Water Quality and the Conservation Reserve Program: Empirical Evidence from the Mississippi River Basin*

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1 Introduction

Nearly 1.2 billion acres of the 2.3 billion acres in the United States are dedicated to agriculture (Bigelow and Borchers 2017). In 2023, cropland, pasture, rangeland, and grazed forestland contributed over $1.5 trillion to the nation's gross domestic product (Kassel et al. 2024). The extensive agricultural activity and its intensive impact on the land have made agricultural runoff the primary cause of water quality impairment in our nation's surface waters. Ribaudo et al. (2008) estimate that non-point contributes over 90% of the nitrogen in two-thirds of impaired watersheds. The major agricultural stressors to water quality are soil erosion, nutrient runoff, bacteria from livestock manure, and pesticides. Each year, around 500,000 tons of pesticides, 12 million tons of nitrogen, and 4 million tons of fertilizer are used on crops across the United States (Environmental Protection Agency (EPA) 2023). As a result, over half of the country's surface waters (more than 700,000 miles of waterways), fail to meet quality standards for swimming, recreation, aquatic life, fish consumption, or as drinking water sources.

Excess nutrients lead to an overabundance of algae and low levels of oxygen in waterways. This eutrophication process make the surface waters unsustainable for aquatic life and can lead to "dead zones" with degraded marine populations and habitat loss (NOAA 2024). This has costly economic and social welfare implications for communities along the water (Rabotyagov et al. 2014). Hypoxic conditions have been tied to losses in productivity, particularly for fisheries (Dodds et al. 2009; Huang et al. 2012; Mistiaen, Strand and Lipton 2003), lost recreation opportunities (Lipton and Hicks 2003; Massey, Newbold and Gentner 2006), lower housing prices (Wolf, Gopalakrishnan and Klaiber 2022; Wolf, Klaiber and Gopalakrishnan 2022; Zhang, Phaneuf and Schaeffer 2022; Mamun et al. 2023), and impaired human health outcomes from foodborne and respiratory illnesses (Grattan, Holobaugh and Morris Jr 2016; Kouakou and Poder 2019) and blue-baby syndrome (Knobeloch et al. 2000).

There has been significant abatement investment for point-source pollutants. Since the Clean Water Act, surface water quality has generally experienced improvements: fecal coliforms, total suspended solids, and the share of waters unsafe for fishing have experienced large declines in the past half-century (Keiser and Shapiro 2019a,b). However, not all forms of surface water pollution are decreasing. Agricultural activities, which are mostly outside the scope of Clean Water Act regulations, release large amounts of nutrients such as nitrogen and phosphorus into the environment. As a result, trends in nutrient pollution remain relatively stable, and in some cases, certain pollutants are on the rise (Shapiro 2022; Rossi et al. 2023). Abatement efforts for non-point solutions have been limited and largely voluntary.

Perhaps the largest effort to tackle nonpoint source pollution in the U.S. is the Conservation Reserve Program (CRP). With an annual budget of $1.8 billion, the CRP is one of the largest voluntary private-lands conservation program in the world in terms of scale and spending. As of 2023, there were nearly 23 million acres enrolled in the conservation program (1% of land in the US). The CRP was started in 1985 to remove environmentally sensitive land from production and protect topsoil from erosion. Producers receive an annual payment to retire their land from cropping and establish resource-conserving plant species (e.g. cover crops) for a duration of 10-15 years. The CRP environmental benefits include wildlife habitat provision, air quality benefits, carbon sequestration, soil health, and improved surface/ground water quality. CRP improves water quality in two ways: 1) by decreasing nutrient runoff through land retirement, and 2) by increasing vegetation (i.e. grasslands, wetlands, riparian buffers) to intercept nutrients before they enter waterways. Despite the scope and budget of CRP, relatively little research has investigated the environmental impacts of the program. Accurately characterizing how incentive programs like CRP catalyze land use change and subsequently improve water quality is critical given policymakers' continued reliance on such programs to mitigate agricultural non-point source water pollution.

Here we address this gap by assessing the water quality impacts of CRP in the Mississippi River Basin (MRB). We estimate how CRP acreage impacts water quality outcomes in the MRB from 2000-2018 at the subwatershed (HUC-12) level. We leverage CRP contract data and recently harmonized nutrient readings (Krasovich et al. 2022) to better understand how land conservation impacts surface water quality. We start by using a panel model with HUC-8, year, and month fixed effects to understand the relationship between the share of land in CRP and water nutrient outcomes. In a subsample of counties that ever receive a CRP contract, we find that increasing the share of agricultural land in CRP is associated with decreased phosphorous and increased ammonia levels. These mixed results highlight the downsides of our panel approach: CRP is more likely to occur in degraded watersheds with already low water quality and the decision to enroll in CRP is endogenous to individual producers and likely correlated with other agricultural practices that aim to improve water quality. Moreover, the recent additionality literature suggests that many producers would be in relatively non-intensive land uses without program payments (Rosenberg and Pratt 2024).

