Estimating the Impact of Cover Crop Adoption on Ambient Water Quality in the Upper Mississippi River Drainage

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Abstract

Agricultural conservation practices have long been promoted for resource conservation and environmental benefits. We examine cover crop adoption with ambient water quality to estimate the influence this soil health practice hashad on non-point source pollution from agriculture. We use remotely sensed data on practice adoption and control for the direction of hydrological flow, weather, and land use to econometrically measure the impact of cover cropping on total Nitrogen concentrations in surface water while controlling for pollutant inflow from upstream. The spatial unit of analysis is a HUC8, also examined in other recent research using different treatment variables to explain variation in surface water quality. Our results provide novel estimates based on observed data that can be compared to more common biophysical simulations of conservation practice effectiveness.

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1 Introduction

Non-point source (NPS) pollution from agriculture has been identified as the leading cause of water quality impairments in the U.S. The increasing percentage of land covered by crops and the heavy use of fertilizer in modern intensive agriculture harm the health of local streams and rivers. 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 include a range of structural and non-structural approaches, including many that are relatively low cost and effective in reducing nutrients and sediment losses (Guiling et al., 2006). This study explores the environmental outcomes of cover crops (CCs) on ambient water quality in the U.S. Corn Belt.

CCs are non-cash crops that are usually established and grown after low-residue row crops are harvested and remain until the next crop is planted. They are then killed (most often referred to as "terminated") and left on the surface as residue or tilled into the soil before planting a cash crop. The soil health improvements that come with implementing CCs imply various on- and off-farm benefits ('Cover Crop (Ac.) (340) Conservation Practice Standard', n.d.). 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 as well as N leaching 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; 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 texture 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, the 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 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.

This study fills a gap in the literature identifying the effect of CCs on ambient water quality at the watershed scale. Kladivko et al. (2014) uses simulated models (i.e., the Root Zone Water Quality Model) to evaluate the effect of CCs on nitrate reduction. The 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 come along with practice adoptions (Fleming et al., 2018).

Our study quantifies the effect of adopting CCs on ambient water quality measures (i.e., total nitrogen, TN) 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, perhaps due to continued low adoption of practices like CCs. 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 explicitly control for time-varying confounders (e.g., drought, precipitation, and crop yield). Also, we capture upstream-to-downstream spatial spillovers of nutrients to isolate the impact of CC adoption on surface water quality. We find that a ten percent increase in the share of cropland with CCs in a monitoring basin reduces in-stream N concentration by 0.15 mg/l, on average. This amount of abatement is about five 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 of 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 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 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 practice adoptions (Sun et al., 2018). Such findings may help improve the effectiveness of implementing and designing conservation programs in the future.

2 Data

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, Rejesus, Aglasan, Hagen et al., 2022; L. Chen, Rejesus, Aglasan, Hagen et al., 2022). Our study exploits OpTIS's cover crop acreage 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 reports CC acres for four crop categories (i.e., corn, soybeans, small grains, and others) based on the cash crop harvested before the CC is detected. 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 treatment variable. Practice treatment is measured as the percentage of cropland acres planted in CCs in each monitoring basin composed of aggregated HUC8s (details in the next section).

Figure 1 displays CC adoption rates by constructed monitoring basin in the U.S. Corn Belt from 2008 to 2018. 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 (i.e., northern Missouri, southern Illinois, Indiana, and

Ohio). Figure 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. A noted increase in the percentage of cropland acres with CCs was first detected 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 as much as the mean annual CC planting rate over all years and locations in the data. The expansion 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 (NASS) and other remote-sensing based studies ('More farmers are adding fall cover crops to their corn-for-grain, cotton, and soybean fields', 2022; 'USDA - National Agricultural Statistics Service - Census of Agriculture', n.d.; Wallander et al., 2021; Zhou et al., 2022).

