars of EQIP cost-share assistance from 1996 to the present paired with water quality data where monitoring stations are located. Each monitoring location measurement reflects drainage from upstream areas with varying levels of treatment or no treatment in the pre-EQIP period. The empirical strategy to identify the impact of EQIP

on nutrient and sediment pollution levels is a linear panel fixed-effects model that controls for drought, recent precipitation, land use, gross farm income, and cash crop yield. This study found that a ten-thousand-dollar increase in EQIP cost share for water quality related conservation practices is estimated to lead to a 0.06 mg/l decrease in average ambient N levels. This estimated effect is equivalent to 40 percent of the average in-stream N concentration.

To my family.

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Special thanks to the Economic Research Service of USDA for offering me a voluntary service agreement to gain access to the confidential contract data to complete my dissertation. I am also grateful to my cohort members for the cherished time spent together in the office, in classes, and in social settings.

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Chapter 1

THE EFFECT OF THE CONSERVATION STEWARDSHIP PROGRAM ON AMBIENT WATER QUALITY IN THE ILLINOIS RIVER BASIN*

1.1 Introduction

Agricultural activities are the leading sources of phosphorus (P) and nitrogen (N) in aquatic ecosystems due to the high percentage of land covered by crops in most watersheds and the heavy use of fertilizers in modern intensive agriculture (Matson et al., 1997; V. H. Smith, 2003). Farms are nonpoint sources of pollution that have been identified as the largest source of water quality degradation (Bennett et al., 2001; Howarth et al., 2002; Sharpley

*The findings and conclusions in this chapter are those of the authors and should not be construed to represent any official USDA or U.S. Government determination or policy. This research was supported in part by the U.S. Department of Agriculture, Economic Research Service.

et al., 1987). Diffuse nonpoint inputs of nutrients impair the ecological health of rivers, streams, and coastal zones nationwide (Tilman et al., 2001). Hypoxia, an area of low oxygen threatening marine ecosystems, is one of the consequences of nutrient over-enrichment with P and N. According to the United States Environmental Protection Agency (EPA), the hypoxic zone in the Gulf of Mexico is a result of excess nutrients from the Mississippi River. More than 70 percent of the land in the watershed is used for intensive agricultural production with nutrients coming from fertilizer and livestock manure. One way to address the nutrient impairment is by incentivizing a change in practices with green payments, which subsidize farmers either to retire cropland or to adopt conservation practices on working land. The Agricultural Act of 2014 emphasized conservation practices on working lands by increasing the share of conservation expenditures on the Environmental Quality Incentive Program (EQIP) and the Conservation Stewardship Program (CSP) by nearly 50 percent while reducing funding for the largest land retirement program, the Conservation Reserve Program (CRP) (“USDA ERS - Agricultural Act of 2014”, 2014).

This study investigates the environmental effects of the CSP in the Illinois River Basin (ILRB), a tributary of the Mississippi River that drains Illinois and smaller areas of Indiana and Wisconsin in the Corn Belt. The study focuses on exploring the effect of the CSP on ambient water quality (i.e., N). The CSP is administered by the USDA Natural Resources Conservation Service (NRCS), and is one of the largest federal conservation programs by acreage, with a primary goal to address concerns about water quality from agricultural runoff. Over 72 million cumulative acres had been enrolled in CSP nationwide through 2017. CSP provides cost-share financial assistance to farmers through a five-year contract. Because the CSP started recently this helps identify the impact of treated land areas on nutrient loss reduction. Together EQIP and CSP are the largest working-land conservation programs by acreage and spending. EQIP was implemented continuously throughout the entire analysis period from 2006 to 2015, while the CSP started in 2010, allowing us to observe water quality before and after CSP was in operation. Thus, this study focuses on identifying the impact of

CSP on pollution reduction while controlling for the effect of EQIP.

The effects of nutrient loss reduction from agricultural cost sharing have been investigated along several dimensions. The effects of agri-environmental programs on the change in overall land use have been quantified in the literature as slippage effects, which describe the conversion of non-cropped land to agriculture. In the land retirement program CRP, slippage effects have been found to partially offset the environmental benefits from the program because of the increased share of land outside CRP converted to cropland (Uchida, 2014; Wu, 2000). Incentive payments for conservation practices on working lands may induce slippage as well when the subsidy makes it profitable to turn some share of land allocated to vegetative cover into cropland (Khanna et al., 2002; Lichtenberg, 2004; Lichtenberg & Smith-Ramírez, 2011). Studies have explored the indirect effects of incentive payments in terms of the change in a portion of land use; still, the impact of the cost-sharing programs on ambient water quality has not been discussed.

To assess the effect of agri-environmental policies on local and downstream water quality, integrated models have incorporated econometric estimation at the watershed scale, with ex-ante hydrologic simulation models (e.g., Soil and Water Assessment Tool (SWAT)) (Fleming, 2017; Fleming et al., 2018; Wu & Tanaka, 2005; Wu et al., 2004). Wu et al. (2004) applied discrete-choice empirical models to predict crop choice and tillage practices before implementing environmental production functions to predict the corresponding environmental consequences, such as nitrate runoff and leaching.² Fleming et al. (2018) estimated the direct effect of the Maryland cover crop cost-share program on the acres of cover crops, the indirect effect on the acres of conservation tillage, and the slippage effect on the share of lands allocated to vegetative cover. They translate the estimated treatment effects from the econometric model into nitrogen abatement by using estimates from the Chesapeake Bay Program (CBP) watershed simulation model.³ Distinct from their approach, our study employs a reduced-form

²The environmental production functions are estimated using the Erosion Productivity Impact Calculator (EPIC model) to simulate environmental impacts based on crop management practices, soil characteristics, and climate factors.

³The CBP watershed model simulates pollution loads using 20 years of historical monitoring data on

econometric approach to evaluate the impact of working lands conservation program contracts on ambient water quality. We model the relationships between agricultural pollutants and essential biophysical and socio-economic determinants of water quality in a straightforward and transparent manner.

Reduced-form econometric studies of water quality outcomes have not been widely implemented in the literature. Existing studies have (i) evaluated policies related to water quality improvement and (ii) explored the relationship between agriculture and water nutrient pollution. Keiser and Shapiro (2019) evaluate the regulatory impact of the 1972 Clean Water Act (CWA) on point source water pollution from watershed treatment plants. Using treatment plant-level data, they construct a dataset to exploit the discontinuity in ambient water pollution level created by point source discharges to estimate the impact of grants for treatment upgrades. Distinct from the CWA regulation of point sources, nonpoint source agricultural pollution abatement is voluntary despite agricultural lands being the largest source of nutrient pollution.⁴ Liu et al. (2022) estimate the impact of the EQIP payments on local water quality at a national scale. They link water quality readings with EQIP contract data and exploit river flow direction as identification. Following Keiser and Shapiro (2019), they use the upstream of a watershed as a counterfactual for the downstream of a watershed to identify the influence of EQIP on the downstream water quality. The regression analysis has also been applied to explore the causal link between agriculture and nutrient pollution in ambient water. Paudel and Crago (2020) employ watershed-level panel data on ambient nitrogen and phosphorus concentrations to empirically estimate the relationship between fertilizer application and nutrient pollution. Metaxoglou and Smith (2022) improve upon the treatment measured by the nitrogen fertilizer sale. They focus on the relationship

precipitation, streamflow, and land uses. It is the most policy-relevant in their study region, which is used by the EPA and jurisdictions to evaluate compliance with the Chesapeake Bay Total Maximum Daily Load requirements.

⁴Given the diffuse nature of nonpoint source pollution, pollutants emissions from agriculture lands are not readily observable and monitored, which implies the policy instruments based on emissions cannot be implemented in this context. This explains the fact that subsidizing farm operators with green payments to voluntarily adopt conservation practices is an alternative to policy instruments for the control of nonpoint source pollution.

between nitrogen pollution and corn acreage, which is the driving force behind the amount of nitrogen fertilizer used. We improve upon the measurement accuracy by utilizing the area under conservation contracts at the smallest possible watershed to minimize aggregation measurement error. Raff and Meyer (2021) identify that increasing concentrated animal feeding operation (CAFO) intensity increases the levels of nutrients in surface water. Unlike their work, we control for the immediate upstream water quality measurement and create a spillover effect of nutrient pollution to isolate the influence of conservation contracts.

Our study contributes to the literature on agri-environmental policy evaluation in several ways. First, we provide *ex post* econometric estimates of the effect of the working land program on ambient surface water quality distinct from the integrated modeling literature that relies on *ex ante* engineering simulation models. Nutrient concentration serves as the dependent variable explained by the percentage of land area under CSP in the sub-watershed to identify the contemporaneous magnitude of the impacts of conservation contracts on ambient surface water quality. Second, our study enlightens policymakers and researchers on the cost-effectiveness of investments in the CSP. An important feature of the analysis is modeling the complicated spatial networks of streamflow and the spatial spillovers of nutrients to isolate the effect from the agri-environmental policy. The constructed monitoring basins allow us to estimate the direct effect of program treatment as well as address the interactive effect of treatment with the weather (Sun et al., 2018). Such findings may help improve the effectiveness of implementing and designing conservation programs in the future.

We present two complementary empirical approaches to investigate the effects of the conservation program. We begin with a standard panel two-way fixed effects strategy (TWFE) with a continuous treatment measure to identify the impact of CSP on total N (nitrate and nitrite) concentration in the Illinois River Basin (ILRB) from 2006 to 2015. We quantified conservation contract data as the percentage land area under contract in CSP and EQIP and weighted them by the distance between contract HUC12 and the nearest downstream monitoring site in each monitoring basin. The first time land is treated under

CSP is in 2010, while EQIP conservation contracts are in place over the entire study period. We capture the spatial spillovers of nutrients from upstream in locations with upstream neighbors. We include the following controls in the model: recent rainfall, drought index, and their interaction to capture key hydrological factors affecting flow and nutrient loss from agricultural land; economic variables such as gross farm income; and corn and soybean yield. We condition the estimates on month, year, and monitoring basin fixed effects. We find that a ten percent increase in the share of land receiving CSP payments in a monitoring basin reduces in-stream N concentration by 1.0 mg/l, on average, for all monitoring basins in ILRB. Overall, this estimated effect from CSP is about 23 percent of the mean N measurements.

We conduct a complementary analysis using a novel machine learning (ML) methodology; this approach develops an ML river basin model of ambient N concentrations that is used to generate counterfactual post-CSP ambient water quality estimates in the absence of the program. These constructed counterfactuals are used in a panel fixed effects model to estimate treatment effects. We regress the difference between predicted counterfactuals and observed readings on CSP treatment, weather-treatment interactions, and a set of fixed effects. This methodology was recently introduced to understand the effect of energy efficiency upgrades on energy consumption by Burlig et al. (2020), and has not been previously applied in the agri-environmental policy literature. This complementary approach allows us to overcome the empirical challenge of very few untreated units because CSP begins everywhere simultaneously. Additionally, the complex non-linear relationships between nutrients concentrations and confounding biophysical and socio-economic factors are included in fully out-of-sample predictions. The estimated effects from the ML approach are very similar for both headwaters and monitoring basins with upstream neighbors. Distinct from TWFE, a 10 % increase in CSP area in both types of monitoring basins is estimated to reduce ambient surface N by 0.5 mg/l on average. Near-term rainfall and drastic dry-to-wet transitions minimally offset the effect of CSP treatment on ambient N, while drought conditions lower ambient total N (improve water quality). The estimated CSP treatment effect using the ML

approach based on constructing an unobservable counterfactual is qualitatively similar to and entirely consistent with the treatment effect from the TWFE approach; ML estimated treatment effects are most quantitatively similar to TWFE estimates for basins with upstream neighbors.

1.2 Data

1.2.1 USDA-NRCS conservation programs

The study involves conservation contracts in the ILRB from EQIP and CSP that provide financial and technical assistance to promote conservation practices on private working lands. One of the goals of these programs is to reduce nutrient loadings from agricultural activities within watersheds. Producers with eligible land can apply for EQIP with plans describing the conservation and environmental purposes that will be achieved using one or more USDA-approved conservation practices. Unlike EQIP, the CSP is for land operators who have already adopted some conservation practices and plan to adopt more. CSP contract payments are based on two components: (1) payments to maintain the existing level of conversation, based on the land uses in the contract and existing stewardship at the time of enrollment, and (2) payments to implement additional conversation activities as Enhancements (Enhn.) to address additional levels of conservation beyond what the minimum conservation practice standard requires. The payments from CSP are allocated to top-ranked applicants according to the evaluation of the existing management practices and the proposed new practices. Land can only be enrolled in one program at a time; land under an EQIP contract could be enrolled in CSP after the EQIP contract ends if additional conservation measures are taken with the CSP funding.

This study focuses on isolating the effect of CSP on ambient water quality while controlling for the conservation contracts from EQIP. EQIP was first authorized in the 1996 Farm Bill legislation, but the conservation contract data are only available since 2006. In

other words, EQIP is continuously implemented throughout all periods of the study (i.e., 2006 to 2017), while CSP was first implemented in 2010. Continuous treatment over the observable years makes it relatively challenging to isolate the water quality impact of EQIP contracts empirically. The treatments are measured as the percentage of acres under conservation contracts in each monitoring basin. Figure 1.1 presents the total acres of lands under CSP and EQIP contracts in the ILRB from 2006 to 2015. For CSP, the total treated acres have been increasing and reached 650,000 acres in 2015. There are fewer total treated acres under EQIP, and EQIP acres have been decreasing since 2011. Note that the total treated acres under EQIP have been relatively stable over the years.

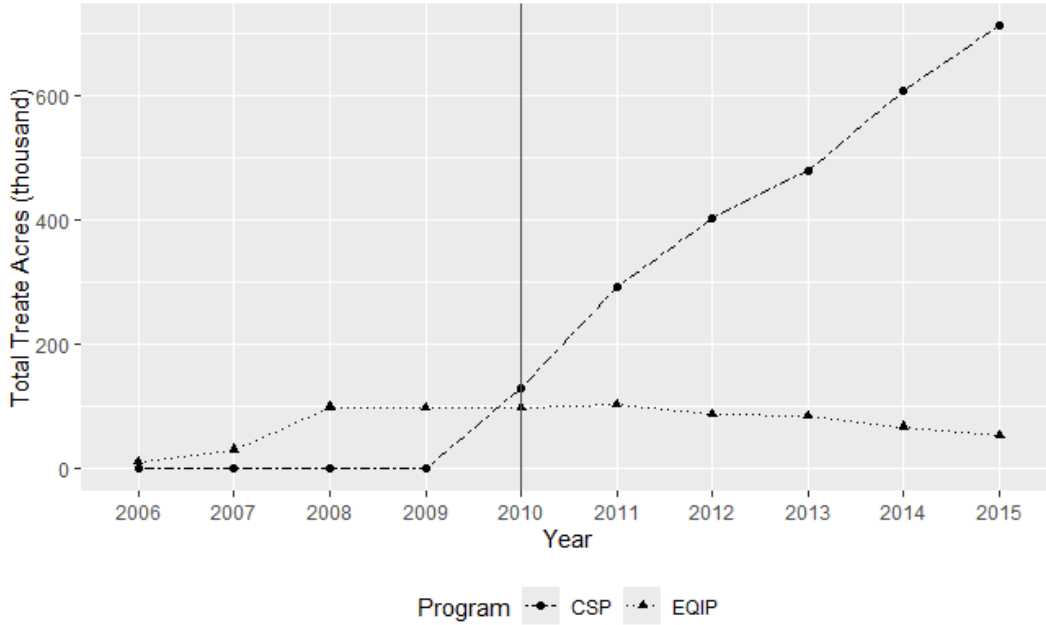


Figure 1.1: Total acres under EQIP and CSP in the ILRB, 2006-2015

Notes: We first calculate the annual mean of total area acres under conservation contracts for each monitoring basin. Then, we sum it across all the monitoring basins in the ILRB over the years as the annual total treated acres shown at the y-axis.

1.2.2 Watershed Hydrology Network

The monitoring basins and spatial connectivity are constructed based on the water flow direction and connectivity of HUC12 sub-watersheds from the National Hydrography Dataset (NHD) and the location of the water quality monitoring stations (i.e., longitude

and latitude) from the federal Water Quality Portal (WQP).⁵ Based on the nature of streamflow, the smallest Hydrologic Units in the NHD, HUC12s, are assigned to nearest downstream monitoring stations and are aggregated to form monitoring basins that are the unit of analysis controlling for active conservation contracts, land use land cover, and weather. Each monitoring basin is constructed by identifying all contiguous HUC12s that drain the land located between two monitoring stations, one upstream and one downstream, of this land. A spatial connectivity matrix is constructed that identifies which monitoring basins are located upstream (i.e., first-order-neighbor monitoring basin) of every other monitoring basin and which monitoring basins do not have any upstream neighbors, referred to as headwater basins.

This process delineates a total of 49 monitoring basins, with 25 basins having upstream inflow and 24 headwater basins.⁶ We show the spatial variation of the average percentage of lands under CSP in each monitoring basin in Figure 1.2. The mean percentage of lands under CSP from 2010 to 2015 varies across monitoring basins. We find the highest rate (over 75 percentile) of installed conservation practices from active CSP contracts in the middle of ILRB, and six monitoring basins have no active CSP contracts.⁷

⁵The R-code for aggregating the HUC12 sub-watersheds to construct monitoring basins was developed by Shanxia Sun, Department of Economics and Finance, Shanghai University. More details of constructing MS basins, flow mapping, and mapping error diagnosis are provided in appendix A.

⁶In Appendix A, we show more details of constructing the monitoring basins. Specifically, we describe the measurement errors when aggregating up HUC12s and their corresponding solutions. Appendix Figure C.6 shows where two types of basins (i.e., basins with upstream neighbors and headwater basins) are located in the ILRB, as well as the location of water monitoring stations for each basin.

⁷We include the quartile map of mean percentage lands under EQIP as a reference in Appendix Figure C.9. On average, the rate of lands under EQIP is lower than under CSP. Some of the basins that do not have CSP have active EQIP contracts.

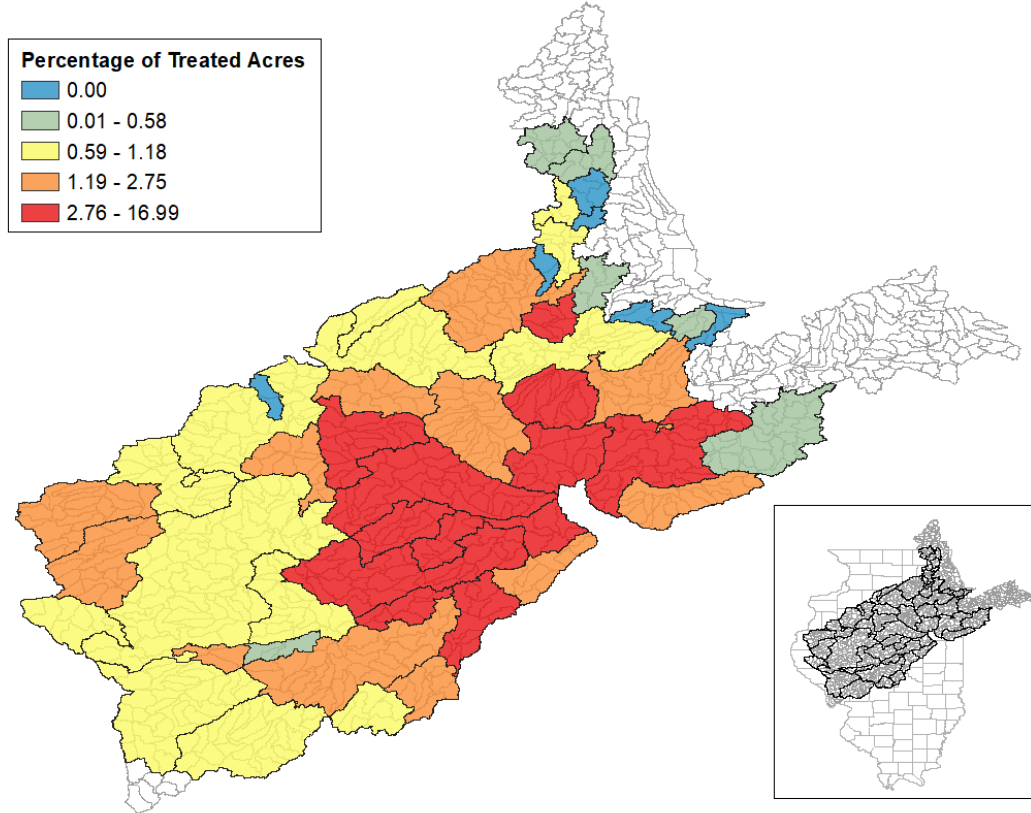


Figure 1.2: Quartile map of mean percentage of area acres under CSP from 2010 to 2015

Notes: The map presents the monitoring basins (dark black lines and colored areas) and the HUC12 sub-watersheds (light gray lines) in the ILRB. The bins of active CSP treatment rate are minimum, first quartile, median, third quartile, and maximum.

1.2.3 Water quality

The ambient water quality measure used is the total nitrogen (N) concentration (mg/l) (i.e., nitrite and nitrate). The Water Quality Portal (WQP) is the water quality monitoring data source, including information on the location of monitoring stations and corresponding nutrient concentrations by the dates they were sampled. Monitoring stations are unevenly spatially distributed. If multiple stations are located in a single HUC12 sub-watershed, the one station is retained that captures the largest upstream area and has the most available pollutant readings, to reduce measurement errors. Also, stations with nutrient measurements for less than three years were removed from the analysis due to the lack of temporal coverage over the study period.

The frequency of water quality sampling is unbalanced, but it does not vary systematically by location over the months and years. The correlation test between the frequency of available N samples and the average percentage of lands under CSP is insignificant. Also, the correlation between the rate of N measurement availability and land use type (i.e. developed, cropland) is not statistically different from zero.⁸ We will further explore possible empirical threats posed by unbalanced water quality sampling data in the robustness check section.

1.2.4 Control variables

All else equal, larger rainfall amounts lead to an increase in agricultural runoff and higher N losses to streams are expected (Baeumler & Gupta, 2020; Bowles et al., 2018; Congreves et al., 2016). The daily precipitation data from the PRISM climate group are at 4x4 kilometer spatial resolution. We use the daily precipitation to construct the 7-day cumulative rainfall prior to each water quality sampling date in each monitoring basin. Near-term cumulative rainfall serves as one of the control variables for estimating the effect of CSP on ambient surface N concentration. We include both the direct effect of recent rainfall and its interaction with CSP contracts. The direct effect of the near-term rainfall on ambient N is expected to be positive, as well as the interactive effect with treatment. The interaction term measures how the near-term cumulative precipitation may mitigate the impact of conservation practices on nutrient loss reduction.

The Palmer Drought Severity Index (PDSI) serves as a proxy for streamflow because observed flow at the HUC12 or monitoring basin level is not generally available (Dai, 2011). The calculation of the PDSI is based on historical weather data. The monthly average precipitation and temperature data are from the PRISM climate group. We used the historical weather from the year 1950 to 2015 to construct the monthly PDSI for the analysis. The PDSI is a standardized index that generally spans the range from -10 to 10 . A PDSI value ≥ 4 refers to extremely wet, while a PDSI ≤ -4 refers to extreme drought. The

⁸These results are shown in Appendix Table B.1.

PDSI value is multiplied by a negative one to focus interpretation on drought conditions, with more positive PDSI indicating drier conditions. Drought is expected to negatively influence the ambient N reading due to the soluble characteristic of N. The interaction between drought and rainfall events is included to measure drastic dry-to-wet transitions. Bowles et al. (2018) states that extreme dry-to-wet transitions during the growing season cause high N losses via leaching and denitrification losses.

Our analysis also controls for agricultural and socioeconomic characteristics, including corn and soybean yield data from the USDA National Agricultural Statistics Service (NASS) and gross farm income data from the Bureau of Economic Analysis (BEA). We aggregate county-level socioeconomic characteristics at the monitoring basin level. We overlay the monitoring basin polygons with the county boundaries to derive a basin-county cover weighting factor. We then apply the weighting factor to the county-level socioeconomic controls for counties within each monitoring basin polygon and sum them to obtain the basin-level variables.

1.2.5 Summary statistics and trends

Table 3.1 reports the summary statistics for two subgroups of monitoring basins: one for headwater basins and another for basins with upstream neighbors. The mean N reading for headwater basins is 25 percent higher than basins with inflow from upstream, and the standard deviation is about 40 percent higher among headwater basins than those with inflow from upstream. The distance-weighted percentage of lands under CSP is the treatment measure. The distance-weighted factor is the inverse of the distance between the centroid of the HUC12 sub-watershed and the nearest downstream sampling site in the monitoring basin. We then apply the weight factor to the HUC12-level percentage of land under CSP and sum across HUC12s to obtain the weighted treatment in each monitoring basin. Another treatment, CSP land share (WQ), is further refined from all practices under CSP to those conservation practices that are related to nutrient pollution in streams and rivers, e.g., cover

crops, no-till, resource-conserving crop rotation, etc. The last treatment measures those WQ-related practices, which are paid as CSP enhancements (WQ-Enh.).⁹ Overall, the CSP land shares in headwater basins are about twice the shares in the downstream basins. The percentage of land implementing WQ-related practices under CSP is nearly the same as the CSP land share, including practices that are related to nutrient pollution and enhancements. It's not surprising since most CSP applicants have already applied conservation practices to their land. Operators improve their conservation efforts with enhancements through CSP. On average, all basins have a higher portion of land under CSP than EQIP. Note that the mean percentage of the cropland is as high as 63 percent, but, on average, only 1.5 to 2.2 percent of lands treated under CSP. The mean and standard deviation of 7-day near-term rainfall are nearly the same between these two groups, reflecting how weather conditions are more randomly distributed over space. Gross farm income is higher among basins with upstream neighbors, while annual average corn and soybean yields are similar between basins with and without upstream neighbors.

⁹The quartile maps of mean CSP land share accounting for WQ and WQ-Enh. practices over monitoring basins can be found in Appendix Figures C.7 and C.8, respectively.

Table 1.1: Summary statistics

Variable	<i>Basins w/ upstream neighbors</i>		<i>Headwater basins</i>	
	Mean	SD	Mean	SD
Nitrogen concentration (mg/l)	3.847	2.791	4.821	3.897
CSP land share (%)	1.491	2.592	2.179	5.233
CSP land share (WQ, %)	0.810	1.478	1.410	3.920
CSP land share (WQ-Enh., %)	0.802	1.472	1.393	3.875
Cropland land share	63.159	27.628	56.222	24.156
PDSI	1.06	2.26	1.04	2.20
7-day cumulative rain (mm)	20.50	21.78	20.83	21.99
Gross farm income (million \$)	217.94	173.67	117.59	116.29
Corn Yield (bu/acre)	154.14	38.93	153.60	45.50
Soybeans Yield (bu/acre)	47.32	10.91	47.04	14.12
EQIP land share (%)	0.599	0.709	0.548	0.781
Upstream N (mg/l)	4.401	3.452	0.000	0.000
Average basin size (acre)	415648.9		208045.4	
Observations	1,656		1,680	

Notes: WQ represents the conservation practices under CSP that are related to nutrient pollution in streams and rivers. WQ-Enh. are WQ-related practices under CSP that are enhancements. All three specifications of treatment are distance-weighted. Statistics for pre-weighted treatment measurements are included in Table B.2.

We next discuss the water pollution trend. We use the following equation to assess year-by-year changes in ambient surface N (Keiser & Shapiro, 2019):

$$Y_{i,c,t} = \sum_{t=2006}^{t=2015} \alpha_t 1[year = t] + X'_{ict} \beta + \eta_i + \epsilon_{it} \quad (1.1)$$

The variable $Y_{i,c,t}$ represents the ambient N reading at monitoring basin i , hour and day-of-year c , and year t . The matrix X'_{ict} includes cubic polynomials in time of day and in day of year. In Appendix graphs (Figure C.1), we show the annual N trend, where X'_{ict} includes PDSI and near-term precipitation. The time-invariant characteristics of monitoring

basin i are captured by η_i . It is important to control the basin fixed effects in the trend analysis because they adjust the cross-sectional differences in the baseline N measurements across monitoring basins in the unbalanced panel. This approach ensures that identification comes only from changes in ambient N within each monitoring station over time. We then plot the year coefficients $\alpha_{2006} \dots \alpha_{2015}$ and the constant in Figure 3.3. The year-by-year mean N measurements shifted downward from 2006 to 2010 but bounced back to a high in 2013. To explore the spike in 2013, we also plot the trends of PDSI and the recent rainfall variable in Figures 1.4a and 1.4b, respectively. According to hydrology, intense and season-long droughts will have lagged effects on agricultural N losses (Bowles et al., 2018). During the drought period, decreased plant N uptake causes high residual soil inorganic N, resulting in higher ambient N concentrations during subsequent rain events (Greaver et al., 2016). In our case, the average rain events in 2013 that followed a historic drought in 2012 appear to have resulted in elevated N concentrations in streams. Metre et al. (2016) also found that the 2012 drought in the US Midwest was followed by extremely high river N concentrations in the spring of 2013.

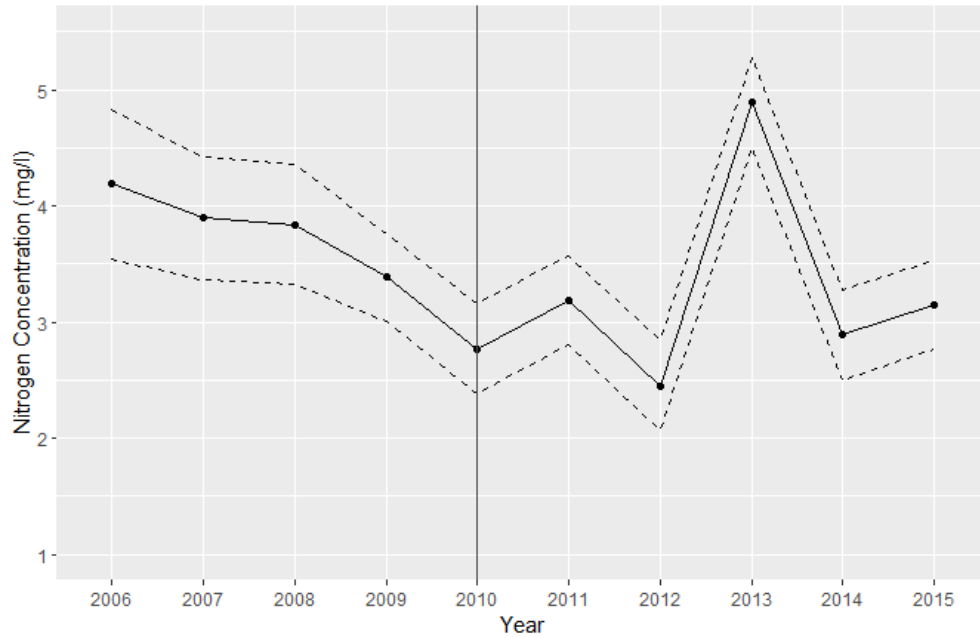


Figure 1.3: Nitrogen concentration trends, 2006-2015

Notes: The year-specific points in the graph represent the mean N concentrations, controlling for time and monitoring basin characteristics. Dashed lines have a 95% confidence interval, and 2006 is the reference category.

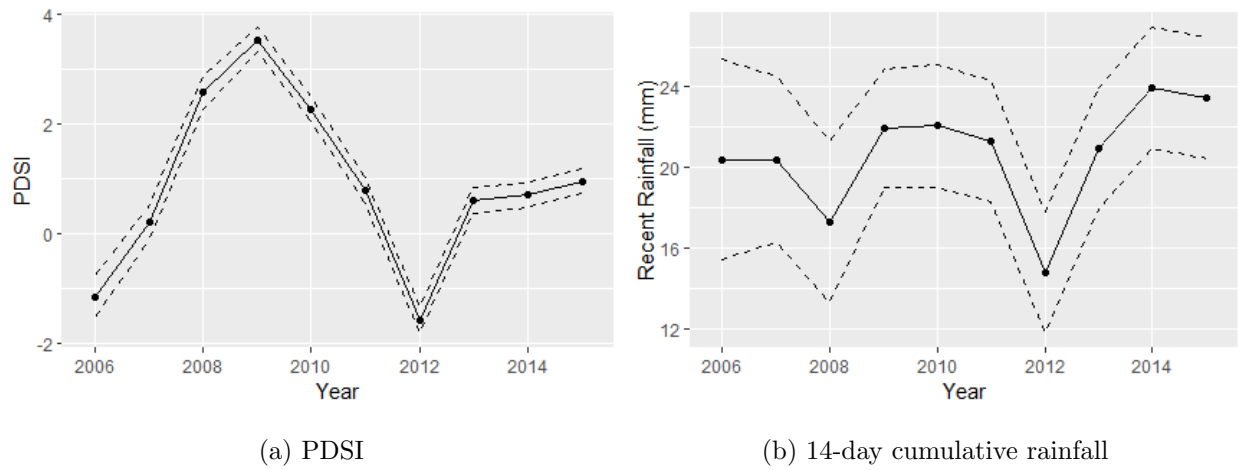


Figure 1.4: Trends of drought index and recent rainfall

Notes: Connected dots show yearly values of PDSI and 7-day cumulative precipitation prior to the water sampling day. The PDSI is a standardized index that generally spans the range from -10 to 10 . A PDSI value ≥ 4 refers to extremely wet, while a PDSI ≤ -4 refers to extreme drought. Dashed lines have a 95% confidence interval, and 2006 is the reference category.

1.3 Empirical strategy and results

1.3.1 Panel two-way fixed effects approach

I begin with a standard two-way fixed effects (TWFE) approach with a continuous treatment (share of land under CSP conservation contracts) for the unbalanced monthly panel data and separate the analyses for basins with and without upstream neighbors because headwater basins do not have upstream stations to control for pollution spillovers inherent in the hydrological network. This approach relies on the same identifying assumptions as the discrete treatment difference-in-differences strategy (Angrist & Pischke, 2009; Bertrand et al., 2004), and has been widely used to evaluate non-discrete treatment effects (Acemoglu et al., 2004; Adhvaryu et al., 2019; Card, 1992; Herbst, 2017; Lewis & Severnini, 2020a). For monitoring basins with inflow from upstream, I include the corresponding upstream pollutant measurements as one of the controls for the downstream water quality readings (Paudel & Crago, 2020). Controlling the pollution spillovers isolates the effect of active conservation contracts in a given monitoring basin on ambient water quality. The estimating equation includes an error term, ϵ_{it} , and is given by:

$$\begin{aligned} N_{it} = & \beta CSP_{it} + \\ & \alpha_1 CSP_{it} \times R_{it} + \alpha_2 CSP_{it} \times D_{it} + \alpha_3 CSP_{it} \times R_{it} \times D_{it} + \\ & \mathbf{X}_{it}'\boldsymbol{\gamma} + \rho \sum_{k \in \Lambda_{i-1}} \psi_k N_{kt} + \tau_t + \theta_y + \eta_i + \epsilon_{it} \end{aligned} \quad (1.2)$$

The dependent variable N_{it} describes ambient N concentration (mg/l) in monitoring basin i and month t . The treatment, CSP_{it} , is the distance-weighted percentage of acres installing conservation practices under the CSP. Hence, the coefficient of interest, β , represents the average treatment effect, indicating how an increase in the percentage of land under CSP impacts the N concentration in the stream. The three different indirect treatment effects are the interactions between treatment and 7-day near term rainfall (R_{it}), drought condition

(D_{it}) , and both recent precipitation and drought ($R_{it} \times D_{it}$). The interactions measure how different weather conditions mediate or enhance the effect of CSP on N loss.