To find a causal estimate we use an instrumental variables approach. We exploit variation in the national CRP acreage cap as well as changes in local commodity prices to explore random shifts in CRP enrollment. With this approach, we find that increases in CRP land share leads to significant decreases in phosphorus, nitrogen, and ammonia at the subwatershed level. We estimate that a 1% increase in CRP agricultural land share reduces phosphorous levels by -0.03 mg/L (15%), total nitrogen levels by -0.28 mg/L (13%), and ammonia by -0.01 mg/L (5%). These results highlight the importance of CRP in determining water quality outcomes while making significant contributions to the broader literature.

First, we contribute to the broader understanding of how the CRP impacts water quality. This strand of the literature relies on process-based models that leverage physical mechanisms governing nutrient transport to simulate how changes in land cover translate into changes in water quality (FAPRI 2007; Schilling and Spooner 2006; Schilling et al. 2011; Melland, Fenton and Jordan 2018).The USDA-FSA's reporting on the environmental benefits of CRP still relies on a process-based model developed by the Food and Agricultural Policy Research Institute (FAPRI) FAPRI (2007). These models allow for high levels of spatial specificity but are highly data intensive and rely crucially on assumptions made about the land use impacts of CRP (Schwarz et al. 2006; Broussard and Turner 2009). We employ a reduced-form, data-driven approach to estimate program impacts based on variation in CRP enrollment within a given watershed over time, avoiding the need to make assumptions regarding land use in counterfactual without-CRP scenarios. Furthermore, empirical approaches allow for the estimation of program impacts based on the actual land use of CRP enrolled land (e.g., riparian buffers, shrubs, grasses) rather than assuming all CRP enrolled land utilize only a few differing cover types.

Second, we explore the net costs and benefits of the CRP in relation to water quality. Some of the earliest studies modeled the economic benefits of CRP at a regional level using a non-market valuation approach (Ribaudo 1989a,b; Feather and Hellerstein 1999; Fleming 2004). In a similar vein, Hansen (2007) estimate the soil erosion benefits of the CRP and estimate that resulting benefits total \$1.32 billion per year, yet find that the program fails a cost benefit analysis. Building on this work, Keiser (2019) uses upstream nutrient concentrations as an instrument for erosion as well as more recent water-based recreation benefits to find that CRP benefits may outweigh the costs by 2 to 1. Although early studies suggested that the CRP might not be cost-effective, access to higher quality data plus improved methodology has allowed us to better identify the ecosystem services of land conservation, indicating that CRP is an efficient policy instrument.

Third, we contribute to the literature on the relationship between agricultural practices and ambient water quality. One segment of the literature measures the extent that crop and livestock production impair water quality. (Paudel and Crago 2021) finds that increasing cropland fertilizer use by 10% leads to a 1% increase in nitrogen and phosphorus levels for local watersheds. (Raff and Meyer 2022) estimate that an additional CAFO operation at the HUC8 has a similar sized effect on phosphorous and ammonia levels (1.7% and 2.7% increases respectively). The other half of the literature examines the effectiveness of different policy instruments to reverse elevated nutrient levels. There is evidence that farm-level practices such as nutrient management plans, cover crop adoption, and wetland restoration are associated with reductions in ammonia concentrations (Skidmore, Andarge and Foltz 2023; Hsieh and Gramig 2023; Karwowski and Skidmore 2023). Liu, Wang and Zhang (2023) find that voluntary conservation on working agricultural lands have mixed effects on downstream nutrient concentrations: Environmenal Quality Incentive Program (EQIP) payments are associated with reduced nitrogen concentrations but increased phosphorous levels. Our assessment of the water quality impacts of CRP, constitutes an important advancement in the conservation program and water quality literature.

The paper continues as follows: section 2 provides background, sections 3 and 4 describes our methods and data, section 5 presents the results, and section 6 concludes.

2 Background

Established by the Food Security Act of 1985, the Conservation Reserve Program (CRP) is the USDA's primary program for retiring environmentally sensitive land from crop and pastureland production. Various land retirement programs had existed in the U.S. before CRP, going back to the 1930s, but were typically focused on short-run commodity production control, rather than environmental protection (Hellerstein 2015; Ferris and Siikamäki 2009). The early CRP was primarily designed to reduce soil erosion and surplus commodity production, though water quality and wildlife habitat were secondary environmental goals (Barbarika 2021). Through the years the emphasis has broadened, with more prominent focus on wildlife protection, as well as water and air quality (Hellerstein 2015).