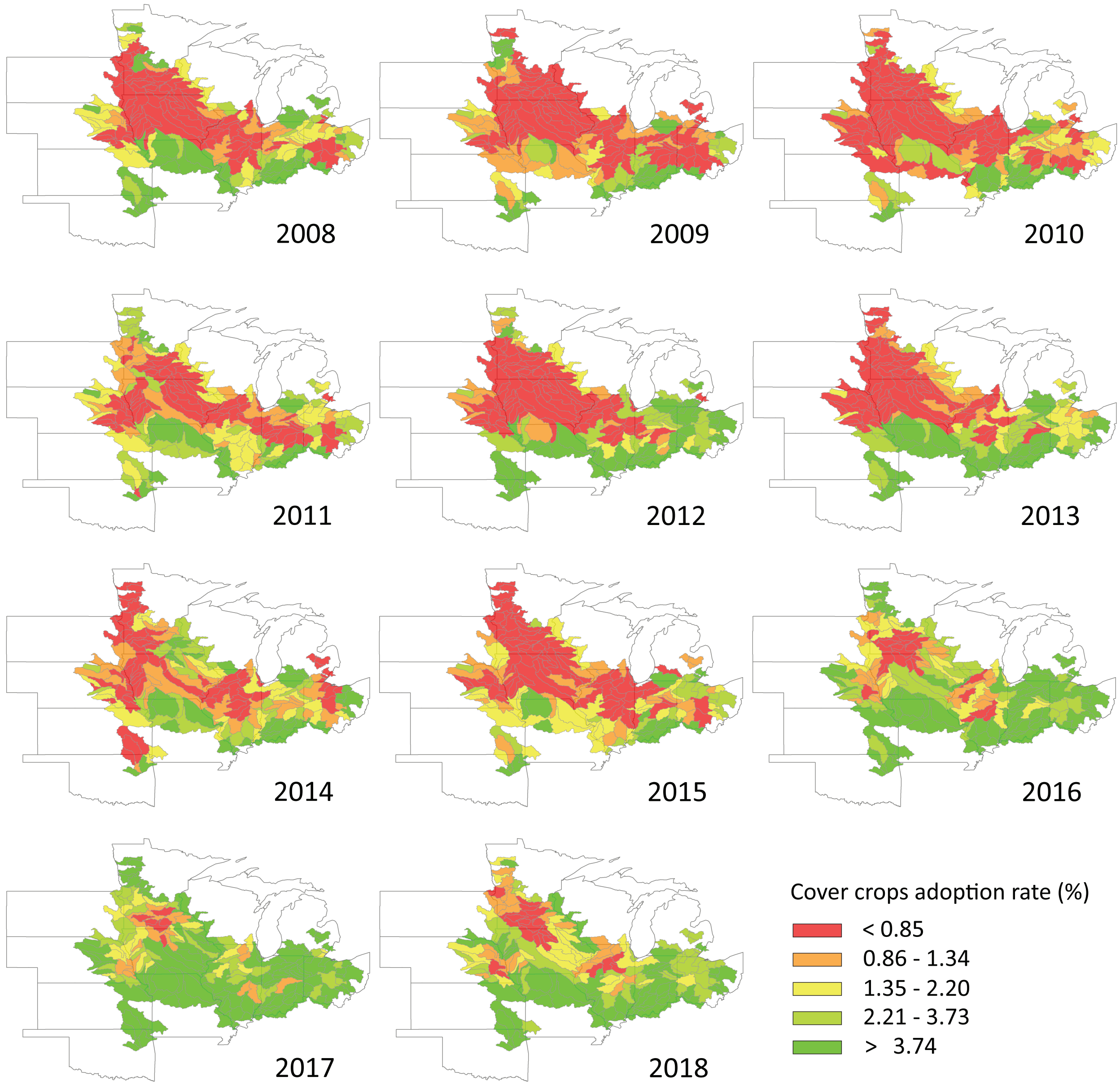

Figure 1: Cropland percentage of CC adoption by monitoring basins, 2008-2018

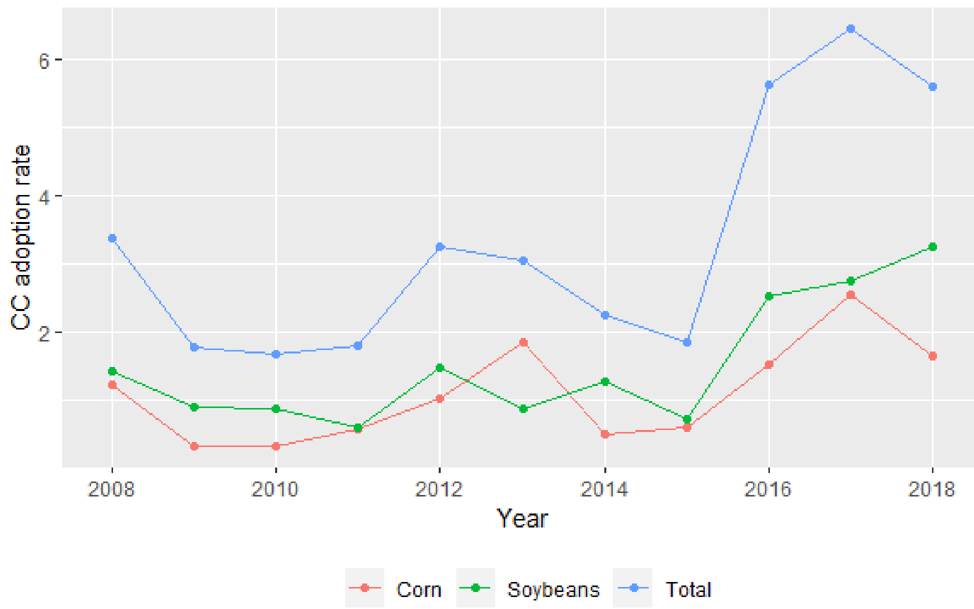

Figure 2: Average adoption rate of CC from 2008 to 2018

2.2 Watershed hydrology network

The monitoring basins and spatial connectivity are constructed based on the water flow direction and connectivity of the HUC8 sub-basin from the USGS Watershed Boundary Dataset (WBD) and the National Hydrography Dataset (NHD).[1] Based on the nature of streamflow and the location (i.e., longitude and latitude) of the 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 the monitoring basins that are the unit of analysis controlling for land use land cover, socioeconomic, and weather ('Water Quality Data Home', n.d.). Smaller spatial units 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