Equation 3.3 includes several sets of controls. The upstream pollution spillovers, $\sum_{k \in \Lambda_{i-1}} \psi_k N_{kt}$, is the weighted average N measurement of the entire set of the immediate upstream monitoring sites, Λ_{i-1} , of the monitoring basin i . ψ_k is the inverse count of upstream basins, and N_{kt} is the N readings in the upstream sites. The vector of time-varying controls, $\mathbf{X}'_{it}$, includes weather, socio-economic determinants, and the conservation contracts under EQIP. Weather controls are 7-day cumulative precipitation (mm) prior to the water quality sampling date, drought condition measured by PDSI, and their interaction capturing extreme dry-to-wet transitions.¹⁰

Gross farm income is measured by total cash receipts from marketings (thousands of dollars) based on data from BEA that includes crops, livestock, and related products. Corn and soybean yields (bushels per acre) are aggregated from the county-level annual average to the monitoring basin level in proportion to a county's share of each basin. We control for the share of land under EQIP contracts because EQIP persists throughout all periods in the study. Last, the analysis includes month, year, and monitoring basin fixed effects. τ_t are month fixed effects that control for the seasonality of the N concentration. θ_y are year fixed effects that control for factors changing over years but not across the monitoring basins, such as changing physical, chemical, and biological attributes of the receiving water body. The basin fixed effect, η_i , captures the time-invariant unobservables, such as the size of basins and stream, soil characteristics, the distance between fields and streams, and other characteristics influenced by topography and geography, which are hard to observe but influence nutrient loss.

¹⁰We initially specify the near-term cumulative precipitation as 3-, 7-, 14-, and 21-day cumulative rainfall leading up to the date of water quality sampling for each monitoring basin. Findings are robust to the specification of the recent cumulative rainfall period.

1.3.2 Machine Learning approach

We propose Machine Learning (ML) as a complementary method to the TWFE approach to explore if the limited number of untreated control units biases the estimated treatment effect. Recall that, in Figure 1.2, only six monitoring basins do not have conservation practices installed under CSP contracts because the conservation program begins everywhere simultaneously. In other words, once CSP starts in one or more HUC12 sub-watersheds, the entire monitoring basin is considered a treated unit. And so, the baseline difference in control groups over time is absent in the TWFE approach because we cannot observe untreated units after CSP began. This empirical challenge represents one threat to identification because the TWFE estimator is only estimated by the difference in the timing and the continuous level of treatments between treatment groups due to the lack of untreated control groups. Therefore, we adopt a recently applied ML approach from economics to construct the potential outcomes with no treatment (i.e., unobservable counterfactual) in the post-treatment period as the baseline for the identification of the CSP treatment effect.

We follow a two step approach. First, we use ML tools to create separate models of the outcome of interest (i.e., ambient N) for headwater basins and basins with upstream neighbors. We train the model using pre-treatment data only (i.e., 2003-2009 before CSP started in 2010), which ensures that the prediction model is not confounded by structural changes occurring in the post-treatment period. Then, we use the model to create (fully out-of-sample) predictions of the outcome of interest as if units were not treated (i.e., counterfactual) in the post-treatment period.¹¹ Specifically, we perform spatial recursive prediction for basins with inflow from upstream because upstream pollutant measurement is an important covariate in the ML model like it is in the hydrological network. The predicted counterfactual in each

¹¹ML methods to forecast a post-treatment counterfactual have been implemented in the literature. Varian (2016) and Burlig et al. (2020) use the pre-treatment data to train ML models to predict the post-treatment outcome of interest in the absence of treatment. Souza (2019) also uses a similar approach to construct the counterfactuals and highlights the add-on features of the approach to explore heterogeneous treatment effects with time-varying treatment/exposure dates. He emphasizes the robustness of the ML approach to concerns about near-term biased TWFE estimators raised in Borusyak and Jaravel (2017) and Goodman-Bacon (2021).

monitoring basin is applied to forecast the next downstream outcome of interest.

In the second step, we take the difference between the ML predicted values from the first step and the real observed outcomes (i.e., $N - \hat{N}$) for each basin. We then regress the difference between the counterfactual prediction and the observed outcome on conservation contracts and their interaction with weather. Analogous to the panel TWFE approach (Equation 3.3), we control for the upstream pollution concentration using the upstream spatial lag of the dependent variable, as well as month and monitoring basin fixed effects:

$$\begin{aligned}
N_{it} - \hat{N}_{it} = & \beta CSP_{it} + \\
& \alpha_1 CSP_{it} \times R_{it} + \alpha_2 CSP_{it} \times D_{it} + \alpha_3 CSP_{it} \times R_{it} \times D_{it} + \\
& \mathbf{X}_{it}'\boldsymbol{\gamma} + \rho \sum_{k \in \Lambda_{i-1}} \psi_k(N_{kt} - \hat{N}_{kt}) + \tau_t + \theta_y + \eta_i + \epsilon_{it}
\end{aligned} \tag{1.3}$$

The dependent variable is the difference between the actual and the predicted N concentration, $N_{it} - \hat{N}_{it}$. We construct the predicted N concentration, $\hat{N}_{it}$, using the supervised ML method Random Forest (RF) with 10-fold cross-validation (CV) to prevent over-fitting (Geurts et al., 2006).¹² We include interaction terms between treatment and weather (i.e., the cumulative rainfall and drought) to capture the indirect effects of CSP that contribute to the difference between the observed N readings and the predicted counterfactuals without CSP treatment. The vector of time-varying controls, $\mathbf{X}_{it}'$, contains conservation contracts under EQIP and their interaction with weather. Note that the available EQIP contract data are from 2006, but the water quality data are available since 2003. As a result, we exclude the rate of lands under EQIP from training the ML prediction model; instead, we include it in the panel regression to control any deviation of the actual readings from

¹²In the Hydrology literature, ML has been widely implemented for water quality prediction (Ahmed et al., 2019; Bui et al., 2020; Haghiabi et al., 2018; Meyers et al., 2017). Castrillo and Garc  a (2020) claimed that RF models have great potential to reproduce environmental phenomena. They show that the RF outperformed the linear model when more than one predictor was used to construct the water quality prediction model.

the prediction. Upstream pollution spillovers are controlled for analogously to Equation 3.3. However, the specification is changed to the weighted average of the difference between the actual and the predicted N concentration of the entire set of the immediate upstream monitoring sites, $\sum_{k \in \Lambda_{i-1}} \psi_k(N_{kt} - \hat{N}_{kt})$. Monitoring basin fixed effects, time trends, and seasonality of water quality (i.e., η_i , θ_y , and τ_t , respectively) and the error term, ϵ_{it} , are defined as in Equation 3.3.

1.3.3 Identification

The identifying assumption for Equations 3.3 and 1.3 to provide an unbiased estimate of the parameter β is that the percentage of acres under CSP is independent of the regression error, conditional on other explanatory variables (Barnow et al., 1980; Heckman & Robb, 1986):

$$E[CSP_{it} \cdot \epsilon_{it} | \mathbf{X}'_{it}, N_{kt}, \tau_t, \theta_y, \eta_i] = 0 \quad (1.4)$$

This assumption would be violated if the percentage of CSP-treated lands at the monitoring basin level responded to unobserved variables, which themselves affect N measurements. There are two types of selection into program bias that could be potential threats to the identification: 1) self-selection of the individual land operators and 2) selection by federal agents. Farm and farmer's characteristics affect the individual's adoption decision (Prokopy et al., 2019). Meanwhile, the federal agents evaluate and rank CSP applicants according to the existing management practices and the proposed new practices.

First, consider self-selection bias. Economic factors, such as yields and farm income, potentially result in positive self-selection bias if they affect both N concentration and treatment distribution. Prokopy et al. (2019) find that yields and farm income have positive effects on the individual's adoption of agricultural conservation practices. However, I do not find statistically significant correlations between the annual percentage of treated areas under

CSP and either annual gross farm income or corn and soybean yields.¹³ This suggests that these variables do not determine the amount of treated land under CSP at the monitoring basin level.¹⁴ Farm characteristics, such as farm size, percentage row crop, and the distance between farms and waterbody have been found to positively affect individuals’ adoption decisions (Prokopy et al., 2019). However, these factors can potentially be captured by monitoring basin and year fixed effects in the analysis.¹⁵

Another potential selection bias results when government agencies select CSP applicants for funding. Already having demonstrated stewardship by using conservation practices is one of the eligibility criteria for CSP. We do not model individual applications or contracts because we have grouped data at the monitoring basin level and because unsuccessful CSP application data are not publicly available. We have implicitly captured basin-level factors that could contribute to inter-basin variation in treatment levels by including economic controls and year and monitoring basin fixed effects. As we mentioned previously, the individual’s CSP participation decision depends on the characteristics of the farm and farm operator, which change little over time at the monitoring basin level. Another possible source of CSP treatment selection stems from whether the most heavily N-polluted basins are prioritized for selection. We test the correlation between N concentration in the pre-treatment period and the post-treatment percentage of land under CSP in each cross-section, and find no statistically significant relationship.¹⁶

¹³The test results are shown in Appendix Table B.3.

¹⁴Cross correlation tests between the annual percentage of treated lands under CSP and economic factors (i.e., corn yields, soybeans yields, and gross farm income) were performed across years. We find most of them to be statistically insignificant at the .05 level.

¹⁵To check if the model controls for farm size in the fixed effects, we obtained every five-year average (i.e., 2007, 2012, and 2017) farm size at the county level from the Census of Agriculture and aggregate to the basin level. I find the average farm size (i.e., acres per operation) is positively correlated to both treatment and N concentration. However, the change in the standard deviation of average farm size across basins changes little over time. The finding implies that the variation in farm size can be captured by the location fixed effect. Even if the average farm size does change over time, it can be considered a common change among basins since the variation of farm size changes little over time, and hence can be captured by the year fixed effects.

¹⁶The test result is in Appendix Table B.3, and we also show the boxplots of treatment allocation and N concentration across monitoring basins in Appendix Figures C.2 and C.3. The comparisons between the boxplots allow us to visualize the likelihood of obvious treatment trend in the change of pre-treatment N. Besides, we check the correlation between the amount of treatment and the N concentration in each pre-treatment year (i.e., 2006-2009). Again, we do not find these correlations to be significant. Note that

Other threats to bias the estimates may come from N concentration changes that coincide directly with CSP’s subsidized conservation practices but occur outside of the program. If a basin has additional unsubsidized management practices installed simultaneously with CSP treatment, the effect of the CSP on N concentration will be overestimated. As a result, the fixed effects approach is likely to deliver, if anything, estimates that are biased away from zero, providing an upper bound on the treatment effect of the CSP on ambient N concentration.

1.3.4 Results

We demonstrate the estimation results for Equations 3.3 and 1.3 with the treatment of the CSP land share (including all contracts) in Tables 1.2 and 1.4, respectively. We estimate the effect for headwater basins and basins with upstream neighbors separately in columns (2) and (3), as well as for all the monitoring basins in column (1). We also compare the estimation results across three specifications of treatment measurement: (1) all CSP contracts, (2) WQ-related practices under CSP contracts, and (3) WQ-related practices, meanwhile, enhancements, for all the monitoring basins in Tables 1.3 and 1.5

The TWFE estimators show that the direct effect of CSP conservation contracts on ambient N is negative and significant across three different samples. A ten percent increase in land under CSP leads to a decrease in average ambient N levels of 1.0 mg/l for all the basins (1.0 and 0.7 mg/l, respectively, for headwater basins and basins with upstream neighbors). This estimated effect is equivalent to 23 percent of the average N concentration (21% and 18% for headwater basins and basins with upstream neighbors, respectively). Weather conditions interact with treatment to have different impacts on this main effect. Among downstream basins in column (3), drought (PDSI dry conditions) has a reinforcing effect when combined with CSP treatment equal to about half the direct CSP treatment effect. The interactive effect of recent cumulative rainfall has the opposite directional effect of CSP alone on N

exploring the decisions of federal agents on the allocation of subsidized agricultural conservation practices is outside the scope of this analysis and not possible using the data available.

among headwater basins. However, the magnitude of this positive indirect effect is only about three percent of the main effect, and the effect is marginally significant. Drastic dry-to-wet transitions theoretically increase N losses via leaching and dry conditions during the growing season (e.g., late Spring to Summer) combined with recent rainfall are estimated to partially offset the impact of CSP on N readings. However, the indirect effects are not significant for all basins and headwater basins only, while among basins with upstream inflow, it marginally reinforces the main effect.¹⁷

Similar results from TWFE model can be found across different specifications of treatment measurements in Table 1.3. A ten percent increase in CSP land share accounting WQ-related practices (in Column (2)) leads to a decrease in average ambient N levels of 1.1 mg/l, which is about 25 percent of the average N concentration. The identical estimate of the direct effect of CSP land share containing WQ-Enhanced practices can be found in Column (3). It is not surprising, given the fact that most CSP applicants have already implemented conservation practices in their field, so the additional acres treated under CSP contracts are mostly enhancements. The mean CSP land share, including WQ-related practices (1.12%), is 40 percent lower than the land share containing all CSP contracts (1.85%). However, the estimated effects on N concentration are very similar, which implies our model is robust to different specifications of treatment measurements.¹⁸

¹⁷Appendix Table B.4 tabulates the complete results for the estimation of Equation 3.3 with the treatment as CSP land share, including all contracts. The upstream pollutant measurement controls for N spillovers are measured as the average ambient N among all nearest (i.e., single spatial lag) upstream neighbors. The pollution concentrations at the upstream sites determine a significant portion of their immediate downstream neighbors' measurements due to the fate of N and the connectivity of streams and rivers. By directly controlling for these pollution spillovers, the model specification prevents the effect of CSP from being confounded with N and treatment in upstream basins. Drought conditions, a proxy of lower streamflow, decrease N measured in streams, consistent with the hydrology literature (Bowles et al., 2018; Mosley, 2015; van Vliet & Zwolsman, 2008). Rainfall and drastic dry-to-wet conditions increase ambient surface N concentration, which is also consistent with findings in the hydrology literature (Bowles et al., 2018).

¹⁸Appendix Table B.5 includes the complete results for the estimation of Equation 3.3 with three specifications of treatment for all basins. The coefficient estimates of weather controls, i.e., PDSI and drastic dry-to-wet conditions, are consistent across three treatment specifications.

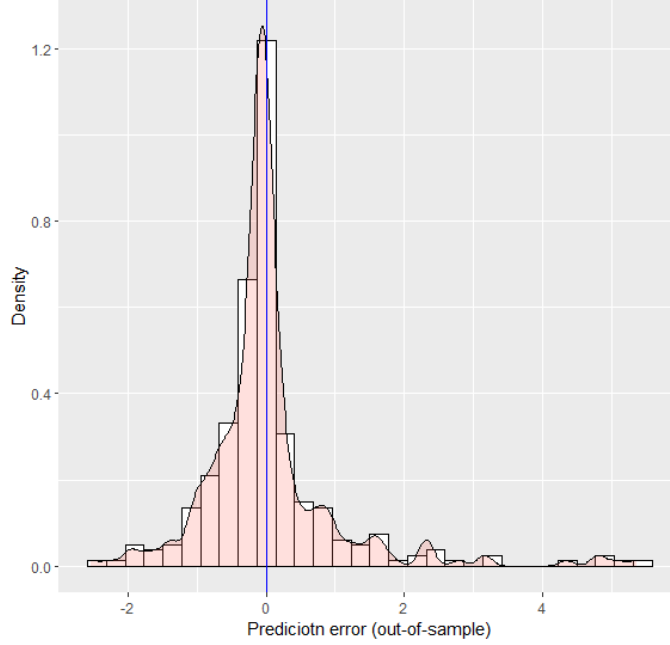


Figure 1.5: Distribution of out-of-sample prediction errors

Notes: The graph shows the distribution of out-of-sample prediction errors for monitoring basins, which have no CSP conservation contracts.

Before we discuss the result for the estimation of Equation 1.3, we first check the validity and performance of the ML predictions. To perform a fully out-of-sample test (, or called forward-predicting capability test) of the ML prediction approach, we inspect prediction errors at untreated monitoring basins in the post-treatment period. If the prediction model performs well, then we expect to see that the out-of-sample prediction errors for untreated basins are close to zero.¹⁹ Figure 1.5 plots the distribution of prediction errors for untreated basins in the post-treatment period. Although there are only six untreated basins in our study region, the distribution is within a standard deviation of N measurements and nearly centered around zero, which provides us evidence that the ML approach performs well for

¹⁹Beside the approach of visualizing prediction errors in the post-treatment period among untreated bains, I use the last year (2009)in the pre-treatment period as an out-of-sample year to check if ML prediction model is valid. That is, the ML prediction model is built with the years 2003 to 2008 in the pre-treatment period, and the year 2009 is used to perform out-of-sample prediction. Appendix Figure C.10 plots the density of prediction errors for all basins in 2009. Although only 80% of the pre-period data is used to construct the ML model, the prediction errors are within a standard deviation of N and nearly centered around zero, which supports the validity of the ML model.

water quality prediction even out-of-sample.²⁰

The estimation results for Equation 1.3 are reported in Table 1.4. We find that a ten percent increase in the land area treated under CSP leads to a decrease in average ambient N level of 0.5 mg/l across all monitoring basins (0.4 and 0.5 mg/l for headwater basins and basins with upstream neighbors, respectively). The estimated effect is about 12 percent of the average N level (9% and 12% for headwater basins and basins with upstream neighbors, respectively).²¹ The indirect effect of CSP with drought is about 70% of the magnitude of the main effect. We find that recent rainfall and dry soils combined with rainfall (three-way interaction) minimally mediate the effect of CSP, where the positive indirect effect of CSP is only one percent of the main effect. The estimation results for Equation 1.3 when comparing three specifications of CSP treatment for all basins are shown in Table 1.5.²² Similar coefficient estimates can be found across treatment specifications. A ten percent increase in the CSP land shares for WQ and WQ-enhanced practices (Columns (2) and (3), respectively) lead to a decrease in the mean in-stream N level of 0.5 mg/l, which is about 12 percent of the mean N level. Our findings are robust to different treatment specifications.

Overall, both approaches give us qualitatively similar results from the estimation of different models from different data constructed to estimate the same policy treatment effect. The estimated effect size based on the TWFE model of the difference between observed treated and ML counterfactual water quality is more consistent across all three types of basins than for the TWFE models without the post-treatment counterfactual.

²⁰To further check if the zero-centered distribution of out-of-sample prediction errors for untreated basins undermines identification, we create an out-of-sample indicator and regress the prediction errors (i.e., $N - \hat{N}$) on the indicator along with controls and fixed effects. The estimation equation is similar to Equation 1.3, but we change the treatment measurement to the out-of-sample indicator: $N_{it} - \hat{N}_{it} = \beta out-of-sample_{it} + \mathbf{X}_{it}'\boldsymbol{\gamma} + \rho \sum_{k \in \Lambda_{i-1}} \psi_k(N_{kt} - \hat{N}_{kt}) + \tau_t + \theta_y + \eta_i + \epsilon_{it}$, where $out-of-sample_{it}$ is a dummy, equal to one during the post-treatment prediction period. We do not find the indicator to be statistically significant in Table B.8. The result provides evidence that prediction error has a minimal impact on the outcome of interest.

²¹Appendix Table B.6 includes the complete results for all variables in estimation Equation 1.3.

²²Appendix Table B.7 includes the complete results for all variables in estimation Equation 1.3 with different treatment specifications.

Table 1.2: Panel two-way fixed effects (TWFE) for monitoring basins with distance-weighted treatment

	<i>Dependent variable:</i>		
	Nitrogen concentration (mg/l)		
	(1) All basins	(2) Headwater basins	(3) Basins w/ upstream neighbors
Treatment (CSP)			
Pct. of Treated Ac.	-0.096** (0.039)	-0.099** (0.040)	-0.067*** (0.017)
Pct. of Treated Ac. $\times$ PDSI (+:Dry)	-0.034 (0.021)	-0.033 (0.022)	-0.034** (0.013)
Pct. of Treated Ac. $\times$ 7-D Cum. Rain	0.002 (0.001)	0.003* (0.001)	-0.002 (0.0010)
Pct. of Treated Ac. $\times$ 7-D Cum. Rain $\times$ PDSI (+:Dry)	0.0001 (0.0004)	0.0003 (0.0005)	-0.0007* (0.0003)
Observations	3,336	1,680	1,656
mean N concentration	4.337	4.821	3.847
Fixed effects:			
Month	Yes	Yes	Yes
Year	Yes	Yes	Yes
Basin	Yes	Yes	Yes
EQIP	Yes	Yes	Yes
Weather	Yes	Yes	Yes
Socioeconomic Char.	Yes	Yes	Yes
Pollution Spillovers	Yes	No	Yes
R ²	0.56945	0.51017	0.78996

Note: Each column presents the results for estimating Equation 3.3 with different sets of observations. Models 2 and 3 are analyses for headwater basins and basins with upstream neighbors, respectively. Column 1 is the analysis for all basins. Controls for other conservation contracts include the percentage of lands under EQIP. PDSI is a drought index. 7-day recent cumulative precipitation and their interaction are the weather controls. Socioeconomic characteristics controls are gross farm income and corn and soybean yields. Month fixed effects control for seasonality of N concentrations, and year fixed effects capture the trend of water pollution. Monitoring basin fixed effects capture time-invariant determinants of water pollution specific to the basin. Robust standard errors are in parentheses and are clustered at the monitoring basin and year level. Appendix Table B.4 reports the complete estimation results. Asterisks denote p-value<0.1(*), <0.05(**), or <0.01(***)

Table 1.3: Panel two-way fixed effects (TWFE) for monitoring basins with three specifications of treatment

	<i>Dependent variable:</i>		
	Nitrogen concentration (mg/l)		
	(1) All	(2) WQ	(3) WQ-Enhancement
Treatment (All)			
Pct. of Treated Ac.	-0.096** (0.039)		
Pct. of Treated Ac. $\times$ PDSI (+:Dry)	-0.034 (0.021)		
Pct. of Treated Ac. $\times$ 7-D Cum. Rain	0.002 (0.001)		
Pct. of Treated Ac. $\times$ 7-D Cum. Rain $\times$ PDSI (+:Dry)	0.0001 (0.0004)		
Treatment (WQ)			
Pct. of Treated Ac.		-0.112** (0.047)	
Pct. of Treated Ac. $\times$ PDSI (+:Dry)		-0.034 (0.026)	
Pct. of Treated Ac. $\times$ 7-D Cum. Rain		0.003 (0.002)	
Pct. of Treated Ac. $\times$ 7-D Cum. Rain $\times$ PDSI (+:Dry)		0.0003 (0.0006)	
Treatment (WQ-Enh.)			
Pct. of Treated Ac.			-0.112** (0.047)
Pct. of Treated Ac. $\times$ PDSI (+:Dry)			-0.034 (0.026)
Pct. of Treated Ac. $\times$ 7-D Cum. Rain			0.003 (0.002)
Pct. of Treated Ac. $\times$ 7-D Cum. Rain $\times$ PDSI (+:Dry)			0.0003 (0.0006)
Observations	3,336	3,336	3,336
mean N concentration	4.337	4.337	4.337
Fixed effects:			
Month	Yes	Yes	Yes
Year	Yes	Yes	Yes
Basin	Yes	Yes	Yes
EQIP	Yes	Yes	Yes
Weather	Yes	Yes	Yes
Socioeconomic Char.	Yes	Yes	Yes
Pollution Spillovers	Yes	Yes	Yes
R ²	0.56945	0.56676	0.56678

Note: Each column presents the results for estimating Equation 3.3 with different treatment specifications for all basins. Models 1, 2, and 3 are analyses with the treatment capturing (1) all practices under CSP, (2) WQ-related practices, and (3) WQ-related practices, which are enhancements. Controls for other conservation contracts include the percentage of lands under EQIP. PDSI is a drought index. 7-day recent cumulative precipitation, and their interaction are the weather controls. Socioeconomic characteristics controls are gross farm income, and corn and soybean yields. Month fixed effects control for seasonality of N concentrations, and year fixed effects capture the trend of water pollution. Monitoring basin fixed effects capture time-invariant determinants of water pollution specific to the basin. Robust standard errors are in parentheses and are clustered at the monitoring basin and year level. Appendix Table B.5 reports the complete estimation results. Asterisks denote p-value<0.1(*), <0.05(**), or <0.01(***)

Table 1.4: TWFE of observed total Nitrogen (N) minus ML predicted counterfactual ($\hat{N}$)

	<i>Dependent variable:</i>		
	$N - \hat{N}$		
	(1) All basins	(2) Headwater basins	(3) Basins w/ upstream neighbors
Treatment (CSP)			
Pct. of Treated Ac.	-0.048** (0.019)	-0.043* (0.022)	-0.050*** (0.011)
Pct. of Treated Ac. $\times$ PDSI (+:Dry)	-0.033*** (0.008)	-0.034*** (0.009)	-0.033*** (0.006)
Pct. of Treated Ac. $\times$ 7-D Cum. Rain	0.002*** (0.0003)	0.002*** (0.0003)	-0.0005 (0.0008)
Pct. of Treated Ac. $\times$ 7-D Cum. Rain $\times$ PDSI (+:Dry)	0.0005*** (0.00005)	0.0007** (0.0002)	-0.0003 (0.0003)
Observations	3,285	1,642	1,643
mean N concentration	4.337	4.337	4.333
Fixed effects:			
Month	Yes	Yes	Yes
Year	Yes	Yes	Yes
Basin	Yes	Yes	Yes
EQIP	Yes	Yes	Yes
Weather	Yes	Yes	Yes
Socioeconomic Char.	No	No	No
Pollution Spillovers ($N_{up} - \hat{N}_{up}$)	Yes	No	Yes
R ²	0.34885	0.22557	0.54098

Note: Each column presents the results for estimating Equation 1.3 with different sets of observations. Columns 2 and 3 are analyses for headwater basins and basins with upstream neighbors, respectively. And, column 1 is the analysis for all basins. Controls for other conservation contracts include the percentage of lands under EQIP and the interaction with weather. Drought index (i.e., PDSI), recent cumulative precipitation, and their interaction term are the weather control. We do not include the socioeconomic characteristics as controls since, at the stage of ML prediction, these confounding factors have been taken care of nonparametrically. Month and year fixed effects control for the seasonality and the trend of N concentration, respectively. Monitoring basins fixed effect adjusts for any cross-sectional differences in baseline pollution rates and ensures the identification comes only from changes in N concentration within each basin over time. Robust standard errors are in parentheses and are clustered at the monitoring basin and year level. Asterisks denote p-value<0.1(*), <0.05(**), or <0.01(***)

Table 1.5: TWFE of observed total Nitrogen (N) minus ML predicted counterfactual ($\hat{N}$) across three treatment specifications for all monitoring basins

	<i>Dependent variable:</i>		
	(1) All	(2) WQ	(3) WQ-Enhancement
Treatment (All)			
Pct. of Treated Ac.	-0.048** (0.019)		
Pct. of Treated Ac. $\times$ PDSI (+:Dry)	-0.033*** (0.008)		
Pct. of Treated Ac. $\times$ 7-D Cum. Rain	0.002*** (0.0003)		
Pct. of Treated Ac. $\times$ 7-D Cum. Rain $\times$ PDSI (+:Dry)	0.0005*** (0.00005)		
Treatment (WQ)			
Pct. of Treated Ac.		-0.048** (0.021)	
Pct. of Treated Ac. $\times$ PDSI (+:Dry)		-0.038*** (0.009)	
Pct. of Treated Ac. $\times$ 7-D Cum. Rain		0.003*** (0.0004)	
Pct. of Treated Ac. $\times$ 7-D Cum. Rain $\times$ PDSI (+:Dry)		0.0007*** (0.0002)	
Treatment (WQ-Enh.)			
Pct. of Treated Ac.			-0.049** (0.021)
Pct. of Treated Ac. $\times$ PDSI (+:Dry)			-0.038*** (0.009)
Pct. of Treated Ac. $\times$ 7-D Cum. Rain			0.003*** (0.0004)
Pct. of Treated Ac. $\times$ 7-D Cum. Rain $\times$ PDSI (+:Dry)			0.0007*** (0.0002)
Observations	3,285	3,285	3,285
mean N concentration	4.337	4.337	4.337
Fixed effects:			
Month	Yes	Yes	Yes
Year	Yes	Yes	Yes
Basin	Yes	Yes	Yes
EQIP	Yes	Yes	Yes
Weather	Yes	Yes	Yes
Socioeconomic Char.	No	No	No
Pollution Spillovers ($N_{up} - \hat{N}_{up}$)	Yes	Yes	Yes
R ²	0.34885	0.34656	0.34652

Note: Each column presents the results for estimating Equation 1.3 with different treatment specifications for all basins. Models 1, 2, and 3 are analyses with the treatment capturing (1) all practices under CSP, (2) WQ-related practices, and (3) WQ-related practices, which are enhancements. Controls for other conservation contracts include the percentage of lands under EQIP. Drought index (i.e., PDSI), recent cumulative precipitation, and their interaction term are the weather control. We do not include the socioeconomic characteristics as controls since, at the stage of ML prediction, these confounding factors have been taken care of nonparametrically. Month and year fixed effects control for the seasonality and the trend of N concentration, respectively. Monitoring basins fixed effect adjusts for any cross-sectional differences in baseline pollution rates and ensures the identification comes only from changes in N concentration within each basin over time. Robust standard errors are in parentheses and are clustered at the monitoring basin and year level. Asterisks denote p-value < 0.1(*), < 0.05(**), or < 0.01(***)

1.3.5 Robustness of Results

This section discusses the possibility of endogenous water quality sampling and explores the effects of CSP on placebo outcomes to support the identification. Unbalanced water quality data may threaten identification if water quality sampling is more likely to occur under certain circumstances that also impact nutrient concentrations. A pertinent example of this would be if government agents are more likely to collect water quality samples on the same day or a few days after a rainfall event because precipitation triggers agricultural runoff that pollutes receiving waterbodies. Thus, we control for recent cumulative rainfall in our estimated models. Another potential threat to identification would occur if federal agents were more likely to sample monitoring basins with higher shares of CSP lands. Another plausible problem for identification would arise if water quality were sampled more frequently, where treatment levels are higher when precipitation events occur. Empirically, a statistically significant interaction effect between treatment and precipitation could be a reflection of sampling endogeneity and raise concerns about the estimator being biased (Raff & Meyer, 2021).

To test for such sampling endogeneity, we examine the effect of CSP and near-term precipitation on the odds ratio of water quality sampling at a given monitoring basin on a given day of the month.²³ We first create a balanced monthly panel dataset of all the monitoring basins in all months, and link them with rainfall events and the levels of CSP treatment. Because water quality is not sampled every month in every basin, we must construct an assumed sampling date for every month when a monitoring station sample was not actually collected to be able to test whether such sampling (or non-sampling) is somehow endogenous. For all months in all locations when a sample is not taken in the unbalanced monitoring data, we assign an assumed sampling date based on the observed basin-specific average sampling interval (mean days between when samples are collected over the entire

²³We also check if the annual mean percentage of land under CSP changes the annual counts of water quality sampling in Appendix Table B.9.

year). Then, we estimate the following equation using the logistic regression:

$$WQS_{it} = \beta_1 CSP_{it} + \beta_2 R_{it} + \beta_3 CSP_{it} \times R_{it} + \tau_t + \theta_y + \eta_i + \epsilon_{it} \quad (1.5)$$

The notation is similar to Equation 3.3, but, here, the dependent variable, WQS_{it} , is a dummy that indicates the availability of a water quality sample at a given monitoring basin i on a given day of the month t . For those basins and months when water quality measurements were taken but not usable, we treat WQS_{it} to be one because water quality samples were obtained, but readings were reported as being "not applicable" (i.e., there is no systematic non-sampling, rather a usable sample). Precipitation, R_{it} , was measured using four different multi-day periods of prior cumulative rainfall: (1) 3-day, (2) 7-day, (3) 14-day, and (4) 21-day cumulative rainfall.

Table D.5 shows the results for the estimation of Equation 3.5 using logistic regression. We do not find the percentage of CSP, rainfall events, or their interactions to have statistically significant effects on the probability of water quality being sampled. Also, the coefficient estimates are close to zero, implying that the odds ratio of water quality sampling is near one. In sum, rainfall events do not influence the likelihood that a given monitoring basin is sampled, regardless of whether there are lands treated under CSP. Further, the probability that water quality is measured on days with rainfall events does not change as the percentage of land under CSP increases or decreases. Therefore, we conclude that the unbalanced nature of the water quality sampling data does not bias our estimates.

Next, we discuss the possibility of model misspecification by estimating Equation 3.3 with placebo outcomes. Our main specification is likely to be misspecified if the percentage of land under CSP affects water quality measurements for pollutants unrelated to agricultural production that are most likely to be influenced by the CSP. To test this, we identify water pollutants that are not clearly related to field crops (e.g., corn, soybeans, wheat) but

ubiquitous throughout the US and IL and included in ambient water quality monitoring. The selected placebo outcome pollutant is arsenic (As), which has no established biological function for row crops and is a priority pollutant of great public health significance (Tchounwou et al., 2012). Table 1.7 tabulates the results for estimating Equation 3.3 with arsenic as the dependent variable for all monitoring basins with three specifications of treatments. The percentage of land under CSP does not have any impact on arsenic in surface streams and rivers in our study area, as hypothesized under the placebo test. These results help justify our identification strategy and the validity of our primary estimates.