In its current form, the CRP is comprised of three main components. The General Signup subcomponent is the oldest of the three and is characterized by a competitive auction mechanism. Specifically, the General Signup is a reverse auction wherein offers are ranked according to the Environmental Benefits Index (EBI), and those offers above a specific EBI threshold are accepted in a given Signup. Fields being offered in General Signups must either have an erodibility above a certain threshold or must fall within a designated Conservation Priority Area (CPA); and must have been cropped for a specified number of years prior to enrolling or must have been enrolled in CRP during that same time span. EBI scores associated with offers to General Signup depend on the inherent characteristics of the offered parcels, the land cover to be implemented if accepted into the program, and a rental rate proposed by the landowner making the offer. Rental rates are capped at a level depending on the average dryland cash rental rate in the county of the offered parcel, as well as a field-specific adjustment for soil productivity (Rosenberg and Pratt 2024).

The Continuous Signup was introduced in 1996 (Barbarika 2021) and is currently the largest part of the CRP in budgetary terms (U.S. Department of Agriculture 2023). In contrast to the General Signup, which has limited enrollment periods, Continuous Signup is open for enrollment all year long. Eligibility requirements for Continuous Signup tend to be stricter, but parcels are typically enrolled automatically into the program if these are satisfied (Hellerstein 2015). The Continuous Signup places great emphasis on wildlife habitat and water quality. Several practices targeted to improving water quality in particular, such as filter strips, riparian buffers, grass waterways and wetland restoration, are funded primarily through Continuous Signup. Though these practices tend to be more expensive to implement, per acre payments through Continuous Signup tend to be higher than through General Signup. This is in part reflects additional payments not typically provided in General Signup, such as one-time incentive payments received at signup and practice incentive payments (U.S. Department of Agriculture 2024). It also reflects the concentration of Continuous Signup in regions with higher valued cropland, though recent research has shown that many rejected CRP offers subsequently enroll in Continuous Signup (Rosenberg and Pratt 2024). The Conservation Reserve Enhancement Program (CREP), which falls within Continuous Signup, involves partnerships between USDA and States, in which individual States help determine local priorities. Many past and ongoing CREP projects have emphasized enrollment of water quality practices.

Enrollment in CRP has varied quite a bit since its inception (see Figure 1). Acres enrolled increased rapidly in the first few years, with multiple General Signups starting in 1986, reaching 33 million acres by 1990 (Barbarika 2021). As soon as it was introduced, acres enrolled through Continuous Signup grew steadily. In contrast to General and Continuous Signup, Grasslands CRP is not characterized by land retirement, but by enrollment of existing grasslands in threat of conversion to other land uses (U.S. Department of Agriculture 2024). Consequently, though Grasslands CRP is characterized by lower payments per acre than either other Signup, enrollment in terms of acres has grown rapidly and is the largest portion of the program by acres as of October 2023 (U.S. Department of Agriculture 2023).

[Figure 1 about here.]

The CRP is likely to impact water quality through several mechanisms. Land cover change from productive uses to conservation covers will likely reduce soil erosion, surface runoff, and leaching of nutrients to groundwater. Compared to annual commodity crops, land covers commonly installed during CRP contracts, such as perennial grasses, use minimal amounts of nitrogen and phosphorus, limiting the amount available for loss in sedimentation, leaching and runoff (FAPRI 2007). Vegetation from CRP can also serve to absorb and utilize nutrients before they enter water bodies, and wetlands restored through CRP can lead to nitrogen removal by increasing levels of denitrification (FAPRI 2007). CRP impacts that depend on land cover change depends crucially on the counterfactual land use that would have been implemented in the absence of the program (Roberts and Lubowski 2007; Rosenberg and Pratt 2024). Further, many CRP practices such as riparian buffers and filter strips are designed to help improve water quality largely by absorbing nutrients (U.S. Department of Agriculture 2023). These practices are largely funded by Continuous Signup CRP and Conservation Reserve Enhancement Program (CREP) projects that put special emphasis on addressing water quality concerns (U.S. Department of Agriculture 2023).

Across regions, and even within a farm, different CRP projects may exhibit different levels of potential to improve water quality. Through its several components and initiatives, the CRP uses multiple policy levers to target projects likely to improve water quality. First is the EBI, which awards variable points based on expected influence of particular fields on water quality and soil erosion when conserved (U.S. Department of Agriculture 2021). Together, estimated potential impacts on water quality and soil erosion account for a major portion of the EBI formula. Across components, CRP uses CPAs to target funds towards regions for higher emphasis. Further, some initiatives within Continuous Signup such as the Clean Lakes, Estuaries and Rivers Initiative (U.S. Department of Agriculture 2022), and specific state CREP projects, have explicit water quality emphasis, incentivizing practices aimed specifically at reducing agricultural impacts on water quality.