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

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 158 monitoring basins, with 54 basins having upstream inflow and 104 headwater basins. Among headwater basins, there are 23 basins that have monitoring sites located in the uppermost part of the basin which are used to control for upstream pollution inflow similar to non-headwater basins. Figure 3 shows where the two types of basins (i.e., basins with and without inflow from upstream) in our data are located in the U.S. Corn Belt, as well as the location of water monitoring sites for each basin.[2] We show the spatial variation of the average percentage of cropland planted in CCs in each monitoring basin in Figure 4. The mean annual percentage of cropland with CCs over the period 2008 to 2018 varies across monitoring basins. We find the highest rate (over 75th percentile) of CC adoption in the southern and eastern Corn Belt, and the lowest rate (under 25th percentile) at the northwestern Corn Belt.

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

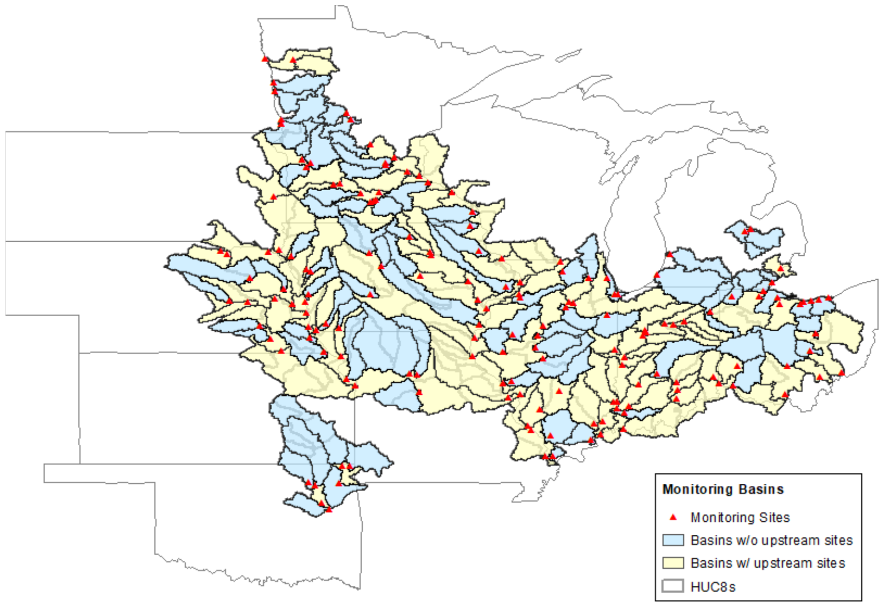

Figure 3: The monitoring basins aggregated by HUC8 sub-basins in the U.S. Corn Belt

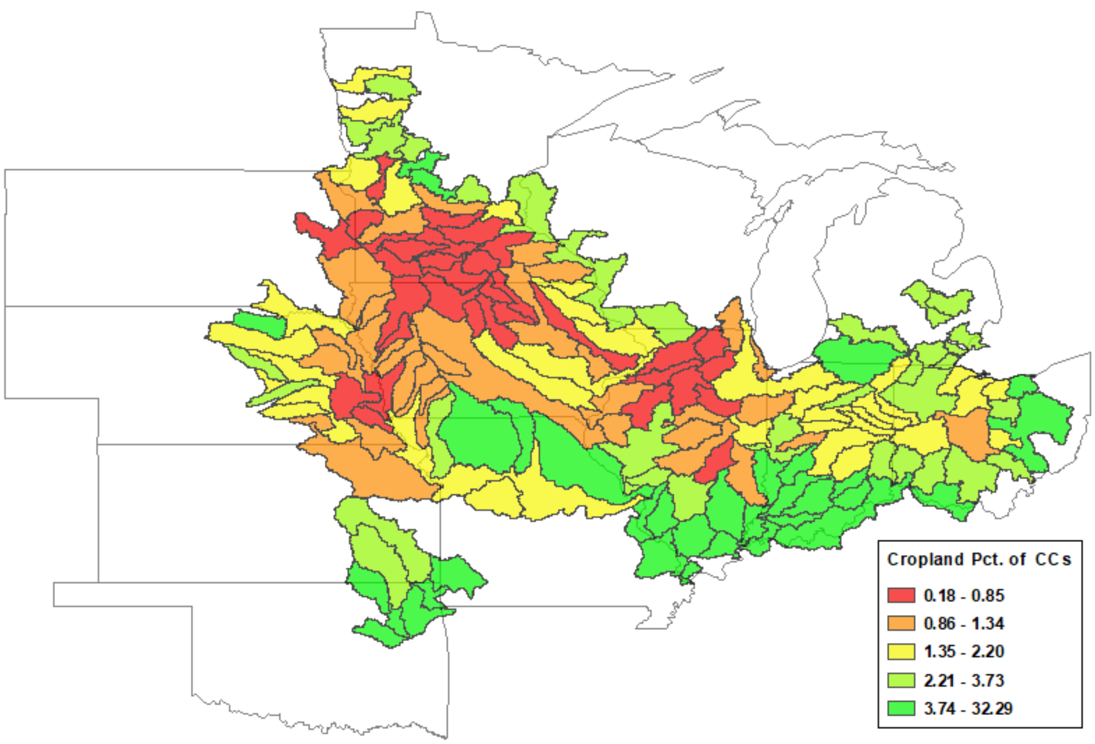

Figure 4: Quantile map of the average cropland adoption rate of CCs from 2008 to 2018