Table 1.6: Effect of CSP and recent rainfall on water quality sampling

	<i>Dependent variable:</i>			
	Sampling dummy			
	(1)	(2)	(3)	(4)
Pct. of Treated Ac. (CSP)	-0.019 (0.016)	-0.022 (0.017)	-0.020 (0.016)	-0.026 (0.017)
3-D Cum. Rain	0.0000 (0.003)			
7-D Cum. Rain		0.0007 (0.003)		
14-D Cum. Rain			-0.0003 (0.002)	
21-D Cum. Rain				-0.0007 (0.001)
Pct. of Treated Ac.(CSP) $\times$ 3-D Cum. Rain	-0.0005 (0.0007)			
Pct. of Treated Ac.(CSP) $\times$ 7-D Cum. Rain		0.0000 (0.0004)		
Pct. of Treated Ac.(CSP) $\times$ 14-D Cum. Rain			-0.0001 (0.0002)	
Pct. of Treated Ac.(CSP) $\times$ 21-D Cum. Rain				0.0001 (0.0002)
Month fix effects	Yes	Yes	Yes	Yes
Year fix effects	Yes	Yes	Yes	Yes
Basin fix effects	Yes	Yes	Yes	Yes
Observations	6,115	6,115	6,115	6,115

Note: Each column shows the logistic regression results for estimating Equation 3.5 with different days of cumulative precipitation. The outcome of interest is the odds ratio of water quality sampling. Each specification includes month, year, and monitoring basin fixed effects. CSP is measured as the percentage of lands under contracts. The rainfall events are specified as the cumulative rainfall of 3-, 7-, 14-, 21-day prior. Robust standard errors are in parentheses and are clustered at the monitoring basin and year levels. Asterisks denote p-value <0.1 (*), <0.05 (**), or <0.01 (***)

Table 1.7: Placebo test for all monitoring basins

	<i>Dependent variable:</i>		
	Arsenic (ug/l)		
	(1) All	(2) WQ	(3) WQ-Enh.-EAP
Treatment (All)			
Pct. of Treated Ac.	0.048 (0.034)		
Pct. of Treated Ac. $\times$ PDSI (+:Dry)	0.005 (0.004)		
Pct. of Treated Ac. $\times$ 7-D Cum. Rain	-0.0007 (0.0006)		
Pct. of Treated Ac. $\times$ 7-D Cum. Rain $\times$ PDSI (+:Dry)	-0.0002 (0.0001)		
Treatment (WQ)			
Pct. of Treated Ac. (WQ)		0.044 (0.042)	
Pct. of Treated Ac. (WQ) $\times$ PDSI (+:Dry)		0.006 (0.007)	
Pct. of Treated Ac. (WQ) $\times$ 7-D Cum. Rain		-0.0007 (0.0009)	
Pct. of Treated Ac. (WQ) $\times$ 7-D Cum. Rain $\times$ PDSI (+:Dry)		-0.0003 (0.0002)	
Treatment (WQ-Enh.)			
Pct. of Treated Ac. (Enh.)			0.042 (0.041)
Pct. of Treated Ac. (Enh.) $\times$ PDSI (+:Dry)			0.006 (0.007)
Pct. of Treated Ac. (Enh.) $\times$ 7-D Cum. Rain			-0.0007 (0.0009)
Pct. of Treated Ac. (Enh.) $\times$ 7-D Cum. Rain $\times$ PDSI (+:Dry)			-0.0003 (0.0002)
mean dep. var.	3.123	3.123	3.123
Fixed effects:			
Month	Yes	Yes	Yes
Year	Yes	Yes	Yes
Basin	Yes	Yes	Yes
EQIP	Yes	Yes	Yes
Weather	Yes	Yes	Yes
Socioeconomic Char.	Yes	Yes	Yes
Pollution Spillovers	Yes	Yes	Yes
Observations	1,555	1,555	1,555
R ²	0.35044	0.34979	0.35000

Note: These falsification tests are estimated by Equation 3.3 with arsenic surface water concentrations as placebo outcomes. Weather controls include the drought index, rainfall events, and their interaction. Upstream arsenic is controlled as pollution spillovers. Economic controls are gross farm income and corn and soybean yields. Last, we include the same sets of fixed effects as our main specification. Month fixed effect captures the seasonality of water pollution, and year fixed effect captures the overall trend of pollution. Monitoring basin fixed effects control for time-invariant unobservables. Robust standard errors are in parentheses and are clustered at the monitoring basin and year levels. Asterisks denote p-value<0.1(*), <0.05(**), or <0.01(***)

1.4 Conclusions

This study explores the relationship between agricultural conservation practice adoption that takes place under active CSP contracts and surface water quality outcomes in the Illinois River Basin (ILRB). The analysis is unique in some ways. First, the carefully constructed observation units capture hydrological detail from the National Hydrography Dataset that have been used in a few empirical economic research (Keiser & Shapiro, 2019; Liu et al., 2022; Paudel & Crago, 2020; Raff & Meyer, 2021; Sun et al., 2018). The constructed monitoring basins play an important role in measuring the environmental benefits of agricultural conservation contracts by isolating their influence on downstream ambient surface water quality while controlling for weather conditions and land use.

Second, the novel dataset is both longitudinally and spatially explicit, which allows the analysis to isolate the impact of land enrollment in the cost-share program on ambient water quality separately from non-agricultural sources and pollution spillovers from upstream. Last, the *ex post* econometric estimates provide an alternative to *ex ante* hydrological simulation modeling. Combining panel fixed effects with novel machine learning methods allows us to capturing confounding trends and address other possible threats to identification. We take advantage of within-basin within-time-period variation for identification while considering the non-linearity of water pollutants and the set of control variables in a highly flexible and computationally feasible way.

This study finds that the installation of agricultural conservation practices under CSP reduces ambient surface N in the ILRB. The findings from both the conventional TWFE estimation approach and the integration with the novel ML method are robust to the type of monitoring basin (with or without upstream pollution spillovers). Overall, the findings suggest a 10% increase in the share of land enrolled under CSP reduces average ambient surface N concentration by 23% and 12% from the TWFE and ML-TWFE approach, respectively. The direct impact of CSP is also influenced by weather conditions, such as droughts, recent precipitation, and extreme dry-to-wet transitions. Drought conditions

interacted with treatment decrease N measured in streams about 70% of the direct impact, while the interactive effects of rainfall events and drastic dry-to-wet change minimally offset the estimated main effect.

The Illinois Nutrient Loss Reduction Strategy (NLRs) has an interim goal to reduce nitrate-nitrogen load by 15 percent by 2025 and ultimately by 45 percent in 2035. This study finds that at the mean level of CSP contract coverage from 2010 to 2015, the impact on N concentration has been a 12-23% reduction of the mean of N across treated sub-watersheds in the ILRB. Although this study has explored the average treatment effect of a single conservation program, the scale of nutrient loss reduction possible under different treatment intensities remains to be explored. A future study could extend the work to multiple river basins within the Upper Mississippi River that contribute the largest amount of N to the Gulf of Mexico.

Chapter 2

ESTIMATING THE IMPACT OF COVER CROP ADOPTION ON AMBIENT NITROGEN CONCENTRATION IN THE UPPER MISSISSIPPI RIVER DRAINAGE

2.1 Introduction

Non-point source (NPS) pollution from agriculture has been identified as the leading cause of water quality impairments in the United States (U.S.). The increasing percentage of land covered by crops and the heavy use of fertilizer and manure nutrients in modern intensive agriculture harm the health of local streams and rivers (US-EPA, 2015). Excess nutrients (e.g., phosphorus, P, nitrogen, N) degrade waterways, and eutrophication leads to hypoxia or dead zones in water bodies. To mitigate these water quality impacts, federal and state governments encourage and incentivize farm operators to adopt best management practices

(BMPs) through agricultural cost-share programs. Agricultural conservation practices may be structural or non-structural and many are relatively low cost and effective in reducing nutrient and sediment losses (Guiling et al., 2006). This study explores the environmental outcomes of one such practice, cover crops (CCs), on ambient water quality in the U.S. Corn Belt.

CCs are over-wintering crops that are usually established and grown after row crops are harvested and remain until the next crop is planted. They are then killed (referred to as "terminated") and left on the surface as residue or tilled into the soil before planting a summer cash crop. The soil health improvements that come with implementing CCs imply various on- and off-farm benefits (USDA-NRCS, 2022a). Quick-growing CCs during the winter can hold soil in place to reduce erosion, decrease the breakdown of soil aggregates, and further protect against runoff (Blanco-Canqui et al., 2013; De Baets et al., 2011). Residue from killed CCs increases water infiltration and reduces evaporation, leading to greater drought resilience (Myers et al., 2019). Adoption of CCs can reduce sediment runoff and nutrient loss from croplands, thereby mitigating NPS pollution and improving water quality (Kladivko et al., 2014).

Agronomic studies have explored the effect of CCs on water quality based on experiments and field trials and have found that the effectiveness of CCs at reducing sediment and nutrient runoff and N leaching can vary based on factors, such as CC biomass amount, species, tillage and other management, climate, and soil texture (Blanco-Canqui, 2018; Meisinger & Ricigliano, 2017; D. R. Smith et al., 2017). A global meta-analysis by Blanco-Canqui (2018) found that CC performance on water quality parameters can be complex and site-specific. Ritter et al. (1998) found low effectiveness of CCs for reducing N leaching when CCs are grown under sub-optimal soil and climate conditions for the primary cash crops. CCs that produce a large amount of biomass will dominate how effective CCs are for taking up nutrients and preventing leaching (Blanco-Canqui et al., 2014).

Field experiments that have directly assessed the effect of CCs on water quality

may have limited implications in practice for the following reasons. First, the variation of CC performance on water parameters suggests that the amount of nutrient loss reduction from adopting CCs is influenced by site-specific factors, and thereby the experimental results based on samples at certain locations may not generalize to regions with different soil textures and climate conditions. Specifically, Blanco-Canqui (2018) indicates that few field-level studies are from the Midwestern U.S., where nutrient losses from agricultural lands are a significant concern. Second, CC effectiveness not only varies from site to site but also from year to year at the same site depending on the annual weather conditions (Blanco-Canqui et al., 2014). The findings imply that cross-sectional experimental studies may be insufficient to conclude the average effects of decentralized CC adoption. Third, changes in nutrient or sediment loss at the field or farm level cannot be easily related to changes in ambient pollution concentration farther from the farm or directly scaled to a river basin; this despite ambient water quality being the driver of stated policy objectives and the basis for tracking progress. We study observed ambient water quality outcomes directly.

The broader applied economics literature has investigated the role of agri-environmental programs in the overall adoption of cover crops (Park et al., 2023), reviewed issues of additionality and targeting for cover crop adoption (Pannell & Claassen, 2020), and considered the potential role of cover cropping in voluntary carbon markets (Wongpiyabovorn et al., 2023). This study fills a gap in the literature identifying the effect of CCs on ambient water quality at the watershed scale. Kladvko et al. (2014) uses a simulation model (the Root Zone Water Quality Model) to evaluate the effect of CCs on nitrate reduction. This simulation tool models the complex relationships between landscape and water quality that determine contaminant fate and transport in rivers and lakes by capturing a watershed’s essential biophysical and hydrological processes. However, the assumed scenarios in the conceptual model may have limitations in reflecting current management practices, and the underlying parameters estimated from different studies that are not at the methodological frontier can affect the reliability of the simulation results (Keiser et al., 2019). Besides, modeling studies

do not consider the behavioral adjustments (e.g., slippage and spillover effects) that may accompany practice adoption (Fleming et al., 2018).¹

Our study quantifies the effect of CCs on ambient total nitrogen measures in rivers and streams using remotely-sensed CC data at the watershed level across eleven Corn Belt states in the U.S. from 2008 to 2018. We provide *ex post* econometric estimates of the effect of conservation practices on ambient surface water quality distinct from the modeling literature that relies on *ex ante* engineering simulation models. This is important because water quality improvements predicted by hydrological simulations have not been widely realized to date. Hydrological modeling research is extensive and very important, but *ex ante* modeling scenarios often consider management changes like planting CCs across the entire landscape or in targeted locations with the highest expected pollution abatement effect rather than the non-uniform deployment of these practices over much more limited acreage that we observe today. We employ a linear panel fixed effect model in the analysis, that uses watershed fixed effects to control for basin-specific heterogeneity such as soil texture and land slope, and explicitly control for time-varying confounders (e.g., drought, precipitation, and crop yield). We control for upstream-to-downstream spatial spillovers of nutrients to isolate the impact of CC adoption on surface water quality. We also introduce the second-order polynomial term to explore the nonlinear relationship between the CC adoption rate and in-stream N. We find that every percent increase in the share of cropland planting CCs is estimated to lead to a range of 0 to 0.06 mg/l decrease in annual mean ambient N concentration when the CC implementation rate is lower than 31.8%. The amount of abatement is about 0 to 2 percent of the average N concentration in the study area.

This study contributes to the recent literature using reduced-form econometrics to study water quality outcomes. Existing studies have evaluated policies or programs related to water quality improvement (Keiser & Shapiro, 2019; Liu et al., 2022; Sun et al., 2018). Previous literature has also explored the relationship between agriculture and nutrient

¹Carefully designed behavioral experiments may be able to address some of these issues. We are grateful to paper discussant Sheila Olmstead for making this point.

concentration in ambient surface water quality (Metaxoglou & Smith, 2022; Paudel & Crago, 2020; Raff & Meyer, 2021). Although our focus is not on specific agri-environmental policies, our study can inform policymakers and researchers on the cost-effectiveness of investments in specific conservation practices to improve surface water quality. An important feature of our analysis is carefully modeling the complicated spatial networks of streamflow and the spatial spillovers of nutrients to isolate the effect of conservation practice adoption that varies across the landscape and over time. The constructed monitoring basins allow us to estimate the direct effect of aggregate CC adoption (Sun et al., 2018). Such findings may help improve the effectiveness of implementing and designing conservation programs in the future.

2.2 Data

2.2.1 Cover crop data

We obtain CC data for the years 2008 to 2018 from the Operational Tillage Information System (OpTIS), an automated system to detect and map residue cover across the U.S. Corn Belt (Hagen et al., 2020). The OpTIS is a software tool that analyzes remotely sensed agricultural landcover data and provides trends of cover cropping and conservation tillage (CT). OpTIS has previously been used to investigate the relationship between CT and soybean yield, land values in the Midwest USA, and soil erosion (B. Chen et al., 2021; L. Chen et al., 2022b, 2022a). Our study exploits the OpTIS (version 1) cover crop acreage estimates at the 8-digit U.S. Geological Survey (USGS) Hydrologic Unit Code (HUC8) watershed level, to construct the treatment variable for regression analysis. The OpTIS uses a time series of the Normalized Difference Vegetation Index (NDVI), extending from November through July in each crop year, to identify winter cover crops.² The OpTIS reports CC acres for four crop categories (i.e., corn, soybeans, small grains, and all other crops) based on the cash crop

²The OpTIS defined crop year as 1 November of the previous year through 31 October of the current year. For example, the 2008 crop year extends from 1 November 2007 through 31 October 2008.

harvested before the CC is detected in the over-winter period. We sum over all crop types to get the total CC acres and divide by the total cropland acres in each observation unit to construct the annual practice treatment variable.

Figure 2.1 displays CC adoption rates by constructed monitoring basin (details in the next section) in our study. Substantial variation in CC adoption rates can be found across basins over time. The data show relatively lower CC adoption rates in southern Wisconsin and higher in the southern Corn Belt. Figure 2.1 also indicates an increasing trend of CC adoption rates across monitoring basins over time that is seen more directly in a plot of the average annual CC adoption rate over the entire study region in figure 2.2. A noted increase in the percentage of cropland acres with CCs was first detected by OpTIS in the year 2012 and further surged in the year 2016; in 2017, the aggregate adoption rate reached over six percent, which is three times greater than the mean annual CC planting rate over all years in the data. The expanded use of CCs documented in the OpTIS data has also been documented using farmer survey data from the Agricultural Resource Management Survey , the Census of Agriculture and other remote-sensing based studies (“USDA ERS - Agricultural Act of 2014”, 2014; USDA-ERS, 2022; Wallander et al., 2021; Zhou et al., 2022).

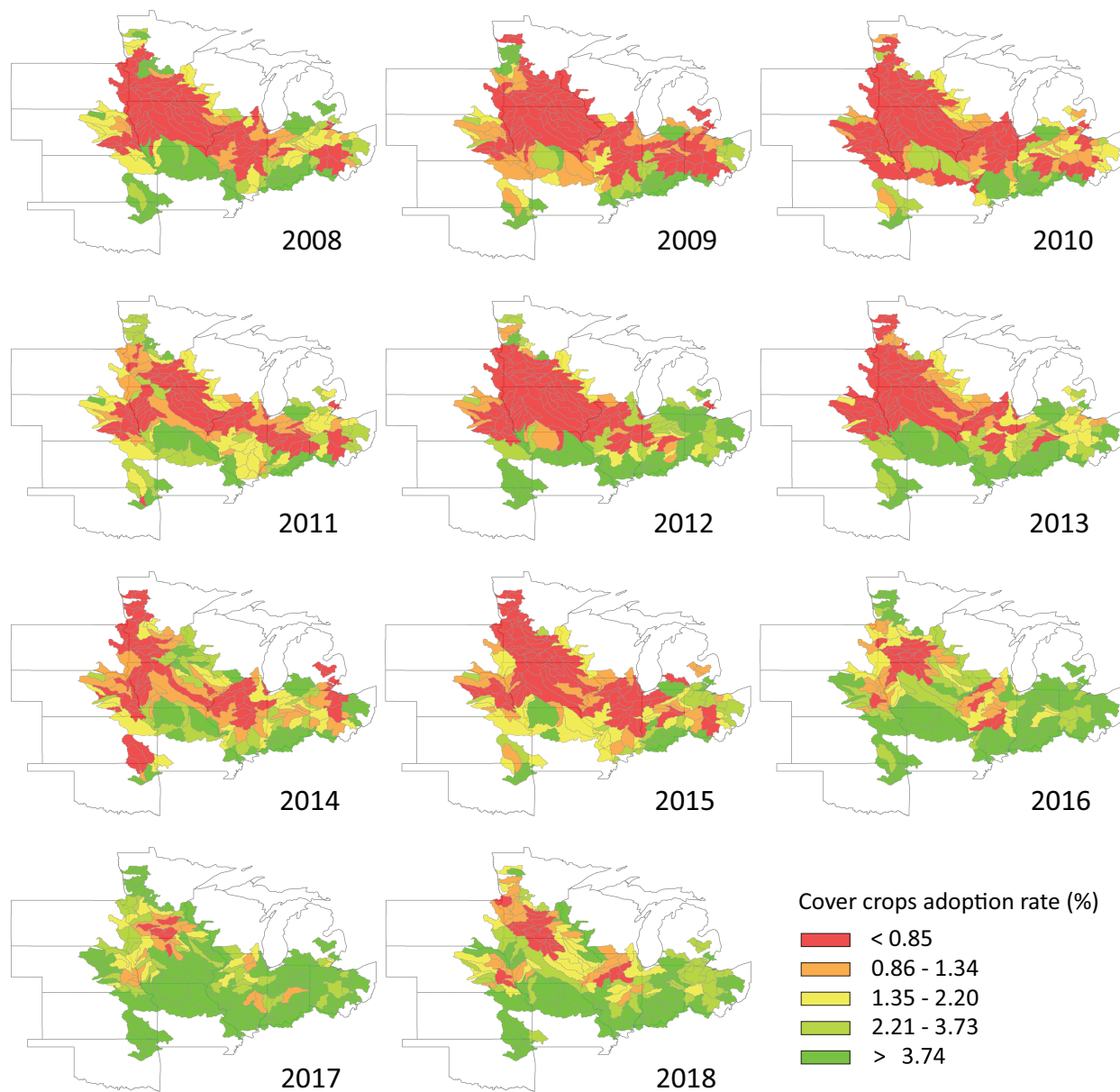


Figure 2.1: Annual percentage of cropland adopting cover crops by water quality monitoring basin, 2008-2018

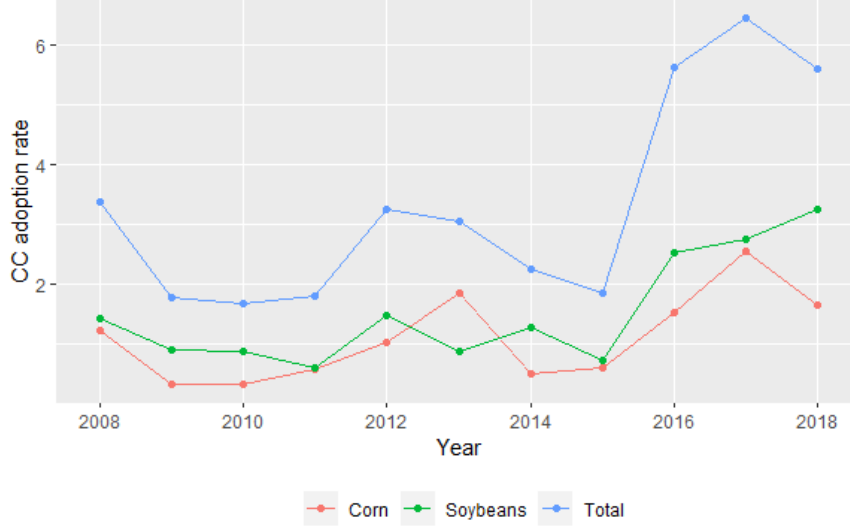


Figure 2.2: Average annual cover crop adoption rate in all monitoring basins studied, 2008 to 2018

2.2.2 Watershed hydrology network

The monitoring basins and spatial connectivity in our econometric model are constructed based on the water flow direction and connectivity of HUC8s from the USGS Watershed Boundary Dataset (WBD) and the National Hydrography Dataset (NHD).³ Based on the direction of streamflow and the location (i.e., longitude and latitude) of water monitoring sites obtained from the Water Quality Portal (WQP), all HUC8s are matched to the nearest downstream monitoring stations and are aggregated to form unique monitoring basins that are our unit of analysis controlling for land use land cover, socioeconomic, and weather variables. Spatial units smaller than HUC8s are not available due to the spatial resolution of the OpTIS data the authors were able to obtain. Each monitoring basin is constructed by identifying all contiguous HUC8s that drain the land located between two monitoring stations, one upstream and one downstream, of this land. A spatial connectivity matrix is constructed that identifies which monitoring basins are located upstream (i.e.,

³The R-code we employ to aggregate the HUC8s to construct monitoring basins was originally developed by Shanxia Sun, Department of Economics and Finance, Shanghai University. More details on constructing monitoring basins, flow mapping, and mapping error diagnosis are provided in appendix A.

first-order-neighbor monitoring basin) of every other monitoring basin and which monitoring basins do not have any upstream neighbors, referred to as headwater basins without any inflow.

The process delineates a total of 158 monitoring basins, with 54 basins having upstream inflow (hereafter, "downstream" basins) and 104 headwater basins. There are 23 headwater basins that have monitoring sites located in the uppermost part of the basin which are used to control for upstream pollution inflow similar downstream basins. Figure 2.3 shows where the two types of basins in our data are located across the study region, as well as the location of water monitoring sites nearest the outlet of each basin.⁴ The spatial variation of the average percentage of cropland planted in CCs in each monitoring basin is mapped in Appendix figure E.1. The mean annual percentage of cropland with CCs over the period 2008 to 2018 varies across monitoring basins. We find the highest rate (> 75 th percentile) of CC adoption in the southern and eastern Corn Belt, and the lowest rate (< 25 th percentile) in the northwestern Corn Belt.

⁴Appendix A provides details on constructing the monitoring basins. We describe the measurement errors possible when aggregating HUC8s and their corresponding solutions.

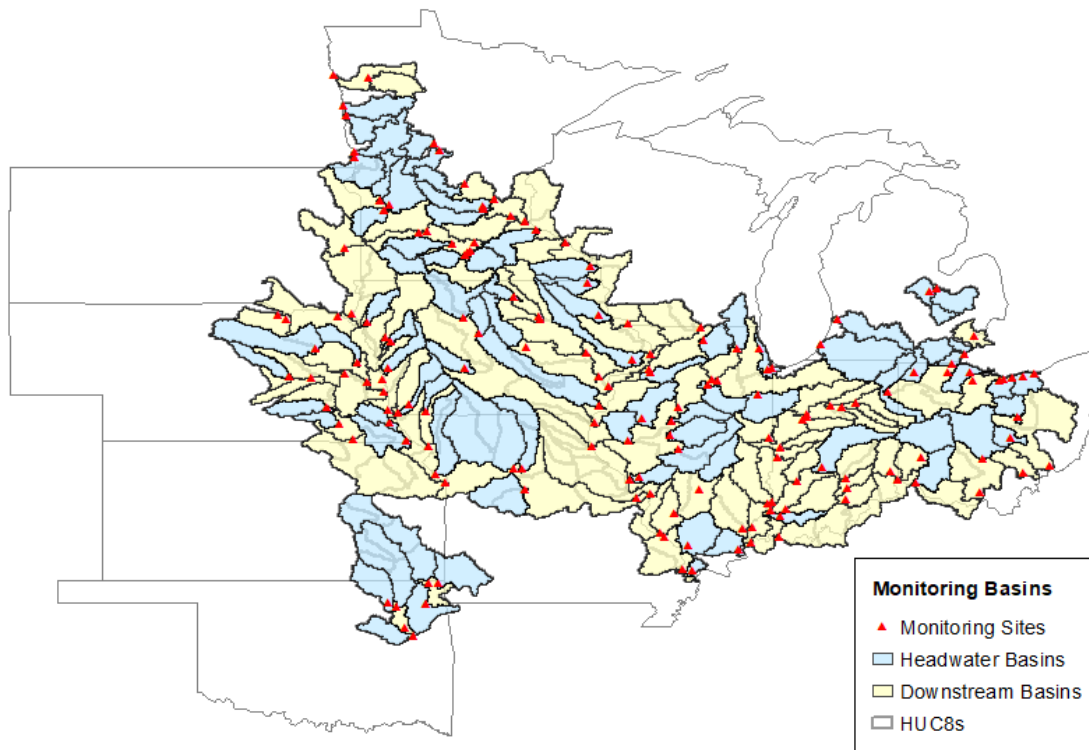


Figure 2.3: Constructed monitoring basins aggregated from HUC8 sub-basins in the U.S. Corn Belt

2.2.3 Water quality

The ambient water quality measure used is the total inorganic nitrogen (N) concentration (mg/l) (i.e., nitrite and nitrate). The Water Quality Portal (WQP) is the source of the water quality monitoring data, including information on the location of monitoring stations and corresponding nutrient concentration by date sampled (WaterQualityPortal(WQP), 2022). Monitoring stations are unevenly spatially distributed. To reduce measurement errors, if multiple stations are located in a single HUC8 sub-basin, one station is retained that captures the largest drainage area and has the most available pollutant readings. Also, stations with nutrient measurements for less than three years were removed from the analysis due to a lack of temporal coverage over the study period.⁵ The frequency of water quality sampling is

⁵We include river and stream monitoring sites (i.e., lakes, reservoirs, and groundwater water resources are excluded) with repeated measurements. We only use station data from the NWIS (USGS) and STORET

unbalanced, but it does not vary systematically by location over the years. Appendix figure G.2 is the density plot of total inorganic N measured at U.S. Corn Belt monitoring sites.⁶ The distribution is skewed to the right, similar to the N distribution in Paudel and Crago (2020).

We focus our analysis on the months between fall harvest and spring planting when cover crops are in the field and expected to have the largest potential impact on water quality. Winter cover crops are generally terminated two to four weeks prior to the anticipated cash crop planting date. Summer cash crops are mostly established no later than June. Accordingly, we match the N concentrations with the months that cover crops are in place (i.e., before termination) to estimate the main effect of CC on ambient N pollution. A robustness check that includes all months is in Appendix table D.2. The months included in our model are November through May.

2.2.4 Weather, land use, and socioeconomic data

All else equal, larger rainfall amounts lead to an expected increase in agricultural runoff and leaching that results in higher N losses to streams (Baeumler & Gupta, 2020; Bowles et al., 2018; Congreves et al., 2016). We acquire daily precipitation data from the PRISM climate group at 4x4 kilometer spatial resolution (PRISM, 2022). We use the daily precipitation to construct the 7-day cumulative rainfall prior to each water quality sampling date in each monitoring basin to control for recent rainfall that is most likely to influence in-stream N measurements. Because our data are an annual panel, we take the mean of these recent cumulative rainfall totals for each basin over each hydrological year to measure the annual average near-term cumulative rainfall; this serves as one of the control variables for estimating the effect of CC adoption on ambient surface N concentration. The effect of the

(US EPA based on state regulatory authority reporting) in our analysis to control for data quality. We require stations to report at least two readings per year and require repeated pollutant readings for at least three years to be included in our study. The monthly N readings at each site are averaged over each year to construct the annual mean measurement to match the annual temporal resolution of the CC land use data.

⁶N concentrations over 15 mg/l, which are less than 0.05% of the data, are excluded in the plot.

mean near-term rainfall on ambient N is expected to be positive, but we recognize that by taking annual means the temporal variation of these data on individual days throughout the year is likely diminished and what would be a potentially important source of cross-sectional and temporal variation in a monthly panel is likely less informative in the annual model we are constrained to presenting here.

The Palmer Drought Severity Index (PDSI) is calculated based on historical weather data. The monthly average precipitation and temperature data are from the PRISM climate group. We use the historical weather from the year 1950 to 2018 for monthly PDSI calculation and average them to construct the seasonal PDSI in the analysis. The PDSI is a standardized index that generally spans the range from -10 to 10 . A PDSI value ≥ 4 refers to extremely wet, while a PDSI ≤ -4 refers to extreme drought. The PDSI value is multiplied by a negative one to focus the interpretation of the estimated parameter on drought conditions, with more positive PDSI indicating drier conditions in our regressions. Drought is expected to negatively influence ambient N readings due to the soluble characteristic of N.

We obtain land use and land cover measures from the Cropland Data Layer (CDL) provided by the National Agricultural Statistics Service (NASS-USDA) (USDA-NASS, 2022a). Based on satellite remote sensing, the CDL is a series of 30x30 meter resolution raster files for each year in our study. The extraction of monitoring basin land use and land cover (LULC) is processed by overlaying the polygon boundary of the constructed monitoring basins on the CDL. This process generates nine categories (i.e., corn, soybeans, pasture, wheat, forest, wetland, developed, water, and other minor uses) of LULC. We divide CC acres by the total cropland acreage of corn, soybeans, wheat, and other crops to calculate our treatment measure. Appendix figure E.3 shows the variation of land use over time, as well as the proportion of LULC across all basins for each year. Each land use category exhibits limited change over the years with slight overall increases in corn, soybean and forest accompanied by a decline in pasture. Not surprisingly, cropland occupies more than half of the Corn Belt land in our study area.

Our analysis also controls for agricultural and socioeconomic characteristics, including NASS-USDA average crop yield data and gross farm income data from the Bureau of Economic Analysis (BEA) (BEA, 2022). We aggregate county-level socioeconomic characteristics to the monitoring basin level by overlaying the monitoring basin polygons on the county boundaries to derive a basin-county coverage weighting factor. We then apply the weighting factor to the county-level socioeconomic controls for counties within each monitoring basin polygon and sum them to obtain basin-level variables.

2.3 Empirical strategy

We employ a standard panel fixed-effect (FE) econometric approach with a continuous treatment variable (i.e., the share of cropland planting CCs) using the unbalanced annual panel data, and separate the analyses for downstream and headwater basins because headwater basins do not receive pollution spillovers from upstream. This approach relies on the same identifying assumptions as the discrete treatment difference-in-differences strategy (Angrist & Pischke, 2009; Bertrand et al., 2004), and has been widely used to evaluate non-discrete treatment effects (Acemoglu et al., 2004; Adhvaryu et al., 2019; Card, 1992; Herbst, 2017; Lewis & Severnini, 2020b). For downstream monitoring basins, we include the corresponding nearest upstream pollutant measurements as one of the controls affecting downstream water quality readings, consistent with related prior research (Paudel & Crago, 2020). Controlling for these pollution spillovers is key to isolating the effect of CC adoption on ambient water quality. The estimation equation includes an error term, ϵ_{it} , and is given by:

$$N_{it} = \alpha_1 CC_{it} + \alpha_2 CC_{it}^2 + \mathbf{X}_{it}'\boldsymbol{\beta} + \gamma \sum_{k \in \Lambda_{i-1}} \psi_k N_{kt} + \theta_i + \eta_{rt} + \epsilon_{it} \quad (2.1)$$

The dependent variable N_{it} describes ambient total N concentration (mg/l) in monitoring basin i and year t . The treatment variable, CC_{it} , is the percentage of cropland

with CCs. We include a second-order polynomial term to allow CCs to have a nonlinear impact on ambient N. Hence, the coefficients of greatest interest, $\hat{\alpha}_1$ and $\hat{\alpha}_2$, represent the treatment effect depending on the aggregate CC adoption rate, indicating how a marginal increase in the CC adoption rate linearly (in parameters) impacts the N concentration in the stream. We use the percentage of cropland in CCs as our treatment variable to aid the interpretation of the estimated coefficient and to normalize treatment by cropland area, given size differences across basins.⁷

Equation 3.3 includes several sets of controls. The upstream pollution spillovers, $\sum_{k \in \Lambda_{i-1}} \psi_k N_{kt}$, is the weighted average N measurement of the entire set of monitoring sites, Λ_{i-1} , immediately upstream of monitoring basin i . ψ_k is the inverse count of upstream basins, and N_{kt} is the N readings in the upstream sites. The vector of time-varying controls, $\mathbf{X}'_{it}$, includes weather, LULC (i.e., corn, soybeans, and developed land), corn and soybean yields, and gross farm income. Weather controls are average 7-day cumulative precipitation (mm) prior to the water quality sampling date, quadratic term of near-term rainfall, and seasonal drought conditions measured by PDSI.⁸ We include the mean monthly PDSI in Spring (includes April, May, June, and July) because this is historically the wettest season of the year. PDSI (times negative one) is included to strengthen the identification by controlling for hydrological drought which is closely related to streamflow and captures more than recent precipitation alone by taking into account multiple months addressed later.

Gross farm income is measured by total cash receipts from marketings (thousands of dollars) based on data from BEA that includes crops, livestock, and related products. Farm income together with annual average corn and soybean yields (bushels per acre) are aggregated from the county-level to the monitoring basin level as described previously. Last, the analysis includes monitoring basin fixed effects, θ_i , to capture time-invariant determinants

⁷We estimate a linear treatment model of Equation 3.3 (without the quadratic term) and show the results in Appendix Table D.6. We also include estimation results using the Equation 3.3 with the absolute CC acreage as the treatment variable in Appendix Table D.4 for the interested reader.

⁸We considered average near-term cumulative precipitation as 3-, 7-, and 14-day cumulative rainfall leading up to the water quality sampling date for each monitoring basin in each year. Findings are robust to these alternative specifications of the recent cumulative rainfall period.

of water quality, such as the size of basins and streams, soil characteristics, the distance between fields and streams, and other characteristics influenced by topography and geography, which are hard to observe but influence nutrient loss. Water resource region HUC2-by-year fixed effects, η_{rt} , allow water quality to differ by year in ways that are common across neighboring monitoring basins in the same water resource region, such as changes in point sources, population, water quality regulations, and physical, chemical and biological attributes of the receiving water body.