Despite the continued focus on water quality, there has been limited direct empirical investigation of the impacts of CRP on water quality. To date, most water quality assessments of CRP have relied primarily on process-based models (e.g., FAPRI 2007). Process-based models allow for precise estimates of water quality impacts, with high levels of spatial specificity. However, these models are highly data intensive, and rely crucially on assumptions made about the land use impacts of programs like CRP (Schwarz et al. 2006). For example, FAPRI (2007) assume that, in their without-CRP scenario, land uses would reflect the mix of crop rotations and tillage practices used within the State as a whole. In general, model-based estimates of the impacts of land use change and best management practices do not always correspond with empirical ones (Schilling et al. 2011). As Lintern et al. (2020) explain in a review of many studies on the impacts of best management practices on water quality, the majority of studies have found significant improvements to water quality from BMPs. However, as the authors find, studies relying on predictions from models are much more likely than those based on observations to find detectable improvements in water quality.

Schilling and Spooner (2006) is a notable exception, using empirical modeling to show that an increase in CRP land in an Iowa watershed led to a decrease in downstream nitrate levels, in contrast to an increase in an adjacent watershed without an increase in preserved land. However, this study is relatively small scale, comparing two local watersheds. More recently, due to availability of data from the Water Quality Portal (Read et al. 2017), many studies have allowed for more extensive empirical analysis of water quality impacts of policy (e.g., Hsieh and Gramig 2023; Raff and Meyer 2022; Paudel and Crago 2021; Skidmore, Andarge and Foltz 2023). Still, empirical measurement poses significant identification challenges. Though the impacts of management practices and land cover change have been established at field and micro-catchment scales, difficulties such as complex data requirements and measurement time lags may make measured impacts less easily detected at large scales (Melland, Fenton and Jordan 2018). In larger catchment zones, it can take years to detect significant impacts of practices on water quality (Melland, Fenton and Jordan 2018; Meals, Dressing and Davenport 2010). Keeping these challenges in mind, the following study is an attempt to estimate similar impacts for the Conservation Reserve Program.

3 Empirical Model

We aim to estimate the effects of CRP enrollment on downstream surface water quality. We first estimate equation (1), a two-way fixed effects specification. Here, $Y_{i,t,m}$ is the average measured concentration of phosphorus, nitrogen, or ammonia for metering stations located in subwatershed (HUC-12) i, in the subbasin (HUC-8) j, taken in month m and year t. The explanatory variable of interest is $CRP_{i,t}$, which represents the percent of agricultural land enrolled in CRP in subwatershed i and year t. Note that since $CRP_{i,t}$ is annual and $Y_{i,t,m}$ is sub-annual, there can be multiple observations corresponding with a particular level of CRP enrollment. In general, the data are an unbalanced panel. We also include a vector of variables affecting water quality outcomes (e.g., monthly precipitation and temperature), $X_{i,t,m}$. We also include a rich set of fixed effects, including HUC-8 fixed effects, α_j, to account for unobserved time-invariant factors at the subbasin level; and year and month of measurement fixed effects, δ_t and θ_m, to reflect impacts of seasonality on water quality.

$$Y_{i,t,m} = \beta * CRP_{i,t} + \gamma * X_{i,t,m} + \alpha_j + \delta_t + \theta_m + \varepsilon_{i,t,m}. \tag{1}$$

Here, a sufficient condition for β is strict exogeneity, which requires that $E[CRP_{i,s,}\varepsilon_{i,t,m}] = 0, s,t = 1,2,\ldots,T$ (Wooldridge 2010). In other words, levels of CRP enrollment in any period cannot be correlated with the idiosyncratic error, conditioned on controls and fixed effects in the specification above. For example, this includes contemporaneous effects, so that an increase in CRP enrollment from one year to the end cannot be correlated with other factors related to water quality. It also means that CRP enrollment cannot be correlated with unobserved factors related to water quality in other years. For example, it requires that higher ammonia levels in one year does not increase CRP enrollment in a later year.

However, it is possible that the assumption of strict exogeneity may fail and that estimates will be biased without a valid instrument. Endogeneity could come from multiple avenues. First, it could take the form of higher a likelihood of CRP enrollment by farmers that are environmentally conscious and take a number of actions to improve water quality apart from CRP adoption. In this case, a naive model would overestimate the impact of CRP on water quality. Second, there may be reason to believe that trends in practices or land use change are correlated with enrollment in CRP or exits from the CRP.

Thus, we also explore an alternative identification strategy, employing instrumental variables that serve as exogenous sources of variation in CRP enrollment. A valid instrument $Z_{i,s}$, requires that $E(Z_{i,s}\varepsilon_{i,t,m}) = 0, s,t = 1,2,\ldots,T$ (Wooldridge 2010). Here, $\varepsilon_{i,t,m}$ is the error term from the second stage, where the first stage involves regressing $CRP_{i,t}$ on $Z_{i,s}$, as well as the same controls in (1). Intuitively, the identifying assumption requires that the instrument only affects the outcome through the endogenous variable. In our case, it must be that the instruments only affect water quality through CRP enrollment.