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. Monitoring stations are unevenly spatially distributed. 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, 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 years. Figure 5 is the density plot of total inorganic N measured at U.S. Corn Belt monitoring sites.[3] The distribution is skewed to the right, which is similar to the N distribution in Paudel and Crago (2020).

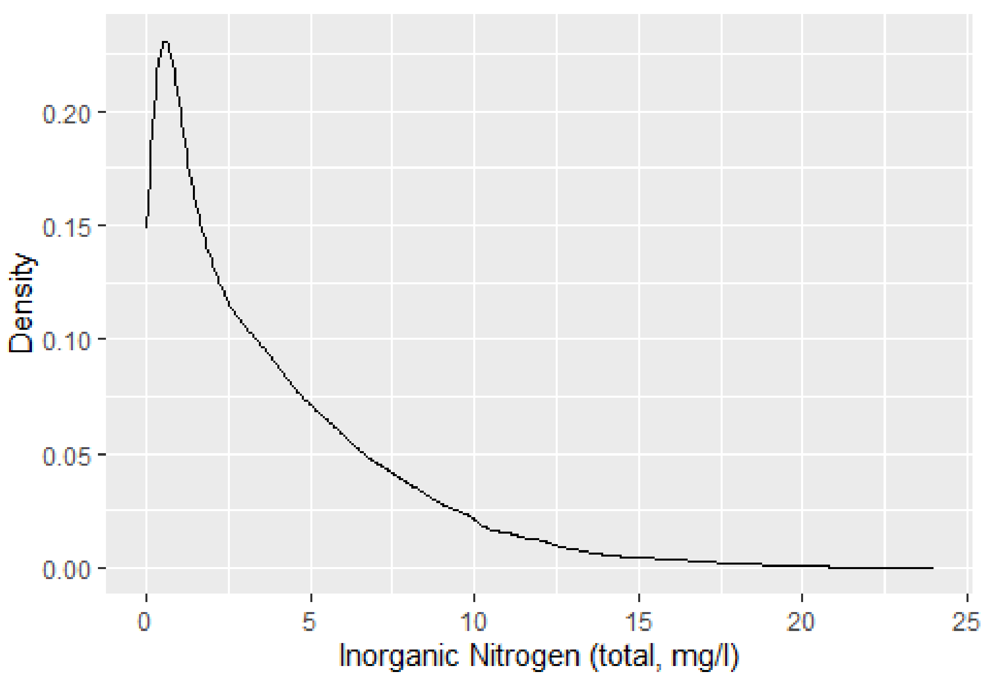

Figure 5: Density plot of total inorganic nitrogen

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

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 Climate Group, Oregon State U', n.d.). We use the daily precipitation to construct the 7-day cumulative rainfall prior to each water quality sampling date in each monitoring basin throughout the year to control for recent rainfall 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 annual 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.

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 -4 (extreme drought) to 4 (extremely wet). The PDSI value is multiplied by negative one to focus interpretation of the estimated parameter 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.

We obtain land use and land cover measures from the Cropland Data Layer (CDL) provided by the National Agricultural Statistics Service (NASS-USDA) ('CropScape - NASS CDL Program', n.d.). Based on satellite remote sensing, the CDL is a series of 30x30 meter resolution raster files for each year, except for 2006 and 2007, which are 56x56 meter in resolution. The extraction of land use and land cover is processed by overlapping the CDL with the polygon boundary of the constructed monitoring basins. This process generates nine categories (i.e., corn, soybeans, pasture, wheat, forest, wetland, developed, water, and other minor uses) of land use and land cover. We combine the acreage of corn, soybeans, wheat, and other crops as cropland and divide by CC acres to calculate our treatment measure. Figure 6 shows the variation of land use over time, as well as the proportion of land use across all basins for each year. Each land use category exhibits little change over the years with slight overall increases in corn, soybean and forest, and an accompanying decline in pasture. Not surprisingly, the share of cropland, the primary land use, occupies more than half of the Corn Belt land in the study area.

Our analysis also controls for agricultural and socioeconomic characteristics, including NASS-USDA average corn and soybean yield data and gross farm income data from the Bureau of Economic Analysis (BEA) ('U.S. Bureau of Economic Analysis (BEA)', n.d.). We aggregate county-level socioeconomic characteristics to the monitoring basin level. To achieve this aggregation, we overlay the monitoring basin polygons with 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 the basin-level variables.