Table 3.1 reports the summary statistics for each monitoring basin subgroup: the group of downstream basins and headwater basins. The mean N reading in headwater basins is 20 percent higher ($p = 5.1e - 05$) than in downstream basins, and the standard deviation is about 30 percent higher in headwater basins. The share of cropland acres adopting CCs in headwater basins is 24 percent lower than ($p = 0.016$) the share in downstream basins. This difference between basin types is especially important because this is the treatment of interest in our econometric study. Examining total cover-cropped acres directly reveals that this difference in the share of cropland with CCs follows from there being more than twice as many acres that were covered cropped in downstream basins compared to headwaters (see Appendix table D.1).

Note that the mean LULC percentages are not significantly different between the two types of basins, nor are 7-day near-term rainfall and spring PDSI (Figure E.4). Aggregate gross farm income is higher ($p = 2.2e - 16$) among downstream basins despite average corn and soybean yields not being significantly different in each type of basin. The higher mean gross farm income follows directly from the fact that downstream basins are over 70 percent larger ($p < 0.01$) than headwater basins (Appendix table D.1).

Table 2.1: Summary statistics

	<i>Downstream Basins</i>		<i>Headwater Basins</i>	
	Mean	St. Dev.	Mean	St. Dev.
Nitrogen concentration (mg/l) ***	3.412	2.326	3.828	2.981
Percentage of cropland with cover crops **	3.216	5.898	2.452	5.279
7-day cumulative rain (mm)	17.124	11.421	16.949	10.685
Spring PDSI	-1.344	1.729	-1.267	1.845
Corn Yield (bu/acre)	154.920	40.568	156.208	41.061
Soybeans Yield (bu/acre)	46.508	10.438	45.605	11.477
Farm income (millions of dollars) ***	910.368	768.010	561.358	401.655
Percentage of corn land	28.337	12.962	28.430	14.753
Percentage of soybeans land	23.479	9.355	23.233	10.198
Percentage of developed land	10.003	7.502	9.385	10.181
Upstream N (mg/l)	3.954	2.705		

Notes: Asterisks denote p-value<0.1(*), <0.05(**), or <0.01(***). Appendix Figure E.4 reports t-tests of differences in means for each variable between basin subgroups in Table 3.1. Additional summary statistics for basin size, total acres of cover crops, and the amount of cover crop acres funded by EQIP are listed in Appendix Table D.1.

The statistically significant difference in ambient N concentration and share of cropland treated with CC between headwater and downstream basins reported in table 3.1 are notable. We consider a biophysical reason for the former difference and a policy explanation for the latter. From a biophysical standpoint, higher N concentrations in headwater basins may be consistent with there being smaller volume stream and river segments in headwaters before the main channel of a waterway reaches its full width and depth. Intuitively, this would tend to increase concentration, holding other relevant covariates constant, compared to downstream basins if there is a similar delivery of NPS N pollution to waterways in both types of basins. Similar N loading in both monitoring basin types is consistent with yields, land cover, and weather not being statistically different from one another. Perhaps more convincing is the fact that higher headwater nitrate concentration, consistent with ambient

water quality data in our study, have been documented in the literature (Royer et al., 2004).

Higher rates of CC adoption in downstream basins could plausibly be explained by policy intervention through the administration of agri-environmental programs or local initiatives. Despite normalizing cover cropped acres by basin size, the higher average adoption rate of CCs in downstream basins could arise if these basins or landscape positions closer to water quality monitoring sites were prioritized by incentive programs that provided funding to new adopters. One national program that we have annual practice-level contract data about is the Environmental Quality Incentives Program (EQIP). If EQIP (or another program we do not have data for) subsidized CCs more heavily in downstream basins than in headwaters, this could provide a policy explanation, or at the very least a contributing factor, for why there is a higher mean CC adoption rate in downstream basins. We find that EQIP did fund 1875 more acres of cover crops ($p = 2.7e09$) on average in the larger downstream basins relative to headwater basins. However, this statistically significant difference in EQIP subsidization of CCs is nowhere near large enough to explain CC adoption levels that are more than twice as large (12627 more acres on average) in downstream basins (see Appendix table D.1 and figure E.4). Thus, while it is plausible that policy may influence adoption differently in each basin type, there is no evidence that higher EQIP investments in cover crops explain the higher rate of CC adoption on cropland in downstream basins. There is clearly a difference in the CC adoption rate between the two basin types that should be captured by monitoring basin or HUC2 water resource region-by-year fixed effects if there is an important biophysical or other time-invariant unobservable that is correlated with CC adoption.

The identifying assumption for Equation 3.3 to result in an unbiased estimate of the parameter α is that the CC adoption rate is independent of the regression error, conditional on other explanatory variables (Barnow et al., 1980; Heckman & Robb, 1986):

$$E[CC_{it} \cdot \epsilon_{it} | \mathbf{X}_{it}', N_{kt}, \theta_i, \eta_{rt}] = 0 \quad (2.2)$$

This assumption would be violated if the CC adoption rate at the monitoring

basin level responded to unobserved variables, which themselves affect N measurements. Self-selection of individual operators into CCs could be a potential threat to identification in our basin-level adoption data if farmers in downstream basins that have higher adoption rates than farmers in headwater basins face different costs or incentives to adopt CCs. For example, if agri-environmental subsidies to plant CCs generally available to all farmers were utilized by downstream basin farmers at a higher rate than by farmers in headwaters, this information would be unobserved heterogeneity in the error term that could threaten identification. As discussed above, there is no evidence this is happening in our study area. Despite higher adoption of CCs in downstream basins (table 3.1), the largest program supporting CC planting (EQIP) subsidized a larger share ($p = 0.056$) of total cover cropped acres in headwater basins (18.6%) than it did in downstream basins (16.3%) during the study period. The EQIP policy intervention clearly cannot explain the higher rate of downstream CC adoption. The difference in CC adoption rate between basin types may simply be 'large enough' when combined with the ability to control for upstream pollution to be able to identify a clear treatment signal from the noise in ambient N water quality data.

Economic factors, such as yields and farm income, potentially result in positive self-selection bias if they affect both N concentration and treatment distribution. We include yields and farm income in the set of control variables consistent with Prokopy et al. (2019)'s finding that these are positively associated with individuals' adoption of agricultural conservation practices. Additional farm characteristics, such as farm size, percentage row crop, and the distance between a farm and a waterbody have also been found to positively affect individuals' adoption decisions (Prokopy et al., 2019); to the extent that these factors are highly correlated within a monitoring basin or HUC2 they may be captured by the basin fixed effects. Drought conditions could also be a source of positive self-selection bias because it is likely that drought affects both ambient N measurement and the implementation of conservation practices. Individuals' expectations of drought conditions before a growing season could positively affect their adoption decisions. Myers et al. (2019) finds the CCs

reduce nutrient and pesticide losses, increase infiltration, and increase the volume of water retained in the soil profile, which leads to greater drought resilience. Thus, we control for Spring PDSI to limit endogeneity concerns related to contemporaneous drought.

Another threat to identification may come from N concentration changes that coincide directly with the CC adoption rate but are the result of other conservation practices. If a basin has additional management practices installed simultaneously with CCs that have an effect on N concentrations, this will result in overestimating the effect of the CCs on N concentration. An example of this would be adopting a nutrient management practice, such as post-planting fertilizer application in combination with CCs. As a result, the panel FE approach is likely to deliver, if anything, estimates that are biased away from zero, providing an upper bound on the treatment effect of CC adoption on ambient N concentration. To the extent that fertilizer application is correlated with yields, that are included in our model, this potential bias may not be a concern. No other practices are known to have changed over the same period on anywhere approaching the same level as CC adoption.

2.4 Results

We report the estimation results for Equation 3.3 in table 2.2. We estimate the treatment effect for basins with and without upstream N measurements separately in columns (1) and (2), as well as for all monitoring basins pooled together in column (3) treating the upstream pollution reading as zero for headwater basins.

The panel FE estimators in all three models with different basin types show that the effect of CC adoption on ambient N is negative but with diminishing proportional changes in N.⁹ To assist the interpretation, we evaluate the effect of CCs on N at the mean of the control variables and fixed effects. Figure 2.4 shows that the impact of CCs on N decreases as

⁹A robustness check on these findings is performed in the Appendix table D.2 by including all months in the estimation, not just those when CCs are in the field and expected to have the greatest potential impact on water quality. The auxiliary regressions include additional water quality measurements in June through October to construct the dependent variable. The results indicate that the CC effect is only robust throughout the entire hydrological year in downstream basins, not in headwaters.

CC cropland share increases.¹⁰ When the CC adoption rate is below 31.8% (approximately the 99th percentile of the observed data), every percent increase in the share of cropland planting CCs is estimated to lead to between 0 and 0.06 mg/l decrease in annual mean ambient N levels among downstream basins (model 1). This estimated effect size is equivalent to between 0 and 2 percent of the average N concentration. We don't find the CC effects on ambient N to be significant in headwater basins; we suspect this is because the lack of upstream controls makes it challenging to discern a clear signal from the noise (i.e. isolate the effect of a very small change in the CC implementation rate). The upstream pollutant measurement controls indicate that downstream N spillovers determine the largest amount of their immediate downstream neighbors' ambient N measurements. By directly controlling for these pollution spillovers, the model specification prevents the effect of CCs from being confounded with N or treatment in upstream basins.

Larger amounts of rainfall over the week prior to measurement increase ambient N concentrations, and drier spring conditions measured by the PDSI variable have a negative significant effect on N concentrations. These results are consistent with the hydrology literature; increased rainfall accelerates drainage increasing ambient N concentration in surface water (Bowles et al., 2018) and drought conditions that reduce streamflow are accompanied by a decrease in N measured in streams (Bowles et al., 2018; Mosley, 2015; van Vliet & Zwolsman, 2008). The corn yield is found to be negatively associated with N measurements, while the soybean yield has a positive effect on N measurements among downstream basins. The result does not seem to be consistent with the findings from the agronomy literature. However, given the cropping system of the corn-soybean rotation in the Corn Belt, separating out the effect on ambient N is challenging.

¹⁰We also include a figure that compares the polynomial model to a linear treatment model in Appendix Figure E.6. Both models yield similar results. The linear model gives us the overall average effect of CC implementation on pollutant measurements. The polynomial model reveals the diminishing proportionality of changes in ambient N as the share of cropland planted in CCs increases. The linear fitted line is tangent to the second-order polynomial fitted curve, revealing how adoption rates below the tangent point have a larger impact on water quality measurements.

Table 2.2: Panel fixed-effect (FE) estimates for monitoring basins

	<i>Dependent variable:</i>		
	Nitrogen concentration (mg/l)		
	(1) Downstream Basins	(2) Headwater Basins	(3) All basins
Treatment			
Cropland Pct. of Cover Crops	−0.064*** (0.021)	−0.023 (0.022)	−0.033** (0.013)
Cropland Pct. of Cover Crops (quadratic)	0.001*** (0.0003)	0.0002 (0.0002)	0.0003* (0.0002)
Weather			
7-D Cum. Rain	0.008 (0.006)	0.015** (0.006)	0.010*** (0.004)
Spring PDSI	−0.105*** (0.031)	−0.180*** (0.058)	−0.147*** (0.037)
Socioeconomic Char.			
Corn Yield (bu/acre)	−0.002 (0.002)	−0.0003 (0.002)	−0.001 (0.002)
Farm Income (Ten million of \$)	0.001 (0.0004)	−0.003*** (0.001)	−0.00004 (0.0005)
Land use			
Corn	0.060** (0.031)	0.079** (0.036)	0.078*** (0.026)
Soybean	−0.006 (0.030)	−0.123*** (0.043)	−0.067** (0.029)
Developed	−0.056 (0.100)	0.396* (0.214)	0.130 (0.144)
Pollution Spillovers			
Upstream N (mg/l)	0.442*** (0.094)		0.337*** (0.087)
Observations	574	728	1,302
R ²	0.331	0.106	0.130

Note: Asterisks denote p-value<0.1(*), <0.05(**), or <0.01(***). Each analysis includes monitoring basin and HUC2-by-year fixed effects. Standard errors are clustered by monitoring basin.

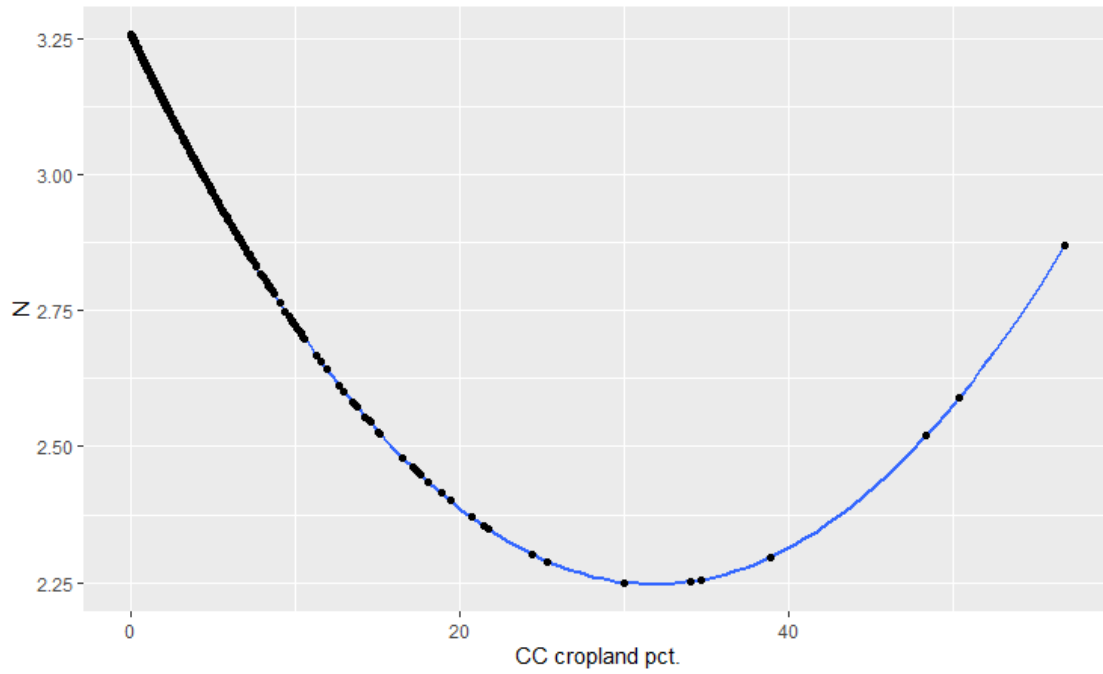


Figure 2.4: Fitted curve of the cropland percentage of CCs

2.5 Conclusion

This research is the first attempt the authors are aware of to estimate the effect of cover crop adoption on ambient N pollution levels using observed water quality and landscape-scale farm practice adoption data. Prior related work has investigated point source pollution (Keiser & Shapiro, 2019), the EQIP program that includes many different practices in addition to cover crops (Liu et al., 2022), pollution from animal feeding operations in Wisconsin (Raff & Meyer, 2021), and fertilizer sales as a proxy for N application (Paudel & Crago, 2020). There has been a major effort to promote and support CC adoption in recent years due to the enthusiasm surrounding soil health management and regenerative agriculture, in addition to continuing efforts to reduce nutrient loss from agriculture. According to the USDA Natural Resource Conservation Service, cover crops (CP 340) were subsidized on over 3 million acres of land in fiscal year 2021 across the entire set of programs the agency administers. (USDA-NRCS, 2022b)

Not surprisingly, we find that pollution spillovers from upstream to downstream are very important, having by far the largest estimated coefficient explaining variation in observed ambient total N (nitrate + nitrite) pollution. This control variable in our model is extremely important for identification, as evidenced by the fact that the CC treatment variables are highly significant only in the subset of models where we are able to control for upstream pollution levels. Without this independent variable the econometric model is unable to detect a clear signal of the effect of cover crop adoption on ambient total N levels. Robustness checks indicate that the causal effect of cover crops on ambient total N is most widespread in the months when cover crops are in fields between fall harvest and spring planting. When considering the entire year, including post-termination through summer cash crop harvest, the estimated effect may be limited to basins with inflow from upstream. Most likely, it is not the case that cover crops are any less effective at reducing N loss in headwater basins but that lower levels of average adoption observed in the headwaters of our study area may not be sufficient to detect nutrient loss abatement effects except during the over-winter

months when cover crops are *in situ*.

The overall CC adoption rate has increased dramatically in recent years, and we present nascent evidence to support biophysical modeling and experimental findings that have found CCs can reduce nitrogen nonpoint source pollution from farm fields. The estimated treatment effect may be a direct result of the cover crops themselves reducing runoff and retaining more N in plant biomass and soil, or it may be the result of accompanying changes to fertilizer management or tillage that are necessary to accommodate a CC in farmers' cropping systems. We cannot observe other specific changes in management in the OpTIS CC data, but the most recent years of the Agricultural Resource Management Survey (ARMS) suggest that a larger share of N is applied at or after planting with less fall-applied N in corn and cotton fields that are sown following a winter cover crop compared to fields without cover crops. Eliminating fall N application and applying more N as side-dress after planting are widely recommended agronomic practices to reduce N loss. Because cover crops introduce many new management considerations that increase management complexity, it should not be surprising that other coincident changes may occur that, together, reduce in-stream pollution readings.

Chapter 3

THE EFFECT OF THE ENVIRONMENTAL QUALITY INCENTIVES PROGRAM ON TOTAL NITROGEN IN UNITED STATES RIVERS AND STREAMS*

3.1 Introduction

Intensive management practices in modern agriculture have been identified as a leading source of water resource degradation (US-EPA, 2015). Excessive nutrient loading has become an important driver of aquatic ecosystem impairment. Nutrient over-enrichment with phosphorus or nitrogen is the cause of "dead zones" (i.e., hypoxia) and algal blooms in Chesapeake Bay, Lake Erie, and the Gulf of Mexico. To mitigate these water quality impacts,

*The findings and conclusions in this chapter are those of the authors and should not be construed to represent any official USDA or U.S. Government determination or policy. This research was supported in part by the U.S. Department of Agriculture, Economic Research Service.

federal and state governments provide voluntary incentive-based conservation programs to encourage farm operators to retire vulnerable cropland or to adopt conservation practices on working land. Historically, the expenditure on paid land idling programs was big relative to spending on subsidies for implementing conservation on working farmland. However, since 2002, the federal cost-share financing for working land conservation has been increasing as a share of total agricultural conservation expenditures. According to the Agricultural Act of 2014, the Environmental Quality Incentives Program (EQIP) and the Conservation Stewardship Program (CSP) on working lands represented nearly half of all federal farm conservation expenditures, while spending on the largest land retirement program, the Conservation Reserve Program (CRP), was significantly reduced (Lichtenberg, 2014). In recent years, the federal government has continued to emphasize working lands conservation programs by obligating over 13.8 billion dollars in financial and technical assistance through EQIP contracts alone. However, the cost-effectiveness of EQIP in delivering water quality improvement benefits has not been thoroughly explored using observational data yet. This study provides an econometric evaluation of the impacts of EQIP on ambient water quality by constructing monitoring basin level data matched to EQIP contract data at the national scale from 1985 to 2020.

Agronomic and engineering studies have explored conservation practices' effects on nutrient loss through field experiments. Field-level approaches allow studies to identify the effect of each individual management practice applied to the types of crops given specific soil and climate conditions. However, the experimental results may have limited implications for the following reasons. First, the off-site water quality benefits of conservation practices beyond the field are influenced by site-specific factors, and thus the field trial and plot experiment results based on samples at certain locations are hard to generalize to regions with different soil textures and climate conditions. Second, the effectiveness of management practices can vary within and across years, depending on weather conditions (Blanco-Canqui et al., 2014). Site-specific experimental studies may be insufficient to conclude the average

effects of practice adoption on nutrient runoff over decades. Last, nutrient or sediment loss changes at the farm level (edge of field) cannot be easily related to changes in ambient pollution concentration farther downstream away from the site, and it is challenging to scale up the field-level findings to a river basin.

The hydrology literature has implemented watershed-scale simulation models to estimate the impacts of aggregate field-level management practices on nutrient reductions in waterways. The Soil and Water Assessment Tool (SWAT) model (Arnold et al., 1998), created and maintained by the USDA Agricultural Research Service, has proven to be an effective tool for assessing the impact of management on water supplies and non-point source pollution in watersheds. The USDA Conservation Effects Assessment Project (CEAP) has utilized the model for individual watershed assessment studies to quantify soil and water conservation benefits of working land conservation practices. These engineering simulation models are able to predict contaminant fate and transport in rivers and lakes by capturing the essential hydrological and biochemical processes of watersheds based on the adoption of different management and conservation practices. However, *ex ante* hydrological models do not take into account behavioral adjustments (e.g., slippage and spillover effects) that accompany practice adoption (Fleming, 2017; Prokopy et al., 2019; Wu, 2000). Also, the complexity of the simulated relationships among variables and underlying parameters estimated by different studies that are not at the methodological frontier make it difficult to verify the predicted results and understand the mechanisms behind them (Keiser et al., 2019; P. W. Gassman et al., 2007).

This paper contributes to the recent literature using *ex post* reduced-form econometrics to explore water quality outcomes. Previous literature has explored the relationship between agriculture and nutrient concentration in ambient surface water quality (Metaxoglou & Smith, 2022; Paudel & Crago, 2020; Raff & Meyer, 2021). Existing studies have also evaluated policies or programs related to water quality improvement (Keiser & Shapiro, 2019; Liu et al., 2022; Sun et al., 2018). Especially, Liu et al. (2022) estimate the impact of the

EQIP payments on local water quality at a national scale. Following Keiser and Shapiro (2019), they use the upstream pollution measurement of a watershed as a counterfactual for the downstream pollution measure of a watershed to identify the influence of EQIP on downstream water quality. However, their design suffers from several limitations that this research will address.

This study implements a panel fixed effects model on watershed-level data to identify the impacts of EQIP on ambient nitrogen concentrations nationally from 1985 to 2022. The EQIP was originally authorized in the 1996 Farm Bill, and practices covered by EQIP contracts were first certified the next year (i.e., 1997). We quantify program treatment as the certified payments for practices that are related to water quality. In our treatment variables, we account for the entire lifespan of individual practices. That is, the associated green payments are included in the treatment variables for the entire lifespan of each contracted practice beyond the official end of the contracts. The lifespan of practices can be as short as one year (e.g., cover crops and conservation tillage) or last 20 years (e.g., surface drain and sediment basin). The estimates suggest that the certified EQIP payments on water quality-related practices have significantly reduced the ambient N concentration (i.e., total nitrate and nitrite). A ten-thousand-dollar increase in the total amount of EQIP cost share in a monitoring basin is estimated to lead to a 0.06 mg/l decrease in average ambient N levels, which is equivalent to 40 percent of the average N concentration. The interactive effects of green payments with weather conditions on the total nitrogen concentration are also significant. When interacting with the recent rainfall events and drastic dry-to-wet transitions (rainfall interacted with drought), these interactive effects with EQIP treatment are found to minimally offset the main program effect; in contrast, the interactive effect of EQIP with drought has a significant decreasing effect on in-stream N concentration that reinforces the direct estimated program effect.

The proposed study fills a gap in the literature and improves upon the limitations of previous work as follows. First, we include the pre-treatment period before any EQIP-funded

conservation practices were adopted by farm operators. The inclusion of multiple years of ambient pollution data before EQIP began serves as an important baseline for comparison to estimate the effect of the program more accurately with smaller standard errors (Egami & Yamauchi, 2023). The prior literature has not included the pre-treatment period and is necessary to causally identify the impact of EQIP on water quality. For example, some farmers adopt best management practices without green payments and this background conservation activity during the pre-EQIP period aids identification compared to using only post-EQIP data that includes private conservation. If adopted practices that are not included in an EQIP contract reduced nutrient loss, it is likely that the treatment effect is over-estimated when only post-treatment observations are accounted for (as in Liu et al. (2022)). Second, our treatment variable captures the fact that the influence of some structural management practices can last longer than the years when the cost share contracts are in place. If treatment is only modeled in the years payments for a given practice are received, the full practice lifespan effects of EQIP-contracted conservation practices are not taken into account. In this case, underestimation of the treatment effect of EQIP occurs.

3.2 Data

3.2.1 EQIP

EQIP is an agricultural conservation program that provides technical and financial assistance to eligible agricultural operators who wish to implement soil and water conservation practices on their working agricultural lands. The program encourages farmers and ranchers to participate in conservation efforts by paying a portion of the cost of installing or constructing approved conservation practices. Approved activities are performed according to a conservation plan developed together with the producer that identifies the appropriate conservation practice(s) to address resource concerns on the land. To be eligible for EQIP, applicants who own or operate the eligible land are ranked based on criteria developed by

the Natural Resources Conservation Service (NRCS) national headquarters and NRCS State Conservationists. The ranking criteria vary by state, but generally, applications are ranked based on the overall cost-effectiveness of the proposed approach, comprehensiveness and effectiveness of achieving specified resource concerns, fulfillment of EQIP program goals, and improvement of conservation practices or systems.

The EQIP was originally authorized in the 1996 Farm Bill, and practices covered by EQIP contracts were first certified the next year. We quantify program treatment as the cost-share amount (in dollars) for practices certified as having been installed. Importantly, this considers conservation under the program only after practices have been verified as installed as opposed to having been planned but not yet installed. Our treatment variable accounts for the entire lifespan of individual practices under the NRCS conservation practice standard. That is, the associated green payments are included in the treatment variables for the entire lifespan of each contracted practice beyond the official end of the contracts. The lifespan of practices can be as short as one year (e.g., cover crops and conservation tillage) or last 20 years (e.g., surface drain and sediment basin). Figure 3.1 shows the trends of total EQIP cost share, from top to bottom, accounting for (1) all certified contract items, (2) only acreage-measured practices (ac), and (3) conservation practices related to the water quality (wq), respectively. Some practices do not have acre units and instead are count variables (e.g. livestock waste storage systems) or are quantified in terms of linear feet (e.g. piping or fence installations), so using dollars to quantify total treatment includes all types of practices not just those that can be measured in terms of total acres installed. The EQIP annual payments, overall, have increased since 1997 and are over 875 million dollars in 2020. The total cost share of acreage-measured practices is about half of all payments, and the cost share for WQ-related practices is less than half of the total cost share.

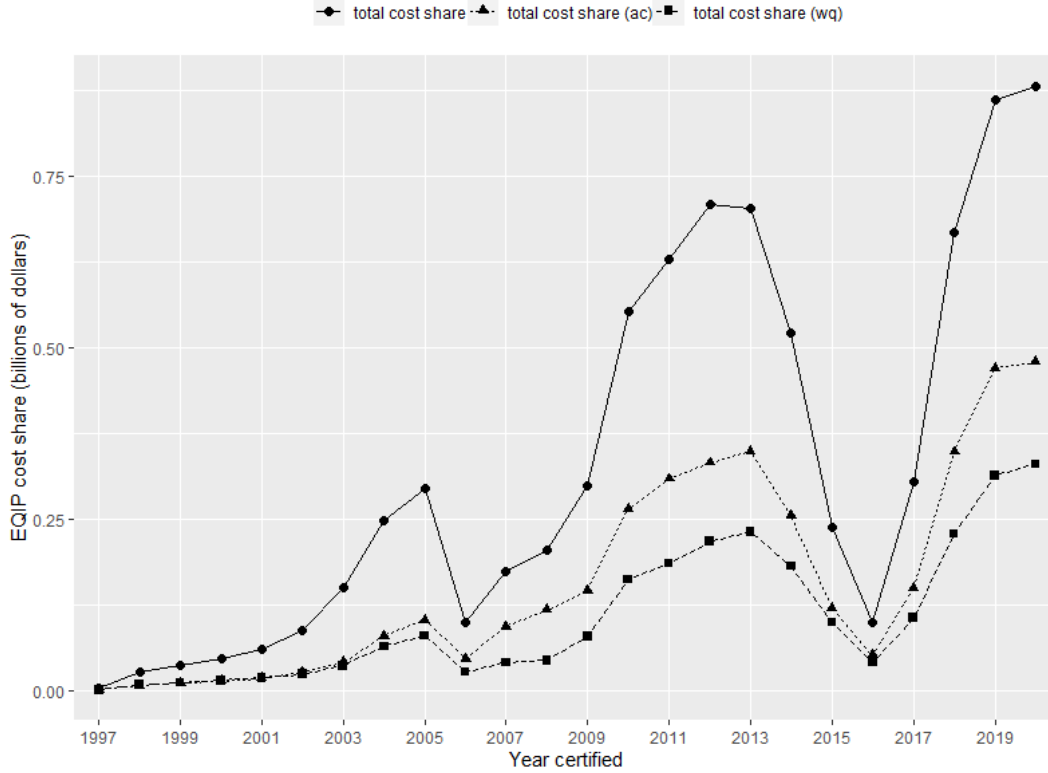


Figure 3.1: EQIP financial assistance trend, 1997-2020

Notes: Author calculations from NRCS Protracts database. The annual certified payments from EQIP contract items are summed across all the monitoring basins as the EQIP cost share shown at the y-axis. Obligated or planned payments are not included, only practices certified as having been installed

3.2.2 Watershed Hydrology Network

The monitoring basins and spatial connectivity are constructed based on the water flow direction and connectivity of HUC8s from the USGS Watershed Boundary Dataset (WBD) and the National Hydrography Dataset (NHD). All watersheds are indexed by USGS using hydrologic unit codes (HUCs) with smaller numbered HUCs indicating larger aggregation of sub-watersheds (e.g. HUC2 water resource regions) and higher numbered HUCs indicating smaller watersheds (e.g. HUC12s) such that HUC12s combine to form a larger HUC10 and HUC10s combine to form a HUC2. Based on the direction of streamflow and the location (i.e., longitude and latitude) of water monitoring sites obtained from the Water Quality Portal (WQP) (WaterQualityPortal(WQP), 2022), all HUC8s are matched to the

nearest downstream monitoring stations and are aggregated to form unique monitoring basins that are the unit of analysis in this study controlling for land use/land cover, socioeconomic, and weather variables. Note that the monitoring sites used are located (1) within 100 meters to the mainstem of a waterbody to ensure that the sites used capture the correct inflows from the upstream HUC8s and (2) at the outlet of each monitoring basin to capture the largest amount of drainage possible from the upstream HUC8s² Each monitoring basin is constructed by identifying all contiguous HUC8s that drain the land located between two monitoring stations, one upstream and one downstream, of this land. A spatial connectivity matrix is constructed that identifies which monitoring basins are located upstream (i.e., first-order-neighbor monitoring basin) of every other monitoring basin and which monitoring basins do not have any upstream neighbors, referred to as headwater basins without any inflow.

The process delineates a total of 1203 monitoring basins, with 64 basins having upstream inflow (hereafter, "downstream" basins) and 1139 headwater basins. There are 380 headwater basins that have monitoring sites located in the uppermost part of the basin, which are used to control for upstream pollution inflow similar to downstream basins. Figure 3.2 shows the mean annual EQIP cost share for a subset of WQ-related conservation practices varied across monitoring basins.³ This map reveals that Illinois, one of the major corn production states, has less than average EQIP payments. Runoff from agricultural areas into western Lake Erie is the major source of nutrient loadings into the lake, and most basins in this drainage received EQIP cost share in the upper quantiles of the average annual distribution,

²To ensure that monitoring stations measure more than 50% of the HUC8 where they are located, the stream length from monitoring sites to the outlet is required to be less than half the total stream length of each HUC8. If a monitoring site in a HUC8 is located upstream of inflow points from other HUC8s (not monitored by that site's readings) the HUC8 is aggregated to the next downstream HUC8 with a monitoring station that captures the majority of streamflow below the nearest upstream station. Stations, capturing less than 50% of the HUC8 where located, but measure the entirety of the upstream HUC8s, are reassigned to the upstream HUC8, and the HUC8 where the station is physically located is reassigned to the next downstream basin.

³Appendix Figure ?? presents the mean annual EQIP-certified payments (for all practices) across all monitoring basins from 1997 to 2020. Appendix Figure G.1 shows the mean annual EQIP land share across all monitoring basins from 1997 to 2020. The percentage of land under EQIP only accounts for acreage-measured conservation practices.

except for the Metro Detroit area. No monitoring basins are constructed in areas of Nevada, western Utah, and southern California due to the limited number of monitoring stations in these desert areas. Other desert dominated areas of the southwest where monitoring basins can be constructed (e.g. Arizona and southern Utah) show very low levels of EQIP funding given that these land areas are not major agricultural production regions.

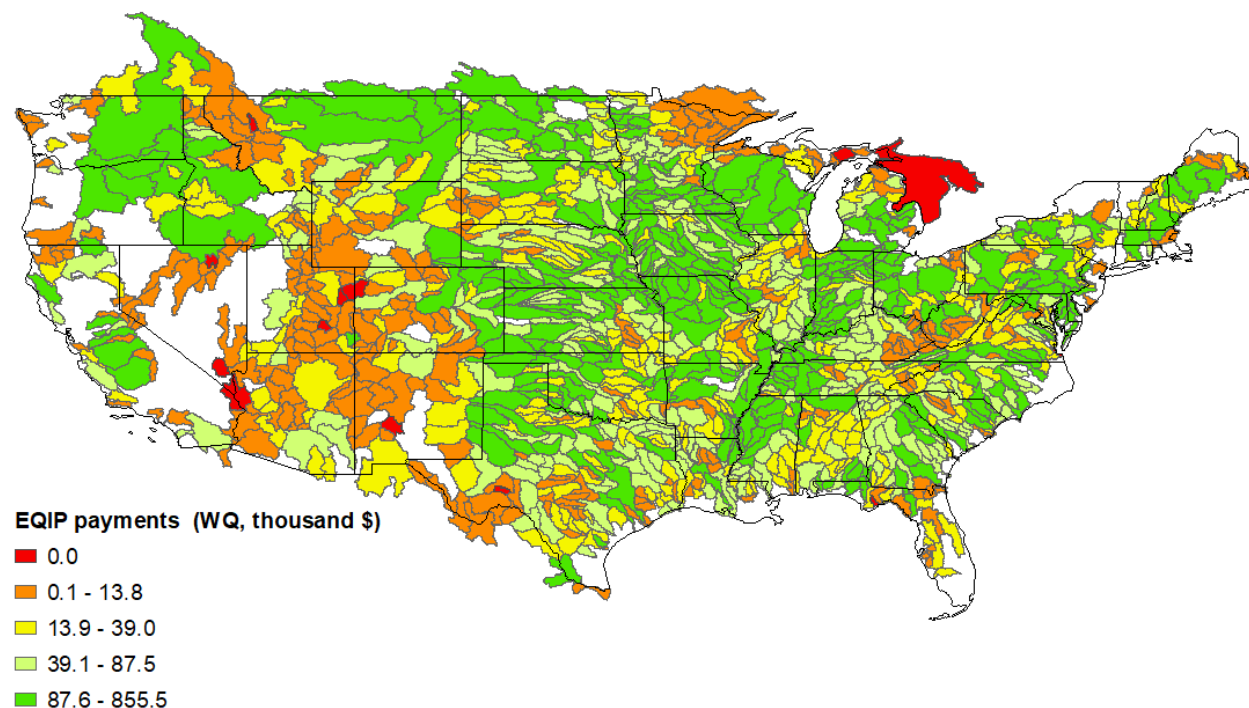


Figure 3.2: Quartile map of mean annual EQIP certified payment for WQ-related practices from 1997 to 2020

Notes: The map presents the monitoring basins (colored areas) and states (black-bordered hollow areas) in the contiguous United States. The bins of mean annual certified EQIP payments are minimum, first quartile, median, third quartile, and maximum.