We then estimate two-stage models for each nutrient including two instrumental variables. First, we use an instrument that interacts the federal CRP acreage cap in a particular year with subwatershed agricultural acreage in 1985. The first instrument exploits supply side variation in eligibility for CRP. The CRP acreage cap is a valuable source of variation, since it was set anywhere between zero and five years ago. Multiplied by agricultural acreage, this represents variation in potential acres that could be enrolled in CRP, unrelated to any specific time-varying factors. Second, we use a Laspeyres price index that weights prices based on proportions of the 10 major commodities in a county (Li, Miao and Khanna 2019). The idea of this index is that relative changes in prices will impact landowner's desire to enroll in CRP, and provides a source of exogenous variation since commodities will move in different directions based on global market factors, in ways that are not correlated with water quality fluctuations.

4 Data

To characterize the relationship between CRP and water quality outcomes, we link novel contract-level CRP data to watersheds throughout the MRB to generate a temporally variable and spatially explicit measure of land conservation enrollment over the 2000 to 2018 time period. The merging of these data sources is a primary component of this study's important contributions to the water quality and conservation program literature, which has typically aggregated conservation program enrollment decisions at spatial units (e.g., counties) which do not reflect how water moves across the landscape Liu, Wang and Zhang (2023).

CRP contract data, which are collected by the USDA-FSA in their administration of the program, detail the length, conservation practices adopted, and county of all land enrolled in CRP. The MRB has more than 3.8 million unique CRP contracts over the 2000 to 2018 time period. We aggregate CRP contract data to the watershed level using hydrologic unit code (HUC). HUCs are watershed boundaries defining 'the areal extent of surface water drainage' developed in the U.S. Geological Survey's (USGS) Watershed Boundary Dataset (U.S. Geological Survey 2023). The HUC dataset divides the country into

22 regions (2-digit HUC), 245 subregions (4-digit HUC), 405 basins (6-digit HUC), approximately 2,400 subbasins (8-digit HUC), approximately 19,000 watersheds (10-digit HUC), and approximately 105,000 subwatersheds (12-digit HUC). HUCs are hierarchical consisting of 2 additional digits for each level in the hydrologic unit system. We opt to aggregate CRP land enrollment to the subwatershed (HUC-12) level, which are the most spatially disaggregated watershed measurement available for the MRB. There are approximately 32,000 subwatersheds within the MRB.

Unfortunately, only a small percentage of the 3.8 million CRP contracts within the MRB contain a subwatershed (HUC-12) identifier. In some cases, the contract data contain a subbasin or watershed identifier but no subwatershed identifier. In most cases, the subwatershed field within the contract data is missing. Fortunately, the contract data include several identifiers which we leverage to estimate the precise geography of each CRP contract within the MRB. Specifically, contract data include a farm identifier, contract identifier, and in some cases a tract identifier which are all unique within a given county. Farm and tract identifiers within the CRP contract data are also present in USDA-FSA's common land unit (CLU) geospatial data. CLUs are individual farming parcels which is the smallest unit of land which has a permanent, contiguous boundary, common land cover/management, common owner, and common producer association. USDA-FSA uses CLU data to administer farm programs and regularly updates the data to reflect changes in land ownership, management, etc. We spatially join 2008 and 2022 CLU data to USGS's Watershed Boundary Dataset to associate farm and tract identifiers within a given county to their respective subwatershed. We leverage CLU data from both 2008 and 2022 to account for potential changes in CLU data due to evolving land ownership or management.

Aggregating CRP contract data at the subwatershed and year level yields a panel dataset tracking CRP enrollment over time within a given subwatershed. We opt to focus our analysis on only those subwatersheds that ever have any land enrolled in CRP i.e., ever-treated. Given the relatively significant variation in the size of subwatersheds within the MRB, we transform our primary explanatory variable of interest, land enrolled in CRP, to a percentage of total agricultural land within the subwatershed enrolled in CRP. To do so, we use remotely sensed land use data which we aggregate at the subwatershed-year level. We calculate the share of agricultural land enrolled in CRP using land use classifications from the Land Change Monitoring, Assessment, and Projection 1.3 (U.S. Geological Survey 2022). The USGS provides 30-meter spatial resolution land use data for the conterminous United States from 1985-2021. The agricultural land use category captures land used in the production of food, fiber, and fuels: cultivated and uncultivated croplands, hay lands, orchards, vineyards and confined livestock operations. We calculate shares based on agricultural land use from 1985, prior to the advent of the modern CRP, to ensure that the denominator does not vary based on CRP enrollment as land enrolled in CRP may no longer be classified as agricultural. Figure 2 demonstrates the spatial heterogeneity in CRP within the Mississippi River Basin by plotted average percentage of agricultural land, as of 1985, enrolled in CRP at the subbasin level (8-digit HUC). We map CRP enrollment at the subbasin level rather than the subwatershed level for visual simplicity given that the Mississippi River Basin contains more than 30,000 subwatersheds.

[Figure 2 about here.]