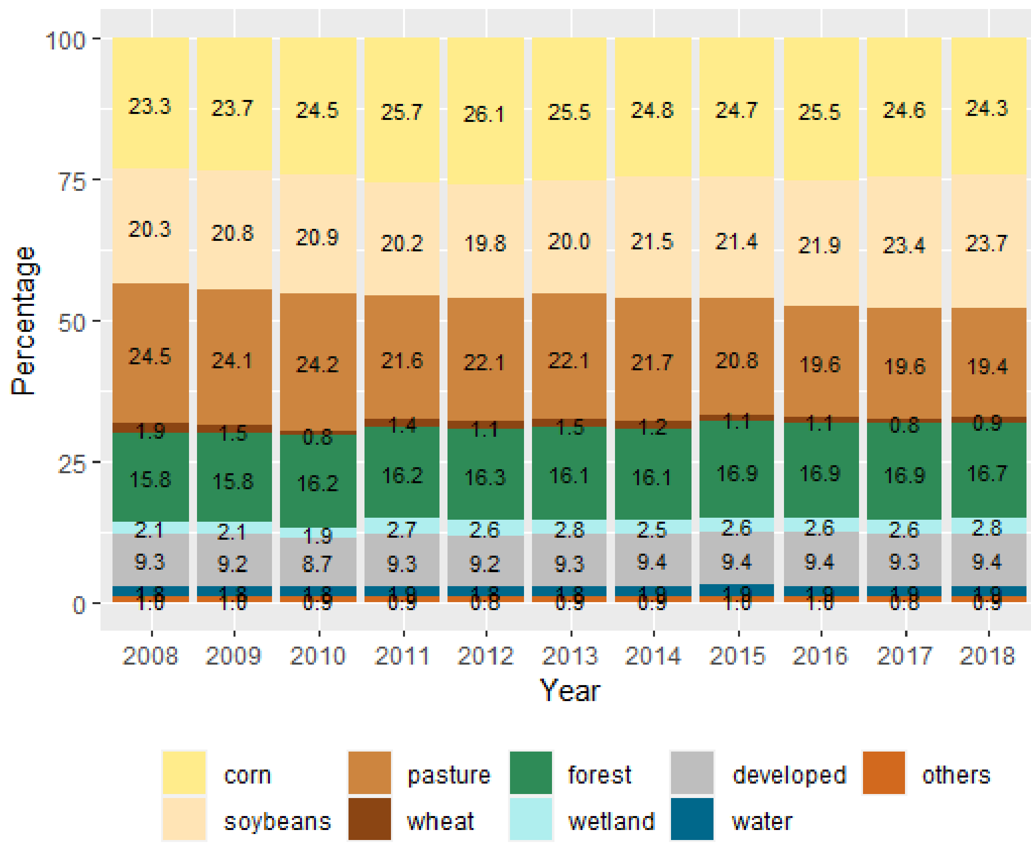

Figure 6: Percentage of land use over the years 2008 to 2018

3 Empirical strategy

We employ a standard panel fixed-effect (FE) approach with a continuous treatment (i.e., the share of cropland planting CCs) for the unbalanced annual panel data, and separate the analyses for basins with and without upstream pollution control because some headwater basins do not have water quality sites located in the uppermost part of the headwater basin 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, 2020). For monitoring basins with upstream water quality stations, we include the corresponding upstream pollutant measurements as one of the controls affecting downstream water quality readings consistent with related prior research (Paudel & Crago, 2020). Controlling these pollution spillovers isolates the effect of CC adoption in a given monitoring basin on ambient water quality. The estimating equation includes an error term, ϵ_{it}, and is given by:

$$N_{it} = \alpha CC_{it} + \boldsymbol{X'_{it}\beta} + \gamma \sum_{k \in \Lambda_{i-1}} \psi_k N_{kt} + \theta_i + \eta_{rt} + \epsilon_{it} \tag{1}$$

The dependent variable N_{it} describes ambient N concentration (mg/l) in monitoring basin i and year t. The treatment variable, CC_{it}, is the percentage of cropland with CCs. Hence, the coefficient of greatest interest, $\hat{\alpha}$, represents the average treatment effect, indicating how an increase in the CC adoption rate impacts the N concentration in the stream.

Equation 1 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, $\boldsymbol{X'_{it}}$, includes weather, land use and land cover (i.e., corn, soybeans, and developed land), yields of corn and soybeans, 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.[4] We construct the average seasonal drought based on the hydrological year, which spans the period between October 1 and September 30 of the following year. For example, the 2008 water year started on October 1, 2007, and ended on September 30, 2008. Seasonal dummies are defined as follows: Fall includes the months October and November; Winter includes December, January, February, and March; Spring includes April, May, June, and July; Summer is August

[4]We initially specify the 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 the specification of the recent cumulative rainfall period.

and September. We include the mean monthly PDSI in Spring because this is historically the wettest season of the year. PDSI (times negative one) is included to strengthen the identification by controlling for drought which is closely related to streamflow and captures more than recent precipitation alone by taking into account multiple months. More details will be addressed later in this section.