3.2.3 Water quality

The ambient water quality measure used is the total inorganic nitrogen (N) concentration (mg/l) (i.e., nitrite and nitrate). The Water Quality Portal (WQP) is the source of the water quality monitoring data, including information on the location (i.e., longitude and latitude) of monitoring stations and corresponding nutrient concentration by date sampled

(WaterQualityPortal(WQP), 2022). Monitoring stations are unevenly spatially distributed. If multiple stations are located in a single HUC8 sub-basin, stations that measure the largest drainage area and have the most available pollutant readings are retained to reduce measurement errors. Also, stations with nutrient measurements for less than three years were removed from the analysis due to the lack of temporal coverage over the study period. The frequency of water quality sampling is unbalanced but has not varied systematically by location over the years. Appendix figure G.2 is the density plot of total inorganic N measured in the contiguous U.S..⁴ The distribution is skewed to the right, similar to the N distribution in Paudel and Crago (2020).

3.2.4 Weather, land use, and socioeconomic data

All else equal, larger rainfall amounts lead to an expected increase in agricultural runoff and leaching that results in higher N losses to streams (Baeumler & Gupta, 2020; Bowles et al., 2018; Congreves et al., 2016). We acquire daily precipitation data from the PRISM climate group at 4x4 kilometer spatial resolution (PRISM, 2022). We use the daily precipitation to construct the 14-day cumulative rainfall prior to each water quality sampling date in each monitoring basin to control for recent rainfall that is most likely to influence in-stream N measurements. The effect of the near-term rainfall on ambient N is expected to be positive.

The Palmer Drought Severity Index (PDSI) serves as a proxy for streamflow and is calculated based on historical weather data from 1950 to 2020 (Dai, 2011). The monthly average precipitation and temperature data from the PRISM climate group are used to calculate monthly PDSI. The PDSI is a standardized index that generally spans the range from -10 to 10 . A PDSI value ≥ 4 refers to extremely wet, while a PDSI ≤ -4 refers to extreme drought. The PDSI value is multiplied by a negative one to focus the interpretation of the estimated parameter on drought conditions, such that more positive values indicate

⁴N concentrations over 13 mg/l, which are less than 0.01% of the data, are excluded in the plot.

drier conditions in our regressions. Drought is expected to negatively influence ambient N readings due to the soluble characteristic of N (Dahm et al., 2003).

We obtain land use and land cover measures from the Land Change Monitoring, Assessment, and Projection (LCMAP) provided by the U.S. Geological Survey’s (USGS) Earth Resources Observation and Science (EROS) Center (USGS-EROS, 2022). Based on satellite remote sensing, the LCMAP is a series of 30x30 meter resolution raster files for each year in our study. Land use and land cover extraction at the monitoring basin level are processed by overlaying the polygon boundary of the constructed basins on the LCMAP raster. This process generates eight categories of land cover (i.e., cropland, developed, grass/shrub, tree cover, water, wetland, ice/snow, barren). Appendix figures G.3 and G.4 show the variation of land use over time and the proportion of land cover across the contiguous U.S. for each year. Each land use category exhibits limited change over the years, with slight overall increases in developed and grass/shrub land and a decline in tree cover. Cropland as a share of total land decreased since 1985 and reached the lowest share in 2008. Following the spike in crop prices in 2008, the cropland area has increased by 8 million acres in 2020 since 2008.

Our analysis also controls for agricultural and socioeconomic characteristics, including USDA-NASS average crop yield data and gross farm income data from the Bureau of Economic Analysis (BEA) (BEA, 2022). We aggregate county-level socioeconomic characteristics to the monitoring basin level by overlaying the monitoring basin polygons on the county boundaries to derive a basin-county coverage weighting factor. We then apply the weighting factor to the county-level socioeconomic controls for counties within each monitoring basin polygon and sum them to obtain basin-level variables.

3.2.5 Summary statistics and water pollution trends

Table 3.1 reports the summary statistics for each monitoring basin subgroup separately for downstream basins and headwater basins. The mean N readings in headwater and downstream basins are statistically equivalent. The mean certified total EQIP payments

are significantly higher ($p < 2.2e - 16$) among downstream basins. This higher mean EQIP cost share is consistent with the fact that the average size of downstream basins is about 30 percent larger ($p < 2.2e - 16$) than headwater basins. Despite downstream basins being larger and receiving higher average total payments than headwater basins, the mean share of land treated by EQIP conservation contracts is higher ($p = 7.2e - 09$) among headwater basins. Note that the mean and standard deviation of 14-day near-term rainfall and PDSI are negligibly different between the two types of basins, reflecting the random spatial distribution of weather conditions. Aggregated gross farm income is higher ($p < 2.2e - 16$) among downstream basins, which is consistent with significantly higher cash crop (i.e., corn, soybeans, and upland cotton) yields, larger basin size, and cropland occupying a higher ($p = 1e - 11$) percentage of all land in downstream basins compared to headwaters.

Table 3.1: Summary statistics

	<i>Downstream Basins</i>		<i>Headwater Basins</i>	
	Mean	St. Dev.	Mean	St. Dev.
Nitrogen concentration (mg/l)	1.445	1.956	1.413	2.158
EQIP cost share (thousand \$)	13.365	28.891	9.448	23.080
EQIP cost share (WQ, thousand \$)	5.465	11.788	3.959	9.361
PDSI	-0.394	2.322	-0.389	2.364
14-day cumulative rain (mm)	39.810	35.172	39.193	34.873
Gross farm income (billion \$)	0.347	0.512	0.220	0.366
Corn Yield (ten bu/ac)	9.478	5.449	8.380	5.765
Soybeans Yield (ten bu/ac)	2.628	1.765	2.150	1.860
Upland Cotton Yield (hundred kg/ha)	1.652	3.627	1.318	3.314
Cropland share (%)	37.683	26.649	36.232	28.144
Developed land share (%)	7.189	9.024	6.378	8.612
Upstream N (mg/l)	1.751	2.601	0.000	0.000
Monitoring basin size (million ac)	1.640	1.740	1.266	1.123
Observations	21,405		64,530	

Notes: WQ represents the conservation practices under EQIP that are related to nutrient pollution in streams and rivers. Appendix table F.1 includes the t-test significant differences for each variable between downstream and headwater basins.

We next discuss the water pollution trend. We use the following equation to assess year-by-year changes in ambient surface N (Keiser & Shapiro, 2019):

$$Y_{i,c,t} = \sum_{t=1985}^{t=2020} \alpha_t 1[year = t] + X'_{ict} \beta + \eta_i + \epsilon_{ict} \quad (3.1)$$

The variable $Y_{i,c,t}$ represents the ambient N reading at monitoring basin i , hour and day-of-year c , and year t . The matrix X'_{ict} includes cubic polynomials in time of day and in day of year. In Appendix Figure G.5, we show the annual N trend, where X'_{ict} includes PDSI and near-term precipitation. The time-invariant characteristics of monitoring basin i are captured by η_i . It is important to control the basin fixed effects in the trend analysis because they adjust the cross-sectional differences in the baseline N measurements across monitoring basins in the unbalanced panel. This approach ensures that identification comes only from changes in ambient N within each monitoring station over time. We then plot the year coefficients $\alpha_{1985} \dots \alpha_{2020}$ and the constant in Figure 3.3. During the pre-treatment period, the ambient N concentrations shifted slightly upward. Then, the year-by-year mean N measurements during the post-period do not seem to have a clear upward or downward trend. Instead, the N level fluctuated higher and lower over the post-treatment years. Note that the N concentrations reached relatively low points in the years 2000 and 2012 due to drought.⁵ According to hydrology, intense and season-long droughts will have lagged effects on agricultural N losses (Bowles et al., 2018).

⁵The drought trend in Appendix Figure G.6 shows the historic drought years in 2000 and 2012.

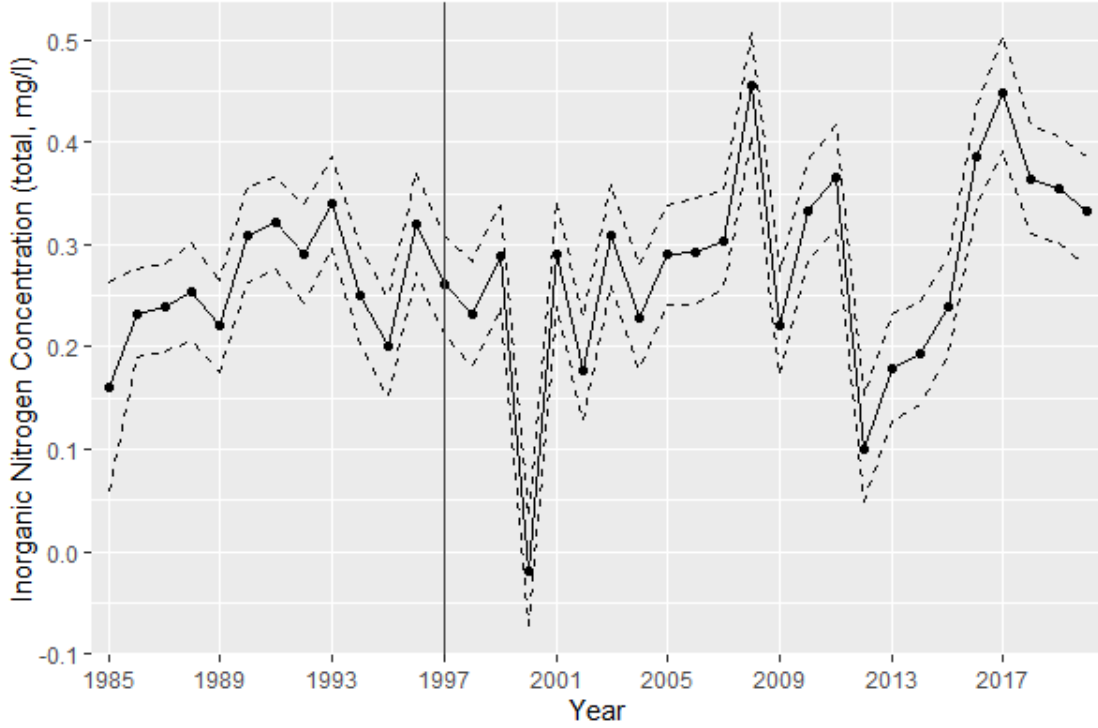


Figure 3.3: Nitrogen concentration trends, 1985-2020

Notes: The year-specific points in the graph represent the mean N concentrations, controlling for time and monitoring basin characteristics. Dashed lines have a 95% confidence interval clustered by monitoring basin, and 1985 is the reference category.

The estimation of linear N trends is also explored by the following equation (Keiser & Shapiro, 2019):

$$Y_{i,c,t} = \alpha y_t + X'_{ict}\beta + \eta_i + \epsilon_{ict} \quad (3.2)$$

The main coefficient of interest, α , represents the mean annual change in N concentration, conditional on the other controls in the regression. Another specification interacts the year trend term with an indicator $1[y \geq 1997]$ for whether an observation is in the post-treatment period. This interaction measures how N pollution trends differ after versus before the start of EQIP. Note that the estimation from linear N trend here can only assist the interpretation of the nonlinear trend in the graph based on Equation 3.1 because the nonlinear N trend shown in Figure 3.3 is roughly approximated with the linear trend from

Equation 3.2 for a 35-year long period. The linear N pollution trend estimations are shown in Table 3.2. Based on Equation 3.2, the estimations of linear N trend over the years in Models (1) and (2) show no obvious evidence of N increasing or decreasing over time. However, the trend break specifications in Models (3) and (4) indicate that the N has increased slightly over the years (i.e., about half a percentage point per year) but has experienced less rapid rises after 1997 than before it.

Table 3.2: Nitrogen concentration linear trends, 1985-2020

	<i>Dependent variable:</i>			
	Nitrogen concentration (mg/l)			
	(1)	(2)	(3)	(4)
Year	0.00264*	0.00122	0.00587***	0.00373**
	(0.00158)	(0.00156)	(0.00182)	(0.00169)
Year*1[Year >= 1997]			-0.00005***	-0.00004***
			(0.00001)	(0.00001)
Site fixed effects	Yes	Yes	Yes	Yes
Season controls	Yes	Yes	Yes	Yes
Time of day controls	Yes	Yes	Yes	Yes
Weather controls		Yes		Yes
Observations	139,255		139,255	
Mean N concentration	1.2871		1.2871	

Notes: Columns (1) and (2) are the estimation results of Equation 3.2. Columns (3) and (4) show the results of another specification, including the interaction term between the year and a post-1997 indicator in Equation 3.2. Season controls are a cubic polynomial on the day of the year. Time of day controls is a cubic polynomial in the hour of the day. Robust standard errors are in parentheses and are clustered at the monitoring basin level. Asterisks denote p-value < 0.1(*), < 0.05(**), or < 0.01(***)

3.3 Empirical strategy and identification

This study implements a panel fixed effects (FE) model with a continuous treatment (certified EQIP payments) on watershed-level data to identify the impacts of EQIP on ambient water quality in the contiguous U.S. from 1985 to 2020. Analyses are separated for basins with and without upstream pollution measurements because most headwater basins do not have upstream stations to control for pollution spillovers inherent in the hydrological

network.⁶ This approach relies on the same identifying assumptions as the discrete treatment difference-in-differences strategy (Angrist & Pischke, 2009; Bertrand et al., 2004), and has been widely used to evaluate non-discrete treatment effects (Acemoglu et al., 2004; Adhvaryu et al., 2019; Card, 1992; Herbst, 2017; Lewis & Severnini, 2020b). For monitoring basins with upstream pollution measurements, I include the corresponding upstream pollutant measurements as one of the controls for the downstream water quality readings (Paudel & Crago, 2020). Controlling for pollution spillovers isolates the effect of active conservation contracts in a given monitoring basin on ambient water quality. The estimating equation includes an error term, ϵ_{it} , and is given by:

$$\begin{aligned}
N_{it} = & \beta EQIP_{it} + \\
& \alpha_1 EQIP_{it} \times R_{it} + \alpha_2 EQIP_{it} \times D_{it} + \alpha_3 EQIP_{it} \times R_{it} \times D_{it} + \\
& \mathbf{X}_{it}' \boldsymbol{\gamma} + \rho \sum_{k \in \Lambda_{i-1}} \psi_k N_{kt} + \eta_i + \tau_{it} + \theta_{wy} + \epsilon_{it}
\end{aligned} \tag{3.3}$$

The dependent variable N_{it} describes ambient N concentration (mg/l) in monitoring basin i and month t . The treatment, $EQIP_{it}$, measures the certified EQIP payments to conservation practices that are associated with water quality. Hence, the coefficient of interest, β , represents the average treatment effect, indicating how an increase in EQIP cost share to conservation practices associated with water pollution impacts the N concentration in the streams and rivers. The three indirect treatment effects are the interactions between treatment and 14-day near-term rainfall (R_{it}), drought condition (D_{it}), and both recent precipitation and drought ($R_{it} \times D_{it}$). The interactions measure how different weather conditions mediate or enhance the effect of EQIP on ambient N.

Equation 3.3 includes several sets of controls. The pollution spillovers from upstream,

⁶Some headwater basins have water monitoring sites located at both the mouth and the upper stream of the given basin. The analysis for these headwater basins is categorized together with downstream basins since they have upstream pollution controls.

$\sum_{k \in \Lambda_{i-1}} \psi_k N_{kt}$, is the weighted average N measurement of the entire set of the immediate upstream monitoring sites, Λ_{i-1} , of the monitoring basin i . ψ_k is the inverse count of upstream basins, and N_{kt} is the N readings in the upstream sites. The vector of time-varying controls, $\mathbf{X}'_{it}$, includes weather, land use, and socioeconomic determinants. Weather controls are 7-day cumulative precipitation (mm) prior to the water quality sampling date, drought conditions measured by PDSI, and their interaction capturing extreme dry-to-wet transitions.⁷ Two types of land use capture the annual percentage change in cropland and developed land at each monitoring basin.

Socioeconomic characteristics include farm income and yields of major crops. Gross farm income is measured by total cash receipts from marketings based on data from BEA that includes crops, livestock, and related products. Corn, soybean, and upland cotton yields are aggregated from the county-level annual mean to the monitoring basin level in proportion to a county's share of each basin. Last, the analysis includes monitoring basin, basin-by-month, and water resource region-by-year fixed effects. The monitoring basin fixed effects, η_i , captures the time-invariant unobservables, such as the size of basins and streams, soil characteristics, the distance between fields and streams, and other characteristics influenced by topography and geography, which are hard to observe but influence nutrient loss. τ_{it} are basin-by-month fixed effects that control for the seasonality of the N concentration at each monitoring basin. θ_{wy} are water resource region-by-year fixed effects that allow factors to change over years in ways that are common to all monitoring basins in a water resource region (HUC2), such as changes in point source pollutants or regulations, adoption of other conservation practices having N trends associated with the EQIP cost share, and shifting physical, chemical, and biological factors of the receiving water body.

The identifying assumption for Equation 3.3 to provide an unbiased estimate of the parameter β is that the EQIP cost share is independent of the regression error, conditional

⁷We initially specify the near-term cumulative precipitation as 14-, 21-, and 30-day cumulative rainfall leading up to the date of water quality sampling for each monitoring basin. Findings are robust to the specification of the recent cumulative rainfall period.

on other explanatory variables (Barnow et al., 1980; Heckman & Robb, 1986):

$$E[EQIP_{it} \cdot \epsilon_{it} | \mathbf{X}_{it}', N_{kt}, \tau_t, \theta_y, \eta_i] = 0 \quad (3.4)$$

This assumption would be violated if the certified EQIP payments at the monitoring basin level responded to unobserved variables, which themselves affect in-stream N measurements. There are two types of selection into program bias that could potentially threaten the identification: 1) self-selection of the individual farm operators and 2) selection based on federal and state criteria. Farm and farmer characteristics affect the program participation and adoption of conservation practices (Prokopy et al., 2019; Reimer et al., 2013). Meanwhile, each NRCS state and local office develops its own EQIP ranking tools to select applications and determine the cost share rates subject to the available budget allocated by NRCS headquarters (U.S. Government Accountability Office, 2017).

Economic factors, such as yields and farm income, potentially result in positive self-selection bias if they affect both N concentration and treatment distribution, and we fail to control for this. Farm financial capacity at the state level positively influenced participation in conservation programs (i.e., EQIP) (Reimer et al., 2013). At the individual level, Prokopy et al. (2019) also found that farm-level economic factors are positively associated with the adoption of agricultural conservation practices. The model here includes yields and gross farm income in the set of control variables consistent with the literature. Additional farm characteristics, such as farm size, percentage row crop, and the distance between a farm and the nearest waterbody, have also been found to positively affect individuals' adoption decisions (Prokopy et al., 2019); to the extent that these factors are highly correlated within a monitoring basin or HUC2, they may also be captured, respectively, by the basin and water resource region fixed effects.

Land tenure is considered an important and controversial factor affecting the adoption decision. Reimer et al. (2013) found that pure tenant farmers may be more likely applicants to the program than those who own all or part of the land they operate, while other

studies found farm operators who own their lands are more inclined to adopt conservation practices (Bosch et al., 1995; Khanna, 2001). Recent literature explores the patterns across farmland tenancy and land ownership in adopting management practices and finds little evidence of systematic differences in conservation practice (i.e., conservation tillage and six structural practices) adoption between owner-operated and rented fields at the national level (Burnett et al., 2024). The ownership status of farmland has limited inter-annual change; thus, the monitoring basin and HUC2 fixed effects can capture differences in conservation practice adoption found to vary regionally based on land tenure (Burnett et al., 2024).

Program eligibility and funds allocation cause selection bias from government sectors if they systematically affect both ambient pollutants and treatment assignments and are unobservable. Producers with eligible land (i.e., land on which resource concerns related to agricultural production could be addressed through an EQIP contract) can apply for the program (Stubbs, 2010). The annual cropland share included in Equation 3.3 controls the eligible land for program applications. EQIP funds allocation attempts to optimize environmental benefits, but studies have shown little change in funds received by states over the years. According to USDA-NRCS guidance, annual EQIP funding is allocated to the state by NRCS based on national priorities, natural resource needs, efficiency and performance measures, and regional equity (Stubbs, 2010). However, U.S. Government Accountability Office (2017) states that national allocations, in practice, are influenced primarily by historical funding amounts. Stubbs (2010) also find that the top two states with the most EQIP funds obligated remained the same (i.e., Texas, California) from the fiscal year 2004 to 2010. Besides, the ranking tools used to select qualified applicants largely depend on the state and local offices, which account for the majority (65 percent) of an applicant's score. Given these patterns of funding allocation and ranking system, the monitoring basins and water resource region fixed effects are capable of controlling for such spatial differences across states and locally. If there are any inter-annual changes in the ranking systems designed by states and local offices, the location-by-year fixed effects can capture such variation over time by

location.

Another threat to identification may come from N concentration changes that coincide directly with the EQIP funds obligated for WQ-related practices but result from other conservation practices. If a basin has additional management practices installed simultaneously with EQIP-funded practices, the effect of the EQIP on N concentration will be overestimated. As a result, the panel FE approach is likely to deliver, if anything, estimates that are biased away from zero, providing an upper bound on the treatment effect of EQIP on ambient N concentration.

3.4 Results

We report the estimation results for Equation 3.3 in Tables 3.3 and 3.4 for downstream and headwater monitoring basins, respectively.⁸ We estimate the treatment effect for basins with and without upstream N measurements separately, as well as for all monitoring basins pooled together in Table 3.5 treating the upstream pollution reading as zero for headwater basins in the all basins model.

The panel FE estimators show that the effect of certified EQIP payments on water quality-related practices on ambient N is negative for different fixed effects specifications across the three groups of basins. However, the EQIP effect is only found to be significant in downstream basins across different fixed effects specifications, where the weighted upstream pollutant measurements are included in the estimation to isolate the treatment effect. Column 2 in each table is our preferred model with basin, basin-by-month, water resource region-by-year fixed effects. By adding the water resource region-by-month fixed effects in Column 3, the estimation results and fit statistics are nearly the same compared to the preferred specification in Column 2. The interpretation of the direct treatment effect in Table 3.3 Columns 2 & 3 is: A ten-thousand-dollar increase in EQIP cost-share is estimated to lead to

⁸Downstream basins are monitoring basins with upstream pollutant measurements to control for downstream pollution spillovers. Headwater basins are those that do not have inflow from upstream and lack sites located at the upper reaches of a given basin.

a 0.06 mg/l decrease in average ambient N levels among downstream basins. This estimated effect is equivalent to 40 percent of the average N concentration. The upstream pollutant measurement controls indicate that downstream N spillovers determine the largest amount of their immediate downstream neighbors' ambient N measurements. By directly controlling for these pollution spillovers, the model specification prevents the EQIP effect from being confounded with N or treatment in upstream basins.⁹

The interactive effects of EQIP on ambient N are explored in terms of the interaction with drought, recent precipitation, and both. Weather conditions interacted with treatment have different impacts on the main effect. Among downstream and all basins in Table 3.3 and 3.5, drought (PDSI dry conditions) has a significant reinforcing effect when combined with EQIP treatment equal to about a sixth and a half of the direct EQIP treatment effect among downstream and all basins, respectively. The interactive effect of recent cumulative rainfall has the opposite directional effect of EQIP alone on N among both downstream and all basins. However, the magnitude of this positive interactive effect is only about two and four percent of the main effect among downstream and all basins, respectively. Drastic dry-to-wet transitions (i.e., the interaction of drought and recent rainfall) theoretically increase N losses via leaching, and dry conditions during the growing season (e.g., late Spring to Summer) combined with recent rainfall are estimated to partially offset the impact of EQIP on N readings. Such interactive effects are not significant among headwater basins, while for downstream and all basins, the main effect is minimally offset (less than a percentage point of the main effect). Although limited evidence shows the direct and interactive effect of certified EQIP payments related to water quality practices on ambient water quality among headwater

⁹The complete estimation results are presented in Appendix Tables F.2, F.3, and F.4 respectively for downstream, headwater, and all basins. The upstream pollutant measurement controls for N spillovers are measured as the average ambient N among all nearest (i.e., single spatial lag) upstream sites. Consistent with estimation results reported in dissertation essays one and two, the upstream pollution concentration positively and significantly contributes to the immediate downstream nutrient reading due to the fate of N and the connectivity of streams and rivers. Drought conditions, a proxy of lower streamflow, decrease measured total N levels in streams, consistent with the hydrology literature (Bowles et al., 2018; Mosley, 2015; van Vliet & Zwolsman, 2008). Rainfall and drastic dry-to-wet conditions increase ambient surface N concentration, which are also consistent with the literature (Bowles et al., 2018; Congreves et al., 2016; Nangia et al., 2010).

basins, the directional effects are the same among the other basins across the different fixed effect specifications.

Table 3.3: Effects of EQIP payments on ambient Nitrogen concentration for downstream basins

	<i>Dependent variable:</i>		
	Nitrogen concentration (mg/l)		
	(1)	(2)	(3)
EQIP cost share (million \$)	-8.13*** (2.39)	-5.59** (2.51)	-5.59** (2.52)
EQIP cost share (million \$) $\times$ PDSI (+:Dry)	-1.25** (0.630)	-1.09** (0.479)	-1.09** (0.482)
EQIP cost share (million \$) $\times$ 14-D cum. rain	0.107** (0.044)	0.118*** (0.045)	0.118*** (0.046)
EQIP cost share (million \$) $\times$ PDSI (+:Dry) $\times$ 14-D cum. rain	0.018** (0.009)	0.018** (0.008)	0.018** (0.008)
Observations	21,405	21,405	21,405
mean N concentration	1.45	1.45	1.45
<i>Fixed-effects</i>			
Basin	Yes	Yes	Yes
Basin by month	Yes	Yes	Yes
Water resource region by month	Yes		Yes
Water resource region by year		Yes	Yes
Weather	Yes	Yes	Yes
Socioeconomic Char.	Yes	Yes	Yes
Pollution Spillovers	Yes	Yes	Yes
R ²	0.83575	0.85162	0.85162

Note: Each column presents the results for estimating Equation 3.3 for monitoring basins with upstream pollutant measurements with different fixed effects specifications, including monitoring basin, basin by year, water resource region by month, and water resource region by year. Column 2 excludes water resource-by-month fixed effects and is the preferred specification. Column 3 includes all fixed effects. Column 1 excludes water resource region-by-year fixed effects. Controls include weather (i.e., PDSI and near-term rainfall), socioeconomic characteristics (i.e., corn and soybean yield and gross farm income), and upstream pollution spillovers (i.e., upstream weighted average N measurements). Monitoring basin fixed effects capture time-invariant determinants of water pollution specific to the basin. Basin-by-month fixed effects control for the seasonality of N concentrations specific to the basin. Water resource region-by-year fixed effects capture the annual trend of water pollution within each water resource region. Robust standard errors are in parentheses and are clustered at the monitoring basin level. Asterisks denote p-value < 0.1(*), < 0.05(**), or < 0.01(***)

Table 3.4: Effects of EQIP payments on ambient Nitrogen concentration for headwater basins

	<i>Dependent variable:</i>		
	Nitrogen concentration (mg/l)		
	(1)	(2)	(3)
EQIP cost share (million \$)	-4.92 (4.03)	-0.846 (3.78)	-0.846 (3.79)
EQIP cost share (million \$) $\times$ PDSI (+:Dry)	-1.16 (0.975)	-1.46 (0.922)	-1.46 (0.924)
EQIP cost share (million \$) $\times$ 14-D cum. rain	0.082 (0.052)	0.076 (0.048)	0.076 (0.048)
EQIP cost share (million \$) $\times$ PDSI (+:Dry) $\times$ 14-D cum. rain	0.013 (0.011)	0.013 (0.011)	0.013 (0.011)
Observations	64,530	64,530	64,530
mean N concentration	1.41	1.41	1.41
<i>Fixed-effects</i>			
Basin	Yes	Yes	Yes
Basin by month	Yes	Yes	Yes
Water resource region by month	Yes		Yes
Water resource region by year		Yes	Yes
Weather	Yes	Yes	Yes
Socioeconomic Char.	Yes	Yes	Yes
Pollution Spillovers			
R ²	0.78384	0.79952	0.79952

Note: Each column presents the results for estimating Equation 3.3 for headwater monitoring basins with different fixed effects specifications, including monitoring basin, basin by year, water resource region by month, and water resource region by year. Column 2 excludes water resource-by-month fixed effects and is the preferred specification. Column 3 includes all fixed effects. Column 1 excludes water resource region-by-year fixed effects. Controls include weather (i.e., PDSI and near-term rainfall), socioeconomic characteristics (i.e., corn and soybean yield and gross farm income), and upstream pollution spillovers (i.e., upstream weighted average N measurements). Monitoring basin fixed effects capture time-invariant determinants of water pollution specific to the basin. Basin-by-month fixed effects control for the seasonality of N concentrations specific to the basin. Water resource region-by-year fixed effects capture the annual trend of water pollution within each water resource region. Robust standard errors are in parentheses and are clustered at the monitoring basin level. Asterisks denote p-value<0.1(*), <0.05(**), or <0.01(***)

Table 3.5: Effects of EQIP payments on ambient Nitrogen concentration for all basins

	<i>Dependent variable:</i>		
	Nitrogen concentration (mg/l)		
	(1)	(2)	(3)
EQIP cost share (million \$)	-6.59** (2.80)	-2.46 (2.62)	-2.46 (2.63)
EQIP cost share (million \$) $\times$ PDSI (+:Dry)	-1.27* (0.653)	-1.19** (0.580)	-1.19** (0.581)
EQIP cost share (million \$) $\times$ 14-D cum. rain	0.098** (0.038)	0.092*** (0.035)	0.092*** (0.035)
EQIP cost share (million \$) $\times$ PDSI (+:Dry) $\times$ 14-D cum. rain	0.016** (0.008)	0.015** (0.007)	0.015** (0.007)
Observations	85,935	85,935	85,935
mean N concentration	1.42	1.42	1.42
<i>Fixed-effects</i>			
Basin	Yes	Yes	Yes
Basin by month	Yes	Yes	Yes
Water resource region by month	Yes		Yes
Water resource region by year		Yes	Yes
Weather	Yes	Yes	Yes
Socioeconomic Char.	Yes	Yes	Yes
Pollution Spillovers			
R ²	0.78734	0.80212	0.80212

Note: Each column presents the results for estimating Equation 3.3 for all monitoring basins with different fixed effects specifications, including monitoring basin, basin by year, water resource region by month, and water resource region by year. Column 2 excludes water resource-by-month fixed effects and is the preferred specification. Column 3 includes all fixed effects. Column 1 excludes water resource region-by-year fixed effects. Controls include weather (i.e., PDSI and near-term rainfall), socioeconomic characteristics (i.e., corn and soybean yield and gross farm income), and upstream pollution spillovers (i.e., upstream weighted average N measurements). Monitoring basin fixed effects capture time-invariant determinants of water pollution specific to the basin. Basin-by-month fixed effects control for the seasonality of N concentrations specific to the basin. Water resource region-by-year fixed effects capture the annual trend of water pollution within each water resource region. Robust standard errors are in parentheses and are clustered at the monitoring basin level. Asterisks denote p-value < 0.1(*), < 0.05(**), or < 0.01(***)

3.5 Robustness of Results

Similar to Chapter 1, this section discusses the possibility of endogenous water quality sampling. Unbalanced water quality data may hinder the identification, if water quality sampling is more likely to occur under certain circumstances that also impact nutrient concentrations. A plausible problem for identification would arise if water quality were sampled more frequently in locations where treatment levels are higher when precipitation events occur. Empirically, a statistically significant interaction effect between treatment and precipitation could be a reflection of sampling endogeneity and raise concerns about the estimator being biased (Raff & Meyer, 2021). To test for such sampling endogeneity, we examine the effect of EQIP cost share and near-term precipitation on the odds ratio of water quality sampling at a given monitoring basin on a given day of the month.

$$WQS_{it} = \beta_1 EQIP_{it} + \beta_2 R_{it} + \beta_3 CSP_{it} \times R_{it} + \eta_i + \tau_{it} + \theta_{wy} + \epsilon_{it} \quad (3.5)$$

The notation is similar to Equation 3.3, but, here, the dependent variable, WQS_{it} , is a dummy that indicates the availability of a water quality sample at a given monitoring basin i on a given day of the month t . For those basins and months when water quality measurements were taken but not usable, we treat WQS_{it} to be one because water quality samples were obtained, but readings were reported as being "not applicable" (i.e., there is no systematic non-sampling, rather a usable sample). Precipitation, R_{it} , was measured using four different multi-day periods of prior cumulative rainfall: (1) 7-day, (2) 14-day, (3) 21-day, and (4) 30-day cumulative rainfall.