Our primary outcome variables of interest are measures of water quality observed at monitoring stations. Specifically, we use SNAPD (Krasovich et al. 2022) which harmonizes readings in the Water Quality Data Portal across the 226 distinct water quality monitoring authorities. SNAPD pulls station-level readings for over 100,00 sites and creates a comprehensive sample of measurements for nitrogen, ammonia, and phosphorus that are comparable across time and space. SNAPD allows us to compare water quality across multiple decades (2000-2018) for the Mississippi River Basin. Our main outcomes are concentrations of total nitrogen, ammonia, and phosphorous. [1] We use these nutrient concentrations since they represent the most comprehensive water quality measurements in the data and to allow us to make comparisons within the literature (Hanrahan et al. 2021; Liu, Wang and Zhang 2023; Skidmore, Andarge and Foltz 2023). Concentration values are standardized to units of milligrams per liter (mg/L). We take the average of all water quality readings in the same subwatershed for a particular month-year combination to allow us to estimate the broad-level effects of the CRP as well as to create a more balanced panel.

Table 1 presents summary statistics for the data used to estimate the impact of CRP enrollment on water quality outcomes. Table 1 also includes summary statistics for the variables used to instrument for subwatershed CRP enrollment. Specifically, we instrument using the national CRP acreage cap interacted with subwatershed agricultural acreage as of 1985 as well as a commodity price index. The national CRP acreage cap is determined by Congress and has varied between 24 and 39.2 million acres between 2000 and 2018. The price index is a Laspeyres price index calculated following methods outlined in Li, Miao and Khanna (2019) and is based upon deflated state-level received prices and production levels for 10 major crops using 2002 as the base year. The number of observations varies for our outcome variables of interest, concentrations of phosphorous, ammonia, and nitrogen, as not all water quality monitoring stations within the basin sample in every month and year over the 2000 to 2018 time period.

[1] Specifically, we use the variables Ammonia (filtered), Total Nitrogen (filtered), and Total Phosphorus (filtered). "Total" indicates that a sample contains several nutrient chemical forms, such as ammonia (NH3) and organic nitrogen (N), and that these nutrient chemical forms are added to find the total concentration of the the nutrient's elemental form (total nitrogen). "Filtered" refers to the sample fraction of the observation. In a field or lab setting, filtration is the physical process done used to separate the particulate and aqueous fractions of a water sample. Filtered results will include the amount of nutrient associated with just the aqueous fraction, and not the particulate fraction. We focus on readings that are within the same sample fraction to ensure comparability of observations.

[Table 1 about here.]

5 Results

In this section, we present results generated by estimating the equation outlined in equation 1 to understand how CRP enrollment impacts concentrations of phosphorous, nitrogen, and ammonia within the waterways of the Mississippi River Basin.

Table 2 presents regression results for the non-instrumental variable specification of equation 1. Results suggest that increasing enrollment of agricultural land in CRP decreases concentrations of phosphorous and nitrogen in surface water, although the coefficient estimate for nitrogen is not statistically significant. Alternatively, model results counterintuitively indicate that increasing enrollment in CRP increases surface water concentrations of ammonia. However, as discussed in section 3 potential endogeneity between water quality outcomes and CRP enrollment may impact these estimated coefficients and bias them towards zero. Results indicate a negative relationship between monthly average temperatures and pollutant concentrations and a positive relationship between monthly total precipitation and pollutant concentrations for all pollutants except ammonia.

[Table 2 about here.]

Table 3 presents results estimating equation 1 using an instrumental variable (IV) specification to address potential endogeneity between water quality outcomes and CRP enrollment. Results from the first stage of IV specification are presented in table 4 where the reported F-statistic indicates that our instrumental variables reject the null hypothesis of weak instruments (Stock, Wright and Yogo 2002).

IV regression result parameters estimating the relationship between percentage of subwatershed agricultural land enrolled in CRP and concentrations of phosphorous, nitrogen, and ammonia are all negative and statistically significant. This result suggests that increasing enrollment in CRP decreases surface water concentrations of phosphorous, nitrogen, and ammonia. A one percentage point increase in subwatershed CRP enrollment, which at the mean of subwatershed CRP enrollment is equal to 134 acres, is associated with reductions of 0.0320, 0.2842, and 0.0139 mg/L for phosphorous, nitrogen, and ammonia, respectively. Evaluating these coefficient estimates at the mean of pollutant concentration levels (see table 1) indicates that a one percentage point increase in subwatershed CRP enrollment decreases subwatershed pollutant concentration levels by 15%, 13%, and 5% for phosphorous, nitrogen, and ammonia, respectively.

[Table 3 about here.]

[Table 4 about here.]

Coefficients estimates for control variables suggest a negative relationship between monthly average temperature and pollutant concentrations. Meanwhile, consistent with the literature we find a positive relationship between precipitation and pollutant concentrations for all pollutants except ammonia.