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 land area share of each basin. Last, the analysis includes monitoring basin fixed effects, θ_i, to capture the time-invariant determinants 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, physical, chemical, and biological attributes of the receiving water body.

Table 1 reports the summary statistics for each monitoring basin subgroup: headwater basins without upstream monitoring sites and the group of basins with upstream pollution measurements. The mean N reading for basins without upstream sites is 20 percent higher (p = 5.1e-05) than basins with inflow from upstream, and the standard deviation is about 30 percent higher in headwater basins than those with upstream neighbors. The share of cropland acres adopting CCs in basins without upstream sites is 24 percent less than (p = 0.016) the share in basins with upstream pollution measurements. Note that the mean land use percentages are not significantly different between the two basin sub-groups, nor are 7-day near-term rainfall and spring PDSI (Figure 7). Gross farm income is higher (p = 2.2e-16) among basins with upstream sites, while annual average corn and soybeans yields are not significantly different in basins with and without upstream pollution controls.

Table 1: Summary statistics

	Basins w/ upstream		***Basins w/o upstream***	
	Mean	St. Dev.	Mean	St. Dev.
Nitrogen concentration (mg/l) ***	3.059	2.176	3.617	2.830
Cropland percentage of cover crops **	3.196	5.832	2.453	5.294
7-day cumulative rain (mm)	20.843	9.644	21.311	9.224
Spring PDSI	-1.364	1.725	-1.253	1.843
Corn Yield (bu/acre)	153.982	41.239	156.063	41.016
Soybeans Yield (bu/acre)	46.224	10.628	45.526	11.466
Farm income (millions of dollars) ***	898.854	764.487	554.275	402.825
Percentage of corn land	27.970	13.186	28.269	14.841
Percentage of soybeans land	23.283	9.389	23.324	10.174
Percentage of developed land	10.072	7.927	9.444	10.222
Upstream N (mg/l)	3.567	2.383		

Notes: Asterisks denote p-value<0.1(*), <0.05(**), or <0.01(***). Figure 7 reports t-tests of differences in means for each variable between basin subgroups in Table 1.

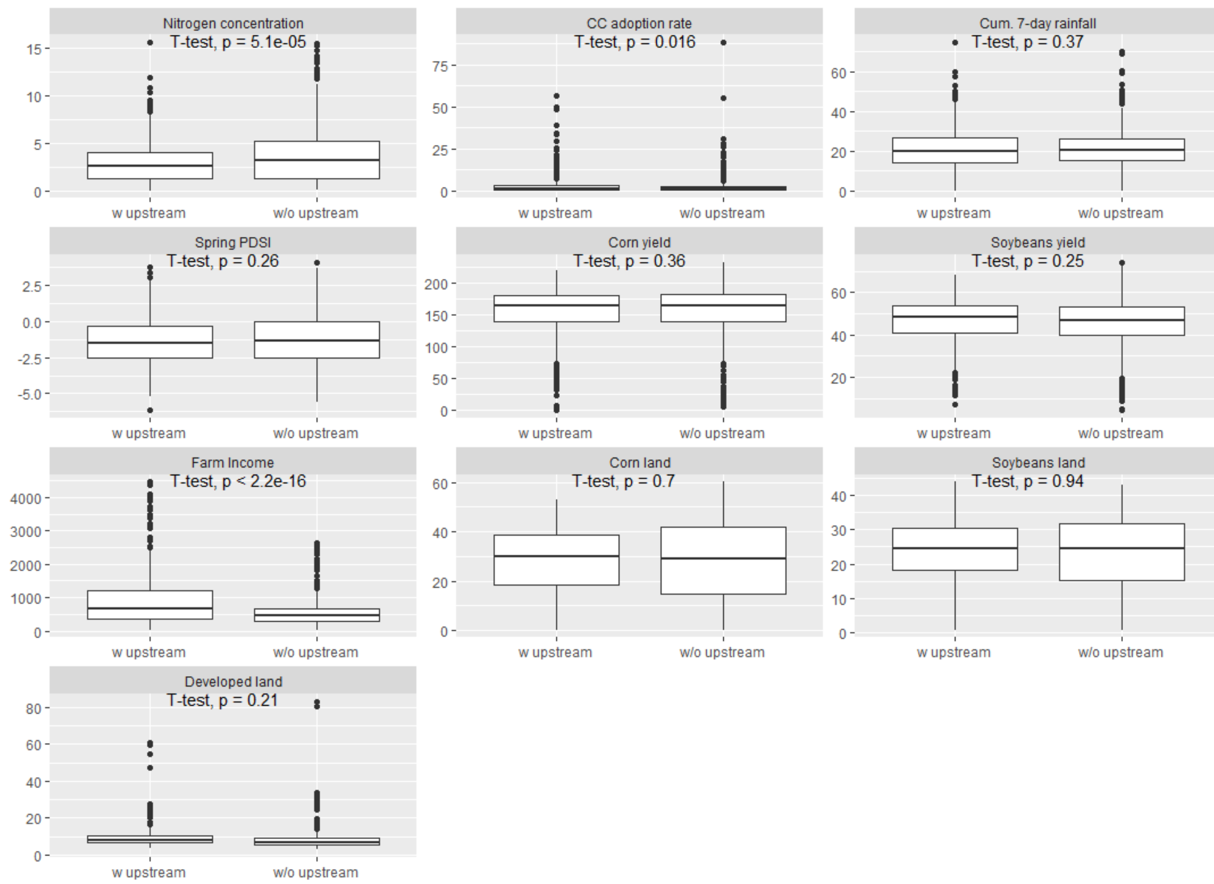

Figure 7: Mean difference of each variable between two types of basins (t-test)