Table D.5 shows the results for the estimation of Equation 3.5 using logistic regression. We do not find the percentage of EQIP, and the interactions with near-term rainfall to have statistically significant effects on the probability of water quality being sampled. The estimates

Table 3.6: Effect of EQIP and recent rainfall on water quality sampling

	<i>Dependent variable:</i>			
	Sampling dummy			
	(1)	(2)	(3)	(4)
EQIP cost share (million \$)	-2.06 (3.26)	-2.53 (3.29)	-2.64 (3.37)	-2.88 (3.48)
7-D cum. rain $\times$ EQIP cost share	0.016 (0.029)			
14-D cum. rain $\times$ EQIP cost share		0.019 (0.023)		
21-D cum. rain $\times$ EQIP cost share			0.014 (0.020)	
30-D cum. rain $\times$ EQIP cost share				0.013 (0.018)
7-D cum. rain	0.002*** (0.0003)			
14-D cum. rain		0.001*** (0.0002)		
21-D cum. rain			0.001*** (0.0002)	
30-D cum. rain				0.001*** (0.0001)
<i>Fixed-effects</i>				
Basin	Yes	Yes	Yes	Yes
Basin by month	Yes	Yes	Yes	Yes
Water resource region by year	Yes	Yes	Yes	Yes
Observations	679,349	679,349	679,349	679,349

Note: Each column shows the logistic regression results for estimating Equation 3.5 with different days of cumulative precipitation. The outcome of interest is the odds ratio of water quality sampling. Each specification includes monitoring basin, basin-by-month, and water resource region-by-year fixed effects. EQIP cost share is the sum of obligated funds for WQ-related practices. The rainfall events are specified as the cumulative rainfall of 7-, 14-, 21-, and 30-day prior. Robust standard errors are in parentheses and are clustered at the monitoring basin levels. Asterisks denote p-value < 0.1(*), < 0.05(**), or < 0.01(***)

for the recent cumulative rainfall specifications are significant; however, the effects are near 0, implying that the odds ratio of sampling is indifferent from one. In sum, rainfall events do not influence the likelihood that a given monitoring basin is sampled, regardless of whether receiving EQIP funds. Further, the probability that water quality is measured on days with rainfall events does not change as certified EQIP payments increase or decrease. Therefore, we conclude that the unbalanced nature of the water quality sampling data does not bias our estimates.

3.6 Conclusions

EQIP, the largest conservation program on working agricultural land in terms of acreage and spending in the U.S., has offered substantial financial and technical assistance to field operators. However, the realized environmental benefits of the program still remain unclear and our understanding of these benefits is incomplete. This study attempts to provide a more comprehensive analysis than prior empirical work evaluating EQIP by including the entire program duration and the period before EQIP was first authorized in the 1996 Farm Bill. The pre-EQIP period serves as the baseline condition when no practices funded by EQIP are implemented on agricultural lands. This research evaluates the impact of EQIP on ambient N pollution levels using observed water quality and contract-level program expenditure data. The monthly panel study design allows for important intra-annual variation in total nitrogen concentration and associated weather, as opposed to the annual mean pollutant concentrations. The *ex-post* econometric estimates provide an alternative to hydrological simulation modeling, which has been widely implemented in the Conservation Effects Assessment Project (CEAP) to evaluate conservation outcomes. Literature has partially evaluated the impact of the EQIP program on water quality by exploring the years 2005 to 2015 (Liu et al., 2022). Other related work has investigated the effect of the Clean Water Act on point source pollution (Keiser & Shapiro, 2019), quantified non-point source pollution from concentrated animal feeding

operations in Wisconsin (Raff & Meyer, 2021), and the environmental externalities from use of fertilizer in modern intensive agriculture (Paudel & Crago, 2020).

This study finds that certified EQIP payments for water quality-related conservation practices have significantly reduced in-stream N pollutant levels in downstream basins. The interactive effects of EQIP with weather conditions have also been found to be significant in downstream basins. The interactions with recent rainfall and extreme dry-to-wet transition minimally reduce the direct effect of EQIP; while the drought and EQIP interaction is found to reduce ambient N. Note that pollution spillovers from upstream to downstream play an important role in the identification of the treatment effect, as evidenced by the fact that the EQIP treatment variable is highly significant only in the subset of models where we are able to control for upstream pollution levels. Without this independent variable, the econometric model is unable to detect a clear signal of the effect of EQIP on ambient total N levels.

Between fiscal years 2005 and 2020, USDA-NRCS has increased obligated funds from one to nearly two billion dollars in financial and technical assistance to subsidize the adoption of conservation practices on working agricultural land under EQIP. The cost-effectiveness of EQIP in achieving intended environmental benefits is an important policy question. A five-thousand-dollar increase in EQIP cost-share payments is estimated to reduce ambient total N concentrations by 20% (0.03 mg/l) of the average N measurements. This is compared to the average annual EQIP payments received by downstream basins equal to 5465 dollars over the entire lifespan of each practice. This analysis provides novel evidence for policymakers and researchers to evaluate the cost-effectiveness of total nitrogen reduction achieved by EQIP. Additional research will be needed to explore the heterogeneous program effects of individual practices in different states, farm resource regions, or water resource regions. In order to conduct a cost-benefit analysis of the program, policymakers would require a benefit estimate of the total N reduction achieved. The EQIP has reduced the total N concentrations in rivers and streams. Additional studies are needed to determine if the program has additional environmental benefits.

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Appendix A

SPATIAL UNITS CONSTRUCTION

When initially constructing the observation units (i.e., monitoring basins), the location of ambient water quality stations was assumed to be at the outlet of each HUC12 sub-watershed, but this assumption (when uniformly applied) causes two types of measurement errors when constructing spatial units using the National Hydrography Dataset (NHD).

First, some station locations only capture a subset of the basin’s drainage area and thus do not accurately measure drainage from the entire set of upstream HUC12s in a monitoring basin without considering the precise location of the monitoring station closest to the outlet of the NHD-delineated boundary. Note that multiple HUC12s are combined to construct the monitoring basins that are the observational units in this study. When a subset of the monitoring basin does not flow through the monitoring station located closest to the basin’s outlet, any effect of treatment on this subset of land will not be measured at such a station. To address such measurement error, HUC12s that contain monitoring stations that do not capture the majority of drainage from the HUC where they are located, are reassigned to the next downstream monitoring basin. An example of this first kind of measurement error is illustrated in Appendix Figure C.4 by the station named DE-01. The pink-shaded monitoring basin in panel (1) consists of two HUC12s, with borders colored Turquoise in panel (2). The lines with the arrows indicate streams and the direction of flow. Note that station DE-01 does not capture flow through the HUC12 at the very bottom of the pink-shaded basin because the stream merges with the top HUC12 at the mouth of the hydrologic unit, where

no monitoring station is located. Hence, panel (3) of Appendix Figure C.4 depicts how the HUC12 at the bottom of the panel (2) is reassigned to the next downstream monitoring basin so that its contribution to ambient water quality is being captured by the correct monitoring station.

Second, some monitoring sites, despite being located in the HUC12, measure only a small share of the total area drained by the HUC12. Instead, such stations measure upstream HUC12s in the monitoring basin to a greater extent than the HUC12 where they are physically located. In other words, stations capture less than 50% of the HUC12 where located, but measure the entirety of the other upstream HUC12s in the basin. In this case, a site is artificially reassigned to (associated with) the upstream HUC12 and reassign the HUC12 where the station is located to the next downstream monitoring basin. An example of such an error is shown in Appendix Figure C.5 with a station named EOA-01. The pink-shaded land is a monitoring basin that contains this station, and the red-bordered area is the HUC12, where the station is located, where the black directional arrow shows the general direction of flow of the mainstream (purple line). In the right-top map, the station EOA-01 captures less than 50% of the self-located HUC12. Thus, as in panel (3) of Appendix Figure C.5, the station EOA-01 is reassigned to the upstream HUC12 in which the reassigned station is named EOA-01n on the map, and I reassign the original HUC12 where EOA-01 is located to the next downstream monitoring basin shaded with beige. After the adjustment of these measurement errors, I obtain a total of 49 monitoring basins with one monitoring station for each basin in Appendix Figure C.6. The red dots represent the water monitoring stations. The orange and blue shaded areas stand for basins with and without upstream neighbors, respectively.

Appendix B

TABLES (CHAPTER 1)

Table B.1: Pearson's correlation test of the frequency of N measurement availability

	<i>Frequency of available N samples</i>	
	corr.	t-stat.(p-value)
Percentage of treated acres	0.0711	0.4888 (0.6272)
Percentage of treated acres (WQ)	0.0508	0.3492 (0.7285)
Percentage of treated acres (WQ-Enh.)	0.0188	0.1291 (0.8978)
Developed land share	0.0080	0.0550 (0.9563)
Cropland land share	-0.0167	-0.1141 (0.9096)

Notes: WQ represents the conservation practices under CSP that tackle nutrient pollution. WQ-Enh. is WQ-related practices under CSP that are enhancements. Cropland land share is defined by the summation of corn, soybean, and wheat land shares.

Table B.2: Supplemental summary statistics

Variable	<i>Basins w/ upstream neighbors</i>		<i>Headwater basins</i>	
	Mean	SD	Mean	SD
CSP land share	1.12	1.99	1.84	4.04
CSP land share (WQ)	0.61	1.11	1.12	2.80
CSP land share (WQ-Enh.)	0.61	1.11	1.12	2.80
EQIP land share (%)	0.43	0.33	0.30	0.19

Notes: WQ represents the conservation practices under CSP that tackle nutrient pollution. WQ-Enh. are WQ-related practices under CSP that are enhancements. The summary statistics here show the results of pre-weighted measurements.

Table B.3: Pearson's correlation test of the percentage of treated acres under CSP

	<i>Percentage of treated acres under CSP</i>			
	(1)		(2)	
	Headwater basins		Basins w/ upstream neighbors	
	corr.	t-stat.(p-value)	corr.	t-stat.(p-value)
N concentration (mg/l)	0.3521	1.2798 (0.2139)	0.3300	1.677 (0.1071)
Gross farm income (million of \$)	0.3521	1.7649 (0.0915)	0.4161	2.195 (0.0585)
Corn yield (bu/acre)	0.2930	1.4376 (0.1646)	0.2362	1.166 (0.2555)
Soybeans yield (bu/acre)	0.2720	1.3259 (0.1985)	0.2550	1.265 (0.2185)

Note: The correlation is tested cross-sectionally. The percentage of lands under CSP is the average rate of treatment in the post-treatment period (i.e., 2010-2015). The N concentration is the mean measurement in the pre-treatment period (i.e., 2006-2009). Socioeconomic factors are the average values over the year 2006 to 2015. None of them shows statistical significance at the .10 level.

Table B.4: Panel two-way fixed effects (TWFE) for monitoring basins with distance-weighted treatment

	<i>Dependent variable:</i>		
	Nitrogen concentration (mg/l)		
	(1) All basins	(2) Headwater basins	(3) Basins w/ upstream neighbors
Treatment (CSP)			
Pct. of Treated Ac.	-0.096** (0.039)	-0.099** (0.040)	-0.067*** (0.017)
Pct. of Treated Ac. $\times$ PDSI (+:Dry)	-0.034 (0.021)	-0.033 (0.022)	-0.034** (0.013)
Pct. of Treated Ac. $\times$ 7-D Cum. Rain	0.002 (0.001)	0.003* (0.001)	-0.002 (0.0010)
Pct. of Treated Ac. $\times$ 7-D Cum. Rain $\times$ PDSI (+:Dry)	0.0001 (0.0004)	0.0003 (0.0005)	-0.0007* (0.0003)
Controls			
PDSI (+:Dry)	-0.223** (0.087)	-0.325* (0.144)	-0.053 (0.030)
7-D Cum. Rain	0.004 (0.004)	0.003 (0.009)	0.009** (0.004)
PDSI (+:Dry) $\times$ 7-D Cum. Rain	0.003** (0.001)	0.003 (0.002)	0.004*** (0.0009)
Gross Farm Income (million of \$)	0.0004 (0.002)	-0.006 (0.004)	0.001 (0.001)
Corn Yield (bu/acre)	0.004 (0.003)	0.008* (0.004)	-0.001 (0.004)
Soybeans Yield (bu/acre)	-0.015 (0.018)	-0.042* (0.019)	0.005 (0.007)
Pct. of EQIP Ac.	0.049 (0.092)	0.191*** (0.056)	0.024 (0.074)
Pollution Spillovers			
Upstream N (mg/l)	0.420*** (0.061)		0.605*** (0.035)
Observations	3,336	1,680	1,656
R ²	0.56945	0.51017	0.78996

Note: The table tabulates the complete results for the estimation of Equation 3.3. The treatment variable measures the distance-weighted percentage of acres from all conservation practices under CSP. Each specification includes year, month, and monitoring basin fixed effects. Robust standard errors are in parentheses and are clustered at the monitoring basin and year level. Asterisks denote p-value<0.1(*), <0.05(**), or <0.01(***)

Table B.5: Panel two-way fixed effects (TWFE) for all monitoring basins with three specifications of treatment

	<i>Dependent variable:</i>		
	Nitrogen concentration (mg/l)		
	(1) All basins	(2) Headwater basins	(3) Basins w/ upstream neighbors
Treatment (All)			
Pct. of Treated Ac.	-0.096** (0.039)		
Pct. of Treated Ac. $\times$ PDSI (+:Dry)	-0.034 (0.021)		
Pct. of Treated Ac. $\times$ 7-D Cum. Rain	0.002 (0.001)		
Pct. of Treated Ac. $\times$ PDSI (+:Dry) $\times$ 7-D Cum. Rain $\times$ 7-D Cum. Rain $\times$ PDSI (+:Dry)	0.0001 (0.0004)		
Treatment (WQ)			
Pct. of Treated Ac. (WQ)		-0.112** (0.047)	
Pct. of Treated Ac. (WQ) $\times$ PDSI (+:Dry)		-0.034 (0.026)	
Pct. of Treated Ac. (WQ) $\times$ 7-D Cum. Rain		0.003 (0.002)	
Pct. of Treated Ac. (WQ) $\times$ 7-D Cum. Rain $\times$ PDSI (+:Dry)		0.0003 (0.0006)	
Treatment (WQ-Enh.)			
Pct. of Treated Ac. (Enh.)			-0.112** (0.047)
Pct. of Treated Ac. (Enh.) $\times$ PDSI (+:Dry)			-0.034 (0.026)
Pct. of Treated Ac. (Enh.) $\times$ 7-D Cum. Rain			0.003 (0.002)
Pct. of Treated Ac. (Enh.) $\times$ 7-D Cum. Rain $\times$ PDSI (+:Dry)			0.0003 (0.0006)
Controls			
PDSI (+:Dry)	-0.223** (0.087)	-0.252** (0.085)	-0.253** (0.085)
7-D Cum. Rain	0.004 (0.004)	0.004 (0.004)	0.004 (0.004)
PDSI (+:Dry) $\times$ 7-D Cum. Rain	0.003** (0.001)	0.003** (0.001)	0.003** (0.001)
Gross Farm Income (Ten million of \$)	0.0004 (0.002)	0.0000 (0.001)	0.0000 (0.001)
Corn Yield (bu/acre)	0.004 (0.003)	0.004 (0.003)	0.004 (0.003)
Soybeans Yield (bu/acre)	-0.015 (0.018)	-0.014 (0.018)	-0.014 (0.018)
Pct. of EQIP Ac.	0.049 (0.092)	0.036 (0.101)	0.037 (0.101)
Pollution Spillovers			
Upstream N (mg/l)	0.420*** (0.061)	0.422*** (0.062)	0.422*** (0.062)
Observations	3,336	3,336	3,336
R ²	0.56945	0.56676	0.56678

Note: Each column presents the results for estimating Equation 3.3 with different treatment specifications for all basins. Models 1, 2, and 3 are analyses with the treatment capturing (1) all practices under CSP, (2) WQ-related practices, and (3) WQ-related practices, which are enhancements. Each specification includes year, month, and monitoring basin fixed effects. Robust standard errors are in parentheses and are clustered at the monitoring basin and year level. Asterisks denote p-value<0.1(*), <0.05(**), or <0.01(***)

Table B.6: TWFE of observed total Nitrogen (N) minus ML predicted counterfactual ($\hat{N}$)

	<i>Dependent variable:</i>		
	$N - \hat{N}$		
	(1) All basins	(2) Headwater basins	(3) Basins w/ upstream neighbors
CSP			
Pct. of Treated Ac.	-0.048** (0.019)	-0.043* (0.022)	-0.050*** (0.011)
Pct. of Treated Ac. $\times$ PDSI (+:Dry)	-0.033*** (0.008)	-0.034*** (0.009)	-0.033*** (0.006)
Pct. of Treated Ac. $\times$ 7-D Cum. Rain	0.002*** (0.0003)	0.002*** (0.0003)	-0.0005 (0.0008)
Pct. of Treated Ac. $\times$ 14-D Cum. Rain $\times$ PDSI (+:Dry)	0.0005*** (0.00005)	0.0007** (0.0002)	-0.0003 (0.0003)
Controls			
PDSI (+:Dry)	-0.073* (0.033)	-0.078 (0.051)	-0.046 (0.029)
7-D Cum. Rain	-0.002 (0.002)	-0.008 (0.006)	0.005 (0.003)
PDSI (+:Dry) $\times$ 7-D Cum. Rain	0.0009** (0.0003)	-0.0003 (0.0009)	0.002** (0.0009)
Pct. of EQIP Ac.	-0.083 (0.121)	-0.213* (0.107)	0.074 (0.098)
Pollution Spillovers			
$N_{up} - \hat{N}_{up}$	0.488*** (0.028)		0.514*** (0.036)
Observations	3,285	1,642	1,643
R ²	0.34885	0.22557	0.54098

Note: The table tabulates the complete results for the estimation of Equation 1.3. Robust standard errors are in parentheses and are clustered at the monitoring basin and year level. Asterisks denote p-value<0.1(*), <0.05(**), or <0.01(***)

Table B.7: TWFE of observed total Nitrogen (N) minus ML predicted counterfactual ($\hat{N}$) across three treatment specifications for all monitoring basins

	<i>Dependent variable:</i>		
	(1) All	(2) WQ	(3) WQ-Enhancement
Treatment (All)			
Pct. of Treated Ac.	-0.048** (0.019)		
Pct. of Treated Ac. $\times$ PDSI (+:Dry)	-0.033*** (0.008)		
Pct. of Treated Ac. $\times$ 7-D Cum. Rain	0.002*** (0.0003)		
Pct. of Treated Ac. $\times$ 7-D Cum. Rain $\times$ PDSI (+:Dry)	0.0005*** (0.00005)		
Treatment (WQ)			
Pct. of Treated Ac.		-0.048** (0.021)	
Pct. of Treated Ac. $\times$ PDSI (+:Dry)		-0.038*** (0.009)	
Pct. of Treated Ac. $\times$ 7-D Cum. Rain		0.003*** (0.0004)	
Pct. of Treated Ac. $\times$ 7-D Cum. Rain $\times$ PDSI (+:Dry)		0.0007*** (0.0002)	
Treatment (WQ-Enh.)			
Pct. of Treated Ac.			-0.049** (0.021)
Pct. of Treated Ac. $\times$ PDSI (+:Dry)			-0.038*** (0.009)
Pct. of Treated Ac. $\times$ 7-D Cum. Rain			0.003*** (0.0004)
Pct. of Treated Ac. $\times$ 7-D Cum. Rain $\times$ PDSI (+:Dry)			0.0007*** (0.0002)
Controls			
PDSI (+:Dry)	-0.073* (0.033)	-0.091** (0.034)	-0.091*** (0.029)
7-D Cum. Rain	-0.002 (0.002)	-0.002 (0.002)	-0.002 (0.003)
PDSI (+:Dry) $\times$ 7-D Cum. Rain	0.0009** (0.0003)	0.0009** (0.0004)	0.0009 (0.0006)
Pct. of EQIP Ac.	-0.083 (0.121)	-0.119 (0.114)	-0.118 (0.114)
Pollution Spillovers			
$N_{up} - \hat{N}_{up}$	0.488*** (0.028)	0.492*** (0.030)	0.492*** (0.031)
Month fix effects	Yes	Yes	Yes
Year fix effects	Yes	Yes	Yes
Basin fix effects	Yes	Yes	Yes
Observations	3,285	3,285	3,285
R ²	0.34885	0.34656	0.34652

Note: The table tabulates the complete results for the estimation of Equation 1.3 with different treatment specifications for all basins. Models 1, 2, and 3 are analyses with the treatment capturing (1) all practices under CSP, (2) WQ-related practices, and (3) WQ-related practices, which are enhancements. Robust standard errors are in parentheses and are clustered at the monitoring basin and year level. Asterisks denote p-value<0.1(*), <0.05(**), or <0.01(***)

Table B.8: Validity check of out-of-sample prediction

	<i>Dependent variable:</i>
	$N - \hat{N}$
Out-of-sample Dummy	0.250 (0.152)
Fixed effects:	
Month	Yes
Year	Yes
Basin	Yes
EQIP	Yes
Weather	Yes
Socioeconomic Char.	No
Pollution Spillovers ($N_{up} - \hat{N}_{up}$)	Yes
Observations	403

Note: We check if the prediction errors for untreated monitoring basins are different between pre- and post-treatment periods. The out-of-sample dummy equals to one during the post-treatment period. We regress the prediction errors on the out-of-sample dummy along with controls and fixed effects. We do not find prediction errors to be significantly different between pre- and post-treatment periods. This result supports that the out-of-sample prediction error minimally biases the estimation. Asterisks denote p-value<0.1(*), <0.05(**), or <0.01(***)

Table B.9: Effect of annual mean weighted CSP on water quality sampling counts

	<i>Dependent variable:</i>
	Sampling counts
Annual Mean Pct. of Treated Ac.(CSP)	-0.001 (0.005)
Observations	486

Note: We regress the annual count of available water quality samples on the yearly mean percentage of CSP lands. We do not find evidence that the levels of treatment affect the total counts of water quality sampling. Asterisks denote p-value<0.1(*), <0.05(**), or <0.01(***)

Appendix C

FIGURES (CHAPTER 1)

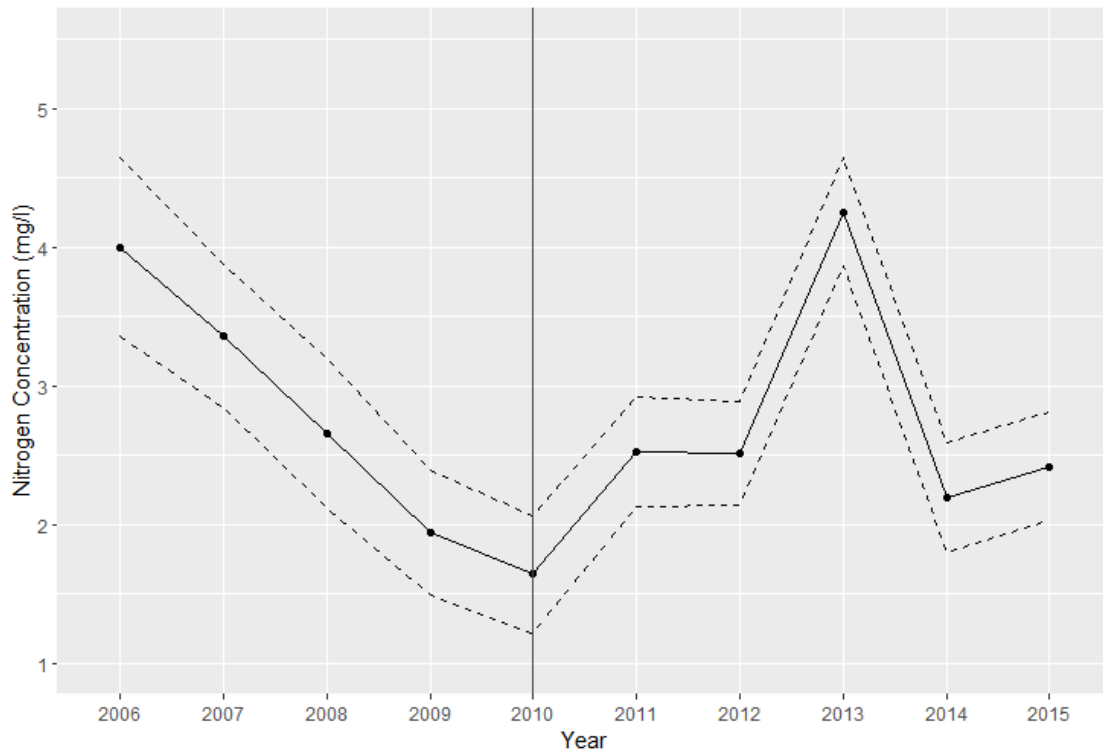


Figure C.1: Nitrogen concentration trends, 2006-2015

Notes: The annual N trend is based on Equation 3.1, where we add the recent precipitation events and drought index in the matrix X'_{imt} .

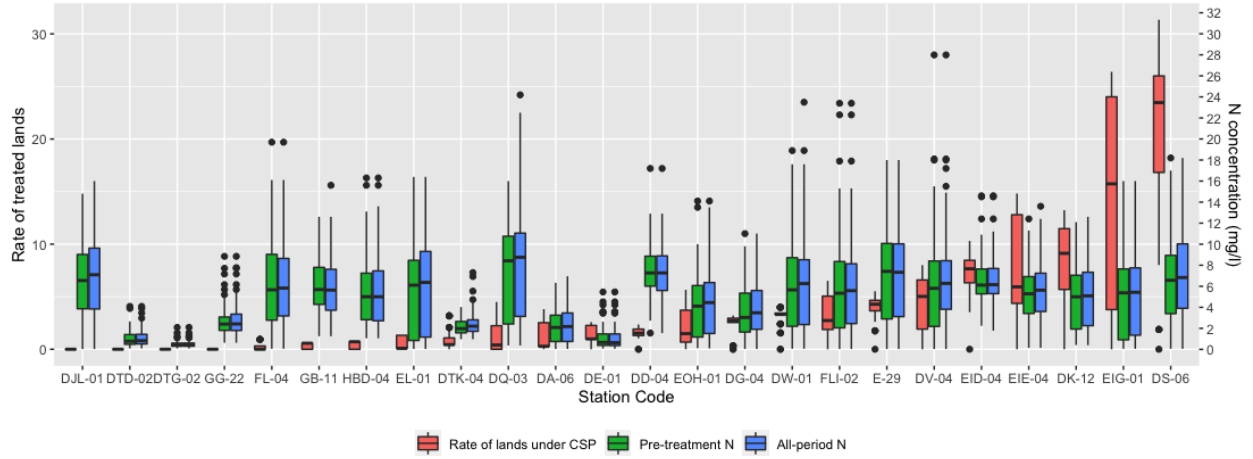


Figure C.2: Boxplots of CSP and N concentration for headwater basins

Notes: We demonstrate the boxplots of the rate of CSP, as well as the N concentration in the pre-treatment and all periods for headwater basins. The x-axis is ordered ascendingly from left to right by the mean percentage of lands under CSP. We do not observe increasing or decreasing trends in pre-treatment N as the rate of CSP increases.

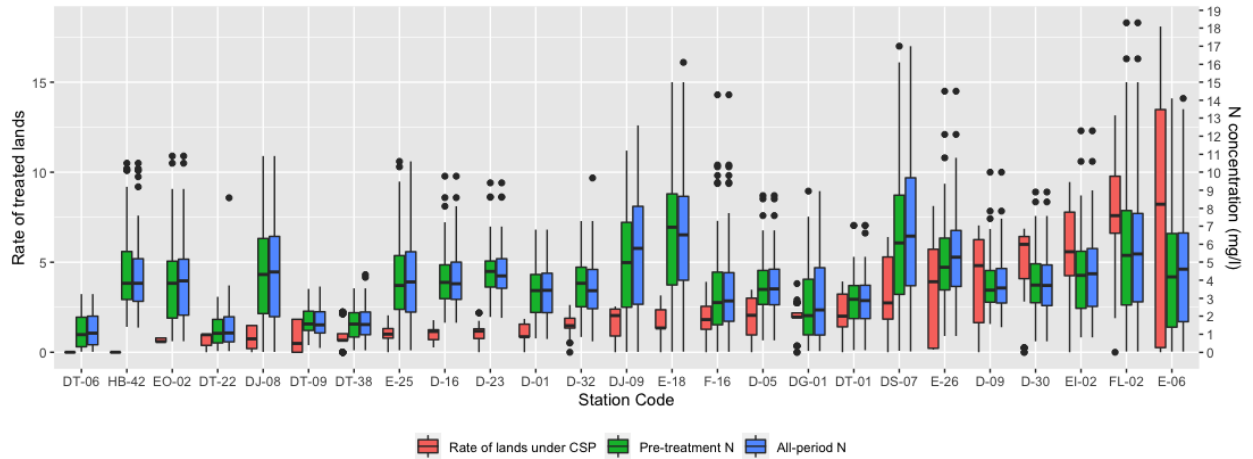


Figure C.3: Boxplots of CSP and N concentration for basins with upstream neighbors

Note: We demonstrate the boxplots of the rate of CSP, as well as the N concentration in the pre-treatment and all periods for basins with upstream neighbors. The x-axis is ordered ascendingly from left to right by the mean percentage of lands under CSP. We do not observe increasing or decreasing trends in pre-treatment N as the rate of CSP increases.

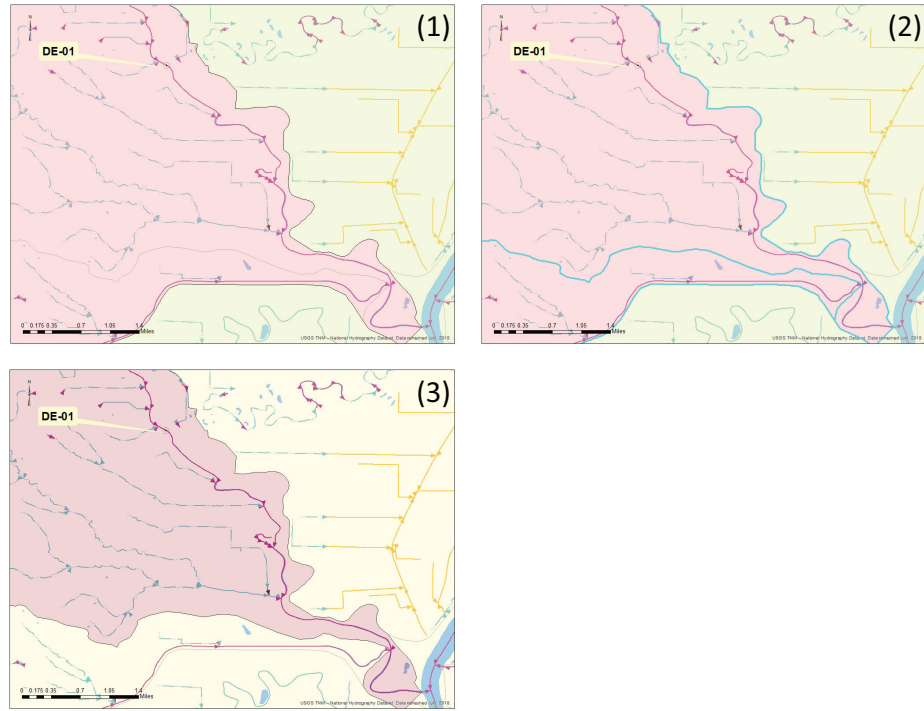


Figure C.4: Maps of first type of measurement error: mis-assignment of HUC12s to upstream monitoring stations

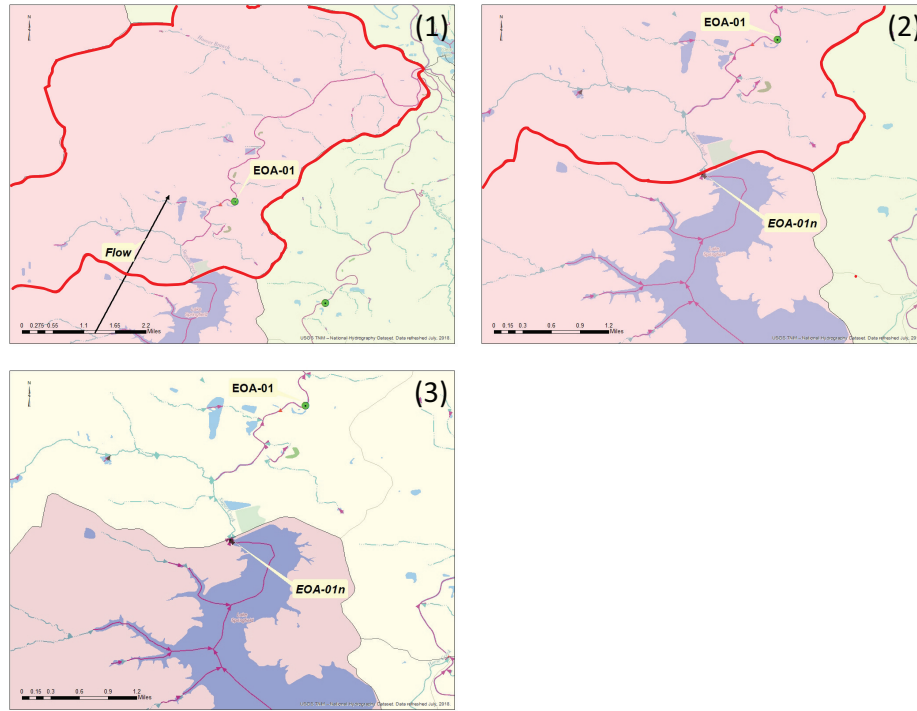


Figure C.5: Maps of the second measurement error

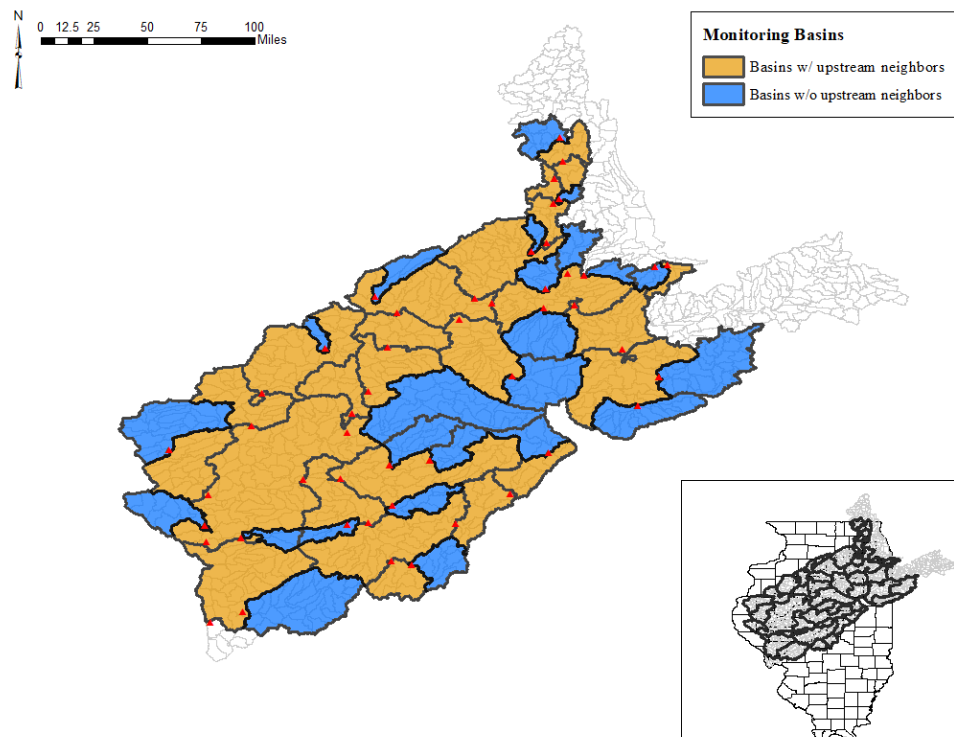


Figure C.6: The monitoring basins (black lines) aggregated by HUC12 sub-watersheds (fade lines)