Comparing results between tables 2 and 3 demonstrates the potential bias introduced by the potential endogeneity between CRP enrollment and water quality outcomes. Specifically, the relatively smaller in magnitude, or positive, coefficient estimates from the non-IV specification suggest that this endogeneity may bias estimates towards zero indicating that the bias introduced by subwatersheds with lower quality may attract more CRP enrollment may outweigh bias introduced by landowners already enrolled in CRP implementing additional water quality enhancing production practices (e.g., cover cropping).

6 Conclusion

Agri-environmental policy-making aims to diminish the environmental costs of agricultural production. This paper investigates the effects of one of the world's largest and longest running agri-environmental policies, the Conservation Reserve Program which pays farmers in the U.S. to take previously cultivated agricultural land out of production. Specifically, we empirically estimate how land enrolled in CRP impacts water quality outcomes. We leverage novel contract level data to summarize CRP enrollment decisions at the subwatershed level and econometrically relate these enrollment decisions to observed water quality outcomes using an instrumental variable model.

Our results indicate that increases in CRP enrollment at the subwatershed decrease the concentration of several key pollutant associated with agricultural production. Moreover, we find relatively large effect sizes indicating that even relatively small changes in CPR enrollment can have a large impact on water quality outcomes. These results have significant policy relevance as they demonstrate the magnitude of the potential environmental benefits associated with expanding agricultural land retirements programs like CRP.

Finally, CRP is just one example of current agri-environmental policies in the use in the U.S. Many other state and federal programs (e.g., the Environmental Quality Incentives Program) also aim to minimize the environmental costs of agricultural production. While this paper focuses solely on CRP, additional research is needed to understand how agri-environmental policy-making as a whole impacts water quality outcomes and environmental outcomes more broadly.

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Figures

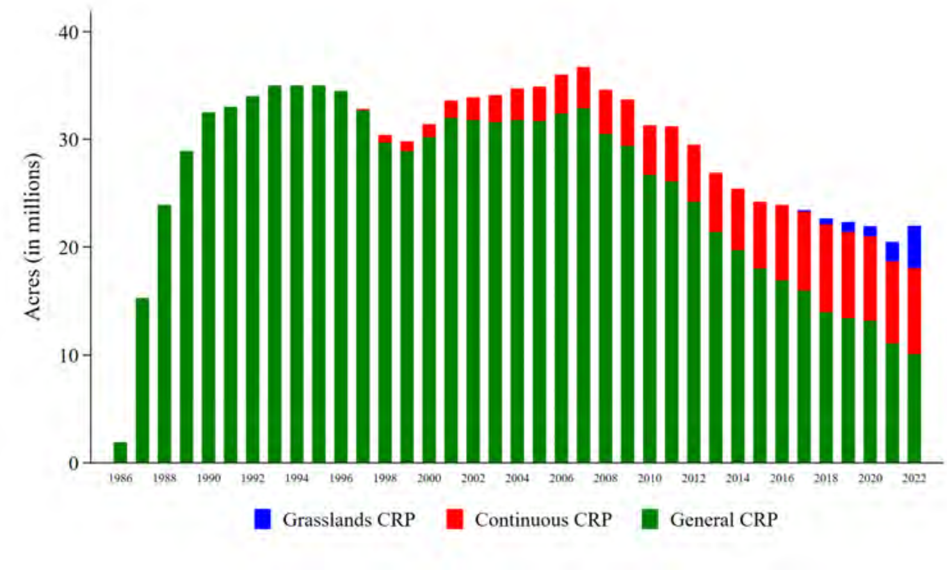

Figure 1: Acreage Enrolled in Differing CRP Subprograms, 1986-2022
Source: https://www.fsa.usda.gov/programs-and-services/conservation-programs/reports-and-statistics/conservation-reserve-program-statistics/index