The identifying assumption for Equation 1 to deliver 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):

$$E[CC_{it} \cdot \epsilon_{it} | \boldsymbol{X'_{it}}, N_{kt}, \theta_i, \eta_{rt}] = 0 \tag{2}$$

This assumption would be violated if the CC adoption rate at the monitoring basin level responded to unobserved variables, which themselves affect N measurements. The self-selection of individual land operators into CCs could be a potential threat to identification, but this would only be the case if individuals in each basin systematically made the same adoption decision. Operation and farmer characteristics generally affect an individual's adoption decision (Prokopy et al., 2019), but our data are aggregate adoption data that are the result of many individualized adoption decisions such that no individual unobserved variable is systematically correlated with the CC adoption rate.

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 they may be captured by the monitoring basin fixed effect. Drought conditions could be a potential source of positive self-selection bias since 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.

Other threats to bias the estimates may come from N concentration changes that coincide directly with the CCs adoption rate but are the result of different types of conservation practices. If a basin has additional management practices installed simultaneously with CCs, this will result in overestimating the effect of the CCs on N concentration. 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. No other practices are known to have changed over the same period on anywhere approaching the same level as CC adoption.

4 Results

We report the estimation results for Equation 1 in Table 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 show that the effect of CC adoption on ambient N is negative and significant only in basins with upstream water quality measurements. A ten percent increase in the share of cropland planted in CCs is estimated to lead to a 0.15 mg/l decrease in average ambient N levels only in non-headwater basins. This estimated effect is equivalent to five percent of the average N concentration. 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 the largest amount of their immediate downstream neighbors' ambient N measurements due to the connectivity and directional flow of streams and rivers. By directly controlling for these pollution spillovers, the model specification prevents the effect of CCs from being confounded with N and treatment in upstream basins. The hydrology literature has established that hydrological 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) and increased rainfall accelerates drainage increasing ambient N concentration in surface water (Bowles et al., 2018).

Table 2: Panel fixed-effect (FE) estimates for monitoring basins

	Dependent variable:		
	Nitrogen concentration (mg/l)		
	(1) Basins w/ upstream site	(2) Basins w/o upstream sites	(3) All basins
Treatment			
Cropland Pct. of Cover Crops	−0.015**	0.003	−0.006
	(0.007)	(0.006)	(0.005)
Weather			
7-D Cum. Rain	0.008	0.022*	0.016*
	(0.012)	(0.012)	(0.009)
7-D Cum. Rain (quadratic)	−0.0001	−0.0001	−0.0001
	(0.0002)	(0.0002)	(0.0002)
Spring PDSI	−0.098***	−0.152***	−0.132***
	(0.025)	(0.042)	(0.027)
Socioeconomic Char.			
Corn Yield (bu/acre)	−0.005**	0.001	−0.002
	(0.002)	(0.002)	(0.001)
Soybeans Yield (bu/acre)	0.029***	0.011	0.021***
	(0.009)	(0.010)	(0.006)
Farm Income (million of $)	0.0001	−0.002***	−0.0005
	(0.0003)	(0.001)	(0.0004)
Land use			
Corn	0.052**	0.045*	0.054***
	(0.023)	(0.026)	(0.019)
Soybean	−0.035	−0.094***	−0.057*
	(0.030)	(0.033)	(0.024)
Developed	0.160*	−0.139**	0.006
	(0.091)	(0.065)	(0.072)
Pollution Spillovers			
Upstream N (mg/l)	0.509***		0.374***
	(0.084)		(0.084)
Observations	590	725	1,315
R^2	0.594	0.344	0.371

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

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 farm practice adoption data. Prior work has investigated point source pollution (Keiser & Shapiro, 2019), a major conservation program that includes many different practices in addition to cover crops (Liu et al., 2022) 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.

We find that pollution spillovers from upstream to downstream are very important, having by far the largest estimated coefficient explaining variation in observed ambient N pollution. This control variable in our model is extremely important for identification, as evidenced by the fact that the CC treatment variable of greatest interest is only significant in the subset of basins where we are able to control for upstream pollution levels. Without this independent variable the econometric model is unable to detect a clear signal from the noise about the effect of cover crop adoption on ambient total N levels.

As the overall CC adoption rate has increased in recent years we present nascent evidence to support 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 the estimated effect 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 practices to reduce N loss. Because cover crops introduce many new management considerations that increases management complexity, it should not be surprising that other coincident changes may occur that, together, reduce in-stream pollution readings.