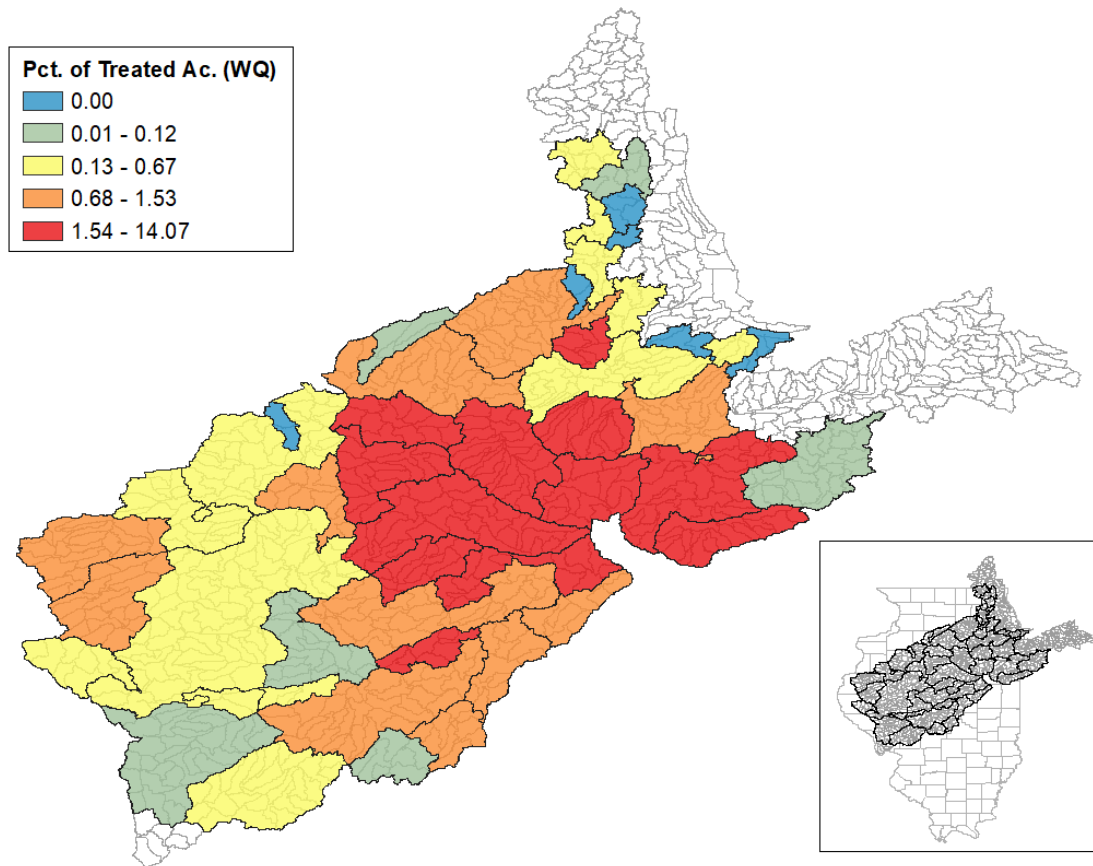


Figure C.7: Quantile map of mean percentage CSP lands tackling nutrient pollution in ILRB from 2010 to 2015

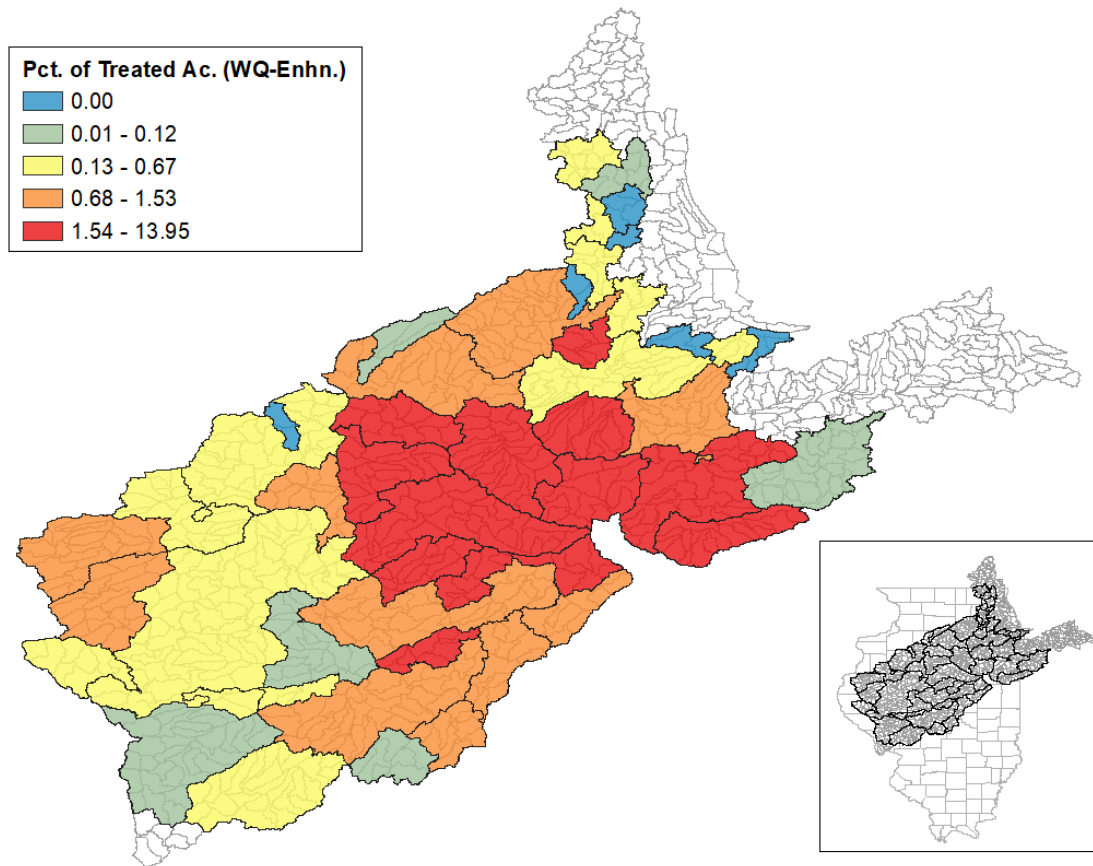


Figure C.8: Quantile map of mean percentage CSP lands that tackle nutrient pollution and are enhancement practices from 2010 to 2015

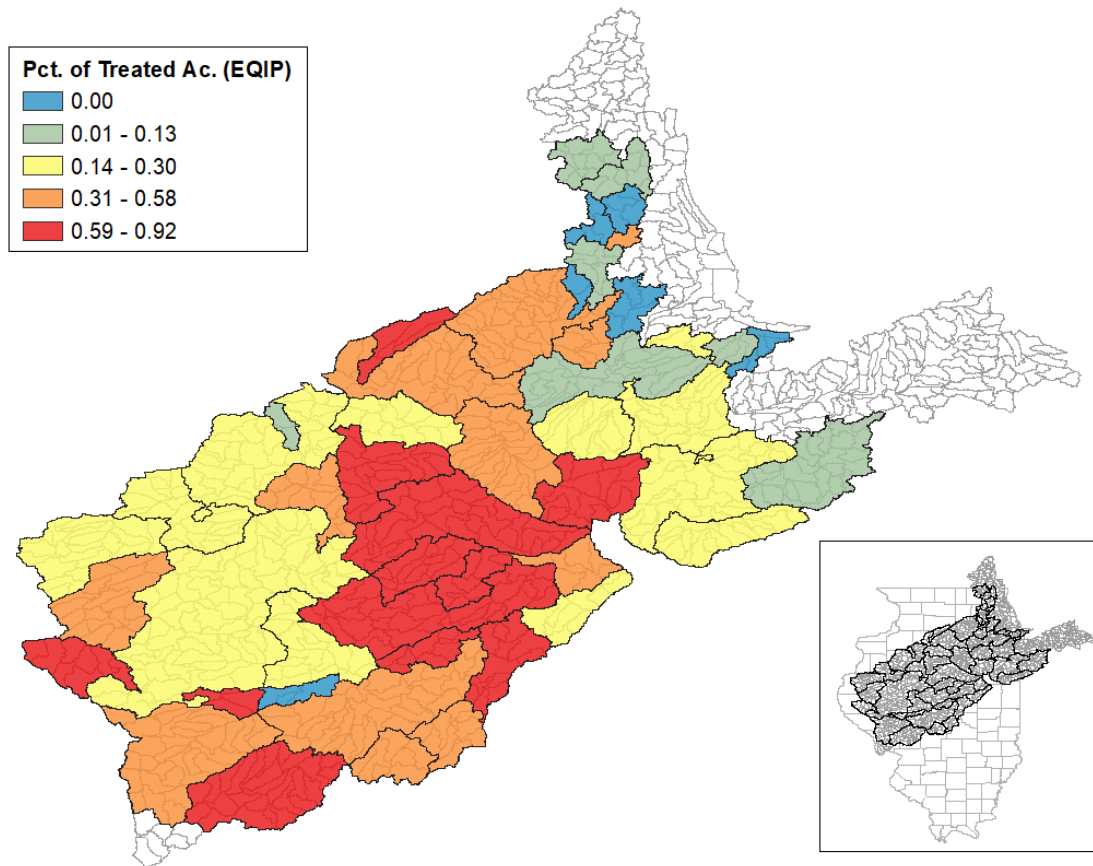


Figure C.9: Quantile map of mean percentage of lands under EQIP from 2006 to 2015

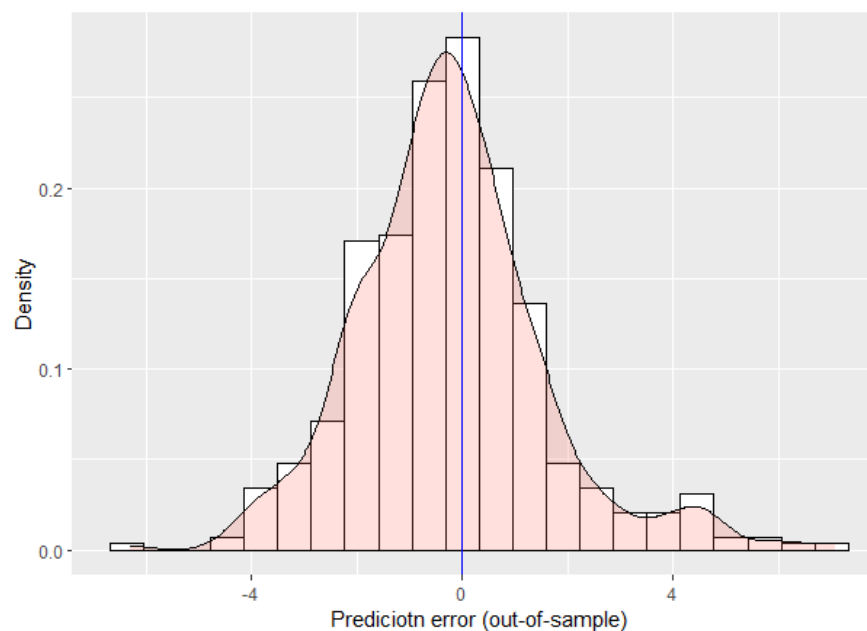


Figure C.10: Distribution of out-of-sample prediction errors

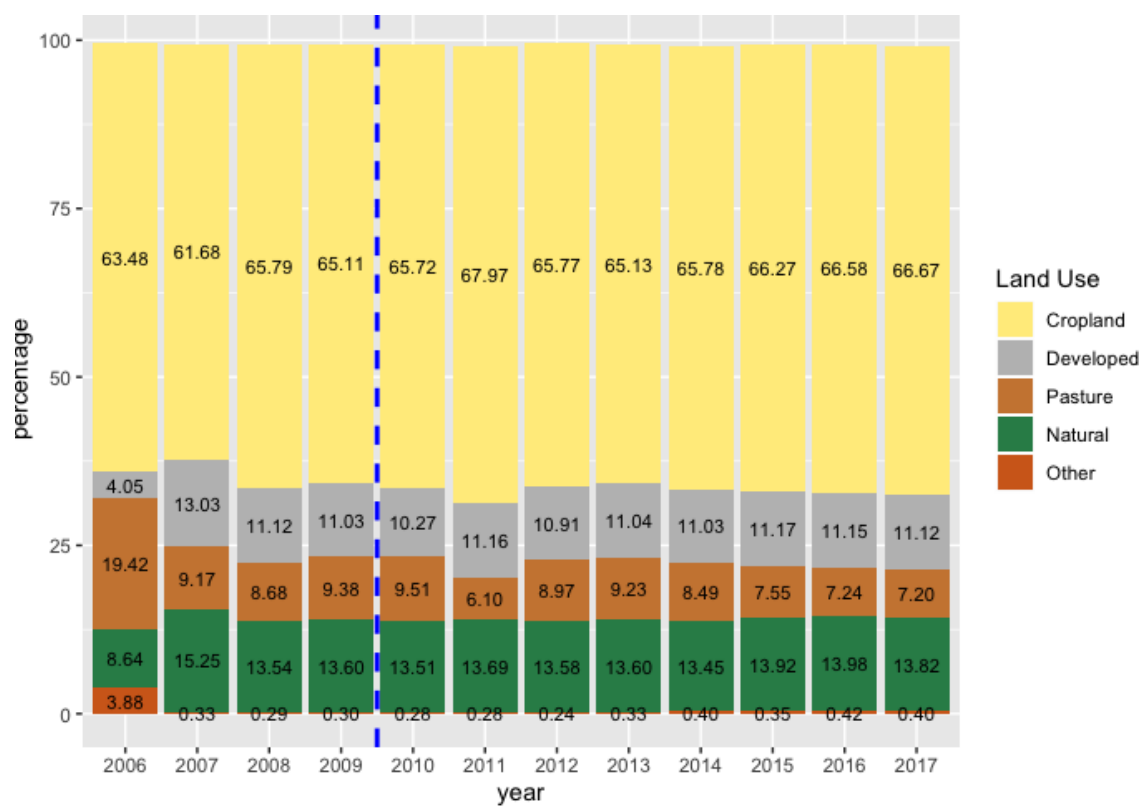


Figure C.11: Percentage of land use over the year 2006 to 2017 on 49 monitoring basins

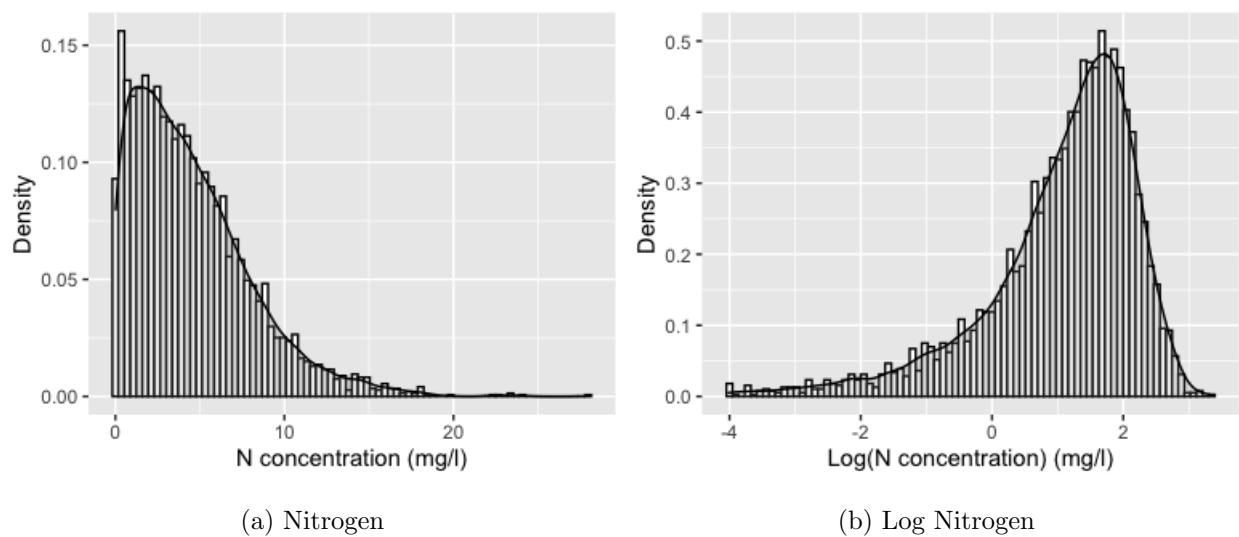


Figure C.12: Densities of pollution readings

Notes: Data include years 2006-2017 for all basins.

Appendix D

TABLES (CHAPTER 2)

Table D.1: Appendix summary statistics

	<i>Downstream Basins</i>		<i>Headwater Basins</i>	
	Mean	St. Dev.	Mean	St. Dev.
Basin Size (acres) ***	1777423.862	1426777.16	1024921.292	630902.05
CC adoption (acres) ***	21736.548	37359.17	9109.480	14723.22
Funded CC from EQIP (acres) ***	2276.201	4783.609	1029.496	2016.122
Share of CC funded by EQIP (%) *	19.057	28.820	22.276	31.648

Note: Asterisks denote p-value<0.1(*), <0.05(**), or <0.01(***)

EQIP is the Environmental Quality Incentives Program.

Table D.2: Panel fixed-effect (FE) estimates for monitoring basins (Sensitivity Check)

	<i>Dependent variable:</i>		
	Nitrogen concentration (mg/l)		
	(1) Downstream Basins	(2) Headwater Basins	(3) All basins
Treatment			
Cropland Pct. of Cover Crops	−0.042** (0.018)	0.016 (0.023)	−0.013 (0.013)
Cropland Pct. of Cover Crops (quadratic)	0.001** (0.0003)	−0.0002 (0.0002)	0.0001 (0.0002)
Weather			
7-D Cum. Rain	0.004 (0.004)	0.017*** (0.005)	0.010*** (0.003)
Spring PDSI	−0.093*** (0.024)	−0.151*** (0.041)	−0.129*** (0.027)
Socioeconomic Char.			
Corn Yield (bu/acre)	−0.0002 (0.001)	0.002 (0.002)	0.001 (0.001)
Farm Income (Ten million of \$)	0.0001 (0.0003)	−0.002*** (0.001)	−0.0003 (0.0003)
Land use			
Corn	0.068*** (0.023)	0.044* (0.026)	0.057*** (0.018)
Soybean	−0.019 (0.029)	−0.094*** (0.033)	−0.052** (0.023)
Developed	0.136 (0.104)	−0.152** (0.065)	−0.013 (0.078)
Pollution Spillovers			
Upstream N (mg/l)	0.512*** (0.085)		0.375*** (0.085)
Observations	590	725	1,315
R ²	0.349	0.086	0.128

Note: Asterisks denote p-value<0.1(*), <0.05(**), or <0.01(***).

Standard errors are clustered by monitoring basin.

Each analysis includes monitoring basin and HUC2-by-year fixed effects.

Water quality measurements in June, July, August, September, and October are included in the analysis to explore the treatment effect on overall annual ambient water quality, not only the months when cover crops are in the field.

Table D.3: Panel fixed effects with lag CC land share

	<i>Dependent variable:</i>		
	Nitrogen concentration (mg/l)		
	(1) Downstream Basins	(2) Headwater Basins	(3) All basins
Treatment and lag			
Cropland Pct. change of Cover Crops	−0.076** (0.036)	−0.010 (0.044)	−0.054** (0.026)
Lag Cropland Pct. of Cover Crops	−0.100** (0.041)	0.001 (0.060)	−0.047 (0.035)
Weather			
7-D Cum. Rain	0.005 (0.005)	0.016*** (0.006)	0.009** (0.004)
Spring PDSI	−0.124*** (0.032)	−0.239*** (0.068)	−0.191*** (0.044)
Socioeconomic Char.			
Corn Yield (bu/acre)	−0.0004 (0.002)	−0.002 (0.002)	−0.001 (0.002)
Farm Income (Ten million of \$)	0.0004 (0.0004)	−0.003** (0.001)	−0.0002 (0.001)
Land use			
Corn	0.049 (0.033)	0.013 (0.047)	0.023 (0.032)
Soybean	−0.025 (0.036)	−0.143*** (0.053)	−0.094*** (0.036)
Developed	−0.050 (0.089)	0.296 (0.199)	0.056 (0.136)
Pollution Spillovers			
Upstream N (mg/l)	0.480*** (0.105)		0.362*** (0.093)
Observations	523	667	1,190
R ²	0.379	0.116	0.151

Note: Asterisks denote p-value < 0.1(*), < 0.05(**), or < 0.01(***).

We explore the relationship between pollutant measurements and the lag of CC adoption rate, controlling for the change in the CC percentage: $N_{it} = \alpha_1 CC_{it-1} + \alpha_2 [CC_{it} - CC_{it-1}] + \mathbf{X}_{it}'\boldsymbol{\beta} + \gamma \sum_{k \in \Lambda_{i-1}} \psi_k N_{kt} + \theta_i + \eta_{rt} + \epsilon_{it}$. The notation is the same as Equation 3.3 with CC_{it-1} as the temporal lag of CC cropland share and $[CC_{it} - CC_{it-1}]$ as the change in the percentage of cropland planting CCs. We cannot make a causal claim here, but we can tell both the lag of CC cropland share and the CC percentage change are negatively correlated to the pollutant measurements.

Table D.4: Panel fixed effects with the total CC acres

	<i>Dependent variable:</i>		
	Nitrogen concentration (mg/l)		
	(1) Downstream Basins	(2) Headwater Basins	(3) All basins
Treatment			
Total Cover Crops acres (thousand acre)	−0.008** (0.003)	−0.002 (0.008)	−0.006** (0.002)
Total Cover Crops acres (quadratic)	0.00001** (0.00001)	−0.00002 (0.0001)	0.00001* (0.00000)
Weather			
7-D Cum. Rain	0.008 (0.006)	0.015** (0.006)	0.010*** (0.004)
Spring PDSI	−0.099*** (0.030)	−0.180*** (0.058)	−0.144*** (0.037)
Socioeconomic Char.			
Corn Yield (bu/acre)	−0.002 (0.002)	−0.0003 (0.002)	−0.001 (0.002)
Farm Income (Ten million of \$)	0.001 (0.0004)	−0.003*** (0.001)	−0.00002 (0.0005)
Land use			
Corn	0.061* (0.031)	0.079** (0.036)	0.079*** (0.026)
Soybean	−0.006 (0.031)	−0.123*** (0.043)	−0.066** (0.029)
Developed	−0.063 (0.100)	0.390* (0.213)	0.123 (0.144)
Pollution Spillovers			
Upstream N (mg/l)	0.445*** (0.096)		0.340*** (0.088)
Observations	574	728	1,302
R ²	0.331	0.106	0.130

Note: Asterisks denote p-value < 0.1(*), < 0.05(**), or < 0.01(***).

In this analysis, we estimate the Equation 3.3 with the CC acreage as the treatment variable. Note that the CC acreage is scaled, so we interpret the effect as every thousand acres of CC implementation. We evaluate the CCs impact on ambient N by holding all the other terms in the entire equation fixed at their mean multiplied by the estimated coefficients. Then, we plot the curve, as well as the point estimates in Appendix Figure E.5. We can tell the diminishing marginal return to scale in ambient N measurements as increasing acres in CC adoption.

Table D.5: Effect of CCs and recent rainfall on water quality sampling

	<i>Dependent variable:</i>			
	Sampling dummy			
	(1)	(2)	(3)	(4)
CCs cropland pct.	−0.101*	0.013	0.131	0.028
	(0.057)	(0.073)	(0.113)	(0.126)
Day of Sample Rain	−0.007			
	(0.037)			
3-D Cum. Rain		−0.007		
		(0.017)		
7-D Cum. Rain			0.010	
			(0.011)	
14-D Cum. Rain				0.008
				(0.007)
CCs cropland pct. × Day of Sample Rain	0.013			
	(0.014)			
CCs cropland pct. × 3-D Cum. Rain		−0.012		
		(0.008)		
CCs cropland pct. × 7-D Cum. Rain			−0.010*	
			(0.005)	
CCs cropland pct. × 14-D Cum. Rain				−0.002
				(0.003)
Observations	1,896	1,896	1,896	1,896

Note: Asterisks denote p-value < 0.1(*), < 0.05(**), or < 0.01(***)

To test for the sampling endogeneity, we examine the effect of CCs and the annual mean of near-term precipitation on the odds ratio of water quality sampling at a given monitoring basin annually. We first create a balanced monthly panel dataset of all the monitoring basins in all months and link them with rainfall events. Because water quality is not sampled every month in every basin, we must construct an assumed sampling date for every month when a monitoring station sample was not actually collected to be able to test whether such sampling (or non-sampling) is somehow endogenous. For all months in all locations when a sample is not taken in the unbalanced monitoring data, we arbitrarily assign an assumed sampling day. Further, to match up with the annual CC adoption rate, we aggregate the near-term precipitation to the annual mean. Then, we estimate the following equation using the logistic regression: $WQS_{it} = \beta_1 CC_{it} + \beta_2 R_{it} + \beta_3 CC_{it} \times R_{it} + \eta_i + \epsilon_{it}$. The notation is similar to Equation 3.3, but here, the dependent variable, WQS_{it} , is a dummy that indicates the availability of at least one water quality sample at a given monitoring basin i at a given year t . For those basins and months when water quality measurements were taken but not usable, we count them as active water sampling because water quality samples were obtained, but readings were reported as being "not applicable" (i.e., there is no systematic non-sampling, rather a usable sample). Precipitation, R_{it} , was evaluated using four different multi-day periods of prior cumulative rainfall: (1) the same day as water quality sampled (2) 3-day, (3) 7-day, and (4) 14-day cumulative rainfall. We do not find the cropland percentage of CCs, rainfall events, or their interactions to have statistically significant effects on the probability of water quality being sampled. In sum, rainfall events do not influence the likelihood that a given monitoring basin is sampled, no matter whether there are lands implementing CCs or not. Further, the probability that water quality is measured annually with average rainfall events does not change as the rate of CC adoption increases or decreases. Therefore, we conclude that the unbalanced nature of the water quality sampling data does not bias our estimates.

Table D.6: Linear panel fixed-effect estimates

	<i>Dependent variable:</i>		
	Nitrogen concentration (mg/l)		
	(1) Downstream Basins	(2) Headwater Basins	(3) All basins
Treatment			
Cropland Pct. of Cover Crops	−0.020** (0.009)	−0.009 (0.006)	−0.014*** (0.005)
Weather			
7-D Cum. Rain	0.007 (0.006)	0.015*** (0.006)	0.010*** (0.004)
Spring PDSI	−0.108*** (0.031)	−0.181*** (0.058)	−0.148*** (0.037)
Socioeconomic Char.			
Corn Yield (bu/acre)	−0.002 (0.002)	−0.0004 (0.002)	−0.001 (0.002)
Farm Income (Ten million of \$)	0.001 (0.0004)	−0.003*** (0.001)	−0.00002 (0.0005)
Land Use			
Corn	0.055* (0.031)	0.079** (0.036)	0.076*** (0.026)
Soybean	−0.016 (0.032)	−0.122*** (0.043)	−0.070** (0.029)
Developed	−0.047 (0.101)	0.395* (0.214)	0.128 (0.144)
Pollution Spillovers			
Upstream N (mg/l)	0.443*** (0.096)		0.336*** (0.088)
Observations	574	728	1,302
R ²	0.327	0.106	0.129

Note: Asterisks denote p-value < 0.1(*), < 0.05(**), or < 0.01(***).

Each analysis includes monitoring basin and HUC2-by-year fixed effects.

Standard errors are clustered by monitoring basin.

Appendix E

FIGURES (CHAPTER 2)

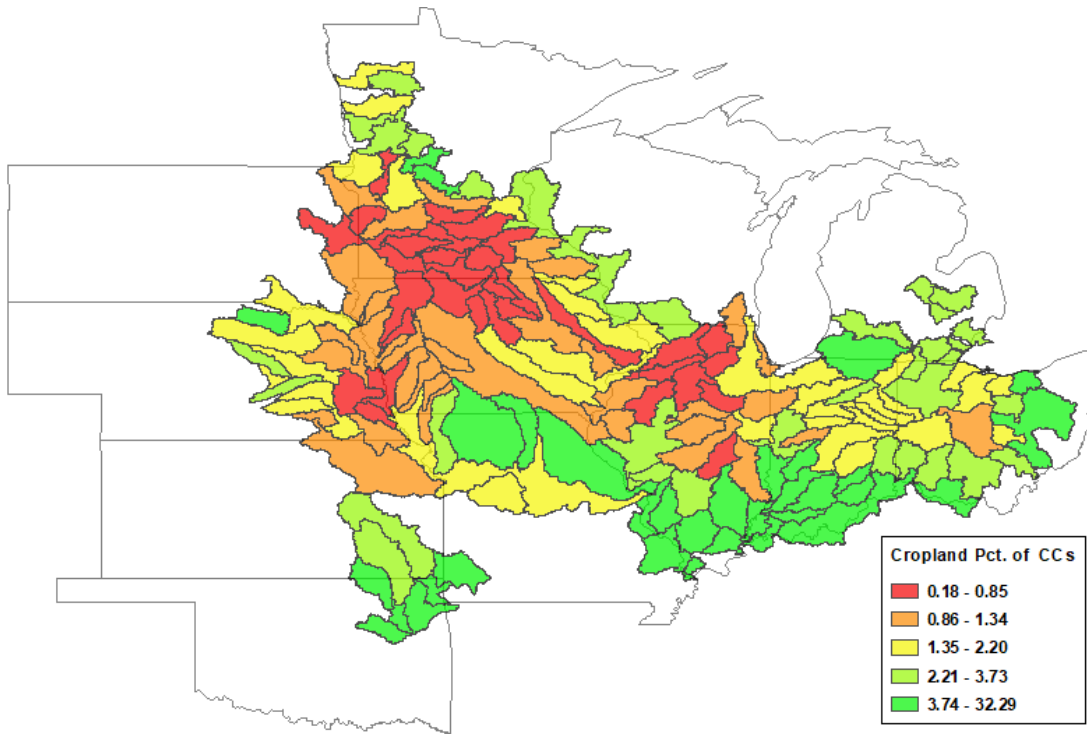


Figure E.1: Quantile map of the average cropland adoption rate of CCs from 2008 to 2018