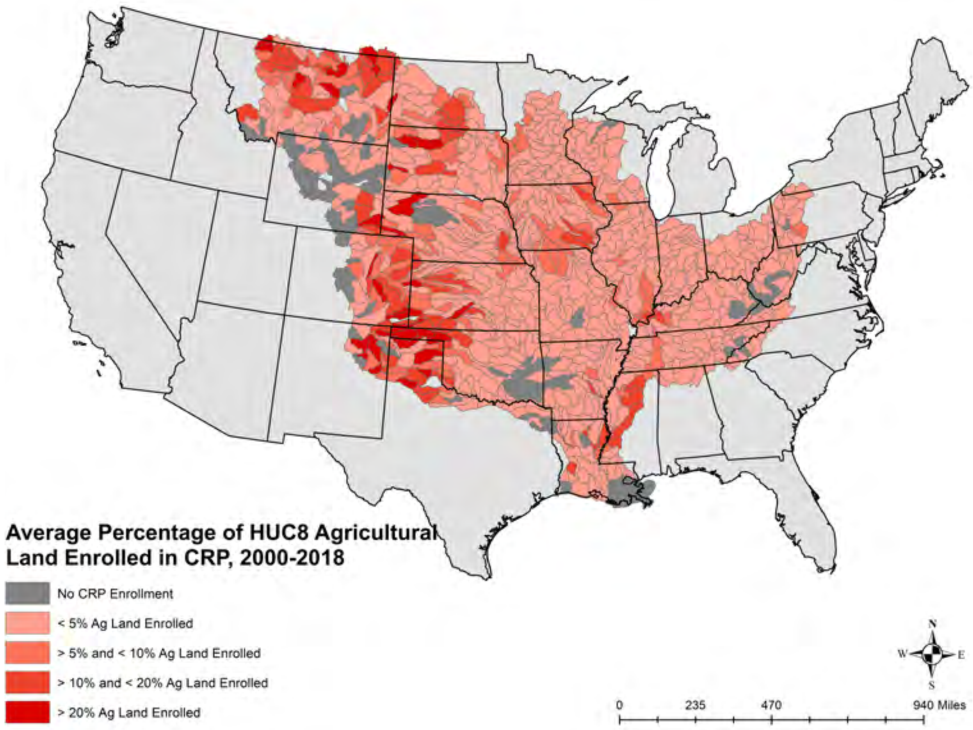

Figure 2: CRP Enrollment within Mississippi River Basin

Tables

Table 1: Summary Statistics

Statistic	N	Mean	St. Dev.	Min	Max
CRP enrollment (Percent of subwatershed ag land)	322,169	3.246	5.455	0.000	74.623
Temperature (Celsius)	322,169	14.102	9.148	−18.608	33.921
Precipitation (mm)	322,169	89.756	60.606	0.000	625.425
Phosphorous (mg/L)	205,024	0.209	0.302	0.006	3.560
Nitrogen (mg/L)	66,139	2.139	2.525	0.051	25.330
Ammonia (mg/L)	119,731	0.283	0.415	0.002	6.820
Subwatershed ag land, 1985 (thousands of acres)	322,169	13.492	8.116	0.012	363.420
Laspeyres Commodity Price Index	269,524	1.256	0.415	0.000	2.397

Table 2: Panel Regression Results

	Dependent variable:		
	Phosphorous	Nitrogen	Ammonia
	(1)	(2)	(3)
Percent of subwatershed ag land in CRP	-0.0018^{*}	-0.0026	0.0016^{**}
	(0.0011)	(0.0055)	(0.0008)
Temperature	-0.0010	-0.0214^{**}	-0.0044^{***}
	(0.0007)	(0.0099)	(0.0009)
Precipitation	0.0004^{***}	0.0015^{***}	-0.0001^{***}
	(0.00003)	(0.0003)	(0.00003)
HUC8 Fixed Effect	Yes	Yes	Yes
Year Fixed Effect	Yes	Yes	Yes
Sampling Month Fixed Effect	Yes	Yes	Yes
Observations	205,024	66,139	119,731
R^2	0.2089	0.4312	0.1061
Residual Std. Error	0.2688	1.9138	0.3931

Notes: * p<0.1; ** p<0.05; *** p<0.01. Standard errors clustered at the HUC-8 level.

Table 3: Instrumental Variable Panel Regression Results

	Dependent variable:		
	Phosphorous	Nitrogen	Ammonia
	(1)	(2)	(3)
Percent of subwatershed ag land in CRP	-0.0320^{***}	-0.2842^{**}	-0.0139^{*}
	(0.0070)	(0.1409)	(0.0076)
Temperature	-0.0009	-0.0295^{**}	-0.0057^{***}
	(0.0007)	(0.0142)	(0.0008)
Precipitation	0.0005^{***}	0.0018^{***}	-0.0002^{***}
	(0.00003)	(0.0003)	(0.00003)
HUC8 Fixed Effect	Yes	Yes	Yes
Year Fixed Effect	Yes	Yes	Yes
Sampling Month Fixed Effect	Yes	Yes	Yes
Observations	174,385	55,127	99,744
R^2	0.0290	0.1672	0.0698
Residual Std. Error	0.2859	2.2898	0.3677

Notes: * p<0.1; ** p<0.05; *** p<0.01. Standard errors clustered at the HUC-8 level.

Table 4: Instrumental Variable Panel Regression Results, First Stage

	Dependent variable:
	Percent of Subwatershed in CRP
CRP Nat. Acreage Cap X Baseline Subwatershed Ag Acreage	-2.4701^{***}
	(0.3893)
Commodity Price Index	0.6171
	(0.4139)
Temperature	-0.0161^{**}
	(0.0073)
Precipitation	-0.0002
	(0.0002)
HUC8 Fixed Effect	Yes
Year Fixed Effect	Yes
Sampling Month Fixed Effect	Yes
Observations	269,524
R^2	0.4209
Residual Std. Error	4.0060
F Statistic(full)	295.201*** (df = 662; 268861)
Note:	*p<0.1; **p<0.05; ***p<0.01