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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 HUC8 sub-basin, 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 HUC8s 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 HUC8s 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, HUC8s 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 Fig. B.1 by the station named DE-01. The pink-shaded monitoring basin in panel (1) consists of two HUC8s, 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 HUC8 at the very bottom of the pink-shaded basin because the stream merges with the top HUC8 at the mouth of the hydrologic unit where no monitoring station is located. Hence, panel (3) of Fig. B.1 depicts how the HUC8 at the bottom of 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 given HUC8, measure only a small share of the total area drained by the HUC8. Instead, such stations measure upstream HUC8s in the monitoring basin to a greater extent than the HUC8 where they are physically located. In other words, stations capture less than 50% of the HUC8 where is located, but measure the entirety of the other upstream HUC8s in the basin. In this case, a site is manually reassigned to (associated with) the upstream HUC8 and reassigned the HUC8 where the station is located to the next downstream monitoring basin. An example of such an error is shown in Fig. B.2 with the 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 HUC8. Thus, as in panel (3) of Fig. B.2, the station EOA-01 is reassigned to the upstream HUC8 in which the reassigned station is named EOA-01n on the map, and we reassign the original HUC8 where EOA-01 is located to the next downstream monitoring basin shaded with beige. After the adjustment of these measurement errors, we obtain a total of 158 monitoring basins with one monitoring station for each basin in Fig. 3. The red dots represent the water monitoring stations. The yellow and blue shaded areas stand for basins with and without upstream pollution measurements, respectively.

B Appendix graphs

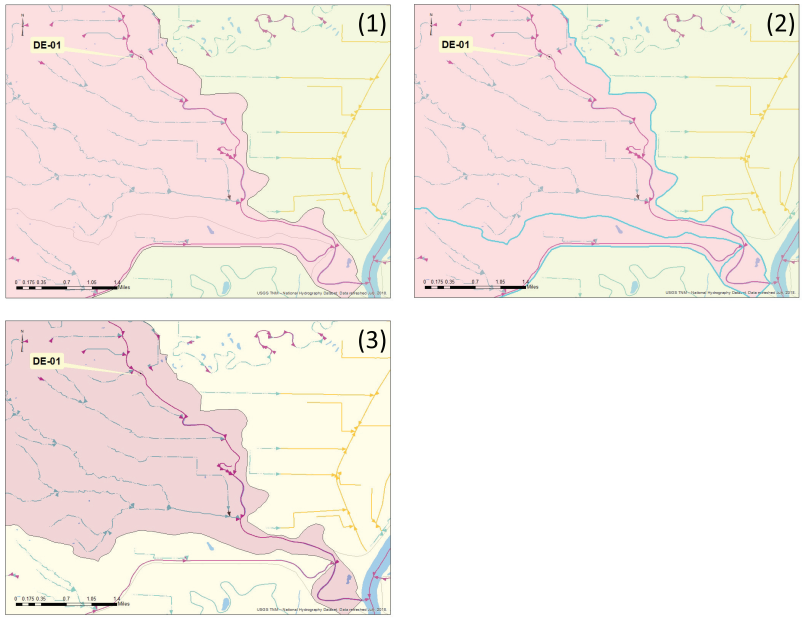

Figure B.1: Maps of the first type of measurement error

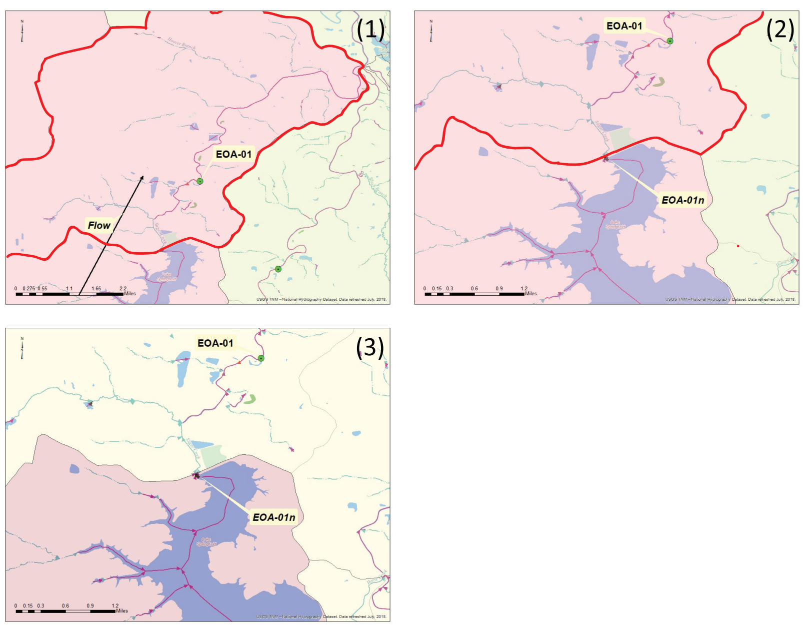

Figure B.2: Maps of the second measurement error