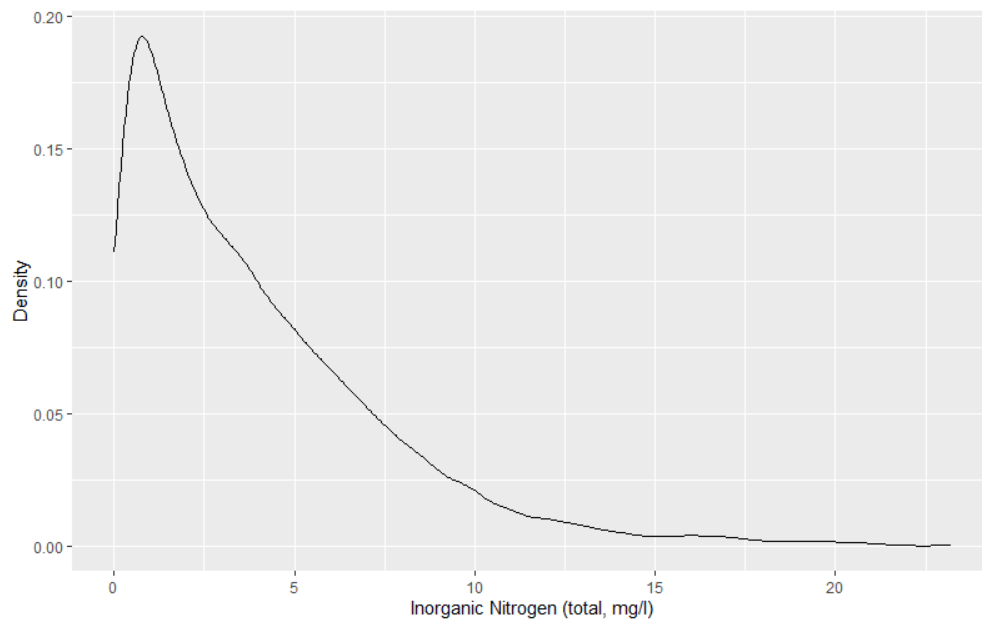


Figure E.2: Density plot of total inorganic nitrogen

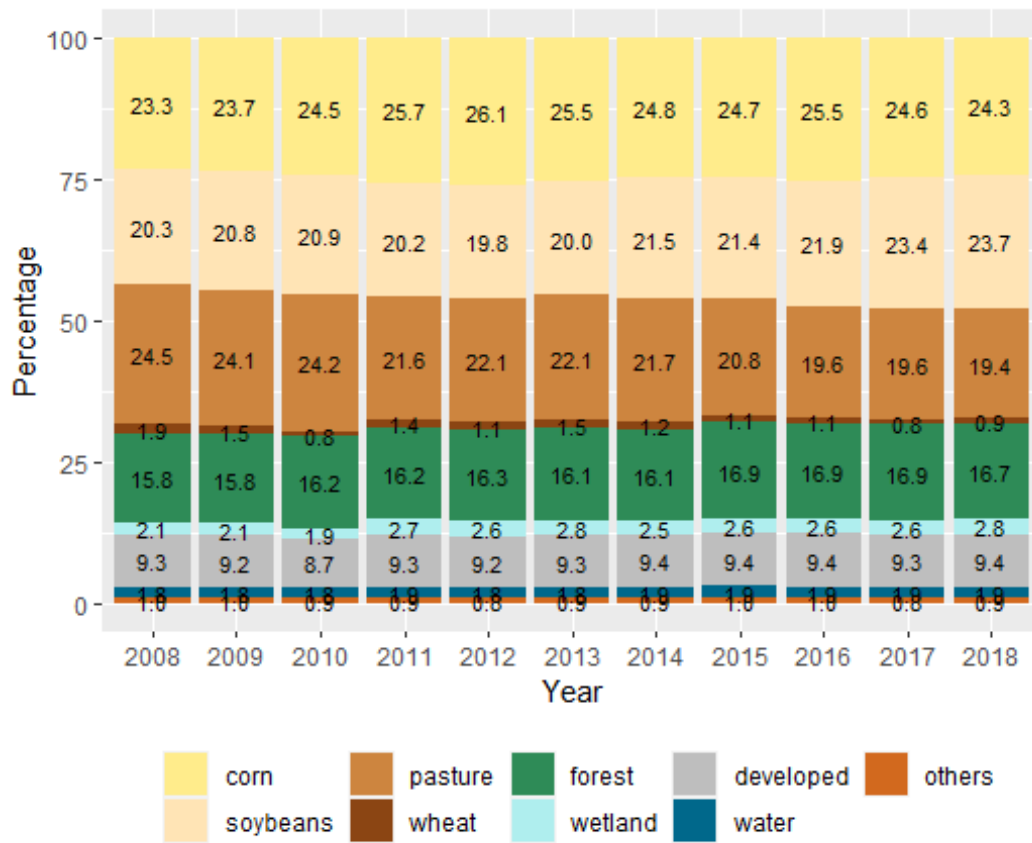


Figure E.3: Annual percentage of land in different crops and uses, 2008 to 2018

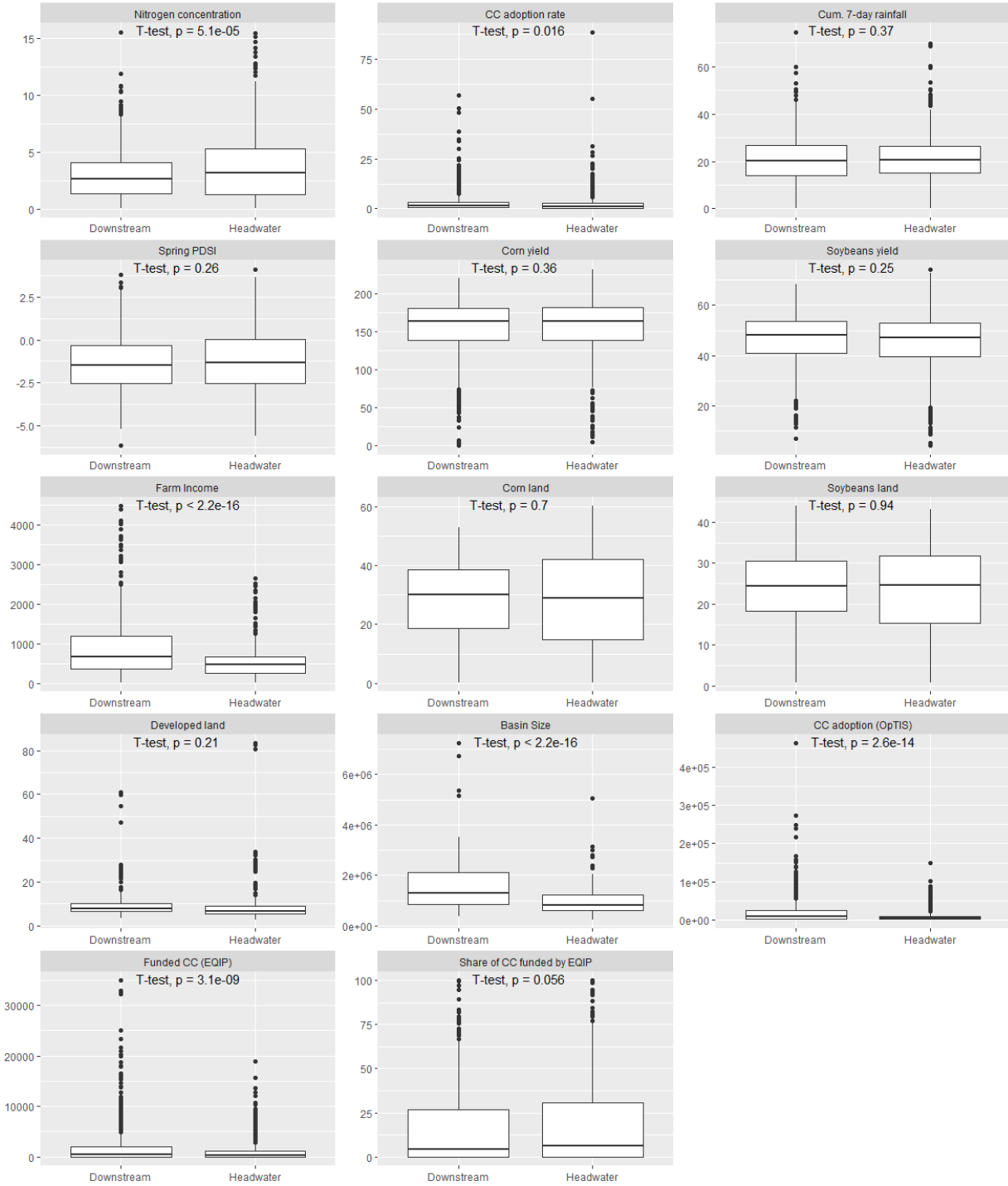


Figure E.4: Mean difference of each variable between two types of basins (t-test)

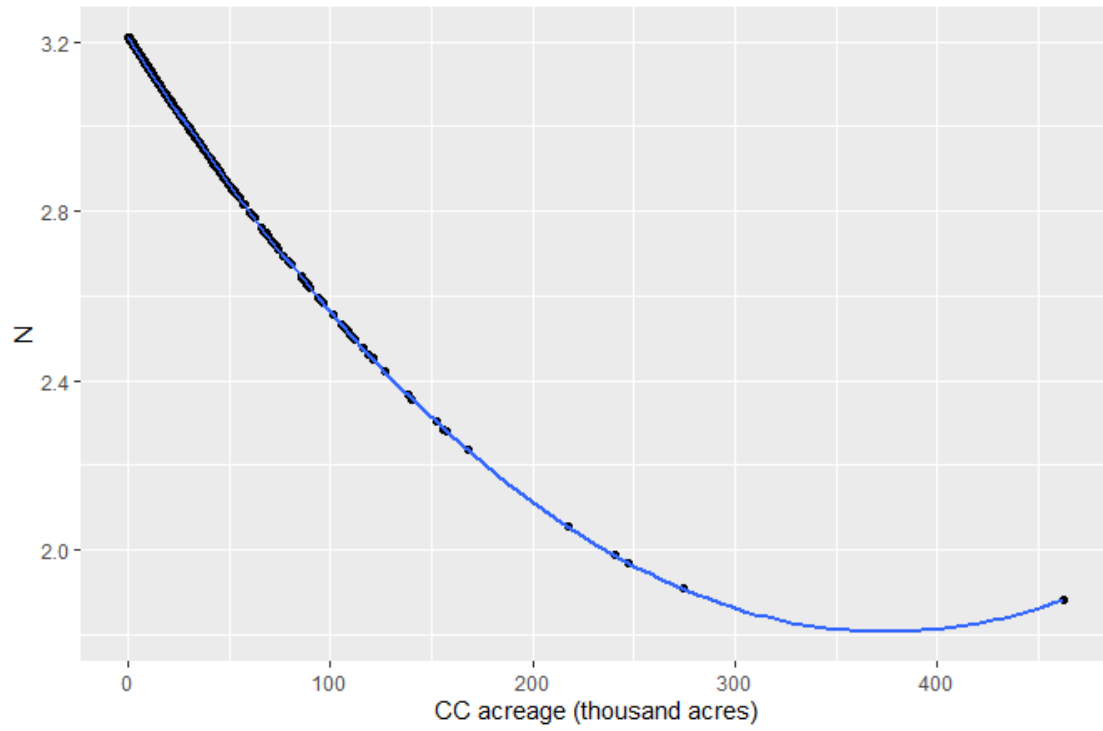


Figure E.5: Polynomial fitted curve for CC acreage (table D.4)

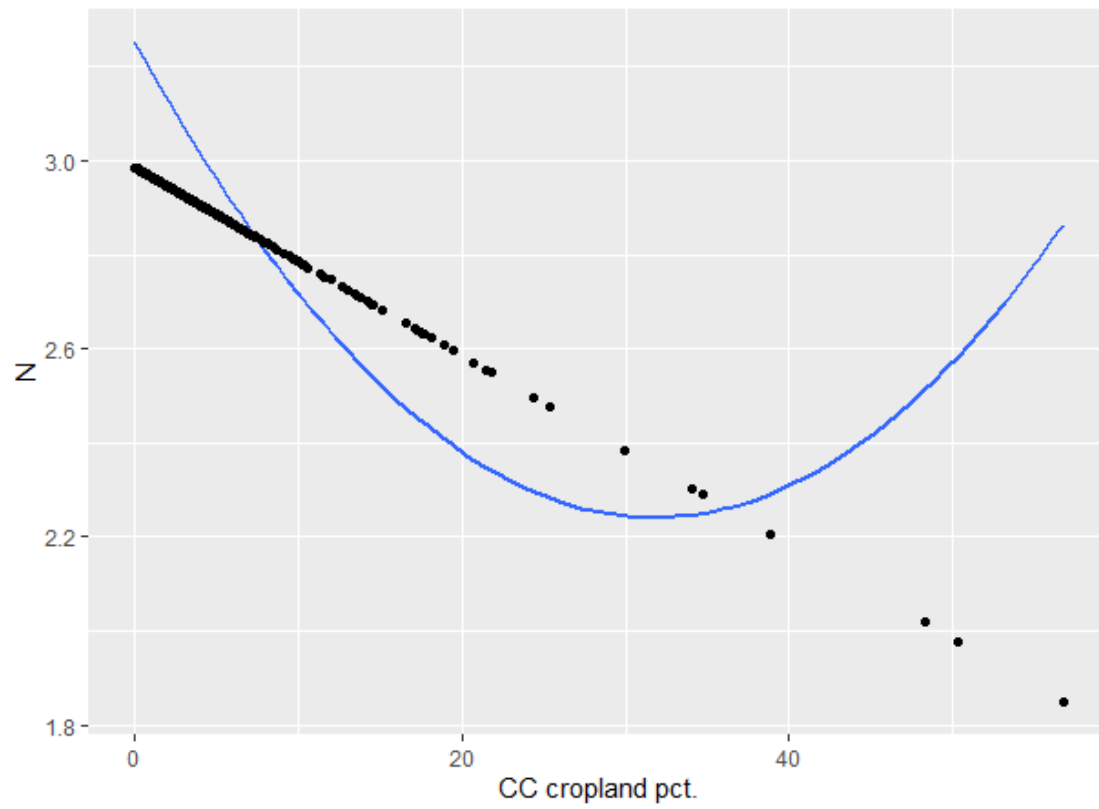


Figure E.6: Polynomial fitted curve for CC acreage (table 2.2) and linear fitted line (table D.6) plotted together

Appendix F

TABLES (CHAPTER 3)

Table F.1: Summary statistics

	<i>Downstream Basins</i>		<i>Headwater Basins</i>	
	Mean	St. Dev.	Mean	St. Dev.
Nitrogen concentration (mg/l)	1.445	1.956	1.413	2.158
EQIP cost share (thousand \$)***	13.365	28.891	9.448	23.080
EQIP cost share (WQ, thousand \$)***	5.465	11.788	3.959	9.361
EQIP cost share (AC, thousand \$)***	7.010	15.615	5.349	13.714
EQIP treated land share (AC, %)***	1.528	5.243	1.789	6.983
PDSI	-0.394	2.322	-0.389	2.364
14-day cumulative rain (mm)	39.810	35.172	39.193	34.873
Gross farm income (billion \$)***	0.347	0.512	0.220	0.366
Corn Yield (ten bu/ac)***	9.478	5.449	8.380	5.765
Soybeans Yield (ten bu/ac)***	2.628	1.765	2.150	1.860
Upland Cotton Yield (hundred kg/ha)***	1.652	3.627	1.318	3.314
Cropland share (%)***	37.683	26.649	36.232	28.144
Developed land share (%)***	7.189	9.024	6.378	8.612
Upstream N (mg/l)	1.751	2.601	0.000	0.000
Monitoring basin size (million ac)***	1.640	1.740	1.266	1.123
Observations	21,405		64,530	

Notes: WQ represents the conservation practices under EQIP that are related to nutrient pollution in streams and rivers. AC means the acre-measured conservation practices under EQIP. The statistically significant differences in each variable between headwater and downstream basins are reported here. Asterisks denote p-value<0.1(*), <0.05(**), or <0.01(***).

Table F.2: Effects of EQIP payments on ambient Nitrogen concentration for downstream monitoring basins

	<i>Dependent variable:</i>		
	Nitrogen concentration (mg/l) (1)	(2)	(3)
Treatment			
EQIP cost share (million \$)	-8.13*** (2.39)	-5.59** (2.51)	-5.59** (2.52)
EQIP cost share (million \$) $\times$ PDSI (+:Dry)	-1.25** (0.630)	-1.09** (0.479)	-1.09** (0.482)
EQIP cost share (million \$) $\times$ 14-D cum. rain	0.107** (0.044)	0.118*** (0.045)	0.118*** (0.046)
EQIP cost share (million \$) $\times$ PDSI (+:Dry) $\times$ 14-D cum. rain	0.018** (0.009)	0.018** (0.008)	0.018** (0.008)
Weather			
PDSI (+:Dry)	-0.012 (0.009)	-0.008 (0.010)	-0.008 (0.010)
14-D cum. rain	0.002*** (0.0007)	0.002*** (0.0007)	0.002*** (0.0007)
PDSI (+:Dry) $\times$ 14-D cum. rain	0.0002 (0.0001)	0.0001 (0.0001)	0.0001 (0.0001)
Socioeconomic			
Gross farm income (billion \$)	-0.062 (0.148)	0.0007 (0.172)	0.0007 (0.173)
Corn yield (ten bu/ac.)	0.017** (0.007)	0.015** (0.006)	0.015** (0.006)
Soybean yield (ten bu/ac.)	0.021 (0.023)	-0.005 (0.017)	-0.005 (0.017)
Upland cotton yield (hundred kg/ha.)	-0.005 (0.009)	-0.007 (0.009)	-0.007 (0.009)
Land Use and Land Cover			
Cropland share (%)	0.032 (0.051)	0.052 (0.044)	0.052 (0.045)
Developed land share (%)	-0.029 (0.029)	-0.017 (0.043)	-0.017 (0.044)
Pollution Spillovers			
Upstream N (mg/l)	0.204** (0.090)	0.193** (0.086)	0.193** (0.086)
Observations	21,405	21,405	21,405
mean N concentration	1.45	1.45	1.45
<i>Fixed-effects</i>			
Basin	Yes	Yes	Yes
Basin by month	Yes	Yes	Yes
Water resource region by month	Yes		Yes
Water resource region by year		Yes	Yes
<i>Fit statistics</i>			
R ²	0.83575	0.85162	0.85162

Note: Robust standard errors are in parentheses and are clustered at the monitoring basin level. Asterisks denote p-value<0.1(*), <0.05(**), or <0.01(***)

Table F.3: Effects of EQIP payments on ambient Nitrogen concentration for headwater monitoring basins

	<i>Dependent variable:</i>		
	Nitrogen concentration (mg/l)		
	(1)	(2)	(3)
Treatment			
EQIP cost share (million \$)	-4.92 (4.03)	-0.846 (3.78)	-0.846 (3.79)
EQIP cost share (million \$) $\times$ PDSI (+:Dry)	-1.16 (0.975)	-1.46 (0.922)	-1.46 (0.924)
EQIP cost share (million \$) $\times$ 14-D cum. rain	0.082 (0.052)	0.076 (0.048)	0.076 (0.048)
EQIP cost share (million \$) $\times$ PDSI (+:Dry) $\times$ 14-D cum. rain	0.013 (0.011)	0.013 (0.011)	0.013 (0.011)
Weather			
PDSI (+:Dry)	-0.007 (0.009)	-0.002 (0.008)	-0.002 (0.008)
14-D cum. rain	0.002*** (0.0006)	0.001*** (0.0006)	0.001*** (0.0006)
PDSI (+:Dry) $\times$ 14-D cum. rain	0.0001 (0.0001)	0.0000 (0.0000)	0.0000 (0.0000)
Socioeconomic			
Gross farm income (billion \$)	-0.403 (0.260)	-0.066 (0.207)	-0.066 (0.207)
Corn yield (ten bu/ac.)	0.019*** (0.004)	0.014*** (0.004)	0.014*** (0.004)
Soybean yield (ten bu/ac.)	0.054*** (0.018)	0.041** (0.017)	0.041** (0.017)
Upland cotton yield (hundred kg/ha.)	-0.029*** (0.010)	-0.021** (0.009)	-0.021** (0.009)
Land Use and Land Cover			
Cropland share (%)	0.057 (0.037)	0.016 (0.038)	0.016 (0.038)
Developed land share (%)	0.105 (0.081)	0.091 (0.084)	0.091 (0.084)
Observations	64,530	64,530	64,530
mean N concentration	1.41	1.41	1.41
<i>Fixed-effects</i>			
Basin	Yes	Yes	Yes
Basin by month	Yes	Yes	Yes
Water resource region by month	Yes		Yes
Water resource region by year		Yes	Yes
<i>Fit statistics</i>			
R ²	0.78384	0.79952	0.79952

Note: Robust standard errors are in parentheses and are clustered at the monitoring basin level. Asterisks denote p-value<0.1(*), <0.05(**), or <0.01(***)

Table F.4: Effects of EQIP payments on ambient Nitrogen concentration for all monitoring basins

	<i>Dependent variable:</i>		
	Nitrogen concentration (mg/l) (1)	(2)	(3)
Treatment			
EQIP cost share (million \$)	-6.59** (2.80)	-2.46 (2.62)	-2.46 (2.63)
EQIP cost share (million \$) × PDSI (+:Dry)	-1.27* (0.653)	-1.19** (0.580)	-1.19** (0.581)
EQIP cost share (million \$) × 14-D cum. rain	0.098** (0.038)	0.092*** (0.035)	0.092*** (0.035)
EQIP cost share (million \$) × PDSI (+:Dry) × 14-D cum. rain	0.016** (0.008)	0.015** (0.007)	0.015** (0.007)
Weather			
PDSI (+:Dry)	-0.007 (0.007)	-0.005 (0.007)	-0.005 (0.007)
14-D cum. rain	0.002*** (0.0005)	0.002*** (0.0005)	0.002*** (0.0005)
PDSI (+:Dry) × 14-D cum. rain	-0.0001 (0.0001)	0.0000 (0.0001)	0.0000 (0.0001)
Socioeconomic			
Gross farm income (billion \$)	-0.238 (0.159)	-0.047 (0.138)	-0.047 (0.138)
Corn yield (ten bu/ac.)	0.018*** (0.004)	0.015*** (0.004)	0.015*** (0.004)
Soybean yield (ten bu/ac.)	0.046*** (0.014)	0.033** (0.014)	0.033** (0.014)
Upland cotton yield (hundred kg/ha.)	-0.026*** (0.008)	-0.021*** (0.008)	-0.021*** (0.008)
Land Use and Land Cover			
Cropland share (%)	0.042 (0.028)	0.016 (0.030)	0.016 (0.030)
Developed land share (%)	0.052 (0.053)	0.061 (0.057)	0.061 (0.057)
Pollution Spillovers			
Upstream N (mg/l)	0.154*** (0.048)	0.133*** (0.042)	0.133*** (0.042)
Observations	85,935	85,935	85,935
mean N concentration	1.42	1.42	1.42
<i>Fixed-effects</i>			
Basin	Yes	Yes	Yes
Basin by month	Yes	Yes	Yes
Water resource region by month	Yes		Yes
Water resource region by year		Yes	Yes
<i>Fit statistics</i>			
R ²	0.78734	0.80212	0.80212

Note: Robust standard errors are in parentheses and are clustered at the monitoring basin level. Asterisks denote p-value<0.1(*), <0.05(**), or <0.01(***)

Appendix G

FIGURES (CHAPTER 3)

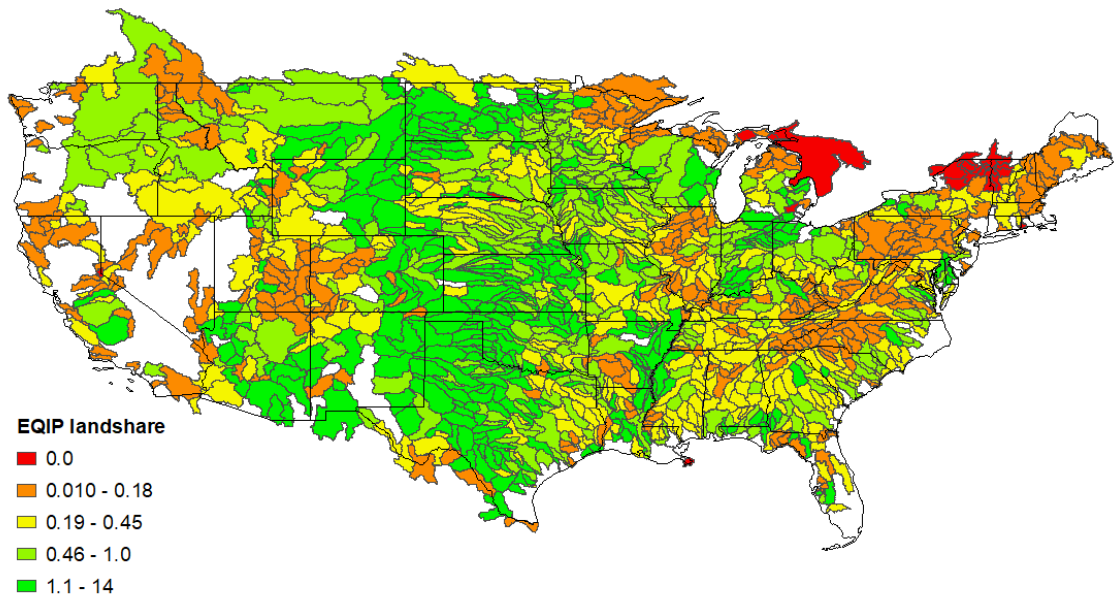


Figure G.1: Quantile map of the average EQIP land share from 1997 to 2020

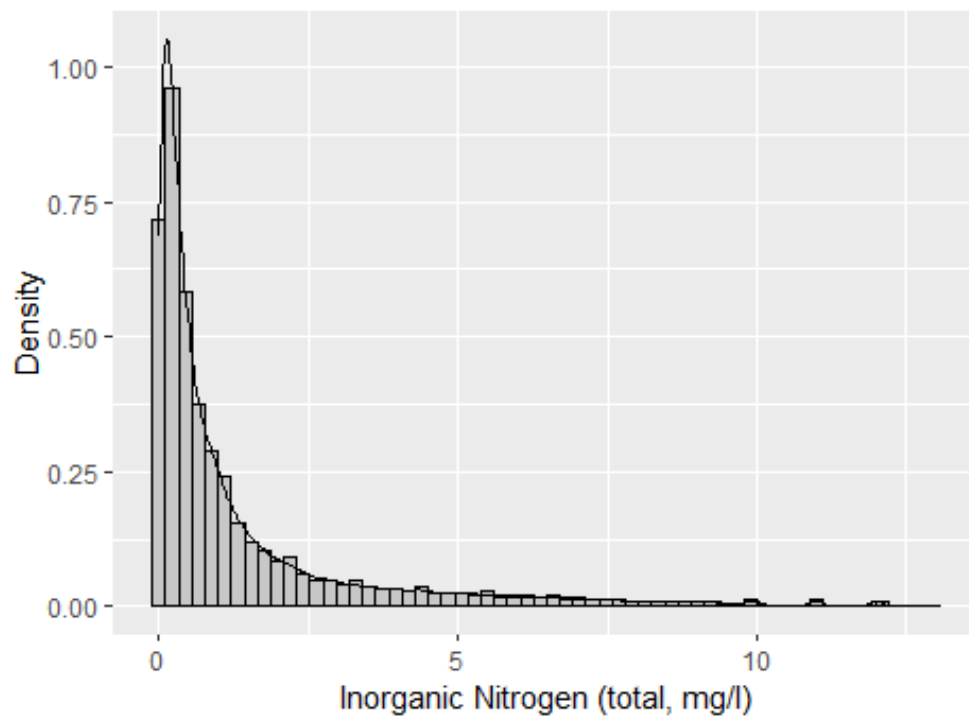


Figure G.2: Density plot of total inorganic nitrogen

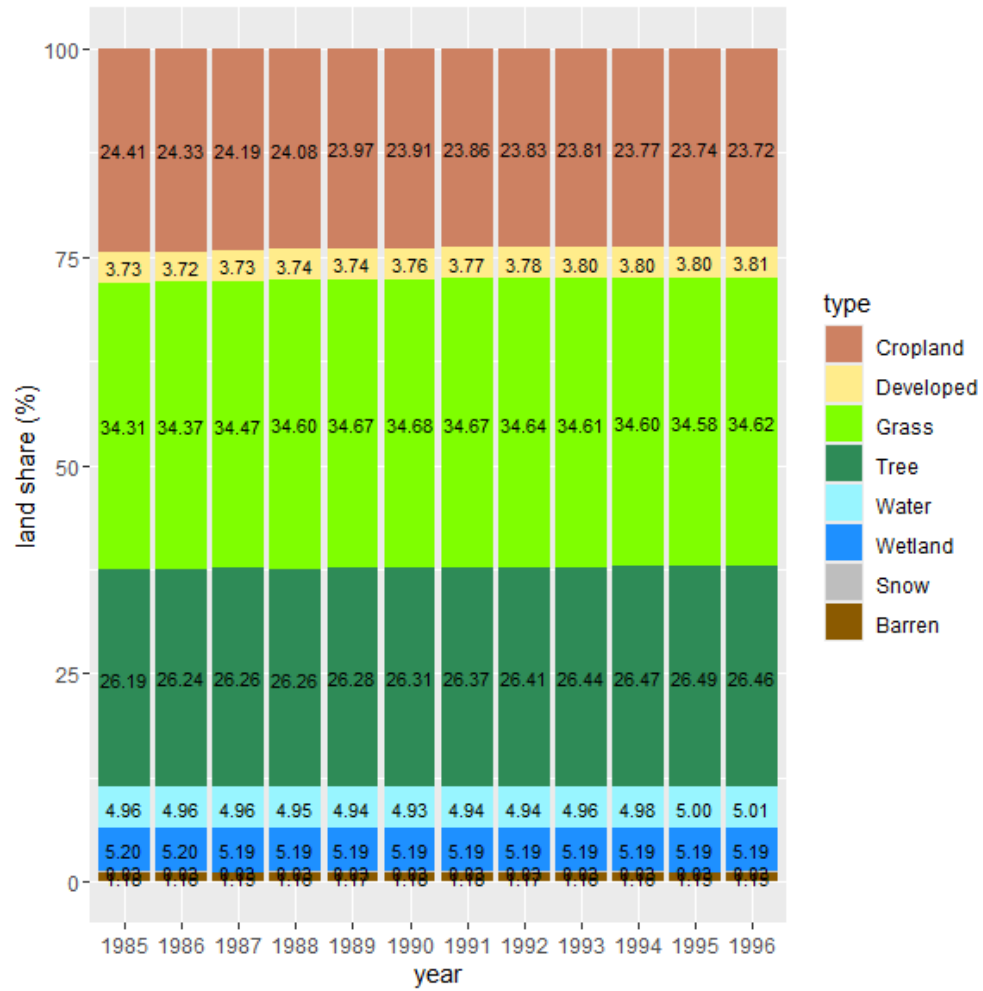


Figure G.3: Land use and land cover in the contiguous United States during pre-treatment, 1985-1996

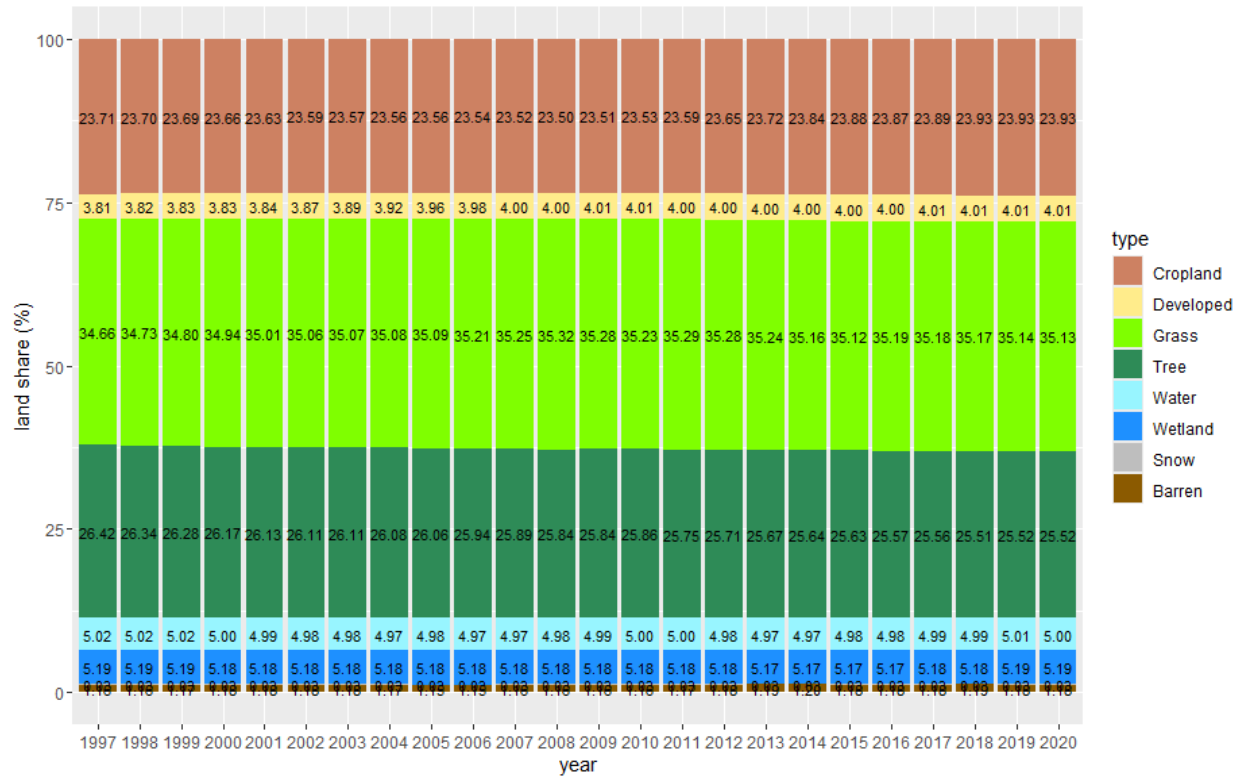


Figure G.4: Land use and land cover in the contiguous United States during post-treatment, 1997-2020

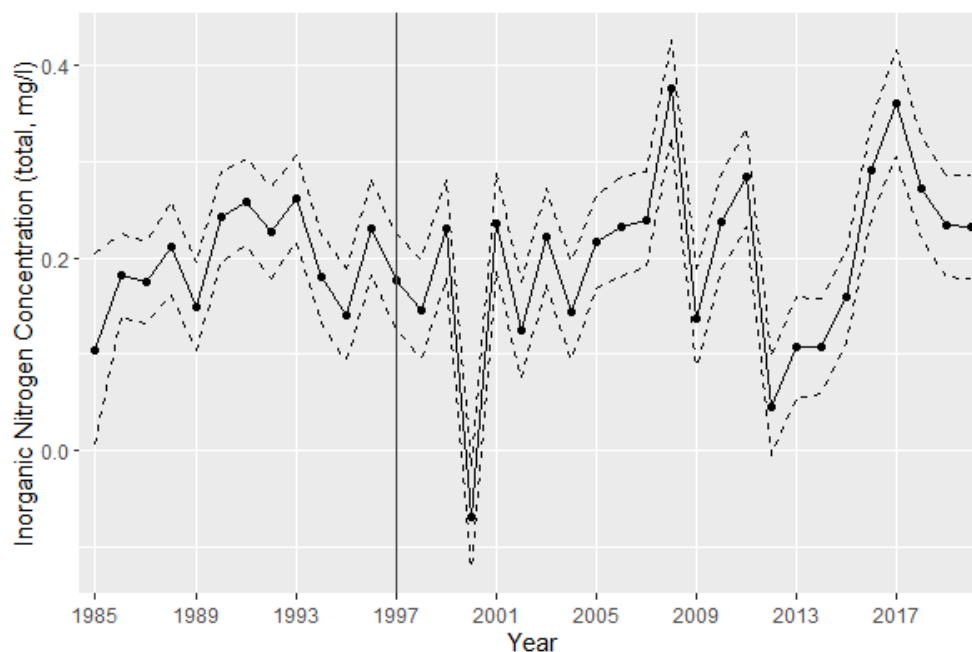


Figure G.5: Nitrogen concentration trends, 1985-2020

Notes: The year-specific points in the graph represent the mean N concentrations, controlling for time, weather, and monitoring basin characteristics. Dashed lines are 95% confidence interval, and 1985 is the reference category.

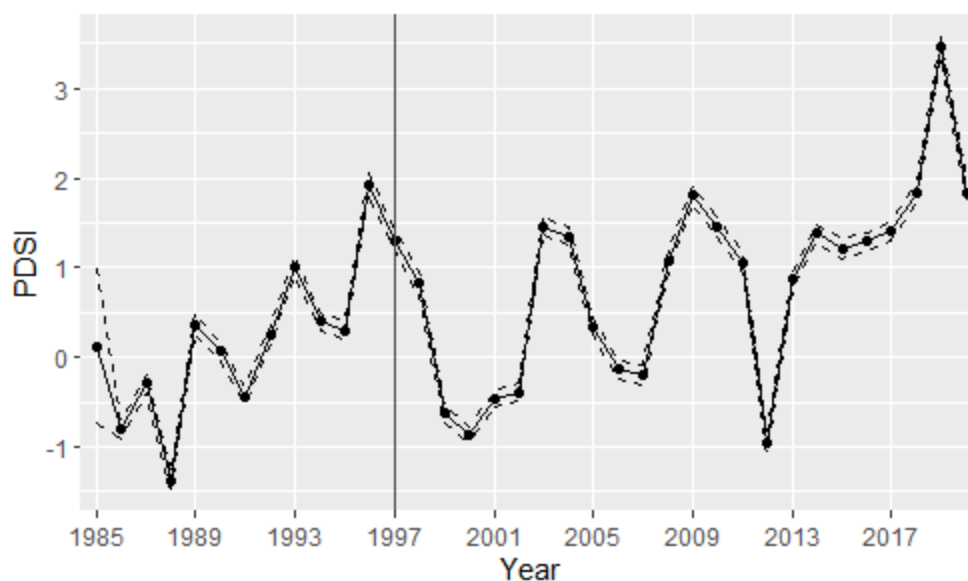


Figure G.6: Palmer Drought Severity Index trends, 1985-2020

Notes: The year-specific points in the graph represent the annual mean PDSI, controlling for monitoring basin characteristics. Dashed lines have a 95% confidence interval, and 1985 is the reference category.